Methods for Text-Based Emotion Recognition Using Machine Learning and Deep Learning: A Comparison

[1] K. Rajkumar, [2] A. Sushmitha,

[1]Assistant Professor, Megha Institute of Engineering & Technology for Women, Ghatkesar.
[2] MCA Student, Megha Institute of Engineering & Technology for Women, Ghatkesar.

Abstract:

Every day, there are a lot of comments because of social media platforms. In general, the remarks are kind and well-meaning. However, comments can also express emotions like fear, despair, or rage. Negative remarks might be discouraging since they show that you are incapable of achieving your objectives. Predicting the different sentiments of the comments is our task. Decision Trees, Random Forests, SVMs, Logistic Regression employing tf-idf and count vectors based models, and deep learning models are examples of machine learning techniques employed in this work. With an accuracy of 92%, the deep learning model outperformed all other machine learning models.

Keywords:

Machine learning, Deep learning, Emotion Detection, and Comparative Analysis

I. INTRODUCTION

Understanding and managing one's own and other people's emotional states is a key component of emotional intelligence. Text emotion detection is a content-based classification issue that combines techniques from machine learning and natural language processing [1]. Being emotionally intelligent means being able to read and manage your own and other people's emotions as well as the complexities of social relationships. To have emotional intelligence is to know that your feelings influence your choices and the results you get. One way to look at self-management is as the capacity to consciously regulate one's own feelings and behaviors, particularly when faced with difficult circumstances. "Empathy" refers to the ability to understand and share another person's feelings, while "relationship management" refers to the ability to build and sustain positive relationships with others. Both are components of social awareness. Machine learning is a subfield of AI that teaches computers new skills, such how to use algorithms and statistical models to make predictions and judgments completely autonomously. A primary objective of machine learning researchers is the development of models and algorithms capable of autonomously detecting emotions in a variety of input formats, such as text, audio, and facial expressions. An curiosity in learning about the many uses of emotion recognition and machine learning drives this effort. Deep learning, supervised learning, and unsupervised learning are some of the machine learning approaches used to detect and classify emotions in various datasets. By training on a dataset where each sample already has such labels assigned, an algorithm may be trained to recognize certain emotions in supervised learning. Predictions may be derived from the program's exploration of previously unseen patterns in the data. The system acquires pattern recognition capabilities using unsupervised learning, a technique that does not use predefined labels. For the purpose of making predictions, deep learning makes use of neural networks to learn complex representations of data. There is a vast array of potential fields that might benefit from emotion detection algorithms powered by machine learning, including advertising, journalism, healthcare, and academics. In the future, medical emotion recognition systems could aid in the diagnosis of stress, anxiety, depression, and other mental health issues by studying patterns of facial expressions and speech. Emotion recognition might help marketers sift through social media data and customer reviews for insights about consumer tastes and habits. Our current methods of instruction would undergo a sea shift if computers could decipher students' emotional cues from their facial expressions and speech patterns. Potentially enhanced VR and gaming experiences could result from the capacity to track user emotions in real-time using entertainment emotion detection. Using machine learning to identify emotions has several promising advantages but also some significant disadvantages. Lack of large and diverse datasets is one of the main issues in training ML models. The fact that emotions are subjective adds another layer of complexity, since various individuals have different ways of expressing the same sensation. Cultural variations, individual traits, and environmental variables are only a few of the many potential determinants of emotion detecting system efficacy [2].

II. LITERATURE REVIEW

One characteristic of emotionally intelligent individuals is their ability to understand and share the feelings of others around them. Studies have shown that those with higher levels of emotional intelligence also tend to be more empathetic [3]. This is fundamental to text-based communication because it allows us to grasp textual messages and emotional cues. The term "emotional labor" describes the work that people put in to try to rein in their own emotions when they are under pressure from others [4]. Higher EQs are associated with happier and more productive workers who are better able to manage emotional labor [5, 6]. Studies have also indicated that EQ improves the efficacy of dispute resolution via textual communication. Those with higher EQ are more likely to use cooperative dispute resolution processes, which are advantageous for everyone concerned, according to the study [7]. One of the most popular machine learning approaches for detecting tone of voice in text is supervised learning. Before training the model with a pre-classified dataset, this approach entails assigning an emotion label to each text sample. For text emotion recognition, several Deep Learning models such as CNNs and RNNs have been used, along with Naive Bayes and Support Vector Machines (SVMs) [8][9].

TABLE I. LITERATURE REVIEWFINDINGS

Reference No.	Paper Year	Remarks
[3]	2008	Research has shown that individuals with higher levels of emotional intelligence tend to have **greater empathy**.
[5,6]	2008, 2000	Individuals with higher emotional **intelligence are better able to manage emotional labor, leading to improved job performance and job satisfaction.**
[7]	2006	Research has found that individuals **with higher levels of emotional intelligence are more likely to use collaborative conflict resolution strategies, leading to better outcomes for all parties involved.**
[8,9]	2018, 2020	Various machine learning models, including Support Vector Machines (SVM), Naive Bayes, and Deep Learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have been used for emotion detection on text.
[2, 11]	2022, 2021	Explored the impact of different feature extraction techniques such as Bag of Words, Word Embedding, and Contextualized Word Embedding on emotion detection accuracy.

III. METHODOLOGY

Collection of Datasets We obtained the dataset using Kaggle. This dataset contains English phrases that convey different moods. The phrases are divided into six categories. Among them are the following emotions: joy, sorrow, shock, love, anger, and fear. Fifteen thousand training instances, two thousand validation examples, and two thousand test examples make up this dataset. Figure 1 is a bar graph displaying the number of terms in our sample with various labels. Emotion detection accuracy is substantially improved by integrating text, auditory, and visual inputs, according to many research [10]. Bag of Words, Word Embeddings, and Contextualized Word Embeddings are just a few of the feature extraction approaches that have been investigated for their impact on emotion recognition accuracy [11]. Tabulated below are the key points from the literature study. Numerous fields, including medicine, social media analysis, and advertising, stand to benefit from more research into the application of machine learning to the problem of text emotion recognition. We need further research on the implications of different machine learning and feature extraction methods on the accuracy of emotion identification.

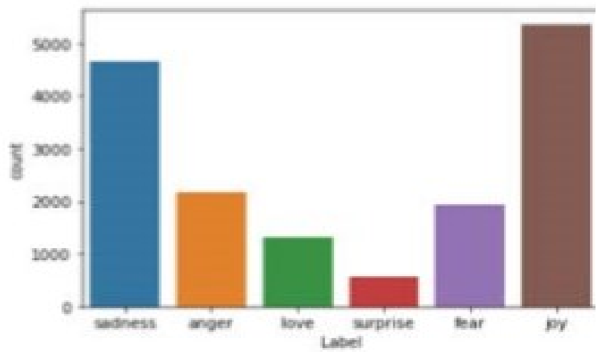

Fig. 1. Count of various Emotions

You can see the dataset snapshot and labels utilized for our testing in Figure 2.

	Text	Label
0	i didnt feel humiliated	sadness
1	i can go from feeling so hopeless to so damned...	sadness
2	im grabbing a minute to post i feel greedy wrong	anger
3	i am ever feeling nostalgic about the fireplac...	love
4	i am feeling grouchy	anger

Fig. 2. Snapshot of the Dataset

Preprocessing Data The technique by which we alter the raw data to improve our model's performance is known as data preprocessing. Here, we will convert our data to lower case and eliminate all punctuation, stop words, and white spaces. Lemmatization will then be used to change the word into its lemma, or base form. Model construction and assessment LSTM, multinomial Naive Bayes, Random Forest, SVM, and ANN are just a few of the machine learning and deep learning models that we will construct in this part using a variety of embedding techniques. They will then be assessed using a variety of metrics, including f1-score, accuracy, recall, and precision. The Naïve Bayes Classifier's confusion matrix is displayed in Figure 3.

Fig. 3. Confusion Matrix of Naive Bayes Classifier

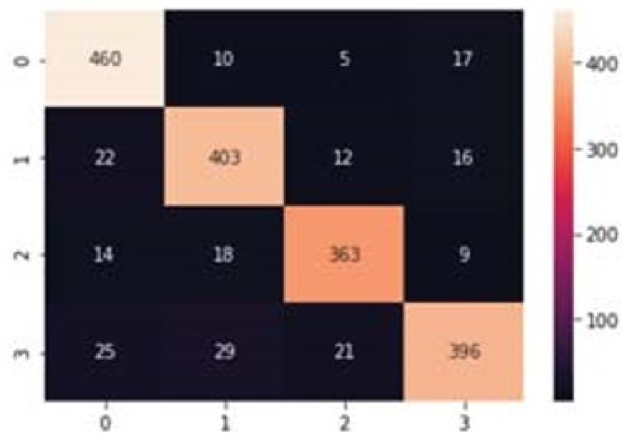

Fig. 4. Confusion Matrix of Random Forest Classifier

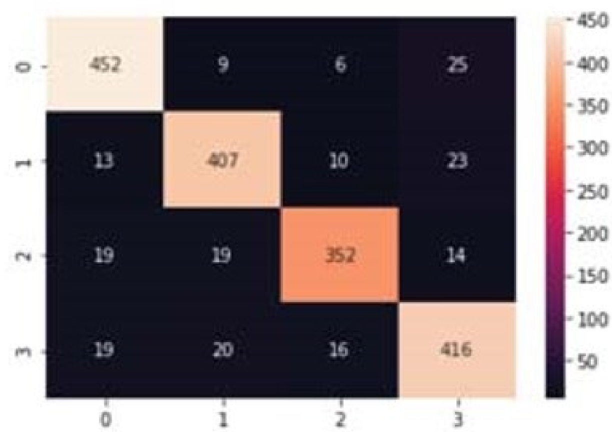

Fig. 5. Confusion Matrix of SVM

Artificial Neural Network (ANN) has also been used and model is build whose layers are shown in fig 6.

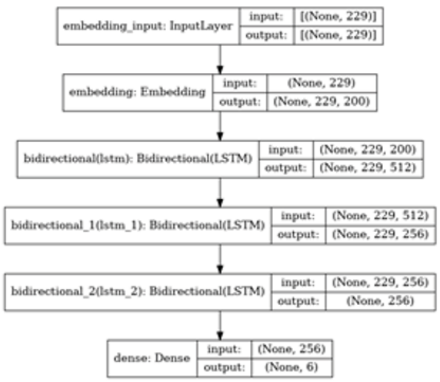

Fig. 6. ANN Architecture

The methodology used for this research paper is shown in figure 7. Fig

Fig. 7. Research Methodology

Figure 8 compares a number of machine learning and deep learning models, including ANN, SVM, Random Forest, Naïve Bayes, and Logistic Regression. The formulas for accuracy, recall, f1-score, and precision are provided in equations (I) to equation, and the comparison is based on these parameters.

(IV). ANN model gives the highest accuracy among all the classifiers.

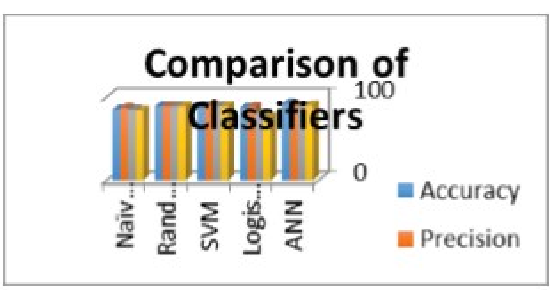

Fig. 8. Classifier Comparison on Test Dataset

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (I)$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (II)$$

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + False\ Positives + False\ Negatives + True\ Negatives} \quad (III)$$

$$F1\ Score = \frac{2 * (Precision * Recall)}{Precision + Recall} \quad (IV)$$

IV. RESULTS

Machine learning techniques, including Naïve Bayes, Random Forest, SVM, ANN, and Logistic Regression, are used in the experiments conducted in this study. Out of all the classifiers tested on the text emotion dataset, ANN classifiers had the highest accuracy, according to the results in the chart in Figure 8.

V. CONCLUSION

While other machine learning models attain accuracy below 90%, the Deep Learning model with Tfidf Vectorizer yields the best results with an accuracy of 92%. In addition to having a high accuracy, ANNs have a very low validation loss. In the future, we will use text augmentation to address the dataset's imbalance and develop a number of massive deep learning models. All things considered, these results point to the importance of emotional intelligence in text-based communication and associated concepts. To completely comprehend how emotional intelligence affects text-based communication in many locations and scenarios, more research is required.

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