A Framework for Youth Sentiment Analysis Using Natural Language Processing

Rasha A. ElStohy [1,2]

[1] Department of Information Systems, Obour Institutes, EL Sharqia, Egypt
[2] Department of Information Communication Technology, New Cairo Technological University, Cairo, Egypt
Email: rashastohy@oi.edu.eg, rashastohy@nctu.edu.eg

***Abstract*—Social networks are currently the most widely used platforms for exchanging thoughts on various subjects or events, particularly those geared at young people. Consequently, the Natural Language Processing (NLP) industry has access to an abundant source of data provided by those applications. This paper presents a model for sentiment analysis using Naive Bayes algorithm. A proposed model is applied to two dataset samples to train, create, and test classification models. The supervised approach combined unigram for feature extraction and the Naive Bayes algorithm to extract the trending topics for youth Tweets. The model is evaluated on a test set during the worldwide crisis and is shown to be effective in predicting opinions on new reviews. The results of the evaluation demonstrate that the model is capable of accurately predicting opinions with a high degree of accuracy.**

***Keywords*—Natural Language Processing (NLP), sentiments, social networks, tweeter, machine learning**

I. Introduction

The huge number of perspectives held by social media users have caused the platform to become overcrowded. This information is extremely valuable because it reveals the degree to which a society is vulnerable to a certain which is especially relevant during times of crisis. By analyzing these viewpoints, the various organizations can enhance the quality of the services they provide to avoid any unfavourable responses from the local community [1].

Twitter is a social networking website that enables users to send and read brief messages, known as tweets. These tweets from millions of active users worldwide are regarded as a treasure trove of information that draws the attention of academics interested in learning about user interests and keeps the attention of organizations.

Eventually, data collection from sources, such as search engines, blogs, microblogs, and social media sites, is referred to as opinion mining. Tweets on Twitter are a fantastic source for this kind of information since they showcase the diversity of people's perspectives [2].

Although it is considered a good way to collect people's opinions, there are issues related to the vast volume and the unstructured character of the collected data, it might be challenging to conduct an effective analysis of text and opinion data. Because of this, efficient algorithms and computational approaches are required for data mining and condensing, discovering sentiment, or even more fine-grained emotions in words. To test the effectiveness of various feature combinations and to determine the sentiment of tweets, multiple machine-learning approaches are utilized [3, 4].

As a result, Natural Language Processing (NLP) has emerged as a technology for machine learning that may serve as an activity of sentiment analysis, which entails identifying and classifying various sentiments in written content. Natural Language Processing (NLP) is a technique that allows machines to "read" text by emulating the human capacity to comprehend language. This is accomplished by combining the power of artificial intelligence, computational linguistics, and computer science [5].

The task of identifying and categorizing the feelings conveyed by written expressions is known in NLP as sentiment analysis. In most cases, "positive", "negative", and "neutral" categories are considered [5]. Finding sentiments or even more fine-grained emotions in words requires sophisticated algorithms and computational methodologies. Mining and condensing data also require these algorithms. Several distinct machine-learning algorithms have been used to analyze the efficacy of various feature combinations and determine whether tweets can be classified according to their sentiments [6], Support Vector Machines (SVM), one of the most common types of supervised NLP machine-learning algorithms, can be found in [7]. Bayesian Networks, and Maximum Entropy [8]. In this study, we have a set of objectives: first, finding emotions and sentiments inside unstructured data was a major goal, which used a supervised classification method. Meanwhile, we performed sentiment classification on the Twitter sentiment corpus by combining text analysis and machine learning methods. Applying on feelings expressed by teens and young people from various nations, particularly during times of crisis such as the lockout during the pandemic of COVID-19, and that followed the Russian-Ukrainian war, to see whether it had an impact on their tweets. As a consequence, we made use of n-gram models for the ordering of words, as well as the Naive Bayes Classifier, which is an efficient classification method that assists in the construction of rapid machine learning models

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that assists in the construction of rapid machine learning models [9].

Another goal is to propose a model that can extract trending topics from eleven emotions. By using eleven emotions rather than the traditional four and eight, it is gaining more detailed insight into the sentiment expressed in a text is possible. This makes it easier to accurately pinpoint the opinion of the user, as the nuances between emotions, such as anger, annoyance, and frustration, can be better observed. Moreover, applying this method results in enhanced precision in sentiment analysis, as the accuracy of categorizing emotions proportionally improves the availability of broader range of emotions for classification.

Remaining parts of this work are structured in the following manner. In Section II, we offer a concise discussion of related research on sentiment analysis. Section III presents the structure of the proposed technique. In Section IV, we will discuss the experimental setup, datasets used, and assessment measures. In Sections V and VI, we conclude and discuss what follows.

II. Literature Review

Several publications provide a comprehensive review of the various sentiment analysis methods currently in use across a variety of industries.

In Ref. [8], the authors described how to determine a person's level of depression by analyzing and deducing emotions from texts using theories of emotion, machine learning, and natural language processing techniques on a variety of social media channels. They accomplished this using techniques such as Support Vector Machines (SVMs), Naive Bayes (NB) classifiers, and Maximum Entropy (ME) classifiers for sentence-level sentiment analysis for depression estimation.

Elbagir and Yang [10] demonstrated the importance of emotional analysis in Bangladeshi literature. They analyzed Bangla text using NB classifiers and the current approach to derive subjects' sentiments. They found that topical treatment had a 90% success rate, regardless of the situation, when compared to other approaches.

Hassan *et al.* [11] proposed a technique that evaluates the quality of a text based on the annotations found in scientific journals. This issue arises from the complex nature of the interactions between annotations. In this study, the researchers calculated the accuracy of sentiment using three different machine learning algorithms: the naive Bayes classifier, k-nearest neighbor method, and random forest algorithm. They found that using the random forest algorithm helped to boost the classifier's overall performance. The presented classifier achieved a 62% accuracy rate (the upper bound human agreement rate was 72%).

Shukla [12] showed a considerable increase in the amount of data obtained from Twitter in recent years. This study used a feature extraction method to generate effective features after studying Twitter datasets made publicly available through the NLTK Corpora. The study used various machine learning algorithms, including multinomial Naive Bayes (NB), Bernoulli NB, logistic regression, Stochastic Gradient Descent (SGD) classifier, Support Vector Classifier (SVC), linear SVC, and nuSVC. The results of the experiments showed that the Bernoulli NB, logistic regression, and SGD classifiers achieved an accuracy of up to 75%.

Tuhin *et al*. [13] examined the problem of multiclass categorization of online posts made by Twitter users. Their findings pointed out the feasibility of this study and the limitations and challenges associated with it. This resulted in an accuracy of only 60.2% for the seven sentiment classes, compared to an accuracy of 81.3% for binary classification.

Kumar and Rajini [14] resulted in the creation of a feature matrix that considers positive, negative, and negation-oriented terms. In this study, NB, SVM, and RF approaches were utilized. The RF classifier that utilized unigram in conjunction with SentiWordNet and included negation words had the highest accuracy (95.6%).

Mathur *et al.* [15] reveals that the machine learning techniques of Multilayer Propon (MLP), Nave Bayes, Fuzzy Classification, Decision Tree, and Support Vector Machines (SVM) were surveyed to categorize tweets.

Such tactics have been employed to help examine various component vectors using a doled-out class to differentiate between the evaluation and relation dependencies of each element. This was accomplished using doled-out classes. Performance parameters, such as accuracy, duration, warning, and F-estimate, were analyzed using the Twitter dataset. Subsequently, these strategies were examined and evaluated.

In addition, Barzenji [16] suggests the dissemination of opinions. The overall volume of the corpus comprised these source–quote pairings, which accounted for 69 percent of the total. A Random Forest model was used in this investigation. They concluded that approximately 80 percent of the criteria that described O.I. were connected with the perspective that the original message had toward the dispute. The feeling expressed in these quotes, which accounted for 14% of all the pairings of Source and Quote, was consistent with that expressed in Source.

On the other hand, Almotiri [17] mentioned Natural Language Processing (NLP) computed the sentiment value of all tweets by using the AFINN Lexicon sentiment analysis approach. The findings of this investigation showed that the sentimental state at two separate periods throughout the region's lockdown was positive in the samples used in this study. These samples are unique to a geographical region in New Zealand and are not found anywhere else in the world. During the shutdown, Twitter users in New Zealand exchanged positive phrases at a rate of approximately 71% and, correspondingly, 61%, which suggests that the overall sentiment situation was relatively good.

According to the aforementioned literature, various authors have explored different experimental scenarios to analyze text datasets for various nations and durations using various ML algorithms, and we determined that the Twitter dataset is commonly used among the conducted experiments. Therefore, we decided to employ the proposed emotion classification framework using a Twitter social media dataset during crisis periods based on the Naïve Bayes algorithm.

III. Proposed Framework

A. General Framework Architecture

The procedure for detecting user's opinion is illustrated in Fig. 1. Where Twitter contains an unlimited quantity of data, the suggested framework design is centered on the analysis and classification of multilabel emotions into 11 emotions using the data obtained from Twitter. This demonstrates the sequential processes involved in supervised machine learning algorithms for sentiment analysis and emotion recognition. The first step in the process is data gathering, which entails collecting pertinent tweets from Twitter [18].

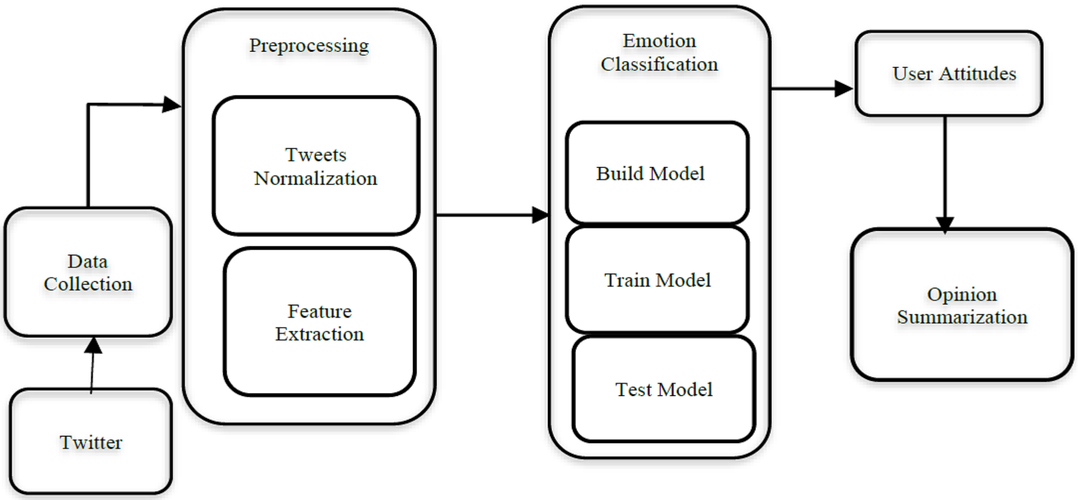


Figure 1. Emotion detection workflow.

The second phase involves preprocessing and feature extraction by filtering out important tokens and then encoding them into the appropriate feature vector. Following this is the emotion categorization phase, which focuses on model construction, training, and testing. Finally, the opinion summary phase collects data and determines the threshold output to create a choice regarding the sample input.

B. Data Preprocessing

Texts gathered for this study were obtained using Twitter API. During the training phase, approximately 9,000 tweets were utilized between March and April 2020 [19]. Other tweets obtained in June 2022 were also utilized [20]. The data pretreatment stage is critical to our workflow. For computerized operations with data, we needed to change it into understandable format, bring in the library files, Import the dataset, and proceed.

The data set was divided into a Training Set and a Test Set, emojis were translated, URLs were removed, and stopwords, punctuation, and unnecessary spaces were eliminated, as illustrated in the algorithm in Fig. 2 which depicts several procedures taken while the data was being prepared, Fig. 3, provides a snapshot of the dataset after it had been preprocessed.

The preprocessed tweets were then analyzed and classified into 11 different emotions depending on the data received from Twitter. As Twitter contains an uncountable quantity of data, the counting of emotions that occur after preprocessing is illustrated in Table I.

Algorithm: Extract Hashtags

INPUT: Training, Develop and Testing Data

OUTPUT: Data with Hashtags

1. Import NumPy and Pandas libraries

2. For each of the three datasets (training, develop, testing)

   a. Create a new column called 'hashtags'

   b. Extract all words following the '#' symbol and add them to the 'hashtags' column

3. Import the emoji library

4. For each of the three datasets (training, develop, testing)

   a. Create a new column called 'clean'

   b. Use the emoji library to translate any emojis found in the 'Tweet' column and add the translated text to the 'clean' column

END

Figure 2. Data preparation algorithm.

worry the current crisis to derail the future of next generation."
his wrong steps has cost him and the rest of the world angery.
people need look definition protest protesting called stop war angry stop
children look child abuse
It only takes one bad apple to spoil all the rest

Figure 3. Data set after preprocessing.

TABLE I. COUNTING EACH EMOTION

Emotion	Count
anger	2,544
anticipation	978
disgust	2,602
fear	1,242
joy	2,477
love	700
optimism	1,984
pessimism	795
sadness	2,008
surprise	136
love	700
trust	357

C. Feature Extraction

A large set of raw data is divided into smaller groups for processing using a dimensionality reduction technique known as feature extraction [21]. Feature extraction can also help eliminate duplicate data for a particular investigation. Additionally, it attempts to generate variable combinations (features), and the reduction of data speeds up the learning and generalization phases of the machine learning process [22].

The most traditional language models offer an arrangement of n words; here, and for the sake of computational simplicity, we will focus on unigram rather than other forms of frequency distribution. We describe tweets using N-grams in order to study the influence of feature representation.

The frequency distribution [23] of n-grams is determined to identify the n-grams used as features; consequently, n-grams that occur more than 10 times are included in the feature list, and FreqDist [24] which is a class that implements a special object type called frequency distributions and offers helpful methods for word frequency analysis. We calculate the Point-wise Mutual Information (PMI) between a word and each emotion label for each word w that appeared more than ten times in the corpus using Eq. (1).

$$\mathrm{PMI}(w, e) = \log \frac{\mathrm{freq}(w,e)}{\mathrm{freq}(w) \times \mathrm{freq}(e)} \tag{1}$$

where "freq (w, e)" is the frequency of the occurrence of w in a phrase with label e. The frequencies of the letters w,e in the corpus are "freq (w)" and "freq (e)". A term will have a PMI score greater than 1 if it has a larger-than-chance propensity to appear in tweets with a certain emotion descriptor. We included all phrases from the Hashtag Emotion Corpus with a PMI > 1 for each emotion.

To visualize emotions in plots, function of plot in maximum of 20 tokens in each emotion applied as in illustrated at algorithm below:

1. Define a function plt_freq(rows, cols, lst, i)
2. Set rows and cols equal to 6 and 2 respectively.
3. Create a figure with 6 rows and 2 columns using the function plt.subplots(rows, cols, figsize(15,25)).
4. Loop through the list of emotions using for i,x in enumerate(em)
5. Call the plt_freq (rows, cols,uni_lst[i].most_common(20), i+1) function to plot the highest common 20 tokens in each emotion.
6. Create an axis at the bottom row and set it to off using plt.axis("off").
7. Show the plot using plt.show().

D. Machine Learning Algorithm

The Naive Bayes algorithm is a supervised learning method for classification based on Bayes' theorem. It is primarily used for text categorization and has a large training dataset [25]. One of the most straightforward and efficient classification algorithms is the naive Bayes classifier, which aids in the development of rapid machine-learning models capable of making accurate predictions. As a probabilistic classifier, it makes predictions based on the likelihood that an object will occur. Spam filtration, Sentimental analysis, and categorizing articles are some examples of Naive Bayes algorithms that are often used [26].

In the classification of emotions, tweets from the training phase were separated into two domains (small and big), the first of which was (anger, fear, joy, and sadness), and the second was (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust), up to 3,000 tweets from the dataset were used for testing. The results section covers several images and graphs demonstrating the model's architecture.

IV. RESULTS AND DISCUSSION

In our experiment, the Pandas' library was used for data preparation with extracted emotions to import our dataset in.csv file format, then analyze, classify multi-label emotions, and visualize results using Microsoft Excel. Other libraries were also used, such as Numpy for scientific computing with Python.

Fig. 4 displays statistics of emotions for two separate datasets after preprocessing following the instructions in the method section. 2,500 tweets were used to create the graph.

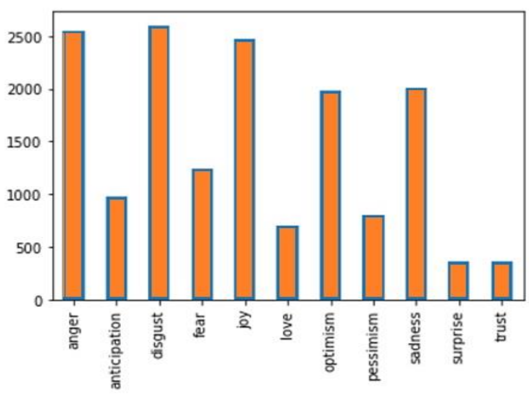


Figure 4. Statistics of emotions for two separate datasets after preprocessing.

Fig. 4 shows that anger and disgust outweigh feelings like fear and trust. This may be because of the global inflammation caused by the crisis, but it also shows that optimism outweighs pessimism owing to diplomatic negotiations and vaccine campaigns announce.

We filtered the unigrams in the collection of tweets shown in Fig. 5 to only include those that appear more than 10 times after applying n-gram distribution, which revealed that the relevant unigrams typically had a frequency between 20 and 200.

Once again, Unigram demonstrates how emotions of anger and disgust are stronger emotions than love and surprise.

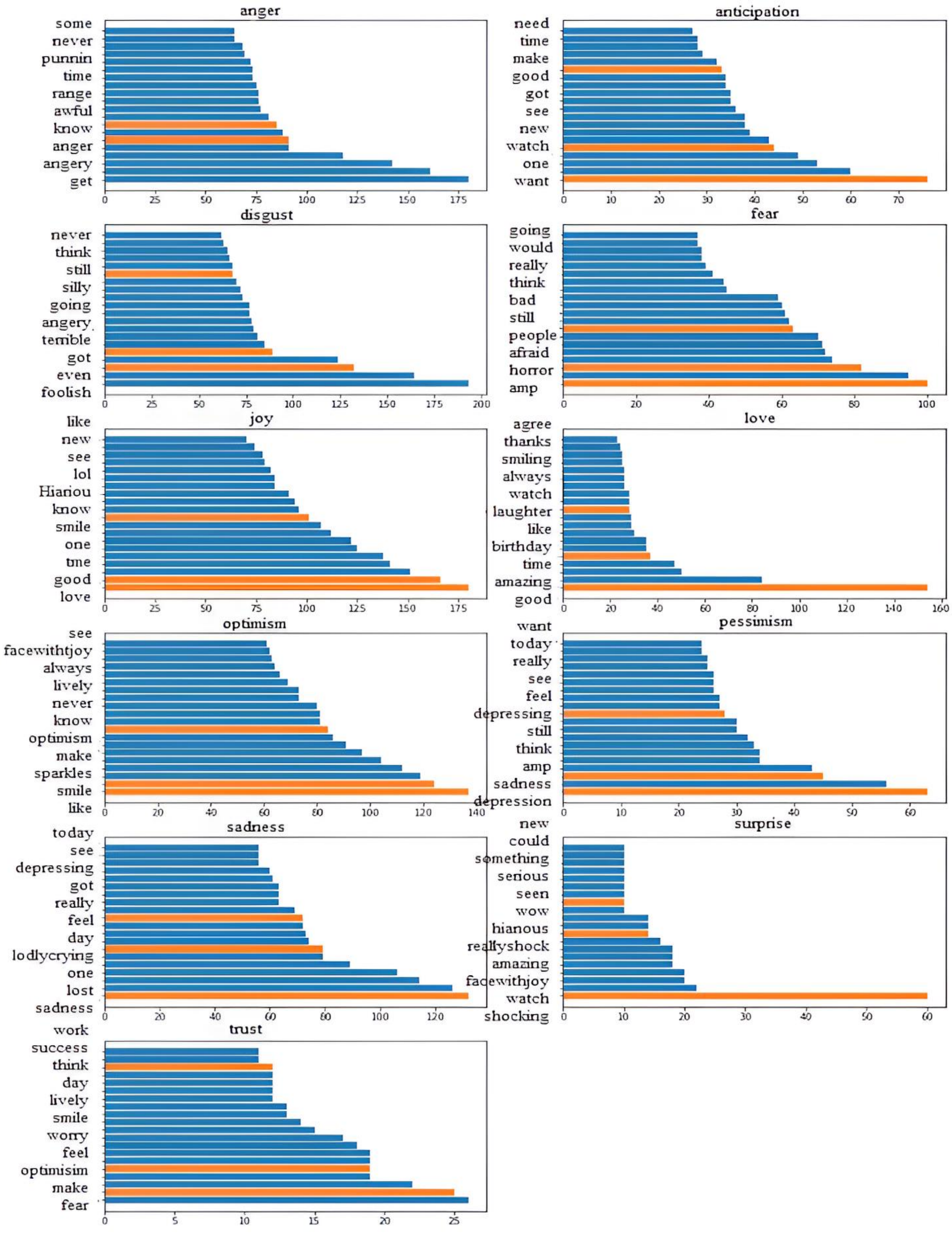


Figure 5. Unigram frequency distribution and explanatory analysis.

The results were manually compared to the annotated data to create a confusion matrix, which yielded the recall, precision [27], and F1 measure values [23], Tables II–VII concern emotion classification among Naïve Bayes (NB) model training and testing for 4, 8, 11 emotions.

The results showed that the naive Bayes approach could extract the trending topics for young Twitter users with an average recall value of 0.77, average precision value of 0.61, and average F1 measure value of 0.68 for four emotions compared to average recall, precision, and F1 of 0.88, 0.40, 0.55 for eight emotions and 0.84, 0.37, 0.51 for eleven emotions.

TABLE II. NB TRAINING DATA EVALUATION OF 4 EMOTIONS PER CATEGORY PRECISION (P), RECALL (R), AND F SCORE

Classification report	Precision	Recall	F-score	Support
Anger	0.80	0.74	0.77	2544
Fear	0.73	0.89	0.80	1242
Joy	0.61	0.71	0.66	2008
Sad	0.21	0.92	0.34	357
Avg Micro	0.61	0.77	0.68	6151

TABLE III. TESTING DATA EVALUATION OF 4 EMOTIONS PER CATEGORY PRECISION (P), RECALL (R), AND F SCORE

Classification report	Precision	Recall	F-score	Support
Anger	0.76	0.57	0.65	315
Fear	0.79	0.28	0.41	121
Joy	0.85	0.57	0.68	400
Sad	0.75	0.20	0.31	265
Avg Micro	0.80	0.45	0.57	1101

TABLE IV. NB TRAINING DATA EVALUATION OF 8 EMOTIONS PER CATEGORY PRECISION (P), RECALL (R), AND F SCORE

Classification Report	Precision	Recall	F-score	Support
Anger	0.55	0.91	0.68	2544
Anticipation	0.41	0.65	0.51	978
Disgust	0.54	0.90	0.68	2602
Fear	0.36	0.96	0.52	1242
Joy	0.66	0.85	0.74	2477
Sad	0.40	0.89	0.55	2008
Surprise	0.08	0.96	0.15	361
Trust	0.14	0.94	0.25	357
Avg Micro	0.40	0.88	0.55	12569

TABLE V. TESTING DATA EVALUATION OF 8 EMOTIONS PER CATEGORY PRECISION (P), RECALL (R), AND F SCORE

Classification report	Precision	Recall	F-score	Support
Anger	0.72	0.58	0.65	315
Anticipation	0.00	0.00	0.00	124
Disgust	0.68	0.55	0.61	319
Fear	0.82	0.27	0.41	121
Joy	0.87	0.56	0.68	400
Sad	0.72	0.25	0.37	265
Surprise	0.00	0.00	0.00	35
Trust	0.00	0.00	0.00	43
Avg Micro	0.76	0.42	0.54	1622

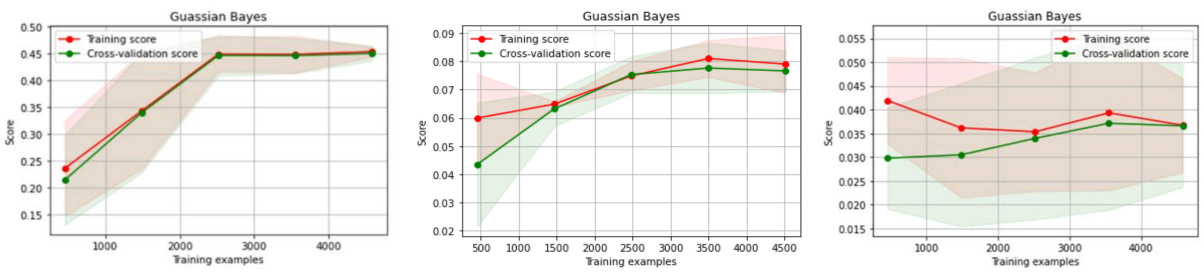
TABLE VI. NB TRAINING DATA EVALUATION OF 11 EMOTIONS PER CATEGORY PRECISION (P), RECALL (R), AND F SCORE

Classification Report	Precision	Recall	F-score	Support
Anger	0.73	0.61	0.66	315
Anticipation	0.00	0.00	0.00	124
Disgust	0.69	0.55	0.61	319
Fear	0.82	0.26	0.40	121
Joy	0.88	0.52	0.66	400
love	0.50	0.02	0.04	132
Optimism	0.75	0.31	0.44	307
Pessimism	0.00	0.00	0.00	100
Sad	0.73	0.24	0.37	265
Surprise	0.00	0.00	0.00	35
Trust	0.00	0.00	0.00	43
Avg Micro	0.76	0.36	0.48	2161

TABLE VII. TESTING DATA EVALUATION OF 11 EMOTIONS PER CATEGORY PRECISION (P), RECALL (R), AND F SCORE

Classification Report	Precision	Recall	F-score	Support
Anger	0.52	0.92	0.66	2544
Anticipation	0.50	0.53	0.51	978
Disgust	0.52	0.93	0.67	2602
Fear	0.30	0.96	0.46	1242
Joy	0.68	0.84	0.76	2477
love	0.25	0.90	0.39	700
Optimism	0.68	0.51	0.58	184
Pessimism	0.19	0.93	0.31	795
Sad	0.39	0.91	0.55	2008
Surprise	0.08	0.94	0.15	361
Trust	0.13	0.93	0.22	357
Avg Micro	0.37	0.84	0.51	16048

Python and Jupyter Notebook were used in all experiments to visualize the results and to show the model's performance as the training set size increased. We imported the most popular library Matplotlib [28] to produce 2D plotting publication quality figures. In addition, Seaborn [29] based on matplotlib is also available. Plot learning curve offers a high-level interface for creating visually appealing educational statistical graphics. It analyses a model using training and validation datasets before plotting the measured performance as shown in Fig. 6.



(a) plot learning curve in 4 emotions (b) plot learning curve in 8 emotions (c) plot learning curve in 11 emotions

Figure 6. Plot learning curve in 4,8,11 emotions.

V. CONCLUSION AND FUTURE WORK

This research offers a unique method for predicting various emotions in a sample input tweet and introduces a supervised machine-learning methodology to identify the various emotions existing in the input tweet sample.

This work, which is based on artificial intelligence and machine learning, explores a novel method for extracting opinions and analyzing sentiments in multi-label classification using a real-world Twitter database that has been divided into a range of emotional categories.

Unstructured slang and bipolarity languages were managed using feature vectors to represent tweets. Different classifier designs were developed and then trained using real-world data to yield various outcomes.

Up to 9,000 tweets out of the multi-region data collection were utilized in the training phase. Anger, fear, pleasure, and sadness made up the first (small) and second (big) domains of these tweets' emotions categorized as (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust) respectively. These tweets were individually trained using the Naive Bayes algorithm with the binary relevance approach, and the final sentiment was determined by adding the output of the algorithm.

For testing, an additional 3,000 tweets were used. To classify the tweets, two domains (large and small) were employed. Tweets were processed using the most valuable symbols. Different vectors are created from these tokens. Both large and small feature vectors were subjected to the aforementioned methods. Frequency distribution, the huge feature vector, the model architecture, the characteristics represented, and the development of each model during training are displayed in various images and graphs.

The study's findings revealed that the naive Bayes approach effectively identified trending topics among young Twitter users. The results showed an average recall value of 0.77, an average precision value of 0.61, and an average F1 measure value of 0.68 for four emotions. As the performance of the approach decreased as the number of emotions increased, the average recall, precision, and F1 values for eight and eleven emotions were 0.88, 0.40, 0.55 and 0.84, 0.37, 0.30, 0.51, respectively.

As a consequence of the eight-emotion classifier still requiring more tweets to train, the findings revealed that four emotion ranges were superior to eight emotion ranges.

However, the convolutional neural network's design might be tweaked to increase its effectiveness even further. Future work will focus on refining the framework by addressing the sample size issue and combining results from multiple models, such as K-means, Support vector machines, and logistic regression.

The extraction of social media posts from other sites such as Instagram and Facebook is another potential extension of this research.

Conflict of Interest

The author declares no conflict of interest.

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