Volume: 14 Issue: 03 Pages: 5429-5435(2022) ISSN: 0975-0290

Emotion Detection from Multilingual Text and Multi-Emotional Sentence using Difference NLP Feature Extraction Technique and ML Classifier

Shahidul Islam Khan
Dept. of Computer Science and Engineering, International Islamic University Chittagong, Chittagong, Bangladesh
Email: nayeemkh@gmail.com
FaisalBinAziz
Dept. of Computer Science and Engineering, International Islamic University Chittagong, Chittagong, Bangladesh
Email: faisalbinaziz007@gmail.com
MdMisbah Uddin
Dept. of Computer Science and Engineering, International Islamic University Chittagong, Chittagong, Bangladesh
Email: misbah.6180@gmail.com

ABSTRACT

Machines can read, comprehend, and extrapolate meaning from human languages, thanks to natural language processing.In this paper, we have detected emotion from multilingual text and multi-emotional sentences.For our research, we have collected a dataset containing around 7000 tweets on 4 emotions (Anger, Fear, Joy, and Sadness). After pre-processing our data, we used 2 NLP feature extraction models and trained those with the help of 4 different Machine Learning classifiers. We have also developed an algorithm for detecting exact emotions from multi-emotional sentences. Also, we compared our result with a research paper using the same dataset (ISEAR). And found out our model provides relatively better resultsthan that model. We also tried to determine emotion from the Bangla text. Although there is not much data regarding emotion in Bengali. We managed to get around 600 data on Bangla.

Keywords - **Emotion, Machine Learning, Multi-Emotional Sentence, Multi-Lingual, NLP, Bangla**

Date of Submission: Sep 29, 2022 Date of Acceptance: Nov 16, 2022

1. INTRODUCTION

Emotion detection is the process of identifying human expression. This can be done through verbal expression, facial expression, or text. Improving computational methodologies helped us to complete this task. However, Emotion detection from textual data is not done much. It could be important research since most people use the internet and social media. Implementing this system would certainly allow people to understand their emotional state based on this. Also, there is very little research on detecting emotion from Bangla text[1]-[7].

In this paper, we have prepared a model which can successfully detect emotion from textual data. There is already some work regarding this topic. But in this research, we have used a feature extraction model (Count Vectorizer) which was never used for detecting emotion. Also, our model can detect correct emotions from a complex sentence that contains multiple emotional words. For our work, we have used a publicly available dataset (WASSA-2017) [8]. We've applied 2 feature extraction models and then trained those using 4 different Machine Learning classifiers. Finally, we calculated which feature extraction model's classifier gave the best accuracy and based on that tested some random examples. We have compared it with a research paper using the ISEAR dataset [9] which was used on that paper. And we've found relatively better results with our model. Also, we've compared our accuracy in detecting emotion from Bangla text with an existing work [10]. We've managed around 600 data and tried to determine emotions from them.

2. LITERATURE REVIEW

The task of emotion recognition falls under Affective Computing. There are various sorts of computational techniques used in emotional text analysis tasks.These are keyword-based methods, lexicon-based methods, and learning-based methods.

2.1 Keyword-based Approach

Keyword based method is the most straightforward approach. Finding patterns and matching them with terms associated with emotions is the concept. The emotion of the particular sentence is whatever emotion belongs to the term. The usual method for doing this is to use a POS tagger to tag the words in the phrase before extracting the nouns, verbs, adjectives, and adverbs. M. Chunling et al. [11] proposed a methodology to detect emotion in a chatting system. They use Word Net Affect DB. WordNet 1.6. The knowledge base includes emotional weight and an Open mind common senseas features. An online chat experiment in a lab to validate reporting techniques for sad, happy emotions done by J T Hancock et al.[12]

This work is done based on social information processing model and two emotions (sadness and happiness).This model works for Linguistic inquiry and word count program LIWC features. H. Li et al. [13] try to accurately detect emotion by incorporating personality factors into the chatting system.
They use the OCC model, and Five-Factor Model (FMM) and consider OMCS and Concept Net as features. Binali Het al. tried to detect emotion using a gazetteer list in conjunction with data. They use a gazetteer [14].

2.2. Lexicon-based Method

This method uses a Lexicon (a knowledge base of information with text that is annotated with its emotional valence). While the procedure of recognizing emotions in this instance is identical to that in the previous way, an emotion lexicon is employed in place of an emotional keyword list.The quality and coverage of the selected emotion lexicon determine the capabilities of lexicon-based systems [15] [16].Some of the frequently used emotion lexicons are EmoSenticNet (ESN) and the National Research Council of Canada (NRCC) [17]. Lexical-based methods perform poorly when there are no emotional terms present in the text [18]. Additionally, it performed poorly when processing text with more intricate linguistic structures.

2.3 Learning-basedMethod

Statistical algorithms are used by machine learning techniques to analyze linguistic information. To train and test the classifier for the supervised technique, an annotated emotion dataset is employed. an effort made by Qadir et al. [19] to learn lists of emotion hashtags using just a bootstrapping framework. They trained emotion classifiers to recognize and score candidate emotion hashtags, starting with a modest sample size of seed hashtags. Five classes of emotions 'hashtags' for emotion were gathered e.g. affection, anger, anxiety, joy, and sadness.

A text mining program that analyzestweets to identify Ekman 6 basic emotions was developed by Liza Wikarsa and SherlyNoviantiThahir based on the Naïve Bayes classifier [20]. Li Yu et al [21] carried out the job of multi-source emotion labeling for internet news. To create a new classifier that is capable of making more accurate predictions, they presented a two-layer logistic regression classification model. Their work served as the foundation for multi-source tagging. Using data that is automatically labeled. Purver et al.'s[22] attempt to train a supervised classifier for emotion identification from tweets. They made use of a collection of tweets that were all tagged with an emotion or a hashtag that belonged to one of the six emotion classes. Some emotions responded better to their approach than others.

Each emotion's seed word is used as the starting point for an unsupervised classifier, which then compares it to the parent phrase. In this manner, sentences are categorized according to the associated emotion. This was afterward utilized to train the classifier to label test data. Although the unsupervised method is more widely applicable, supervised classification typically produces superior accuracy.An unsupervised concept based on the dimensional emotionmodel proposed by Calvo et.al [23]. They created tree-dimensional vectors (valence, arousal, and dominance) for each page using the normative database ANEW [24].Another unsupervised learning method was proposed by researcher Agrawal and an [25]. Their research uses a methodology that is context-based and unsupervised, and it is not dependent on any current affect lexicon. Beyond Ekman's fundamental emotion concept, their classification system is adaptable. the use of a dimensional emotion model in yet another unsupervised approach. They assessed three-dimensionality methods for categorical approaches using Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA), and Nonnegative Matrix Factorization (NMF). Their study yields result for the NMF and dimensional models.

3.METHODOLOGY

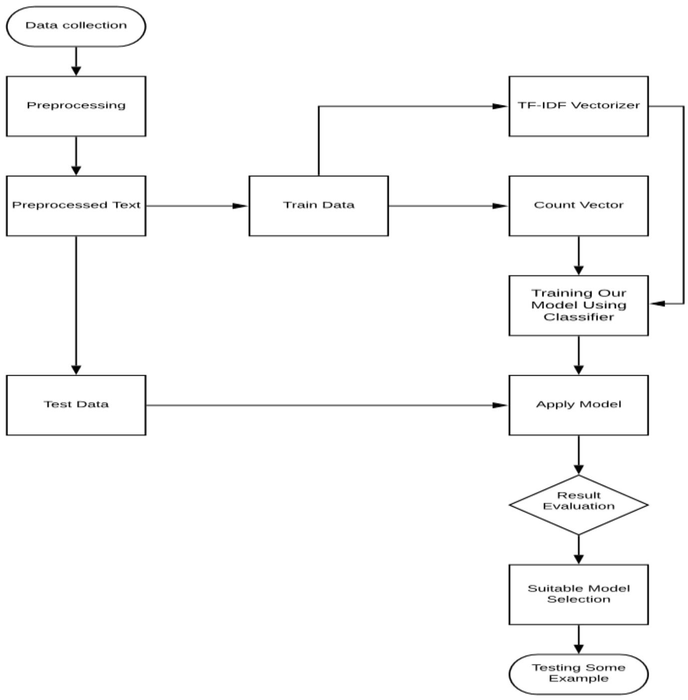

Figure1.Block diagram

After collecting the dataset, we need to pre-process the dataset. Then, with pre-processed text, we divide it into 2-part training and testing where the training part contains 90% data and the testing contains the rest 10%. Then, we use our 2 NLP feature extraction models separately on the training dataset and apply an ML classifier to them. When this part is done, we tested our model on that 10% data that we kept for testing. After that, we'll surely know, which model is better based on its accuracy, precision, recall, and f1-score.Then, we can identify the best feature extraction model along witht h e ML classifier. We'll test our model with some random sentences to see if our model can correctly detect emotion.

With the help of this model, we compared it with another research paper using an identical dataset to check whether our model provides higher accuracy than the existing work. We've also tried to determine emotion from Bangla text although it's difficult due to the availability of data. In total, using our model we were capable of detecting emotion from both Bangla and English text.

3.1Dataset

For the Dataset we've used publicly available WASSA- 2017 [8]. This dataset was used to detect emotion using WEKA software. This Dataset contains around 7000 data which contain 4 different emotions (Anger, Fear, Joy, and Sadness). In the data, there are 7103 rows and each row consists of 4 columns (ID, author, sentiment, content). ID is the tweet number, the author represents which user tweeted that particular sentence, sentiment represents the emotional state, and contents contain the actual tweets. We've removed the 2nd row (author) from the dataset since it has no use in our model. Below we've provided a partial dataset picture.

3.2 Steps for Detecting Exact Emotion from Multi-emotional Sentence

Step 1: Separate sentence from a document based on full stop. E.g. "I thought this was a comedy film and preparing to be in a jolly mind. But turned outthis is a horror film. It is really terrifying." Here, the example is the documentand it contains 3 sentences. We're going to separate sentences based on full-stop.

Step 2: Sentences which are not in present tense, drop those. Identify based on past form of verbs such as: was, were, had.

Step 3: if there are multiple sentences containing present tense related verb, count emotional keyword. Such as: happy, terrify, anxious.

Step 4: show output based on emotional keyword. Whichever keywords counted most, close to that emotion show the output. For my given example, there were 'horror' and 'terrify'. Both keywords imply the emotion fear.

Fig2.Algorithmic step for emotion detection from a multi-emotional sentence.

There are 12 words total in 3 sentences and each sentence contains 6 words, 4 words, and 2 words respectively.

3.3TF-IDF Vectorizer

TF-IDF stands for 'Term Frequency—Inverse Document Frequency' which is, a numerical statistic that is intended to reflect how important a word is to a document. The tf–idf is the product of two statistics, *term frequency,*and *inverse document frequency*.

Term frequency (TF) is how often a word appears in a document, divided by how many words there are.

$$\text{tf(t,d)}= \frac{\textit{number of occurences of term in document}}{\textit{total number of all words in document}}$$

Example: Let us consider a sentence, "**I thought this was a comedy film and preparing to be in a jolly mind. But turned out this was a horror film. It is really terrifying**." After pre-processing the document, we get,

thought	comedy	film	prepare	jolly	mind
out	horror	film	really	terrify	turn

Now, to calculate TF for every word we have to divide each word's total appearance by the total words in the document.

CALCULATING TERM FREQUENCY FOR EACH WORD,

TABLE1Calculating Term Frequency

thought=$\frac{1}{12}$ =0.08
comedy=$\frac{1}{12}$ =0.08
film=$\frac{2}{12}$ =0.17
prepare=$\frac{1}{12}$ =0.08
jolly=$\frac{1}{12}$=0.08
mind=$\frac{1}{12}$=0.08
turn=$\frac{1}{12}$=0.08
out=$\frac{1}{12}$= 0.08
horror=$\frac{1}{12}$=0.08
film=$\frac{2}{12}$ =0.17
really=$\frac{1}{12}$=0.08
terrify=$\frac{1}{12}$=0.08

TF for 1st sentence:

$$\frac{0.08+0.08+0.17+0.08+0.08+0.08}{6} = 0.095$$

TF for 2ndsentence:

$$\frac{0.08+0.08+0.08+0.17}{4} = 0.1025$$

This sentence has the highest TF value for this document.

Volume: 14 Issue: 03 Pages: 5429-5435(2022) ISSN: 0975-0290

TF for 3rd sentence:

$$\frac{0.08 + 0.08}{2} = 0.08$$

Now, The **Inverse Document Frequency (IDF)** measures the importance of the word, by comparing it with its commonality of occurrence in other documents. IDF considersthe number of sentences in the whole document rather than frequently used words.

We can calculate ID Fusing the formula below:

$$log_{10}\frac{How\ many\ documents\ there\ are\ (sentences)}{How\ many\ times\ that\ word\ appears\ in\ all\ document}$$

Now, calculating the IDF value for each word and sentence,

TABLE 2 Calculation Inverse Document Frequency

thought=$\log(\frac{3}{1})$=0.477
comedy=$\log(\frac{3}{1})$=0.477
film= $\log(\frac{3}{2})$ =0.176
prepare=$\log(\frac{3}{1})$ =0.477
jolly= $\log(\frac{3}{1})$=0.477
mind=$\log(\frac{3}{1})$=0.477
turn=$\log(\frac{3}{1})$=0.477
out=$\log(\frac{3}{1})$= 0.477
horror=$\log(\frac{3}{1})$=0.477
film= $\log(\frac{3}{2})$ =0.176
really= $\log(\frac{3}{1})$ =0.477
terrify= $\log(\frac{3}{1})$ =0.477

As a result, the 3rd sentence has the maximum TF-IDF score through out the entire text.

TF-IDF for 1st sentence,

$$\frac{0.038 + 0.038 + 0.03 + 0.038 + 0.038 + 0.038}{6} = 0.037$$

TF-IDF for 2nd sentence,

$$\frac{0.038 + 0.038 + 0.038 + 0.03}{4} = 0.036$$

TF-IDF for 3rd sentence,

$$\frac{0.038 + 0.038}{2} = 0.038$$

3.4Count Vectorizer

Here, a word's weight is determined by counting how frequently it appears in the document. We will increase the number of words we have already noted each time we come across one.

Example: We'll use the same example we used to calculate TF-IDF value which was "**I thought this was a comedy film and preparing to be in a jolly mind**. **But turned out this was a horror film**. **It is terrifying**."

After pre-processing we get,

thought	comedy	film	prepare	jolly	
mind	turn	out	horror	film	really

After completing n-gram and word count:

Table 3. N-gram And Word Count

WORD	COUNT
Thought	1
Comedy	1
Fil m	1
Prepare	1
Joll y	1
Min d	1
Turnout	1
Horror	1
Fil m	2
Rea lly	1
terri fy	2

Since the most counted word is related to the emotion 'Fear', the sentence implies Fear emotion.

4. RESULTS AND DISCUSSIONS

Table 4.English Text usingTf_Idf

	Accuracy	Precision	Recall	F-score
Naïve Bayes	28.69	29.97	28.69	29.2
LSVM	27.71	30.62	27.71	28.92
Logistic Regression	27.57	30.86	27.57	28.89
Random Forest	26.44	28.65	26.44	27.26

Table 6. Bangla Text usingTf- Idf Vectorizer

	Accuracy	Precision	Recall	F-Score
Logistic Regression	74	62	72	65
LSVM	77	79	77	73
Random Forest	74	60	62	65
Naïve Bayes	74	62	74	65

Table8. Comparison of English Text

Method	Accuracy(%)
ProposedModel	**87**
[9]	**70**

4.1. Result Comparison

We've compared our result with existing work using the ISEAR dataset.

Testing our model with example:'*Anger=0,Fear=1,Joy =2,Sadness=3*'

Table 5. English Text using Count Vectorizer

	Accuracy	Precision	Recall	F-score
Naïve Bayes	83.54	83.49	83.54	83.48
LSVM	87.48	87.8	87.48	87.54
LogisticRegression	86.5	87	86.5	86.6
Random Forest	85.09	85.999	85.09	85.14

Table 7. Bangla Text using Count Vectorizer

	Accuracy	Precision	Recall	F-score
NaïveBayes	83.54	83.49	83.54	83.48
LSVM	87.48	87.8	87.48	87.54
Logistic Regression	86.5	87	86.5	86.6
Random Forest	85.09	85.999	85.09	85.14

Table9. Comparison of Bangla Text

Method	Accuracy (%)
ProposedModel	**74.3**
[10]	**65.97**

We've compared our results using a similar dataset which is publicly available.

Table 10.Test Sentence with Output

Sentence	Output
After hearing Is tood first in the exam, I became so happy but found out that was a prank. It's so depressing.	3
Please, don't do that. You may find joy in that but its actually dangerous	1
This was supposed to be my best birthday but his presence made it worst. I just cant stand his sight	0
I was up set earlier but all on a sudden my father gave me a nice present. I am sooo happy	2
I thought this was a comedy film and preparing to be in a jolly mind. But turned out this a horror film. It is really terrifying.	1
I feel very sad even though I got the scholarship which was amazing	3
I am pretty angry at him. They thought it was funny but it wasn't	0
That was the most intense viva exam I ever had. But I'm happy that I passed the exam successfully.	2
I feel so sad about the incidence. Who could've thought this wonderful and charming day is going to end like this.	3

5. CONCLUSIONS

Emotion detection is an important task since the world is becoming digital and everything is now done by automation. Implementing this system in EHR (Electronic Health Record) may play an important role in improving the mental health care system.

We have tried to add some novelty to this research by implementing the Count Vectorizer feature extraction model which wasn't used practically in emotion detection before. Also, we were successful to detect complex emotional sentence which has multiple emotional keywords. In our research, LSVM Machine Learning gave the best accuracy. In computer science, natural language processing is a significant field.It is becoming an important thing fast in the modern world. Every time we search for something on the internet, we use NLP. As for Emotion detection it is already used on Twitter to search for depression or SOS types of posts. Also, there isasystem that can predict any terrorist threat or tweets which contain a harmful message. And all of this is happening because of NLP.

Therefore, there can be plenty of research work in this regard which can play an important role. Our proposed model can be implemented ON EHR (Electronic Health Record) for detecting patients' mental health improvement which is a crucial thing. Other than that, NLP can be usedfor interpreting human language more easily, more efficiently.

6. FUTURE WORK

We can determine depressive emotions for upcoming tasks.

Additionally, we can increase the data to get higher accuracy. I've worked only with Twitter data. In the future, we can collect more data to determine emotion. We can always try to increase the accuracy of the model or try determining accuracy via alternative classifiers to measure accuracy. EHR (Electronic Health Record) which storesdiscussions between patients and doctorscan be used to implement work on emotion recognition. And by implementing this system, a doctor would know their patient's emotional improvement over time.

REFERENCE

[1] Nasr, M., Karam, A., Atef, M., Boles, K., Samir, K., &Raouf, M. (2020). Natural Language Processing: Text Categorization and Classifications. International Journal of Advanced Networking and Applications, 12(2), 4542-4548.

[2] Mubassıra, M., & Das, A. K. (2021). Implementation of Recurrent Neural Network with Language Model for Automatic Articulation Identification System in Bangla. International Journal of Advanced Networking and Applications, 12(6), 4800-4808.

[3] Khan, S. I., &Hoque, A. S. M. L. (2016, December). Similarity analysis of patients' data: Bangladesh perspective. In 2016 International Conference on Medical Engineering, Health Informatics and Technology (MediTec) (pp. 1-5). IEEE.

[4] Khan, A. B. A., Ghazanfar, M. S., & Khan, S. I. (2017, December). Application of phonetic encoding for analyzing similarity of patient's data: Bangladesh perspective. In 2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC) (pp. 664-667). IEEE.

[5] Rajarajeshwari, K., &Radhamani, G. (2019). A Naïve Bayes Model using Semi-Supervised Parameters for Enhancing the Performance of Text Analytics. International Journal of Advanced Networking and Applications, 10(6), 4083-4089.

[6] Chowdhury, A. N., Guha, S., Amin, N., & Khan, S. I. (2022, February). Exploiting Diverse Contextual Features through Transformers for Detecting Informative Tweets. In 2022 International Conference on Innovations in Science, Engineering, and Technology (ICISET) (pp. 350-355). IEEE.

[7] Khan, S. I., Hasan, M., Hossain, M. I., &Hoque, A. S. M. (2019). nameGist: a novel phonetic algorithm with bilingual support. International journal of speech technology, 22(4), 1135-1148.

[8] S. Mohammad, F. Bravo-Marquez, "WASSA- 2017 Shared Task on Emotion Intensity" In *Proceedings of the 2016 IEEE/WIC/ACM International Conference on Web Intelligence*. Omaha, NE, USA, pages 536–539.

[9] M. Hasan, T. Ahsan '*Emotion Detection from Text Using Skip-thought Vectors*' 2nd Int. Conf. on Innovations in Science, Engineering, and Technology (ICISET), 2018.

[10]N.Ertiza, M.Yunus '*Detecting Multilabel Sentiment and Emotions from Bangla YouTube Comments*' international Conference on Bangla Speech and Language Processing (ICBSLP), 2018

[11]M. Chunling, H. Prendinger, and M. Ishizuka, "Emotion Estimation and Reasoning Based on Affective Textual Interaction " in *Affective Computing and Intelligent Interaction*. vol. 3784/2005 (Springer Berlin / Heidelberg, 2005), pp. 622-628.

[12]J. T. Hancock, C. Landrigan, and C. Silver, "Expressing emotion in text-basedcommunication," in *Proceedings of the SIGCHI conference on Human factors in computing systems*, 2007, pp. 929 – 932

[13]H. Li, N. Pang, and S. Guo, "Research on Textual Emotion Recognition Incorporating Personality Factor," in International Conference on Robotics and Biomimetics, Sanya, China, 2007.

[14]H. Binali, C Wu, Potdar V (2010) Computational approaches for emotion detection in text. In: IEEE international conference on digital ecosystems and technologies (DEST), pp 172–177

[15]D. Ghazi, D. Inkpen and S. Szpakowicz, "Prior versus Contextual Emotion of a Word in a Sentence," in *Proceedings of the 3rd Workshop in Computational Approaches to Subjectivity and Sentiment Analysis*, 2012.

[16]M. Taboada, J. Brooke, M. Tofiloski, K. VollandM.Stede,"Lexicon based methods for sentiment analysis," Computational linguistics, vol. 37, pp. 267-307, 2011

[17]Abak FS, Evrim, V HONET-ICT. IEEE, pp 154–158, 2016

[18]A. Koumpouri, I. Mporas, and V. Megalooikonomou, "Evaluation of Four Approaches for Sentiment Analysis on Movie Reviews: The Kaggle Competition, "*in Proceedings of the 16th International Conference on Engineering Applications of Neural Networks (INNS)*, 2015.

[19]Qadir, A., Riloff, E.: Bootstrapped learning of emotionhashtags#hashtags4you.WASSA 2013, 2 (2013)

[20]L. Wikarsa, S. NoviantiThahir, "A text mining application of Emotion Classifications of Twitters Users using NaveBayes Method", IEEE 2015.

[21]Li Yu, Zhifan Yang, Peng Nie, Xue Zhao, Ying Zhang,"Multi-Source Emotion Tagging for Online News", 12th Web Information System and Application Conference 2015.

[22]Purver, M., Battersby, S.: Experimenting with distant supervision for emotion classification. In: *Proceedings of the 13th EACL, Association for Computational Linguistics*, pp. 482–491 (2012)

[23]Calvo, R.A., Mac Kim, S.: Emotions in text: dimensional and categorical models. Computat. Intell. 29(3), 527–543 (2013)

[24]Bradley, M.M., Lang, P.J.: Affective norms for English words (anew): Instruction manual and affective ratings. In: Technical Report Citeseer(1999)

[25]Agrawal, A., An, A: Unsupervised emotion detection from text using semantic and syntactic relations. In: *Proceedings of The 2012 IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology-Volume01*,pp. 346–353.IEEE Computer Society (2012).