IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Analyzing Natural Disaster Intensity With Machine Learning And Ai

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ABSTRACT

Disaster management platforms like emergency services offer important information to help respond to disasters. Machine learning could help identify this information. Using social media data for emergency response has challenges like reliability, performance measurement, deception, attention focus, and turning observations into usable information. During the Haiti earthquake, many technical volunteers tried to help by sending mapping and translation services via text messages. However, the systems couldn't handle the high volume of information. Despite good intentions, organizations weren't prepared to handle data from outside their networks. They lacked technical staff and tools to use the data effectively. To solve this, we propose using a domain adaptation approach, which learns from available data with labels. Our approach uses the Linear SVC Algorithm with Self-Training. Experimental results show that our method can identify emergency messages relevant to disasters.

1. INTRODUCTION

Natural disasters are unavoidable events that have a significant impact on the economy, environment, and human lives. They result in the collapse of buildings, the spread of diseases, and can devastate entire nations. Events like tsunamis, earthquakes, and forest fires can cause widespread destruction. For instance, earthquakes can lead to the collapse of millions of buildings due to seismic activity.

Since the 1990s, various machine learning methods have been used for predicting wildfires. A recent study in Italy utilized the random forest technique for mapping wildfire susceptibility. Floods, being one of the most damaging natural disasters, cause destruction to properties, human lives, and infrastructure. To predict flood susceptibility, a combination of machine learning techniques including random forest (RF), random subspace (RS), and support vector machine (SVM) was used.

With the rapid growth of the population, there is an increased demand for land, leading to disturbances in the ecosystem, which in turn contribute to global warming and the rise in natural disasters. This particularly affects underdeveloped countries, where populations cannot afford the damages caused by disasters to their infrastructure.

After disasters, humans often find themselves in dire situations, with rescue operations hampered by geographical factors and victims often left unidentified. Disasters like forest fires spread rapidly in dense areas, making firefighting challenging. Hence, developing strategies to predict such circumstances is crucial for preventing disasters. As technology advances, aviation systems are incorporating smart technologies to develop unmanned aerial vehicles (UAVs) equipped with cameras. These UAVs can reach remote areas to assess the impact of disasters on human life, infrastructure, and transmission lines by capturing images and videos.

Problem statement

Temporally, the above problems arise at the stage when emergency responders and organizations begin engaging their organizational mechanisms to respond to the crises in question (Munro, 2011). For decades, these organizations have operated with a centralized command structure, standard operating procedures, and internal vetting standards to ascertain appropriate responses to emergencies. While not optimized to current expectations of speed, efficiency and knowledge, these mechanisms have been successful at bringing rescue, response and recovery to millions.

1.1 Objective

Towards optimizing current organizational mechanisms in terms of speed, efficiency and knowledge, machine learning algorithms have been used to help responders sift through the big crisis data, and prioritize information that may be useful for response and relief.

2. SYSTEM ANALYSIS

2.1 Existing System

During the Paris attacks in November 2015, eyewitnesses, or friends of eyewitnesses, shared information about gunfire and dangerous places through Twitter, to alert people within minutes after attacks in different places.

Parisians also launched the hashtag #PorteOuverte (meaning "open door") to offer, through Twitter, safety and refuge to those affected by the attacks.

Therefore, microblogging data from Twitter like platforms are seen to have intrinsic value for both responder organizations and victims, due to their growing ubiquity, communications rapidity, and cross-platform accessibility.

a) Disadvantages of Existing System

- One problem became apparent during the earthquake in Haiti when thousands of technical volunteers from around the world suddenly attempted to provide responders with mapping capabilities, translation services, people and resource allocation, all via SMS at a distance.
- Despite the good will of field staff, their institutions' policies and procedures were never designed to incorporate data from outside their networks, especially at such an overwhelming flow. In addition, the organizations did not have the technical staff, or the analytical tools, to turn the flow of data into actionable knowledge.

2. Proposed System

We propose to use a domain adaptation approach, which learns classifiers from available dataset, with labeled data. Our approach uses the Linear SVC Algorithm, together with an Self-Training strategy. Experimental results on the task of identifying emergency messages classification relevant to a disaster of interest show that the domain adaptation classifiers.

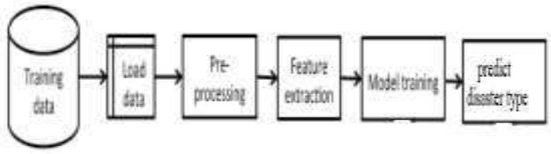
SYSTEM DESIGN

a. System architecture

The automatic classification of tweets begins with the manual classification of a dataset which serves as the ground truth for evaluating the performance of two machine classifying algorithms, Naive Bayes (NB) and Support Vector Machine (SVM). The following sub-sections describe the dataset and the approach used in the study.

b. Data Source

Habagat hit the Philippine's capital Manila and its neighboring provinces last August 1-8, 2012. The monsoon brought about eight days of torrential rain and thunderstorms which caused flooding in several areas and consequently caused massive damages and loss of properties and lives. At the onset of the Habagat until its aftermath, subscribers of Twitter used this social medium to send relevant or personal messages to their intended recipients. A



sample of Habagat tweets were collected by the researchers of Ateneo de Manila University using the Twitter API. The sample has a total of 612,622 tweets, of which 373,771 are unique tweets and 238,851 are retweets. Unique tweets are the original messages that are sent by the author of a tweet which can be viewed by his or her followers and followees. Retweets on the other hand are messages received by a subscriber and are forwarded to another user or set of users.

c. Manual Classification

From the collected Habagat tweets, a sample of 4,000 tweets was randomly selected. Annotators initially classified the randomly selected tweets as to whether they are encoded in English, Tagalog, combination of English-Tagalog or other languages or dialects. The annotators further classified the English tweets as informative or uninformative based on the given definitions. Informative tweets are tweets that provide useful information to the public and are relevant to the event, while uninformative tweets are tweets that are not relevant to the disaster and these do not convey enough information or are personal in nature and may only be beneficial to the family or friends of the sender.

d. Information Extraction

Using conditional probability and Bayes' theorem, information can be extracted from the statistics of manually classified tweets. Conditional probability is defined as $P(A|B) = P(A \cap B)/P(B)$, provided $P(B) > 0$. Bayes' theorem , also known as Bayes' rule or Bayes' law, is a result in probability theory that relates conditional probability. If A and B denote two events, $P(A|B)$ denotes the conditional probability of A occurring, given that B occurs [22]. Bayes theorem is mathematically defined as:

$$P(A|B) = P(B|A)\, P(A) / P(B)$$

where:

P(A) is the prior probability or marginal probability of A.

It is ‖prior‖ in the sense that it does not take into account any information about B

P(A|B) is the conditional probability of A, given B

P(B|A) is the conditional probability of B given A

P(B) is the prior or marginal probability of B, and acts as a normalizing constant

In the context of this study, *P(A)* is the probability of a tweet being informative, while *P(B)* is the probability of a tweet being unique. Therefore, information of the probabilities of tweets being informative or not informative, given that these are unique or are re tweets were then extracted.

3. IMPLEMENTATION

a. Machine Learning Algorithms for Classification

a) Supervised Learning

Supervised learning was used in training the machine to classify a tweet as informative or not informative. Supervised learning is a training in which the class attribute values for the dataset are known (labeled data) before running the algorithm [24]. Supervised learning builds a model that maps x to y;
where **x** is a vector and *y* is the class attribute. A model is generated when the supervised learning algorithm is run on a training set, which maps the feature values (**x**) to the class attribute values (*y*). After training, the model is tested on a dataset which will predict class attributes. In the context of this study, **x** = vector of features and *y*
{informative, uninformative}.

In order to minimize bias related to the sampling of data, the stratified 10-fold cross validation was used to estimate the performance of the model. In a 10-fold cross validation, the dataset is randomly split into 10 mutually exclusive subsets (DS1, DS2...DS10) of approximately equal sizes and with proportional representation of the tweet classes. Using the data set, the classification model is trained and tested 10 times, with the 9-folds used as the training data set and the remaining 1-fold as the testing data set. The algorithms Naive Bayes and Support Vector Machine (SVM) were compared in terms of the different metrics of evaluation.

Naive Bayes' and Support Vector Machine are two of the most commonly used machine learning algorithms for classification. Naive Bayes classifier is robust and has a good performance in several real-world classification tasks. A Naive Bayes classifier is a simple probabilistic classifier basedon Bayes' theorem (from Bayesian statistics) with strong (naive) independence assumptions [25]. In simple terms, a Naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature [26]. Support Vector Machine is a learning method used for binary classification. The basic idea is to find a hyperplane which optimally separates the *d*-dimensional data into its two classes [26]. However, since example data is often not linearly separable, SVM incorporates the notion of a kernel induced feature space which projects the data into a higher dimensional space where the data is more easily separable [27].

b) Evaluation of the Machine Learning Algorithms:

In this study, accuracy, recall, precision, area under curve (AUC) and F-measure were used as metrics in the empirical evaluation of the classification algorithms Naive Bayes and Support Vector Machine. Table I presents the description of each metric of evaluation, as described in Rapid miner.

Table I: Metrics of Evaluation

Metric	Description
Accuracy	Relative number of correctly classified examples or in other words percentage of correct predictions.
AUC	AUC is the Area Under the Curve of the Receiver Operating Characteristics (ROC) graph which is a technique for visualizing, organizing and selecting classifiers based on their performance.
Precision	Relative number of correctly as positive classified examples among all examples classified as positive
Recall	This parameter specifies the relative number of correctly as positive classified examples among all positive examples
F-measure	This parameter is a combination of the *precision*and the *recall*i.e. *f=2pr/(p+r)*where *f,r*and *p*are *f-*

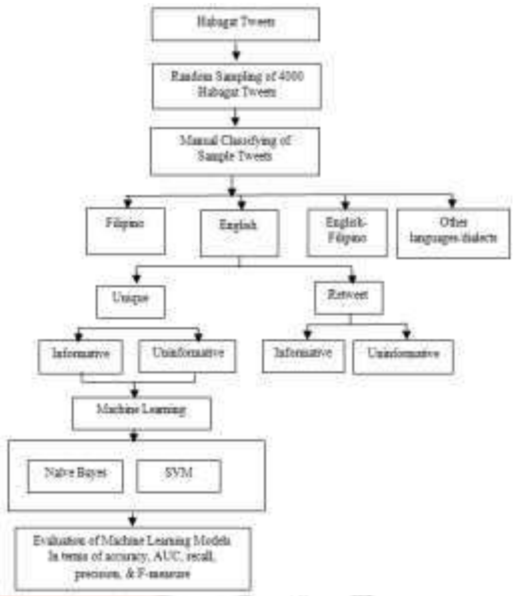


Figure: Methodology Structure

4. RESULTS AND DISCUSSION

5.5 Manual Classification of Habagat Tweets

From the 4000 tweets randomly selected, there were 1,563 English tweets, 1,393 Tagalog tweets, 913 tweets using a combination of English and Filipino and 121 tweets using other languages or dialects. Table III presents a summary of the manually classified English tweets.

Based on the labeling of the annotators, the computed ICC or multi-rater Kappa coefficient is 0.671, which apparently is substantial [33][34][35] or there is a good level of agreement among the annotators in classifying whether a tweet is informative or not.

In case of conflict in label, a discussion among the three annotators was necessary to resolve such differences. After thorough discussion, annotators agreed on a specific label for the tweet.

5.2 Extracted Information

By applying conditional probability and Bayes' theorem, data was analyzed from the manually classified tweets. According to the statistics, uninformative tweets outnumbered informative ones by a ratio of 65% to 35%. An example of an uninformative tweet is: "Stay safe everyone!!! #PrayForThePhilippines #TrustGOD".

Unique tweets are more likely to be uninformative (71.72%) compared to informative ones, which have a probability of 28.28%. Additionally, the probabilities of retweeted tweets being uninformative and informative are almost equal, at 49.22% and 50.78% respectively.

Despite the prevalence of uninformative tweets, informative tweets are more likely to be retweeted (41.99%) compared to uninformative ones (21.67%). This suggests that retweeted informative tweets carry significance and urgency, potentially enhancing public awareness and disaster response.

The results indicate that subscribers primarily used Twitter to share subjective messages and emotions regarding the Habagat event. These findings are consistent with previous studies on hurricanes by Hughes and Palen, flooding and wildfires by Starbird and Palen, and the Haiti earthquake by Starbird and Palen. These studies reveal that users tweet to share crisis information, express opinions and emotions, and offer aid to those in need.

5.2 Evaluation of Machine Learning Algorithms:

Table IVpresents the results of the 10-fold cross validation for all folds for all the metrics of evaluation. Using the Kolomogorov-Smirnov and Shapiro Wilk for normality testing, the data is normally distributed and this is true to all the five evaluation metrics. The normality of these variables has also been validated by their Normal Probability Plots.

Since the data are normally distributed, parametric testing was performed. The parametric t-test was specifically used to determine the significant differences between Naive Bayes and SVM. Table Vpresents the results of the experimentation.

The paired t-test results shown in Table V demonstrate that there is a significant difference between Naive Bayes and SVM (p<0.001). This is true to all the five parameters namely, accuracy, AUC, precision, recall, and F-measure. In particular, SVM is significantly higher than Naive Bayes in accuracy, AUC, recall, and F-Measure, though Naive Bayes is significantly higher than SVM in precision. Table VI shows the mean values for the paired sample statistics.

	Informative Tweets	Uninformative Tweets	Total
Unique	315	799	1114
Retweets	228	221	449
Total	543	1020	1563

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Table IV: Results Of 10-Fold Validation

	ACCURACY		AUC		PRECISION		RECALL		F-MEASURE	
FOLD	NB	SVM	NB	SVM	NB	SVM	NB	SVM	NB	SVM
1	[illegible]	[illegible]	0.7200	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.6400	[illegible]
2	[illegible]	[illegible]	0.7200	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.0000	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MEAN	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

TABLE V: Paired T-Test Results

		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of Difference Lower	Upper	T	df	Sig(2-tailed)
Pair 1	Accuracy (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	13.952	9	<0.001
Pair 2	AUC (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	11.346	9	<0.001
Pair 3	Precision (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	-2.266	9	<0.001
Pair 4	Recall (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	21.981	9	<0.001
Pair 5	F-measure (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	0.288441	15.252	9	<0.001

Table VI: Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	NB_Accuracy	0.60172	10	0.5014710	0.0158579
	SVM_Accuracy	0.80207	10	0.0265764	0.0084042
Pair 2	NB_AUC	0.72350	10	0.0958443	0.0310821
	SVM_AUC	0.86880	10	0.0620767	0.0196304
Pair 3	NB_Precision	0.86546	10	0.0648431	0.0205052
	SVM_Precision	0.79652	10	0.0186738	0.0059052
Pair 4	NB_Recall	0.51856	10	0.0510700	0.0161498
	SVM_Recall	0.96747	10	0.0253584	0.0080190
Pair 5	NB_F-Measure	0.64702	10	0.0479798	0.0151726
	SVM_F-Measure	0.87349	10	0.0162222	0.0051299

Confusion matrices of SVM and Naive Bayes as shown in Table VII and Table VIII respectively. Using the same trainingdata set for both algorithms, the SVM model achieved an average accuracy of 80%, while Naive Bayes had 57% average accuracy. This indicates that the SVM model returned 892 correct classifications out of 1,114 unique tweets while Naive Bayes model correctly classified only 633 tweets.

In terms of recall, the SVM model correctly classified 780 uninformative tweets and only 19 labeled uninformative tweets as informative resulting to a recall value of 97.62% for the uninformative class. For Naive Bayes, the model correctly classified 396 uninformative tweets over 799 uninformative tweets yielding a 49.56% recall value.

AUC is a measure of quality of a probabilistic classifier. A random classifier has an area under curve 0.5, while a perfect classifier has 1. Binary classifiers used in practice should therefore have an area somewhere in between, preferably close to 1 [41]. In this experiment, SVM demonstrated an average AUC of 0.884 which indicates that the classifier ranked positive examples higher than the negative examples.

5. CONCLUSION

We compared two classification algorithms, SVM and Naïve Bayes, using a 10-fold cross-validation. SVM performed better than Naïve Bayes in terms of accuracy, recall, AUC, and F-measure, while Naïve Bayes was more precise. In the future, we plan to explore different features and weights to create word vectors and see how they affect evaluation metrics. We'll also focus on feature selection, parameter optimization, and semantics. Additionally, we'll evaluate other machine learning algorithms using metrics other than accuracy, recall, precision, AUC, and F-measure. Determining the most important evaluation metrics will help researchers choose the right algorithm for specific tasks. Multi-label classification of English and multilingual tweets is crucial for extracting relevant information, which can improve situational awareness. We aim to develop a real-time system that can detect and filter disaster-related tweets for effective disaster response management.

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