ISSN 2278-3091
Volume 9, No.4, July – August 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse264942020.pdf
https://doi.org/10.30534/ijatcse/2020/264942020

Emotion Recognition from Blog Comments Based Automatically Generated Datasets and Ensemble Models

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ABSTRACT

Emotions have a large influence on product loyalty and found that an individual have a positive emotional relationship with identified product, trust in the company and make purchases. The customer's decision is not founded on their facts/ information, but they rely on their emotions to get brand loyalty decisions. However, companies are struggling to adapt this strategy even with the huge amount of data they acquired, their utilization of this data as marketing influence and ongoing personalization tactics is limited due to the problem of analyzing voluminous data. This work offers new approach for automated categorization of emotions from textual data and was based on a sentence level utilizing the language translation machine and applying of learning machines and ensemble models. The experiment reveals that the proposed automatic emotion classifier performs well in classifying angry comments both in training and testing evaluation periods. Furthermore, the proposed emotion classifier produces a result of 75% accuracy under ensemble Naïve Bayes (NB) in the classification of sentence emotion during training period. Although during the actual testing period of the test data set, the proposed system was able to correctly classify 76% emotions of the sentences. Some of the reasons and causes for misclassification are analyzed and presented in this paper.

Key words : Automated Annoted Dataset, Blog Comments, Emotion Detection, Emotional Recognition.

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1. INTRODUCTION

Internet users are continuing increasing because of the growth of technology and the advent social media and review blog sites. The said internet users sometimes express their opinion with emotions about the services, products or commodities they consume in the review blog site. Understanding client's emotions are very important for organization since clients are able to express their opinions and feelings more openly than ever before [1]. This scenario paid way to the conceptualization of domain emotion analysis. Furthermore, leads to the development of automatic customer feedback analyzer, from opinions or answers to social media conversations, companies are able to listen responsively to their clients, and refocus their products and services to meet their customer needs. This situation is helpful for both the consumers as well as for the producers because they know what the general public think about a particular product or service.

In a 2016 study conducted by Tempkin Group that "emotions have a strong influence on brand loyalty, furthermore, the research show that when people have a positive emotional relationship with a certain brand, they trust the company 8.4 times, they likely purchase more 7.1 times and 6.6 times more likely to forgive a company's mistake". In addition, a study by Nielsen in 2016 shows that advertisements with an above average emotional answer from their clients produced a 23% increase in their sales compared to average advertisements. The Harvard Business Review has also stated that a positive emotional bond with a company is more important to consumers than customer satisfaction [2]. Emotion recognition has many applications one of which is emotional marketing which is exceedingly important if a company desires to accept a successful product/service selling. The research found out that emotional ads motivate customers to buy because they rely on emotions to make brand decisions, not on information about the product/service [3].

The human emotions are recognized and can be analyzed by voice, motion, face inputs and peoples' opinions. In addition, there are 7 universally accepted emotions - sadness, surprise, fear , contempt, joy, disgust, and anger. Emotion analytics is the analysis, detection and recognition of a person's non-verbal and verbal communications in order to understand the mood and attitude. With the advent of internet access and social media, people are voicing out their sentiments, opinions, emotions, and feelings utilizing text/comments, emojis, likes, and dislikes. Text is an important means, not just to convey facts, but similarly to show emotions. Text-based emotion detection is the computational field of natural language expressed in text, in parliamentary procedure to identify its association with emotions such as wrath, awe, joy, sorrow, surprise etc. Emotion knowledge discovery can have a direct impact on the marketing applications concerning industry specially to customer experience, employee engagement, media and government organizations. However, there are challenges involved in modelling fine-grained subjectivity and the subtlety of emotive expressions in text. Today's data is more than 80 percent unstructured or semi-structured data. The discovery of appropriate patterns and trends to analyze the text documents from massive volumes of data is a big issue, especially in the area of the sentence or phrase annotation. This is the bottleneck of text mining and emotion analysis, the process of naming/labeling emotions in the sentence from the vast amount of text documents. In addition, unstructured text datasets label with markers of emotional content are also limited. According to Yong, Wang & He emotion analysis needs a lot of label data, moreover, this task is a labor-intensive process and often needs instructions of experts to annotate data [4].

This research aimed to propose an emotion classifying model utilizing automated emotional annotation of the text using a dictionary based emotion lexicon and the application of ensemble model. This research will focus on classifying emotion on blog comments with the variety of tasks such as creation of a word emotion dictionary derived from online dictionaries and tried out with blog comments using different learning machines. Specifically, the study addresses the following specific objectives:

1. To get an efficient methodology to produce an emotion dictionary derived from online dictionaries.
2. To utilize the created emotion dictionary that will extract emotions from blog comments and automatically labeled emotion of the blog comments.
3. To determine the performance of the proposed blog comment emotion models in classifying emotions in the blog comments.

2. RELATED LITERATURE AND STUDIES

Compared with sentiment analysis, unstructured text data set annotated with labeler of emotional content are rare and it is a task that is tough due to the its complexity. Experimentation of emotion recognition in text utilizing conventional supervised classifiers or learning machines needs voluminous amounts of pre-annotated data for training, testing and development. Furthermore, emotion domain analysis is considered a new field in the area of natural language processing (NLP) and emotion recognition and detection is considered as a multi-class classification problem which needs massive amount pre-annotated data.

Some of the most prominent and publicly available sources will be discussed.

2.1 Self-labeled Emotion Manual Labeled Data Creation

Emotion classification techniques need to be supervised annotated for its training and testing dataset. Neviarouskaya et al. [5]; Mathews et al., [6] studies have utilized human annotators to manually label text with getting the emotions. However, they found out that human manual annotation of emotions is usually time-consuming, labor-intensive, and error-prone and the result is a lack of large labeled datasets for emotion research and unreliable research results. Chaffer and ink pen utilized a supervised learning machine method to detect aand recognize 6 emotions (fear, surprise, anger, sadness, happiness, and disgust) applying a heterogeneous emotion-annotated dataset with a combination of fairy tales, news headlines, and blogs [7]. The study utilized different bags of words, and N-grams, feature sets and learning machine Support Vector Machine classifier (SVM). [4] proposes a transfer learning approach for emotion analysis based on dubious (EATAdaBoost) by adapting the knowledge learned from labelled source data. Li et al. [8], Wu et al. [9], Wen and Wan [10] classified the texts into eight classes using a semi-constructed emotion dictionary and different learning machine.

2.2 Emotion Detection sing Automated Labeled Data Creation

It is interesting to explore a method that automatically creates labeled emotion datasets. A study proposed an automatic semi-supervised generated term-sentiment association lexicons detect the polarity of words. Turney and Littman [11] proposed an automatic method of creating an emotion dataset with a minimal supervision to determine the polarity of a certain word by determining if its probability to co-occur with a small set of positive seed words is greater than its probability to co-occur with a small set of negative seed words.

2.3 Emotion Detection Using Hashtags and Emoticons

Putra et al., [12], Oueslati el at., [13] conducted studies on utilizing hashtags and emoticons in tweets to build training datasets for sentiment analysis. The basic idea is to collect tweets containing the sentiment hashtags (e.g., "#sucks", "#notcute") or emoticons (e.g., ":)", ": D", ": -("), and label each tweet as positive or negative based on the polarity of hashtags and emoticons.

Another study conducted by Choudhury et al. [14] filters tweet via mood hashtags and focuses on analyzing users' mood expressions through affective space using valence and activation. A similar study was initiated by Bandhakavi, Anil, et al. which collects emotional tweets with six emotions hashtags or 1 hashtag per emotion [15].

Another paper proposed new module for the prediction of emotions in chat text, oriented to the generation of emotional speech in the chat domain. It makes use of a combination of emotional dictionary and hand-made expert rules, to attempt the identification of some of the most frequent emotions, as well as the intensity of the emotion, appearing in the emotional annotation of a corpus of chat messages [16].

2.4 Emotion Keyword Detection

Strapparava et al. [12] developed a linguistic resource for lexical representation of affective knowledge named WordNet – Affect. This application composed of a subset of synsets that denote affective concepts conforming to affective words. Emotion classification is done by charting emotional keywords that found in the input sentence to their equivalent WordNet-Affect concepts. Subasic and Huettner [17], Zhe applied emotional keywords to recognize emotion and process the level of emotion by calculating level of emotion using scoring[18].

This study explores the possibility of automatically labeled blog comments dataset to recognize and detect emotions in blog comments and replies utilizing machine learning algorithms.

3. METHODS

Figure 1 shows the flow of the research from data gathering to the final models.

3.1 Blog Articles Searching and Selection

In the process of selecting blog articles that were considered to be part of the study, the Google Search engine was utilized to search and review blog sites that feature the services provided and performances of the Smart, Globe and/or Sun Internet providers were explored. The search text queries combined the name of the three (3) ISPs with keyword ***"vs".*** The search text was " Sun vs. Globe Tattoo vs. Smart Bro " which both the name of the ISPs is inhibited plus the word "v's". The return results of this search were manually evaluated, analyzed and filtered such that blog article that contained many comments from their customers and readers were highly considered as part of the dataset. Specifically, the following criteria were used in selecting the articles that were included:

- Blog articles must discuss or compare the services provided and performance of Philippine ISPs.

- Blog articles must have at least 10 comments/replies.

The search engine results were checked sequentially following the order of relevance that the engine returned. Each accepted blog article was immediately scrape, stored and pre-processed in order to update the total count of the blog comment sentences for the dataset.

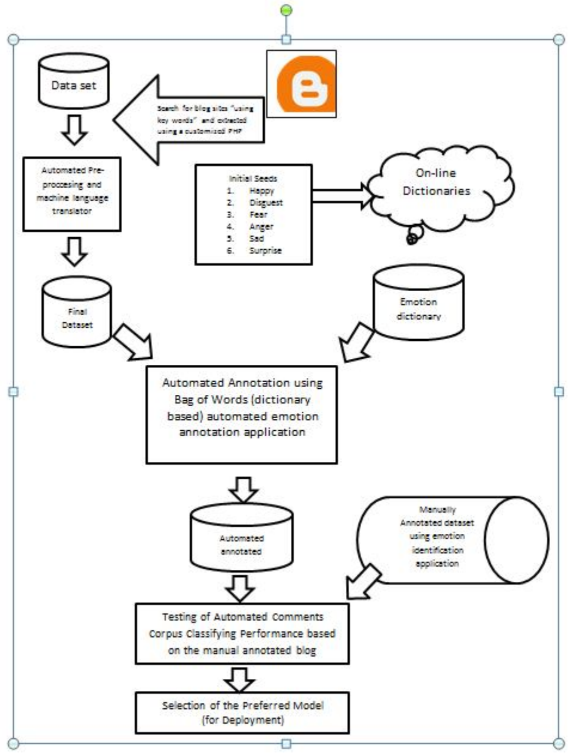

Figure 1: Methodology used in Building and Evaluating the Proposed Automatic Emotion Classifiers

The selection process of blog articles continues until the preferred number/volume of blog comments reaches the minimum size of 14,000. The used of the ISPs company name individualized queries and enabled this study to build a comprehensive dataset that have mentioned at least two name and has no effect on the population of the research blogs comments dataset.

3.2 Data Extraction

Selected blog comments and replies from the selected blog sites that discusses the services provided and ISP performances of the major Internet providers were extracted using a PHP web scraping application which retrieved the customer comments/replies and then stored these in a MySQL database automatically. To extract blog comments /replies a PHP scraping application was developed in which the URLs address was the input.

3.3 Data Cleansing

The retrieved blog comments contain several HTML tags, unnecessary characters, non-textual characters, and web codes which were automatically stripped out using a modified program in PHP. Data obtained from blog comments usually contain syntactic features, html code and entities like < > &amp which are embedded in the original comments. It was thus, necessary to remove those contents from the data because they might affect the result of sentiment classification and were not useful for the machine learning for sentiment analysis. Furthermore, eliminating unnecessary code improved the performance of the classification process [19].

A PHP application was designed and developed for cleaning blog comments. Blog comments contain several syntactic features that may not be useful for emotional analysis processing. Therefore, there is a need of text preprocessing that will remove HTML tags, non-textual contents and unnecessary characters before going on to the next process or analysis.

3.4 Language Translation

Language Translation. The collected blog comments were not all written in English. There were Filipino and English words in some sentences, and even sentences that were written in straight Filipino. In this case, a machine translation using Google Translate was employed. Specifically, a customized application in PHP was used to automatically convert Filipino sentences into their English equivalent utilizing the Google Translate API. However, Filipino words with no equivalent English words were manually translated using the other online dictionary. The translated results in English form were copied and pasted manually to the database.

3.5 Building Emotion Dictionary

Building of the emotion dictionary before carrying out a classification process on the dataset, there was a need to create a word dictionary to be used as a point of reference for emotion classification. Several research works utilized automatic seed selection using a set of words as initial seed for the dictionary. Turney's [12] and Rice & Zorn [20], built a word of seeds using two (2) human-selected seed words (the word "Poor", "Bagel" as negative and "Excellent", "Love" as positive). In another study, Zagibalov and Carroll [21] also utilized this approach and started with only a single, human-selected seed ("Good"). Syamala and Nalini [22], García-Pablos, Montse and German Rigau [23], Abd-Elhamid, Doaa and Ahmed [24] also utilized the seed based method that employed more than two words as their initial seed. They claimed that the almost unsupervised system produces a better result. This research adopts unsupervised system to create an emotion dictionary based on the initial seeds.

3.5.1 Extraction of Initial Seeds.

This research applied automatic initialization of seed of words for the emotion dictionary based on the dataset. The initial seeds were Happy, Disgust, Fear, Anger, Sad, and Surprise. These seeds were utilized to search synonyms in an online dictionary to populated the emotional lexicon.

3.5.2 Populating Emotion Dictionary

Populating emotion words to the dictionary using the emotions keywords as seeds, an application program was developed to automatically search for and retrieve the synonyms and antonyms of the initial seeds from an online thesaurus dictionary http://thesaurus.altervista.org /thesaurus/v1. After the first iteration, the application retrieved the first synonym word found and repeated the process of searching and retrieving of synonyms and antonyms from the online thesaurus dictionary. The process was repeated until no more new words have been added to the word collection.

3.5.3 Building datasets

The study used 14,517 dataset derived from 1,810 blog comments/replies. Such data were used to identify the emotions of the customers, whether they are satisfied or not with the Internet services provided and performances by Globe, Smart, or Sun.

3.5.4 Data Preprocessing

Before the 14,517 sentences were fed to the automated emotion classifier system for emotion identification and labelling, preprocessing of the sentences was required. Removing stop words (common words that have a little value in the process of identifying sentiment analysis, e.g. "and", "the", etc.) and stemming (words that carry similar meanings, but in different grammatical forms such as "connect", "connects" and "connected" were combined into one word "connect") were also applied in the sentence preprocessing. In this way, the comments can attained a better represented (with stronger correlations) of these terms, and have a faster processing time because dataset was reduced.

3.5.5 Automated Emotion Recognition and Annotation

Emotion identification using the emotion dictionary was focused completely on the emotion words in the blog comment sentence. These words have their own emotional value (angry 1, fear -2, disgust – 3, happy – 4, sad – 5, tender – 6, and surprise 7) in the emotion dictionary. When these words are found in the sentences, the values of the emotion words are typically all added up and the result is an emotional estimation of the blog comment sentence. The identification of emotion was done using a modified PHP application specifically to determine the emotion of the blog comment sentence.

- Given a Blog Comment Sentence S
- Identify all emotional words in S based on the emotion dictionary
- For each emotion words in S,
  - Check if emotion word met is (angry 1, fear -2, disgust – 3, happy – 4, sad – 5, tender – 6, and surprise 7)
  - Compute the score of emotional words.

Figure 2: Pseudo code automatic labeling Code that Identify Emotion of the Sentences

As shown in figure 2, the application counts the number of emotion words, then computed the total score. The application will determine the emotion of the comments by getting the most frequent emotion words found in the comments. Table 1 shows the result of the automatic emotion annotation using emotional dictionary.

Table 1: The distribution of the training data per emotion after automatic anotation using emotional dictionary

Emotions	Total number of datasets per emotion
Disgust	284
Sad	55
Happy	575
Tender	29
Angry	8125
Surprise	32
Fear	307
Total number of Dataset	**9407**

3.6 Building Testing Dataset

3.6.1 Manual Emotiony Identification using Sentence Level Annotations

The same 14,517 datasets used as input in the automated sentiment classifier were also used as a testing dataset for our experiential models. Three (3) annotators were tasked to manually label the emotion of the blog comment sentences. The data were distributed equally into three datasets and each group was given an equal number dataset to label manually. The annotators utilized a customized PHP labeler application to annotate the emotion of each dataset. This application provides emotion keywords in the comments to the annotators to lessen the time of emotion detection/recognition and would have better annotation results. Table 2 shows the distribution of manually annotated emotion comments.

Table 2: Distribution of Manually Labeled Emotion Comments

Emotion	Number of comments
Angry	727
Fear	39
Disgust	41
Happy	83
Sad	15
Tender	11
Disgust	17
Total	**933**

3.7 Training and Testing Performance Measurement Tools

3.7.1 Confusion Matrix

The proposed automated polarity classifier was trained to identify the emotions of unlabeled sentences and to use its own predictions to teach itself to classify unlabeled sentences using emotion word dictionary. Training experiments were conducted to evaluate and compare the classification performance of automated emotion labelled dataset utilizing machine learning NB, KNN and ensemble model. Furthermore, the trained models were tested with their classification accuracy using a manually classified emotion dataset. The classification experimentations were carried out utilizing Rapid Miner and applying 10-fold cross validation. In terms of comparing their performance, the confusion matrix that contains the precision, recall, accuracy and F-measure measurement was employed [25].

3.7.2 Confusion Matrix for Multi-Class Classifier

As the name suggests, it is a multi-class confusion matrix that is utilized to present classification performances of multiple classes. This tool is applicable when there are 2 or more-class confusion matrix, it presents the classification performance of a multi-class classification model. Assuming that our multi-class classification model is one that classifies emotions into the following: Angry, Fear, Disgust, Happy, Sad, Tender and Surprise. Table 3 shows the confusion matrix for this classifier.

Table 3: confusion matrix for this classifier can be visualized as such:

	Predicted						
ACTUAL	Angry	Fear	Disgust	Happy	Sad	Tender	Surprise
	Fear	Ftp	Ftn	Ftn	Ftn	Ftn	Ftn
	Disgust	Dtn	Dtp	Dtn	Dtn	Dtn	Dtn
	Happy	Htn	Htn	Htp	Htn	Htn	Htn
	Sad	Stn	Stn	Stn	Stp	Stn	Stn
	Tender	Ttn	Ttn	Ttn	Ttn	Ttp	Ttn
	Surprise	Stn	Stn	Stn	Stn	Stn	Stp

Note that the values in the diagonal would always be the true positives (TP).

Accuracy:

- The accuracy is the fraction of the entire samples that is predicted correct by the classifier. It is computed utilizing the (1):

$$AC = \frac{sum\ of\ tp}{sum\ (tn + fp + fn + tp)}$$

- The recall is the fraction of positive samples that were correctly predicted by the classifier, as computed utilizing the (2):

$$Recall = \frac{sum\ of\ tp}{sum\ of\ tp + sum\ of\ fp}$$

- The recall is the fraction of negative samples that were correctly predicted by the classifier, as computed utilizing the (3):

$$Precision = \frac{sum\ of\ tp}{sum\ of\ tp + sum\ of\ fn}$$

- The F-Measure is the combination of precision and recall to come up with a single measure. It is computed using the (4):

$$FM = 2\frac{(precision * recall)}{(precision + recall)}$$

The F-measure and accuracy were used as the performance indicators for evaluating the models since the models were trained and tested using unbalanced dataset. Furthermore, both of these classifying indicators have been widely used in previous researches [26],[27].

4. RESULT AND DISCUSSIONS

The emotion dataset were labeled by the proposed automated emotion classifiers using the words of an emotional dictionary. The classification experimentations were carried out utilizing 10-fold cross validation using Rapid Miner. In terms of comparing their performances, confusion matrix was used which contains the precision, recall, F-measure and accuracy measurements.

Classification Performance of Proposed automated emotion classified dataset applying different Learning Machine and ensemble model

Table 4 shows the results of training classification of the proposed Proposed Automatic Emotion Classifiers Dataset Utilizing Different Learning Machine and Applying Ensemble Models. In view of precision, recall and F-measure, the angry emotion obtained the highest among other emotions.
Naïve Bayes learning machine obtained the highest precision of 94.64% and in the case of recall boosting Naïve Bayes got the highest Recall of 82.95% under angry emotion. In terms of F-measure and accuracy, boosting Naïve Bayes achieved a f-measure of 82.95% and an accuracy of 75% also under angry emotion. Table 4 also shown that applying KNN and KNN ensembles got the lowest in all measured areas.

Table 4: Training Classification Results of the Proposed Automatic Emotion Classifiers Dataset Utilizing Different Learning Machine and Applying Ensemble Models

Emotions	Naïve Bayes(NB)			KNN			Bagging+NB			Bagging+KNN			Boosting NB			Boosting Knn		
	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure
disgust	11.33%	34.15%	17.01%	5.69%	39.44%	9.95%	11.36%	34.15%	17.05%	5.31%	44.01%	9.48%	13.08%	24.65%	17.09%	4.72%	44.13%	8.53%
sad	9.17%	40.00%	14.92%	17.95%	25.45%	21.05%	9.09%	40.00%	14.81%	21.13%	27.27%	23.81%	9.21%	40.00%	14.97%	24.07%	31.33%	27.22%
happy	14.97%	28.70%	19.68%	20.40%	30.26%	24.37%	14.87%	28.52%	19.55%	21.76%	33.04%	26.24%	18.12%	18.43%	18.27%	21.71%	26.22%	23.75%
tender	13.25%	37.93%	19.64%	22.86%	27.59%	25.00%	13.25%	37.93%	19.64%	20.59%	24.14%	22.22%	13.25%	37.93%	19.64%	12.28%	16.28%	14.00%
angry	94.64%	72.62%	82.18%	90.88%	70.76%	79.57%	94.61%	72.63%	82.18%	91.24%	66.67%	77.04%	92.09%	82.95%	87.28%	90.55%	64.21%	75.14%
surprise	8.57%	46.88%	14.49%	6.67%	3.12%	4.25%	8.57%	46.88%	14.49%	7.69%	3.12%	4.44%	8.57%	46.88%	14.49%	7.14%	6.25%	6.67%
fear	15.48%	36.16%	21.68%	11.45%	4.89%	6.85%	15.57%	36.16%	21.77%	12.70%	5.21%	7.39%	18.05%	27.69%	21.85%	17.80%	9.11%	12.05%
Average	23.92%	42.35%	30.57%	25.13%	28.79%	26.83%	23.90%	42.32%	30.55%	25.77%	29.07%	27.32%	24.62%	39.79%	30.42%	25.47%	28.22%	26.77%
Accuracy	67%			65%			67%			61%			75%			59%		

The result reveals that the volume or the amount of training dataset is an important factor in the emotional detection and recognition performance of the proposed automatic classifier in all measured areas. Angry emotion has the highest number of databases followed by fear and happiness.

Performance of the different machine learning and ensemble models on the performance of the Proposed Automated Emotion dataset.

To test the performance of the proposed automated emotion classifier is presented in table 5. The following experimentation was conducted to assess the effect of learning machine and applying ensemble model in the performance of automated classified sentences dataset against the manually annotated comments (ground truth) as testing dataset. Test results in table 2 indicate a positive results specially in the case of the ensemble boosting model. Applying ensemble model both to NB and KNN obtained more that 70 % in terms of accuracy. The results also reveal that angry emotions obtained the highest value in all measured areas. In addition, the table also reveals that the proposed automated classified achieved a better score in angry emotion when test experimented test data set. In fact, the improvement is almost 5 to more 10%.

Table 5: Testing Classification Results of the Proposed Automatic Emotion Classifiers Dataset Utilizing Different Learning Machine and Applying Ensemble Models

Emotions	Naïve Bayes(NB)			KNN			Bagging+NB			Bagging+KNN			Boosting NB			Boosting Knn		
	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure	Precision	Recall	F-mesaure
disgust	0.00%	80.47%	0.00%	0.00%	60.94%	0.00%	0.00%	80.47%	0.00%	0.00%	57.08%	0.00%	0.00%	89.13%	0.00%	0.00%	95.19%	0.00%
sad	8.82%	0.00%	0.00%	33.33%	0.00%	0.00%	8.82%	0.00%	0.00%	16.67%	0.00%	0.00%	8.82%	0.00%	0.00%	33.33%	0.00%	0.00%
happy	23.53%	11.76%	15.69%	29.31%	0.00%	0.00%	23.53%	11.76%	15.69%	29.82%	0.00%	0.00%	24.44%	11.76%	15.88%	29.31%	0.00%	0.00%
tender	0.00%	24.10%	0.00%	0.00%	20.48%	0.00%	0.00%	24.10%	0.00%	0.00%	20.48%	0.00%	0.00%	13.25%	0.00%	0.00%	20.48%	0.00%
angry	85.78%	20.00%	32.44%	82.50%	13.33%	22.96%	85.78%	20.00%	32.44%	82.02%	6.67%	12.33%	83.61%	20.00%	32.28%	80.56%	13.33%	22.88%
surprise	0.00%	20.51%	0.00%	0.00%	15.38%	0.00%	0.00%	20.51%	0.00%	0.00%	15.38%	0.00%	0.00%	15.38%	0.00%	0.00%	15.38%	0.00%
fear	22.86%	29.27%	25.67%	66.67%	46.34%	54.68%	22.86%	29.27%	25.67%	66.67%	51.22%	57.93%	33.33%	21.95%	26.47%	66.67%	0.00%	0.00%
Average	20.14%	26.59%	22.92%	30.26%	22.35%	25.71%	20.14%	26.59%	22.92%	27.88%	21.55%	24.31%	21.46%	24.50%	22.88%	29.98%	20.63%	24.44%
Accuracy	68%			52%			68%			49%			73%			76%		

The result of the accuracy test suggests that the proposed automatic sentiment emotion classifier does not perform well. The following are contributors in the lower performance:

1. There are mistakes in the translation of sentences or few Filipino words have no equal terms in English that may cause to change the emotion of the sentence. e.g. (Filipino) “Globe Tattoo has BAD service internet mga hrs langang nagagamit mo.” (English Translation) – “Globe Tattoo internet service has BAD 2 hrs only usable to.”
2. Majority of datasets for training and testing that were automatically label were labeled as angry, fear and happy emotions.
3. There were comments that were labeled angry, however, these comments were also labelled fear and disgust.
4. The ambiguity in the emotion word in the sense that emotion word can have different synonym.

5. CONCLUSION

In this study, a new approach for automated classifying of emotions from textual data was based on a sentence level utilizing language translation machine, an application that utilized learning machines and applying ensemble models. The proposed automatic emotion classifier performs well in classifying angry comments both in training and testing evaluation periods. Furthermore, the proposed emotion classifier produces a result of 75% accuracy under ensemble naïve bayes in the classification of sentence emotion during training period. Although during the actual testing period of the test data set, the proposed system was able to correctly classify 76% emotions of the sentences. There are several factors that are contributory to low performance, such as language translation tools, unbalanced dataset and comments that were labeled angry, however these comments were also labelled fear and disgust. For future research, it is suggested to utilized more other automated methods emotion classification and techniques like other online dictionary (Bhing and Mosses), better language translation machine and Part-of-Speech (POS) tagging to improve the performance of our proposed automated emotions classifier. Furthermore, experimenting using balance emotion dataset and try different set features to determined if it has an effect on the classification performance of the proposed method.

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