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Learning from the Past and Preparing for the Future: Cases and Tools for Cultural Heritage during Disasters

PhD Program in Analysis and Management of Cultural Heritage

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By

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To my family

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Publications

This thesis is based on the following articles of which one is co-authored:

1. Kumar, P. Crowdsourcing to Rescue Cultural Heritage during Disasters: A Case of Florence Flood 1966. *International Journal for Disaster Risk Reduction*. Volume 43, 2020, 101371. DOI: 10.1016/j.ijdrr.2019.101371
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4. Kumar P."Cultural Heritage during Disasters," at *University of Manchester*, Lecture to the Students of Master of Disaster Management Programme, 2019.
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6. Kumar P. "Learning from the Past and Preparing for the Future: Cases and Tools in Cultural Heritage Disasters," at *University of Copenhagen*, Research Presentation at the Copenhagen Center for Disaster Research, COPE Visiting Researcher Programme, Copenhagen, Denmark, 2018.
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Abstract

Disasters affecting cultural heritage are one of the greatest threats to humanity; damaging or irreversibly destroying our collective memory. To increase the efficiency of response by utilizing digital technologies, this dissertation addresses three questions: What lessons can be learned from the past initiatives about crowdsourcing in cultural heritage during disasters? How do people respond on social media to cultural heritage affected during disasters? How can social media data be used for rapidly evaluating the situation on the ground when a disaster affects cultural heritage?

The main body of this dissertation is in three distinct parts: the past, the present and the future. Firstly, to understand the efficient application of crowdsourcing in the past, this research analyses the case of the 1966 Florence Flood. The purpose is to understand people's responses and motivations to recuse the cultural heritage damaged by the floods. Secondly, to understand the response to the cultural heritage damaged in present times, this dissertation analyses 201,457 tweets (including retweets) and 6,529 images posted on Twitter during the 2015 Nepal earthquake. The purpose is to understand the underlying themes and patterns in text and images of cultural heritage sites posted on Twitter. Lastly, this dissertation describes a method for early detection of disaster-related damage to cultural heritage based on data from social media.

The findings of this research suggest that the notion of heritage and the approach towards heritage is context-dependent. The cases examined in this dissertation explore two kinds of disasters (flood and earthquake) which tremendously impacted cultural heritage in two different time periods and geographical locations. The difference in time and location provides an in-depth understanding of the overlapping patterns and the impact of technological changes in people's response. This research contributes to a better understanding of the crowd and crowdsourcing for cultural heritage during disasters and promises to aid the experts by providing them with a tool for rapid post-disaster damage assessment.

Chapter 1

Introduction

April 26, 2015

Use #heritagedamagenepal and #culturedamagenepal to tweet pics of earthquake affected cultural heritage of Nepal.

Help us collect information on the Nepal Earthquake......#heritagedamagenepal #culturedamagenepal #culturecannotwait.

Beyond #NepalQuake humanitarian response these resources are 4 documenting #heritagedamagenepal http://www.iccrom.org/help-us-collect-information-on-the-nepal-earthquake/..

A day after a 7.8 magnitude earthquake struck Nepal, which killed thousands of people and affected numerous cultural heritage sites, I encountered tweets like the above in my Twitter news feed. The purpose of these tweets was to disseminate a crowdsourcing[1] initiative 'Kathmandu Cultural Emergency Crowdmap' (KCEC), for rapid damage assessment of cultural heritage[2]. My initial observations helped me to quickly conclude that the dissemination of the

[1]Crowdsourcing is an umbrella term for a variety of approaches (GRFS12) in which a large group of people perform small tasks in order to achieve a collective goal.

[2]Link to the crowdsourcing initiative and request the public to participate in the initiative. The initiative was created by ICCROM (International Centre for the Study of the Preservation and Restoration of Cultural Property) in collaboration with other organizations including ICOMOS-ICORP (International Scientific Committee on Risk Preparedness of the International Council on Monuments and Sites), the Smithsonian Institution, UNESCO and several cultural heritage professionals

initiative on Twitter was rather limited. The 66 unique tweets using the hashtags #heritagedamagenepal and #culturedamagenepal posted by 29 unique users were retweeted only 282 times, liked 174 times and replied 12 times. Compared to a single tweet with 4.68 million retweets in the case of the most popular tweet to date, and several popular tweets retweeted thousands of times, the engagement with the tweets using #heritagedamagenepal and #culturedamagenepal was minimal.

However, this is neither unusual nor surprising. Using social media for disseminating an initiative can be a challenging task and, therefore, needs a different way of thinking. Firstly, disasters generate a large volume of tweets in a very fast pace (Cas16; Mei15) thereby, making it difficult for people, particularly those who are not following the popular hashtags of the event, to discover the information. Hashtags (a form of conversational tagging (HYZ08) an emergent convention for labeling the topic of a micropost and a form of metadata incorporated into posts (Zap12)), are extremely important to quickly find tweets that relate to a particular topic (Mei15). Secondly, even though Twitter is open and searchable (Zap12), a hashtag, if not adopted by several hundred people, is less likely to garner the attention of the public. According to Cunha et al. ($\text{CMC}^{+}11$), short hashtags are more successful in propagating than longer ones. Thirdly, present-day technology biases ones exposure to information on social media. People on social media often find themselves in "social bubbles" (NOFM15) created by conscious or unconscious adoption of filters and algorithms for personalized contents on social media. This results in selective exposure to information from like-minded people and information sources (NOFM15; $\text{SZDV}^{+}17$). In other words, the information dissemination by heritage professionals may have limited reach due to social bubbles. Fourthly, due to the limited time and attention of people in social media spheres, the users may need to be motivated to participate in cultural heritage crowdsourcing in their brief appearance on social media during disasters. Lastly, when a disaster of this scale strikes a nation, the priority is the protection of life and, in fact, heritage is not well integrated into the recovery phase in most cases (GS06; Tan17).

Surprisingly, when following the popular hashtag of the event #nepalearthquake, I encountered some polemic tweets such as:

- *If I hear one more Westerner complaining about the loss of heritage instead of human lives in #NepalEarthquake I am going to SCREAM.*
- *Some tweeters are worried about old Mosques/Temples/UNESCO heritage sites, please grow up, save humans 1st. #NepalEarthquake*

This led me to question: Do people care for heritage when a disaster of this scale strikes? If yes, how do they respond? How can we efficiently analyze information posted on social media? How can we get the attention of people in the rapid pace of social media? How can we motivate them to participate in a crowdsourcing initiative to rapidly collect information on heritage affected by the disaster? This research was conceived following these initial observations and inquisitiveness.

By 2015, significant progress had already been made in the application of crowdsourcing for humanitarian purposes during disasters. For instance, after the 2010 Haiti earthquake, thousands of volunteers around the world collaborated on the Internet to provide aid to the response organizations on the ground (Mei15). Similarly, during the 2013 Typhoon Haiyan in the Philippines, 1,679 contributions from 82 countries were made to the OpenStreetMap (OSM), an online crowdmapping tool (SE15). Similar trends have been seen in many disasters across the world such as the 2011 Queensland floods, the 2011 Christchurch earthquake, and the 2011 tsunami in Japan (KML15). Further, citizens of the affected countries also developed and managed crowdsourcing applications. For instance, Pakreport was established by Pakistani citizens following the floods in 2010 that affected millions of people (CHM12). In comparison, the utility of crowdsourcing in disasters affecting cultural heritage has received less attention to-date.

A more recent example of crowdsourcing was seen after the fire in the National Museum of Brazil in 2018, in which around 20 million items were lost (BBC18). This immense loss of cultural heritage stimulated Wikipedia to launch a crowdsourcing initiative (WCI, henceforth) by inviting the visitors of the museum to upload images taken in the museum to their digital collection. Similar to the KCEC, Wikipedia announced this initiative on Twitter. However, unlike #heritagedamagenepal, this initiative received tremendous attention from the public. A single tweet by Wikipedia was retweeted 5,911 times, liked 4,736 times and commented on 36 times. Moreover, thousands of images have been uploaded to the online archive[3] to preserve the memory of the items impacted by the fire. In comparison, the 85 reports submitted to KCEC gave rather incomplete information, as mentioned by Tandon (Tan17).

These two cases illustrate that social media[4] has been used as a tool for dissemination and coordination during disasters. Moreover, it has also been used as an online repository. Even though both WCI and KCEC used the already available online applications, the resultant public participation in both projects was radically different. Comparing the two cases of crowdsourcing raises a few questions: Why did a single tweet from Wikipedia gain more attention than the dissemination of KCEC on Twitter? Why was more participation seen in the WCI initiative than KCEC?

Crowdsourcing relies heavily on public participation and public participation in any crowdsourcing initiative is subject to certain conditions. Firstly, people need the motivation to participate in an initiative and also to sustain their participation. According to Starbird (Sta12a), the reasons behind people's participa-

[3] Link to Wikipedia Crowdsourcing page

[4] Social media is an umbrella term generally applied to web-based services that facilitate some form of social interaction or networking (Zap12)

tion in crowdsourcing during disasters can be complex and context-dependent. Secondly, public participation in a crowdsourcing initiative may be influenced by the rigor of the 'call to participate'. For instance, Lascarides & Vershbow (LV14) report attention spikes in NYPL's crowdsourcing project 'What's on the Menu' upon press or social media coverage. Large scale organizations that already have a steady audience on social media may be able to attract more attention, as evident in the case of WCI. Available in 303 languages and with approximately 284,915 active contributors (Wik19), Wikipedia is one of the most popular websites as of June 2019 (Ale19). With such a large number of contributors, readers and followers (Cen16), Wikipedia can be termed as an 'influencer' with a capability to influence a disproportionately large number of people (Gla06). Lastly, the familiarity of online applications can also influence the extent of participation in crowdsourcing, as people tend to adopt the systems and networks that are already familiar to them, particularly when a disaster strikes (Pot13).

Tandon (Tan17) argues, using the case of KCEC, that the use of online participatory applications needs training and testing before the disaster strikes to ensure user familiarity. However, this may not always be a possibility due to limited resources availability, the unexpected nature of disasters, and an unknown group of participants. This raises the questions: How can we efficiently utilize data posted on popular social media platforms for rapid damage assessment after a disaster? How can we design an approach which not only requires minimal active public participation but also ensures global applicability? How can we automatically process a large volume of data posted on social media and prioritize action?

To summarize, adding to the already complicated process of disaster management, the tools available in the context of Web 2.0 have changed the dynamics of disasters. The above-mentioned issues point towards a gap in understanding of crowds' response towards disasters affecting cultural heritage and efficient systems that can assist professionals. To address the above-mentioned issues, this dissertation will answer the following Research Questions (RQ, henceforth):

1.1 Research Questions

RQ1 What lessons can be learned about crowdsourcing in cultural heritage during disasters from the past initiatives?

RQ2 How do people respond to cultural heritage affected during disasters on social media?

RQ3 How can social media data be used for rapidly evaluating the situation on the ground when a disaster affects cultural heritage?

1.2 Material and Methods Overview

While RQ1 and RQ2 focus on the people's response in the past and the present, RQ3 focuses on a tool that can be utilized for damage assessment in the future. To address the three above-mentioned research questions, the research focuses on two case studies: the 1966 Florence Flood and the 2015 Nepal Earthquake.

The table below highlights the case studies, data sources and methods adopted for each of the research questions.

RQ1	What lessons can be learned about crowdsourcing in cultural heritage during disasters from the past initiatives?
Case Study	1966 Florence Flood
Data Source	Correspondence from the archives of *Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti*, Lucca, Italy
Data Size	180 out of 753 items of correspondence
Method	Random sampling for selection and content analysis
RQ2	How do people respond to cultural heritage affected during disasters on social media?
Case Study	2015 Nepal Earthquake
Data Source	Twitter
Data Size	201,457 tweets and 6,529 images posted on Twitter
Method	Manual content analysis of text and images
RQ3	How can social media data be used for rapidly evaluating the situation on the ground when a disaster affects cultural heritage?
Case Study	2015 Nepal Earthquake
Data Source	Google and Twitter
Data Size	13,333 images from Google and 6,529 images posted on Twitter
Method	Manual content analysis and deep learning techniques

Chapters 2, 3, 4, and 5 describe the data collection and analysis methodology in-depth.

1.3 Background

Disasters are sudden unexpected events, resulting in a disruption of routine and social structure (PQ05) including the reproduction of economic, cultural, social, environmental and/or political life at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity (NRRvdPK14; UNI09). Often used interchangeably with the term *catastrophe* (RD17), such events can be detrimental to the entire society or humanity in general. Disasters affecting cultural heritage are one of the greatest threats (HC15; Spe99) to humanity; damaging or irreversibly destroying our collective memory (Atw07; Tab00; Spe99). The loss of cultural heritage is often said to represent a loss of identity. In recent years, such events have increased in frequency and severity (RPC15) (refer to Figure 1) globally (refer to Figure 2).

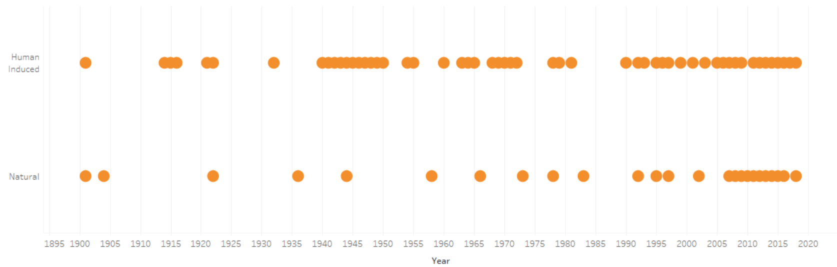

Figure 1: Graph showing cultural heritage affected by conflict and natural disasters since 1900. The frequency of such events has increased in the present time, as evident in the figure. Data from (SGS17; Wik). Own work.

The frequency and severity of such events have increased the international awareness towards protection and conservation of cultural heritage, particularly since the 1990s with the establishment of the International Committee of the Blue Shield. The Radenci Declaration in 1998 (otBS98), Declaration of Assisi in 2000 (ICO98), and the 2009 Dublin Declaration on Climate Change (Org09) point towards the global determination to protect cultural heritage (Wan15). Further, the Strategy for Reducing Risks at World Heritage Properties adopted by UNESCO in 2007 (UNE07), structured around the Hyogo Framework for Action (UNI05), aims to strengthen the protection of cultural heritage properties inscribed in the UNESCO World Heritage list. The Sendai Framework for Disaster Risk Reduction 2015-2030 calls for *"the substantial reduction of risk and losses in lives, livelihood and health and in the economic, physical, cultural and environmental assets of persons, businesses, communities and countries"* (UNI15). The framework clearly recognizes culture as a key dimension of Disaster Risk Reduction (DRR) and draws on heritage through a number of references. However, Dean & Boccardi (DB15) highlight that the challenge is to implement this policy, as it requires considerable capacity building at international, national and local levels and setting up institutional mechanisms complemented by data collection and monitoring (DB15).

At the national level, cultural heritage institutions are investing in disaster management. A substantial amount of work has been done in strengthening the resilience of assets at risk *before, during and after* a disaster (see Figure

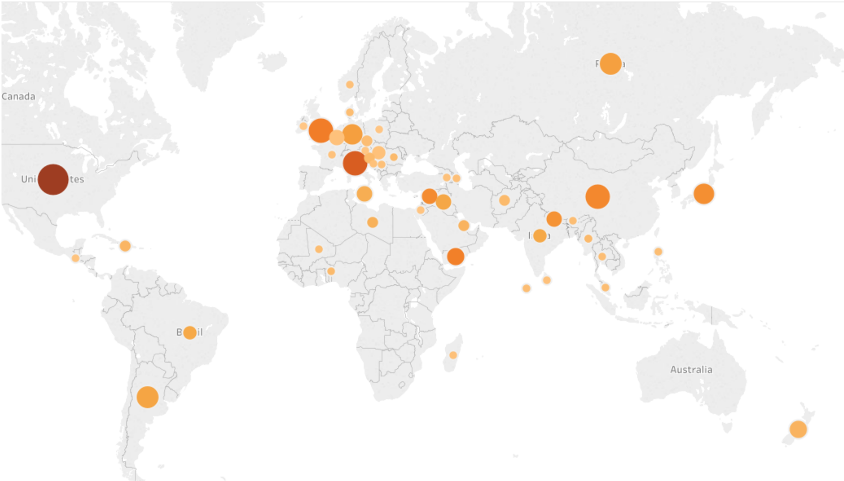

Figure 2: Map showing cultural heritage affected by conflict and natural disasters since 1900. Such events have affected cultural heritage globally as evident by the figure. Data from (SGS17; Wik). Own work.

3). However, as (Jir03) pointed out regarding the case of floods in Prague in 2002 'the situation on the ground is complex during disaster response'. Even the most prepared institutions face unforeseen and unpredictable situations making the disaster response a complicated process. In several cases, the damage assessments were ineffective or incomplete due to lack of inventories, well-established processes or expertise (Tan17). Moreover, these processes can also be time-consuming, as highlighted by Binda et al. (BMC^{+}11). The authors mention that the process of damage assessment of more than 1,000 churches took over eight months after the 2009 earthquake in Italy.

The above mentioned factors point towards the need to utilize the wisdom of the crowd along with digital technologies for rapid and efficient assessment of the situation on the ground after a disaster.

1.4 Defining Heritage

What is cultural heritage can be a confounding question. It has no clear and concise answer applicable to every context. However, the framework within which heritage is defined remains almost the same, i.e. things and practices from the past which are a part of our present should remain so in the future. At the in-

Figure 3: Disaster risk management cycle for cultural heritage sites (JA13)

.

ternational level, since the adoption of Venice Charter in 1964 (ICO64), the scope of the term "cultural heritage" has broadened and is applicable to individual buildings and sites to groups of buildings, historical areas, towns, environments, artifacts, artworks, practices, etc. According to (Ahm06), at the national level, finer terminologies of *heritage* are not standardized; therefore, no uniformity exists between countries. Moreover, researchers have argued that heritage is an inherently complex phenomenon and can contain conflicting meanings (GAT16).

In order to efficiently address the RQs, this research needed two distinct approaches to define heritage, as explained below:

Chapters 2 and 3 needed a flexibility in approach to understand and acknowledge *what is labeled as heritage* by the crowd. Instead of a strict top-down approach towards defining heritage, a flexible approach was necessary to understand people's perception.

Chapters 4 and 5 acknowledge heritage in the form of protected monuments, buildings and objects i.e. *what is already established as heritage* by the governments. The strict approach was necessary to be able to create two distinct classes, *heritage* and *not-heritage*, for image analysis.

1.5 Ethical Aspects of this Research

As this research partly draws its data from the Internet and deals with personal information, it is important to address the issue of ethics and take a position in regards to ethical decision-making. Ethical decision-making in research follows the same general principle of *'do no harm'* while providing evidence of research findings, regardless of the type of data used and methodology adopted. Mackee & Porter (MP09) acknowledge the challenges of ethical decision-making in Internet research due to several factors, such as the global reach of the Internet, the diversity of research sites[5] and online communities, and the diversity of research methodologies. Rapidly changing technology and people's practices on the Internet add more complexity in the ethical decision making process. Consequently, there are several differing opinions about ethics resulting in blurred boundaries (Kit08; MP09; EFS08).

This content-based[6] research takes two key considerations in ethical decision making: privacy and copyright in presenting the analysis of text and images in the following chapters. A balance was sought between maintaining the privacy of the subjects while providing evidence of research, the priority being *what is being done* rather than *who is doing it*. On the other hand, the identity of the subject was revealed where it was essential to acknowledge *who is saying it*.

Text The text analyzed and presented in this dissertation generally contains publicly available non-sensitive information. Correspondence analyzed in Chapter 2 contained personal information including the names of individuals, their address and their involvement in the aftermath of the flood. It also included such information of various organizations, public and private bodies. Even though the correspondence was written more than 50 years ago, the protection of individuals' privacy was a priority in this research. The name and address in correspondence examples provided in Appendix A have been removed. The aim of Appendix A is to provide an overview of the data used for analysis and to support the results described in Chapter 2, instead of highlighting *who* contributed *what* or *how much*.

Tweets analyzed in Chapter 3 posed a different challenge than publishing correspondence in Appendix A. The data posted on Twitter is usually open and searchable, therefore removing personal details (e.g. @username or phone number published in tweets) may not always be sufficient in publishing tweets. This poses risks to marginalized populations, particularly those whose views may

[5]For instance, Facebook is considered a private social media due to its architecture, whereas Twitter is relatively more public. Therefore, the ethics of data collection from Facebook would not be the same as that from Twitter

[6]Mckee & Porter (MP09) identified two kinds of research: content-based and person-based. As a content-based dissertation, this work focuses on the text and images rather than people who are producing it.

not be congruent with the rest of the population. Therefore, in case of such conflicting views, the tweets were slightly modified. The slight modification of tweet content made the tweet unsearchable and hence, the privacy of individuals have been protected. Moreover, personal information in tweets, such as phone numbers, were removed to protect the individuals from any possible harm.

Images In order to maintain the privacy of individuals in the photographs while providing evidence of findings, their faces have been covered where their identity could be revealed. This was particularly necessary for selfies, a controversial practice during disasters that would potentially expose a person to negative public exposure, ridicule and embarrassment. Copyright of images circulated on the Internet can be an extremely complex subject due to the alterable and malleable nature (Han17) of these images. People actively edit, remix, recreate, and reuse images without giving any consideration to their origin. As a result, the Internet is swamped with different versions of the same image, specifically during disasters. This was particularly true for images in the SMERP dataset used for this research and, hence, the copyright of images used in this paper could not be found. However, whenever the source of the image was visible (even if in an edited image) it has been acknowledged.

To summarize, each correspondence, tweet, and image published in this dissertation required a distinct consideration, based on which solution was devised for each case. It can be concluded that the implementation of ethics in research is context-specific and should not be treated as a set of universal principles. This research is informed by Markham & Buchanan's (MB12, p.52) idea that an ethical researcher is present, prepared, honest, reflexive and [most importantly] adaptable.

1.6 Structure of Dissertation

This dissertation consists of six chapters including the introduction and conclusions. The main body of the dissertation is based on three journal articles in process and a manuscript. In order to answer the RQs, the main body of this dissertation is structured in three sections: the past, the present and the future. Chapter 2 addresses the past, Chapter 3 and Chapter 4 analyze the present whereas Chapter 5 envisions the future with the help of present-day technologies. The three distinct approaches were needed to provide a holistic understanding of the problem and to propose a robust solution rather than employing quick fixes.

Chapter 2 address RQ1 *'what lessons can be learned about crowdsourcing in cultural heritage during disasters from the past initiatives?'* The chapter examines the past by analyzing a crowdsourcing initiative during the 1966 Florence Flood to understand the underlying themes in the people's response and the factors motivating people to participate in the crowdsourcing initiative.

Chapters 3 and 4 primarily address RQ2 *'how do people respond to cultural heritage affected during disasters on social media?'* The chapters investigate this issue by analyzing Twitter data posted during and immediately after the 2015 Nepal Earthquake. Content analysis is employed to analyze and construct patterns from 201,457 tweets in Chapter 3 and 6,529 images in Chapter 4. .

Chapter 5 addresses RQ3 *'how can social media data be used for rapidly evaluating the situation on the ground when a disaster affects cultural heritage?'* The chapter proposes a methodology for automatic classification of social media images of cultural heritage sites, including the damaged heritage sites posted during disasters, to assist heritage professionals in rapid damage assessment of cultural heritage sites following a disaster.

Lastly, Chapter 6 concludes this dissertation by providing a discussion on the findings of this research. The chapter cross-compares the results from Chapters 2, 3, 4, and 5 and discusses them under the topics that emerged from the findings. The chapter concludes with stating the contributions and limitations of this work and, highlighting some future areas of work.

Chapter 2

Crowdsourcing to Rescue Cultural Heritage during Disasters: A Case of Florence Flood 1966

Illustrating the application of crowdsourcing in disaster response before the Internet age, this chapter addresses two key questions: How did the people respond to the cultural heritage damaged during the 1966 Florence Flood? How were they motivated to do so? Content analysis of 180 out of 753 correspondence items from the archives of *Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti* in Lucca, Italy shows that the committee received contributions in the form of money, materials, volunteers and knowledge from different parts of the world. The most popular of all contributions, however, was money. Four main factors were found to be motivating people to contribute: 1) the call to participate, 2) the media, 3) influencers, and 4) memory of the city. Of key importance, this chapter emphasizes: how to initiate a crowdsourcing campaign to restore cultural heritage, who will contribute or is most likely to contribute and how to motivate people to contribute.

2.1 Introduction

Crowdsourcing is an umbrella term for a variety of approaches (GRFS12) in which a large group of people perform small tasks in order to achieve a collective goal. While researchers argue that crowdsourcing is an Internet phenomenon (Bra08; EAG12), the practice pre-dates the information age with examples of crowdsourcing evident across history, such as the compilation of the Oxford English Dictionary in 1879 and Mass Observation in 1937 (Ell14). Since the inception of the term *crowdsourcing* in 2006 by Jeff Howe (How06), the term has been applied to several different domains, including disaster management. The existing research on crowdsourcing in disaster management focuses on online participatory and collaborative work. However, even before the Internet age, geographically dispersed crowds of people worked collaboratively, as evident in the case of the 1966 Florence flood.

The 1966 flood was one of the most catastrophic disasters in terms of damage to the cultural heritage of Florence (Nd86). A United Nations Educational, Scientific and Cultural Organization (UNESCO) report estimated that thousands of items in libraries, museums, archives and institutions were affected (UNE67). Many artworks were irretrievably lost or severely damaged. For instance, Cimabue's Crucifix in the Santa Croche lost paint from one-third of its surface (You68). Moreover, many historic buildings were also affected.

The immense loss of cultural heritage stimulated the heritage professionals into immediate action. Carlo Ludovico Ragghianti, a renowned Italian art historian, headed the establishment of *Comitato del Fondo Internazionale per Firenze* (CFIF, henceforth) in Italy. The committee consisted of erudite members of the art and allied fields.[1] It leveraged the capacity of a geographically dispersed crowd of sympathetic people to provide help in any possible form. The committee appealed for contributions towards the restoration of cultural heritage through personal and public communication channels. A letter written by the committee stated:

"The flood in Florence, the 4th of November 1966, has caused more damage to her artistic, cultural, and historic heritage than that done by the war within the walls, in August 1944.
The parliament and government of the nation, the city and all it's (sic) scientific, cultural and artistic groups, are fighting for the immediate salvation of the monuments, works of art, historic archives, and libraries. But the disaster, which has spread through all of

[1] A few of the committee members include: Professor Roberto Salvini, Ordinary of history of art at the University of Florence; Professor Ugo Procacci, Superintendent of Galleries; Professor Guido Morozzi, Superintendent of Monuments; Professor Gulielmo Meetzke, Superintendent of Etrurian Antiquities; Professor Charles de Tolnay, Director of Buonarroti's House; Alessandro Bonsanti; Mr. Myron Piper Gilmore, Director of Berenson's Villa, from Harvard University; Professor Ulrich Middeldorf, Director of German Institute of History of Art; Professor Emanuele Casamassima, Director of the National Library; Professor Sergio Camerani, Director of the State Archives.

Italy, needs just for economic and social measures, many, many hundreds of billions of Lire.
...For centuries Florence has represented the universal spirit of civilization, culture and art in the western world. The testimonies of that historic work, that interests all of the civilized world, must be saved and conserved.
We need everybody.
We send our urgent and painful plea to everyone who wants to give a contribution to the resurrection of Florence, to form an International Foundation destined to recuperate the monuments, documents and artworks.
The contributions, in whatever form they're given, are to be sent to ......"[2]

As a result of this open call, CFIF received contributions in the form of money, materials, volunteers and knowledge from two distinct categories: experts in conservation and restoration, and non-experts. The contributions were received from various parts of the world. Additionally, similar committees were formed in other countries such as the UK, Mexico and the USA; the most notable being the Committee to Rescue Italian Art (CRIA) in the USA, which was under the honorary chairmanship of Jacqueline Kennedy. These committees worked extensively in their respective countries to help restore the cultural heritage of Italy.

This initiative is an example of crowdsourcing before the Internet age, where the geographically dispersed crowd responded to the disaster according to their capacity. Indeed, the 1966 Florence Flood is probably one of the earliest recorded examples of crowdsourcing during disasters. Concurrently, this event is also considered as a catalyst for disaster preparedness, art conservation and historic preservation (Wat16) by utilizing the international cooperation of experts. But while this initiative remains a major part of the oral history of Italy, no systematic investigation has been done to analyze how people were motivated and how they responded to recover the cultural heritage. This chapter will address these gaps through the following questions: **How did the people respond to the cultural heritage damaged during the 1966 Florence Flood? How were they motivated to do so?**

These questions are particularly important in today's context where the intensity and frequency of disasters affecting cultural heritage have increased (Tab03). Even though this crowdsourcing initiative occurred before the Internet age, the findings are still relevant today, not only to prepare for disaster response but also to improve the efficiency of crowdsourcing to utilize the power of decentralized collective action. At the same time, this crowdsourcing initiative has also been criticized. Some of Ragghianti's actions in this initiative were denounced (Gio67; Ema18). Despite the criticism, there are few parallel examples to date of crowdsourcing in disasters affecting cultural heritage.

This chapter is structured in six consecutive parts. Section 2.2 conceptually frames this research, linking it to existing works on the 1966 Florence Flood,

[2] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 1, Fondazione Centro Studi SullArte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

crowdsourcing in disasters and cultural heritage. Section 2.3 describes the data collection and methodology adopted for this research. Section 2.4 describes the results. Lastly, Section 2.5 discusses the implications of this research. The chapter concludes with possibilities for future work.

2.2 Related Works

A wealth of literature is available on the aftermath of the 1966 Florence Flood. These publications can be broadly divided into two categories: people's narration of the event and experts' reports. Taylor (Tay67) wrote a detailed day-to-day experience of the flood as a witness of the event. Clark (Cla08) looked back at the flood through the voice of its witnesses. Barrett & Kraczyna (BK07) compiled a photographic essay through a selection of eighty-four photographs to represent the event and its aftermath. Pucci & Paterson (PP66) provided a brief overview of the floods of the past and illustrated the event through selected photographs. Messeri & Pintus (MP06) compiled the stories of volunteers commonly known as *Mud Angels*. Alexander (Ale80) compared the articles from the Italian and British press to understand the reaction of journalists. He concluded that the Italian press vividly illustrated the dilemmas of the government whereas the British press focused on the art treasures.

The 1966 Florence Flood has also been widely discussed in the field of conservation and historic preservation. Experts reported the damage to books, manuscripts, music manuscripts, archaeological artifacts, etc. They also narrated their personal experiences of the aftermath and elaborated the rescue operations. Phillips (KMP67) mentioned the usefulness of the master plan in the context of archaeological museum recovery. Picker (Pic67) reported the difficulty to accurately determine the extent of damage to libraries and archives in December 1966. He focused specifically on the music manuscripts and books. Hamlin (HT67) also focused on the damage done to the books and libraries. He provided an early record of rescue efforts by the professionals and volunteers. Bonelli (Bon69) described the process of rehabilitation of the *Istituto e Museo di Storia della Scienza*. In contrast, Brommelle (Bro70) provided an overall picture of the restoration works carried out in Florence after the flood. The author described restoration details of stone and marble monuments, sculpture, furniture, woodworks, musical instruments, paintings on wooden panels, paintings on canvas, fresco paintings, metallic objects and textiles. Further, he mentioned the establishment of the Restoration Center at Palazzo Davanzati as a permanent consequence of the international aid to Florence after the 1966 flood.

In 2016, the disaster was widely discussed at numerous events and in many publications on the 50th anniversary of the flood. Conway & Conway(CC16) provided an overview of the progress in art conservation in the past five decades. However, only a few publications focus on correspondence after this disaster.

Waters Rising (Wat16) mainly includes letters between Peter Waters, a pioneering bookbinder, and his wife Sheila Waters, between November 1966 - September 1967. The letters elaborate on the technical and financial challenges faced in handling the mammoth task of restoration and describe the ongoing rescue operations. The letters in this book paint a vivid picture of the event through a family's conversation. Similarly, *Dear Eddie and Popp: Letters from the Florence Flood of 66* (Hog10) includes 11 letters from James Hogg (an American artist living in Florence) to his family. The letters were written between November 4- 21, 1966, describing the situation in Florence in detail. Both Waters Rising and Dear Eddie and Popp focus on personal letters sent from one family member to another. In contrast, this chapter uses correspondence from various sources around the world. The data, therefore, is not limited to a single person witnessing the disaster, but rather includes various sources contributing from different locations, including those who were not necessarily witnesses to the event.

2.2.1 Crowdsourcing in disasters and cultural heritage

Currently, crowdsourcing has gained tremendous attention to increase the efficiency of response in disaster management. Researchers have developed theoretical frameworks, analyzed case studies and also developed new systems for crowdsourcing. Liu (Liu14) developed a conceptual crisis crowdsourcing framework that establishes the 'why, who, what, when, where, and how' of a crowdsourcing system. Authors have studied numerous crowdsourcing applications available for disaster management in order to understand the role of volunteers and improve the efficiency of the process. For instance, Poblet et al. (PGCC13) reviewed online platforms and mobile apps developed and implemented in the context of disaster management. The study concluded that the majority of the reviewed platforms and apps focus on the response and recovery phase of disasters. Further, the authors developed four types of crowdsourcing roles based on the type of participation and data processing, including crowd as a sensor, crowd as a social computer, crowd as a reporter, and crowd as a microtasker. Ernst et al. (EMS17) focused on location-based tasks carried out by volunteers using three core processes: sensing, awareness and adaptability. By studying various mobile-based crowdsourcing applications, the authors suggested that these approaches can help emergency managers to not only gather information but also make accurate decisions. Further, Gao et al. (GWBL11) highlighted the main causes behind a shortfall of crowdsourcing for disaster relief coordination, such as limitations of crowdsourcing applications and the kind of data posted on them. The authors introduce the concept of 'groupsourcing' for efficient coordination between different relief organizations. Kankanamge et al. (KYGK19) concluded that in spite of the wide application of crowdsourcing in disaster management, it is considered a 'random tool', particularly by emergency managers. Further, they highlighted the lack of an agreed-upon definition and application of crowdsourcing in disaster management. The authors carried out a systematic literature review and established four key attributes of crowdsourcing: location awareness, multi-directional communication, situation awareness, and collective intelligence. These key attributes indeed point to the usability of crowdsourcing in disaster management.

Additionally, new crowdsourcing systems have also been developed for increasing efficiency in disaster response in the form of mapping and classification. Researchers have attempted to utilize the skills and expertise of off-site volunteers to provide support to on-site users. For instance, Yang et al. (YZF^{+}14) developed a crowdsourcing disaster support platform by utilizing off-site users. In their platform, they focus on three distinct attributes: the selection of off-site users according to their expertise, mechanisms for off-site users to collaborate and crowd-voting for increasing credibility of the information. Researchers have combined machine learning and crowd participation to improve the crowdsourcing process in disaster management. Artificial Intelligence for Disaster Response (AIDR), developed by Imran et al. (ICL^{+}14a), automatically classifies tweets related to a disaster, using human intelligence to label a sample of tweets in order to train the automatic classifier. Lin et al. (LWT^{+}18) developed the Artificial and Crowd Intelligence filter to improve the crowd response accuracy. In their system, artificial intelligence is used to segregate accurate messages from inaccurate ones. Further, the crowd combines the duplicates, removes inaccurate messages and formats the messages.

In comparison, a limited application of crowdsourcing has been done in the context of cultural heritage during disasters. An attempt to harness the power of digital volunteers was done during the earthquake in Nepal in 2015 through a crowdsourcing application: 'Kathmandu Cultural Emergency Crowdmap' (Tan17). A similar effort was initiated by Wikipedia after the fire in the National Museum of Brazil in 2018 (Pes). Both Kathmandu Cultural Emergency Crowdmap and Wikipedia sought information from the crowd after the disaster. While Kathmandu Cultural Emergency Crowdmap sought information for rapid damage assessment to cultural heritage, Wikipedia sought information to preserve the memory of cultural heritage. Overall, the current research and application of crowdsourcing in the disaster management domain generally refer to a large group of people participating and collaborating via the Internet. In contrast, this chapter shows that crowdsourcing during disasters is not a new practice and is not limited to digital volunteers.

Despite the challenges highlighted by Oomen & Aroyo (OA11) due to a variety of reasons (such as data quality and motivating the crowd), crowdsourcing has also been widely applied in the cultural heritage domain. Libraries and archives invite users to transcribe and/or correct the outputs of the digitization process. New York Public Library's project *What's on the Menu* (LV14), University College London's *Transcribe Bentham* (CT14), and National Library of Australia's *Trove* (Ayr13) are a few examples of crowdsourcing for transcription of archives. *Know Your Place* (NNW17) and Library of Congress's *Flicker The Commons* (oCPDS+08) gather descriptive metadata related to objects in a collection. 9/11 Memorial & Museum's *Make History* (Wal), Brooklyn Museum's projects *Click* and *Go* (Ber16), and University of Sussex's *Mass Observation* (Ell14; Sum85) used the inspiration and expertise of non-professional curators to create (Web) exhibits. In the context of crowdsourcing in cultural heritage, researchers (Owe13) prefer the notion of 'community' over the 'crowd' as a conceptual model, because most of these projects depend on a dedicated community of volunteers instead of large numbers of volunteers. In contrast, a large crowd of volunteers, both on-site and off-site, contributed to rescuing the cultural heritage after the 1966 Florence Flood. Moreover, the current research into crowdsourcing in cultural heritage also focuses on participatory online practices.

The main difference between crowdsourcing in the pre-Internet age and the present times is the medium of communication used. As also evident from other crowdsourcing initiatives before the Internet age, crowdsourcing relied heavily on the manual labor of the crowd. For instance, in 1937, volunteers manually maintained a diary in order to record their daily observations in the Mass Observation project. Volunteers also sent excerpts of word usage in literary works on scraps of chapter to compile the Oxford English Dictionary in the 1870s (Ell14; Win98). As a result, only the crowdsourcer could view and analyze the submissions. Even though the crowd worked independently towards a common goal before the Internet age, the process of crowdsourcing tended to be strictly top-down. Moreover, the crowdsourcing projects operated for years. For instance, the Oxford English Dictionary took approximately 70 years to complete (Win98). Today, the Internet affords instantaneous information creation, dissemination and circulation. Further, various applications ease data collection and processing of large amounts of data available through the Internet. As a result, crowdsourcing initiatives in the present time can instantly utilize a large amount of globally-spread people for disaster response. Moreover, the Internet has also changed the crowdsourcer-crowd relationship from strictly 'top-down' to more diverse relationships including lateral, bottom-up and top-down (Sta12b). While the medium has also had an impact on dissemination patterns, techniques and outreach, this research's findings are applicable for crowdsourcing initiatives even in present times, as will be discussed in the forthcoming sections of this chapter.

2.3 Material and Methods

2.3.1 Material

In conducting this research, I used the 1966 Florence Flood archives of *Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti* in Lucca, Italy as the primary source of information. The archives contain committee reports and correspondence with the committee. The list of documents in the archive is available online on the foundation's website http://www.fondazioneragghianti.it. In this chapter, I focus on the correspondence with the committee. Analysis of correspondence is an obvious choice to answer the research questions guiding this chapter for three reasons. Firstly, the correspondence items are from various parts of the world and truly represent the extent of the committee's outreach. Secondly, many respondents explicitly mention their motivation for contribution. Lastly, the correspondence is not limited to those employed in the art world and includes the responses from a wider section of the global society. Hence, the correspondence provides an in-depth understanding of the process of crowdsourcing.

The correspondence is stored in 11 boxes sorted based on the respondents last name. A total of 753 unique sources of correspondence have been identified. Additionally, a few items of correspondence from unidentified sources are also available in the archive. In many cases, one source wrote multiple letters and telegrams. However, the average number of items of correspondence per donor is 1.3; that is, most sources only corresponded once. The correspondence items are mainly from the sources to CFIF and very few of those sent from CFIF are available in this archive. Moreover, many sources sent attachments with the correspondence. Such attachments included bank drafts, bank checks, newspaper articles, magazine articles, photographs and biographical information describing the prominent people of a country. Section 2.4.1 provides an overall view of the 753 correspondence items. A sample of 24 correspondence items are provided in Appendix A.

2.3.2 Method

The methodology adopted for this chapter is comprised of eight distinct steps, as explained in Figure 4. The 753 unique sources of correspondence mentioned above were tabulated in an Excel sheet in alphabetical order. Additional information such as date of correspondence, type of source, location, language and means of communication for each source was manually added. Section 2.4.1 describes the results of this annotation. Data on five sources was not available. Nevertheless, these sources were kept on the list. A random sampling method was selected in order to avoid any bias in the selection. The random sample was created using the Excel sheet containing metadata on the source of correspondence. A total of 180 out of 753 sources were selected for analysis, i.e. about 24% of the correspondence. In many cases, one source had multiple correspondence items. In such cases, all the correspondence items were selected for analysis. Moreover, the correspondence attachments were also studied to understand the contextual information. The selected sample is diverse. It includes correspondence from Italian and non-Italian individuals, public and private bodies from

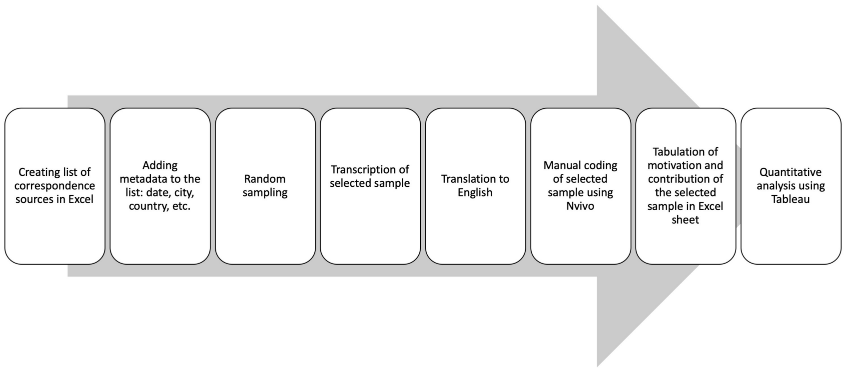

Figure 4: Overview of methodology

Italy and abroad; and a combination of telegrams, typed letters and handwritten letters.

Correspondence items from the selected sources were first transcribed in NVivo, a qualitative data analysis software. It should be noted that handwritten letters were particularly difficult to transcribe. In some cases, a few words were undecipherable and, therefore, not transcribed. However, this did not compromise the understanding of the overall message of the correspondence. The transcribed correspondence items were translated to English with the help of native speakers. Google translator was also used to aid the understanding of correspondence. Translation to English was an essential step in harmonization of the analysis. Manual content analysis of the selected sample was done to understand the thematic patterns of response and construct underlying meanings. As Krippendorff and Weber suggest, content analysis includes analysis beyond the literal message itself (Kri18; Web84). This chapter briefly touches on the correspondents' location, language and means of communication, and their role in society, to understand the context. Lastly, the type of contribution and the motivation for contribution for the 180 selected sources were tabulated in the Excel sheet. Data was quantitatively analyzed using Tableau, a quantitative data analysis software.

To understand communications, it is also important to understand the technological context of 1966. While the first supercomputer was already built and research on networking was ongoing, such technologies were still not available to the masses. People relied on letters, telephones and telegrams for personal communication; and TV, radio, newspapers for mass communication. This is reflected in the nature of the correspondence which includes handwritten letters, postcards, greeting cards, visiting cards, typewritten letters on personal letterheads or institutional letterheads and telegrams. This is also reflected in the content of letters and telegrams. The telegrams tend to be short, and to-the-point as it was an expensive means, whereas the letters give more flexibility to the correspondent and range from just a few words to long letters of 2-3 pages.

It is also important to elaborate on the specific language type used in telegrams. Sending telegrams was expensive and, therefore, people aimed to provide as much information in the smallest possible number of words. Hence, some of the words were abbreviated, omitted or added for a specific purpose. For instance, the term 'stop' in a telegram refers to the end of a sentence, as elaborated in the telegram *"WILL CERTAINLY SEND DONATION STOP CONTACTING BRITISH ITALIAN SOCIETY LONDON STOP DEEPEST SYMPATHY YOUR TERRIBLE DISASTER"*[3] . In the absence of this knowledge about specific language usage in telegrams, one might risk a wrong analysis of correspondence.

2.4 Results

The results are divided into three main parts. Section 2.4.1 describes the generic results of data annotation. It provides an overall view of the 753 correspondence items, whereas Sections 2.4.2 and 2.4.3 refer to the 180 randomly selected correspondence items. Sections 2.4.2 and 2.4.3 answer the primary research questions in this chapter. A sample of 24 items of correspondence is provided in Appendix A. These correspondence samples are frequently referred to in Sections 2.4.2 and 2.4.3.

2.4.1 General observations

The 753 unique sources of correspondence can be divided into 20 categories (refer to Table 1), based on the role of the source as a respondent. The table also highlights the location of sources, the number of sources from each country and the total number of correspondence items from sources. There are a total of 1,019 items of correspondence from 753 sources in this dataset. From Table 1, it is clear that individuals, institutes, universities and schools communicated the most with the committee. Moreover, Table 1 and Appendix A are useful in defining the 'crowd' for this chapter as a large number of people and organizations who did not necessarily know each other (EAG12). The crowd was also heterogeneous in composition (Sur05), including Italian and non-Italian individuals, and public and private bodies from Italy and abroad. Moreover, the crowd was a combination of both non-professionals (e.g. children, students, school teachers, young

[3]Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 4, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

graduates) and professionals, and organizations in heritage, arts and allied fields, as evident from Table 1 and various correspondence items in Appendix A.

Figure 5 shows that most of the correspondence was written from Italy and the USA. Interestingly, the correspondence is in many different languages such as Italian, English, French, German and Portuguese. Table 3 shows that the most of the correspondence is in Italian (64%), followed by English (29.6%), French, German, Spanish, etc. Table 2 shows the distribution of correspondence with regard to means and type of correspondence. Data on five sources was not available, as highlighted in Section 2.3. From Table 2, it is clear that letters are the dominant means of communication in this dataset. However, some sources sent both letters and telegrams to CFIF. Moreover, people preferred to send typewritten communication over handwritten letters, as evident in Table 2.

Lastly, the correspondence was written between November 1966 - October 1967. Figure 6 shows that most of the correspondence was written in November-December 1966. The intensity of incoming correspondence decreased with time. On average, seven items of correspondence were sent/received per day between November 1966 - December 1967. While the restoration of cultural heritage was ongoing even after 1967, this correspondence is limited in the time frame. Nevertheless, it provides an in-depth understanding of people's response.

S.no	**Source Type**	**Location**	**No. of Sources**	**Items of Correspondence**
1	Bank	Italy	4	11
2	Business	France	1	1
		Italy	6	8
		UK	2	3
3	Club	Italy	8	13
		Switzerland	1	2
4	Committee	Germany	2	6
		Italy	3	5
		USSR	1	2
5	Commune	Italy	4	9
6	Embassy	Belgium	1	1
		France	1	1
		Italy	1	1
		Sweden	1	1
		Switzerland	3	7
		UK	1	2
7	Federation	Italy	2	2
8	Foundation	Italy	1	3
		Sweden	1	1
		USA	1	1
9	Friends of..	Italy	5	8

10	Gallery, Library, Archive, Museum	Austria	1	3
		Canada	1	1
		Denmark	1	1
		Germany	3	3
		Ireland	1	3
		Italy	3	7
		Netherlands	1	1
		Norway	1	1
		Spain	1	1
		Switzerland	2	4
		UK	1	2
		USA	2	2
11	Individuals	Argentina	1	2
		Austria	1	1
		Belgium	2	3
		Brazil	1	1
		Canada	1	1
		Croatia	1	1
		Denmark	1	1
		France	16	30
		Germany	14	15
		Italy	266	322
		Malta	1	1
		New Zealand	1	1
		Spain	1	1
		Sweden	2	2
		Switzerland	5	6
		Undefined	39	39
		UK	7	7
		USA	207	214
12	Institutes	Argentina	1	1
		Belgium	1	3
		Brazil	3	14
		France	4	8
		Germany	1	2
		Italy	36	63
		Mexico	2	2
		New Zealand	1	4
		Poland	1	1
		Portugal	1	1
		Spain	2	2
		Sweden	2	5
		Switzerland	4	6
		UK	1	1
		USA	1	1
13	Ministry	Italy	1	9

14	Newspaper or Magazine	Italy	6	10
		UK	1	1
15	Political Party	Italy	1	1
16	Society	Germany	2	3
		Italy	3	11
		Uruguay	1	4
17	Theater	Italy	2	2
		Sweden	1	1
		UK	1	2
18	Trade Union	Italy	1	1
		USA	1	1
19	TV/Radio	Belgium	1	2
20	University or School	Belgium	1	3
		Brazil	1	1
		Germany	2	3
		Italy	23	50
		Sweden	1	1
		UK	1	2
		USA	6	32
	Total		**753**	**1,019**

Table 1: The sources were categorized in 20 classes according to the role of the source. The table highlights the location of each source type, number of sources and total number of items of correspondence.

Means of Communication	**No. of Correspondence Items**
Letters	689
Telegrams	48
Letter + Telegram	11
Unknown	5
Total	**753**

Type	**No. of Correspondence Items**
Typewritten	421
Handwritten	321
Hand + Type	6
Unknown	5
Total	**753**

Table 2: Most of the correspondence items were letters and typewritten.

Many of the correspondence items are replies to the communication sent by CFIF. On the other hand, some are self-initiated. Different levels of formality can be seen in the letters. Some of the letters have a personal tone, whereas some have a formal tone. This represents the different relationship levels members of CFIF had with the correspondents.

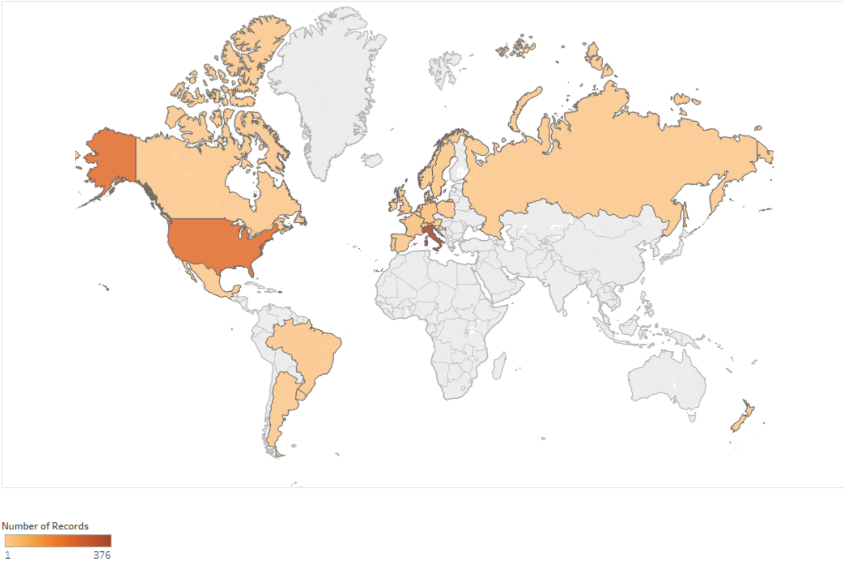

Figure 5: Contributions from 25 countries were received. Most contributions were received from Italy and the USA.

2.4.2 How did the people respond?

Three main themes emerged from the analysis- action, memory and sentiment. The items of correspondence which elaborated any form of contribution or willingness to contribute were coded under the theme of 'action'. Correspondence items which described sources' past experience(s) in Florence were coded under the theme 'memory'. Lastly, correspondence items which expressed any sentiment over the loss of heritage were coded under the theme 'sentiment'. It should be noted that the themes were not necessarily mutually exclusive. Some examples of coding can be seen below:

1. **Action** *Please accept this small contribution towards the fund for helping the city of Florence.*[4]
2. **Action + Memory** *Here is my little contribution to your fund for the restoration of the art treasures of your wonderful city which I enjoyed greatly two years ago. I read in the New York Times of Nov 9th that such gifts could be addressed to you*

[4] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 2, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

Language	No. of Correspondence Items
Italian	482
English	223
French	16
German	14
Spanish	6
Multilingual	5
Unknown	5
Portuguese	1
Maltese	1
Total	**753**

Table 3: The correspondence was written in seven different languages. Some correspondence was multilingual.

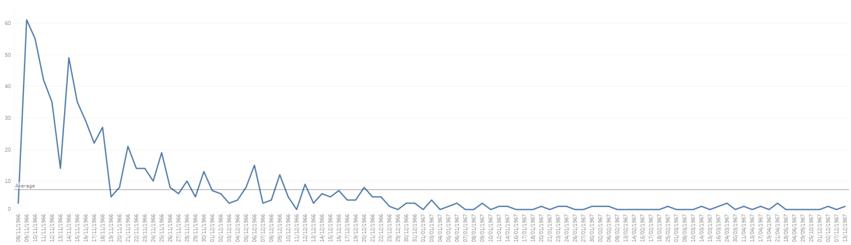

Figure 6: The intensity of correspondence decreased with time. On average, seven items of correspondence were sent/received per day.

for the committee.[5]

3. **Action + Sentiment** *Mr. Days and I adore Italy- and particularly, Florence. We're so upset about your disaster. Am enclosing check- only wish it could be for a much greater sum.*[6]
4. **Action + Memory + Sentiment** *In 1925 I was in Florence 12 days and these few days have given me a new idea of art. For me, not only this door of the Baptistery, but every stone in Florence, every fresco, every painting, was almost a door to paradise. This tragedy of Florence is something entirely personal. Please accept this small sum of twenty dollars .... excuse my poor use of the beautiful language.*[7]

Most of the correspondence refers to some sort of action; either immediate or a promise of future action. In some correspondence, action taken is not evident but implied. Since the telegrams tend to be short, very few telegrams express sentiment and none of them describes past experience in Florence. On the other hand, the letters were found to be a hybrid of themes in that they not only focused on action but also expressed sentiments and/or shared memories. None of the letters only shared a memory or expressed sentiment. Action was certainly the prime objective of this correspondence. In letters, the three themes were found to be closely related, particularly in the communication of the international respondents. People who had visited Florence whether as a tourist, student or professional vividly remembered their time in Florence, expressed sadness about the loss of heritage and contributed towards response according to their own capacity.

As evident from the correspondence, contributions came in four specific forms: money, materials, volunteers and knowledge. Table 4 highlights that most sources contributed money (80.5%), followed by volunteers (3.3%), knowledge (2.2%) and material (1%). Moreover, Table 4 also highlights that some correspondents (7.7%) promised to contribute at a later date. A few correspondence also mentioned the inability to contribute (1.7%). Lastly, Table 4 highlights that a few sources (3.3%) sent multiple forms of contributions. Appendix A provides examples of correspondence and attachments.

Contribution of money

The most popular contribution was money, as evident from Table 4. People contributed according to what they could afford, as expressed in many letters. Some of the letters explicitly mention the amount contributed whereas others

[5] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 9, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[6] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 5, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[7] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 5, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

Contribution Type	No.	%
Money	145	80.5%
Promise to Contribute	14	7.7%
Volunteer	6	3.3%
Knowledge	4	2.4%
Money+ Volunteer	3	1.7%
Unable to Contribute	3	1.7%
Material	2	1.1%
Money+Material	2	1.1%
Material+ Volunteer	1	0.5%
Total	**180**	**100%**

Table 4: Distribution of the type of contributions. The most popular amongst all was the contribution of money.

mention 'a small contribution' instead of the actual amount. From the data available, individuals contributed from 5 USD to 10,000 USD in a personal capacity. Interestingly, the contribution of money also came from children (refer to 17 in Appendix A). The organizations had the capacity to contribute more (800 USD - 1,600 USD) and many organizations kept sending contributions at regular intervals. References 1, 2, 4, 5, 6, 12, 13, 14, 17, 19, 22 and 23 in Appendix A are examples of correspondence which show the contribution of money. Example 11 mention that the goal of the American committee was to raise $3.2 million.

Fundraising through events Some letters highlight the fundraising campaign through events such as lectures, conferences, musical recitals, exhibitions and lotteries (see 13, 14, 15 in Appendix A). Such events happened in both Italy and abroad. The contributions received were not only through art events organized by large scale organizations, but also through other, smaller events. Example 17 shows the organization of a cookie and candy sale by children to raise money for the restoration.

Contribution as volunteers

Students had a crucial role in the restoration of cultural heritage after the flood. Cultural institutions sent art student volunteers with professional restorers to carry out the restoration work. Some art students volunteered help in the rescue work by covering their own expenses, whereas others showed an inclination to volunteer if any opportunity was available (refer to 3 and 21 in Appendix A). However, the interest in volunteering to rescue cultural heritage was not limited to the people in art and allied fields. The correspondence highlights other professionals, such as doctors, who were willing to work as volunteers to restore the cultural heritage of Florence. Table 4 highlights that six sources in the selected sample expressed a willingness to volunteer, three sources sent money and volunteers, and one source donated materials and volunteers.

Contribution of knowledge

The field of conservation was still evolving in 1966. As a result, knowledge was also exchanged through letters on conservation techniques. Howard E. Gruber from Rutgers University suggested a technique based on his own experience of salvaging several hundred books (refer to example 16 in Appendix A). As seen in Table 4, four out of 180 sources contributed knowledge to rescue cultural heritage affected by the floods.

Contribution of materials

The contribution also came in the form of materials (see example 20 in Appendix A). Materials donated ranged from paintings to cleaning equipment and air heaters for efficient drying of artworks. While some sources donated single items, a few donated a large number of materials. Most such donations came from large scale organizations like businesses and universities. Table 4 shows that two sources contributed materials, two sources donated materials with money, and one source donated materials and volunteers to rescue cultural heritage.

A promise to contribute

Fourteen out of 180 correspondence items highlight a promise to contribute at a later date. These correspondence items explicitly mention the ongoing (collection) efforts. Examples 8 and 9 in Appendix A correspondence show the ongoing efforts in Canada and the USA. These letters do not mention any contribution being sent with the correspondence; however, they exemplify that the bigger organizations worked in a formal way.

Unable to contribute

Three out of 180 correspondence explicitly mentioned their inability to contribute due to a variety of reasons. Firstly, the mandate of a few contacted institutions barred them from contributing (see 18 in Appendix A). Secondly, the letters elaborate that some sources received requests from different committees working towards the same cause. Obviously, the sources could not contribute to multiple committees. Lastly, those who could not contribute financially found other ways to contribute. For instance, example 10 in Appendix A was written by an individual who was not able to contribute financially.

2.4.3 How were people motivated?

The analysis highlights four main factors in motivating people: 1) the call to participate, 2) media, 3) influencers, and 4) memory. However, several correspondence items (37%) in the selected sample did not explicitly mention their motivation for contributing, as evident from Table 5. Memory was found to be the greatest motivation behind contributions, followed by the call to participate, media and influencer. Table 5 further highlights that these factors also worked in combination.

Motivating Factor	No.	%
Not Mentioned	67	37.2%
Memory	32	17.7%
Call to Participate	29	16.2%
Media	20	11.2%
Media + Influencer	12	6.7%
Media + Memory	11	6.2%
Influencer	7	3.8%
Influencer + Memory	1	0.5%
Media + Call to Participate	1	0.5%
Total	**180**	**100%**

Table 5: Distribution of the motivating factors. Most of the correspondence did not mention the motivation for sending a contribution.

Role of memory

The greatest motivation for people to contribute was their having visited Florence in the past. In this, memory played an important role in people's perception of the need for action (see 2, 4, 5, 7, 12, and 17 in Appendix A).

The call to participate

The call to participate, initiated by CFIF, is essentially what attracted people initially and motivated them to participate in the initiative. The call to participate was rigorous. The committee personally sent cables and letters to many sources, as evident from correspondence 6 and 9 in Appendix A. Section 2.1 provides an example of a letter written by CFIF. This personal call to participate meticulously utilized the already existing network of possible respondents. Such letters have a personal tone, often addressing committee members as friends. Some of the sources were contacted more than once and by different members of CFIF. Moreover, the committee did not hesitate to contact sources whose mandate was outside cultural heritage (refer to 18 in Appendix A). While the telegrams sent by CFIF are not stored in the archive, some drafts of letters are available. The letter in section 2.1 elaborates that the call for aid gave a sense of urgency. The call compared the 1966 flood to previous disasters, such as the 1944 war and flood of 1277. Moreover, a short notice on university and office notice-boards was also helpful in motivating people to participate (refer to 11 in Appendix A).

Role of the media

The news media played a crucial role in organizing the response, as evident from Table 5. People were motivated to contribute through media such as newspapers, magazines, television and radio. This appeal to masses through media was done in various countries. Example 24 in Appendix A is a newspaper article published on 30 November 1966 in Wellington, New Zealand. Example 23 illustrates that images printed were useful in evoking emotions, thereby motivating individuals to send a contribution. Examples 1, 7 and 22 in Appendix A show that people sent contributions to CFIF after reading a news article in their local newspapers. Moreover, people also showed a willingness to work as volunteers after reading newspaper articles (refer to 21 in Appendix A). On the other hand, some magazines targeted niche interest-groups in appealing for assistance.

Role of influencers

Some of the sources were influential people at the time. Philanthropists, art collectors, professors, writers, journalists and political figures contributed generously to the initiative. Prominent figures like Jacqueline Kennedy (see 9 in Appendix A) and Sir Ashley Clarke chaired similar committees in the USA and UK, respectively. The correspondence highlights that an influencer need not be a prominent figure in society but can be a teacher, parent, friend or colleague (refer to examples 12 and 17 in Appendix A). As evident from Table 5, seven sources were solely motivated by an influencer. The table also illustrates that 13 sources were motivated by media and memory, in addition to an influencer.

2.5 Discussion

Three main themes emerged from the analysis- action, memory and sentiment. In letters, the three themes were found to be closely related, particularly in the internationals' response. On the other hand, telegrams were short and focused only on action. Whether these themes will still be present in people's response to disasters affecting cultural heritage during the Internet age is a question that requires further research. Indeed, the technological context of 1966 was different from the present times. With participatory technologies such as Twitter, people are able to instantaneously post about disasters. The overall trend of Figure 6 may remain the same in the present times, i.e. the interest in the event is shown to diminish with time. However, the number of respondents may increase significantly due to the availability of the Internet. Moreover, the delay of five days in the response of people visible in Figure 6 is almost incomprehensible in today's context, particularly for a connected city such as Florence.

Money, materials, volunteers and knowledge were the contributions of the crowd. The most popular contribution was money. While this research did not aim to analyse *how much money was contributed to CFIF*, it is not surprising that most people contributed money. The committee primarily requested money, through personal and public communication channels. Even though most people (80.5% in the selected sample) contributed money, this case is not an example of crowdfunding where people micro-finance initiatives. Firstly, the contributions received were certainly more than money and included materials, knowledge and volunteers. Secondly, the correspondence also highlights that money was not the only valuable contribution. In fact, people wanted to contribute in more personal ways. Some of those who could not help financially wrote an article about Florence and the flood. This, in turn, would have raised awareness and motivated people to contribute.

The role of volunteers in the aftermath of the 1966 flood has been widely discussed. The volunteers are popularly referred to as *Mud Angles* (Era06; Era16). Waters (Wat16) mentioned that students worked in removing the books from the affected area by forming human chains. Ted Kennedy (Tat) appreciated the work of Italian students. However, volunteering was not limited to students and Italians only. The correspondence suggests international individuals volunteered as experts and non-experts. People's willingness to volunteer in Florence at their own expense highlights their attachment to the cultural heritage of the city. It also suggests that cultural heritage can be valuable to people beyond a country's national boundaries.

Current research on crowdsourcing elaborately discusses the motivation to participate, particularly focusing on *why people volunteer or contribute*. Understanding volunteer's motivation is important for retaining them (Cas16). Starbird et al. mention that these reasons are complex and context-dependent (SMP12). In this chapter, I analyzed *how the crowd was motivated*. This understanding will help in defining rules of engagement that can be useful for crowdsourcing initiatives. Four main factors were found to be motivating people to contribute: 1) the call to participate, 2) the media, 3)influencers, and 4) a strong personal memory of the city. Memory was found to be the greatest motivating factor, followed by the call to participate, media and influencers. However, it is difficult to assess the true degree of influence of the motivating factors. Firstly, Table 5 illustrates that the motivating factors were close in numbers. Secondly, multiple factors were also found to be motivating a few sources. Moreover, the degree of influence of the motivating factors may differ in the whole dataset. Therefore, these findings cannot be generalized.

As we saw in section 2.4.3, the call to participate was elaborate, extensive and gave a sense of urgency. The analysis demonstrate the importance of utilizing the existing network of potential contributors. Moreover, it also highlights the importance of utilizing public communication channels to disseminate the initiative. It can be concluded from the analysis that the more rigorous a call is, the more likely it is to attract participants in a crowdsourcing initiative.

The analysis revealed that the news media played a crucial role in organizing the response after the flood. This highlights the importance of mainstream media organizations during disasters. Starbird & Palen (SP10) and Bruns et al. (BBCS12) found that users tend to circulate messages from established media organizations. Lascarides & Vershbow (LV14) report attention spikes from the public upon significant new press or social media coverage. The news media can play a vital role in disseminating news and gaining participants in crowdsourcing initiatives. Hence, the need to build a community around the media between crises, as suggested by Castillo (Cas16).

The analysis revealed that some of the sources were influential people in society. The role of prominent politicians, activists and professors in the context of the 1966 flood has been documented and widely discussed. Prominent figures René Maheu (the Director-General of UNESCO), Ted Kennedy, Jacqueline Kennedy and Liz Taylor appealed to the public to contribute. The role of influencers is mirrored in today's context as well. Starbird & Palen (SP10) and Sutton et al. (SSJ$^+$14) found that messages from Twitter accounts with many followers are circulated more. The analysis also suggests that an influencer need not be a prominent figure in society but also can be a teacher, parent, friend or colleague. This highlights the importance of "the crowd" in motivating others. In other words, the crowd also performs the call to participate, thereby creating motivation in their network.

The analysis has a few limitations. The selected sample is limited, representing only about 24% of the correspondence. There is over-representation of language and location in the available dataset, in that the majority of correspondence (64%) is in Italian and sent from Italy. As a result, the selected sample also has over-representation of language and location. The dataset contains mostly correspondence sent from sources, and little correspondence sent from CFIF is available. Lastly, the analysis presented in this chapter refers only to the work of the CFIF and does not include the committees in other countries.

2.6 Concluding Remarks

This research addressed two questions: How did the people respond to the cultural heritage damaged during the 1966 Florence Flood? And, moreover, how were they motivated to do so? A total of 180 out of 753 correspondence sources were selected for analysis, using random sampling. The selected sample is diverse, and includes correspondence from Italians and internationals; and public and private bodies; as well as a combination of telegrams, typed letters and handwritten letters. Three main themes emerged from the manual content analysis of the correspondence- action, memory and sentiment. In letters, the three themes were found to be closely related, particularly in internationals' responses. On the other hand, telegrams were short and focused only on action. The committee received contributions in the form of money, materials, volunteers and knowledge from two distinct categories: experts in conservation and restoration, and non-experts. The most popular contribution was money. Four main factors were found to be motivating people to contribute: 1) the call to participate, 2) media, 3) influencers, and 4) memory of the city. Memory was the greatest motivating factor, followed by the call to participate, media and influencers.

Overall, this initiative is particularly relevant in today's context where the frequency and severity of disasters affecting cultural heritage have increased tremendously (Tab03). In particular, it emphasizes how to initiate a crowdsourcing campaign to restore cultural heritage; who will contribute, or who is most likely to contribute; and, finally, how to motivate people to contribute. Further work includes analysis of all 753 sources of correspondence. The scope of work can also be extended to use archival material such as the Arthur T. Hamlin papers at the Columbia University, Borsook Eve. Papers and CRIA archives at the Villa I Tatti, The Harvard University Center for Italian Renaissance Studies, to understand the response in depth. Archives of newspapers and magazines from across the world can also be referred to in conducting further research. This case can also be compared with case studies from present times in order to compare and contrast the findings of this study.

Chapter 3

Twitter, Disasters and Cultural Heritage: A Case Study of the 2015 Nepal Earthquake

The purpose of this chapter is to understand how Twitter users responded to the cultural heritage damaged during the 2015 Nepal earthquake. This chapter utilizes 201,457 tweets (including retweets) from three different datasets. The analysis shows that approximately 4% of tweets were regarding cultural heritage. Moreover, asymmetrical information was available on Twitter regarding cultural heritage during the Nepal earthquake, i.e. not every site received equal attention from the public. Damaged sites received more attention than unaffected sites. The content of tweets can be divided into five categories: information, sentiment, memory, action, and noise. Most people (89.1%) used Twitter during the disaster to disseminate information regarding damaged cultural heritage sites.

3.1 Introduction

Social media is an umbrella term generally applied to web-based services that facilitate some form of social interaction or networking (Zap12). They have been noted for their ability to rapidly and continuously be updated by numerous users. In the present day context, there are more than 200 social networking sites globally, each dedicated to a specific function such as friend connections, professional connections, photo sharing, video sharing, blogging, chat, etc. A users choice of social media may depend on the popularity of the media, its purpose and expected dissemination. Twitter, a microblogging platform is a popular choice for instantaneous dissemination of information due to several reasons such as openness, searchable contents, dissemination, and ability to share any media. Originally envisioned to facilitate circulation of a ”short burst of inconsequential information” (Joh13), it has grown into a globally significant outlet for instantaneous information and news dissemination, particularly during disasters (SBCB13).

With over 320 million active users (Sta19) . Twitter can increase awareness of the situation, facilitate coordinated response and reduce the time lag between crisis and action. Twitter has received tremendous attention from researchers in disaster management regarding how information is created, distributed, collected, processed and utilized. However, the role of Twitter in the context of cultural heritage during such events has received less attention. Addressing the gap in research, this chapter is the first step towards understanding the response on Twitter by addressing the following question: How did the users respond on Twitter to the cultural heritage damaged during the 2015 Nepal Earthquake?

How did the users respond to the cultural heritage damaged during the 2015 Nepal Earthquake on Twitter? This chapter aims to understand what kind of data was posted regarding cultural heritage during the earthquake and whether this data can be used to analyze the situation on the ground. The 2015 Nepal Earthquake is an appropriate case study as the earthquake damaged many important cultural heritage sites of the country. A report of the Department of Archaeology estimated that out of 743 affected buildings in 20 districts of Nepal, 133 collapsed, 95 partially collapsed and 515 suffered part damage (oAN15). The post-disaster needs assessment report of the Government of Nepal estimated that the total value of cultural heritage effects (damages and losses) caused by the earthquakes is US$ 171 million (Nep15).

The sites included in UNESCO World Heritage property Kathmandu Valley suffered to a different degree. The property includes seven groups of monuments and buildings including Durbar Squares of Hanuman Dhoka (Kathmandu), Patan and Bhaktapur, the Buddhist stupas of Swayambhu and Bauddhanath and the Hindu temples of Pashupati and Changu Narayan. Several temples in Darbar Square in Kathmandu, Patan and Bhaktapur and Changu Narayan had collapsed. The Buddhist stupas of Swayambhunath were also affected, whereas the Buddhist stupas of Bauddhanath and Pashupatinath temple had minor damages. On the other hand, UNESCO World Heritage property Lumbini, the Birthplace of the Lord Buddha did not suffer any damage. Dharahara Tower was completely collapsed. Other heritage sites such as Janaki

Mandir in Janakpur, a monastery in Ghiling village, Upper Mustang, National Museum in Kathmandu, Living Traditions Museum at Changu also suffered damages (ICC15).

To address the user response on Twitter, this chapter is structured in six additional parts. Section 3.2 conceptually frames this research, particularly linking it to other works on the use of Twitter during disasters and the 2015 Nepal Earthquake. Section 3.3 describes the data collection and methodology adopted for this research. Section 3.4 describes the results. Section 3.5 discusses the implications of this research. Lastly, Section 3.6 concludes the chapter with possibilities for future work.

3.2 Related Works

3.2.1 Twitter, disasters and cultural heritage

In recent years, Twitter has been used extensively during disasters due to its instantaneous nature, widespread dissemination and openly available information. As a result, the role of Twitter in disaster management has gained tremendous attention amongst researchers. Researchers have studied several aspects of Twitter during disasters such as crisis communication (WZ17; BB14) situation awareness (VHSP10) information credibility (MPC10; GK12), etc. by focusing on case studies from different parts of the world.

Murthy Longwell (ML13) use the case of 2010 Pakistan floods to understand the patterns of tweeting behavior of the public based on their location. Their study concluded that the Western users preferred traditional media whereas the Pakistani users linked to data posted on social media. Acar & Muraki (AM11) analyzed tweets from directly and indirectly hit areas from the Great Tohoku earthquake. Their analysis concluded that the contents of tweet during posted was related to the users location. Users in affected areas tweeted regarding their uncertain situation, whereas users in remote areas tweeted regarding their safety.

Moreover, researchers have also constructed different categories of tweets posted during disasters (KHPK14) using supervised and unsupervised classification methods (Cas16). For instance, Qu et al. (QHZZ11)used the case of the 2010 Yushu Earthquake to understand the type of messages posted and re-posted on Sina-Weibo, a Chinese microblogging system. Their study identified four main categories of microblogging: information, opinion, emotion, and action. Shaw et al. (SBCB13) also developed typologies of tweets 2010-2011 Queensland floods in Australia as: information, media sharing, help and fundraising, experience, discussion, and reaction. David et al. (DOL16) analyzed tweets posted during 2013 Typhoon Haiyan and developed the following categories: information, expressions of support, emotion, disaster relief and aid, and political expressions. The overlapping categories in researchers works hint at the common practices adopted by the Twitter users during disasters regardless of their geographical location.

In contrast, research on the use of Twitter regarding cultural heritage damaged during disasters is limited. In the cultural heritage domain, Twitter is mainly used for dissemination of initiatives. For instance, during the 2015 Nepal Earthquake heritage professionals disseminated the Kathmandu Cultural Emergency Crowdmap (Tan17) using two dedicated hashtags #heritagedamagenepal, #culturedamagenepal. As evident from the 83 tweets using these hashtags, the professionals requested to use the dedicated hashtags and submit data (reports and images) about damaged cultural heritage. Moreover, they also shared news from the mainstream media. A similar effort was initiated by Wikipedia after the fire in the National Museum of Brazil in 2018. Wikipedia also used Twitter to disseminate its crowdsourcing initiative to preserve the memory of objects damaged by the fire. In contrast, this chapter analyzes the tweets posted regarding cultural heritage during the Nepal earthquake.

3.2.2 The 2015 Nepal Earthquake

The participative technological applications used during the 2015 Nepal Earthquake have been studied from many perspectives. Researchers have focused on Twitter, mobile applications and crowdsourced mapping both during the disaster response and recovery phase. Thapa (Tha16) analyzed location-based tweets posted during the 2015 Nepal Earthquake to understand the spatial and temporal characteristics of the tweets. The study concluded that a relatively small number (22%) of people used hashtags related to the event, whereas most of the tweets were without any hashtag. Moreover, amongst the people using hashtags, more than 25% of tweets posted were not related to the earthquake. The study also found a hike in the number of tweets upon an earthquake of high intensity and concluded that English was a preferred language amongst Twitter users. Priya et al. (PBD+18) developed a framework for retrieving tweets providing information about infrastructure damage during earthquakes. Moreover, the framework also determines the damage score of affected locations. Using the case of the 2015 Nepal Earthquake, the authors demonstrated that their approach can efficiently measure the extent of infrastructure damage in the region. On the other hand, Subba & Bui (SB17) focus on the use of Twitter by the National Police headquarters in Nepal to communicate with the citizens. The study concluded that Twitter was an effective communication and collaboration platform between the emergency managers (i.e. the police) and the citizens, which also lead the police to reconsider its planning activities. Poiani et al. (PdSRDdA16) focused on the use of OpenStreetMap, a collaborative mapping platform during the 2015 Nepal Earthquake in which a large number of off-site users had contributed to the platform. On the other hand, Bossu et al. (BLMR+15) studied the adoption of LastQuake smartphone application by the on-site users.

In comparison, the participatory applications in the context of cultural heritage during the 2015 Nepal Earthquake was limited. Kathmandu Cultural Emergency Crowdmap (Tan17) utilized the Ushahidi Platform to rapidly assess damage to cultural heritage after the earthquake. However, cultural heritage damaged during the 2015 Nepal Earthquake has received the attention of researchers from different perspectives. Researchers have studied the causes of damage to heritage sites (SSSM17; BBA^{+}18; Gau17), its impact on tourism (KC16), and coverage in the media reports (Hut18). Bhagat et al. discussed the reasons behind the collapse of cultural heritage buildings. They concluded that the main reasons behind the extent of damage were the magnitude of the earthquake, lack of maintenance of the buildings and deterioration of the construction materials. Further, KC et al. (KSP17) concluded that structures that were seismically retrofitted were least damaged during the earthquake. Kunwar & Chand (KC16) assess the impact of the earthquake on tourism in Bhaktapur [1] highlighting the importance of heritage in the tourism industry. Hutt concluded that Dharahara tower received more attention than the countrys World Heritage properties in the media to the extent that it became a point for the revival of Nations identity (Hut18). To date, it appears that no prior study deals with the study of tweets posted regarding cultural heritage during the 2015 Nepal Earthquake.

3.3 Material and Methods

In this section, I will discuss the data collected for this study and the methodology adopted for analysis.

3.3.1 Material

This study utilizes 201,457 English tweets (including Retweets or RTs) from three different datasets. Table 6 provides details of the datasets. The data is of two kinds: 1) Manually collected heritage specific data (Dataset 1) 2) data collected on Nepal Earthquake through APIs (Dataset 2 and 3). The date of collection of the datasets corresponds to the event, i.e. the collection of data started on 25 April 2015. However, the period of collection is different, as evident from Table 6. Dataset 1 contains 449 tweets posted between 25 April 2015- 28 September 2016. Twitter search '#Nepaleathquake heritage' was used to collect tweets in this dataset. The purpose of this dataset was to create a baseline for analyzing datasets 2 and 3, as we will see in the next section. Dataset 2 contains 150,940 tweets collected using AIDR (ICL^{+}14b) on 25 April 2015. As evident in the table below, the data was collected using 30 keywords including some heritage sites (e.g. Dharahara Tower, Darbar Square). Dataset 3 contains 50, 068 tweets

[1] One of the seven monument zone included in the UNESCO World Heritage property 'Kathmandu Valley'.

collected between 25 April 2015- 10 May 2015 from SMERP Workshop (MJG[+]18). This data was collected using keywords Nepal earthquake and Nepal quake.

Dataset 1	
Date	25.04.2015 28.09.2016
Number of Tweets	449
Keywords	#Nepalearthquake, Heritage
Dataset 2	
Date	25.04.2015 25.04.2015
Number of Tweets	150,940
Keywords	Basantapur, Patan, Anamnagar, Bhaktapur, Durbar Square, Nuwakot, Dharahara Tower, Gorkha, Lamjung, Khudi, Kathmandu, Sankhu, Sunsari, Solu district, Okhaldhunga, Nepal, nepal earthquake, ktmearthquake, IndiaWithNepal, NepalQuake, NepalQuakeRelief, NepalEarthquake, KathmanduQuake, KathmanduQuakeRelief, KathmanduEarthauqke, QuakeNepal, EarthquakeNepal, QuakeKathmandu, EarthquakeKathmandu, PrayForNepal
Dataset 3	
Date	25.04.2015 10.05.2015
Number of Tweets	50, 068
Keywords	Nepal earthquake, Nepal quake

Table 6: Details of datasets.

3.3.2 Methods

This chapter aims to analyze tweets relevant to cultural heritage sites affected during the 2015 Nepal Earthquake. This chapter uses a methodology for retrieving data regarding a niche subject (i.e. cultural heritage sites) from the big datasets. As evident from Table 6, the big datasets were not curated for heritage purposes. Nevertheless, the datasets contain information regarding cultural heritage sites damaged due to the disaster. The method consists of the following steps:

1. **Baseline construction**
   - Building a preliminary set of query keywords manually from dataset 1
   - Manual content analysis of tweets to build preliminary categories
2. **Examining tweets from datasets 2 and 3 with the help of the baseline**
   - Retrieving the relevant tweets from dataset 2 and dataset 3
   - Expanding query keywords with the help of the word tree of query keywords

- Retrieving more relevant tweets from dataset 2 and dataset 3
- Manual content analysis of tweets to build categories

Manual generation of query keywords and content analysis were selected for three reasons. First, significant expertise was required at each step mentioned above. Secondly, to my knowledge, no prior studies have examined the content of tweets posted regarding cultural heritage sites affected during disasters. Therefore, in the absence of any previous study which could serve as a reference, I decided to manually analyze the data. Lastly, the language used in Twitter tends to be informal and often contain typographical errors. Therefore, manual methods for analysis was considered suitable for this research.

Baseline construction using dataset 1

Twitter data from the 2015 Nepal Earthquake was used to construct a baseline for this research to build an initial, yet flexible understanding of the nature of data posted during the disaster. Since dataset 1 is a small dataset containing heritage-specific tweets, therefore, this dataset was the most appropriate for constructing a baseline for examining datasets 2 and 3. The dataset was used to 1) construct a set of query keywords 2) construct preliminary categories of tweets.

Constructing a set of query keywords

The 449 heritage specific tweets were analyzed to build a preliminary set of query keywords using NVivo, a qualitative data analysis software. First, the data was cleaned for the main attributes using NVivo. The stop words were removed, data was normalized and lemmatized (SM17). The resultant frequently occurring words were summarized and sorted by the frequency.

Out of the most frequent words, I selected the words occurring at least 5 times. Thus, 152 unique keywords were defined as the initial query keywords. Similar words were then grouped manually under the following categories: action words, descriptive words, generic words, organizations name, sentiment, site-type, site-name and situational word. The manual grouping of frequently occurring words was done to evaluate the utility of each category for query keywords in datasets 2 and 3. Table illustrates the categories with a few examples.

Constructing preliminary categories of tweets

The 449 tweets were coded in NVivo to understand the underlining patterns of communication. Manual content analysis was used to identify preliminary common themes and constructing underlying meanings in tweets. As Krippendorff, Weber (Kri18; Web84) suggest, the content analysis can include beyond the message itself. This chapter briefly focuses on the number of retweets, the type of users, to understand the context and impact of the tweets.

It is important to acknowledge the language of the Internet is ever-evolving. However, the language is based on a set of established principles (Cry06) the tweets can be brief, informal, and often contain slangs, typographical errors, abbreviations, and incorrect grammar (HCB13). Therefore, each tweet was read and re-read in order to understand the usage of words, possible errors and correct tone of the tweet. Table 7 provides some examples of the language usage found in the tweets.

Type	**Example**
Typographical Error	#Kathmandu 's Darbar Square, A UNESCO World Heritage Site!! :(:(#EarthquakeinNepal #PreyforNepal #Earthquake
Abbreviations	#PrayForNepal We lost our 19th century Dharahara Tower; life of so many ppls in Capital Kathmandu R.I.P. to all of them
Abbreviations	It's v hard to see #Kathmandu devastated by d #earthquake. Most of d historical places r gone including #Dharahara d landmark of Kathmandu.
Emphasize by capitalization	Very SAD. #Kathmandu 's Darbar Square, a UNESCO World Heritage site, in ruins after today's #Nepalquake

Table 7: Examples of language usage

3.3.3 Examining datasets 2 and 3

With the results from the analysis of dataset 1 in hand, rest 201,008 tweets in datasets 2 and 3 were approached with flexibility if more keywords and categories were to be found.

Retrieving the relevant tweets from dataset 2 and dataset 3

Datasets 2 and 3 were imported in NVivo and the 152 query keywords were used to find relevant data in the datasets. The 152 query keywords were tested, regardless of the frequency of the keyword. In other words, the less frequently occurring words such as landmark or old (see Table 11) were also used to find relevant data. It should be noted that not all 152 query keywords were useful. Some query keywords resulted only in irrelevant data. Certain categories of keywords were found to be better suited to find relevant data. For instance, the words falling under site name, site type and descriptive words in Table 11 resulted in most tweets related to cultural heritage. The resultant relevant tweets using the query keywords were coded under the node heritage in NVivo. Nevertheless, some unrelated tweets were also found with the relevant data. Such tweets often contained information regarding the cultural heritage sites of other countries. The unrelated tweets were coded under the same node heritage, to understand noise generated from the search terms.

Expanding query keywords and retrieving more relevant tweets

To ensure that I find all the tweets related to cultural heritage, I used the word tree of each query keyword to understand the usage of words in context. Figure 7 shows the example of a world tree for the term heritage. Word trees were particularly important to understand the nuances of language usage in the tweets. For instance, different spellings were used for the cultural heritage sites name. Moreover, certain words in the local language were also used to refer to a site. Consequently, the query keywords were expanded and used to retrieve more relevant tweets

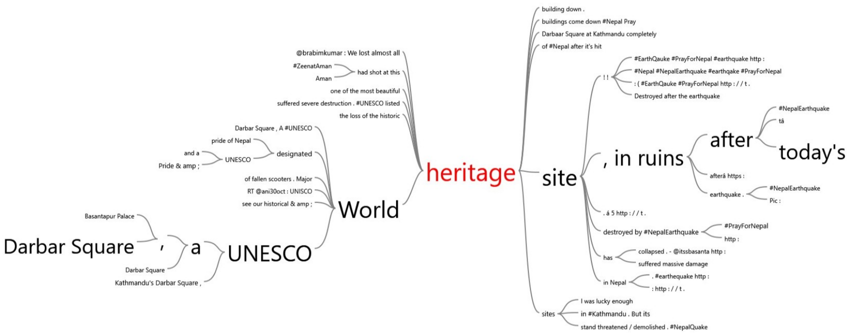

Figure 7: Word trees were used to explore a keyword in context.

Manual content analysis of tweets to build categories

Content analysis of tweets coded under the node heritage was done to understand the underlining patterns of communication. With the preliminary categories in hand from dataset 1, the analysis was carried out to understand the categories in bigger datasets. The tweets were approached with flexibility if new categories were to be found or certain categories from the preliminary analysis were absent in the bigger datasets. The coding scheme is explained in Table 8. Furthermore, quantitative analysis was done to understand the patterns in overall data, dominant category and sub-categories.

Category	Details
Information	The tweets which had information regarding the situation of heritage sites were coded under this category. These tweets describe the extent and type of damage to heritage sites, or scale of the impact.
Action	The tweets which had the information regarding ongoing efforts to rescue heritage or future steps towards restoration were coded under this category.
Memories	Any kind of recollection of events or facts in the context of cultural heritage was coded under memory.
Sentiments	Tweets which had an expression of emotion were coded under sentiments.
Noise	The tweets which did not information about the cultural heritage of Nepal were coded under this category.

Table 8: Coding scheme

	k	**Percentage of Agreement**	**Agreement Level**
Information	0.794	92.4	Substantial
Sentiment	0.831	92.4	Almost Perfect
Memory	0.711	89.3	Substantial
Action	0.554	91.6	Moderate
Noise	0.917	97.7	Almost Perfect

Table 9: Intercoder reliability per category (Kappa and percentage of agreement)

Verification of coding scheme

To verify the reliability of the coding scheme, two coders coded a sample of 131 relevant tweets. Cohens Kappa (Coh60) was calculated to identify intercoder reliability per category. Table 9 shows the Kappa (k), percentage of agreement and agreement level for each category. The intercoder reliability of action was rated as moderate, information and memory as substantial, sentiment and noise as almost perfect. Moreover, the percentage of agreement indicate good agreement for each of the category. Therefore, it was decided to retain the coding scheme.

3.4 Results

The results are divided into three main parts. Section 3.4.1 describes the generic results of data analysis. It provides an overall view of the data analysis. Section 3.4.2 describes the results of keyword analysis. Section 3.4.3 answers the primary research question in this chapter.

3.4.1 General observation

The analysis shows that only a small number of tweets were posted regarding cultural heritage during the 2015 Nepal Earthquake. A total of 7,989 (approximately 4%) relevant tweets were extracted from datasets 2 and 3.

Asymmetrical information was available on Twitter regarding cultural heritage during the Nepal Earthquake, i.e. not every site received equal attention from the public. Sites which were damaged received more attention than the unaffected sites. The tweets contain a combination of user-generated and mainstream media tweets (see Table 10). The mainstream media tweets include tweets from professional journalists and media outlets.

Type	Tweet	Number of Retweets	Number of Comments	Number of Favorites
User-generated content	Darbar Square, #Nepal's Pride & UNESCO designated World Heritage Site destroyed by #NepalEarthquake #PrayForNepal	877	13	121
	Pictures of Patan Durbar Hall, a UNESCO world heritage site, in #Kathmandu one hour apart before & after #earthquake	135	4	34
	Dharara Tower, built in 1832, collapses in #Kathmandu during earthquake, Plz Guru ji please help them victims ppl #MSGHelp	102	0	0
Mainstream Media	Truly awful sight. Kathmandu's Darbar Square, a UNESCO World Heritage site, in ruins after today's earthquake.	2084	54	376
	@BBCWorld: Before and after: Kathmandu's historic Dharahara Tower flattened by #earthquake	2012	55	534
	@nytimes: Photos of Nepals landmarks, before and after the earthquake	1509	65	417

Table 10: The tweets are a combination of user-generated contents and from mainstream media

The tweets from the mainstream media outlets were found to be factual, formal and informative. On the other hand, some professional journalists also tweeted emotional contents (see Table 10. The goal of the mainstream media tweets was to provide as much information on the current-situation in as little words as possible. Often the information about heritage sites was coupled with humanitarian information, i.e. how many people were affected by the damage to the site. The user-generated tweets were found to be mainly emotional, personal and informative. However, some user-generated tweets were also formal and factual (see Table 10). These tweets often contain contextual information such as the meaning of the name of the site, information about its construction (date and people), its role in the society and the users relationship with it. Overall, the tweets from mainstream media were retweeted more than the user-generated tweets. Table 10 provides examples of most retweeted tweets from mainstream media and users.

3.4.2 Building and expanding query keywords

As explained in Section 3.3.2, the query keywords were first built from 449 heritage-related tweets. Later, the keywords were expanded with the help of the word tree of initial query keywords. Table 11 exemplifies manually categorized query keywords.

Category	**Word**	**Similar Words**	**Count**
Action	rebuilding	rebuild	16
Action	reconstruction	reconstruct, reconstructing	15
Descriptive	heritage	-	479
Descriptive	culture	cultural	74
Generic	architecture	architectural	11
Generic	landmarks	landmark	5
Organization	UNESCO	-	122
Sentiment	heartbreaking	heartbreak	7
Sentiment	tragic	-	6
Site Type	temples	temple	29
Site Type	monuments	monumental, monument	13
Site Name	durbar	-	29
Site Name	dharahara	-	15
Situation	destroys	destroyed, destroying	64
Situation	damages	damaged, damage	53

Table 11: Categorization of keywords

While expanding the query keywords, one of the important findings was different names and spellings of sites. For example, the Dharahara Tower was also referred to as Bhimsen Tower, Dharara Tower, Kathmandu Tower, Gharahara Tower, 19th century Tower, Famous Tower, Historic Tower, Tower, and so on. Similarly, Darbar Square was often referred to as Durbar Square. Moreover, it was found that many terms in the local language were also used instead of English terms. For instance, many tweets referred to a temple as a mandir.

3.4.3 Categories

Three categories of tweets were established from the analysis of dataset 1: information, action, and sentiment. Two additional categories emerged from the analysis of datasets 2 and 3: memory and noise. However, none of the categories had to be removed from the original classification. Table 12 provides an example of each category and its distribution. As evident from the table, Twitter was used mainly for circulating information (89.1%), followed by expressing sentiment (25.4%), sharing and recalling memory (5%), and organizing and suggesting action (3.8%). It should be noted that the four categories are not mutually exclusive. Most of the tweets are hybrid i.e. they follow at least two of the above-mentioned categories. Table 13 provides examples of hybrid tweets.

Type	Number	Percent	Tweet
Information	7119	89.1%	Historic Dharara Tower collapses in Kathmandu after 7.9 earthquake
Sentiment	2034	25.4%	The sadness is sinking in. We have lost our temples, our history, the places we grew up. #NepalEarthquake
Memory	406	5%	Apparently this is what Durbar Square used to look like.
Action	306	3.8%	@NepalPoliceHQ Protect the heritage sites! Our own people are looting #Nepalearthquake
Noise	306	3.8%	Earthquake in #Nepal Golden Temple send 1 lac and Delhi Gurdwaras send 25k meals daily. Those who share sardar jokes, please share this too

Table 12: Examples and distribution of tweets

Information

The analysis shows that Twitter was used mainly for disseminating information. Approximately 89.1% of the relevant tweets (see Table 12) provide some information regarding the situation of sites. Table 10 and Table 14 provide examples of tweets which disseminated information during the earthquake. Tweets also illustrate how the sites were used after the earthquake. For instance, people continued praying in the damaged temples and took selfies in damaged sites (see Table 14). Attempts of information seeking were also evident, particularly for the sites which were not extensively covered in the mainstream media reports. Overall, some tweets are more useful in assessing damage to the heritage sites and understanding the situation on the ground. Such tweets include the name of the site, information about its condition, the number of humans affected by its damage, and so on. Table 10 shows that the most popular tweets disseminated

Type	Tweet
Information+ Sentiment	Awful sight. Kathmandu's Darbar Square, a UNESCO World Heritage site, in ruins after today's earthquake.
Information+ Action	Nepal Quake: search for survivors, with 50 people missing in Dharahara Tower collapse
Information+ Memory	Historical Dharahara tower (1832) was built by the Prime Minister BHIMSEN THAPA. Just collapsed due to #earthquake
Sentiment + Action	—-
Sentiment + Memory	Never knew last time I visited #Kathmandu and roamed around #Basantapur was the last time I saw those ancient temples. :(rip to history
Action + Memory	Durbar Square damaged in 1934 earthquake & again today. We need to learn and not let this keep happening #NepalQuake
Information+ Sentiment+ Action	Oh, MY! GOD!! The Durbar Square is GONE!!! 7.9 Magnitude #earthquake HELP IS NEEDED Immediately! @UNDP #RedCross
Information+ Sentiment+ Memory	One hour before Nepal earthquake. Small temple behind me completely collapsed. Absolutely surreal. #NepalQuake
Information+ Action+ Memory	—-
Information+ Sentiment+ Memory + Action	I visited #Nepal in 2009. Devastated to see Durbar Square in ruins. My thoughts go to all victims; I urge immediate #humanitarian response

Table 13: Examples of hybrid tweets

information regarding the situation of the sites. Table 14 exemplifies tweets that mention how the sites were used after the earthquake (i.e. practice) were also reposted extensively.

Sentiment

Approximately 25.4% of the relevant tweets expressed sentiments using emoticons, words, hashtags and phrases. The sentiments can be divided into two polar categories: sympathy and indifference towards heritage. Tweets showing sympathy are the ones which express sadness, disappointment over the loss of heritage, whereas the indifference tweets display antipathy towards heritage. Table 15 some examples of both categories. The sympathetic tweets exceed in number than the indifferent tweets. Only about 5% of users expressing emotions showed indifference to heritage. People who posted antipathy thought that humans should be the first concern during this disaster rather than the heritage. However, people who showed sympathy towards heritage also showed sympa-

Type	Tweet	Number of Retweets	Number of Comments	Number of Favorites
Situation	ancient monuments are no more than a debris in NEPAL AFTER 7.9 RICHTER EARTHQUAKE!!!	0	0	0
	Nepal's historic Kasthamandap temple wiped off in earthquake	0	0	0
Practice	A woman bows her head in prayer in Patan Darbar Square on the morning after the #earthquake	40	1	18
	Nepals famous Dharahara Tower becomes site for selfies after devastating Earthquake	95	8	42
Information Seeking	Anyone in Nepal can tell us if the Pashupatinath temple is alright? #earthquake	6	1	1

Table 14: Tweets that shared information disseminated the on-site situation and practice around the sites. Attempts of information seeking were also evident.

thy for the loss of life. Interestingly, the Nepali users posted only sympathetic tweets, as evident from Table 15. Moreover, on average the sympathy tweets had more engagement than the indifferent tweets. On the other hand, users who posted indifferent tweets were located outside Nepal.

Memory

The analysis shows that 5% of the relevant tweets shared memories that were historically relevant or personally meaningful. This includes users visit to the heritage site, others experience of disaster in the context of cultural heritage. Heritage as a context in movies was also remembered. People also remembered the impact of the 1934 earthquake and compared the 2015 earthquake with the 1934 earthquake. Twitter was used to post regarding memorials constructed for the damaged heritage sites. Lastly, the dissemination of memorial events was also done via Twitter. Table 16 provides examples of tweets coded under this theme. As evident from the Table, these tweets were not reposted extensively and had minimal engagement.

Action

The analysis shows that approximately 3.8% of the relevant tweets are action-related. There are two types of action: immediate action, future action. Table 17 provides examples of immediate action and future action. Immediate action

Type	Tweet	Number of Retweets	Number of Comments	Number of Favorites
Sympathy	When not only u feel 4 ur luvd ones but also 4 ur country & ur ppl & even ur heritage is cald patriotism. A lesson hard learned.#NepalEarthquake	0	0	0
	it's v hard to see #Kathmandu devastated by d #earthquake. Most of d historical places r gone including #Dharahara d landmark of Kathmandu.	1	0	0
	A tragic scene in my country Nepal. Historic buildings and monuments, all destroyed. #NepalEarthquake #PrayForNepal	46	1	8
Indifference	If I hear one more Westerner complaining about the loss of heritage instead of human lives in #NepalEarthquake I will SCREAM.	0	0	0
	Rs 2 is trending. it is price of your brain if u r worried about unesco world heritage sites in #Kathmandu instead of human lives. #NepalEarthquake	3	1	3
	Some tweeters are worried about old Mosques/Temples/UNESCO heritage sites, please grow up and save humans 1st. #NepalEarthquake	5	2	12

Table 15: Tweets coded in sentiment category showed both sympathy and indifference towards heritage

includes tweets where users demand action and informed about ongoing action. In the context of cultural heritage, the user demand for immediate action was found to be extremely crucial. These tweets represent a call for action and coordination from public on-site. They show the urgency of action required to address a specific issue urgent in order to prevent more damage to cultural heritage. However, as evident from Table 17, these tweets had very little engagement. The tweets referring to future action are comparatively less. These tweets discuss the need to rebuild or reconstruct these monuments. They often look up to the government for this. People also directly urge the political leaders by mentioning them (using @) on the tweet to help in the process.

Type	Tweet	Number of Retweets	Number of Comments	Number of Favorites
Other's Experience	People on my flight had injuries from the earthquake–scrape on head / broken leg. One person saw the big tower collapse #Nepal.	5	0	0
Past visit	I visited #Nepal in 2009. Devastated to see Durbar Square in ruins	1	0	0
	I went there about 20 years ago (travelled through India and Nepal) so sad to see the temples turned in piles of rubble.	0	0	0
	I always make a point to visit the Patan museum+Durbar Sq when I'm in Nepal. It saddens me now to think that it would never be the same now	0	0	0
Heritage as context	#DarbarSquare in rubble, @SrBachchan and #ZeenatAman had shot at this heritage site in Nepal. #earthequake	1	0	0
Past disaster Comparison	History repeated 1934 damage and 2015 damages #NepalEarthquake.	10	1	4
	Imagine a fire ripped through the #Louvre. That's what #Kathmandu is suffering today. Ancient treasures now dust. #WorldHeritage rubble.	9	0	4
Memorial in a different context	New York City Museum Celebrates the Culture of Earthquake-Ravaged Nepal	5	0	2
	Rubin Museum Highlights Nepalese Culture in Wake of Earthquake	0	0	0

Table 16: Types of memory

Noise

This category includes tweets which included one of the query keywords, however, were not relevant to the cultural heritage of Nepal. The analysis shows that approximately 3.8% of tweets were irrelevant. Table 18 provides examples of such tweets and their impact.

Type	Tweet	Number of Retweets	Number of Comments	Number of Favorites
Immediate Action	Some Volunteers are required to sort out the debris and recover save heritage artifacts at Basantpur, Contact ... #NepalEarthquake	3	0	1
	@NepalPoliceHQ Protect the heritage sites! Our own people are looting	2	0	0
	#Nepalearthquake and Thieves & smugglers are active, keeping an eye open on our heritage leveled to ground. Our priceless jwels also need rescue #Nepalearthquake.	1	0	0
Future Action	The Historic Pillar Dharahara is now gone. Govt. should take actions to reconstruct it. #PrayForNepal #Dharahara.	0	0	1
	Dear @narendramodi Ji, let India take pledge to rebuild all historic Nepal temples destroyed in the #earthquake after Rescue & Relief is done.	Not available	Not available	Not available

Table 17: Types of action

3.5 Discussion

Approximately 4% of the total tweets were about cultural heritage. However, this is not surprising. First, this study used datasets that were not curated for heritage purposes. Secondly, during disasters, an enormous amount of irrelevant, redundant and repetitive content is posted on Twitter (NAOI17; Cas16). Lastly, cultural heritage formed only a small section of the elements affected by the earthquake. Therefore, the small quantity of relevant data is not necessarily a limitation. On the contrary, the small quantity of relevant information posted on social media during disasters can give accurate information about the situation on the ground. The combination of sources (user-generated contents and mainstream media) represent the real influence of social networking sites, where everyone has the power to share information. Hence, the dissemination pattern is not a strict top-down controlled environment rather a network of free-flowing information curated by the mainstream media and people simultaneously. However, messages from mainstream media tend to be circulated more. The findings of this chapter support the findings of previous studies that mainstream media is extremely

Tweet	Number of Retweets	Number of Comments	Number of Favorites
Historic #earthquake in #Nepal; much lost, many to mourn, as much to rebuild. Hopefully worst is over. Stay alert, safe	692	36	225
Nepal Earthquake.Golden Temple to send 1 lac; Delhi Gurdwaras to send 25 k meals daily.Those who share sardar jokes, please share this too.	5	0	2
When Sonia was disallowed her entry in Pashupati Nath Temple in 80,on limited Darshan by Rajeev in 80s,Nepal started decaging ?	0	0	0
Biggest Earthquake ever in the history of Nepal!! #PrayForNepal	0	0	0
Hats off to our army and government for providing aid to Nepal...This is our culture..#Earthquake	0	0	0

Table 18: Examples of noise

important in the present times (MG09; Ali13; Joy18). Moreover, unlike Verma et al.'s (VVC^{+}11) findings, some tweets that provided information on the situation of heritage sites also expressed emotions.

The analysis shows that people mainly posted information regarding the situation of heritage sites. This research supports the findings of previous studies which recognize microblogging sites as a source for situation update (VHSP10; QHZZ11). Information from Twitter can reduce uncertainties and can be used for rapid damage analysis particularly after a disaster, a phase often characterized by the lack and need of information to prioritize action (ZGSG10; HCH10). However, asymmetrical information poses a challenge in the evaluation of the overall situation. The asymmetrical attention to heritage sites was not only prevalent in Twitter but also media report. Hutt's (Hut18) analysis concluded that the Dharahara tower received more attention than the countrys World Heritage properties in the media. It could be due to several factors such as popularity as a tourist destination and amount of damage to the site. Heritage professionals seeking information from Twitter during disasters may need to request the on-site users, in case such asymmetrical patterns are evident. Despite the limitations, information from Twitter is irreplaceable, as suggested by Castillo (Cas16).

Action-related tweets illustrate the importance of social media during disasters. Although the action-related tweets were small in number (3.8% of the relevant tweets), they show the direct action taken by the on-site users during the earthquake. The on-site users can be sensors/respondents and may help in protecting the heritage from any further damage.

The analysis of sentiments highlights an ideological divide amongst the users regarding what should be important during disasters. These concerns, though not too common, as seen in Section 3.4.3, needs addressing in this research. Indeed, life should be the prime importance during disasters and this research does not intend to undermine the importance of humanitarian response. Culture (or heritage) may not be an immediate need or priority in disaster struck societies (GS06; Tan17). However, it is indeed an integral part of a society, as evident from the findings of this chapter. First, the action-related tweets in number prove that the Nepalese people care about their heritage. They worked collaboratively to protect their heritage during the earthquake. Secondly, sentiment-related tweets show peoples attachment to their monuments. Lastly, people continuing prayers in the damaged heritage sites exemplifies the relationship people share with their heritage and the role of heritage in distressful situations. The findings of this research confirm Kunwar and Chand's (KC16, p.32) argument that "heritage in Nepal is deeply connected to the nations pride, the peoples souls, belief and identity", making the heritage in Nepal exceptional examples of living heritage (Wei15). The indifferent tweets clearly illustrate that social media affords visibility to voices marginalized in the mainstream. These tweets can be useful in raising awareness, initiating debates and generating interest in the event.

Lastly, Twitter was also used as a space for the recollection of personal experiences and past events. Many memories illustrated in Table 15 may be a part of the peoples daily lives, however, such discussions surface on Twitter only when a disaster strikes. The category 'memory' may be unique to cultural heritage during disasters, as it has not appeared earlier in other studies of tweet classification during disasters (Cas16). It clearly illustrates that people who visited the cultural heritage sites, regardless of how much time has passed after their visit, remember the sites. Moreover, a visit to a heritage site may not be necessary for people to remember it. Users also remembered heritage sites from movies. Heritage of a country may be remembered and celebrated in other countries after a disaster. This clearly shows the that often heritage is valuable to the people outside the national boundaries. Lastly, memories of a historically significant disaster were also shared during the 2015 earthquake. These memories are important for socially distributed curation (Liu12) to preserve the memory of events for future generations. Moreover, these memories can also be used to inform the possible vulnerabilities of heritage sites and thus, help in disaster risk reduction.

Tweets coded in the category noise clearly illustrates the complexity of the task. The language usage in Twitter poses a challenge in data collection and analysis. First, query keywords can have different meanings. Secondly, the use of different spellings can make data collection even more challenging. Lastly, often people use words in regional language to refer to heritage sites. All the above-mentioned factors illustrate the complexity of the process.

3.6 Concluding Remarks

This chapter set out to understand the response to cultural heritage damaged during Nepal Earthquake by utilizing 201,457 tweets (including RTs) from three different sources, collected at different timespans using different keywords. The analysis shows that only a small number of tweets (approximately 4%) were posted regarding cultural heritage. These tweets can be divided into 5 categories: information, sentiment, memory, action, and noise. It should be noted that most of the tweets are hybrid i.e. they followed at least two of the above-mentioned categories. The analysis shows that people use Twitter during disasters mainly for information dissemination regarding damage to the sites. Such dissemination is in the form of sharing mainstream media reports and also retweeting people on site. Overall, some tweets are more useful than the other in assessing damage to the heritage sites and understanding the situation on the ground. Such tweets include the name of the site, information about its condition, the number of humans affected by its damage, information about rescue operations, and so on. The chapter has a few limitations. First, it utilizes only Twitter as a source. The results of this research may not apply to other social networking sites such as Facebook, Instagram. Secondly, it focuses only on the 2015 Nepal Earthquake. Whether the results of this research are applicable during other disasters is a matter of future work. Future work can also include analysis of posts on other social networking sites.

Chapter 4

Social Media, Disasters and Cultural Heritage: An Analysis of Twitter Images of the 2015 Nepal Earthquake

This purpose of this chapter is to understand the underlying themes and patterns in the pictures of cultural heritage sites posted on Twitter during and immediately after the 2015 Nepal Earthquake. I analyzed 6,529 images available in the SMERP dataset to identify and understand the main themes emerging from the discussion on Twitter regarding the damages to cultural heritage sites. Only a fraction lower than the 10% of the tweets sharing images available in the dataset have cultural heritage sites as the subject. Among them, six main themes emerged from the analysis presented. The dominant theme, with 67% of the heritage images posted, involves some kind of situational awareness when Twitter users aimed to witness the state of heritage sites after the earthquake. Interestingly, the analysis shows that the images posted on the online social network not only represent eye-witness reports of the event but also illustrate people's relationship with the disaster, the place affected and the use of the technology or even the lack of it.

4.1 Introduction

Online social networks have changed how we create, interact with and disseminate news. The availability of smartphones makes instantaneous creation of image and videos possible and online participatory applications such as Twitter help people not only to create news but also rapidly circulate it, thereby making the common man a citizen journalist. This instantaneous creation and circulation of content on social media increase multi-fold during a crisis. For instance, during the Great Thoku Earthquake of 2011 in Japan, approximately 1,200 tweets were posted per second (Cro12). Similar trends have been observed in different countries across the world. In Thailand, not only did social media usage increase during the 2010 flood, but the number of users also increased significantly (LPRK15). At the same time, a large number of images are posted on social media during such events. For instance, Meier reported that social media use during Hurricane Sandy in 2012 produced a haystack of half-a-million Instagram photos and 20 million tweets (Mei13).

Indeed, crises are becoming increasingly and intensely visual (VFP$^+$13). As Vis et al. (VFP$^+$13) note, it is through images we discover, explore and remember such events. It may be partly due to the fact that images are simple, easy to digest, emotionally evocative, (Seo14; ML16) and attention-getting in the fast pace of social media that they are prominently connected to social media (AJ16) during events. Often images are user-generated, bottom-up creation of content as against the authoritative visual agenda setting (ML16) practiced by mainstream-media before Web 2.0. Therefore, images posted during crisis not only bear the eyewitness report but also show people's relationship with the event, place and technology. In addition, the images show the lack of such a relationship as social media contains a serious amount of irrelevant or redundant contents. In spite of the irrelevant content, information from social media is often irreplaceable, particularly immediately after the disaster (Cas16).

Consequently, researchers have studied several aspects of images posted on social media during disasters such as underlying themes and patterns (Seo14), implications of images posted (BS17), the authenticity of images (GLKJ13), and automatic classification of images (AOI18b). However, images depicting cultural heritage posted on social media during disasters have not received much attention. Aiming to bridge this gap in research, this chapter focuses on the 2015 Nepal Earthquake to answer the following research question: **What types of images depicting cultural heritage sites were posted on Twitter during and immediately after the earthquake? What is the dominant theme in images of cultural heritage sites posted on Twitter during and immediately after the earthquake?**

This study investigates the use of images of cultural heritage sites during a disaster by utilizing the 2015 Nepal Earthquake as a case study for two reasons. First, the earthquake damaged several cultural heritage sites in Nepal, as described in Chapter 3. Secondly, a large number of reports were published on Twitter during the disaster including reports from individual users and mainstream media. Further, several images showing the on-site situation were instantaneously posted on Twitter. Even though a small number of images were posted regarding cultural heritage sites, this chapter's findings are important to understand the experience of disasters affecting cultural heritage through images.

The chapter is structured in four additional sections. Section 4.2 conceptually frames this research. Section 4.3 describes the data collection and methodology adopted for this research. Section 4.4 describes the results. Section 4.5 discusses the implication of this research. Section 4.6 concludes this chapter suggesting possible future works.

4.2 Related Works

There is a growing interest among researchers to study images posted on social media, despite the difficulties in obtaining images from social media due to limitations of API and methodological challenges (Han17). Faulkner et al. (FVD18) present an overview of the current research on social media images by using three methodological approaches: large-scale image analysis, working with images at different scales and in-depth qualitative analysis of images (FVD18). Researchers have studied images from many different perspectives including typology analysis (HMK14), spatial and temporal pattern analysis (HM13), and ethics (Pea15; GKR03). The importance of images posted on social media during disasters was highlighted in Peters and De Albuquerque's work (PdA15). Their analysis of Twitter, Flicker and Instagram images posted during the 2013 floods in Saxony, Germany, revealed that on-topic messages with images are closer to the event than the posts without images, and the content of images posted provided important information regarding the event.

Researchers have done an in-depth qualitative analysis of images to understand the underlying themes and patterns of images posted during a crisis. For instance, Hjorth & Burgess (HB14) analyzed the 100 most re-tweeted images during the Queensland flood to understand the genres and resonating themes in images. Their work revealed the use of vernacular aesthetics in images circulated, especially in 'larrikin', a type of Australian humor used as a coping mechanism. Moreover, traditional photographs and a conventional documentary style with do-it-yourself aesthetics photographs were amongst the most retweeted images. Vis et al.'s (VFP$^+$13) exploratory study of the images tweeted during the 2011 UK riots also considers different types of images posted during the event. Their analysis highlighted 13 different categories of images based on their content including police car, burning bus, other vehicle, building, looting, screenshots, police, arrest, image of text, riot clean up and other. Seo (Seo14) identified themes and frames prominently appearing in a total of 243 Twitter images posted by the Twitter accounts of the Israel Defense and Hamas Alqassam Brigades during the Israeli-Hamas Conflict between November 2012-January 2013. The author highlighted that resistance and unity were the two main themes in the images posted by Israel whereas causalities of civilians and resistance were the main themes in Hamas's posts.

Further, researchers have studied the implications of images posted on social media during a crisis. Bozdag and Smets's (BS17) qualitative study using small data concluded that the images of Alan Kurdi, a three-year-old Syrian boy who drowned in the Mediterranean Sea in 2015, did not cause a major shift in common discourses and representations. Similarly, Kharroub & Bas's (KB16) analysis of 518 images circulated during the 2011 Egyptian Revolution revealed more efficacy-eliciting than emotionally arousing content posted by Egyptian users.

Additionally, a few studies focus on the analysis of *selfies* posted on social media during disasters. Ibrahim (Ibr15) explored the moral politics of selfies taken in disaster and the search for immortality by the act of selfie. Hartung (Har17) studied two kinds of selfies posted during the 2015 Nepal Earthquake: selfies taken in Nepal and selfies taken outside Nepal to show support to the Nepalese. She challenges the notion that selfies *for* and *of* Nepal can be regarded as 'good' and 'bad' selfies, respectively. The ones taken outside Nepal can be seen as 'savior citizenship' bearing the witness of global cooperation, whereas the ones taken in Nepal are globally controversial due to the ethical and moral standards that label these images as disaster tourism or disaster porn. She challenges these quick reactions and suggests that selfies are a relational practice that can have strong political resonance with intended or even unintended consequences.

Lastly, researchers have also developed tools for automatic classification of the large volume of images posted on social media during disasters for different purposes such as detecting fake images, assessing the damage and identifying duplicate and relevant images. Gupta et al.'s (GLKJ13) work focused on automatic detection of fake images posted on Twitter during the 2012 Hurricane Sandy. The authors used 10,350 unique tweets containing fake image URLs and 5,767 tweets containing real image URLs to test two classification models. Their experiments concluded that one of the classification models could identify fake images with high accuracy (97%). Alam et al.'s (AOI18b) work combines human and machine intelligence to filter duplicate and irrelevant social media images and extract images that can raise situational awareness.

4.3 Material and Methods

4.3.1 Material

This chapter utilized 6,529 images from the Nepal Earthquake from the SMERP dataset (MJG$^+$18). The dataset used in this chapter is identical to dataset 3 used in Chapter 3. The tweets in this dataset were collected using the keywords Nepal earthquake and Nepal quake. Table 19 provides details of the data.

Category	Detail
Date	25.04.2015 to 10.05.2015
Number of Tweets	50, 068
Number of Images	6,529
Keywords	Nepal earthquake, Nepal quake

Table 19: Details of SMERP dataset

4.3.2 Method

The methodology adopted in this chapter involves two steps, as illustrated in Figure 8. The 6,529 images were imported into NVivo, a qualitative data analysis software. The content of each image was analyzed qualitatively. First, the images were manually classified under categories *heritage* or *not-heritage*. This was done to extract the images depicting cultural heritage sites. It was found that two new categories, *maybe-heritage* and *remove*, were needed due to the nature of data from social media, which not only includes irrelevant images but also indecipherable images. The classification scheme is explained in Table 20. Secondly, the images classified under the heritage category were classified again to understand the underlying theme and patterns. The coding scheme used is explained in Table 21.

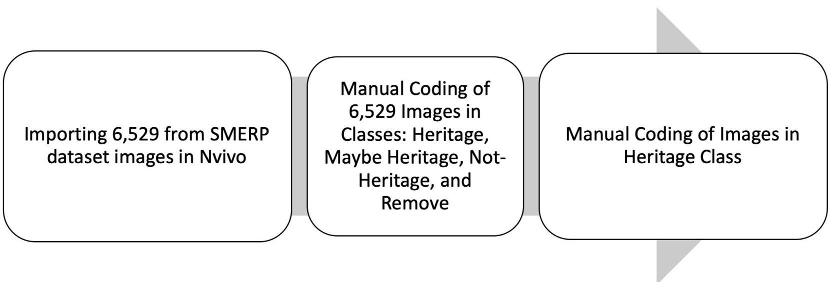

Figure 8: Overview of methodology

Category	Description
Heritage	All images of cultural heritage sites (whether damaged or not-damaged, in Nepal or outside Nepal) were classified in this category.
Not-Heritage	All images that did not include cultural heritage sites were classified in this category. It included images that showed other aspects of the 2015 Nepal earthquake and irrelevant images.
Maybe-Heritage	Images which had little or no contextual information to firmly label them as heritage.
Removed	Images in which the content was not visible and, therefore, could not be analyzed.

Table 20: Classification details

Category	Description
Situation	Images showing the state of cultural heritage sites after the earthquake
Message	Images in which cultural heritage sites were used as a background to convey a message
Memory	Images showing the state of cultural heritage sites before the earthquake, personal images taken before the earthquake and images of sites damaged in previous earthquakes in Nepal
Practices	Images showing how people used the cultural heritage sites after they were damaged
Screenshots and Edited Images	Edited images and screenshots of media articles, videos
Heritage from other Countries	Images of heritage sites not from Nepal

Table 21: Coding scheme

4.4 Results

Table 22 illustrates the result of the first round of classification to identify images of cultural heritage sites from the entire dataset. As evident from the Table, the majority of images fall in the *not-heritage* category (5,833) followed by *heritage* (566), *maybe-heritage* (71) and *removed* (59). The results of the following analysis are divided in two parts. Section 4.4.1 briefly describes images which were classified in the not-heritage, maybe-heritage and remove categories. Section 4.4.2 answers the research questions of this chapter.

Class	Number	Percent
Not-Heritage	5,833	89.4
Heritage	566	8.7
Maybe-Heritage	71	1.0
Remove	59	0.9

Table 22: Distribution of the images dataset among the four top-level classes

4.4.1 Not-Heritage images, maybe-heritage and removed images

The *not-heritage* category includes several irrelevant images posted during the earthquake. The irrelevant images are not related to the earthquake in any way. Figure 9 (left) shows a sample of irrelevant images. The not-heritage category also includes images related to the Nepal Earthquake which do not depict cultural heritage sites. These images show the damage of infrastructures and lives. It also includes helpline numbers, calls for help and images of memorial events, as evident in Figure 9 (right).

Figure 9: Not-Heritage category contains both irrelevant images (left) and images from Nepal Earthquake (right) which are not relevant for cultural heritage.

The *maybe-heritage* category includes images that did not have enough information to label them as *heritage*. However, the presence of a few elements such as building materials or architectural style make them a potential candidate for the *heritage* category. Figure 10 (left) shows a sample of images in this category.

Images whose contents were not clear were classified in the *remove* category. Mostly, these are pixelated images, as evident in Figure 10 (right).

Figure 10: Maybe-heritage and removed images

4.4.2 Heritage images

There are six themes in the 566 images of cultural heritage sites posted on Twitter during the 2015 Nepal Earthquake and available in the SMERP dataset: situation, message, memory, practice, screenshots and edited images, and other country's heritage sites. The classification scheme is explained in Section 4.3. Table 23 shows the distribution of the type of images posted. The most dominant theme in

Class	**%**
Situation	67%
Message	12%
Memory	10%
Practice	5%
Screenshots and edited images	4%
Other country's heritage	2%

Table 23: Distribution of images classified under the heritage category

the images classified under the heritage category is 'situation'; with 67% images posted on Twitter during the 2015 Nepal Earthquake mainly showed the state of heritage sites after the earthquake. Twelve percent of the images in the heritage category were used to convey a message such as 'Pray for Nepal'. Ten percent of the images depicted some form of personal memory, the memory of the heritage site or the memory of a past earthquake. Five percent of the images showed practices i.e. how people in Nepal used the heritage sites after the earthquake, whereas 4% of the images were screenshots or edited images. Lastly, 2% of the images were of heritage sites outside Nepal.

Situation

The analysis shows that 67% of the images posted on Twitter during the earthquake are photographs that show the situation of heritage sites after the earthquake. There are various kinds of images depicting the situation. First, the photographs which solely shows the situation of the heritage site. Second, the photographs which show rescue efforts in heritage sites, both humanitarian and heritage materials. Lastly, before-after images are two juxtaposed photographs showing the original form of the building and the extent of damage the site suffered. Figure 11 shows examples of images classified under this theme.

Figure 11: Images classified under the theme *situation*.

Message

The images classified under this category are edited images with a cultural heritage site as a background to convey sympathy, solidarity, aid and fundraising messages. During the earthquake, messages such as *Pray for Nepal*, *Stay Strong Nepal* were circulated on social media. Images of both intact and damaged heritage sites were used to convey these messages. Moreover, images of heritage sites were also used as a background for conveying important messages such as the phone numbers of the 24-hour control room. Lastly, heritage also served as a background for fund-raising activities after the earthquake. Figure 12 shows examples of such images.

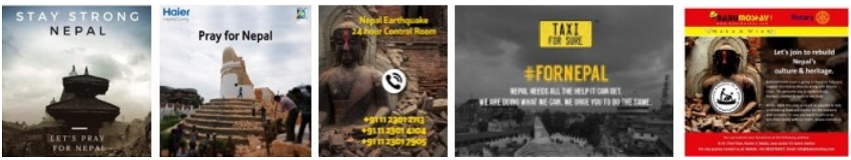

Figure 12: Images classified under the theme message

Memory

Images were also used to recollect events, the original form of the buildings and personal memories. Memories of the 1934 earthquake were shared. Images showing the form of buildings before the disaster were also shared, i.e. original form of the buildings was remembered after the earthquake. Lastly, people shared their personal photographs in the context of cultural heritage, thereby remembering their visit to cultural heritage sites. Figure 13 shows examples of images classified under this category.

Figure 13: Images showing memories shared

Practice

The images classified under this category represent the practices in the context of cultural heritage in Nepal. The images show people's relation to their heritage. Even after the sites were severely damaged, people continued to pray in these sites. Moreover, the images classified under this category also show the practice of selfies being taken in the context of a damaged heritage site. Figure 14 shows examples of images classified under this category.

Figure 14: Images showing practices around cultural heritage

Screenshots and Edited Images

Screenshots and edited images are not original reports. Therefore, these two types were classified under one theme. Only 4% of images in the heritage category were classified under this theme. Images classified in this theme include screenshots of mainstream media reports in TV or newspapers and screenshots of images and videos posted during the earthquake. Moreover, images which were edited to a significant degree were also classified in this theme. Examples of images classified under this theme are provided in Figure 15.

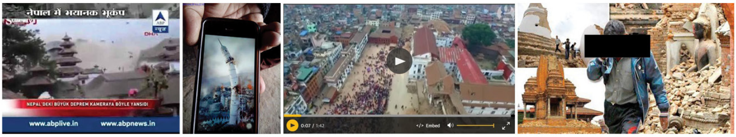

Figure 15: Screenshots and edited images

Other Country's Heritage Sites

The analysis shows that images posted on Twitter during the 2015 Nepal Earthquake also included images of heritage sites in countries other than Nepal. Figure 16 shows some examples of images classified under this theme.

Figure 16: Other country's heritage sites mainly included images from India

4.5 Discussion

The analysis shows that less than 10% of images available in the SMERP dataset were regarding cultural heritage. This is not surprising given the high intensity of redundant or irrelevant data posted during disasters. Moreover, cultural heritage forms only a small section of items (in addition to human lives) affected during the 2015 Nepal Earthquake such as infrastructure and other buildings.

The majority of images posted regarding cultural heritage (67%) showed the current situation of the heritage sites, whether in the form of before-after images, or images depicting ongoing rescue efforts. This highlights that Twitter is primarily used for information sharing during disasters and, in turn, this information can be used to assess the situation on the ground without necessarily being on-site.

Use of images of the heritage site as a background for conveying prayers, solidarity, aid and fundraising messages highlight that the built heritage serves as an identity of the nation. It confirms the researchers' argument that cultural heritage has the ability to represent a place and its people and creates a distinct sense of nationhood (Pal99), not only for its own citizens but also outsiders both in crises and peaceful times (Dup02; Mun05; Aka14).

Images were also used to recollect events, the original form of the buildings and personal memories. This highlights that Twitter is used not only for instantaneous information dissemination but also for preserving and sharing an individual's memory of events, sites and visits. Further, the practice of collective online remembering, commemorating and curating a crisis has been seen in several cases such as the 9/11 attack, Hurricane Katrina (Rec12), and the 1984 Bhopal gas leak (Liu12). This research confirms Van House & Churchill's argument that (VHC08) in the digital age, *what is remembered* individually and collectively is partly dependent on technologies of memory and socio-technical practices. Further, it also suggests that digital recollection is also dependent on events such as crises.

Images depicting practices in the cultural heritage sites illustrate that heritage in Nepal is an inseparable part of people's daily life (BBA^{+}18). People continued to pray even after the sites were severely damaged, showing that for the Nepalese, the physical structure is not essential for it to serve as a place for prayer. These images confirm Kunwar and Chand's (KC16)(p.32) argument that "heritage in Nepal is deeply connected to the nation's pride, the people's souls, belief and identity", making the heritage sites in Nepal exceptional examples of living heritage (Wei15), as also seen in Chapter 3. On the other hand, the practice of selfies represents an inseparable integration of techniques afforded by online participatory applications in people's daily lives which can force them to disregard the condition of the context. This insertion of self in disaster settings certainly raises the question of ethical behavior (Har17) and also reconfigures our relationship with death in the virtual world (Ibr15).

The images posted on Twitter during the 2015 Nepal Earthquake vividly illustrate people's relationship with events, place and technology. Moreover, irrelevant images (images not related to the Nepal Earthquake, illustrated in Figure 9) and 'other country's heritage' demonstrate the lack of relationship with the event or place. The findings of this chapter confirms Murthy et al.'s (MGM16) argument that images produced during disasters have the potential to show the social experience of disasters.

4.6 Concluding Remarks

This chapter set out to understand the types of images and dominant theme in the images of cultural heritage sites posted on Twitter during the 2015 Nepal Earthquake by utilizing 6,529 images from the SMERP dataset. First, these 6,529 images were classified under the following categories: heritage, not-heritage, maybe-heritage and remove, to extract images of cultural heritage sites for further analysis. The analysis shows that only a small number of images (less than 10%) posted depicted cultural heritage sites, including some images of heritage sites outside Nepal. Most of the images were classified under not-heritage (5,833), followed by heritage (566), maybe-heritage (71) and removed (59).

The 566 images classified under the heritage category were analyzed to understand the underlying themes and patterns. Six themes were found in these images: situation (67%), message (12%), memory (10%), practice (5%), screenshots and edited images (4%) and other country's heritage sites (2%). 'Situation' was the dominant theme in the images posted during the 2015 Nepal Earthquake, i.e. the majority of the images showed the state of heritage sites after the damage. Images of heritage sites were also used to convey messages like 'Pray for Nepal', 'Stay strong Nepal'. Users posted personal memories, memories of the 1934 earthquake, and memories of sites before the earthquake. Moreover, images also show how heritage sites were used after the earthquake whether for praying or taking a selfie.

The chapter has a few limitations. First, it utilizes only Twitter as a source. Whether results are applicable to other social networking sites, particularly the image-based sites such as Instagram and Flicker, is a matter of future works. Secondly, the study is limited to the 2015 Nepal Earthquake. Future work can include analysis of images posted during other disasters.

Chapter 5

Detection of Disaster-Affected Cultural Heritage Sites from Social Media Images Using Deep Learning Techniques

This chapter describes a method for early detection of disaster-related damage to cultural heritage. It is based on data from social media, a timely and large-scale data source that is nevertheless quite noisy. First, we collect images posted on social media that may refer to a cultural heritage site. Then, we automatically categorize these images according to two dimensions: whether they are indeed a photo in which a cultural heritage resource is the main subject, and whether they represent damage. Both categorizations are challenging image classification tasks, given the ambiguity of these visual categories; we tackle both tasks using a convolutional neural network. We test our methodology on a large collection of thousands of images from the web and social media, which exhibit the diversity and noise that is typical of these sources, and contain buildings and other architectural elements, heritage and non-heritage, damaged by disasters as well as intact. Our results show that while the automatic classification is not perfect, it can greatly reduce the manual effort required to find photos of damaged cultural heritage by accurately detecting relevant candidates to be examined by a cultural heritage professional.

5.1 Introduction

Cultural heritage resources are finite, scarce, non-renewable, and valuable (Spe99). They represent our collective memory, shape our identity, and also drive the economy (Jig16; SGS17; JMB+13). These resources are globally under immense threat in present times due to natural and human-induced disasters. The increased frequency and severity of disasters affecting cultural heritage (Tab03) has increased the international awareness towards protection and conservation of cultural heritage (UNI15; BMD+18). It also points towards the need for an organized response in such cases by utilizing efficient tools.

Social networking sites, particularly Twitter, have been acknowledged as an efficient communication tool for disaster management due to its instantaneous nature (MCLR09). Twitter has been used to disseminate news, support the immediate disaster response, and track efforts of relief and reconstruction. Consequently, developing efficient systems to harness and use real-time information from social media to help relief activities for humanitarian response in disasters has been a priority area for researchers (MWM15; Cas16). Researchers have developed methods for timely detection of events (ACLP+14; ACM+14; ABNC14; RGG+15), automatic extraction of information from postings (IEC+13; YKRC12), and automatic classification of images (AOI18c), among many other tasks. Most works have focused on extracting urgent needs from the affected populations, while in comparison applications for detecting and evaluating damage to cultural heritage using social media data have not been studied.

This chapter aims to bridge this gap by describing a method to automatically detect images of cultural heritage sites, particularly images depicting damage.

The need for this automation arises from the quantity and variety of images posted on social media. Firstly, the amount of images posted on social media is enormous. According to (MW16), approximately 1.8 billion images are shared daily on social media platforms (MW16). The quantity of images posted on social media during disasters is even larger (Cas16). Secondly, this enormous amount of images posted during disasters contain irrelevant and redundant content, including images not related to the disaster, duplicate images, and "memes," among many others (NAOI17). In fact, the images of cultural heritage sites are a small proportion of the total images: in our datasets from social media during disasters we estimate that less than 10% of images shared might be about heritage sites. Nevertheless, these images are an unparalleled source of information to detect in near real-time if a cultural heritage site has been affected by a disaster.

Considering the enormous amount of relevant and irrelevant images, manual annotation of each image might not be feasible. In this work, we propose to use supervised machine learning techniques, specifically deep neural networks, to automatically identify heritage sites and detect if they show any damage. The models trained on images found through Google Image Search are evaluated on a real-world disaster dataset collected from Twitter. The automatic classification methodology discussed in this chapter provides a helpful tool to support the work of heritage preservation professionals. By examining a relatively small set of potentially relevant candidate images extracted by automatic means from a much larger collection, professionals are able to understand the extent of damage to cultural heritage without necessarily being on site, saving time and resources. Given the immediacy of social media, the tool is particularly useful for preliminary analysis, and therefore, can help towards organizing the response by identifying priority areas.

There are four main contributions of this chapter:

1. A methodology for collecting, annotating, and learning classifiers to identify heritage sites images
2. An evaluation of this methodology performed on a real-world dataset taken from a disaster event
3. A corpus of annotated images into heritage vs. not-heritage sites with/without damage labels
4. A lexicon of heritage-related keywords for social media filtering tasks

The rest of this chapter is structured in five parts. Section 5.2 conceptually frames this research, particularly linking it to similar techniques used in the heritage context and beyond. Section 5.3 briefly describes the methodology adopted for this work. Section 5.4 discusses the process of data collection and annotation. Lastly, Section 5.5 describes the experiments and results. The chapter concludes with possibilities of future work in Section 5.6.

5.2 Related Work

5.2.1 Images of disaster and cultural heritage in social media

There is a growing interest among researchers to study images about disasters posted on social media. Images have been studied from many different perspectives including typology analysis (HMK14), spatial and temporal pattern analysis (HM13), and ethics (Pea15; GKR03), among others. Section 4.2 provided an overview of current research in images posted during disasters on social media.

The cultural heritage domain use the images on social media for two main purposes: (i) enable users to interact with an already existing image database, and (ii) create new databases of (heritage) images on social media. The US Library of Congress uses photo sharing platform Flicker to enable users to interact with old photographs (oCPDS[+]08). Other cultural institutions in the US such as The Smithsonian carried out similar initiatives (JSP12; KKS[+]08). In contrast, Terras (Ter11) investigated the growing trend of the creation of digital images of cultural and heritage materials by amateurs on Flickr. Freeman studied the public engagement with the world heritage site Sydney Opera House on Flicker and argued that such socio-visual practices themselves constitute an intangible heritage (GF10). A number of studies focus on cultural heritage institution's use of image based social media such as Flicker and Instagram to understand the content created by the institutions, the relation between audience and institution, among other topics (Jen13; Mag14). To the best of our knowledge, no prior study deals with the analysis of images depicting cultural heritage circulated on social media during disasters.

5.2.2 Automated processing of images from heritage sites

Image processing techniques have been used in the cultural heritage context for various purposes. For example, Hurtut et al. introduced a method for the analysis of the pictorial content of line drawings using the geometrical information of stroke contours (HGCS11). They showed that the proposed method could be used successfully for the indexing of line drawings in a retrieval framework. In another example, Makridis & Daras presented a technique for automatic archaeological sherd classification based on a bag-of-visual-words representation of local color and texture information and discriminative feature selection (MD13). Amato et al. defined a pipeline that combined a convolutional neural network with Fisher vector features for visual recognition of ancient inscriptions. Their study suggested that these features could be effective in visual retrieval of other types of objects related to cultural heritage such as landmarks and monuments (AFV16). Can et al. studied visual analysis of Maya glyphs using both handcrafted and data-driven shape representations in a bag-of-words-based pipeline (COGP16). Similarly, Hu et al. proposed a system for automatic extraction of hieroglyph strokes from images of degraded ancient Maya codices via a region-based image segmentation framework (HOGP17). According to their experimental results, automatically extracted glyph strokes achieved comparable retrieval results to those obtained using glyphs manually segmented by epigraphers.

Focusing more on architectural heritage, Shalunts et al. presented an approach based on clustering and learning of local features to classify the architectural style of facade windows (SHS11). Mathias et al. used features extracted by a steerable pyramid of Gabor filters to train a Support Vector

Machine for automatic architectural style recognition (MMW+11). To tackle the same problem, Chu & Tsai proposed a higher-level feature representation that takes into account spatial relationships between local features to identify repetitive subgraphs as visual patterns in an image (CT12). Furthermore,Goel et al. explored the utility of mining characteristic configurations of low-level discriminative features in categorizing different architectural styles and used them for improving classification performance (GJJ12). Alternatively,Oses et al. presented a semi-automatic approach for delineation of the masonry to classify architectural style (OD13) whereas Zhang et al. introduced blocklets that capture the morphological characteristics of buildings and developed an architectural style recognition model based on hierarchical sparse coding of blocklets (ZSL+14). Xu et al., on the other hand, adopted Deformable Part-based Models to capture the morphological characteristics of basic architectural components and proposed Multinomial Latent Logistic Regression for architectural style classification (XTZ+14). Amato et al. combined k-nearest neighbor classification and landmark recognition techniques to tackle the problem of monument recognition in images efficiently (AFG15). More recently, Llamas et al. explored deep learning-based techniques, specifically convolutional neural networks, for the classification of architectural heritage images into one of the ten types of architectural elements of heritage buildings (LMLM+17). However, their dataset consists mostly of churches and religious temples. More importantly, they do not consider images from any damage or disaster context. In contrast, in this chapter, our goal is to analyze the visual content of images to determine whether they show any type of cultural heritage, even when the image is taken potentially in some damage or disaster context.

5.2.3 Detection of images showing damaged structures

There has been a significant increase in the use of image analysis techniques for automatic damage assessment in the last couple of decades. Most of these studies can be divided into two groups based on the type of data and domain knowledge they use.

The first group of studies corresponds mainly to the *remote sensing domain* and mostly rely on the analyses of images obtained from satellites, aircrafts, and unmanned aerial vehicles (UAVs). Early examples include detection of damaged or collapsed buildings using aerial photographs collected from earthquake-hit regions (TS04; TS08). Similarly, Pesaresi et al. investigated rapid damage assessment of built-up structures using satellite data in tsunami-affected areas (PGH07). In order to produce comprehensive per-building damage scores,Fernandez et al. studied UAV-based urban structural damage assessment using object-based image analysis and semantic reasoning (FGKG15) whereas Attari et al. explored fine-grained segmentation of UAV imagery based on deep learning techniques for damage assessment (AOA+17). Alternatively, Vetrivel et al. combined multiple kernel learning with 3D point cloud features derived from high resolution oblique aerial images to detect disaster damage (VGK+18). Likewise, Cusicanqui et al. investigated the usability of aerial video footage for 3D scene reconstruction and structural damage assessment (CKN18). To maximize their data utilization, Kakooei & Baleghi (KB17) and Duarte et al. (DNKV18) explored fusion of multiple data sources such as satellite, aircraft, and UAVs for automatic disaster damage assessment.

The second group of studies includes relatively recent work in the *crisis informatics domain* and rely mostly on the analyses of ground-level images collected from online social media platforms during disasters (BPB17; NAOI17; AOI18c). Early examples specific to damage assessment task are presented by Lagerstrom et al. (LAS+16) and by Daly & Thom (DT16) where both studies analyzed social media data in a binary image classification setting for fire/not-fire detection. Later, Nguyen et al. investigated a more generic solution to classify disaster images according to damage severity using convolutional neural networks (NOIM17). Similarly, Li et al. proposed a method based on class activation mapping to localize and quantify damage in social media images posted during disasters (LZCI18). Taking a step further, Li et al. explored domain adaptation approach to identify disaster damage images during an emergent event when there is scarcity of labeled data (LCC+19). To advance the state of the art in this area, Alam et al. (AOI18a) and Mouzannar et al. (MRA18) recently introduced multimodal datasets comprising both social media text messages and images. Furthermore, they defined a deep learning approach to identify damage images in their dataset (MRA18). Inspired by these recent advancements, Alam et al. developed an image processing pipeline to extract meaningful information from social media images during a crisis situation, including damage severity assessment (AIO17). In this study, we ran the images in our heritage image datasets through (AIO17)'s system to perform the damage assessment task. It is important to note that our dataset, in contrast to previous works, focuses on elements from cultural heritage sites that often look old or aged. This makes the damage assessment task more challenging than the aforementioned studies, which use all kinds of images; indeed, the vast majority of images processed in previous work to identify damaged structures are not images of heritage sites.

5.3 Methodology Overview

The methodology adopted for this research has the following steps:

1. Definition of elements and categories of interest
2. Data collection
3. Data filtering and annotation

4. Construction of classification models

Figure 17 outlines the overall methodology.

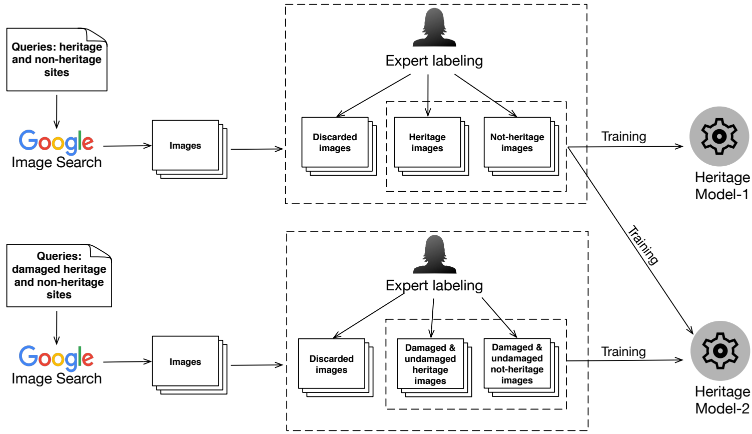

Figure 17: Overview of methodology.

Definition of elements and categories of interest. The elements we want to classify are images embedded in social media postings. The category of interest corresponds to all images that show damage to a heritage site. This is the intersection of two broader categories: images depicting heritage sites, and images depicting damaged structures.

Firstly, a balanced list containing the names of cultural heritage and not-cultural heritage sites was created. Given the inherent complexity of cultural heritage, we considered the legal protection status as the criteria for defining cultural heritage and not-cultural heritage. At the international level since the adoption of Venice Charter in 1964 (ICO64), the scope of term cultural heritage has broadened and is applicable to individual buildings, sites to groups of buildings, historical areas, towns, environments, social factors and, intangible heritage. It also includes artifacts, artworks, practices, etc. At the national level finer terminologies of *heritage* are not standardized, therefore, no uniformity exists between countries (Ahm06). Moreover, researchers have argued that heritage is inherently complex phenomenon and can contain conflicting meanings (GAT16). Acknowledging these complexities, we decided to limit our dataset to the legally protected (either by national or local governments) cultural heritage.

The cultural heritage list included archaeological sites, monuments, cultural landscapes, museums, galleries, libraries, and artifacts in urban space. We tried to create a list that was visually varied as well as geographically, in terms of period (ancient to modern), material and construction. The not-cultural heritage lists also included buildings and artifacts in urban space. The list of cultural heritage and not-cultural heritage is provided in Appendices (§B.1) and (§B.2). We must acknowledge that defining heritage is always an ongoing process, depending on what is valuable to people in a given place and time. Indeed, there is even de-listing of protected heritage buildings in some countries. Therefore, the list of heritage sites used as training data for the automatic classifier needs to be updated regularly to maintain the quality of the results.

Data collection (§5.4.1). Google Image Search was used to construct two datasets of images. The first dataset corresponds to images of heritage and not-heritage sites. Figure 18 shows examples of cultural heritage and not-cultural heritage from our list. The second dataset corresponds to damaged heritage and damaged not-heritage sites.

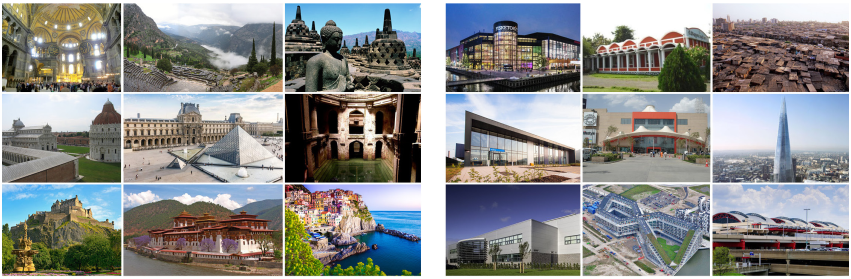

Figure 18: Images in our collection corresponding to heritage sites (left) and non-heritage sites (right).

Data filtering and annotation (§5.4.2). The underlying problem of online images, whether on social media or Google, is that it contains many irrelevant or unusable images. In this study, the irrelevant or unusable images were primarily the ones where heritage was not the primary subject of the image or images which were edited to an extent that the original context was significantly altered. Figure 19 shows some irrelevant images in our dataset. Firstly, these irrelevant images were removed, as explained in Section 5.4.2 in depth. Secondly, the remaining images were annotated using the following criteria: heritage vs. not heritage and damaged heritage (§5.4.2) vs. not damaged heritage (§5.4.2). Both of the tasks were carried out by the lead author, as elaborated in Figures 17 and 22.

Figure 19: Images from Google that could not be used for training the classifier.

Construction of classification models (§5.5) We built two different heritage classifiers using the labeled data annotated by our expert. First, we used only the images collected without any damage queries to train a classifier as shown in Figure 17 (top). Second, we used all images collected both with and without damage queries to train another heritage classifier (Figure 17 (bottom)). The performance of both classifiers is evaluated on the dataset collected during the 2015 Nepal Earthquake (§5.5.3). We remark that the role of the expert annotator, as part of the classification pipeline shown in 17, is only at the machine training time. As we are proposing a system that, when deployed in practice, does not need a human to perform manual annotation, but instead is an automated system that shows to a human potential heritage sites that require attention.

5.4 Data Collection and Annotation

In this section, we discuss our data collection and annotation details.

5.4.1 Cultural heritage and not-cultural heritage images

We select 92 cultural heritage sites around the world and download their images from Google. The list includes sites related to architectural heritage, archaeological, monuments, cultural landscapes, museums, galleries, libraries, and art in urban space. We sought to make the list geographically, period (ancient to modern), material and construction-wise, and visually representative. Since we treat the detection of heritage sites as a binary classification task, we also create another list containing built structures (i.e., buildings and sites) which look somewhat similar to heritage sites but officially they are not designated as cultural heritage. Selecting not-cultural heritage sites is a difficult task, given the ever-expanding boundaries of cultural heritage. Keeping in mind the protection criteria, this list was carefully curated to be geographically and visually representative. Interestingly, some of the buildings in this list are iconic buildings which are not protected. The complete list containing the selected sites related to heritage and not-heritage is provided in Appendices §B.1 and §B.2. Figure 20 shows all the selected sites for both *heritage* and *not-heritage* categories on a map.

We downloaded approximately 100 images of each *heritage* and *not-heritage* site from Google image search using the heritage site name as a query. The image search criteria needed to be robust to yield better results. Some of the site names had more risk of yielding bad results. For instance, image search criterion for the Walkie-Talkie building in London was *Walkie-Talkie London* as the possibility of a bad result was higher if *London* was not included in the search query.

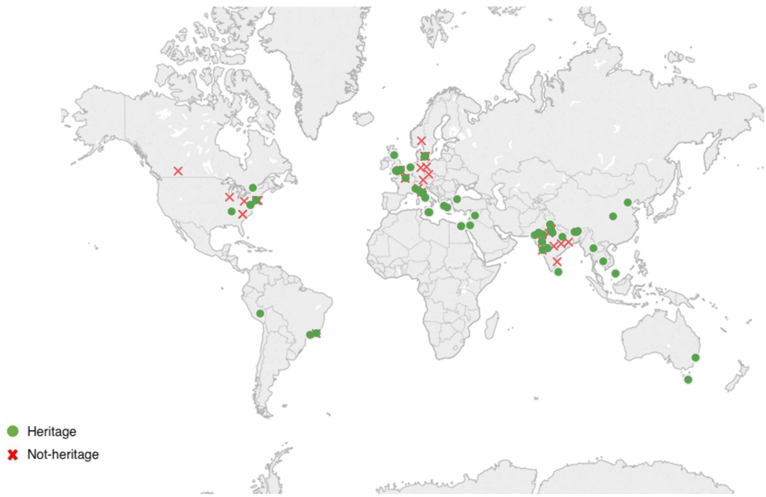

Figure 20: Map showing locations of heritage and not-heritage sites.

In addition to the images that show heritage sites which are potentially undamaged, we searched for images of the heritage sites showing some damage. For this purpose, our query consists of the heritage site name combined with two keywords (i.e., "*damage*" and "*destroyed*") separately. In total, we were able to download 13,333 images from Google.

5.4.2 Data filtering and annotation

Data filtering

Many images, which were collected from publicly available websites using Google Image Search, are not useful for training an automatic classifier and were thus removed. Specifically, images with one of the following issues were removed: images that are significantly edited, images where a heritage site is merely a backdrop and not the main subject (e.g., selfies), images which are covered almost entirely with text, 3D reconstruction or 3D models of sites, paintings of heritage sites, memes, architectural plans and sections of heritage sites, sketches, maps, images in which contextual information is missing (e.g., a close-up photograph of a stone in a building), and images of replicas, unless it has a protected status. Table 24 shows the results of the filtering task. Figure 19 shows a few images which were removed as a result of manual filtering. The remaining images are used to perform two annotation tasks as described next.

Heritage vs. not-heritage annotation

This annotation task aims to identify whether an image contains a heritage site or not. The lead author (a domain expert) labeled 13,333 images as *heritage* (which depict a heritage site) and *not-heritage* (which did not depict a heritage site) using separate folders on a shared drive. The first row in Table 24 shows the results of the filtering and the heritage annotation tasks for images which were collected without damage queries.

Dataset	Removed images	Labeled as Heritage	Labeled as Not-heritage
Images found using heritage/non-heritage queries	2,974	6,612	2,266
Images found using damaged heritage queries	78	836 (447)	567
Total	3,052	7,448	2,833

Table 24: Filtering and annotation results for *heritage* vs. *not-heritage* annotation of images found using Google Image Search. The number in parentheses represents the number of damaged heritage images.

Damaged heritage vs. not-damaged heritage annotation

This annotation task aims to determine whether an image having a heritage site shows any sign of damage to the site or not. It was also carried out by the lead author of this paper using separate folders on a shared drive. The quantification of the scale of damage is a subjective task, hence we follow the annotation scheme described in the literature (NOIM17), which defines the damage concept in three categories: (i) SEVERE damage, (ii) MILD damage, (iii) NO damage. However, in this work, we merged the SEVERE and MILD classes to a single class named "Damage." Table 24 shows the results of the filtering and the damage heritage annotation tasks for images which were collected with damage queries. Images collected from Google using the damage queries contain both heritage sites showing some damage and sites without any damage. The number of heritage sites with some damage are shown in parentheses in the second row of Table 24.

5.5 Experimental Results of Automatic Classification

In this section, we describe our experiments and present our results.

5.5.1 Classification approach

We considered various alternative approaches ranging from more traditional techniques such as bag-of-visual-word models to more advanced deep learning techniques such as convolutional neural networks. Eventually we decided to use a deep learning-based solution since the state-of-the-art performance in many computer vision tasks are achieved by deep learning models (KSH12; SEZ^{+}14; SZ14; SLJ^{+}15; HZRS16) that leverage on large-scale datasets such as ImageNet (RDS^{+}15) and Places (ZLK^{+}17).

In a nutshell, deep learning models, i.e., convolutional neural networks (CNNs) in particular, learn low-, medium-, and high-level features and classifiers in an end-to-end fashion to optimize on the target prediction task directly from raw data (ZF14). For example, the lower layers of deep CNN architectures correspond to a representation suitable for low-level vision tasks while the higher layers represent more domain specific information (GBC16), and hence, eliminate the need for hand-crafted features like Scale Invariant Feature Transform (SIFT) (Low04) or Histogram of Oriented Gradients (HOG) (DT05).

More importantly, the features learned in deep convolutional networks have been shown to be transferable and quite effective when used in other visual recognition tasks (YCBL14; G^{+}14), particularly when training samples are limited and learning a successful deep model is not feasible due to over-fitting. For instance, (NOIM17) show the success of this transfer learning approach for damage assessment tasks performed on disaster images collected from social media (NOIM17). Considering that we also have limited training examples, we adopt a transfer learning approach for the heritage classification problem.

Our heritage classification system is composed of two stages: (i) deep feature extraction, and (ii) training a heritage/not-heritage classification model, as illustrated in Figure 21. In the deep feature extraction stage, each image from the training set is simply fed as input to a deep convolutional neural network (CNN) that is pre-trained on the ImageNet dataset which has over 1.2M images and 1,000 categories (RDS+15). The features extracted from the penultimate layer of the network are then used to represent the input image. Then, in the second stage, these deep features are used to construct the desired heritage classification model. In this study, we experiment with a number of well-known CNN architectures in combination with a variety of classification algorithms. The CNN architectures used in the experiments include `VGG16` (SZ14), `ResNet50` (HZRS16), `DenseNet121` (HLMW17), `InceptionResNetV2` (SIVA17), `Xception` (Cho17), and `NASNetLarge` (ZVSL18). Whereas the classification algorithms employed in the experiments comprise Logistic Regression (Cox58), Support Vector Machines (CV95), Random Forests (Tin98), and AdaBoost (FS97). All the experimental results achieved by different network architectures and classification algorithms are presented in Appendix §B.4. Overall, `DenseNet121` and `NASNetLarge` features seem to yield slightly better results than other feature types. And, in terms of algorithms, Logistic Regression and Support Vector Machines seem to perform better than Random Forests and AdaBoost. For brevity, we hereinafter discuss the results achieved by the model trained by Logistic Regression algorithm using `DenseNet121` features[1]

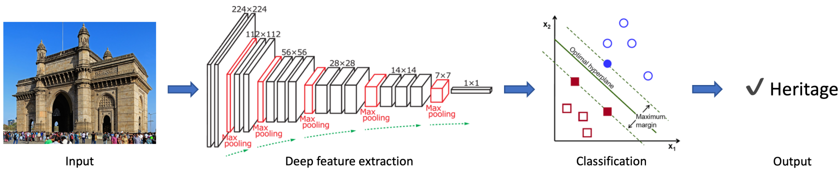

Figure 21: Overview of the heritage classification system.

5.5.2 Heritage/not-heritage classifier training

In our dataset, we have 7,448 images from 92 heritage sites and 2,833 images from 32 not-heritage sites. In order to create disjoint training and test sets, we follow a site-based data split approach. That is, 80% of the heritage sites (i.e., 73 out of 92) are chosen at random and all images (i.e., 6,075) belonging to these sites are assigned to the training set (i.e., Training Set-2 in Table 25). Then, all images (i.e., 1,373) belonging to the remaining 20% of the heritage sites (i.e., 19

[1]The `DenseNet121` network consists of 121 layers and around 8 million weight parameters (HLMW17). We choose the penultimate layer as our 1024-dimensional deep feature extractor.

out of 92) are assigned to the test set (i.e., Test Set in Table 25). We follow the same approach to distribute images from non-heritage sites into training and test sets. To investigate the benefits of having images with damage context while training our heritage classifier, we create another training set (i.e., Training Set-1 in Table 25) where we ablate from Training Set-2 those images collected by *heritage-sites-with-damage* queries. In other words, Training Set-1 is a subset of Training Set-2 where images in Training Set-1 do not show any damage content. The resulting data split is summarized in Table 25. It is important to note that we opt for site-based data split rather than image-based data split to obtain models with better generalization capability on new images from previously-unseen sites.

	Training Set-1		Training Set-2		Test Set	
	Sites	Images	Sites	Images	Sites	Images
Heritage	69	5,376	73	6,075	19	1,373
Not-heritage	25	1,869	25	2,380	7	453
Total	94	7,245	98	8,455	26	1,826

Table 25: Training/test set split by site (80:20 ratio).

Heritage model-1. In this first scenario, we train a heritage classifier using only the images collected by heritage site queries with *no* damage keywords (i.e., Training Set-1 in Table 25).

Heritage model-2. In the second scenario, we train a heritage classifier using all of the images collected by heritage sites queries both with and without damage keywords (i.e., Training Set-2 in Table 25).

		Classified as	
		Heritage	Not Heritage
Actual label	Heritage	1,193	180
	Not Heritage	113	340

(a) Heritage Model-1

		Classified as	
		Heritage	Not Heritage
Actual label	Heritage	1,174	199
	Not Heritage	74	379

(b) Heritage Model-2

Table 26: Confusion matrices of the heritage classifiers.

Results are shown in Tables 26, and 27. Confusion matrices (Tables 26 for both models are dominated by the diagonal, meaning that heritage sites are more likely to be classified as such than as non-heritage. Performance in terms of

	Precision		Recall		F1-score	
	Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Heritage Model-1	0.91	0.65	0.87	0.75	0.89	0.70
Heritage Model-2	0.94	0.66	0.86	0.84	0.90	0.74

Table 27: Performance comparison of the heritage classifiers.

precision and recall (Table 27) shows precision above 0.9 and recall above 0.8 for the heritage class. In practice, this means that at least 9 out of 10 times an image automatically detected as a heritage will be, indeed, heritage; and that at least 8 out of 10 images of heritage will be found by the classifier. Overall, we do not observe much performance difference between the two heritage models on the Google images test set.

5.5.3 Case study: 2015 Nepal Earthquake (SMERP workshop dataset)

We now present the results of our case study in a real-world scenario where we evaluate the performance of both of our heritage classifiers as well as an off-the-shelf damage assessment model of (AIO17) (AIO17) on a Twitter dataset collected during the 2015 Nepal Earthquake (i.e., SMERP Workshop Dataset (MJG$^+$18)). As an alternative baseline, we also consider a lexicon-based model to analyze Twitter text messages for the heritage classification task. Figure 22 illustrates our case study design.

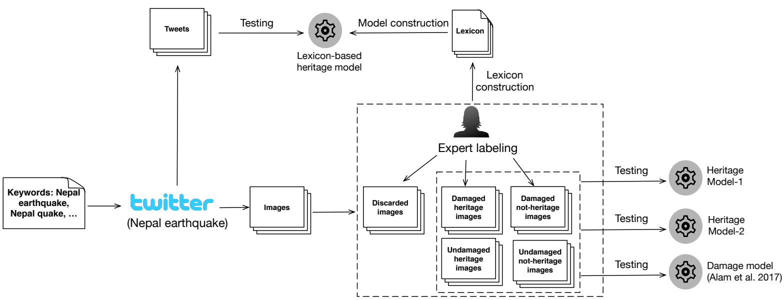

Figure 22: Case study design and testing.

Data filtering and annotation

A dataset containing images of damaged heritage sites, extracted from social media, is essential to evaluate the proposed approach. We use images posted on Twitter during the 2015 Nepal Earthquake, an event that damaged a large number of heritage sites in this country. Specifically, we use the SMERP Workshop Dataset (MJG$^+$18), which contains 6,529 images collected after Nepal Earthquake in 2015. The tweets in this dataset were collected using the keywords "Nepal earthquake" and "Nepal quake." It is evident from the keywords that this dataset was not curated for heritage purposes. Nevertheless, the dataset consists of information regarding heritage damaged due to the disaster. These 6,529 images are annotated manually using Nvivo, a qualitative data-analysis software by our expert for heritage and damage severity classification tasks. At the end of this manual annotation process, there are 6,320 images labeled with heritage and damage categories, excluding the images labeled as "maybe_heritage" or "dont_know" as well as the images with multiple heritage or damage labels. All of these 6,320 images are treated as test images in our case study. Table 28 summarizes the results of both heritage and damage annotation tasks. Figure 23 shows a few images with and without damage. Moreover, the textual content associated with these 6,320 images (i.e., tweet text) is used to test our lexicon-based classifier, which we describe next in detail.

	Heritage	Not-heritage	Total
Damage	377	1,445	1,822
No-damage	110	4,388	4,498
Total	487	5,833	6,320

Table 28: Heritage and damage annotation results for the SMERP dataset.

Performance metrics

In addition to a confusion matrix, that displays the number of correctly and incorrectly categorized instances on each class, we use three standard performance metrics for classification tasks. Precision (positive predictive value) is the probability that an item classified automatically into a class actually belongs to that class. Recall (or sensitivity) is the probability that an item that actually belongs to a class is classified automatically as such. The F1-score is the harmonic mean of precision and recall, and is one of several metrics that can be used to summarize them into a single number.

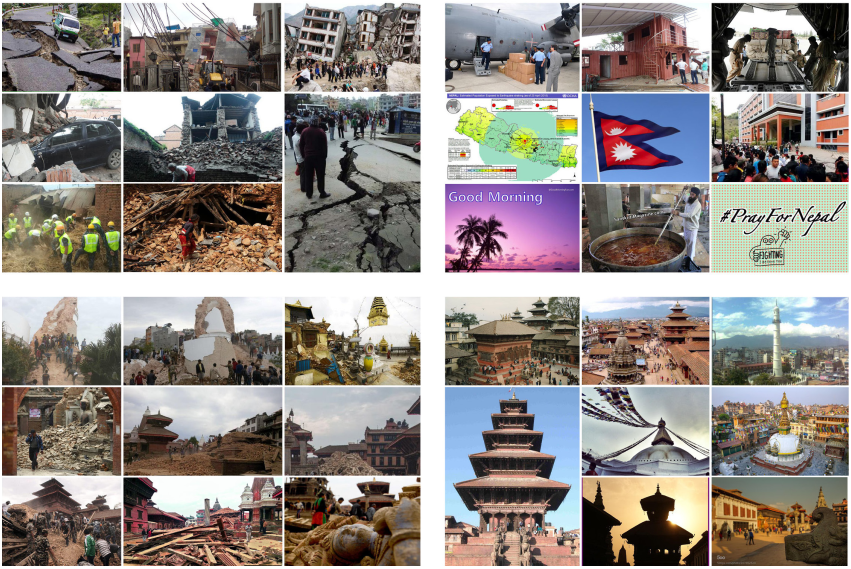

Figure 23: Examples of annotated images from the SMERP dataset, showing heritage with damage (top left), non-heritage with damage (top right), heritage with no damage (bottom left) and non-heritage with no damage (bottom right)

Baseline construction

To set a baseline, we developed a lexicon consisting of 176 terms covering heritage-related concepts such as *museum*, *temple*, *monuments*. The lead author of this study (a domain expert) manually curated the lexicon. The full lexicon is provided in Appendix §B.3. The lexicon terms were then used to categorize tweets from our case study event (i.e., 2015 Nepal Earthquake), as shown in Figure 22. Specifically, we first extract uni-grams and bi-grams features from a tweet content. We then find if any of those extracted features are present in the lexicon. A tweet having at least one of the lexicon terms was categorized as heritage; and not-heritage otherwise. The categorized tweets were evaluated using the ground-truth labels. The resulting confusion matrix is presented in Table 29 and the performance measured in terms of precision, recall, and F1-score are reported in the first row of Table 30. Not surprisingly, the lexicon-based classifier misses many of the true heritage cases (i.e., 388 out of 487) which results in a fairly low Recall=0.20 for the heritage class. In practice, this means that only 1 out of 4 images of the heritage will be identified correctly by the lexicon-based classifier.

Heritage/not-heritage classification

First, we apply our heritage models on the SMERP dataset and compare their predictions with the ground-truth annotations[2] Table 29 shows the resulting confusion matrices between the predicted and groud-truth labels for both heritage models. Figure 24 illustrates the confusion matrices between the predicted and ground-truth with examples of images classified with the Heritage Model-2. It was found that the images which were particularly difficult to accurately classify included edited or altered images, aerial images, satellite images. Images with overlapping architectural elements between the 'heritage' and 'not-heritage' categories were also difficult to classify. Lastly, images in which heritage was not the main subject of the image (refer top-right of Figure 24) tend to be difficult to classify. Further, Figures 27,28 in Appendix B.6 provide examples of images classified with Heritage Model-1 and Lexicon-based Model.

Moreover, Table 30 summarizes the performance of the heritage classifiers in terms of precision, recall, and F1-score. Ideally, the confusion matrix for a perfect model would have non-zero values only in the diagonal entries and zeros elsewhere (i.e., no incorrect predictions). However, this is rarely the case in real-world systems. Likewise, Heritage Model-2 does a decent job in classifying heritage images as heritage (i.e., 369 out of 487), which corresponds to a Recall=0.76, and not-heritage images as not-heritage (i.e., 4,794 out of 5,833), which corresponds to a Recall=0.82. However, the model makes some errors and classifies many not-heritage images also as heritage (i.e., 1,039), which results in a low score of Precision=0.26 although in the other direction, the model makes less errors and classifies fewer not-heritage images as heritage (i.e., 118), which leads to a high score of Precision=0.98.

Another important observation to note is the significant difference in performance between the two heritage models on our case study dataset although they seemed to perform on par on our Google images test set (as presented earlier in Section 5.5.2). First, there is a big difference in precision scores where Heritage Model-2 achieves a score of Precision=0.26 while the Heritage Model-1 achieves only a score of Precision=0.10. As Heritage Model-1 was *not* trained on sample images with damage context, it tends to classify many not-heritage images as heritage (i.e., 3,869 to be specific), which corresponds to a false positive rate of FPR=0.66 based on Table 29 (b). On the other hand, Heritage Model-2 makes

[2]The results discussed in this section are obtained by the heritage models trained by Logistic Regression algorithm using `DenseNet121` features. To examine the performance of other models obtained by different combinations of CNN features and classification algorithms, we refer the reader to Appendix §B.5.

less number of the Type-I errors (i.e., 1,039 to be specific) which brings the false positive rate down to FPR=0.18 according to Table 29 (c).

However, this increase in precision for Heritage Model-2 comes at the expense of a slight decrease in recall since Heritage Model-2 makes more Type-II errors than Heritage Model-1. Specifically, Heritage Model-2 predicts118 heritage images as not-heritage (which corresponds to a false negative rate of FNR=0.24) whereas Heritage Model-1 predicts 64 heritage images as not-heritage (which corresponds to a false negative rate of FNR=0.13). When we compare the F1-scores of both models, which is the harmonic mean of the precision and recall scores, we see that the overall performance of Heritage Model-2 with a score of F1=0.39 is much better than that of Heritage Model-1 with a score of F1=0.18. In other words, Heritage Model-2 presents better generalization capabilities.

Although the lexicon-based model achieves the highest precision score (i.e., Precicion=0.55), its overall performance in terms of F1-score remains at F1=0.30 due to its poor recall rate (i.e., Recall=0.20) for the heritage class. Therefore, we conclude that Heritage Model-2 provides the best compromise for the heritage image classification task in practice.

		Classified as	
		Heritage	Not Heritage
Actual label	Heritage	99	388
	Not Heritage	80	5,753

(a) Lexicon-based Model

		Classified as	
		Heritage	Not Heritage
Actual label	Heritage	423	64
	Not Heritage	3,869	1,964

(b) Heritage Model-1

		Classified as	
		Heritage	Not Heritage
Actual label	Heritage	369	118
	Not Heritage	1,039	4,794

(c) Heritage Model-2

Table 29: Confusion matrices of the heritage classifiers on the SMERP dataset.

Figure 24: Examples of images classified with Heritage model 2.

	Precision		Recall		F1-score	
	Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Lexicon-based Model	0.55	0.94	0.20	0.99	0.30	0.96
Heritage Model-1	0.10	0.97	0.87	0.34	0.18	0.50
Heritage Model-2	0.26	0.98	0.76	0.82	0.39	0.89

Table 30: Performance comparison of the heritage classifiers on the SMERP dataset.

Damage/no-damage classification

Then, we apply the damage assessment model on the SMERP dataset and compare the model's predictions with expert labels. As shown by the confusion matrix in Table 31, the model classifies 1,580 of 1,822 damage images correctly and misses only 242 damage images. Similarly, the model classifies 4,130 of 4,498 no-damage images correctly and misclassifies the remaining 368 images. This yields a classification accuracy of 0.90. Figure 25 shows examples of damage classification images. Moreover, Table 32 summarizes the performance of the damage assessment model in terms of precision, recall, and F1-score. Based on these class-specific assessments, the model seems to perform relatively better on no-damage images with Precision=0.94 and Recall=0.92 than on damage images with Precision=0.81 and Recall=0.87. The weighted average of these precision and recall scores tend to be closer to those for the no-damage class because of the imbalance distribution of damage and no-damage images in the SMERP dataset. Overall, the damage assessment model performs reasonably well on the challenging SMERP dataset.

		Classified as	
		Damage	No-damage
Actual label	Damage	1,580	242
	No-damage	368	4,130

Table 31: Confusion matrix for the damage classification.

Figure 25: Examples of damage classification images.

	Precision	Recall	F1-score
Damage	0.81	0.87	0.84
No-damage	0.94	0.92	0.93

Table 32: Performance of the damage classifier on the SMERP dataset.

5.5.4 Discussion

The results from our experiments suggest that the proposed methodology to classify images from social media is helpful to understand damage to heritage sites during disasters. The proposed method significantly reduces the work of heritage professionals by quickly processing and filtering thousands of images. Its application can contribute towards a better understanding of the impact of disasters on cultural heritage and prepare a coordinated response.

We performed a comparative analysis of the precision and recall of each model to understand their relative performance in our case study. Table 30 summarizes the performances achieved by the three models. Even though the lexicon-based model yields the highest precision in our case study, its applicability can not be generalized for various reasons. First, the manually-curated lexicon contains only English terms. However, people often refer to terms in the local language when describing a heritage site. For instance, a temple is often referred to as a *mandir* in some countries, as we also saw in Chapter 3 . Second, the words in a lexicon can be used in a different context. For instance, heritage has been used to refer to *lineage* in many instances. Third, the lexicon-based model can result in data from undamaged or unaffected areas. We found that the term temple was also used to refer to an unaffected temple in an unaffected region. Fourth, the low recall of the lexicon-based model implies that only 20% of images from heritage sites will be found by this model. While low precision results in more manual work for the heritage professionals, low recall implies that many images simply go undetected. In a real-world scenario, it means that the overall assessment of damaged heritage may be quite incomplete with this model.

In comparison, Heritage Model-2's lower precision implies more manual labour for heritage professionals in sorting the relevant images, but its higher recall suggests that the chances of relevant images being undetected is substantially lower. Therefore, compared to the lexicon-based model, Heritage Model-2 is more likely to provide a better overall picture of the affected areas. On the other hand, Heritage Model-1's lowest precision and higher recall suggest that the manual labor of professionals is more than doubled, even though the overall picture of the affected areas may not be significantly better than the Heritage Model-2. More manual work for heritage professionals in this case would result in a delayed assessment in a real-world scenario. Therefore, we conclude that, among the three models, Heritage Model-2 is the most suitable model for heritage image classification as it will result in better assessment in less amount of time and require less manual work from the heritage professionals.

This is a challenging image classification task, as high performance would require visual features that can characterize *heritage sites* in an unambiguous manner. Overlapping spatial qualities, building form, architectural elements, and material of construction in *heritage* and *non-heritage* categories means this problem is inherently ambiguous. In addition, the fact that we try to identify heritage images in disaster context makes the problem even more challenging. Our case study results revealed that a subtle difference in data curation and training (i.e., including *damaged* heritage and non-heritage images in the training of Heritage Model-2) can lead to significant differences in generalization capabilities and robustness of the trained models, specially when tested in a real-world scenario. To this end, our results highlight that the automatic classification of heritage images in disaster context is not an impossible task.

Many of the images depicting damaged heritage did not contain contextual information. This complicates the task further, even for a professional. However, our damage assessment model gave a high accuracy. Given the precision is above 80% for damaged heritage, a heritage professional examining the output would find false positives (images the system says are damaged heritage, but are not) of up to 20%. Given the recall is above 80% for the same class, 4 out of 5 images of damaged heritage can be found using these methods.

In our case study, we used a single type of disaster i.e. earthquake, a type of geophysical disaster. Therefore, a discussion on the classifiers' applicability in different subgroups of disasters is necessary at this point. The training of Heritage Model-2 using sample images with damage context surely increases the chances of correct predictions in different types of disasters such as geophysical, climatological, and miscellaneous accidents, as defined by EM-DAT (fRotEoD19). It is also likely to perform well in case of deliberate destruction of heritage during wars. However, the Heritage Model-2 may have limited performance in hydrological disasters such as floods, as the training dataset included only the above-mentioned sub-groups of disasters. Indeed, the characteristics of images produced in different types of disasters may vary in various aspects. Further, the characteristics of images produced on social media during two similar events may also vary in attributes. Therefore, further training of Heritage Model-2 with larger datasets from different scenarios will increase the wider applicability of the classifier.

The results from our extensive experiments using various network architectures as feature extractors together with several classification algorithms showed that there can be variations in performance across different configurations. Although these variations are usually not dramatic, it is possible to obtain further performance improvements in precision and recall via some further engineering and parameter fine-tuning efforts. However, such engineered configurations may not translate from one setup to another, and should be part of the work done when deploying and maintaining these systems in practice.

5.6 Concluding Remarks

The process we have described requires many elements: a careful delimitation of the images to be processed, a comprehensive data collection strategy that ensures diversity, a careful annotation of data points that can avoid ambiguities in the training set, a state-of-the-art deep learning method to learn to classify images, and an in-depth evaluation to understand the performance of different classifiers.

The results, however, are in our opinion worth the effort. Social media provides a nearly instantaneous view of cultural heritage sites affected by a disaster, including many ground-level photos that cannot be replaced by the bird's eye perspective provided by UAVs and satellite images. However, photos of heritage sites are a tiny minority of all the images that are posted, and images depicting a damaged heritage site as the main subject are rare. Finding them manually in an avalanche of unrelated images from social media is simply impractical. Our methods can greatly reduce the number of images to be examined by a cultural heritage professional.

Future work The quality of our classifier can be improved by a larger, more diverse training set. However, annotating images selected at random from a social media stream during a disaster is impractical considering the relatively low frequency of damaged heritage photos. Hence, we envision using the classifier we have created to find candidate images for further annotation. Moreover, we can maximize our utilization of multimedia content on social media platforms by formulating the heritage classification problem in a more sophisticated way as a multimodal learning problem where the goal would be to combine features extracted from various modalities (e.g., text, image, video, etc.) to train a heritage classification model. That being said, unlike Twitter, such aligned multimodal data are not prominent on most other social media platforms (e.g., Instagram and Flickr). Therefore, a technology based only on images would still be desirable in such cases. An additional area for further work is the identification of different types of damage, such as mild and severe damage, which may help in the prioritization of efforts. Dealing with images from an earthquake may be easier than dealing with images from a more localized disaster, such as an explosion (intentional or accidental), because after an earthquake there is a large number of people distributed over a large area who can directly witness the consequences of the event. It might also be the case that during natural disasters there is less misleading information than during a human-made disaster such as a war; in any case, further experimentation with other types of disasters would help improve and fine tune these methods. Ultimately, joint modeling of heritage classification and damage assessment tasks in a unified framework bears great potential to provide better understanding of heritage images in disaster context.

Chapter 6

Discussion and Conclusions

After a brief introduction to the research in Chapter 1, Chapters 2, 3, 4 and 5 of this dissertation explored the past, the present, and the future by addressing the following research questions:

- *RQ1* What lessons can be learned about crowdsourcing in cultural heritage during disasters from the past initiatives?
- *RQ2* How do people respond to cultural heritage affected during disasters on social media?
- *RQ3* How can social media data be used for rapidly evaluating the situation on the ground when a disaster affects cultural heritage?

Chapter 2 addressed RQ1 by analyzing the crowdsourcing initiative during the 1966 Florence Flood, Chapter 3 and Chapter 4 addressed RQ2 by analyzing people's response in the current technological context using the case of the 2015 Nepal Earthquake whereas Chapter 5 addressed RQ3 and envisioned the future with the help of present-day technologies. This chapter is structured in 3 parts. Section 6.1 summarizes the main findings of this research. Section 6.2 cross-compares the results from Chapters 2, 3, 4 and 5 and discusses them under the topics that emerged from the findings. Section 6.3 concludes this dissertation stating the limitations and possibilities of future work.

6.1 Summary of Findings

The past

Chapter 2 addressed RQ1 by analyzing the case of the 1966 Florence Flood. The analysis of 180 out of 753 correspondence sources from the archives of *Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti* in Lucca, Italy, suggests that people's response to cultural heritage damaged by the flood can be categorized under three themes: action, memory and sentiment. Action was the most dominant theme as most of the sources sent contributions to the committee. Contributions were received from at least 25 countries in the form of money, materials, volunteering and knowledge from non-experts and experts in heritage conservation. Four main factors were found to be motivating people to contribute: 1) the call to participate, 2) media, 3) influencers, and 4) memory of the city.

The present

RQ2 was addressed by analyzing text (Chapter 3) and images (Chapter 4), respectively, posted on Twitter using the case of the 2015 Nepal Earthquake. Chapter 3 utilized 201,457 tweets (including RTs) from three different datasets to understand people's response to cultural heritage impacted by the earthquake. The analysis suggests that only a small number of tweets (approximately 4%) were posted regarding cultural heritage. Four main themes were evident in the tweets: information, memory, sentiment and action. Most of the tweets were hybrid in nature, i.e. they followed at least two of the above-mentioned categories. Information was found to be the most dominant theme amongst all.

Chapter 4 investigated 6,529 images posted on Twitter during and immediately after the 2015 Nepal Earthquake. The analysis shows that only a small number of images (less than 10%) were posted depicting cultural heritage sites, including some images of heritage sites outside Nepal. The 566 images of cultural heritage sites fall under six themes: situation (67%), message (12%), memory (10%), practice (5%), screenshots and edited images (4%), and other country's heritage sites (2%). Situation was found to be the dominant theme.

The future

Chapter 5 addressed RQ3 by introducing a methodology for automatic classification of images of cultural heritage sites, including the damaged heritage sites posted during disasters. The model proposed can automatically classify thousands of images to identify heritage sites (damaged or undamaged). Even though the precision of the proposed model is lower than other models tested, the chances of relevant images being undetected are substantially lower, i.e. the proposed model can provide a better overall picture of the affected areas.

6.2 Discussion

Heritage: past and present, Europe and Asia

A discussion of *what is heritage* is important at this point, as this research partly took a flexible approach towards defining heritage in Chapter 1. Interestingly, *what is heritage* in people's perception in Chapters 2 and 3 was found to be the same as the *heritage* defined by the professionals. During the 1966 Florence Flood, people characterized an array of resources such as monuments, works of art, archives and libraries as heritage. However, during the 2015 Nepal Earthquake, people mainly labeled historic sites as heritage. It is difficult to assess whether it is due to people having similar values attributed to heritage as those of the professionals or is a result of opinion formation shaped by the mainstream media. Nevertheless, the results of this research suggest that people do not formulate a new concept of heritage in times of disaster. This is evident in both the 1966 Florence Flood and the 2015 Nepal Earthquake, which were not only situated in different times, but also in countries with distinct approaches to heritage.

Since the adoption of the Nara Document of Authenticity (ICO94) in 1994, it is internationally well established that the approach towards heritage and its management is distinct in each region (CI15; Sto08; Aka16). This was also evident in the two cases discussed in this dissertation. During the Florence Flood, people cherished heritage primarily for its artistic and aesthetic value, as evident from the correspondence; during the Nepal Earthquake, people revered heritage for its spiritual value, as evident from the tweets and images (Sil15). Their continued worshiping in the sites destroyed by the earthquake clearly illustrates a distinct relationship between people and their heritage (KC16; Wei15). This confirms Akagawa's (Aka16) argument that meaning and values attributed to heritage are intangible and implicit in understanding any heritage, whether in Europe or Asia. Indeed, the differences point towards a need for a context-sensitive approach to heritage, particularly in the conservation of heritage after disasters.

Comparison of past and present response: text

A comparative analysis of Chapters 2 and 3 suggests that the people's responses in 1966 and 2015 have three overlapping themes: action, memory, and sentiment (refer to Figure 26). Even though the cases are more than 50 years apart and the technological landscape is evidently different, the overlapping themes suggest that memory and sentiment play an important role in the response and organization of action for cultural heritage after a disaster. Indeed, these overlapping themes are present in varying degrees in both cases. Action was the most dominant theme in the 1966 Florence Flood due to the nature of the crowdsourcing initiative in which the committee (CFIF) invited people to contribute to rescue cultural heritage. On the other hand, the theme 'action' was nominal (3.8%) in the tweets posted during the 2015 Nepal Earthquake. The varying degree of themes is not only due to the nature of the crowdsourcing initiative of 1966 but also the architecture of Twitter, as we will discuss later in this section.

Furthermore, people's responses were mainly hybrid both in Chapter 2 and 3, i.e. most of the correspondence and tweets include more than one theme. The co-occurrence of themes in tweets is rather complex, as some themes do not necessarily occur with each other. For instance, the hybrid theme 'action+sentiment', while common in correspondence in Chapter 2, was absent in tweets.

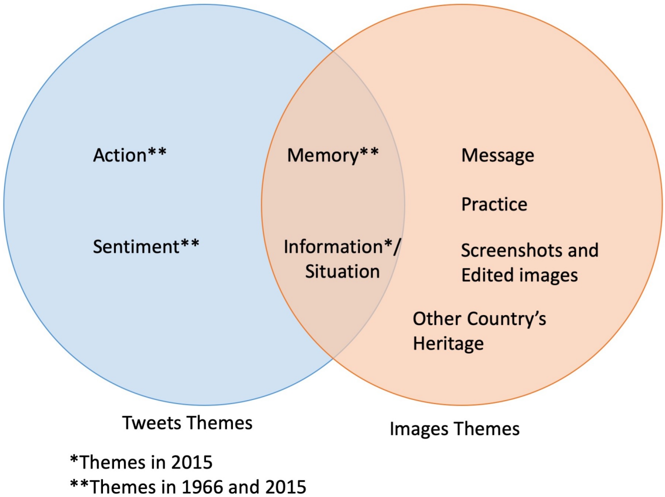

Figure 26: The figure shows overlapping themes in 1. Correspondence in 1966 and Tweets in 2015 Nepal Earthquake 2. Tweets and Images posted during the 2015 Nepal Earthquake.

New element of response in the present times The new theme 'information' that emerged in Chapter 3 (see Figure 26) illustrates the role of Twitter. While Twitter was originally envisioned to facilitate circulation of a "short burst of *inconsequential* information" (Joh13), it has grown into a globally significant outlet for instantaneous information and news dissemination, particularly during disasters (TTJC15; Mur18; SBCB13). This is reflected in the findings of this dissertation also, i.e. during the 2015 Nepal Earthquake people used Twitter to instantaneously circulate and recirculate information regarding the cultural heritage sites of the country. This theme also resonates in Chapter 4, where people updated images representing the situation of the cultural heritage sites. Interestingly, in both Chapters 3 and 4, 'information/situation' was the dominant theme with around 89.1% of the tweets and images giving information on the current situation of the cultural heritage sites. This illustrates that the information from Twitter can be used for rapid damage assessment, particularly immediately after the disaster, a phase often characterized by the lack of and need for information to prioritize action (ZGSG10; HCH10). Nevertheless, due to the large volume and speed of social media (Mei15; Cas16), coupled with the ease of downloading data with the help of APIs, looking for relevant information can be like searching for a needle in a haystack. Moreover, the rapid damage analysis from Twitter may also have some limitations, as we saw information asymmetry in Chapter 3; i.e., not every cultural heritage site received equal attention after the disaster. Despite all the limitations, information from Twitter is irreplaceable, as suggested by Castillo (Cas16). It can help professionals rapidly analyze the situation and evaluate priority action areas, which otherwise is a time-consuming process in the cultural heritage domain, as discussed in Chapter 1.

Role of memory The analysis also suggests that memory played an important role in motivating people to organize a response, as evident in Chapter 2. Similarly, Chapter 3 and Chapter 4 suggest that people who have visited the cultural heritage sites, regardless of the time elapsed since their visit, are sympathetic towards heritage. These people are most likely to contribute to the crowdsourcing initiatives after a disaster.

Indifference towards heritage and social media The indifference towards heritage evident in Chapter 3 exemplifies the influence of social media which affords a voice to the marginalized population, even for expressing conflicting opinions. The absence of indifference to cultural heritage in the correspondence after the 1966 Florence Flood discussed in Chapter 2 also points towards the role of technology. Unlike today, in 1966, the technology available to individuals did not afford them the capacity to publicly voice their opinion, which could be instantly disseminated to a large number of people. Instead, there was a distinct division between personal communication afforded by letters and telegrams and mass-communication through news media. The indifference towards heritage evident in Chapter 3 also triggers an ideological debate amongst researchers, as mentioned by Cindy Ho (Ho15):

> *When life is lost, how can we even speak about old pieces of wood and brick? How can we think about cultural heritage when life is lost?*

Ideological debate One of the concerns raised during disasters is whether the response to cultural heritage during disasters, particularly where lives are at stake, is a necessity or a luxury (Spe99; Ho15). These concerns, though not too common, as seen in Chapter 3, need to be addressed in this research. Indeed, life should be the prime importance during disasters and this research does not intend to undermine the importance of humanitarian response. Culture (or heritage) may not be an immediate need or priority in disaster-struck societies (GS06; Tan17). However, it is indeed an integral part of a society, as evident from the findings of Chapter 4.

To the Nepali people, heritage resources are a part of their daily lives, and hence a part of their identity (KC16; Wei15). People continuing prayers in the damaged heritage sites exemplifies the relationship people share with their heritage and the role of heritage in distressful situations. Thus, it can be concluded that cultural heritage resources are valuable to the people of the country. Moreover, it can also be valuable to people outside the national boundaries, as evident in Chapter 2, where people from at least 25 countries sent contributions to save the cultural heritage in Florence. To summarize, despite the scant hostility towards heritage evident in Chapter 3, the findings of this research suggest that cultural heritage resources are valuable to the citizens and outsiders alike. As Spennemann (Spe99) mentioned, cultural heritage resources are finite, scarce, non-renewable, valuable and, therefore, need cautious addressing when a disaster strikes.

Language and technology Broadly, the content of tweets examined in Chapter 3 is more comparable to the telegrams rather than the letters of Chapter 2. Similar to a telegram, a tweet tends to be short and precise, due to the limitation of the tool. A telegram used to be expensive to send in the 1960s, whereas the architecture of Twitter now limits tweets to 280 characters[1]. Such imposed limitations resulted in alteration of the language in both cases. As we saw in Chapter 2, words were abbreviated, omitted or added for a specific purpose in telegrams. Similarly, a tweet can contain abbreviations, incorrect grammar, and typological errors, as discussed in Chapter 3. Overall, these patterns are based on a small set of established principles, as noted by Crystal (Cry06) in the book 'Language and the Internet'. In other words, people find creative ways of expressing themselves in a context where they are limited by the technology and tools available to them. To sum up, people's response can be partially shaped by the limitations of technology and tools.

The language usage in Twitter poses a challenge in data collection and analysis, as also evident from the baseline construction in Chapter 5. First, the terms presented in the lexicon in Appendix B.3 can have different meanings. For instance, the term *heritage* is often used to refer to lineage. Secondly, the use of homonyms[2] can make data collection and analysis even more challenging. For instance, certain cultural heritage site names are not unique names and hence, result in irrelevant data. Lastly, we also saw in Chapter 3 that often people use

[1] In 2017, Twitter introduced the limitation of 280 characters to allow people to express themselves better (RI17). Before this, the Tweets were limited to 140 characters.

[2] Homonyms are words which sound alike or are spelled alike, but have different meanings.

words in regional language to refer to heritage sites. All the above-mentioned factors illustrate the complexity of the process. On the other hand, it also points to the importance of images posted on social media and the utility of the methodology proposed in Chapter 5 for efficient assessment of the situation on the ground.

Comparison of present response: text vs. image

A comparative analysis of Chapters 3 and 4 suggests that information or situation awareness was the dominant theme in both images and tweets. Information and memory were the only overlapping themes in both images and tweets (refer Figure 26). Figure 26 also illustrates that images were used for many different purposes during and immediately after the earthquake, i.e. more underlying themes were evident in images.

Analysis of text in Chapter 3 and images in Chapter 4 posed different problems. Images analyzed in Chapter 4 largely convey one meaning and were classified under one theme only. However, tweet text tends to be more complicated as most of the tweets are hybrid in nature, i.e. they convey several messages together. Earlier in this section, we also discussed the complexity of processing texts due to several reasons such as the different meaning of the same word, homonyms and regional names. Thus, in comparison to tweets, the images posted on Twitter offer a better avenue for assessment of the situation on the ground. The above-mentioned factors illustrate the importance of images posted on social media during disasters (VFP+13; ML16; AJ16) and their automatic classification provided in Chapter 5. The findings of Chapter 2 further illustrate the utility of images in evoking emotions (Seo14) and motivating people to contribute to a crowdsourcing campaign.

The findings of Chapter 3 and Chapter 4 suggest that only a small percent of tweets and images (less than 10%) were posted regarding cultural heritage during disasters. However, the small quantity of relevant data is not necessarily a limitation. In fact, many researchers (Cas16; NAOI17) have pointed out that social media posts during disasters often contain irrelevant posts as well as not useful and repetitive information. The analysis of images, as discussed in Chapters 4 and 5 also highlights that the images posted during the 2015 Nepal Earthquake contain several irrelevant posts, i.e. images not related to the earthquake. Despite such practices, the small quantity of relevant information posted on social media during disasters can give accurate information about the situation on the ground.

Technological contexts, the role of professionals and media

The instantaneous mass circulation of text and images discussed in Chapters 3 and 4 was impossible in the technological context of 1966, making the rapid damage assessment a task for *on-site* professionals and volunteers. The technology of present times has changed the role of the professionals and the crowd to a certain degree. First, the professional need not be on-site immediately after the disaster to analyze the damage to cultural heritage, as we saw in the case of KCEC. In 1966, the crowdsourcers (i.e. the heritage professionals initiating the campaign) were located *on-site* whereas in 2015 both the crowdsourcers and the crowd were spread globally. A similar pattern of crowd and crowdsourcers' location was seen in WCI. Secondly, online participatory applications can assist anyone interested to instantaneously contribute to an initiative. Lastly, the 'amateur' crowd can no longer be considered passive contributors but an active group of people who can visibly express their opinions. The methodology proposed in Chapter 5 may further change the relationship of the professionals with the crowd as it does not invite the crowd to directly participate in the process, as in the Florence Flood, KCEC or WCI. Nevertheless, it is still subjected to the level of crowd participation on Twitter, the kind of information posted and the speed of the post for rapid, efficient analysis.

The technological context of 1966 was indeed different than the technological context of present times. Unlike today, in 1966, mass communication and its agenda (ML16) were regulated by the mainstream media. As a result, the mainstream media was of utmost importance in disseminate news to the masses, particularly during disasters. The committee (CFIF) extensively utilized the mainstream media to invite the geographically dispersed crowd to participate in the crowdsourcing initiative. As evident from the correspondence, several people were motivated to send contributions due to the mainstream media's coverage. In the digital age, mass communication is possible via the online participatory applications and even individuals have the capacity to communicate directly with a large number of people. However, this does not undermine the role of mainstream media. On the contrary, the mainstream media is all the more important during disasters in the present-times (MG09; Ali13; KL05; Joy18) characterized by the fast pace of information flow and reduced attention span. This is evident in the case of WCI discussed in Chapter 1, with many articles in the mainstream media calling for the contribution of images to Wikipedia (Kea18; Kil18; Dre18), WCI was supported by the mainstream media. On the other hand, KCEC which not disseminated by the mainstream media, received less public participation than WCI, as discussed in Chapter 1.

Comparison of crowdsourcing initiatives

The 1966 Florence Flood, KCEC and WCI cases are representative of their time-period characterized by the immense loss of cultural heritage which inspired a group of professionals to initiate a crowdsourcing campaign. The three crowdsourcing initiatives had different goals. The crowdsourcing initiative in the 1966 Florence Flood discussed in Chapter 2 aimed to receive contributions (mainly money) from a geographically dispersed crowd. On the other hand, the KCEC crowdsourcing initiative discussed in Chapter 1 aimed to rapidly gather information to assess damage to cultural heritage assets immediately after the earthquake. WCI aimed to preserve the memory of cultural heritage affected by the fire in the National Museum of Brazil. The three crowdsourcing initiatives had different goals and received different levels of participation from the crowd, partially based on the intensity and extent of the 'call to participate'.

Indeed, the success of crowdsourcing is more than plain numbers of participants. According to Graham et al. (GCS^{+}15), a successful crowdsourcing initiative will both engage the crowd and satisfy the (data) quality standards. In order to succeed, the initiatives often need to be organized, facilitated and nurtured (Fis00, p.xi). In fact, these were the primary reasons behind the widespread participation in crowdsourcing during the 1966 Florence Flood. The crowdsourcers actively organized and facilitated the campaign for a period over two years using the network and mediums available to them. The case also illustrates the importance of word-of-mouth in crowdsourcing initiatives (Mei15).

The case of KCEC, on the other hand, highlights that the facilitation and nurturing of a crowdsourcing campaign may be limited due to several reasons. KCEC used Ushahidi, an online application widely popular in disaster management, that only minimally facilitates the crowdsourcer and crowd relationship. The crowd could send an email to the crowdsourcer; however, the crowdsourcer did not actively interact with the crowd on the platform, and did not have a visible presence in this application. As found in other crowdsourcing projects in the cultural heritage domain, the crowdsourcer-crowd relationship is an important factor behind the success of an initiative (Bri17). Indeed, unlike the 1966 Florence Flood and WCI, KCEC was a rather short-lived campaign with serious time-constraints. Under such conditions, a careful choice of application for crowdsourcing is of utmost important. As highlighted by Potts (Pot13), due to the abundance of applications available in the online media, users tends to adopt systems and networks that are already familiar to them, particularly when a disaster strikes. This also highlights the utility of the methodology proposed in Chapter 5 for efficient assessment of the situation on the ground, since Twitter is one of the most popular social networking sites during disasters (MCLR09).

6.3 Conclusions

This research explored the past, present and future by addressing three RQs: What lessons can be learned about crowdsourcing in cultural heritage during disasters from the past initiatives? How do people respond to cultural heritage affected during disasters on social media? How can social media data be used for rapidly evaluating the situation on the ground when a disaster affects cultural heritage?

The cases examined in this dissertation explore two kinds of disasters (flood and earthquake) which tremendously impacted the cultural heritage in two different time periods and geographical locations. The selected cases are set in two different time periods, being approximately 50 years apart in two different geographical locations and, therefore, provide an in-depth understanding of the impact of technological changes on people's response. Moreover, the two cases clearly illustrate that the notion of heritage and the approach towards heritage is context-dependent.

The analysis of the past suggests that a different technological landscape than today was not necessarily a limitation in organizing a crowdsourcing campaign. On the contrary, the case of the 1966 Florence Flood clearly illustrates an efficient utilization of the network, communication mediums and media available then. Overall, it points towards the necessity of understanding the technological landscape, the tools available and their strengths and limitations before initiating any crowdsourcing initiative. Since post-disaster damage assessment can be time-sensitive, it should be planned in-between disasters.

This research also provided a realistic understanding of the data produced on social media during disasters. The evidence suggests that one should not presume that big social media data is necessarily better data. On the contrary, there can be an enormous amount of irrelevant data in the big datasets, thereby making the discovery of information for a niche subject (e.g. cultural heritage) all the more challenging during disasters. Nevertheless, it is not impossible. Furthermore, the findings suggest that social media has truly democratized opinion-formation and expression.

The comparison of past and present highlight overlapping themes in people's response: action, memory, and sentiment. The memory of cultural heritage is an important factor to invoke sentiments and organize action after a disaster. It clearly highlights the most likely composition of the 'crowd', in a cultural heritage crowdsourcing. This finding can aid professionals in building a community of heritage enthusiasts on social media, which in turn can contribute to crowdsourcing during disasters.

The future is promising. Whether the heritage professionals decide to invite the crowd to directly participate in an application or use the data from social media, this research will assist the professionals to aptly employ the methods and tools convenient to them.

This research contributes to a better understanding of crowd and crowdsourcing for cultural heritage during disasters. It is a new and emerging field with many possibilities. Through this research, I unpack several under-researched areas and explore avenues for a better future. The findings of this research will assist in efficiently organizing a post-disasters crowdsourcing. It will further reduce the labor of experts and assist them in rapidly evaluating the situation on the ground.

Limitations

Indeed, the dissertation has a few limitations. First, the research used a single data source in every chapter. In Chapter 2 the data source was limited to the archives of *Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti*. Chapters 3, 4, and 5 utilized only Twitter as a source. The results of Chapters 3 and 4 may not apply to other social networking sites such as Facebook, Instagram, etc. The model of Chapter 5 may not work in different social media platforms (e.g., Instagram or Facebook), in which users may post other types of photos. Indeed, different platforms might be used by different users for different purposes (OCDK16). Further research is required to assess the 'external validity' (OCDK19) of the findings.

As explained by Olteanu et al. (OCDK19), data from social media can have inherent biases based on how datasets are created and behavioral biases due to community norms. These biases may be present in this dissertation as well, however, they were not under my control. Further, there are limitations of methodology in this research. Chapters 2, 4, and 5 was annotated by a single annotator due to limitation of resources and expertise. As a result, the annotated data may have some error that I may have overlooked.

The cases selected, even though representative of their times, are only two kinds of disasters. More cases need to be analyzed to evaluate the results of this research in a broader context. This research is conditioned to public participation in social media and, therefore, may have limited applicability particularly in countries with a large digital divide[3].

Future work

The findings of this dissertation can be further enhanced by using more diverse datasets from various sources and case studies, as I have highlighted in each chapter. The data used in this dissertation could also be studied for different attributes, such as the network of users and information flow.

Future studies should also include interviews with crowdsourcing participants to further understand their motivation and expectations. Crowdsourcers interview will enhance the understanding of their role and responsibilities in the process. An analysis of news articles published after disasters affecting cultural heritage will result in an in-depth understanding of the role of media. In addition, a utility study of applications available for crowdsourcing is necessary to understand their applicability in the context of cultural heritage. The abovementioned factors can provide a holistic understanding of the process.

[3]Digital Divide is a term that refers to the gap between demographics and regions that have access to modern information and communications technology, and those that either do not or have restricted access (Rou14)

Appendix A

Examples of Correspondence

This section provides a few examples of correspondence. Some of these correspondence have been translated to English. Also, the spelling or grammatical mistakes in these letters have been kept as is, to maintain the authenticity of the correspondence. Lastly, the personal details (e.g the name of correspondent and location) have been removed where necessary. The aim is to provide an overview of the data used for analysis and support the results described in Section 2.4, instead of highlighting *who* contributed *what* or *how much*.

1. *I read Newyork Times your name glad that initiative is in your hands I offer ten thousand dollars that I send as soon as established American committee greetings to you and Licia.*[1]
2. *I am glad to contribute to an international fund for the resurrection of Florence- I am sad it is necessary. In 1964 through the eyes of Dr Anne Marie Baldoni my guide, I learned to love Florence, which is very easy. Please accept this small token. I am an artist, but I make more money in my shoe store- Place this check where it will do the most good. She will remember me as the man who sketched everything in sight.*[2]
3. *We have heard that you are collecting contribution to help save the heritage to Florence. While my friend and I have no money, we wonder if there is any program whereby we could come to Florence (in perhaps June) to help in any way.*

[1] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 2, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[2] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 6, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

We would be able to pay our fares there and back if only there were a family or someplace to stay. We are both art students and would be honored to be of service to you. If you know of any such programs please advise us.[3]

4. *The great loss which Firenze suffered in the recent floods has touched the heart of a great many Americans. thousands like myself have at one time or another come to worship humbly that wonderful and ancient city from which so much glorious Italian art has drawn its inspiration. When news came of the damages to some of those priceless works of art, we literally wept, as the Florentines must have wept. For we had seen and revered them, had stored up unforgettable memories of their magnificence. My offering is small, but it comes from a full heart. I know some of the treasures are beyond saving, but there is much work that can and must be dome to restore the others. I want to feel I am a part of that work, and of that city. For in a sense, Firenze is the spiritual home of everyone who loves and admires the finest art in Italy's glorious cultural civilization.* [4]
5. *PLEASE ACCEPT THE ENCLOSED CHECK AS A TOKEN OF MY AND MY WIFE'S ESTEEM FOR THE GREAT CITY OF FLORENCE IN THIS TRAGIC HOUR.*[5]
6. *In answer your cable am sending immediate donation from Thos Agnew and Sons 43 Oldbondstreet London to British Italian Society With deepest Sympathy.* [6]
7. *Just a little help out in the emergency in the memory of two short visits in Florence. Address given in New York Times.*[7]
8. *As successor to comfort director National Gallery of Canada Have presented brief to secretary of state offering cooperation national Gallery STOP and asking for financial support for situation in Italy Jean Boggs Director NaGalCan.*[8]
9. *I have your cable and hasten to reply that we are working through the Committee to Rescue Italian Art as organised in the United States under the Honorary Chairmanships of Mrs. John F. Kennedy and Mr. Lehman. All funds raised will be transmitted through this Committee, Rest assured that our sympathies are with you and that we will do everything we can to assist.*[9]

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[3] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 7, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[4] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 5, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[5] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 3, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[6] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 2, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[7] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 3, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[8] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 9, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[9] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 4, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

10. *Dear friend, I am sending you here one of my articles on the wave in Florence. Unfortunately, Jevil's financial situation is bad. I hope, my friends, that you have a friend.*[10]

11. *RESTORATION OF FLOOD-DAMAGED ART in Florence, Italy, is the goal of a drive to raise $3.2 million by a national committee which has UW representatives on Milwaukee and Madison campuses. Kack Wasserman (UWM-Chm Art Hist) was invited to head the campaign in Wisconsin. He said the donation may be sent to him or to the Committee to Rescue Italian Art, Post Office Box 1414, Providence, R.I Meantime, in Madison Olga S. Zingale (Ext) and a community committee said it will forward to the national office the donations sent to the Madison Fund for the Restoration of Art in Florence, Post Office Box 521.*[11]

12. *I am enclosing with this letter a bank draft for $65.00 U.S. to add to the fund which I understand you are heading, for the restoration and repair of the art treasures of Florence. This money represents an informal collection to which most of the members of my company have contributed. Many of us have visited Florence, and many more who contributed have not had the opportunity, but we all feel the urgency of your work demands our reply in this manner. I only regret the sum is not larger.*[12]

13. *A bad grippe and further consequences prevented me to write them down first and then start to take action to help remedy the damage suffered by flooding in Florence. Unfortunately, having passed news of his wishes to the other comrades, I was informed about some facts addressed to the help of the Florentines during these days of disaster. Mrs. Margarita in Ken, from our section, gave a lecture on Florence to the Mexican Architects Society. The entry ticket cost 100 Pesos, both Lire 20,000. About 1,100,000 have gathered. We have contributed with the price of 10 tickets. Between this conference and an evening of cinema organized by the Embassy of Italy, 12,000,000 were sent to the Italian government. Where other contributions were compressed. In these days a Mexican Help Committee has been set up in Florence, where our Association forms part. A large number of painters, engravers and sculptors have donated works that will be auctioned soon. We hope that the economic results are good. I'll let you know, of course.*[13]

14. *The Circolo di cultura di Locarno, which I have the honor to chair, wants to give its modest contribution to those under your guidance who are engaged in the recovery of many works of art and documents of our common civilization offended by the*

[10] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 3, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[11] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 12, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[12] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 5, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[13] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 2, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

recent flood in Florence . In the next few days our cashier will send you the sum of 536 Swiss francs collected at our last meeting. I am also pleased to inform you that the students of the Scuola Magistrale cantonale di Locarno, in which I teach, have organized for the restoration of the works of art of Florence, a public lottery subscription for which many Ticino artists or residents of the Ticino have put available paintings, sculptures, drawings. We hope that this action, extended to the whole of Ticino, will succeed and can make a valid contribution; it will end in mid-January. After 20 January, on a day that has not yet been fixed, the prize draw will take place. On that occasion, your commitments would allow you to be our most welcome guest and to hold a conference on a topic that you may want to propose? I make this proposal on behalf of the Director of the Scuola Magistrale who is also mayor of the city.[14]

15. *At the initiative of the Direction of the Civic Museum of Pistoia, in the next month of December, a large exhibition-sale of works by Italian and foreign artists will be inaugurated in the Ghibelline Room of the Museum. The proceeds of which will be used as a contribution for the restoration of works of art of Florentine museums and art galleries affected by the floods. The initiative, promoted by the Director of the Museum and by a group of Italian and foreign artists, is being flocked by Italy and abroad by artists of all tendencies, all united in the noble intent to contribute to the rescue of deteriorated works of art . They will unite their efforts to contribute with their works to build a solidarity fund that will be able to see Italian and foreign artists in the common intent of bringing help to Italy for the conservation of its works of art. The works offered for sale will be presented by a catalog published by the municipality of Pistoia to which Italian critics will collaborate.*[15]

16. *I hope this suggestion is of some use to you in rescuing the books damaged in the recent floods. HOW TO DRY BOOKS. Use electric fans, preferably oscillating fans. Lay the books down in front of the fan, open edge toward the fan. Some books dry better standing up. Don't put books too close to fan, or the wind may tear the wet paper. While the books are drying, an attendant should move among them. peeling the pages apart gently, so that wet pages do not dry stuck together. When they are partially dry, the pages of each book can be thumbod occasionally to admit dry air. One fan can treat 5-10 books at a time. One person can attend to quite a few fans and books. Dryers using warmed air might be worth trying on some books, but I haven't tried it. I have used the method described above, to salvage several hundred books that were badly soaked, with excellent results, not one stuck page. Deepest sympathy and best wishes.*[16]

[14] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 4, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[15] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 9, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[16] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 6, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

17. *The enclosed letters are from eight and nine year old children. Our project to help was the result of class discussions of current events. It was their own idea to do something to earn money to send to Florence. Though this isn't a large amount, it is sent with sincere concern and desire to help. Our class bulliten board has been crowded with articles and pictures of the flood. These children are genuinely concerned and want to help. I was in Italy during the summer of 1965 and it was a highlight of my life. My particular interest in opera and my feelings at having of 14 feet of mud in the opera house were greatly upset. I'm sure though that the Italian spirit will prevail and repair will quickly be made. I am planning to visit Florence again during the summer of 1967 and even the flood will not change these plans.*
Best wishes to you in your monumental task of repair and restoration.

    I am very sad about the Floods. Our class has made 40$ in a cookie and candy sale. I know it is needed very much, and will be in good use. I hope you can fix the houses and the operas and beautiful pantings (sic).

    This is money we made. I hope it will help your friends and our to get to safety soon. How are things doing? I can answer that, NOT TOO GOOD! Get in shape soon.

    We are sorry that the flood has ruined everything. That is why we are sending money to you. It's about $ 40. We will help Italy in anyway we can. We do hope you and Italy get better.
    Love
    P.s IS POPE HURT and is the VATICAN?
    good-by (sic) for now.[17]

18. *Your circular letter addressed to the President of the Noble Foundation has been forwarded by Dr. Anders Osterling, chairman of the Nobel Committee for Literature, to us for attention. The catastrophe which recently has come to Italy and endangered many of the irreplaceable treasures common to our Western civilization has caused a spontaneous will to help, also in Sweden. The task of the Nobel Foundation, however, is limited by the testament of Alfred Nobel to prize-awarding activities. We therefore regret that our funds cannot be used for the urgent and worthy caused mentioned in your letter.*[18]

19. *In the name of my fellow Professors Kenneth Evett, Maurice Neufeld, Pietro Pucci and Robert Wilson, I enclose a check for $ 1100 collected from the students and*

[17] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 3, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[18] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 9, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

the Cornell University academic body for your International Fund for Florence. We know of your competence, your great love for Florence, your probity, and we therefore thought that you are the best person to use our little help in the best and most effective way, without delay and bureaucratic formalities. We hope to send you another small sum in January, and we wish you the best wishes for the rebirth of Florence.[19]

20. *The professor. Guy Tosi informs me that he heard the Syndacat National des Editeurs franais, which would be willing to ask its members to participate in the replacement of French books in the damaged libraries of Florence. Naturally, it would be to provide all or part of the current works of each publisher. You should let me have, in the shortest possible time, lists in three copies, to be sent to prof. Tosi, who would then carry out the practice at the syndicated publishers. Naturally, I do not know which entity will have this gift, but I think it would still be useful for university libraries. To this end, you should have the courtesy to ask the library managers themselves to fill in the lists indicated, divided by publishers and related works requested by them. with the most cordial thanks and greetings.*[20]

21. *I have read in our newspaper of your most courageous and honorable work in the restoration of Florence, and would like to offer my personal services to assist in any way. I am a student of Brooklyn College, a division of New York University and plan to take a trip of Italy this summer. I have been looking forward to visiting your historic city for a long time. I am 21 years old and will be graduating from college in June. Please reply to me as soon as possible so that my friend, Edward Potter, and myself can make our summer plans accordingly. It is not very often that history can record such an admirable effort by the people of Florence. Much respect is due you and other Florentines for your dedication. Florence has been one of the cultural centers of the world in the past, and I am confident she will remain so. Thank you for your cooperation.*[21]

22. *I have been very moved by the accounts in the newspapers of the terrible artisitic and cultural losses in your city. Please accpet the enclosed small contribution to help you in the work of restoring and repairing which lies ahead of you. All best wishes.*[22]

23. *Enclosed please find a small contribution toward the recovery of the art of Florence. The pictures of the tragedy have made us heartsick. Wish I could be there to help my hands to restore some of the beauty of the most beautiful city in the world. Hope*

[19] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 3, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[20] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 2, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[21] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 2, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[22] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 2, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

some way will be found that we, over here will be able to help in more personal ways than contributing money. [23]

24. *The Evening Post of Wellington, New Zealand reported on 30/11/1966*
"The floods of the last few weeks have been the worst in the history of Florence with water rising far higher than the previous worst flood in 1277. Disaster has overwhelmed the procurators of art galleries, museums, churches, and libraries in Florence, to say nothing of the population. Huge sums of money will be required, and already the Italian Government has suspended various operations to divert funds to saving this enormous collection of masterpieces. As additional funds are urgently required, donations no matter how small will be gratefully received by ... "[24]

[23] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 3, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

[24] Alluvione di Firenze 1966 - Comitato Fondo Internazionale per Firenze, Box 4, Fondazione Centro Studi Sull'Arte Licia e Carlo Ludovico Ragghianti, Lucca Italy.

Appendix B

List of Heritage, Not-Heritage, Lexicon and Experiment Results

B.1 List of heritage sites

Class	Name of the Site	Location	Country
Architectural	Hagia Sophia	Istanbul	Turkey
	Jaisalmer Fort	Jailsalmer	India
	City of Bath	Bath	UK
	Historic city of Ahmedabad	Ahmedabad	India
	Roskilde Cathedral	Roskilde	Denmark
	Tamshing Monastery	Bumthang	Bhutan
	Notre-Dame Cathedral	Paris	France
	Santa Maria Novella	Florence	Italy
	Alhambra, Generalife and Albayzín, Granada	Granada	Spain
	Red Fort	New Delhi	India
	Sydney Opera House	Sydney	Australia
	Summer Palace	Beijing	China
	Borobudur Temple	Jawa Tengah	Indonesia
	Chinque Terre	Chinque Terre	Italy
	Edinburgh castle	Edinburgh	UK
	Capitol Complex	Chandigarh	India
	Ellora caves	Aurangabad	India
	Wellington Arch	London	UK
	Taj Mahal	Agra	India
	Kings Cross St Pancras Station	London	UK
	Trafalgar Square	London	UK
	Chhatrapati Shivaji Terminus	Mumbai	India

	India Gate	Delhi	India
	The Taj Mahal Palace	Mumbai	India
	Adalaj ni Vav	Ahmedabad	India
	Fatehpur Sikri	Agra	India
	Sarnath Stupa	Sarnath	India
	Sun Temple Modhera	Ahmedabad	India
	Gadisar Lake	Jaisalmer	India
	Mehrangarh Fort	Jodhpur	India
	US Capitol Building	Washington DC	USA
	Notre-Dame Cathedral Basilica	Saigon	Vietnam
	Parthenon	Nashville	USA
	Colosseum	Rome	Italy
	Jama Masjid	Delhi	India
	Dochula Temple	Hungtso	Bhutan
	Punakha Dzong	Punakha	Bhutan
	Tiger Nest Monastery	Taktsang trail	Bhutan
	Arc de Triomphe du Carrousel	Paris	France
	Pyathatgyi Temple	Minnanthu Region	Myanmar
	Bamiyan Buddha	Bamyan	Afghanistan
	Palmyra	Tadmur	Syria
	Aleppo's Umayyad Mosque	Aleppo	Syria
	Sanaa old city	Sanaa	Yemen
	Windsor castle	Windsor	UK
Gallery Library Museum	Kensington palace Museum	London	UK
	British Museum	London	UK
	Victoria and Albert Museum	London	UK
	The Louvre	Paris	France
	Uffizi gallery	Florence	Italy
	British Library	London	UK
	Museum Orsay	Paris	France
	Solomon R. Guggenheim Museum	New York	USA
	Rijksmuseum	Amsterdam	Netherlands
	National Museum of Cinema	Turin	Italy
	Camposanto	Pisa	Italy
	The São Paulo Museum of Art	São Paulo	Brazil
	National War Museum Malta	Valletta	Malta
	Library of Parliament Ottawa	Ottawa	Canada
	Metropolitan Museum of Art	New York	USA
	National Museum	Paro	Bhutan
Archaeological	Machu Pichu	Urubamba River valley	Peru
	Stonehenge	Salisbury	UK
	Mohenjo Daro	Sindh	Pakistan
	Teotihuacan	Teotihuacan	Mexico
	Hagar Qim	Qrendi	Malta
	Palmyra	Palmyra	Syria
	Ajanta Caves	Aurangabad	India
	Pyramids of giza	Giza	Egypt
	Golden Temple of Dambulla	Dambulla	Sri Lanka
	Rani ki vav	Ahmedabad	India
	Petra	Petra	Jordan
	Pompeii	Campania	Italy
	Delphi	Phocis	Greece
	Parthenon	Athens	Greece

	Angkor Wat	Siem Reap	Cambodia
Artifact in Urban Space	Christ the Redeemer	Rio de Janeiro	Brazil
	Terracotta warriors of Shaanxi	Shaanxi	China
	Statue of Liberty	New York	USA
	The Little Mermaid statue	Copenhagen	Denmark
	Telephone Booth London	London	UK
	Stroke Fountain	Copenhagen	Denmark
	Lincoln Memorial	Washington DC	USA
	Gateway of India	Mumbai	India
	The Porcellino	Florence	Italy
	Statue of Hans Christian Andersen	Copenhagen	Denmark
	Open hand monument	Chandigarh	India
	Flaminio Obelisk	Rome	Italy
	Christopher Columbus Statue New York	New York	USA
	Dandi march sculpture	New Delhi	India
	Statue of Mahatma Gandhi in London	London	UK
	Marble arch	London	UK
	Sphinx	Giza	Egypt

B.2 List of not-heritage sites

Class	**Name of the Site**	**Location**	**Country**
Architectural	India Habitat Center	New Delhi	India
	The Shard	London	UK
	IIM	Ahmadabad	India
	Walkie Talkie London	London	UK
	Kanchanganga apartment	Mumbai	India
	Dharavi	Mumbai	India
	New Delhi Railway Station	New Delhi	India
	Lucca Railway Station	Lucca	Italy
	IT university of cCpenhagen	Copenhagen	Denmark
	Pittsburgh airport	Pittsburgh	USA
	Northlake Mall	Charlotte	USA
	Wembley stadium	London	UK
	Radisson blu hotel	Copenhagen	Denmark
	Tiaa cref office Charlotte	Charlotte	USA
	University college hospital	London	UK
	Danish opera house	Copenhagen	Denmark
	Hall of nations	New Delhi	India
	Turning Torso	Malmo	Sweden
	Tata steel industry building	Jamshedpur	India
	Volkswagen factory building	Salzgitter	Germany
	bella sky hotel Copenhagen	Copenhagen	Denmark
	CSV building wardha	Wardha	India
	railway office bilaspur	Bilaspur	India
	Navi Mumbai Railway Station	Mumbai	India
	Belapur Housing Building	Mumbai	India
	8 House	Copenhagen	Denmark
	Munich airport	Munich	Germany
	Gherkin building	London	UK
	UNCC	Charlotte	USA
	Fisketorvet	Copenhagen	Denmark
	Great India Place Mall	Noida	India
Gallery Library Museum	Copenhagen Main Library	Copenhagen	Denmark

	Lalit Kala Akademi	Delhi	India
	Husain Doshi Gufa	Ahmadabad	India
	Crafts museum Delhi	New Delhi	India
	The Blue Planet	Copenhagen	Denmark
	The black diamond	Copenhagen	Denmark
	wax museum London building	London	UK
	Sanskriti Kendra	Delhi	India
	Jawahar Kala Kendra	Jaipur	India
	World Trade Center Museum	New York	USA
	New Jewish museum	Berlin	Germany
	5 Pointz	New York	USA
	Niteri Contemporary Art Museum	Rio de Janeiro	Brazil
	Petrie Museum building	London	UK
	UNCC library	Charlotte	USA
Artifact in Urban Space	Tilted Arc by Richard Serra	New York	USA
	Penis Christmas tree	Paris	France
	Brown Nosing sculpture	Prague	Czech
	Milan stock exchange sculpture	Milan	Italy
	Anish Kapoor Versailles	Versailles	France
	Les Deux Plateaux, Colonnes de Buren	Paris	France
	The Vigeland Park	Oslo	Norway
	Sun dial New Delhi barahpulla	New Delhi	India
	sunbather sculpture	Long Island	USA
	Fearless girl	New York	USA
	MGR Memorial	Chennai	India
	Rooster national gallery	London	UK
	Calgary sculpture controversy	Calgary	Canada
	Chicago and Milwaukee eyeball	Chicago	USA

B.3 Lexicon

All terms are case-insensitive. For presentation purposes we divide them into five groups of comma-separated terms; we do not make any difference between the groups for the purposes of matching within a text.

1. Generic words:

heritage, heritages, cultural, culturally, culture, cultured, cultures, historically, historic, historical, ancient, ancients, architecture, architectural, architecturally, architectures, archeology, archaeological, archaeologically, civilizations, civilization.

2. Bi-grams:

traditional building, traditional architecture, cultural center, cultural complex, cultural ensemble, cultural landscape, cultural masterpiece, historic building, historic town, historic city, historic site, historic architecture, historic center, historic settlement, historic settings, historic civilization, historic ensemble, historic built, historic settlement, historic environment, old city, old town, old buildings, sacred building, ancient architecture, ancient building, ancient settlement, heritage building, heritage city, heritage property, heritage site, ceremonial architecture, ceremonial buildings, landmark building, iconic site, iconic building.

3. Site types:

churches, church, palaces, palace, palace, temple, temples, monuments, monumental, monumentality, monuments, monastery, monasteries, towers tower, towered, towering, castles castle, cathedral, cathedrals, tombs, tomb, caves, cave, mosque, mosques, fortresses fortress, fortified, fortify, fortifying, chapels chapel, fortifications fortification, forts, fort, forte, museum, museums, basilicas, basilica, sculptures, sculptural, sculpture, sculptured, sculpturing, monastic, citadels, citadel, mausoleum, mausoleums, abbey, abbeys, pyramids, pyramid, pyramidal, memorial, memorials, memories, memory.

4. Styles and periods:

romans, roman, romane, romanization, romanized, medieval, empires, empire, dynasty dynasties, kingdom, kingdoms, gothicized, gothic, gothicism, gothicized, gothicizing, baroque, renaissance, imperial imperialism, classical, classic, classically, classicism, classics, buddhist, buddhists, byzantine , byzantines, romanesque, prehistoric, prehistorical, neolithic, ottoman, ottomans, hellenistic, neoclassical, 1st century, 2nd century, 3rd century, 4th century, 5th century, 6th century, 7th century, 8th century, 9th century, 10th century, 11th century, 12th century, 13th century, 14th century, 15th century, 16th century, 17th century, 18th century, 19th century.

5. Organization:

unesco, #unesco, @unesco.

B.4 All Experimental Results on Google Images

	Architecture	Precision		Recall		F1-score	
		Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Heritage Model-1	VGG16	0.93	0.64	0.85	0.81	0.89	0.72
	ResNet50	0.94	0.65	0.86	0.82	0.89	0.73
	DenseNet121	0.91	0.65	0.87	0.75	0.89	0.70
	InceptionResNetV2	0.91	0.63	0.86	0.75	0.88	0.69
	Xception	0.92	0.66	0.87	0.78	0.89	0.72
	NASNetLarge	0.92	0.71	0.90	0.78	0.91	0.75
Heritage Model-2	VGG16	0.94	0.63	0.84	0.84	0.88	0.72
	ResNet50	0.93	0.63	0.84	0.81	0.88	0.71
	DenseNet121	0.94	0.66	0.86	0.84	0.90	0.74
	InceptionResNetV2	0.93	0.62	0.84	0.81	0.88	0.70
	Xception	0.94	0.62	0.83	0.84	0.88	0.72
	NASNetLarge	0.94	0.67	0.86	0.84	0.90	0.74

Table 35: Performance comparison of various CNN features with Logistic Regression classifier.

	Architecture	Precision		Recall		F1-score	
		Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Heritage Model-1	VGG16	0.93	0.63	0.84	0.82	0.88	0.71
	ResNet50	0.93	0.64	0.85	0.81	0.89	0.72
	DenseNet121	0.92	0.63	0.86	0.76	0.88	0.69
	InceptionResNetV2	0.91	0.61	0.84	0.74	0.88	0.67
	Xception	0.92	0.64	0.86	0.77	0.89	0.70
	NASNetLarge	0.92	0.70	0.89	0.76	0.90	0.73
Heritage Model-2	VGG16	0.93	0.62	0.83	0.82	0.88	0.71
	ResNet50	0.93	0.62	0.84	0.81	0.88	0.70
	DenseNet121	0.94	0.66	0.86	0.83	0.90	0.73
	InceptionResNetV2	0.93	0.59	0.81	0.80	0.87	0.68
	Xception	0.93	0.58	0.80	0.82	0.86	0.68
	NASNetLarge	0.93	0.64	0.85	0.82	0.89	0.72

Table 36: Performance comparison of various CNN features with Support Vector Machine classifier.

	Architecture	Precision		Recall		F1-score	
		Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Heritage Model-1	`VGG16`	0.89	0.72	0.91	0.66	0.90	0.69
	`ResNet50`	0.90	0.71	0.91	0.69	0.90	0.70
	`DenseNet121`	0.89	0.72	0.92	0.67	0.90	0.70
	`InceptionResNetV2`	0.90	0.68	0.89	0.69	0.90	0.69
	`Xception`	0.88	0.66	0.89	0.64	0.89	0.65
	`NASNetLarge`	0.91	0.73	0.91	0.71	0.91	0.72
Heritage Model-2	`VGG16`	0.91	0.72	0.90	0.74	0.91	0.73
	`ResNet50`	0.93	0.73	0.90	0.78	0.91	0.75
	`DenseNet121`	0.91	0.71	0.90	0.74	0.91	0.73
	`InceptionResNetV2`	0.92	0.68	0.88	0.75	0.90	0.71
	`Xception`	0.90	0.67	0.89	0.70	0.89	0.69
	`NASNetLarge`	0.93	0.72	0.90	0.81	0.92	0.76

Table 37: Performance comparison of various CNN features with Random Forest classifier.

	Architecture	Precision		Recall		F1-score	
		Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Heritage Model-1	`VGG16`	0.91	0.64	0.87	0.74	0.89	0.69
	`ResNet50`	0.92	0.62	0.85	0.77	0.88	0.69
	`DenseNet121`	0.93	0.67	0.87	0.79	0.90	0.72
	`InceptionResNetV2`	0.91	0.65	0.87	0.72	0.89	0.68
	`Xception`	0.90	0.60	0.84	0.73	0.87	0.66
	`NASNetLarge`	0.91	0.70	0.90	0.74	0.90	0.72
Heritage Model-2	`VGG16`	0.92	0.63	0.85	0.78	0.88	0.70
	`ResNet50`	0.94	0.65	0.86	0.82	0.89	0.73
	`DenseNet121`	0.93	0.63	0.84	0.81	0.88	0.71
	`InceptionResNetV2`	0.92	0.61	0.84	0.77	0.88	0.68
	`Xception`	0.91	0.62	0.85	0.74	0.88	0.68
	`NASNetLarge`	0.93	0.64	0.85	0.81	0.89	0.72

Table 38: Performance comparison of various CNN features with AdaBoost classifier.

B.5 All Experimental Results on SMERP Images

	Architecture	Precision		Recall		F1-score	
		Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Heritage Model-1	`VGG16`	0.11	0.97	0.81	0.46	0.20	0.63
	`ResNet50`	0.10	0.96	0.85	0.34	0.17	0.50
	`DenseNet121`	0.10	0.97	0.87	0.34	0.18	0.50
	`InceptionResNetV2`	0.12	0.98	0.85	0.50	0.22	0.66
	`Xception`	0.10	0.97	0.85	0.38	0.18	0.55
	`NASNetLarge`	0.10	0.97	0.91	0.28	0.17	0.44
Heritage Model-2	`VGG16`	0.24	0.97	0.73	0.81	0.36	0.88
	`ResNet50`	0.24	0.97	0.74	0.81	0.37	0.88
	`DenseNet121`	0.26	0.98	0.76	0.82	0.39	0.89
	`InceptionResNetV2`	0.24	0.97	0.74	0.81	0.37	0.88
	`Xception`	0.23	0.97	0.76	0.79	0.35	0.87
	`NASNetLarge`	0.25	0.98	0.79	0.81	0.38	0.88

Table 39: Performance comparison of various CNN features with Logistic Regression classifier.

	Architecture	Precision		Recall		F1-score	
		Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Heritage Model-1	`VGG16`	0.11	0.97	0.81	0.48	0.20	0.64
	`ResNet50`	0.10	0.96	0.83	0.35	0.17	0.51
	`DenseNet121`	0.09	0.97	0.87	0.31	0.17	0.47
	`InceptionResNetV2`	0.12	0.97	0.84	0.48	0.21	0.64
	`Xception`	0.10	0.97	0.85	0.38	0.18	0.54
	`NASNetLarge`	0.10	0.98	0.91	0.32	0.18	0.48
Heritage Model-2	`VGG16`	0.22	0.97	0.72	0.79	0.34	0.87
	`ResNet50`	0.23	0.97	0.73	0.79	0.35	0.87
	`DenseNet121`	0.25	0.97	0.74	0.82	0.38	0.89
	`InceptionResNetV2`	0.23	0.98	0.77	0.78	0.35	0.87
	`Xception`	0.20	0.97	0.73	0.76	0.32	0.85
	`NASNetLarge`	0.22	0.98	0.77	0.77	0.34	0.86

Table 40: Performance comparison of various CNN features with Support Vector Machine classifier.

	Architecture	Precision		Recall		F1-score	
		Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Heritage Model-1	`VGG16`	0.10	0.98	0.94	0.26	0.17	0.41
	`ResNet50`	0.09	0.98	0.96	0.15	0.16	0.26
	`DenseNet121`	0.09	0.98	0.97	0.13	0.16	0.24
	`InceptionResNetV2`	0.09	0.97	0.93	0.23	0.17	0.38
	`Xception`	0.09	0.97	0.93	0.18	0.16	0.30
	`NASNetLarge`	0.09	0.97	0.95	0.15	0.16	0.27
Heritage Model-2	`VGG16`	0.19	0.98	0.86	0.69	0.31	0.81
	`ResNet50`	0.17	0.99	0.90	0.64	0.29	0.78
	`DenseNet121`	0.19	0.99	0.89	0.69	0.32	0.81
	`InceptionResNetV2`	0.20	0.98	0.85	0.72	0.33	0.83
	`Xception`	0.16	0.98	0.84	0.62	0.26	0.76
	`NASNetLarge`	0.18	0.99	0.88	0.67	0.30	0.80

Table 41: Performance comparison of various CNN features with Random Forest classifier.

	Architecture	Precision		Recall		F1-score	
		Heritage	Not-heritage	Heritage	Not-heritage	Heritage	Not-heritage
Heritage Model-1	`VGG16`	0.10	0.97	0.86	0.35	0.18	0.52
	`ResNet50`	0.11	0.97	0.86	0.41	0.19	0.58
	`DenseNet121`	0.10	0.97	0.88	0.30	0.17	0.46
	`InceptionResNetV2`	0.10	0.97	0.88	0.31	0.17	0.47
	`Xception`	0.09	0.97	0.89	0.28	0.17	0.43
	`NASNetLarge`	0.10	0.97	0.86	0.38	0.19	0.55
Heritage Model-2	`VGG16`	0.20	0.98	0.78	0.74	0.32	0.84
	`ResNet50`	0.24	0.98	0.78	0.80	0.37	0.88
	`DenseNet121`	0.24	0.98	0.76	0.80	0.37	0.88
	`InceptionResNetV2`	0.20	0.98	0.80	0.73	0.32	0.84
	`Xception`	0.20	0.98	0.81	0.73	0.32	0.84
	`NASNetLarge`	0.20	0.98	0.82	0.73	0.32	0.84

Table 42: Performance comparison of various CNN features with AdaBoost classifier.

B.6 Images

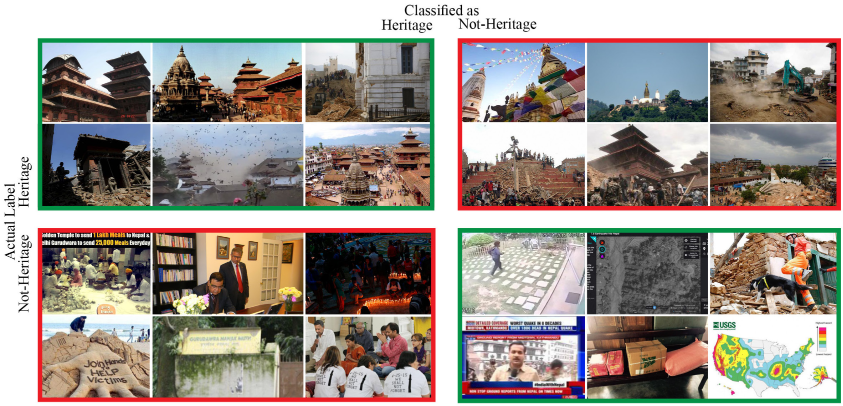

Figure 27: Examples of images classified with Lexicon-based Model.

Figure 28: Examples of images classified with Heritage Model 1.

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