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Earthquake Damage Assessment Based on User Generated Data in Social Networks

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Abstract: Natural disasters have always been one of the threats to human societies. As a result of such crises, many people will be affected, injured, and many financial losses will incur. Large earthquakes often occur suddenly; consequently, crisis management is difficult. Quick identification of affected areas after critical events can help relief workers to provide emergency services more quickly. This paper uses social media text messages to create a damage map. A support vector machine (SVM) machine-learning method was used to identify mentions of damage among social media text messages. The damage map was created based on damage-related tweets. The results showed the SVM classifier accurately identified damage-related messages where the F-score attained 58%, precision attained 56.8%, recall attained 59.25%, and accuracy attained 71.03%. In addition, the temporal pattern of damage and non-damage tweets was investigated on each day and per hour. The results of the temporal analysis showed that most damage-related messages were sent on the day of the earthquake. The results of our research were evaluated by comparing the created damage map with official intensity maps. The findings showed that the damage of the earthquake can be estimated efficiently by our strategy at multispatial units with an overall accuracy of 69.89 at spatial grid unit and Spearman's rho and Pearson correlation of 0.429 and 0.503, respectively, at the spatial county unit. We used two spatial units in this research to examine the impact of the spatial unit on the accuracy of damage assessment. The damage map created in this research can determine the priority of the relief workers.

Keywords: social networks; damage map; support vector machine (SVM); disaster management; earthquake

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1. Introduction

Natural disasters such as earthquakes, floods, tsunamis, or hurricanes can severely damage human societies [1]. Earthquakes are still challenging to predict, despite recent research [2] showing that they can be predicted using natural time analysis [3,4], as demonstrated by forecasting two significant earthquakes in Greece in 2008 [5]. Earthquakes are among a natural phenomenon that causes substantial harm and lives death regularly. Several million earthquakes happen each year globally [6]. Most are not dangerous due to either their small magnitude or remote location, but others can lead to significant financial losses and injuries. [7]. Rescuing people from damaged areas after earthquakes will reduce casualties. But this issue can have the maximum efficiency on which relief and rescue operations are fast and have a plan. Rapid relief after the earthquake is one of the tasks of the relief workers. The damage map can determine the priority of the relief workers. It can also be more efficient in resource allocation [8].

One of the main resources in mapping the damage is remote sensing. Besides all the well-known benefits for traditional methods such as satellite monitoring or post-disaster surveying, methods based on remote sensing usually have a time delay of 48 to 72 h. Furthermore, remote sensing data has spatial, temporal, and spectral constraints.

Besides, its efficiency reduces air constraints such as cloudy weather; they are also very costly. Besides, often, the lack of pre-crisis images makes it difficult to detect the correct changes [1,9,10]. The post-disaster survey may be the most precise technique of identifying the worst harmed regions, but this sort of physical location evaluation takes time and involves a huge quantity of labor and resources [11].

To properly manage emergency conditions, the significance of prompt, precise, and efficient use of accessible data is crucial. Currently, ShakeMaps created by the USGS demonstrate the rapid earthquake intensity and damage estimation. By integration of recordings, a ground motion prediction equation (GMPE), and geological site correction factors, a ShakeMap is generated in a couple of minutes when an earthquake occurs [12].

Emerging technologies have given innovative solutions to the production and procurement of crowdsourced data in the latest years to promote situational awareness and emergency management [13]. As time goes on, the ShakeMap is constantly being upgraded as new kinds of information becomes accessible, which includes DYFI (Did You Feel It) data. These data are first-hand qualitative earthquake data gathered through online surveys. Although this qualitative data is highly insightful, it takes hours to days to obtain, thus, it is generally not used in early intensity and damage estimation [12].

In a wide variety of social networks, mobile phone networks, or micro-blogs, we are presently experiencing the fast development of user-generated information. This human-generated information can effectively complement sensor observations to a reasonable extent, not through well-interpretable calibrated assessments but subjective measurements or human-generated assessments [14,15]. In this regard, the internet and social media already has demonstrated the ability to be an efficient tool for propagating and accessing up-to-date information. Social networks are rich sources of event information and this information can be used at a lower cost in the damage assessment. This information includes text and images shared by witnesses. Given the global coverage of wireless networks and mobile technologies, people can play a major role in news releasement after natural disasters such as an earthquake [16,17]. Since social networks provide the ability to exchange content created by individuals, the information extracted by these networks can include time and space data associated with different events. One of the benefits of social networking data is their online nature means that data is available without delay. The other attribute is its in situ nature, and that it can be gathered in the case of local conditions such as street accessibility, blocked streets, injured people, damages to buildings, etc. [18]. These data can be used in post-crisis assessments in the provision of information layers that are less time-consuming than those based on remote sensing methods. It proved that users tend to share their status during a crisis on the social network, indicating the potential of social networks for a quick damage assessment. Research has shown that the severity of damage in a region was correlated with the amount of crisis-related activities in the social network in that region [19].

Among the most popular social networks, research has pointed to Twitter as a source of information that offers valuable real-time data for decision-making. Twitter is one of the most active social networks in the world and gives us free access to personal information, including text messages, location, and social relationships. All of these features have highlighted the role of Twitter in crisis management studies [13]. Twitter was designed to allow people to post and share short messages very quickly with the rest of the world. The content of the messages (called tweets) usually consists of sharing opinions and feelings from common people or in news and advertisements from commercial organizations [20]. Tweets may be a useful additional data source following significant earthquakes, especially in regions without an extensive network of recording stations [12].

Using social media data to identify damage in real-time can assist crisis administrators not only rapidly identify the most affected regions, but it can also obtain human response data that cannot be detected through physical surveillance, thus providing a prompt and helpful strategy to crisis leadership [11]. Social media gives a better chance to change emergency response by offering effective lines of communication that enable even more

useful data dissemination and public engagement [21]. The worldwide spread of the internet and citizen crowdsourcing has enabled social networks to become a major hub for low-cost earthquake detection. Fast and effective assessment of the affected region in which an earthquake causes injury and property losses is crucial for urgent response procedures and assessment of damages [22]. Rapid assessment of damage data can assist in asset allocation and guide decision-makers in an emergency. This will assist rescue workers in prioritizing their aid activities and initially plan for the worst situations [23].

Social media performs a crucial role in disaster-related data exchange. Unfortunately, the overwhelming quantity and scope of information produced on social media leaves it difficult to properly screen and determine its relevancy for damage estimation through such content; in this regard, classification algorithms can be used. For the general tweet classification task, current literature uses different algorithms. The Enhanced Emergency Response Sector Messaging (EMERSE) system was generated by Caragea et al. [24] who compared various feature representations to categorized tweets for training the support vector machine (SVM) classifiers. Imran et al. [25] classified tweets during disasters with a random forest. They evaluated the classifier using AUC (area under the receiver operating characteristic curve). Parilla-Ferrer et al. [26] developed a warning system that identified the crisis by tracking the stream of Twitter, applying Naive Bayes and SVM to classify tweets with TF-IDF based feature vectors. The classifiers were assessed with the metrics of accuracy, precision, recall, the area under the curve, and F-measure. Their outcome indicated that SVM has significantly better results compared to that of the Naïve Bayes. Ragini and Anand [27] used statistical feature selection methods such as term frequency, Chi-Square in combination with the data classification algorithms SVM, and Naïve Bayes. They used precision, recall, and F-measure to evaluate the efficiency of the classification algorithm. The results revealed that for all classes of data related to a disaster, that SVM performed better than multinomial and Bernoulli Naïve Bayes. Wang et al. [28] developed a classifier for text messages during emergency events, classifying messages to a different topic. Their classifier integrated a latent Dirichlet allocation (LDA) method and a support vector machine (SVM) method. Ghosh and Desarkar [29] used SVM for classifying crisis tweets and used improved TF-IDF for feature selection. In order to recognize data related to damage, Mouzannar et al. [30] suggested a multimodal deep learning framework. They also used ANN (artificial neural network), KNN (k-nearest neighbors), and SVM for classifying text. Bisgin et al. [31] compared SVM and ANN, and concluded that SVM was more accurate. Devaraj et al. [32] compared CNN (convolutional neural network) deep learning, SVM, MLP (multilayer perceptron), AdaBoost, logistic regression, Naive Bayes, decision tree, and ridge classifier for detecting social network-based messages for immediate assistance in hurricanes. They concluded SVM performed better in terms of accuracy and precision. Al Amran et al. [33] compared SVM and random forest on the sentiment analysis resulting from the product reviews text offered by Amazon and used TP rate, FP rate, ROC area, precision, recall, and F-measure to evaluate the efficiency of the classification algorithm. Their research results showed that SVM performed better in all indicators. Several machine-learning algorithms have been used for classifying social network messages. Among these machine learning algorithms, random forest (RF) and support vector Machines (SVM) have drawn attention in the literature. However, the random forest method has a number of disadvantages as it necessitates a significant amount of computing capacity and other resources because it constructs several trees and combines their outputs. It also takes a long time to train because it uses a number of decision trees to define the category and lacks interpretability due to the combination of decision trees and failure to specify the importance of each factor [34]. Although new methods such as deep learning have been used in recent years to classify social network data, one of the major drawbacks of deep learning methods is the presence of hidden layers, and their performance is extremely reliant on the number of training samples. Furthermore, deploying deep learning necessitated specialist expertise, is computationally costly and necessitates appropriate hardware to perform the task [35]. On the other hand, recent

studies have shown that SVM can compare with deep learning in terms of accuracy [32]. In addition, SVM has several advantages; where there is a strong distinction between categories, SVM does not suffer from overfitting and works efficiently. It can execute learning operations with limited training data, is a relatively simple method to execute, and can manage data with many dimensions [35]. Therefore, in this study, we used SVM to extract damage-related messages.

Due to the potential of social networks in this research, they have been used to assess earthquake damage. In this research, the textual content of the Twitter social network during and after the earthquake was analyzed using support vector machine (SVM) supervised classification to classify damage-related messages. The temporal pattern of messages was examined, and an earthquake damage map was created based on damage-related messages. The results of our study were validated by the official intensity map. The main hypothesis of this research was that the spatial scale influences the accuracy of earthquake damage assessment using social networks.

The remainder of the research is structured as follows. In Section 2, we present a review of the literature. The methodology is described in Section 3. Then in Section 4, we discuss our findings. Finally, the conclusion and suggestions are provided in Section 5.

2. Literature Review

In recent years, social networks have been used more frequently in disaster management studies due to their capacity. Most studies are related to earthquake event detection and damage assessment.

Several research efforts have addressed and developed earthquake warning systems. In most studies, time series analysis and burst detectors were used to identify earthquake events. Some of these studies used some burst detection methods across the tweet stream to examine an earthquake, in which a burst was determined as a significant number of tweet incidences within a short period window [36].

Twitter social networking information was used by Earle et al. [37] to identify earthquakes. They discovered that Twitter's surveillance of the earthquake was quicker than conventional surveillance. They also proved that data mining could be applied from a social network to identify and specify an earthquake's affected region. Sasaki et al. [38] used the Twitter social network to monitor earthquakes in the warning system and found that after a massive earthquake, the number of earthquake tweets rose considerably. They showed that users of Twitter like to respond instantly.

Fontugne et al. [39] detected earthquake events from social media users' behavior patterns. Robinson et al. [40] examined to detect earthquakes in Australia and New Zealand. The basic assumption in the research was that with the occurrence of an incident, the messages associated with it also increased, so that the incident could be detected. TwiFelt, an online system, was submitted by D'Auria and Convertito [41] using Twitter social media to estimate the region where an earthquake was experienced in Italy. The system utilized only geolocated tweets for high-intensity earthquakes with good results. Huang et al. [42] provided a CyberGIS environment capable of automatically synthesizing multi-source information, such as social networks and socioeconomic information, for tracking catastrophe occurrences, mapping, and statistical evaluation for emergency management.

Several recent research social networks and other crowdsourcing data can be used for earthquake damage estimation. Corbane et al. [43] investigated the relationship between the geotagged SMS (short message service) spatial pattern and the damage to the building. They used the K-function of Cross Ripley to characterize a bivariate pattern's spatial structure, and more exactly, the spatial relationship among SMS messages and building damage. Their findings proved a robust relationship between SMS and damage to buildings.

Liang et al. [44] explored the capacity of social network text and images to evaluate earthquake damages. They extracted earthquake-related messages based on keywords and predicted the earthquake's actual epicenter, identifying that tweet density could be used as a proxy for rapid damage assessments.

The spatiotemporal features of the association between the seismic wave of an earthquake and social network messages were analyzed by Crooks et al. [45]. They demonstrated that information from Twitter is similar to that gathered through specific crowdsourcing platforms and found that information from Twitter could complement other information sources and increase people's awareness of situations. Avvenuti et al. [46] developed the 'Earthquake Alerts and Report System,' which uses tweets to know how such a system can be helpful in occurrences of crisis. Their system gathered tweets during disasters, filtered meaningless content, identified an incident, and estimated the damage.

Burks et al. [12] demonstrated that Twitter could provide helpful information to assess shaking intensity. They used various regression models and discovered suitable features and models by minimizing the mean square error. They proved an excellent forecast of earthquake intensity when integrating earthquake measurements with tweets.

A crisis mapping system was suggested by Cresci et al. [47], using an SVM classifier to identify dame-related messages among emergency reports. They used visualization methods, integrated geoparsing methods and damage detection to produce a crisis map.

Kropivnitskaya et al. [7] investigated the association between tweet rates and modified Mercalli intensity (MMI) and found that the logarithmic amount of tweets could be used as a substitute for shaking intensity. They proved that tweet rates and Mercalli intensity were correlated in earthquakes in California, Japan, and Chile. Bica et al. [48] investigated the relationship between geotagged image tweets in the impacted region of Nepal and the distribution of structural damage, while Avvenuti et al. [49] displayed the spatial distribution of earthquake-related Twitter text messages.

Bossu et al. [50] developed the LastQuake application, which, after collecting information from individuals, automatically creates a damage estimation map. In the research, instead of collecting data from social networks, direct eyewitness comments were collected. Avvenuti et al. [51] proposed CrisMap, a Big Data crisis mapping system that extracts disaster-related information from tweets. They created a tool for damage identification and an SVM classifier to detect posts that reported building damage or human injury. They also created a text geolocation element by using online semantic annotation tools and cooperative knowledge bases like Wikipedia and DBpedia to perform the geoparsing task. The official information they used for evaluation was the financial loss/damage experienced by the various municipalities using Spearman's rho (quantified in millions of dollars).

Zou et al. [11] investigated Twitter's usefulness in enhancing the assessment of disaster damage. They declared after the crisis, that societies with more damage are also anticipated to have greater levels of Twitter posts. Resch et al. [1] evaluated earthquake damage by integrating spatial and temporal assessment with topic modeling and found hot spots of damages. They used the topic modeling latent Dirichlet allocation (LDA), evaluating and comparing the authoritative earthquake and damage severity maps.

Wang et al. [22] introduced a method for detecting the actual effect region rapidly through social media after a major earthquake. They suggested a theoretical model recognized as the spatial logistic growth model (SLGM), relying on logistics to define the linear development procedures of citizens' information after an earthquake. They evaluated their outcomes with authoritative intensity maps from the United States Geological Survey (USGS).

Shan et al. [52] established a framework for tracking and evaluating real-time metropolitan disaster damage. To obtain damage data from social network reports, they used natural language processing techniques such as semantics and sentiment analysis. For extracting damage-related messages, they used LDA. E2mC was introduced by Fernandez-Marquez et al. [53] to show the technical and functional effectiveness of integrating social media data and crowdsourced data into the Copernicus Emergency Management Service (EMS) Rapid Mapping and Early Warning Components. Cheng et al. [54] used social network information to evaluate the intensity of a natural catastrophe and applied the support vector machine (SVM) to

obtain hashtags related to disasters. To assess the impacted people's intensity, they built the standardized impacted people index (NAPI).

Other studies have just used one spatial unit for damage assessment. To fill this gap, we are motivated to use two spatial units in this research to examine the impact of the spatial unit on the accuracy of damage assessment.

3. Materials and Methods

In this section the study area will be introduced, and the methodology will be examined.

3.1. Data and Case Study

This study uses Twitter data for the M6.0 South Napa (CA earthquake). This earthquake occurred on 24 August 2014, at 10:20:44 UTC time (3:20 a.m. local time). The South Napa Earthquake epicenter (38.22° N, 122.31° W) was situated on the West Napa Fault in the west of the town of Napa. The North San Francisco Bay Area portion of the San Andreas Fault system is a complex network of primarily right-lateral strike-slip faults accommodating motion between the North American and Pacific plates. Severe shaking was encountered by fifteen thousand individuals, 106,000 individuals felt very powerful shaking, 176,000 sensed powerful shaking, and 738,000 felt mild shaking. One individual died, about 200 individuals were wounded, and this incident resulted in more than $400 million in damage [36]. In total, 998,791 georeferenced Tweets in the time period of 17 August 2014 to 31 August 2014 were extracted [1]. Tweets containing earthquake-related keywords were retained. After the filter, 998,791 tweets remained; 10,346 relevant tweets belonged to the earthquake day. Figure 1 displays the Napa earthquake with the number of tweets at the grid level. Figure 2 displays the number of tweets at the county level.

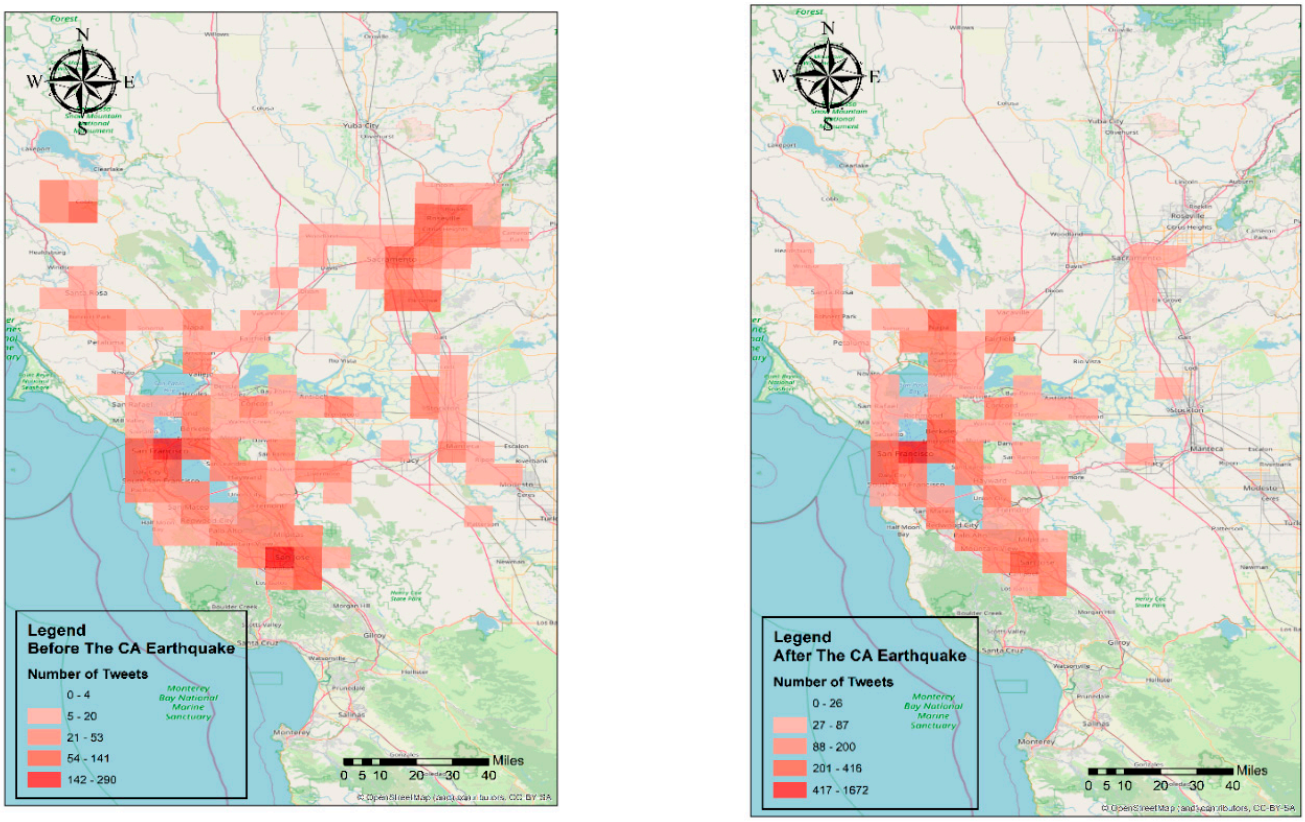


Figure 1. Overview of the study area for the Napa earthquake with the number of tweets at the grid level 7 days before the CA earthquake (**left**) and on the day of the CA earthquake (**right**).

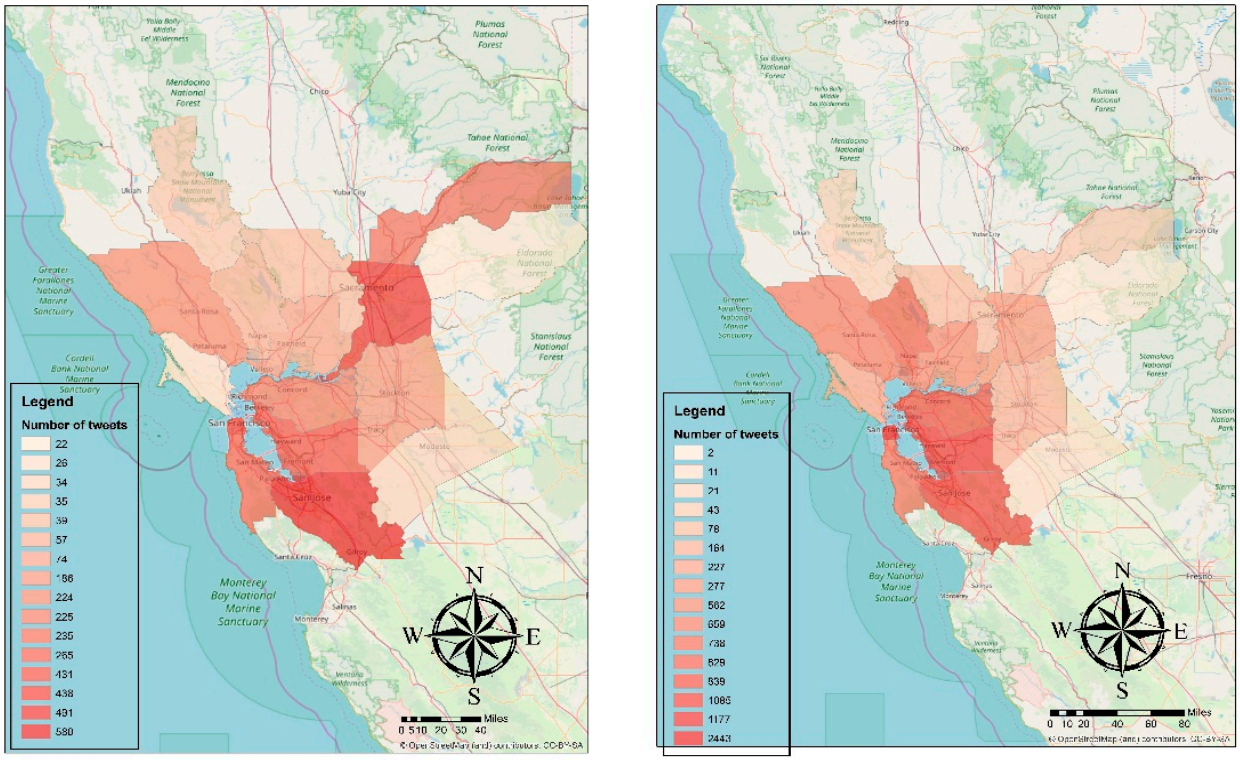


Figure 2. The number of tweets at the county level 7 days before the CA earthquake (**left**) and on the day of the CA earthquake (**right**).

Temporal analysis is important to understand the message propagation behavior in the study area. Figure 3 indicates the number of tweets reported per hour. It can be seen that on the day of the earthquake a special maximum can be found in the general tweets per hour. Clearly, on the day of the disaster, the number of tweets increased sharply. This indicates that when experiencing the earthquake, the messages shared on the social network in this field increased.

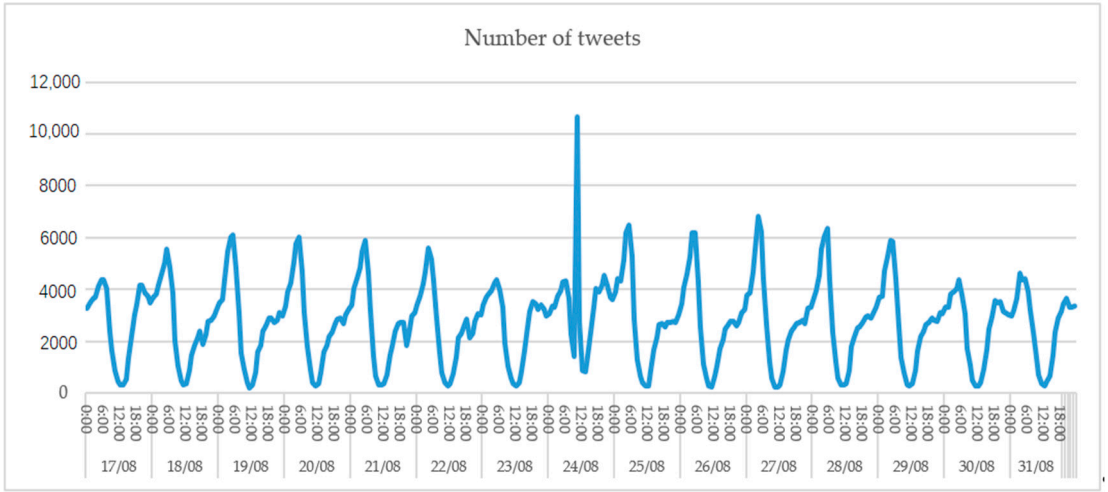


Figure 3. The number of tweets per hour on the day of the CA earthquake.

3.2. Methodology

Figure 4 demonstrates the methodology of this study. Tweet text content is generally short, informal, and full of abbreviated phrases and grammatical errors, and other special features. Before using them for further assessment, we conducted the preprocessing of

tweet content. Then we use the SVM classifier to classify damage and non-damage tweets, and classification was validated by the confusion matrix. Based on the damage-related messages, a damage map was created at two spatial units (damage assessment), including a regular grid (cell size 1 km × 1 km) and county boundaries. In the last phase, the estimated damage map was evaluated by an official intensity map.

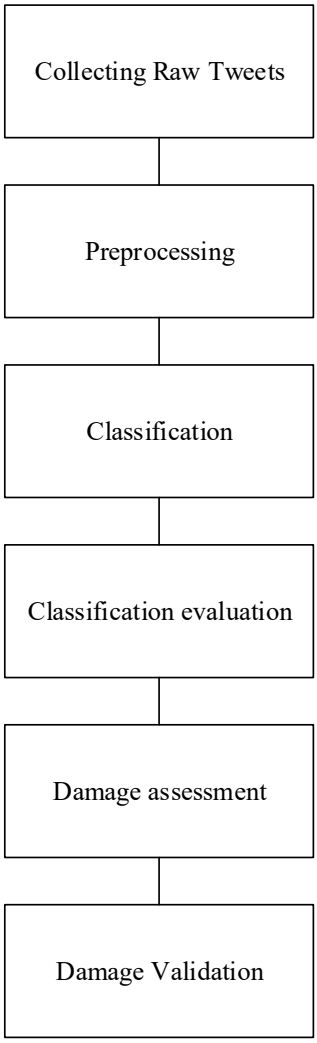


Figure 4. The methodology of this study.

3.2.1. Data Preprocessing

Before classifying with the social network text data, the original social media texts require to be preprocessed to clean noises by sequentially performing the phases below:

- Tokenization

Tokenization is the method of splitting the document into words or sentences called tokens [26]. This stage divides tweet text into a set of separate tokens for each empty character. This processing phase enables one to capture single tokens, for example, for filtering single sentences or letters for further processing phases [1].

- Transform cases

This stage is necessary to create the tokens more comparable and to decrease the sensitivity to typographics, avoiding phrases with the same pronunciation but treating different instances as two contextually distinct tokens. One issue arising from turning all characters into lower cases is that terms that vary in their semantic meaning could not be

distinguished, For example, location names, personal names, organization, and brands or academic titles [1].

- Removing stop words

"Stop phrases" are commonly used terms that do not have separate linguistic meanings (e.g., additional verbs, conjunctions, and articles).

- Removing short words

Short words with three characters or less are filtered due to their little meaning [1]

- Stemming

Porter's method was used in this study as the most common stemming method. This method lessens single words to their root. The preprocessing phases are shown in Figure 5.

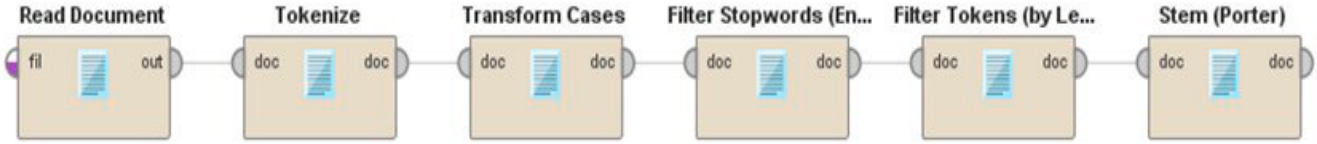


Figure 5. The preprocessing phases.

3.2.2. Classification

For classification, we used SVM to extract damage-related messages; SVM is a machine learning algorithm that is applied for binary classification. The fundamental concept is to discover a hyperplane that divides the d-dimensional information properly into its two classes. Though, as an instance, data is often not linearly distinguishable, SVM includes the concept of a kernel-induced feature space that transfers information into a higher-dimensional space where information is easier to separate [26]. In this research, radial basis function (RBF) kernel function has been used.

The SVM method is a non-parametric supervised method that operates on the assumption that it has no knowledge of how the data set is distributed. The support vector machine is actually a binary classifier that separates two classes using a linear boundary. It is generalized depending on the family of linear classifications. If the data is not linearly separable, the data is transferred to a higher-dimensional space with a nonlinear kernel, and the optimal hyperplanes are determined in that space. These hyperplanes are expressed as Equation (1) [55,56].

$$W^T \times X + b = 0 \tag{1}$$

The SVM model seeks to solve the optimization relation in Equation (2) [55,56].

$$\min_{W,b,\varepsilon}\left(\frac{1}{2}W \times W^T + C\sum_{i=1}^{N}\varepsilon_i\right) \tag{2}$$

$$y_i\left(X_i W^T + b\right) \geq 1 - \varepsilon_i$$

$$i = 1, 2, \ldots, N$$

C is called the penalty factor, and its value increases to the allowable deviation ε. Finally, using Lagrange functions, the linearization function relation will be rewritten as Equation (3) [55,56].

$$maxW(\alpha) = -\frac{1}{2}\left(\alpha_i y_i \alpha_j y_j X_i \times X_j\right) + \sum_{i=1}^{N}\alpha_i \tag{3}$$

$$0 \leq \alpha_i \leq C$$
$$\sum_{i=1}^{N} \alpha_i y_i = 0$$

Figure 6 shows the flowchart of the SVM model.

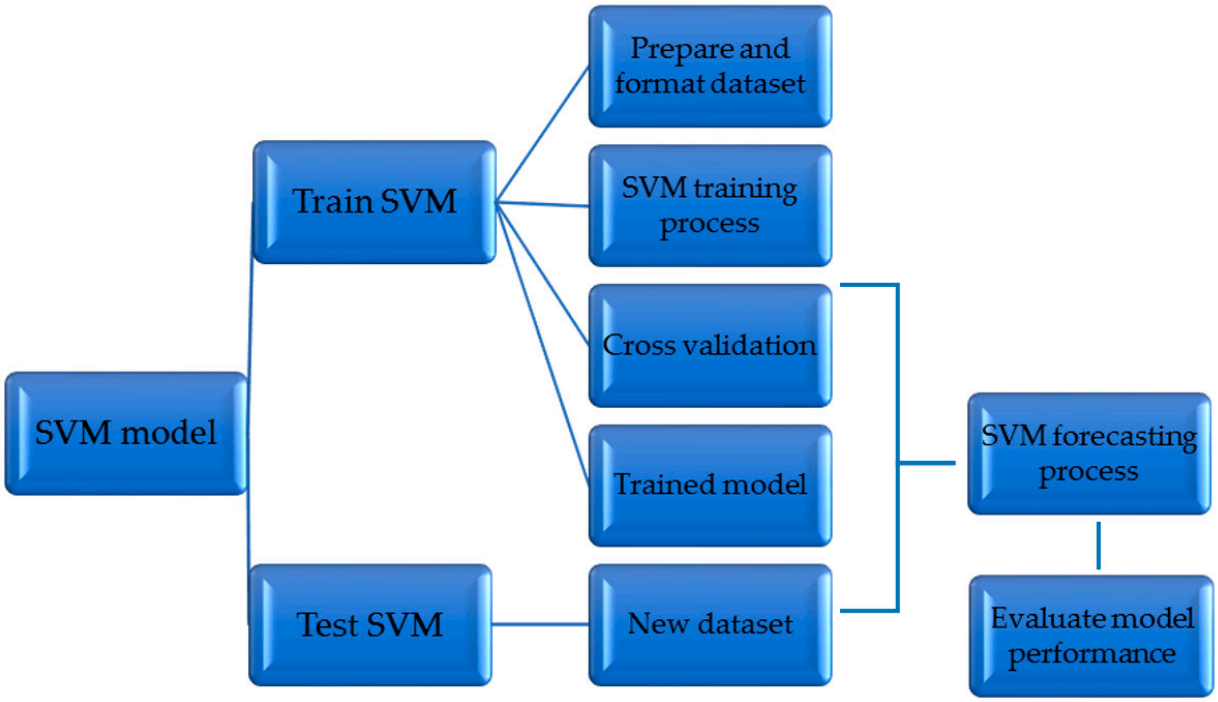


Figure 6. Flowchart of SVM model [55,56].

3.2.3. Assessment Performance of Classification

We trained SVM using the labeled dataset from Imran et al. [23]. For evaluating the accuracy of classification, the confusion matrix was used. The main idea for an automated classification system to comprehend its efficiency is its confusion matrix, which is a table depicting right and wrong categories. The statistical measures such as accuracy, precision, recall, and F-measure are calculated from the confusion matrix. These measures are as follows [57]:

Accuracy: A global rating that refers to the accurately categorized proportion of information.

Precision: The proportion of the amount of properly classified data to the full amount of classified data.

Recall: The ratio of the amount of properly categorized tweets to the complete amount of tweets in the test sets belonging to a specific category.

F-score: The precision and recall geometric mean.

3.2.4. Damage Assessment (Damage Map Creation)

Damage assessment based on social networks can be grouped into two kinds: activity-based and sentiment-based indicators. Researchers on behavior or sentiment indicators have generally suggested this assumption: natural catastrophes impact people's actions and feelings on social networks. The activities and sentiments of an individual's posts can, therefore, show the damage and effect of disasters [55]. A standard activity indicator is the proportion of Twitter posts published for each area unit that is significantly related to the financial damage per capita [7]. In this study, the number of damage related tweets per capita (number of the tweet in each unit divide by population of each unit—we obtained population data from the Socioeconomic data and applications center (SEDAC)) were used

for earthquake damage assessment in two spatial units including regular grid (cell size 1 km × 1 km) and county boundaries.

3.2.5. Validation

For validation, the damage identified by our approach was compared with the official intensity map by the US Geological Survey (USGS) that can be obtained from their portal. The intensity of the earthquake takes into account the magnitude of ground shaking at a distance from the epicenter and offers a specific estimate of the probable damage. ShakeMap uses the modified Mercalli intensity (MMI) scale to measure the impact of earthquakes to provide a representation of the shaking severity after severe earthquakes. The MMI scale consists of 12 intensity levels on a scale from I (not felt) to XII (complete collapse) and is related to measurable damage from the earthquake [22].

The confusion matrix was used for evaluating the damage map at the raster grid spatial unit. We categorized the damage estimated map by our approach and the official map in four categories (weak, strong, very strong, and extreme). Then the statistical measures such as accuracy, precision, recall, and F-measure were calculated from the confusion matrix as Equations (4)–(7):

$$\text{Overall Accuracy} = \text{TP+TN}/(\text{TP} + \text{FP+ TN} + \text{FN}) \quad (4)$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (5)$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (6)$$

$$\text{F-score} = 2 \times ((\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall})) \quad (7)$$

where:

- True Positives (TP): These are cases in which we predicted yes, and they were actually yes.
- True Negatives (TN): We predicted no, and they were actually no.
- False Positives (FP): We predicted yes, but they were actually no.
- False Negatives (FN): We predicted no, but they were actually yes.

For evaluating the damage map at the county spatial unit, we used Spearman's rho and Pearson correlation. Instead of measuring the connection between two factors, Spearman's rho was assessed as Equation (8):

$$\rho = 1 - \frac{6 \sum_i G_i^2}{M(M^2 - 1)} \quad (8)$$

Where M is the number of counties, and $Gi = \mathrm{r_i} - \mathrm{s_i}$ is the distinction between actual ranking (damage ranking of counties based on our approach) and expected position (damage ranking of counties based on official loss model data). This coefficient varies from -1 to 1, with no correlation in the range of 0, a strong positive correlation in the range of 1, and a strong negative coefficient in the range of -1 [52]. Using these coefficients, we evaluated our approach in identifying the most damaged regions compared to the official intensity map.

4. Results

In this section, the results of classification, damage assessment, and damage map evaluation are presented.

4.1. Classification

Table 1 demonstrates the performance of the SVM classifier. Imran et al. [23] datasets, including disaster labeled datasets (Napa and Nepal earthquake labeled datasets) used in this research, were split into two categories. Sixty percent of them were applied for training, and 40% of them are applied for testing. The results showed that SVM classifier

accurately identified damage-related messages (the F-score attained 0.58, precision attained 56.8, recall attained 59.25, and accuracy attained 71.03 for labeled datasets).

Table 1. Performance of the SVM classifier.

Accuracy	Precision	Classification Error	Recall	F-Score
71.03%	56.80%	28.97%	59.25%	58%

The result of classification is shown in Table 2.

Table 2. Results of the classification of our tweets.

2014 Napa Earthquake	
Tweet Text	**Damage Class Label**
#PLEASE pray for all first responders that will assist with fires and floods today due to earthquake damage.	Damage
Napa earthquake: Residents, many of them seniors, flee from devastating mobile home fire: An intense blaze burned.	Damage
Earthquake damage in Napa.	Damage
Hope everyone in and around Solano county is fine! Time to get back to sleep here . . . #earthquake	Non-damage
Too drunk to have felt any earthquake #tbh	Non-damage
@starsandrobots @earthquakesSF though it looks like quakes in the 1–2 scale happen every day . . .	Non-damage

During the crisis, aid workers' search data matched with their objectives for the response, as well as the damage data and temporal pattern over time [20]. Topics of discussion on social networks, especially those related to damage during and after the earthquake, changed quickly. One variable that could lead to a shift in the subject of debate is the different demands of the impacted individuals [56]. To comprehend the temporal variation, we examined the temporal distribution of the damage and non-damage tweets. Figure 7 shows the number of damage and non-damage tweets over time on the day of the earthquake. Figure 8 shows the number of damage and non-damage tweets for each day, and Figure 9 shows the percentage of damage and non-damage tweets for each day. The results indicated that most of the damage-related messages were related to the earthquake day.

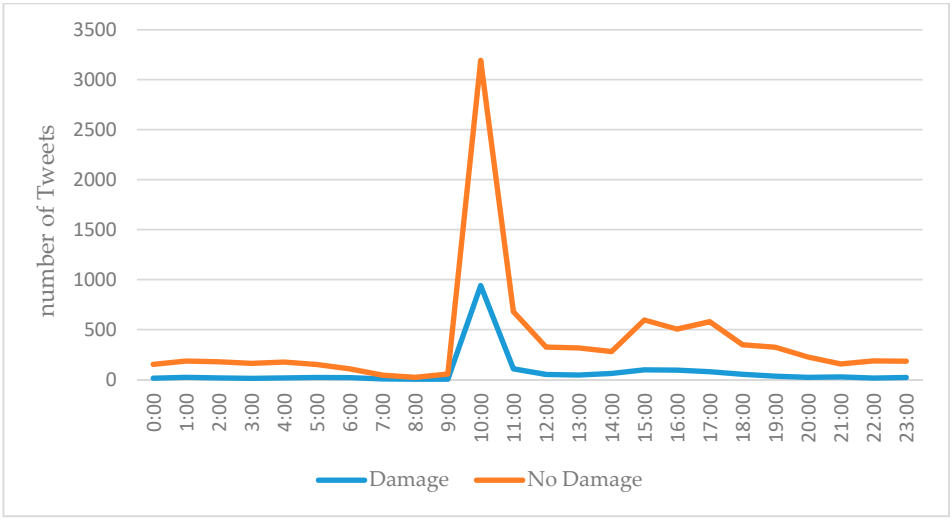


Figure 7. The number of damage and non-damage tweets overtime on the day of the earthquake.

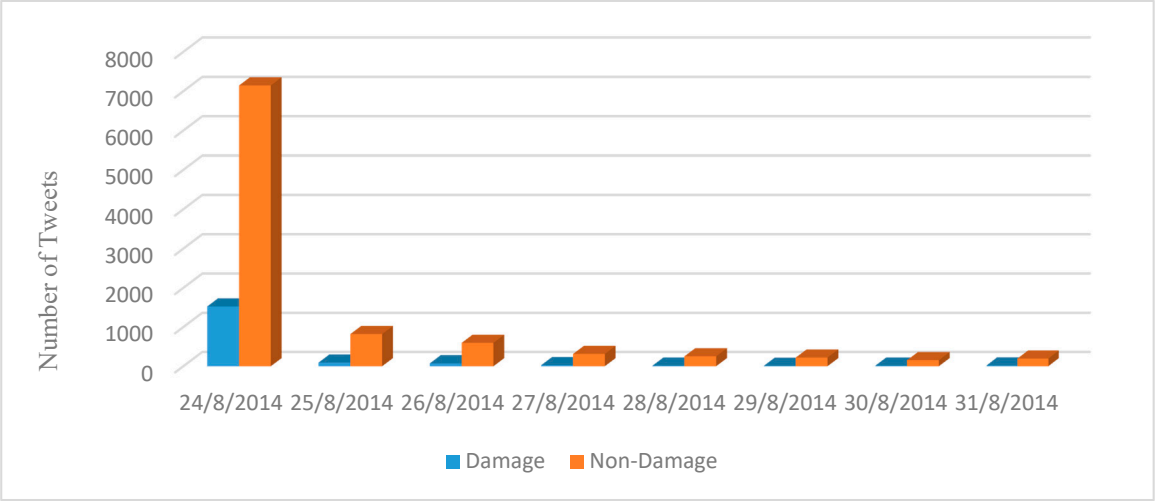


Figure 8. The number of damage and non-damage tweets for each day.

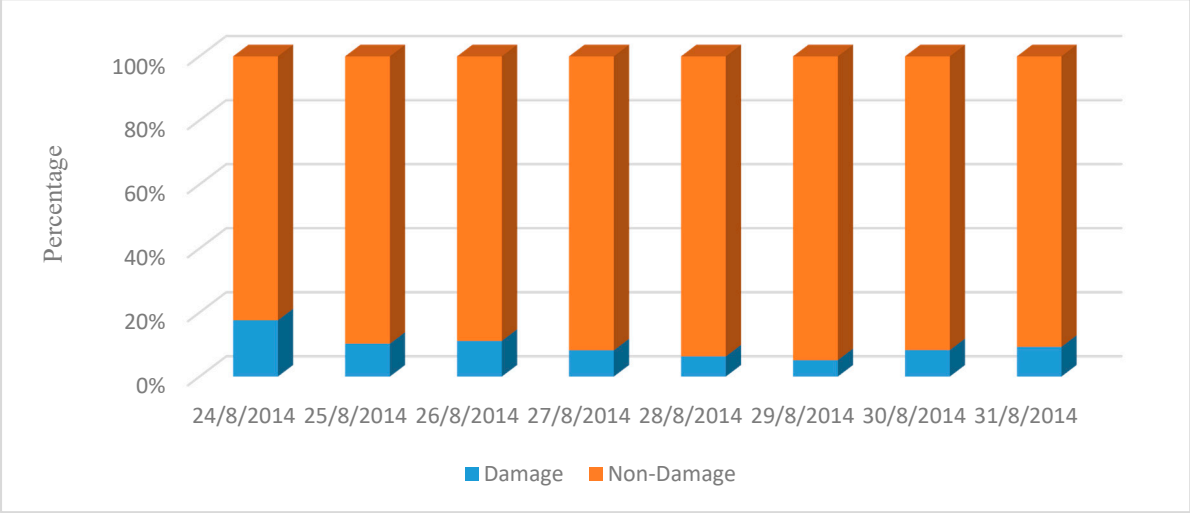


Figure 9. The percentage of damage and non-damage tweets for each day.

4.2. Damage Assessment (Damage Map Creation)

We used disaster-related messages during and after the earthquake for damage assessment. Figure 10 shows the estimated damage by our approach at the grid level and estimated damage by our approach at the county level. Based on this figure, Napa, Petaluma, Santa Rosa, Vallejo, Fairfield, Concord, San Jose, Palo Alto, San Francisco, and San Mateo had greater damage.

4.3. Damage Map Validation

Figure 11 shows the official intensity map at the grid level and the official intensity map at the county level. We overlaid the official intensity map with a damage map created by our approach. We generated a confusion matrix of grid cells matching the official damage map with our approach. Then we compared different damage classes as determined by the official intensity map and our approach. The statistical results are shown in Table 3.

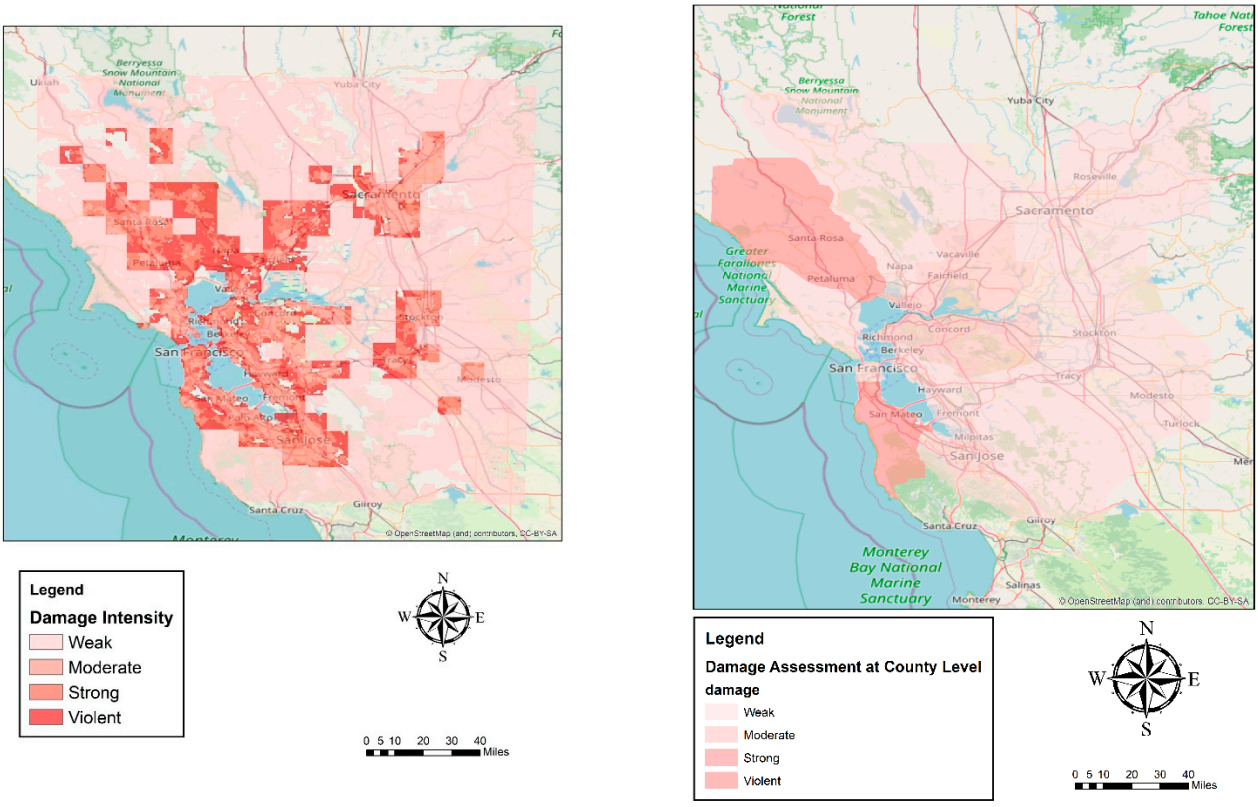


Figure 10. Estimated damage by our approach at the grid level (**left**) and estimated damage by our approach at the county level (**right**).

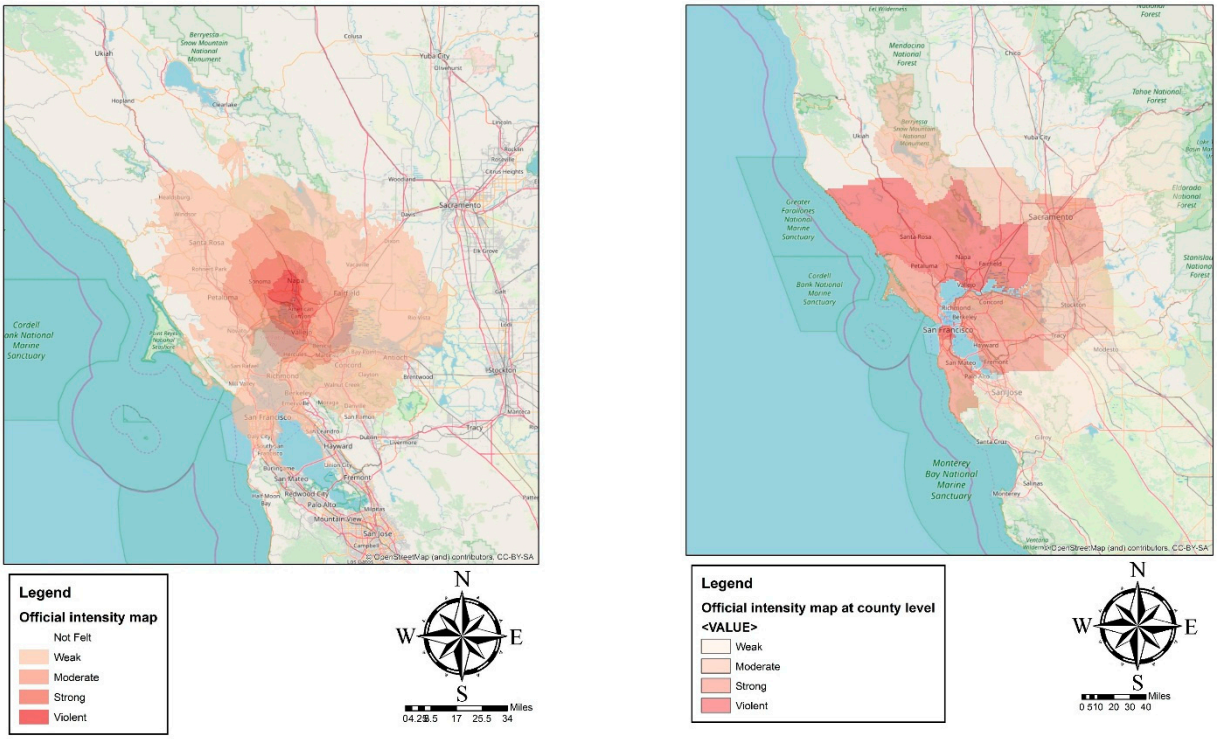


Figure 11. Official intensity map at the grid level (**left**) and official intensity map at the county level (**right**).

Table 3. Results of the evaluation of our damage estimation at the grid level.

Overall Accuracy	Precision	Recall	F-Score
69.89%	48.36%	58.98%	53.14%

We used Spearman's rho and Pearson correlation to evaluate the correlation between counties' damage ranking in our approach and counties' damage ranking based on the official data. Table 4 shows counties damage ranking in our approach and the official intensity map.

Table 4. Counties damage ranking in our approach and in the official intensity map.

County Name	The Official Intensity Map Damage Ranking	Our Approach Damage Ranking
Napa	1	8
Solano	2	3
Sonoma	3	1
San Francisco	4	12
Contra Costa	5	4
Marin	6	14
Sacramento	7	10
San Mateo	8	6
Alameda	9	2
Yoko	10	9
Lake	11	7
San Joaquin	12	11
Placer	13	13
El Dorado	14	16
Stanislaus	15	15
Santa Clara	16	5

Spearman's rho and Pearson correlation were greater than zero, so our results indicated that there was significant consensus, as indicated in Table 5, between our approach and official data ratings.

Table 5. Results of the evaluation of our damage estimation at the county level.

Spearman's Rho	Pearson Correlation
0.429	0.503

5. Conclusions and Suggestions

Conventional post-disaster damage evaluation depends highly on costly data, in particular, remote sensing data. Social network data have become a wealthy source of data about disasters in the past decade, which can help evaluate damage at a lower cost and so rapid. This data involves text messages or images published by a crisis eyewitness.

Our overall research goal is to use Twitter social network text data for creating a damage map. This is a significant phase in offering respondents a quick understanding of the severity of the damage and where the largest damage occurs. During the earlier times of an earthquake, this insight is critical in choosing how to better incorporate the restricted emergency response. So social networks are a strong and useful instrument for managing disaster response, which includes raising awareness of the situation, supporting the distribution of emergency data, anticipating earthquakes, and organizing rescue activities. Rapid identification of affected locations following an incident can consult respondents and humanitarian organizations, assistance logistics engaged in relief activities, speed up the real-time action, and coordinate resource allocation.

Results showed that the damage of the earthquake could be estimated efficiently by our strategy at multispatial units with an overall accuracy of 69.89 at spatial grid unit

and Spearman's rho and Pearson correlation respectively 0.429 and 0.503 at spatial county unit. The results indicated our approach could be used for damage estimation with good reliability at multi-scale spatial units. Furthermore, precision at the grid level was 48.36%, which is in line with the results of [1] that achieved 41.12% precision at the grid level. The results of Spearman's rho at the county level (municipality scale) in [52] were between 0.4 and 0.7, which is consistent with our approach at the county level. The results of the temporal analysis show that most damage-related messages were sent on the day of the earthquake, indicating most of the damages were inflicted on the day of the earthquake, and in the following days, other issues were raised about recovery or assistance and donation, and so on. Temporal analysis indicated that due to the earthquake, the messages shared on the social network in this field increased, and this verified our hypothesis. In addition, they showed SVM classifier accurately identified damage-related messages with the F-score attained 58%, precision attained 56.8%, recall attained 59.25%, and accuracy attained 71.03%. Based on the results of this research, we can conclude that although social networks can be a good starting point for damage assessment, by themselves, they cannot provide very good accuracy for damage assessment and should be used alongside other data sources. The larger spatial unit and aggregated units (such as counties) may have a better result than smaller units such as grids; this is an issue that has received less attention. Therefore, we would suggest that in practical applications of rapid damage assessment at the level of larger spatial units such as counties, the results of the social network can be used. For other spatial units, the results of other data sources can be used. For future research, it is also suggested that social network data in other location units, such as states and cities, be used to estimate the damage. In addition, the accuracy of other data sources should be compared with the social network in different spatial units for damage assessment.

There is a limitation using social media data for damage assessment and these limitations make it difficult to achieve optimal results. Due to an absence of power availability, internet connection, and computing capabilities in disaster areas, the location accuracy is low; furthermore, most do not have a geographic coordinate. Concerning the distribution of incorrect data, the identity of malicious content distributed in an emergency remains a task. Besides, in social networks, there are no laws, norms, or official vocabulary, and the convenience of dissemination creates a large amount of interactions, making it hard to acquire useful data. In areas where the severity of the earthquake is high, people may not be able to share information or be so involved in the crisis that they are not active on social media. In fact, one of the limitations of social networks is the difficulty of information transfer in affected areas for various reasons, such as the disconnection of the internet. In urban areas, there could be a lot of activity on the social network that could affect the results, so in order to achieve optimal results, the spatial coefficient should be considered in proportion to the amount of social network use. Another limitation of the research is that messages could be sent from a location with an earthquake or outside the earthquake areas (e.g., people may discuss earthquakes from outside of the earthquake zone). Therefore, it is necessary to assign the message to the place to which it belongs. For future research, it is recommended that social network data is integrated with other sources of information such a remote sensing and seismic network for damage assessment. It is also suggested to use multi-class classification and to study the trend of change of different topics over time. For future research, it is also suggested that the content of the messages be assigned to the location being discussed using content analysis.

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