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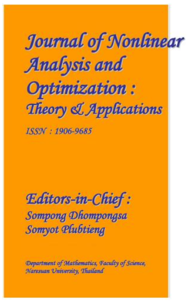

DISASTER IDENTIFICATION VIA SOCIAL MEDIA USING DEEP ATTENTIVE MULTIMODAL LEARNING

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ABSTRACT

Twitter and other microblogging sites are becoming essential for sharing important information, particularly during natural and man-made catastrophes. Multimedia elements including photographs and/or videos are often posted by individuals to provide critical information about events like fatalities, infrastructure damage, and the immediate needs of those impacted. Humanitarian groups may organize an appropriate reaction in a timely way with the use of such information. Nevertheless, it is a laborious effort to extract disaster-related information from a large number of postings. This necessitates the development of an autonomous system that can separate out actionable from non-actionable social media posts. Even though a number of studies have demonstrated the value of combining text and image contents for disaster identification, the majority of earlier research concentrated solely on textual analysis and/or used conventional recurrent neural networks (RNNs) or convolutional neural networks (CNNs), which may cause performance issues with lengthy input sequences. In order to categorize tweets, this research provides a multimodal disaster detection system that synergistically uses textual and visual data by combining the influential word aspects with the visual features. To be more precise, we use a bidirectional long-term memory (BiLSTM) network with attention mechanism to extract textual data and a pretrained convolutional neural network (like ResNet50) to extract visual features. Next, we use a feature fusion technique to combine textual and visual information, and then we use the softmax classifier. The assessments show that the suggested multimodal system improves performance over the current baselines, which include both unimodal and multimodal models, by achieving gains in performance of around 1% and 7%, respectively.

I. INTRODUCTION

In times of disaster events such as earthquake, flood, and hurricane, social media platforms can play a critical role in spreading a large volume of important information. People frequently use these social media platforms to communicate at different hierarchies such as from individual to individual, individual to government, individual to community and government to people . Victim often share information about disaster events on Twitter, such as reporting about injured or deceased people, and infrastructural damages. Affected people also inquire for urgent aids by posting images, tweets, and videos. Analyzing such social media posts and extracting actionable insights in real-time can be very helpful for humanitarian organizations to assist the affected people . However, it is very difficult and time-consuming task to manually analyze and extract actionable insights from large amount of crisis-related tweets.

The humanitarian computing community has attempted to address the above challenge by developing automated systems that can extract and classify crisis-related social media posts . For example, researchers have develop classifiers to identify event types (e.g., flood, hurricane) , whether a post is informative or not , as well as humanitarian information types (e.g., types of damages) . Despite such recent progress, existing works are primarily limited in two ways. First, most works on for damage or disaster response from social media posts have mainly concentrated on textual or image content analysis independently. However, recent studies suggest that information from both texts and images often provides valuable insights about an event and thus leads to more precise inferences than the learning from unimodal content . Second, a very few works that utilize multimodal features focus on applying CNN or RNN models for text feature representation , which might not work well for longer sentences.

In this work, our goal is to develop an effective computational model for identifying disaster-related information by synergistically integrating features from visual and textual modalities. More specifically, we extract the image features using pre-trained visual (i.e., ResNet50) model. We also extract the textual features an attention mechanism with the BiLSTM network to address the long-range dependency problem with traditional RNN with attention mechanism to classify the damage-related posts by exploiting both visual and textual information.

PROBLEM STATEMENT:

Increasing frequency and severity of natural disasters pose a significant threat to human safety and well-being. Social media platforms have emerged as valuable sources of real-time information during such events, with users sharing crucial data through various modalities such as text, intify and prioritize relevant posts for effective disaster management.

Existing approaches to disaster identification from social media posts often struggle to provide accurate and timely insights due to their limited capacity to understand and integrate information from multiple modalities. The lack of a robust and deep learning model capable of effectively capturing the contextual nuances and correlations between textual and visual elements in social media posts hinders the development of efficient disaster identification systems.Therefore, there is a pressing need for a novel approach that leverages deep attentive multimodal learning techniques to enhance the accuracy and efficiency of disaster identification from social media posts. This approach should address the challenges of processing large-scale, unstructured data while effectively integrating both textual and visual information. Developing such a comprehensive model holds the key to advancing the capabilities of disaster response teams, enabling them to make more informed decisions and allocate resources more effectively in the face of natural calamities.

II. LITERATURE SURVEY

A SURVEY ON "TO CONTROL ON TWITTER DISASTERS"

J. Kim and M. Hastak, "Social network analysis: Characteristics of online social networks after a disaster," International Journal of Information Management, vol. 38, no. 1, pp. 86–96, 2018.

Social media, such as Twitter and Facebook, plays a critical role in disaster management by propagating emergency information to a disaster-affected community. It ranks as the fourth most popular source for accessing emergency information. Many studies have explored social media data to understand the networks and extract critical information to develop a pre- and post-disaster mitigation plan.

The 2016 flood in Louisiana damaged more than 60,000 homes and was the worst U.S. disaster after Hurricane Sandy in 2012. Parishes in Louisiana actively used their social media to share information with the disaster-affected community − e.g., flood inundation map, locations of emergency shelters, medical services, and debris removal operation. This study applies social network analysis to convert emergency social network data into knowledge. We explore patterns created by the aggregated interactions of online users on Facebook during disaster responses. It provides insights to understand the critical role of social media use for emergency information propagation. The study results show social networks consist of three entities: individuals, emergency agencies, and organizations. The core of a social network consists of numerous individuals. They are actively engaged to share information, communicate with the city of Baton Rouge, and update information. Emergency agencies and organizations are on the periphery of the social network, connecting a community with other communities. The results of this study will help emergency agencies develop their social media operation strategies for a disaster mitigation plan.

UNIMODAL APPROACHES

TEXT BASED DISASTER ANALYSIS

Many previous studies have utilized social media texts, and leveraged it for damage or disaster identification [15]. Early works focused on feature-engineering based approaches and used models such as support vector machine (SVM) [16], random forest [17], and logistic regression classifiers [18]. Later, researchers have widely used deep learning-based architectures such as CNN [19], and BiLSTM [20] for classifying the disaster-related tweets. Caragea *et al.* [21] and Nguyen *et al.* [19] proposed CNN-based models to classify the tweets into informative and not-informative categories which provides significant improvements over feature engineering-based approaches. Aipe *et al.* [22] also proposed a CNN-based approach but they focus on multi-label classification rather that simple binary classification to label disaster-related tweets. Similarly, Yu *et al.* [23] used CNN, logistic regression, and SVM to classify the tweets related to different Hurricanes into multiple categories. Their CNN-based model outperformed SVM and LR. In contrast to CNN-based approaches we consider BiLSTMs with attention mechanisms with an aim to better captures dependencies between word tokens.

Some researchers have focused on domain adaption and cross-domain classification [24], [25]. Li *et al.* [24] studied the feasibility of domain adaption for analyzing the disaster tweets by applying the naive Bayes classifier on the Boston Marathon bombing and Hurricane Sandy dataset. Graf *et al.* [25] focused on cross-domain classification so that the classifier can be used across different types disaster events. They employed a cross-domain classifier and utilized emotional, sentimental, and linguistic features extracted from the damage-related tweets. Others have focused on text mining and summarization approaches [26], [27]. For example, Rudra *et al.* [26] assign tweets into different situational classes and then summarizes those tweets. Cameron *et al.* [27] proposed an Emergency Situation Awareness-Automated Web Text Mining (ESA-AWTM) system that detects informative damage-related Twitter messages to inform charitable organizations about the incidents of a disaster. Unlike these systems that broadly focused on text mining and summarization, we only focus specifically on a multi-class classification problem on disaster-related tweets.

IMAGE BASED DISASTER IDENTIFICATION

Most works on identifying disasters from social media images have applied CNN-based classifier. For example, Chaudhuri and Bose [28] used CNN-based model to locate the human body parts from the wreckage images. Nguyen *et al.* [29] developed a deep CNN architecture to label the social media images into multiple disaster categories (i.e., severe, mild, and no-damage). Similarly, Alam *et al.* [30] proposed a pretrained CNN (VGG16) based framework that can identify the disaster images uploaded on the online platforms. Daly and Thom [31] culled flicker images to detect the fire event using pretrained classifiers. Finally, Lagerstrom *et al.* [32] developed a system to classify whether the image indicates a fire event or not. In contrast to these works that broadly developed binary classifier for classifying disaster vs. non-disaster images using CNN approach, we focus on identifying multiple disaster categories from the disaster-related images.

MULTIMODAL APPROACHES

In recent years, researchers have used multimodal data (i.e., image and text) to find disaster related information from social media, as information from both modalities often provide valuable insights for disaster classification. Most of the works employed fusion-based [33] approach to aggregate the multimodal features. Chen *et al.* [34] studied the relation between the images and texts and utilize visual features along with socially relevant contextual features (e.g., time of posting, the number of comments, re-tweets) to identify disaster information. Mouzannar *et al.* [7] explored damage detection by focusing on human and environmental damage related posts. They used the Inception pre-trained model for visual feature extraction and designed a CNN architecture for textual features. Similarly, Rizk *et al.* [35] proposed a multimodal architecture to classify the Twitter data into infrastructure and natural damage categories. Ofli *et al.* [8] also presented a multimodal approach for classifying the tweets into two categories: informative task (e.g., informative vs. non-informative) and humanitarian task (e.g., affected individuals, rescue volunteering or donation effort, infrastructure and utility damage). They used CNN based approach for extracting the visual and textual features. Gautam *et al.* [36] showed a comparison between unimodal and multimodal methods on CrisisMMD [37] dataset. They utilized the late fusion [38] approach for combining the image-tweet pairs. All the works reported significant performance improvement using multimodal information in contrast to their counterparts that utilize uni-modal information.

Motivated by the success of these multimodal approaches we focused on effectively utilizing features from text and images using BiLSTM and CNN models and then fusing them to form a joint representation for the classification. However, unlike the above multimodal-based approaches which used simple CNN/RNN models or n-gram features, we extract the textual features using the BiLSTM network with attention mechanism to address the long-range dependency problem

TYPES OF DISASTERS

We experiment with a benchmark multimodal damage dataset[1] from Mouzannar *et al.* [7], which consists of damage-related images along with their associated tweets. The dataset contains following five different categories of disaster image-tweet pairs as well as one category of non-damage (ND) image-tweet pairs.

- Damage to infrastructure (DI): Posts that contain information about wrecked buildings, damaged cars, and destroyed bridges.
- Damage to nature (DN): Posts that contain icehouse, landslides, and falling trees related information.
- Fires (F): Posts that conveys forest and building fires related information.
- Floods (Fl): Posts that contain flood related images and tweets occurred in rural, urban, and cities.
- Human damage (HD): Posts that provide information about injuries and deceased people.

III. SYSTEM ANALYSIS

EXISTING SYSTEM

- Aipe et al. [22] also proposed a CNN-based approach but they focus on multi label classification rather that simple binary classification to label disaster-related tweets. Similarly, Yu et al. [23] used CNN, logistic regression, and SVM to classify the tweets related to different Hurricanes into multiple categories. Their CNN-based model outperformed SVM and LR. In contrast to CNN-based approaches we consider BiLSTMs with attention mechanisms with an aim to better captures dependencies between word tokens.

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their counterparts that utilize uni-modal information.

DISADVANTAGES

- Proposed a CNN-based approach but they focus on multilabel classification rather that simple binary classification to label disaster-related tweets.
- Used CNN, logistic regression, and SVM to classify the tweets related to different Hurricanes into multiple categories.

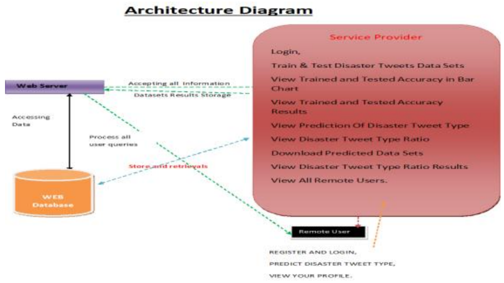
PROPOSED SYSTEM

- The primary contributions of our work are: We propose a multimodal architecture that utilizes ResNet50 and BiLSTM recurrent neural network with attention mechanism to classify the damage-related posts by exploiting both visual and textual information.
- We compare the performance of the proposed model with a set of existing unimodal (i.e., image, text) and multimodal classification techniques.
- We empirically evaluate the proposed model on a benchmark dataset and demonstrated how introducing attention could enhance the system performance through an intrinsic evaluation.
- We perform both quantitative and qualitative analysis to get deeper insights about the error types which provide future directions for improving the model.

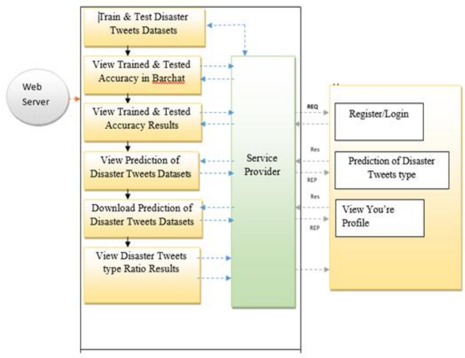
Advantages

- In the proposed system, the system develops an effective computational model for identifying disaster-related information by synergistically integrating features from visual and textual modalities.
- In the proposed system, the system transforms the tweet into a vector representation and then use an embedding layer to obtain semantic representations (embedding features) of the words.
- The project involve analyzing the design of few applications so as to make the application more users friendly. To do so, it was really important to keep them

IV. SYSTEM ARCHITECTURE



BLOCK DIAGRAM



V. SYSTEM IMPLEMENTATION MODULES

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Train & Test Disaster Tweets Data Sets ,View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Disaster Tweet Type, View Disaster Tweet Type Ratio, Download Predicted Data Sets, View Disaster Tweet Type Ratio Results, View All Remote Users.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT DISASTER TWEET TYPE,VIEW YOUR PROFILE.

VI. ALGORITHMS

DECISION TREE CLASSIFIER

Decision tree classifiers are used successfully in many diverse areas. their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. decision tree can be generated from training sets. the procedure for such generation based on the set of objects (s), each belonging to one of the classes c1, C2, …, Ck is as follows:

Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class

Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,… Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

K-Nearest Neighbors (KNN)

Simple, but a very powerful classification algorithm

Classifies based on a similarity measure

Non-parametric

Lazy learning

Does not "learn" until the test example is given

Whenever we have a new data to classify, we find its K-nearest neighbors from the training data

Example

Training dataset consists of k-closest examples in feature space

Feature space means, space with categorization variables (non-metric variables)

Learning based on instances, and thus also works lazily because instance close to the input vector test or prediction may take time to occur in the training dataset

Logistic regression Classifiers

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.

Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logisitic regression is more versatile and better suited for modeling most situations than is discriminant analysis.

This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does.

This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

Naive Bayes

The naive bayes approach is a supervised learning method which is based on a simplistic hypothesis: it assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature .

Yet, despite this, it appears robust and efficient. Its performance is comparable to other supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias. The naive bayes classifier is a linear classifier, as well as linear discriminant analysis, logistic regression or linear SVM (support vector machine). The difference lies on the method of estimating the parameters of the classifier (the learning bias).

While the Naive Bayes classifier is widely used in the research world, it is not widespread among practitioners which want to obtain usable results. On the one hand, the researchers found especially it is very easy to program and implement it, its parameters are easy to estimate, learning is very fast even on very large databases, its accuracy is reasonably good in comparison to the other approaches. On the other hand, the final users do not obtain a model easy to interpret and deploy, they does not understand the interest of such a technique. Thus, we introduce in a new presentation of the results of the learning process. The classifier is easier to understand, and its deployment is also made easier. In the first part of this tutorial, we present some theoretical aspects of the naive bayes classifier. Then, we implement the approach on a dataset with Tanagra. We compare the obtained results (the parameters of the model) to those obtained with other linear approaches such as the logistic regression, the linear discriminant analysis and the linear SVM. We note that the results are highly consistent. This largely explains the good performance of the method in comparison to others. In the second part, we use various tools on the same dataset (**Weka 3.6.0**, **R 2.9.2**, **Knime 2.1.1**, **Orange 2.0b** and **RapidMiner 4.6.0)**. We try above all to understand the obtained results.

SVM

In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed* (*iid*) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point *x* and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space.

SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same optimal hyperplane parameter—in contrast to *genetic algorithms* (*GAs*) or *perceptrons*, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

VII. SCREEN SHOTS

User login

Description:

1. This screen is illustrating the User Login page of the application.
2. Here User will give credentials of username and password.
3. If Login credentials' are valid control goes from login page to User Home Page else user login page only display a dialog box of containing Message "Invalid Username OR Password".

USER REGISTER LOGIN

Description:

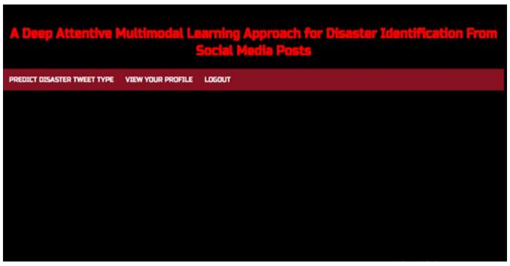
1. This screen is illustrating the User Registration page of the application. And also this having fields all User required fields.
2. A New User need to fill this form for login credentials before entering into application.
3. After successfully registering the user all data user values will be stored into specified database.

View about User Register details

Description

1. This page refer the profile details about user
2. User personal details to login the service provider data
3. After that register successfully enter into in next page

How to predict the disaster tweet type



Description:

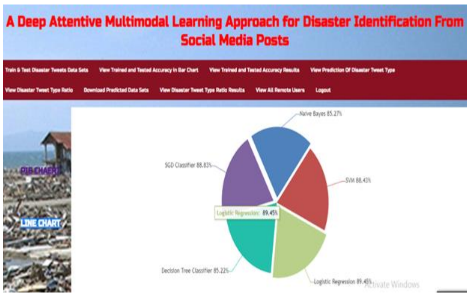
1. This page refers the predict the disaster tweet type by giving database from the twitter .
2. It can shows the data which we have given from the database
3. To predict the tweets by using some data like service provider module to verify te tweets
4. Which are usually represents the data which has been trained and tested

User adding manual data

Description

1. This page refers the user details about disaster tweet
2. We can find the data the given tweet is normal (or) disaster by giving a manual details about tweet
3. Enter user id ,location, keyword, disaster tweet where the database is stored which is tested
4. After texting we can predict the data is disaster or not
5. Here we can use store the data by using manage.cmd with the use of predict datasets

Accuracy results shown in pie chart



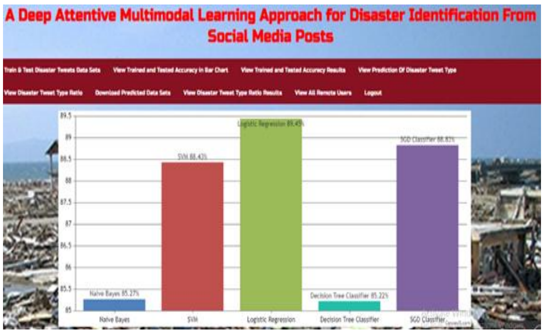
Description

1 .Remote user module which is usually represents trained and tested data shows a accuracy results

2.This page can refers the pie chart representation about percentage of classifiers and algorithms which is tested in accuracy

3.Logistic regression shows the highest accuracy which is 89%

Trained and tested accuracy results represents in bar chart

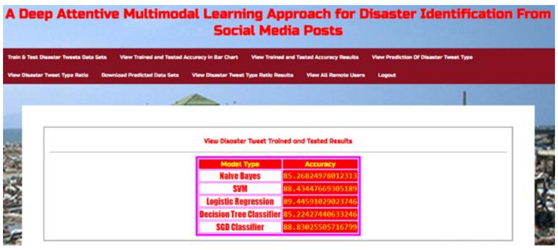


Description

1. This page refers the accuracy represented ratio in bar chart

2. Bar chart can represents the classifiers and algorithms in a remote user module

3. The given data is trained and tested to find accuracy in a given database



Description

1. This page refers the accuracy results which shown highest and lowest ratio values in disaster tweets by using classifier and algorithms

2. The disaster tweets are predicted then we get accuracy based on given database**.**

VIII. CONCLUSION AND FUTURE ENHANCEMENT

I have presented a multimodal approach that can effectively learn from the image and text data to classify the damage-related contents from Twitter. We utilize the pre-trained ResNet model for visual feature extraction and the attention mechanism with a BiLSTM model to extract the tweet features. The early fusion approach is used to aggregate both modalities' features. Besides, this work investigated various visual (i.e., VGG19, Inception) and textual (i.e., BiLSTM, CNN, BiSTM+CNN, BiLSTM+ Attention) approaches for the baseline evaluation and constructed several multimodal models by exploiting them. The evaluation results revealed that the proposed model outperforms the baseline unimodal (i.e., image, text) and multimodal models by acquiring the highest weighted F1-score of 93:21%. Moreover, the comparative analysis illustrated that the proposed method outcome is approximately 1% and 7% ahead of the existing start-of the-art models. Thus, the results confirmed the effectiveness of the proposed method in identifying the disaster content based on multimodal information. The error analysis further showed that it is difficult to identify the damage and non damage contents by analyzing only one modality. At the same time, intrinsic performance analysis elucidated that incorporating an attention mechanism boosts the overall performance.

Despite achieving better performance than unimodal approaches, there are still rooms for improving the proposed method. In the future, we would like to explore different multimodal fusion approaches along with multitask learning technique for the disaster identification task. Besides, we aim to capture the combination of visual and textual features more effectively by employing the state of the art visual (i.e., Vision transformer [58]), textual (i.e., BERT [59], XLM-R [60]), and multimodal (i.e., VL- BERT [61], Visual BERT [62]) transformer models.

REFERENCES

[1] K. K. Kapoor, K. Tamilmani, N. P. Rana, P. Patil, Y. K. Dwivedi, andS. Nerur, "Advances in social media research: Past, present and future,"Information Systems Frontiers, vol. 20, no. 3, pp. 531–558, 2018.

[2] J. Kim and M. Hastak, "Social network analysis: Characteristics of onlinesocial networks after a disaster," International Journal of InformationManagement, vol. 38, no. 1, pp. 86–96, 2018.

[3] J. Son, H. K. Lee, S. Jin, and J. Lee, "Content features of tweets foreffective communication during disasters: A media synchronicity theoryperspective," International Journal of Information Management, vol. 45,pp. 56–68, 2019.

[4] A. Elbanna, D. Bunker, L. Levine, and A. Sleigh, "Emergencymanagement in the changing world of social media: Framing the researchagenda with the stakeholders through engaged scholarship," InternationalJournal of Information Management, vol. 47, pp. 112–120, 2019.

[5] R. Dubey, A. Gunasekaran, S. J. Childe, D. Roubaud, S. F. Wamba,M. Giannakis, and C. Foropon, "Big data analytics and organizationalculture as complements to swift trust and collaborative performancein the humanitarian supply chain," International Journal of Production
Economics, vol. 210, pp. 120–136, 2019.

[6] S. Akter and S. F. Wamba, "Big data and disaster management: asystematic review and agenda for future research," Annals of OperationsResearch, vol. 283, no. 1, pp. 939–959, 2019.

[7] H. Mouzannar, Y. Rizk, and M. Awad, "Damage identification in socialmedia posts using multimodal deep learning." in ISCRAM, 2018.

[8] F. Ofli, F. Alam, and M. Imran, "Analysis of social media datausing multimodal deep learning for disaster response," arXiv preprintarXiv:2004.11838, 2020.

[9] F. Ofli, P. Meier, M. Imran, C. Castillo, D. Tuia, N. Rey, J. Briant, P. Millet,F. Reinhard, M. Parkan et al., "Combining human computing and machinelearning to make sense of big (aerial) data for disaster response," Big data,vol. 4, no. 1, pp. 47–59, 2016.

[10] P. Jain, B. Schoen-Phelan, and R. Ross, "Automatic flood detectionin sentinei-2 images using deep convolutional neural networks," inProceedings of the 35th Annual ACM Symposium on Applied Computing,2020, pp. 617–623.

[11] A. Kumar, J. P. Singh, Y. K. Dwivedi, and N. P. Rana, "A deep multimodalneural network for informative twitter content classification duringemergencies," Annals of Operations Research, pp. 1–32, 2020.

[12] T. Ghosh Mondal, M. R. Jahanshahi, R.-T. Wu, and Z. Y. Wu, "Deeplearning-based multi-class damage detection for autonomous post-disasterreconnaissance," Structural Control and Health Monitoring, vol. 27, no. 4,p. e2507, 2020.

[13] M. Imran, F. Ofli, D. Caragea, and A. Torralba, "Using ai and social mediamultimodal content for disaster response and management: Opportunities,challenges, and future directions," 2020.

[14] L. Dwarakanath, A. Kamsin, R. A. Rasheed, A. Anandhan, and L. Shuib,"Automated machine learning approaches for emergency response andcoordination via social media in the aftermath of a disaster: A review,"IEEE Access, vol. 9, pp. 68 917–68 931, 2021.

[15] C. Castillo, M. Imran, P. Meier, J. Lucas, J. Srivastava, H. Leson, F. Ofli,and P. Mitra, "Together we stand—supporting decision in crisis response:Artificial intelligence for digital response and micromappers," by OCHAand partners. Istanbul: Tudor Rose, World Humanitarian Summit, pp. 93–95, 2016.

[16] C. Caragea, N. J. McNeese, A. R. Jaiswal, G. Traylor, H.-W. Kim, P. Mitra,D. Wu, A. H. Tapia, C. L. Giles, B. J. Jansen et al., "Classifying textmessages for the haiti earthquake." in ISCRAM. Citeseer, 2011.

[17] M. Imran, C. Castillo, J. Lucas, P. Meier, and S. Vieweg, "Aidr: Artificialintelligence

for disaster response," in Proceedings of the 23rd internationalconference on world wide web, 2014, pp. 159–162.

[18] Q. Huang and Y. Xiao, "Geographic situational awareness: mining tweetsfor disaster preparedness, emergency response, impact, and recovery,"ISPRS International Journal of Geo-Information, vol. 4, no. 3, pp. 1549–1568, 2015.

[19] D. Nguyen, K. A. Al Mannai, S. Joty, H. Sajjad, M. Imran, and P. Mitra,"Robust classification of crisis-related data on social networks usingconvolutional neural networks," in Proceedings of the International AAAIConference on Web and Social Media, vol. 11, no. 1, 2017.

[20] O. Sharif, E. Hossain, and M. M. Hoque, "Combating hostility: Covid-19fake news and hostile post detection in social media," 2021.

[1] K. K. Kapoor, K. Tamilmani, N. P. Rana, P. Patil, Y. K. Dwivedi, andS. Nerur, "Advances in social media research: Past, present and future,"Information Systems Frontiers, vol. 20, no. 3, pp. 531–558, 2018.

[2] J. Kim and M. Hastak, "Social network analysis: Characteristics of onlinesocial networks after a disaster," International Journal of InformationManagement, vol. 38, no. 1, pp. 86–96, 2018.

[3] J. Son, H. K. Lee, S. Jin, and J. Lee, "Content features of tweets foreffective communication during disasters: A media synchronicity theoryperspective," International Journal of Information Management, vol. 45,pp. 56–68, 2019.

[4] A. Elbanna, D. Bunker, L. Levine, and A. Sleigh, "Emergencymanagement in the changing world of social media: Framing the researchagenda with the stakeholders through engaged scholarship," InternationalJournal of Information Management, vol. 47, pp. 112–120, 2019.

[5] R. Dubey, A. Gunasekaran, S. J. Childe, D. Roubaud, S. F. Wamba,M. Giannakis, and C. Foropon, "Big data analytics and organizationalculture as complements to swift trust and collaborative performancein the humanitarian supply chain," International Journal of Production
Economics, vol. 210, pp. 120–136, 2019.

[6] S. Akter and S. F. Wamba, "Big data and disaster management: asystematic review and agenda for future research," Annals of OperationsResearch, vol. 283, no. 1, pp. 939–959, 2019.

[7] H. Mouzannar, Y. Rizk, and M. Awad, "Damage identification in socialmedia posts using multimodal deep learning." in ISCRAM, 2018.

[8] F. Ofli, F. Alam, and M. Imran, "Analysis of social media datausing multimodal deep learning for disaster response," arXiv preprintarXiv:2004.11838, 2020.

[9] F. Ofli, P. Meier, M. Imran, C. Castillo, D. Tuia, N. Rey, J. Briant, P. Millet,F. Reinhard, M. Parkan et al., "Combining human computing and machinelearning to make sense of big (aerial) data for disaster response," Big data,vol. 4, no. 1, pp. 47–59, 2016.

[10] P. Jain, B. Schoen-Phelan, and R. Ross, "Automatic flood detectionin sentinei-2 images using deep convolutional neural networks," inProceedings of the 35th Annual ACM Symposium on Applied Computing,2020, pp. 617–623.

[11] A. Kumar, J. P. Singh, Y. K. Dwivedi, and N. P. Rana, "A deep multimodalneural network for informative twitter content classification duringemergencies," Annals of Operations Research, pp. 1–32, 2020.

[12] T. Ghosh Mondal, M. R. Jahanshahi, R.-T. Wu, and Z. Y. Wu, "Deeplearning-based multi-class damage detection for autonomous post-disasterreconnaissance," Structural Control and Health Monitoring, vol. 27, no. 4,p. e2507, 2020.

[13] M. Imran, F. Ofli, D. Caragea, and A. Torralba, "Using ai and social mediamultimodal content for disaster response and management: Opportunities,challenges, and future directions," 2020.

[14] L. Dwarakanath, A. Kamsin, R. A. Rasheed, A. Anandhan, and L. Shuib,"Automated machine learning

approaches for emergency response andcoordination via social media in the aftermath of a disaster: A review,"IEEE Access, vol. 9, pp. 68 917–68 931, 2021.

[15] C. Castillo, M. Imran, P. Meier, J. Lucas, J. Srivastava, H. Leson, F. Ofli,and P. Mitra, "Together we stand—supporting decision in crisis response:Artificial intelligence for digital response and micromappers," by OCHAand partners. Istanbul: Tudor Rose, World Humanitarian Summit, pp. 93–95, 2016.

[16] C. Caragea, N. J. McNeese, A. R. Jaiswal, G. Traylor, H.-W. Kim, P. Mitra,D. Wu, A. H. Tapia, C. L. Giles, B. J. Jansen et al., "Classifying textmessages for the haiti earthquake." in ISCRAM. Citeseer, 2011.

[17] M. Imran, C. Castillo, J. Lucas, P. Meier, and S. Vieweg, "Aidr: Artificialintelligence for disaster response," in Proceedings of the 23rd internationalconference on world wide web, 2014, pp. 159–162.