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Impact of COVID-19 on Human Health using Social Media Sentiment Analysis

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Abstract: Several social media analysis work requires sentiment analysis. The Multi-Layer Perceptron technique is used for analyzing tweet sentiment. It is getting harder and harder to precisely discover and arrange interesting events from vast social media data, which is useful for browsing, searching, and monitoring social events for people and governments due to the Internet's explosive rise in social events. The scope of the unique (COVID-19) epidemic has resulted in severe financial hardships, stress, tension, and other future-related concerns. Networks' positive behavior can be estimated in part because of web-based media. Regarding preprocessing and feature extraction, the research needs to offer higher accuracy. Identify feelings and behaviors in comments, hashtags, posts, and tweets. The primary keyword, "COVID" or "Coronavirus," is the one that is most frequently used by combining NLP (natural language processing) and Multi-Layer Perceptron toward sentiment classification with an accuracy of 0.91 %.

Keywords: C OVID-1, Sentiment Analysis, Tweets Classification, Multi-layer Perceptron.

1. Introduction

As time passes, semantic creation becomes more and more important in analyzing how words and phrases make us feel. It recalls differentiating the degree and effects of invalidation for changing the extremeness of an opinion, as well as assessing its influence of modifiers, like degree qualifiers and intensifiers, in rescaling the force of the sensation. Anvilkar et al. Sentiments Analysis (SA) is a developing field (2018). Many Natural language processing tasks are done with large use of distributed representations of words. Following its breakthrough, Continues is creating much interest among those who want to learn how to use its words in phrases, sentences, paragraphs, and papers (Huang, 2016). Our deep convolutional neural network used to evaluate the overall sentiment of tweets has a structure similar to deep learning systems. Our deep convolutional neural network used to analyze the overall feeling of tweets has a similar architecture to deep learning systems. Sentiment analysis is the study of how a text expresses an opinion. As stated by Aminu Muhammad (2016), sentiment analysis entails extracting the opinion's polarity (positive or negative), the target, or certain elements of the target to which it refers the opinion's bearer (Van Hee et al., 2015).

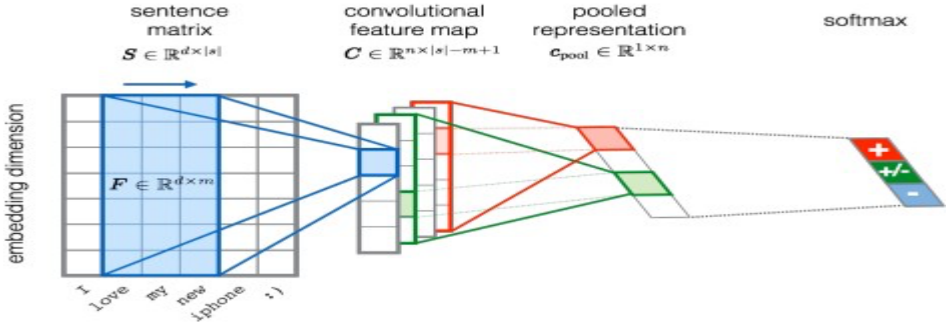

Figure 1. previous working model similar to proposed

The structure of our deep learning model for sentiment analysis is depicted in Figure 1. Its design is most similar to that of the deep learning system that was recently reported to have produced groundbreaking results on various NLP sentence categorization tasks, including sentiment analysis. Numerous IR applications have successfully employed convolutional neural networks (Liangzu, Ruifan, & Yanquan, 2014). Despite already showing excellent results, careful attention is needed to train a convolutional neural network to outperform hand-engineered solutions that rely on numerous manually and automatically created lexicons. This problem gets significantly more difficult if there is only a small amount of labeled data, such as thousands of samples, this problem gets significantly more difficult (Alswaidan & Menai, 2020).

A deep convolutional brain network used to dissect the feeling of tweets has a comparable design to profound learning frameworks. (Weilin & Hoon, 2015) The feeling investigation is the investigation of how a text offers a viewpoint. The objective of feeling investigation is to separate data about the objective or certain qualities of the objective that the assessment connects with the assessment's carrier and the period at which the assessment was voiced. Rather than the conventional abstract text given by the clients, we concentrate and utilize an Objective Text portrayal of pictures consequently recovered from the visual substance. It is extending the significant developments in text-based (Liangzu et al., 2014). It's been enough for precise sentiment labeling. We offer a method for combining the two and framing the sentiment prediction problem in terms of supervised and unsupervised situations (Storey & O'Leary, 2022).

We create an optimization algorithm for locating a local-optima solution within the suggested framework. The more difficult task of predicting the underlying sentiments behind the visuals elevates sentiment prediction challenges (Abd-Alrazaq, Alhuwail, Househ, Hamdi, & Shah, 2020). A cutting-edge framework for tracking and evolving multimodal social events to efficiently collect multimodal social event subjects, learn how social events have evolved over time, and produce efficient event summary details. To achieve this objective, we propose a novel multimodal event topic model (mmETM) that can successfully model social media documents, including lengthy texts accompanied by relevant images, and learn from data. This study can be beneficial for the community in several ways (Berkovic, Ackerman, Briggs, & Ayton, 2020). Here are a few possible ways in which this study can be helpful: Understanding Public Sentiment: Social media sentiment analysis can help us understand how people feel about the pandemic and its impact on human health. By analyzing the sentiment of posts and comments related to COVID-19 on social media platforms, we can gain insights into people's attitudes, emotions, and concerns (Bose, Aithal, & Roy, 2020). This information can be used to inform public health messaging and interventions (Essam & Abdo, 2021).

Monitoring Public Health: Social media sentiment analysis can be used as an early warning system for potential outbreaks of COVID-19. By monitoring social media platforms, public health officials can detect spikes in negative sentiment related to symptoms, testing, or treatment, which may indicate an increase in COVID-19 cases. This information can help public health officials to respond quickly and effectively to potential outbreaks (Chehal, Gupta, & Gulati, 2021).

Improving Mental Health Support: The study can also help to identify the mental health impact of COVID-19 on individuals. By analyzing the sentiment of posts related to COVID-19 on social media platforms, we can understand the emotional toll of the pandemic on people. This information can be used to develop targeted mental health interventions and support services (Gupta et al., 2021).

Identifying Information Gaps: The study can also help to identify gaps in public knowledge and understanding of COVID-19. By analyzing the sentiment of posts related to COVID-19 on social media platforms, we can understand what people know and don't know about the virus, its symptoms, and how to prevent its spread. This information can be used to develop targeted public health messaging and education campaigns (Priyadarshini et al., 2022).

The study can provide valuable insights into the pandemic's impact on individuals and communities. By understanding public sentiment, monitoring public health, improving mental health support, and identifying information gaps, we can develop more effective public health interventions and support services (Khan, Malik, Ruhi, & Al-Busaidi, 2022).

2. Literature Review

In this part, we examine sentiment analysis-related research. When used to mine opinions from textual data like Tweets, sentiment analysis has proven effective. Whether conducting important research or making daily decisions, we frequently seek out the views of others. We refer to several conversation subjects (Ong, Chen, Sung, & Zhu, 2005). The ability to access the thoughts of millions of individuals on everything from the newest technology to political ideologies is now made feasible through the Internet. More than 22% of all online time is now spent on social media, which 65% of adult internet users use. Psychological support is provided to healthcare professionals and patients, but the general public's mental health also requires significant attention (Naseem, Razzak, Khushi, Eklund, & Kim, 2021). During an infectious disease outbreak, the population's psychological responses significantly impact the spread of the disease and the emergence of emotional distress and social disorder during and after the outbreak. There are many reasons for this. It is common knowledge that psychological factors significantly impact people's adherence to public health interventions like vaccination and how they deal with infection risk and subsequent losses (Aslam, Awan, Syed, Kashif, & Parveen, 2020). Beyond a shadow of a doubt, such is critical contemplation to remember while dealing with any popular disease, particularly Coronavirus (Sciandra, 2020). Instances of mental responses to pandemics incorporate maladaptive ways of behaving, profound misery, and guarded activities. Especially in peril are those who are prone to mental issues (Troisi, Fenza, Grimaldi, & Loia, 2022).

The Coronavirus pandemic fundamentally affects individuals' day-to-day routines and brought about huge financial misfortune internationally. In either case, its impact on people's psychological health difficulties hasn't really shone out. We use online entertainment as our primary information source to focus on this aspect (Abd-Alrazaq et al., 2020). We also provide the by far the largest dataset on depression on English Twitter, with 2,575 fascinating famous people with depression and their verified tweets. To investigate the impact of depression on people's Twitter language, we train three transformer-based depression classification models on the dataset (Rustam et al., 2021). Evaluate their performance with progressively larger training sets, and compare the model's "tweet chunk"-level and user-level performances (Rambaccussing & Kwiatkowski, 2020).

The severity of the new coronavirus (COVID-19) pandemic has resulted in significant financial challenges, worry, anxiety, and future concerns. Examining the evolving language use on social media can support conventional survey-based methodologies and offer fresh perspectives on the health of a nation or region during a crisis in public health (Rustam et al., 2021). Media platforms may help with early symptom finding for diseases (Sharma & Sharma, 2020). Whose path physiology is still developing and poorly understood (Mulahuwaish, Gyorick, Ghafoor, Maghdid, & Rawat, 2020).

Examining how the overall population is answering the Coronavirus scourge is fundamental. Information is a huge variable in the infodemiology examination of public reaction checking. The significant target of the review is to research the exchanges, concerns, and mentalities towards Covid disease (Coronavirus) that were communicated in tweets distributed by Twitter clients (Sharma & Sharma, 2020). Utilizing a rundown of 25 hashtags, including "Covid," "Coronavirus," and "quarantine," we look at 4 million tweets about the Coronavirus pandemic from Walk 1 to April 21, 2020. We examine the gathered Tweets utilizing an AI method called Inert Dirichlet Portion (LDA) to find famous unigrams, bigrams, significant subjects and subjects, and feelings (Gadek & Guélorget, 2020).

As cases of the 2019 coronavirus disease, a public health emergency, increased panic buying was seen worldwide, which was indicative of how it affected global mental health. Nothing is known about the pandemic's effects on people's stress, anxiety, and depression levels. This longitudinal study conducted two surveys of the general public to gather information on demographics, symptoms, knowledge, concerns, and COVID-19 precautions at the initial outbreak and at the peak of the pandemic four weeks later (Garcia & Berton, 2021).

From 190 Chinese cities, 1738 people (including 1210 first-survey respondents and 861 s-survey respondents; There were 333 respondents to both). The Depression, Anxiety, Stress Scale (DASS-21) and the Impact of Event Scale-Revised (IES-R) were utilized to assess the mental health status and psychological impact. The IES-R assesses PTSD symptoms in people who have survived an event. Concern about the potential effects of the COVID-19 pandemic on the population's mental health is growing worldwide (Hutto & Gilbert, 2014). Before and after the lockdown, we examine changes in the mental health of adults in the UK (Jang, Rempel, Roth, Carenini, & Janjua, 2021). For this secondary analysis of large, longitudinal cohort research, many households who participated in Waves 8 or 9 of the UK Household Longitudinal Study (UKHLS) panel, including all members who were 16 or older in April 2020, were invited to complete the COVID-19 web survey from April 23 to April 30, 2020. Participants who did not know their postal or international addresses or could not decide were disqualified. Mental health was evaluated using the 12-item General Health Questionnaire (GHQ-12) (Tsao et al., 2021). Numerous cross-sectional analyses were used to evaluate temporal trends (Choi & Lee, 2017).

Fixed-effects regression models were used to compare the within-person change with previous trends. Matthias Pierce in 2020 With the COVID-19 pandemic's onset, we witnessed the generation's greatest challenge globally. The impact on mental health will likely be significant and last for a long time, even though the full extent of it is still unknown (Chandrasekaran, Mehta, Valkunde, & Moustakas, 2020). In this Special Issue on mental health and the COVID-19 pandemic, we hope to lay the groundwork for a deeper comprehension of how COVID-19 affects mental health services worldwide and in Ireland. The Special Edition focuses on how COVID-19 affects almost every facet of society, including mental health (Wong et al., 2021).

Perspectives from a variety of nations, fields, and healthcare settings are presented in this issue. New approaches to mental health care are presented in the Special Issue of the Irish Journal of Psychological Medicine on COVID-19's effects on nearly every aspect of society. The papers in this Unique Issue detail the staggering troubles that this pandemic has introduced in an assortment of mental medical services settings, as well as the motivating endeavors to rapidly change administration conveyance to keep up with the coherence of open consideration for everybody (Chandrasekaran et al., 2020).

3. Proposed Model

Checking that the most recent solution outperforms the competition will lead to a more successful Strategy in all areas of sentiment analysis transitions. The proposed method was contrasted with Established methods with a higher level of response and credibility, particularly in terms of extraction aspects, in a procedure known as sentimental analysis. The following subsections illustrate each phase in detail.

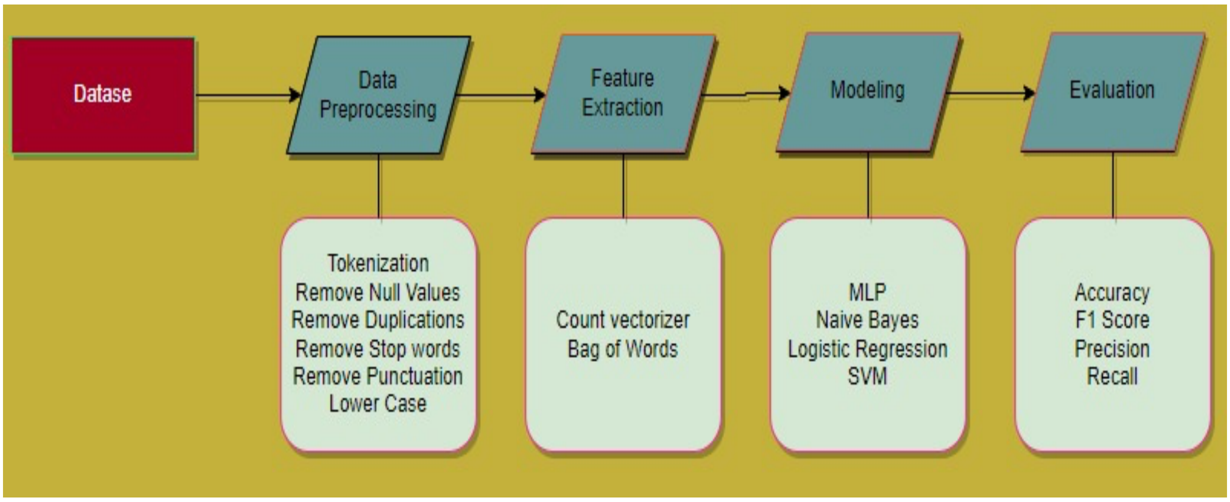

Figure 2. Research methodology of COVID-19 sentiments analysis

3.1. Dataset

The gathering of data is a crucial component of any research project. Data gathering is based on many research methodologies. Quantitative research requires quantitative data, such as numerical values and calculations, while qualitative research requires survey-based data, observational data, etc. We needed text-based data in a supervised format, such as Excel or CSV, for our research (Twitter classification), which also required some preprocessing operations and computations for data analysis utilizing machine learning.

A collection of tweets from various people was chosen as the dataset for this study. The extracted fields, interests, and dates are all included in a full-text analysis. Table I provides specifics about the data collected. Fig. 2 presents the suggested methodology. It includes a number of phases, including preprocessing, aspect and opinion extraction, aspect refinement, and product enhancement results. It is used to sug-gest product enhancement when combined with a relation classifier. Below is a full explanation of each phase and procedure included in the suggested methodology.

Table 1. Dataset Description

Sr. No	Categories	Frequencies
1	Positive	1106
2	Natural	428
3	Negaative	1556
	Total	3090

3.2. Preprocessing of Dataset

In the algorithm, preprocessing is displayed. The entire algorithm adheres to relevant standards and uses duplicate materials from input to output. Algorithm 1 represents the Social media data from Twitter that are analyzed for the sentiment. Data preprocessing, such as tokenization, reduction, and stemming, is visible at all stages.

Algorithm 01: Preprocessing Social media data from Twitter are analyzed for sentiment

```
Input: Dataset of Tweet (Di)
Output: Clean Words (Wall)
Initialize Wall ←φ
    for all D ϵDi5.
        S′ ←lowercase(S)
    end for
    for all Si ϵ S
        S″ ← Removal of stop words (Si)
        S′″ ←Remove Punctuation(S″)11.
    end for
  return Wall
End
```

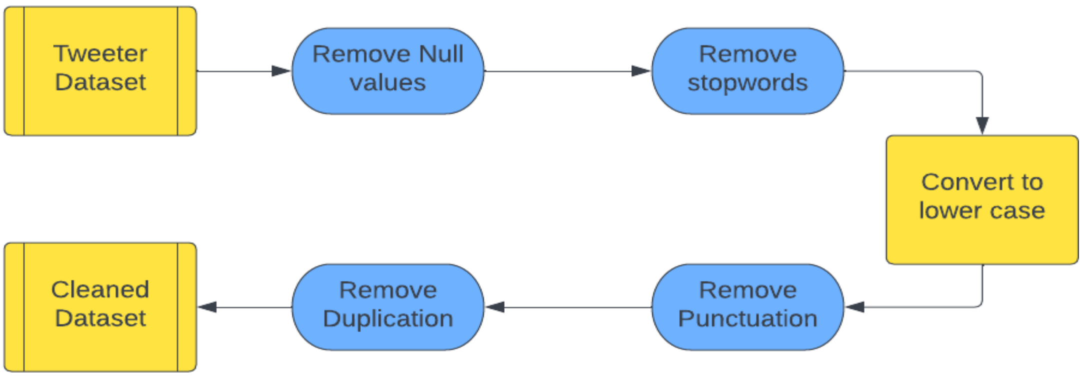

Figure 3. Data preprocessing

a. Tokenization

It may be accomplished by grouping records (crept surveys) into a list of tokens, such as words, numbers, unusual characters, and so forth, and working on the report for further processing. It is a method of dividing the sentence into discrete units known as tokens; it is a list of sub-strings. The modeling approach of each word in a sentence by using its definition from dictionaries and labels and it divides the sentence into letters as shown in figure 3.

b. Lower Case

A final document will be reduced throughout this preprocessing stage. The majority of NLP or sentiment-related issues; will significantly contribute by providing expected results.

c. Remove Stopwords

We must cut out all words in each tweet that keep returning to them during this step. A pre-determined list of stop words has been utilized for this purpose. The stop word list that is available is compared to each word.

d. Remove Punctuation

In this step, we will reduce punctuation from the complete document. It will play a great role in predicting the most coherence for most NLP and text mining problem.

3.3. Feature Extraction

The main aim of our proposed system is to extract Twitter user tweets like opinions related to COVID-19 and how this will affect their mental health. Twitter user expresses their opinion in a single sentence with a single word or phrase. We need to extract their sentiments in the most effective way. We used two methods to extract features from our dataset.

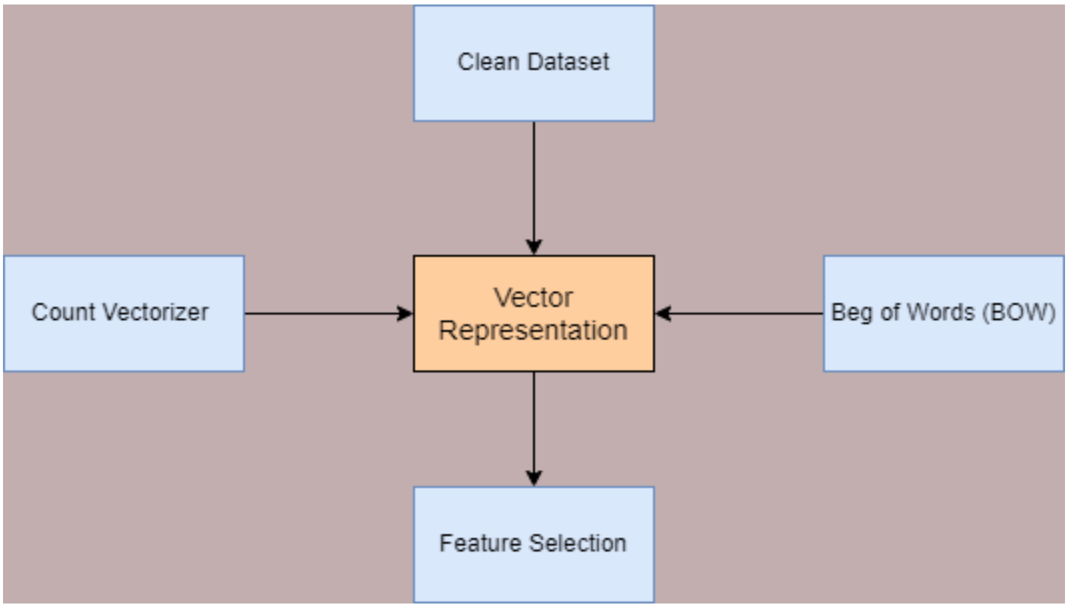

Figure 4. Implementation of Feature extraction

3.4. Count Vectorizer

Term frequency is another name for it. The frequency-based values of the token are determined by the count Vectorizer. Each unique token's event is saved, and the more valuable the token, the more significant the event in the text. The Count Vectorizer method also uses the pack-of-words (Bow) method to evaluate the compared texts; each text is built from unique groups of words that address the occurrence of an explicit word in a clear-cut sentence as shown in figure 4.

3.5. Beg of Words (BoW)

Vector of words is a model that treats the text as a vector of its words, ignoring the structure and word order of the sentence. While storing, the frequent recurrence of each word recalled for that phrase or passage of the dataset that was used to create the classifier. When the BOW model in the sub-module handles, the dataset's sections introduce the structure for the collection of passages in the dataset, which is available in python as the SK-learn library. It distributes the specific number of times a word appears in that specific text.

4. Modeling

It is important to recognize ways of working on the method after the end product is gotten. Social characterization has been utilized for the assessment of class probabilities in a subset of substances with class names as shown in Fig. 5. The strategy for the order depends on two essential presump-tions. The five-star names are considered to be individual classes inside a solitary construction. Fur-thermore, it shows individuals who have a place with a similar social class in at least one aspect. The presentation of the classifier will be frail if each element and imprint is obscure. Bidirectional Encoder Portrayal from Transformers is a diverse encoder. It is utilized for text order for huge datasets. Our proposed framework utilizes Bidirectional Encoder Portrayal from Transformers for improved out-comes.

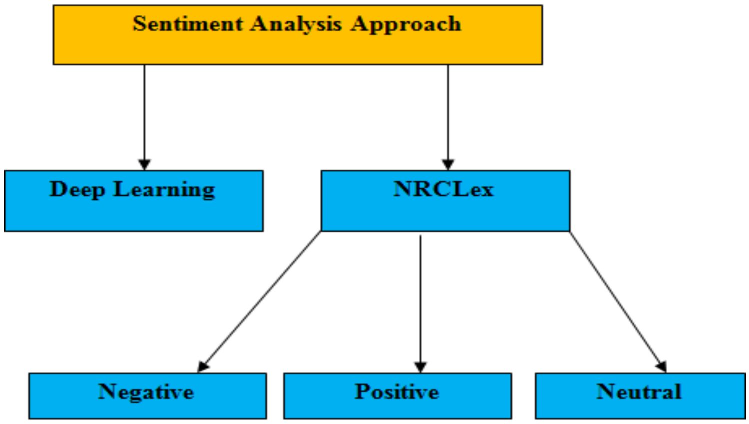

Figure 5. Sentimental Modeling

5. Performance Evaluation Metric

Exactness, Review, F1 Score, and Accuracy are some common execution gauges that we employed to investigate how well our calculations were shown in relation to our output. We used execution metrics to evaluate the exhibition of learning computations. The activities that we look at are:

Accuracy

Recall

F1-score

Precision

Table 2. Evaluation Metric

Evaluation Metrics		Actual	
Prediction	Positive	Positive	Negative
	Negative	Positive (TP)	False Positive (FP)
	Neutral	False Negative (FN)	True Negative (TN)

Tweet dataset is tested based on some attributes checked on the performance matrices accuracy, recall, F1-score and precision. These matrices describe dataset accuracy in terms of different measures. The accuracy metric verifies that the number of predictions a classifier makes is accurate predictions. The dataset, which hasn't been altered due to forecasts which are biased towards the classification with a high recurrence rate and anticipate the other classifications incorrectly, doesn't find this move to be very convincing, though.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (1)$$

TP denotes true positive, TN denotes true negative, FN denotes false negative, and TP denotes true positive in this equation. These metrics are used to evaluate the forecast accuracy for such passing in the same class. The performance of the classifiers is measured using Recall, Precision, Accuracy, and F1- Scores. They are clearly more accurate in determining how calculations should be displayed when the dataset is uneven, and their formulas the following are:

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FP} \quad (3)$$

$$F1Score. = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \quad (4)$$

Table 3. Performance Evaluation Metrics

Models	Accuracy	F1- Score	Precision	Recall
Multi-Layer Perceptron	0.91	0.90	0.97	0.92
Naïve Bayes	0.82	0.81	0.83	0.82
Support Vector Machine	0.79	0.77	0.79	0.74

After the optimum result is achieved, process improvement suggestions are needed. Relational classification is currently being used to generate class probabilities based on Tweets of a similar kind with established class names. It is possible that the categorization cannot be carried out correctly, assuming that items are separated or, on the other hand, assuming that no labels are mentioned.

6. Conclusion

The available Tweets are a mixture of words and emotions which are interlinked. Before inserting into models, these tweets are preprocessed. We are implementing different deep learning algorithms in our research, like the Naïve Bayes Support Vector machine, to categorize the occurrence of words and emotions. Each approach mentioned above is used to improve the algorithm's efficiency. In our study, we intend to employ word2vec to extract data from our models and spot user impersonation tweets. Our Proposed project can be enhanced by including different datasets to obtain more precise results. Each action's result represents the culmination of a variety of evaluating perspectives. The suggested technique yields amazing results compared to the different systems used today. It is strong in all areas, as demonstrated. These techniques can also help us obtain more potent highlights by utilizing more inventive component extraction techniques, and they have played a significant role in developing new systems. The proposed method offers highly promising results compared to the previous method used in different systems.

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