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Machine Learning Approaches to Sentiment Analysis in Social Networks Using Political Tweets

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Abstract. Online social networks offer a quantitative assessment of people's psychological behavior and aid in the general analysis of social or political concerns. In text mining research, opinions, attitudes, and subjectivity in text and other expressions are ascertained by a computational method. Furthermore, the majority of approaches try to simulate word syntactic information without taking sentiment into account. A brief description of the various machine learning (ML) models utilized in sentiment analysis is provided in this paper. Additionally, suggest a productive modular strategy that will provide exact correctness when testing and evaluating the Twitter data. In today's world, when national and international leaders are important, political reviews linked to Twitter data collection are more prevalent. Our work's goal is to find solutions by analyzing and contrasting various approaches. According to a simulation study, there is a practical approach to comprehensively analyze and use a political twitter dataset regarding an international leader, while concentrating on additional sentiment dataset validation to increase the precision of tweet sentiment analysis.

Keywords. Sentiment analysis, regression analysis, machine learning, opinion mining, online social network.

1 Introduction

A large number of people virtually connected through a network known as social network. Human being is more comfortable in social network rather than physical network. Humanity benefits from the social world because it facilitates data analysis that informs decisions made in the real world. Emotions, opinions, sentiments, and attitudes of individuals about things like goods, services, problems, occasions, themes, and their characteristics focuses on sentiment analysis (SA) [1].

Twitter is the best platform used for social networking where people share their feelings or emotions and gives opinion related to product, services politics, movies and so on. Opinions are shared in the form of tweets using certain character limit [2].

Objective of sentiment analysis is to analyze and find out sentiment related to tweets and subjectivity of the text identified. The user views in twitter categorized into Positive, Neutral, and Negative sentiments [3]. The prime goal is to clean the tweets by using several cleaning techniques such as lemmatization, tokenization and others because the data obtained from twitter is very unstructured which contains images, audio, video, emojis, symbols etc. So processing twitter data is a challenging task for which different pre-processing techniques are applied.

The huge amount of user-generated content needs to be minimized and original information should be collected.

Sentiment analysis is beneficial for the extraction of information from tweets. Different techniques are available to analyze approaches used for this purposes. In the present scenario twitter is providing data about national and international leaders which seems very interesting and provides opinion of public regarding their leaders. The most efficient approach used is machine-learning algorithms. Dataset having large volume and dynamic nature implemented by standard machine learning algorithms [4].

The following summarizes the remaining portion of this paper: The connected works are reviewed in Section 2. The classification and regression methods utilized for this are shown in Section 3. The suggested work is shown and explained in detail in Section 4. Comprehensive tests have been carried out on the Twitter real-life dataset in section 5 to assess the performance. This section provides an explanation of the data sets, the experimental findings, and an analysis of those findings. The paper is finally concluded in Section 6.

2 Related Works

In this section, we examine the techniques created to enhance sentiment analysis performance with an emphasis on related works.

Xu and Tan [5] developed a target oriented model for sentiment analysis based on target-oriented aspects. Ligthart et al.'s recent study [7] looked into the difficulties and potential new avenues for sentiment analysis research. Ain et al. [6] assessed the effectiveness of Deep Neural Networks (DNN). Also they listed the salient characteristics of sentiment analysis throughout the previous 20 years. In this research, an overview of the importance of social network analysis (SNA) was presented. Along with this, twitter data collection, cleaning, and analysis done by using python in this paper [8].

Tai et al.'s [9] extensive experimental study aims to enhance the utilization of RNN variation capabilities and LSTM. In order to learn the input sequence appropriately, Xia. and Cho in [10] encoded character input of high-level characteristics blended CNNs and RNNs. Zhang et al. [11] established the CNNs model, which relies on many layers of convolution to capture long-term dependencies in order to extract higher features. Neural network-based techniques, according to Hen.

Shayaa et al. [13] proposed a big data approach to sentiment analysis. Ahmad et al. [14] focused their research on the sentiment-based SVM classification technique. Twitter datasets were examined by Kumar and Jaiswal [15]. Deep learning presents prospects for context-based sentiment analysis, as illustrated by Kumar and Garg [16]. A study by Ligthart et al. [17] looked into customer sentiment analysis. They have read papers that categorize emotions into four to fifty-one classifications. Since Twitter's high dimensionality and structure, Salah et al. [18] have worked in the field of social media sentiment analysis utilizing this data. [12] have proposed that in order to anticipate attitudes, neural network-based techniques receive the input as a vector representation comprising multiple layers.

Zhang et al. [19] synthesized the findings of published secondary studies utilizing various features, techniques, and datasets to examine the state of sentiment analysis research at the moment. Furthermore, they have located and categorized 112 recent publications on sentiment analysis utilizing deep learning and algorithms.

Social networks such as Twitter datasets are complex and unstructured they may contain slang and emotions. Users tweet multiple languages for a single sentence. Thus, the problems lie among data preprocessing and feature extraction steps in sentiment analysis research. Therefore, the primary goals of sentiment analysis address the issues by means of data preprocessing prior to the analysis of the dataset Sentiment analysis is an interdisciplinary discipline that encompasses machine learning (ML), natural language processing (NLP), psychology, and sociology. Recently, more sophisticated analytics have been made possible by rapidly increasing data volumes and processing capacity. As a result, machine learning took center stage in sentiment analysis tools. Diverse machine-learning methodologies have been employed by researchers.

3 Classification Techniques

This part focuses on various techniques of classification to enhance SA. Sentiment classification is roughly categorized as polarity identification, language classification. The approaches used for sentiment analysis are ML approaches, and hybrid approaches [20]. Text

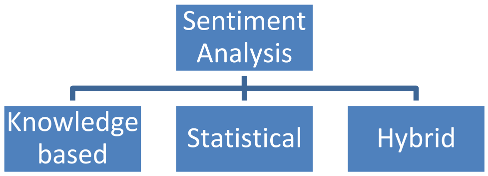

Fig. 1. Approaches of sentiment analysis

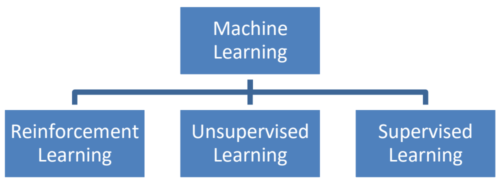

Fig. 2. Types of sentiment classification

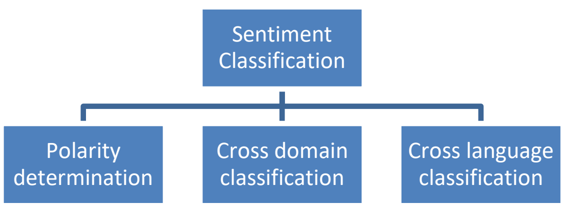

Fig. 3. ML Classification

classification methods using ML may classify into supervised and unsupervised learning methods [21]. Moreover, ML methodologies performed better results as compared with conventional techniques [22, 23]. There is a brief explanation of both approaches, algorithms and related articles mentioned in the next subsections.

The three categories of sentiment analysis methodologies are knowledge-based, statistical, and hybrid:

– Knowledge-Based: Using phrases that arouse powerful emotions, this strategy organized content.

– Statistical: To precisely determine sentiment, this method makes use of machine-learning technologies like deep learning and latent semantic analysis.

– Hybrid: For accurate sentiment analysis, this method combines statistical and knowledge-based techniques [36].

3.1 Classification of Sentiments

In sentiment analysis, the subtask of polarity determination in sentiment classification is often misused. However, this subtask just aims to identify the sentiment polarity in each text fragment. Positive and negative polarity are the usual categories for polarity [37]. Neutral is the third category that is employed in a number of research. Transferring knowledge from a source domain with lots of data to a destination domain with little data and few labels.

It is feasible to add data specific to the target domain to the model [38]. When there is inadequate data, cross-language analysis is performed similarly: a model is developed on a dataset in the source language, and it is tested on a foreign language. It is claimed that when using the Bayesian technique to handle sentiment word polarity ambiguity, opinion-level context is advantageous. ML based methods for word polarity can be replaced by the information retrieval-based model.

3.2 Machine Learning Approaches

When using syntactic and semantic data to solve SA problems, a machine learning (ML) algorithm is dependable. Three types of machine learning models exist: supervised, unsupervised, and reinforcement learning. The following is how they are expressed:

3.2.1 Supervised Learning

The class labels in supervised learning methodologies are known. The number of classes is provided, and the data is labeled. A machine-learning model includes a number of supervised classifiers. Supervised learning again divided into Classification and regression techniques.

3.2.2 Unsupervised Learning

Text classification is used to group documents into a variety of pre-established categories. It can be challenging to construct these labelled training

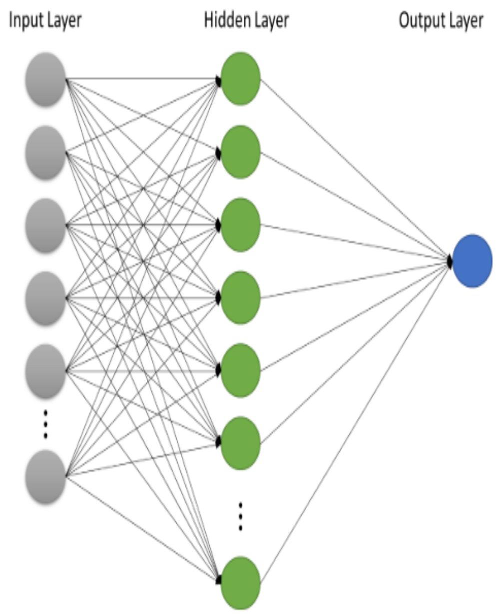

Fig. 4. Multi-Layer Perceptron

documents for text classification. An approach that separates documents into sentences and categorizes each sentence using keywords was proposed by Ahmad M., et al. [15]. As a result, various unsupervised learning techniques are discussed below.

3.2.3 Classification and Regression Techniques

We have used the following classification and regression techniques to analyze our work which is found to give best performance such as logistic regression, Naïve Bayes, LSTM, Multilayer perceptron, etc.

3.2.4 K-nearest Neighbors (KNN)

k-NN, a case-based learning technique, is used to categorize all of the training data. Its sluggish learning curve prevents it from being used in many applications, such dynamic web mining for big repositories. Finding a modest number of representatives to use as the entire training dataset for classification is one method to increase its effectiveness. This would entail using the training dataset to create an inductive learning model, then using this model—representatives—to classification. The evaluation criteria include the performance of different algorithms. We are motivated to develop a model for k-NN [39] that will increase its effectiveness while maintaining its classification accuracy because k-NN is a simple yet powerful technique for text categorization, and it consistently ranks among the best approaches.

3.2.5 Multi-Layer Perceptron (MLP)

MLP designs are based on the ideas of the natural nervous system, able to effectively predict the nonlinear behaviour of complex objects. These frameworks can also be used to handle nonlinear forecasting problems.

This approach learns the procedures required to get the desired results after identifying the underlying relationship between the processes required to address the problem. To do this, the training phase uses a large amount of data, and the relationships that emerge are then used to generate the required output.

The back-propagation net is the most often used kind of neural network, despite the fact that there are many others. All layers are entirely related to all other layers, both above and below. The supervised learning neural network known as the MLP [40] is based on the back-propagation algorithm. A three-layer design represents the ideal MLP setup in Figure 4. Each neuron in this configuration is connected to all the other neurons in the layer below it. There has been a lot of discussion on the application of MLP in non-linear processes.

The variables for input, output, and bias are calculated as follows:

$$c_i = \sum_{i=1}^{n} e_{IJ}\, IN_I + b_i\,, \tag{1}$$

where $E_{ij}, IN_i,\ and\ B_i$ are weight, input, and bias respectively.

The sigmoid function, can be calculated as follows:

$$S_i = \frac{1}{1+e^{c_j}}. \tag{2}$$

The output variable's ultimately calculated as follows:

$$o_i = s_i\left(\sum_{i=1}^{n} e\, IN_i + b_i\right). \tag{3}$$

3.2.6 Long Short-Term Memory (LSTM)

LSTM is extensively utilized [41] in numerous domains, mostly within the realm of machine learning applications, such as speech recognition, natural language processing, and further pattern recognition uses.

The application of LSTM for system identification are as follows:

- The majority of systems identified by neural networks are nonlinear systems, necessitating the use of numerous layers in the network and the problem of vanishing gradient in earlier years.
- The majority of the systems that need to be controlled are dynamic and online, in contrast to a traditional machine learning problem, so there is an extremely high speed requirement when developing a neural network structure for system identification.

3.2.7 Logistic Regression (LR)

To ascertain the result, a dataset including one or more independent variables is statistically evaluated. Like other regression analyses, the goal of logistic regression [43] is to describe data and provide an explanation for the relationship between one or more dependent binary variables and one or more independent nominal, ordinal, interval, or ratio-level variables.

One way to conceptualize logistic regression is as a specific instance of linear regression. The logistic function is shown in Equation 4:

$$\sigma(t) = \frac{e^t}{e^t + 1} = \frac{1}{1 + e^{-t}}. \tag{4}$$

3.2.8 Random Forest (RF)

Breiman first introduced Random Forests (RF) as a technique for managing huge datasets with robust statistical performance. This approach excels at problems requiring prediction because of its remarkable precision. Regression, classification, and other learning-related tasks are handled using RF, a conventional machine learning method. The bagging algorithm is used to aggregate the original dataset, and the decision tree model is used to train each aggregated group separately.

The decision outcomes of several sub-models are combined and assessed to form the final RF model.

The ultimate RF model is based on a voting principle where the output is categorized as that receives the most votes. This method improves overall classification accuracy by reducing the error of individual classifiers. Remarkably, RF performs better in terms of accuracy [42] and classification performance than competing techniques like regression trees and neural networks.

Its effectiveness is especially noticeable while processing massive amounts of data. To evaluate attribute purity, RF employs the indicator of a lower Gini value, which indicates a purer node. The "out of the bag" (OOB) data, or about 36.8% of observations that are not used for any given tree, can be used to assess the accuracy of RF forecasts.

3.2.9 Naïve Bayes (NB)

Nave Bayes, the most basic classifier, quickly classifies the label data. Nave Bayes Classifier uses identity-based components that follow the Bayes Probability Theorem [34] to construct machine learning systems. The Nave Bayes classification is represented mathematically by the following formulas:

$$P(k|a) = \frac{p\left(\frac{k}{a}\right)p(k)}{p(a)}, \tag{5}$$

$$\mathrm{P(k|A)} = \mathrm{p}\left(\frac{\mathrm{a1}}{\mathrm{k}}\right) \times \mathrm{p}\left(\frac{\mathrm{a2}}{\mathrm{k}}\right) \times\times \mathrm{p}\left(\frac{\mathrm{an}}{\mathrm{k}}\right) \times \mathrm{p(k)}. \tag{6}$$

In Eq. (5), P(k|a) stands for the posterior probability, P(k) for the class prior probability, P(a|k) for likelihood, and P(a) for predictor. The posterior probability series up to the nth number [35] is represented here by Eq. 6.

3.2.10 TF-IDF Approach

Text is converted into a matrix of integers using the information retrieval method, TF-IDF. It illustrates significance of a word inside a group of unfinished texts. The frequency with which a word appears in the document directly relates to its TF-IDF value [45]. We have taken n-gram approach here. Frequency84 of Use The raw count of a term in a

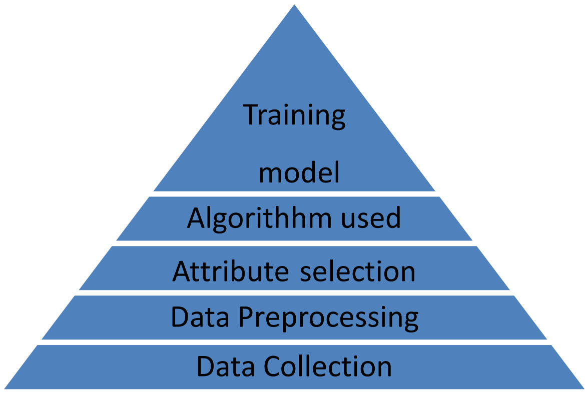

Fig. 5. Methodology used in classified data

document, where t is the term and d is the document, is TF(t,d). The TF technique is specified in Eq. (7) and the raw count is given by $f_{t,d}$:

$$TF(t,d) = f_{t,\,d}. \tag{7}$$

The Inverse Document Frequency (IDF) measures the word based on the occurrence of the word in all the documents, which is defined in Eq. (8):

$$IDF(t, D) = log\frac{N}{|\{d \in D : t \in d\}|}. \tag{8}$$

Finally, the resultant TF-ID maybe defined as in Eq. 9:

$$TF - IDF\ (t, d, D) = TF\ (t, d) \times IDF\ (t, D)\,. \tag{9}$$

4 Proposed Work

As social networks have grown in popularity, more and more individuals want to connect with each other virtually or in person in order to search, share, and exchange information. For this reason, people need quick, free, and simple access to technology that can help them achieve their goals. With almost 330 million users active monthly on Twitter, user activity has significantly increased [34]. The goal of tweet sentiment analysis is to examine user's attitudes or feelings about certain topics because people prefer to share the majority of their information on subjects that interest them. The main objective is to categorize the tweets based on whether they contain positive or negative or neutral content. The machine learning models are the next suitable destination for processing the dataset of tweets.

4.1 Data Description

In this work we have obtained a twitter dataset related to an international leader Donald Trump from Kaggle that contains 957,313 number of instances and 21 attributes. After data collection we have filtered the dataset and extracted the tweets given by only people of USA and data pre-processing performed. After cleaning we have taken 410,372 tweets**.** Tweets taken in English language only are taken. Attribute selection done as per the requirement of sentiment analysis, only tweets are selected. Finally, different classifiers are used to train the model.

4.2 Preprocessing of Data

In general, tokenization, lemmatization, word processing, etc. are used to clean the dataset. The following actions are taken in order to preprocess data:

- Case conversion. Either use upper case letters or lowercase letters for each letter.
- Eliminating words that offer justifications (e.g., therefore, thereof, hence, finally, etc.).
- Erasing the URL and syntactical information.
- Erasing the info that was retweeted.
- Stemming: Using the word's roots as a replacement. Words with comparable meanings were all eliminated.
- Elimination of special characters and symbols.
- Eliminating foreign language terms. Such as the use of Spanish vocabulary in English sentences, etc.
- The use of slang and acronyms has expanded.
- Creating an emoticon dictionary rather than banning them altogether, as they are actually very helpful for conveying emotions.
- Labeling of Sections of Speech.

Table 1. Real Tweets and classification of their algorithms

Tweets	KNN	MLP	LSTM	LR	RF	NB
Proud of how quickly relief was approved. Credit where it's due	Neutral	Neutral	Positive	Positive	Positive	Positive
Another promise broken. Tired of the talk—where's the action?	Negative	Neutral	**Negative**	**Negative**	**Negative**	**Negative**
Debate tonight was… fine? nothing new tbh	Neutral	Neutral	Neutral	Neutral	**Neutral**	**Neutral**
Stop blaming others and fix it	**Negative**	Neutral	**Negative**	**Negative**	**Negative**	**Negative**
Gas prices down again—finally some relief.	Neutral	Positive	**Positive**	**Positive**	**Positive**	**Positive**

	tweet
0	| En : dice que solo se preocupa por ??l mi...
1	: As a student I used to hear for years, for t...
2	You get a tie! And you get a tie! □??s rally
3	Her 15 minutes were over long time ago. Omaro...
4	There won□??t be many of them. Unless you ...

Fig. 6. Sample tweet after preprocessing

	tweet	Subjectivity	Polarity
0	| En : dice que solo se preocupa por ??l mi...	0.000000	0.000000
1	: As a student I used to hear for years, for t...	0.333333	0.333333
2	You get a tie! And you get a tie! □??s rally	0.000000	0.000000
3	Her 15 minutes were over long time ago. Omaro...	0.416667	-0.155208
4	There won□??t be many of them. Unless you ...	0.600000	0.208333

Fig. 7. Subjectivity and polarity of tweets

5 Experimental Setup

The most recent tweets must be acquired from an account and kept before being processed further in order for the current study to conduct an analysis.

The data set then goes through a number of cleaning and checking stages. In Table 1 some real tweets are taken and classification done by using several algorithms.

Figure 6 represents sample tweets after preprocessing for which we have applied different python libraries.

Figure 7 represents subjectivity and polarity for the preprocessed tweets using textblob analysis.

Figure 8 represents subjectivity and polarity of tweets along with sentiment detection as positive, negative, and neutral of the cleaned tweets

Figure 9 represents sentiment distribution in which the neutral sentiment represents the highest frequency.

5.1 Confusion Matrix

One method of measuring the effectiveness of machine learning classification algorithms is the confusion matrix [44]. It is a table arrangement that makes it possible to see how well an algorithm performs. In conclusion, by contrasting actual and anticipated classes, the confusion matrix aids in the visualization of a classification model's performance.

True Positives: The cases in which the model correctly predicted the positive class are known as (TP).

The simulation studies divided into two parts:

- Sentiment analysis.
- Classification using machine learning algorithms.

False Positive (FP): The cases where the model predicted the positive class incorrectly, leading to an actual class that was negative.

	tweet	Subjectivity	Polarity	Sentiment
0	| En : dice que solo se preocupa por ??l mi...	0.000000	0.000000	Neutral
1	: As a student I used to hear for years, for t...	0.333333	0.333333	Positive
2	You get a tie! And you get a tie! □??s rally	0.000000	0.000000	Neutral
3	Her 15 minutes were over long time ago. Omaro...	0.416667	-0.155208	Negative
4	There won□??t be many of them. Unless you ...	0.600000	0.208333	Positive
5	One of the single most effective remedies to e...	0.478571	0.207143	Positive

Fig. 8. Subjectivity and polarity of tweets along with sentiment detection

Table 2. Confusion matrices

Actual Class	Predicted Class	
	Positive	Negative
Positive	True Positive(TP)	False Negative(FN)
Negative	False Positive(FP)	True Negative(TN)

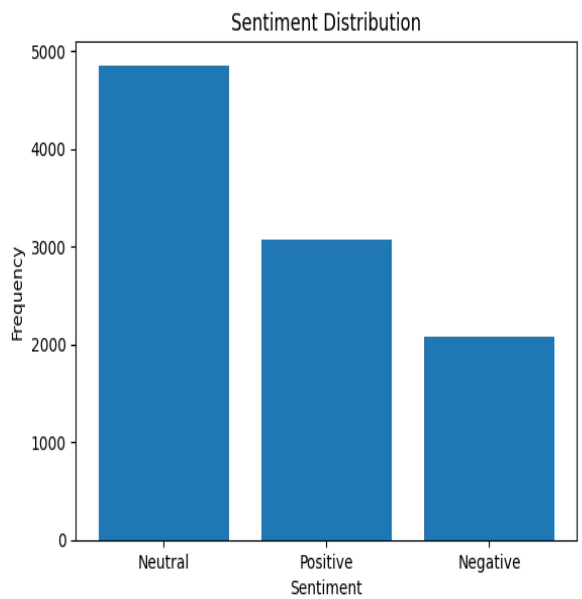

Fig. 9. Sentiment distribution of the dataset: Sample tweet after preprocessing

The cases where the model correctly predicted the negative class are known as True Negatives (TN).

False Negative (FN): The cases where the model forecasted the positive actual class while mispredicting the negative class.

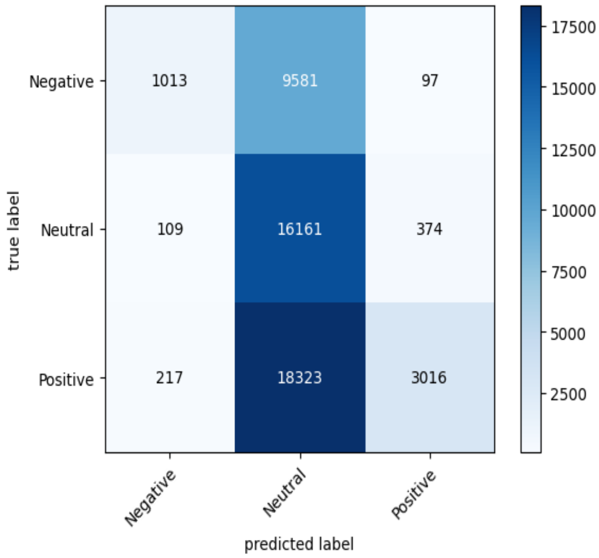

Fig. 10. KNN Confusion Matrix

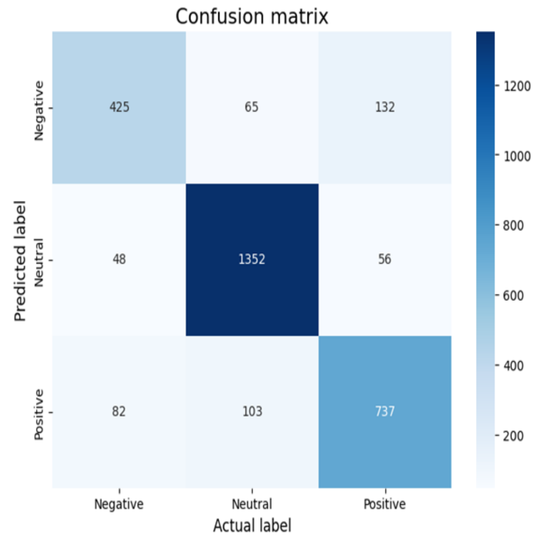

Fig. 11. MLP Confusion matrix

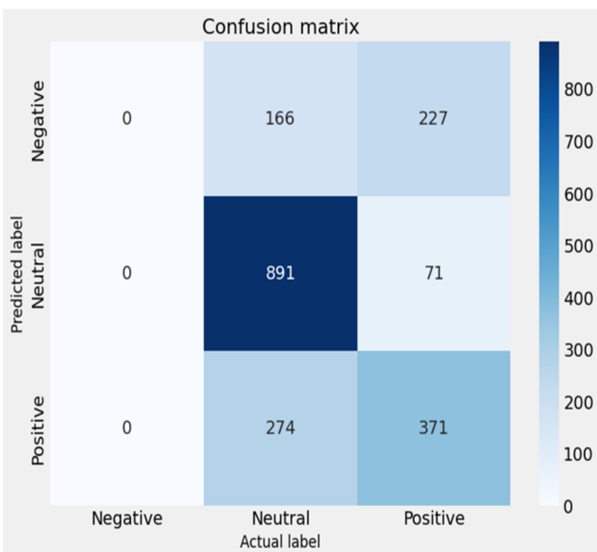

Fig. 12. LTSM Confusion Matrix

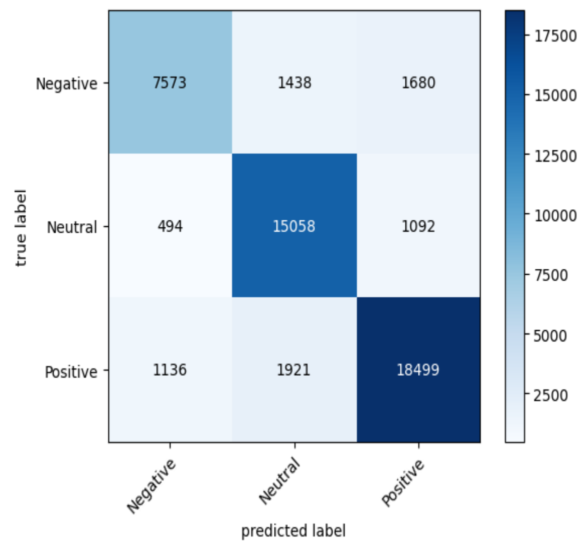

Fig. 13. LR Confusion matrix

Certain metrics that are obtained from a confusion matrix are frequently used to assess how well a classification model is performing.

These indicators offer several viewpoints on a classification model's performance and are frequently combined to provide a thorough grasp of the model's efficacy.

The following are some important metrics:

– Accuracy: The percentage of cases properly classified out of all the occurrences. It is computed as:

$$(TP + TN + FP + FN)/(TP + TN). \quad (10)$$

– Precision: The percentage of all positive predictions that are actually positive. The

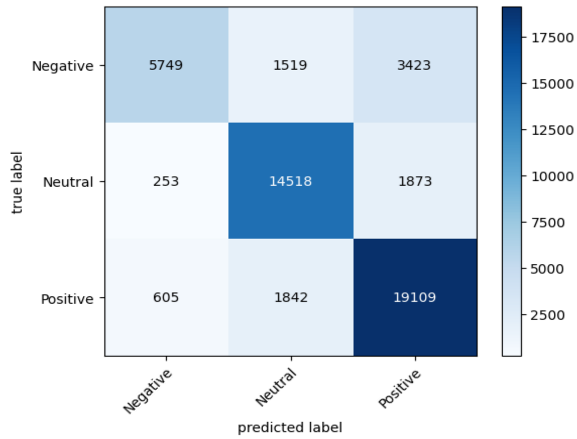

Fig. 14. RF Confusion matrix

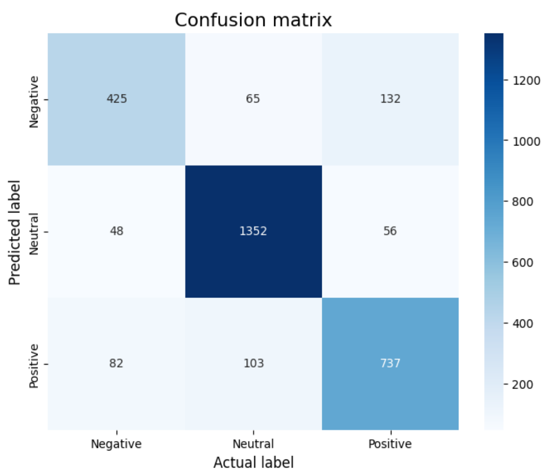

Fig. 15. NB Confusion matrix

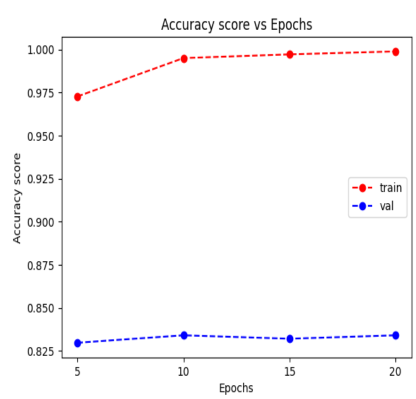

Fig. 16. Trade-off between the accuracy and epochs

precision of a prediction is the proportion of true affirmative cases. The formula is:

$$TP/(TP + FP). \tag{11}$$

Table 2 is a basic structure of a confusion matrix:

– Recall (True Positive Rate): The percentage of real positive occurrences that match true positive expectations. The formula is:

$$TP/\,(TP\;+\;FN). \tag{12}$$

The recall metric quantifies the proportion of true positive cases that are accurately predicted.

The F1 Score represents the harmonic mean of memory and precision:

$$2 \times (Precision \times Recall)/\,(Precision\;+\;\;Recall \tag{13}$$

Recall and precision are balanced by the F1 score.

The figures such as Figure 10 to Figure 15 shows the confusion matrices of all the classifiers used in this work. X-axis represents the predicted label whereas y-axis represents the true label along with positive, negative, and neutral values.

The results of evaluating several classifiers using evaluation measures including accuracy, precision, recall, and F1 score are shown in Table 2. Different performance indicators are represented by the columns, and each row corresponds to a particular algorithm. These measures aid in assessing how well each algorithm performs in terms of accurately classifying instances, striking a balance between precision and recall, and making predictions overall. These findings show that, for the specific dataset we utilized for this study, Naïve Bayes had the best accuracy.

6 Analysis of Results

Figure 16 shows analysis of results using accuracy score verses epochs. We have taken 90 no of epochs and observed that when epoch increases accuracy score increases.

Figure 17 is showing the performance of classifiers in the form of a bar plot using the parameters precision, recall, F1-score and accuracy where Naïve Bayes classifier is showing

Table 3. Result analysis of different classifiers

S. No.	Algorithms	ACCURACY	PRECISION	RECALL	F1- SCORE
1	KNN	41.00%	66.33%	40.62%	31.34%
2	MLP	56.05%	91.28%	11.19%	31.11%
3	LSTM	63.10%	71.33%	51.40%	59.75%
4	LR	78.85%	76.01%	56.40%	64.55%
5	RF	81.11%	82.55%	76.22%	77.66&
6	NB	85.68%	73.27%	73.08%	73.04%

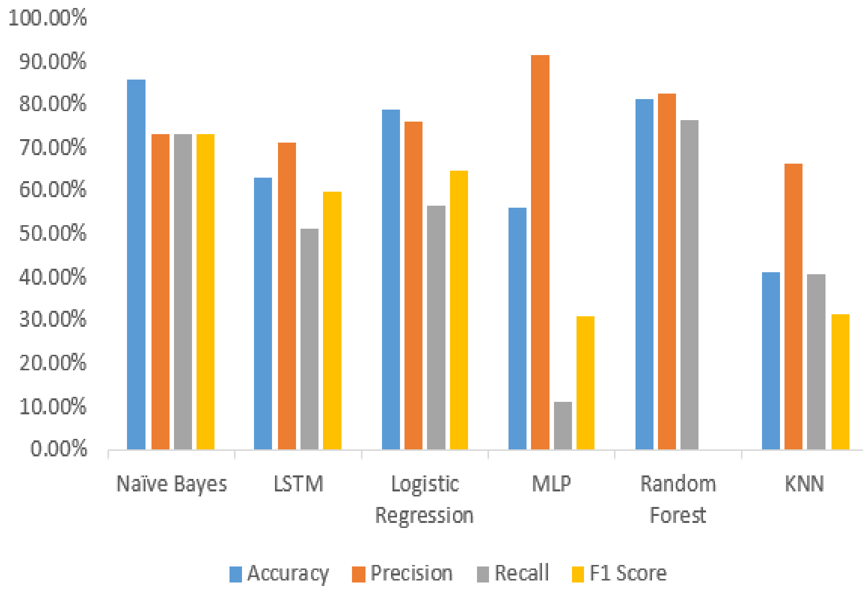

Fig. 17. Performance of classifiers in bar plot

best performance having accuracy of 86% whereas Random Forest is showing best score of precision, recall and f1-score.

7 Conclusion

The optimum model to utilize has been determined in this study by a thorough and practical investigation of the various models for validating and testing the Twitter data set. It's necessary to choose the model that would work best for achieving a higher testing accuracy because there are various models for processing Twitter data. Thus, we analyze the performances of different models and conclude that the Twitter dataset we utilized for this work is best suited for evaluating Naïve Bayes and Random Forest under training.

References

1. **Cambria, E., Poria, S., Gelbukh, A., Thelwall M. (2017).** Sentiment analysis is a big suitcase. IEEE IntellSys., Vol. 32, No. 6, pp. 74–80.
2. **Balabantaray, R. C., Mohammad, M., Sharma, N. (2012).** Multi-Class Twitter Emotion Classification: A New Approach. International Journal of Applied Information Systems (IJAIS), Vol. 4, No. 1, pp. 48–53.
3. **Wang, G., Sun, J., Ma, J., Xu, K., Gu, J., (2014).** Sentiment classification: The contribution of ensemble learning. Decis Support Syst, Vol. 57, pp. 77–93.
4. **Hussein, D.M.E.D.M. (2018).** A survey on sentiment analysis challenges. J. King Saud Univ., Vol. 30, pp. 330–338.

5. **Xu Weidi, Tan Ying (2019).** Semi-supervised Target-oriented Sentiment Classification. Neurocomputing, Vol. 337, No. 8.
6. **Ain, Q.T., Ali, M., Riaz, A., Noureen, A., Kamran, M., Hayat, B., Rehman, A. (2017).** Sentiment analysis using deep learning techniques: A review. Int. J. Adv. Comput., Vol. 8, pp. 424.
7. **Ligthart A., Catal C., Tekinerdogan, B. (2021).** Systematic reviews in sentiment analysis: a tertiary study. Artificial Intelligence Review, Vol. 54, pp. 4997–5053.
8. **Kumar, S., Gahalawat, M., Roy, P.P., Dogra, D.P., Kim, B.G.J.E. (2020).** Exploring Impact of Age and Gender on Sentiment Analysis Using Machine Learning. Electronics. Vol. 9, pp. 374.
9. **Tai, K. S., Socher, R., Manning, C. D. (2015).** Improved semantic representations from tree-structured long–short-Term memory networks. 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, Vol. 1, pp. 1556–1566.
10. **Xiao, Y., Cho, K. (2016).** Efficient character-level document classification by combining convolution and recurrent layers.
11. **Zhang, X., Zhao, J., Lecun, Y. (2015).** Character-level convolutional networks for text classification. Adv. Neural Inf. Process. Vol. 20, pp. 649–657.
12. **Shen, Y., He, X., Gao, J., Deng, L., Mesnil, G. (2014).** Learning semantic representations using convolutional neural networks for web search. Proceedings of the 23rd International Conference on World Wide Web, pp. 373–374.
13. **Shayaa, S., Jaafar, N.I., Bahri, S., Sulaiman, A., Phoong, S.W., Chung, Y., Piprani, A., Al-Garadi, M. (2018).** Sentiment Analysis of Big Data: Methods, Applications, and Open Challenges. IEEE Access.
14. **Ahmad, M., Aftab, S., Bashir, M.S., Hameed N. (2018).** Sentiment analysis using SVM: A systematic literature review. Int. J. Adv. Comput. Sci. Appl., Vol. 9, No. 2, pp. 182–188.
15. **Kumar, A., Jaiswal, A. (2020).** Systematic literature review of sentiment analysis on Twitter using soft computing techniques. Concurrency and Computation: Practice and Experience.
16. **Kumar, A., Garg, G. (2020).** Systematic literature review on context-based sentiment analysis in social multimedia. Multimedia Tools and Applications, Vol. 79, No. 1.
17. **Ligthart, A., Catal, C., Tekinerdogan, B. (2021).** Systematic reviews in sentiment analysis: A tertiary study. Artif. Intell Rev., Vol. 54, pp. 4997–5053.
18. **Salah, Z., et al. (2019).** A systematic review on opinion mining and sentiment analysis in social media. International Journal of Business Information Systems, pp. 530– 554.
19. **Zhang, Z., Zou, Y., Gan, C. (2018).** Textual sentiment analysis via three different attention convolutional neural networks and cross-modality consistent regression. Neurocomputing, Vol. 275, pp. 1407–1415.
20. **Bondielli, A., Marcelloni, F. (2019).** A survey on fake news and rumour detection techniques. InfSci, Vol. 497, pp. 38–55.
21. **Neethu, M.S., Rajashree, R. (2013).** Sentiment Analysis in Twitter using Machine Learning Techniques, 4th ICCCNT, at Tiruchengode, IEEE – 31661.
22. **Behera, R.N., Manan, R., Dash, S. (2016).** Ensemble based hybrid machine learning approach for sentiment classification-a review. Int J. Comput. Appl., Vol. 146, No. 6, pp. 31–36.
23. **Sykora, M.D., Jackson, T.W., Elayan, S. (2013).** Emotive ontology: extracting fine-grained emotions from terse, informal messages. IADIS International Journal on Computer Science and Information Systems, Vol. 8, No. 2, pp. 106–118.
24. **Pak, A., Paroubek, P. (2010).** Twitter as a Corpus for Sentiment Analysis and Opinion Mining. Proceedings of the Seventh Conference on International Language Resources and Evaluation, pp. 1320–1326.
25. **Peng, M., Zhang, Q., Jiang, Y., Huang, X. (2018).** Cross-domain sentiment classification with target domain specific

information. Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, Vol. 1, pp. 2505–2513.

26. **Quinlan, J. R. (1986).** Induction of decision trees. Machine learning, Vol. 1, No. 1, pp. 81– 106.

27. **Agarwal, B., Xie, I., Vovsha, O., Rambow, R. (2011).** Passonneau, Sentiment Analysis of Twitter Data. Proceedings of the ACL 2011 Workshop on Languages in Social Media, pp. 30–38.

28. **Cambria, E., Schuller, B., Xia, Y., Havasi, C. (2013).** New avenues in opinion mining and sentiment analysis. IEEE Intelligent Systems, Vol. 28, No. 2, pp. 15–21.

29. **Walaa, M., Hassan, A., Korashy, H. (2014).** Sentiment analysis algorithms and applications: A survey. AIN Shams Engineering Journal, Vol. 5, No. 4, pp. 1093– 1113

30. **Xia, Y., Cambria, E., Hussain, A., Zhao, H. (2015).** Word polarity disambiguation using bayesian model and opinion-level features. CognitComput, Vol. 7, No. 3, pp. 369–380.

31. **Cruz, F.L., Troyano, J.A., Ortega, F.J., Enríquez, F. (2011).** TOES: A Taxonomy-Based Opinion Extraction System. Natural Language Processing and Information Systems. NLDB 2011. Lecture Notes in Computer Science, Vol. 6716.

32. **Abid, F., Li, C., Alam, M. (2020).** Multi-source social media data sentiment analysis using bidirectional recurrent convolutional neural networks. Comput Commun, Vol. 157, pp. 102–115.

33. **Pang, B., Lee, L, Vaithyanathan, S. (2002).** Thumbs up?: Sentiment classification using machine learning techniques. Proceedings of the ACL-02 conference on empirical methods in natural language processing. Stroudsburg, PA: Association for Computational Linguistics, Vol. 10, pp. 79– 86.

34. **Jooho, K., Makarand, H. (2018).** Social network analysis: Characteristics of online social networks after a Disaster. International Journal of Information Management, Vol. 38, pp. 86–96.

35. **Shah, P. (2020).** Sentiment Analysis using TextBlob.

36. **Analyticsinsight.net (2023).** Types of sentiment analysis. https://www.analytics insight.net/types-of-sentiment-analysis.

37. **Wang, Y., Jodoin, P. M., Porikli, F., Konrad, J., Benezeth, Y., Ishwar, P. (2014).** CDnet 2014: An expanded change detection benchmark dataset. Proceedings of the IEEE conference on computer vision and pattern recognition workshops, pp. 387–394.

38. **Peng, P., Barnes, M., Wang, C., Wang, W., Li, S., Swanson, H. L., Tao, S. (2018).** A meta-analysis on the relation between reading and working memory. Psychological bulletin, Vol. 144, No. 1, pp. 48.

39. **Guo, G., Wang, H., Bell, D., Bi, Y., Greer, K. (2003).** KNN model-based approach in classification. On The Move to Meaningful Internet Systems 2003. CoopIS, DOA, and ODBASE: OTM Confederated International Conferences, CoopIS, DOA, and ODBASE 2003 Proceedings, Springer Berlin Heidelberg, pp. 986–996.

40. **Abd-elaziem, A. H., Soliman, T. H. (2016).** A Multi-Layer Perceptron (MLP) Neural Networks for Stellar Classification: A Review of Methods and Results‖. International Journal of Advances in Applied Computational Intelligence, Vol. 3.

41. **Wang, Y. (2017).** A new concept using LSTM Neural Networks for dynamic system identification. 2017 American control conference (ACC), pp. 5324–5329.

42. **Doz, D., Cotič, M., Felda, D. (2023).** Random Forest Regression in Predicting Students' Achievements and Fuzzy Grades. Mathematics, Vol. 11, No. 19.

43. **Jawa, T. M. (2022).** Logistic regression analysis for studying the impact of home quarantine on psychological health during COVID-19 in Saudi Arabia. Alexandria Engineering Journal, Vol. 61, No. 10, pp. 7995–8005.

44. **Heydarian, M., Doyle, T. E., Samavi, R. (2022).** MLCM: Multi-label confusion matrix. IEEE Access, Vol. 10, pp. 19083–19095.

45. **Panda, B., Panigrahi, C. R., Pati, B. (2022).** Exploratory data analysis and sentiment analysis of drug reviews. Computación y Sistemas, Vol. 26, No. 3, pp. 1191–1199.

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