Determining Disaster Risk Management Priorities Through a Neural Network-Based Text Classifier

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***Abstract*— Community participation and involvement plays a big role in disaster risk reduction. This paper made use of the feedback from public on how local communities can be better prepared in times of disaster. Main goal of this study is to automatically assign qualitative responses into its appropriate category in disaster management using bidirectional recurrent neural network. In building the BRNN model, data corpus was split into training set (85%) and testing set (15%), which achieved acceptable average accuracy rate of 81.67%, 81.17% precision, 81.67% recall and 80.81% f-measure. Output of the classifier showed that the top four priority needs of the respondents in DRR fall under the categories of education and training; communication and coordination; dissemination of information alerts and warnings/ early warning system; and role of local authority. The validated results generated is a useful feedback to concerned agencies, specifically in the Province of Albay in enhancing their existing disaster management plans. Future work may add trained data to achieve higher performance results. Using other hyperparameters in the configuration of neural networks may also be considered for better evaluation result of the classification model.**

***Keywords* — Text Classification, Machine Learning, Neural Networks, Disaster Risk Management**

I. INTRODUCTION

Disaster risk reduction and management is one of the areas which the Philippine government is giving attention over several years, because of the country's vulnerability to natural disasters. Its main goal is to reduce the impact of human and ecological destruction. Hence, there are existing organizations from various government, non-government, civil sector and private sector that aim to attain disaster-resilient communities.

United Nations International Strategy for Disaster Reduction (UNISDR) defined DRRM as the systematic process of using administrative directives, organizations, and operational skills and capacities to implement strategies, polices and improved coping capacities in order to lessen the adverse impacts of hazards and their possibility of disaster. Disaster risk management aims to avoid, lessen or transfer the adverse effects of hazards through activities and measures for prevention, mitigation and preparedness [1].

Community-based disaster preparedness programs that emanate from the smallest unit of government greatly contribute to the success of the over-all goal of DRRM. Members of the communities have important role in disaster management particularly in consultation, decision-making, information dissemination and DRM planning [2]. Risk assessments done in community level can help address DRR challenges by fostering community engagement in climate risk reduction [3]. By doing so, it assures that disaster management plans are aligned to the vulnerabilities and needs of the community [4] [5] [6] [7].

On the other hand, local government entities should take responsibility for disaster risk assessment as a continual activity [8]. A focus on development that neglects to enhance governance and resilience as a prerequisite for managing climate change risks will, in all likelihood, do little to reduce vulnerability to those risks [9].

E -participatory toolkits promotes civic engagement and open participatory governance between the government and its citizens through the use of ICT. Its main goal is to improve access to information and public services as well as to foster participation in drafting effective policies. It can support critical information among members of the public that needs to be better integrated in disaster risk reduction.

e-Bayanihan [10] is a mobile and web-based participatory disaster management system that allows citizen to participate in contributing and receiving disaster related information as part of disaster preparedness and mitigation. It crowdsources information providing actionable response to make communities resilient to disasters. Another e-participatory system, by the CITRIS Connected Communities Initiative at UC Berkeley and National University, Philippines through the Philippine-California Advanced Research Institutes Project is the Malasakit toolkit. Malasakit is a customizable participatory assessment platform that collects and integrates quantitative assessment, qualitative feedback, and peer-to-peer collaborative filtering on ways local communities can become better prepared for typhoons and floods. [11]

Such qualitative responses, which are gathered suggestions from the public aim to address disaster risk reduction management. One way to efficiently analyze these bulks of data and group them to certain classes is the application of natural language processing, particularly text classification approach. This paper aimed to model and analyze the collected textual data which can aid the government in identifying the communities' needs in disaster preparedness. The ability to classify these responses automatically help concerned agencies to timely and efficiently work to identify and address needs and priorities in DRR that include but not limited to (1) communication and coordination; (2) community participation/ volunteerism/ solidarity; (3) dissemination of information alerts and warnings/ early warning systems;(4) education and training; (5) personal preparedness; (6) prevention and mitigation; (7) relief and emergency assistance; and (8) role of local authority.

II. RELATED WORKS

A. Text Classification

Text Classification is a text mining technique, which is used to classify the text documents into predefined classes [12]. It is one computational task in natural language processing that aids the people in cleaning and analyzing data. There are many existing text classification approaches which can be used in assigning documents to its corresponding class/es. Among those are probabilistic classifiers, artificial neural network and decision trees. Many studies have been conducted along the area of disaster management that used this supervised approach.

This research [13] proposed an automated text classification system in order to classify tweets related to disaster. A manual

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vocabulary has been created by considering the nature of the disaster data. The created vocabulary is used for splitting the tweets into various categories. In the categorized data, popular statistical feature selection methods like, term frequency, Chi Square are used in combination with Support Vector Machine (SVM) and Naïve Bayes algorithms to classify the data. Same approach was used by [14] in the classification of tweets into relevant categories, so that concerned entities can quickly find information relevant to them. Tweets domain was also used in the conduct of [15] in identifying flood-related tweets and determining flood-related areas in the Philippines.

The effect of Part of Speech (POS) tag unigrams and bigrams on the performance of the domain adaptation classifiers was studied [16] POS tag unigram and bigram features was utilized in conjunction with a Naive Bayes Domain Adaptation algorithm to learn classifiers from source labeled data together with target unlabeled data, and subsequently used the resulting classifiers to classify target disaster tweets. Domain adaptation approach was also used [17] on disaster response aided by tweet classification. They proposed to use a domain adaptation approach, which learns classifiers from unlabeled target data, in addition to source labeled data.

B. Application of Neural Networks in Disaster Management

An artificial neural network is a computational learning model based on the functions and structure of biological neural networks such as brain or neurons [18], whereas the data and information are the processing paradigm [19]. Many researches along disaster management employed and are now using prediction techniques by these neural networks.

It has been a powerful tool in mitigating floods as previous conducted studies applied ANN prediction models in disaster management. A study[19] proposed a flood forecasting technique that is based on an artificial neural network (ANN) model, namely, multi-layer perceptron (MLP). It showed the relative importance of different environmental parameters used to predict flood and it is found that underground water level is the most significant parameter for the prediction model.

Also the results in the research [20] indicate that the artificial neural network is a powerful tool in modelling rainfall-runoff. It built model for predicting river stream flow coming into the Ringlet reservoir in Cameron Highland, Malaysia. An ANN model was formulated in the research [21] to simulate flows at a certain location in the river reach, based on flow at upstream locations. Different procedures were applied to predict flooding by the ANN. The analysis indicated that the ANN provides a reliable means of detecting the flood hazard in the River Nile.

Application of neural network for prediction of casualties and damages caused by cyclone was done in [22]. This paper also presents the methodology on how to use these models for the analysis of the effects of cyclone parameters. The models developed in this study may be used to plan relief and rehabilitation works judiciously to alleviate economic losses caused by cyclone.

C. Recurrent Neural Networks

Recurrent neural network, shown in Fig. 1 is a type of ANN, where it takes input not just the current example they see, but also what they have perceived previously in time [23]. It has recurrent means of interpreting and assessing the current information being processed [24]. RNN can utilize distributed representations of words by first converting the tokens comprising each text into vectors, which form a matrix [25].Networks main advantage resides in their ability to deal with sequential data. The prediction by the network at timestep T is influenced by the one it made at timestep T – 1.

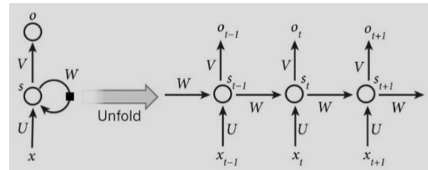

Fig. 1. Recurrent Neural Network

On the other hand, illustrated in Fig. 2, is the bidirectional recurrent neural network. BRNN is just two RNNs stacked on top of each other. The output is then computed based on the hidden state of both RNNs [26].

BRNN can be trained without the limitation of using input information just up to a preset future frame. This is accomplished by training it simultaneously in positive and negative time direction.

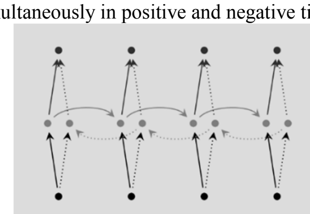

Fig. 2. Bidirectional Recurrent Neural Network

III. METHODOLOGY

A. Data Collection

The first stage is data collection, wherein the collected data from an e-participatory toolkit was augmented using google form and suggestions from online articles related to disaster risk management. Collected responses were used in building the classification model, where 779 of which were collected by research fellows from National University using Malasakit toolkit, 338 responses using google form and DRM suggestions were gathered from eight (8) articles. All of the suggestions were manually annotated using the eight (8) categories presented in table 1. After labeling the collected responses, this resulted to imbalanced datasets. To solve this problem, resampling method was done in the dataset to even-up the instances of all the classes. Over-sampling was the approach applied to the minority classes wherein copies of responses were added from under-represented class. Minority classes include role of local authority, community participation/volunteerism/solidarity, personal preparedness, prevention and mitigation, and relief and emergency assistance. On the other hand, under-sampling method was employed to reduce the number of instances from the majority classes. Dominant data fall into education and training, communication and coordination and dissemination of information alerts and warnings/ early warning systems After applying those techniques, training samples consist of 1,600 qualitative responses and were equally distributed to eight classes. In the conducted experiments, 85% of the collected data were used as training set for building the classification model and 15% as test data set in measuring the model's performance.

TABLE 1
CATEGORIES OF THE LABELED RESPONSES

Category	**Definition**
Communication and coordination	Mentions a 2-way avenue that allows connection between people, in particular through the means of technology
community participation/ volunteerism/ solidarity	Mentions any form of bayanihan spirit or kapitbahayan
Dissemination of information alerts and	Mentions a procedure that allows barangay community officials to

warnings/ early warning systems	notify community members of a potential hazard
Education and training	Mentions any method that allows community members to gain knowledge and be more aware
Personal preparedness	Mentions any general plan to prepare, but with no specific tangible steps
Prevention and mitigation	Mentions any act to reduce the severity of the human and material damage caused by the disaster.
Relief and emergency assistance	Mentions any act that provides humanitarian assistance in the form of food, medicine or clothing to communities who have suffered from hazards
Role of Local Authority	Mentions any form of responsibility in the part of the local government unit

B. Data Cleaning

During this phase, data cleaning methods were performed in the collected data. Pre-processing of the qualitative responses was necessary to present it into clear word format and to improve the quality of dataset. Stop words, words less than three characters and special characters were eliminated from text to reduce dimensionality of term space. Identified common words in the data sets are articles, prepositions and pro-nouns that does not provide measurable meaning to the responses. For further pre-processing, all of the text were also converted to lowercase. After the cleaning process, out of the 26, 856 words, 4,643 words were eliminated from the raw corpus.

C. Feature Extraction

In this procedure, feature vectors for words were created using word2vec. This is necessary in turning pre-processed textual data into numerical form that deep neural networks understand. Each word in the training data is mapped with a unique numerical representation.

D. Data Processing

In this phase both recurrent and bidirectional recurrent neural networks, supervised machine learning algorithms were employed to train the models and automatically classify the qualitative responses into its appropriate classes. The numerical values from feature extraction were then used in generating the classification model which was built with a total of 12,000 iterations. Number of iterations is the number of passes the neural network gone through the 1,600 training data which consists of 10, 286 pre-processed words.

Classification models were generated using the following defined parameters: the number of epochs; batch size; and length of each training data. These parameters also determine the total number of iterations the algorithm gone through the 1600 training data. In generating the model, 150 epoch, 20 batch size, and 20 words text length were defined. One epoch is equivalent to one forward pass and one backward pass of all the training examples. Batch size is the number of training examples in one forward/backward pass. To complete each epoch, 80 iterations (1,600 training data/ 20 batch size) were executed.

E. Performance Evaluation

Performance of the classification models were described by the confusion matrices which were used to properly present the classified data. The classifier configuration that obtained the best accuracy was selected to be used in developing the DRM e-Participatory toolkit qualitative response classification system. The average accuracy, precision, recall were computed to give overall assessment of the effectiveness of the classification across the defined categories for the DRM qualitative responses.

Accuracy measured the effectiveness of the classifier in terms of detections in agreement with the actual classifications. [17] Formula 1 shows the formula on determining the accuracy of the model.

Formula 1. Accuracy

$$Accuracy = \frac{No.\ of\ Correctly\ Classified\ Responses}{Total\ no.of\ Qualitative\ Responses}$$

On the other hand, precision measured the exactness of a classifier and considers false detection. A higher precision means less false positives, while a lower precision means more false positives. [17] Formula 2 shows how precision is computed.

Formula 2. Precision

$$Precision = \frac{True\ Positives}{True\ positives + False\ positives}$$

Recall measures the completeness, or sensitivity, of the classifier. Higher recall means less false negatives, while lower recall means more false negatives. [17]

Formula 3. Recall

$$Recall = \frac{True\ Positives}{True\ positives + False\ negatives}$$

The last metric, which is F-measure is computed using the formula shown below. It is the weighted harmonic mean of precision and recall and its main advantage is it is able to rate a system with one unique rating. [17]

Formula 4. F-measure

$$F - measure = \frac{2 * precision * recall}{precision + recall}$$

IV. RESULTS AND DISCUSSION

A. Results of Experiments

The performance of the classification models were determined by the standard metrics discussed in the previous section. Metric scores of regular and bidirectional neural networks are shown in table 2. It is observed that the two RNN algorithms produced closed evaluation results where Bidirectional RNN obtained accuracy rate of 81.67%, 81.17 precision, 81.67% recall and 80.81% f-measure against performance evaluation result of regular RNN where is obtained 81.25% accuracy, 80.84% precision, 81.25% recall and 80.25% f-measure.

TABLE 2
PERFORMANCE SCORES OF RNN AND BRNN

Standard Metric	Regular RNN	Bidirectional RNN
Accuracy	81.25%	**81.67%**
Precision	80.84%	**81.17%**
Recall	81.25%	**81.67%**
F-measure	80.25%	**80.81%**

The basis of the scores of RNN is based on the generated confusion matrix. Given 240 responses for testing data set, the classifier correctly classified 196 responses into its equivalent classes.

TABLE 3
CONFUSION MATRIX OF BRNN

Actual Label	Classified by model as							
	CC	CPVS	DIA W/E WS	ET	PP	PM	REA	RL A
CC	**13**	0	6	1	5	0	0	5
CPVS	0	**29**	0	0	0	0	1	0
DIAW/ EWS	3	3	**22**	1	0	1	0	0
ET	4	1	1	**23**	0	0	0	1
PP	2	0	0	2	**25**	0	1	0
PM	1	2	0	0	0	**27**	0	0
REA	0	1	0	0	0	0	**29**	0
RLA	3	0	0	0	0	0	0	**27**

CC - communication and coordination
CPVS- community participation/volunteerism/solidarity
DIAW/EWS - dissemination of information alerts and warnings/ early warning systems
ET - education and training
PP -personal preparedness
PM- prevention and mitigation
REA -relief and emergency assistance
RLA -role of local authority

Basic performance measures of the BRNN model were determined by the confusion matrix. Error-rate, accuracy, specificity, sensitivity and precision were derived from the table. The classifier made a total of 240 predictions based on the test set given with eight(8) possible predicted classes in DRM.. BRNN model performed better with a total of 196 correctly classified instances against 195 correct predictions of the RNN model. To further explain how the confusion matrix is used, true positives, false positives and false negatives are whole numbers that determine the metric rates of the model. True positives (TP) are the correctly classified responses. To give example, in Table 3, 23 responses are predicted as education and training and those samples are correctly classified. False positives (FP) in the table are responses that are predicted under certain class which are not really labelled as such. In the set of predicted instances, there are four(4) samples which are labelled as education and training but the true values reveal they are not. False negatives(FN)on the other hand are those instances categorized in other classes. Shown in table 3, education and training has seven (7) false negatives, this indicates that the model predicted those samples belong to other classes, where in fact those are labelled education and training.

Values presented in the confusion matrix were used in computing for the models' accuracy, precision, recall and f-measure. Experiments concluded that bidirectional RNN performed better compared to regular RNN.

B. Labeled Qualitative DRM Responses Using the Classifier

Using the same qualitative question, asking for feedback on how local communities or the general public can be better prepared in times of disaster, 222 respondents from different barangays in the province of Albay have joined, responded and gave their suggestions. These responses were then classified using the text classifier and the results were presented to the Local Association of DRRM Officers of Albay (LADA), an organization established under the management of Albay Public Safety and Emergency Management Office (APSEMO).

TABLE 4
SUMMARY OF THE CLASSIFIED RESPONSES

Category	1st District	2nd District	3rd District	Average
communication and coordination	**32%**	**29%**	**31%**	**31%**
community participation / volunteerism/ solidarity	2%		6%	4%
dissemination of information alerts and warnings/ early warning systems	**22%**	**25%**	**13%**	**20%**
education and training	**27%**	**34%**	**31%**	**31%**
personal preparedness	2%	2%		2%
prevention and mitigation		1%	6%	4%
relief and emergency assistance	2%	2%		2%
role of local authority	15%	8%	**13%**	**12%**

Further analysis was done by comparing the result of the labeled data among the three districts of Albay. Presented in table 4 are the priorities of the respondents in disaster preparedness in their respective localities. It appears that the respondents in the 1st district of Albay, communication and coordination is what they feel as the most important in disaster preparedness. However, in the 2nd district education and training ranked the highest, as they feel the need in enhancing the knowledge and awareness in disaster risk reduction among the community members. On the other hand, in the 3rd district both communication and coordination and education and training were identified as their primary need.

V. CONCLUSIONS AND FUTURE WORK

Bidirectional recurrent neural network was able to build an acceptable classification model which is used in labeling qualitative responses in DRM. The classified responses showed that the top needs and priorities of the local communities fall under: (1) education and training; (2) communication and coordination; (3) dissemination of information alerts/ early warning systems; and (4) role of local authority.

It is also evident that the. mandatory policies and procedures frequently require modification of the existing systems. Thus, APSEMO and LADA could make use of the results to augment their function in disaster planning and to substantially reduce the impact of calamities.

Future work may add trained data to achieve higher performance results of the classifier. It may also be considered using other hyperparameters in the configuration of neural networks for better evaluation result of the classification model.

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