International Journal of Recent Innovations in Academic Research
E-ISSN: 2635-3040; P-ISSN: 2659-1561
Homepage: https://www.ijriar.com/
Volume-5, Issue-12, December-2021: 76-87

Research Article

Sentiment Classification on Twitter Data Using Artificial Intelligence and Natural Language Processing

[*a]Suneel Babu Boppana, [b]Chethan Sriharsha Moore, [c]Varun Bodepudi, [d]Krishna Madhav Jha, [e]Srinivasa Rao Maka and [f]Gangadhar Sadaram

[a]iSite Technologies, Project Manager, [b]Impetus Technologies, Sr Software Engineer, [c]Applab Systems Inc, Computer Programmer, [d]Topbuild Corp, Sr Business Analyst, [e]North Star Group Inc, Software Engineer, [f]Bank of America, DevOps/OpenShift Admin Engineer
*Corresponding Author Email: suneelb@outlook.com

Received: December 10, 2021 **Accepted:** December 22, 2021 **Published:** December 30, 2021

Abstract
Twitter, in particular, has rapidly expanded over the last few years and generates tremendous amounts of text data which can be used to gauge sentiment. This research focuses on the sentiment classification of tweets using the application of ML and NLP techniques. Polarity and client sentiment are other significant aspects of sentiment analysis, whereby extracting views and categorising as good, negative or neutral is important for businesses to make decisions. This research focuses on sentiment classification using machine learning algorithms on a large tweet dataset of SVM, KNN, and LR. The performance of these models was evaluated in terms of F1-score, recall, accuracy and precision. The chosen SVM model showed better performance giving an accuracy of 89%, precision 85%, recall 82%, and F1 score 84% which makes the SVM model as the best model for sentiment classification in this study. However, observed poor performance from KNN and LR models, with KNN giving an accuracy of 62.42%. These findings provide direction for the use of SVM in sentiment classification for huge collections of text data, emphasising fine-grained sentiment classification. For future work, it could be investigated as to how different deep learning models can be adapted to enhance classification accuracy and to test the model on various social media that might have more robust postings. Moreover, the problem of class imbalance, as well as future work with new mixed models, can yield even more accurate sentiment estimations.
Keywords: Social Media, Twitter Data, Sentiment Analysis, Natural Language Processing (NLP), Artificial Intelligence (AI), Machine Learning (ML), Sentiment Polarity.

I. Introduction

The abundance of user-created content in contemporary social networking sites has made these sites inevitable in the sharing of information on public opinion, events, and even consumption patterns. Of these platforms, Twitter is one of the most used that records millions of tweets on different topics stretching from politics to entertainment [1]. The continuous stream of information available on Twitter makes it one of the most valuable tools when it comes to business, authorities, and academics when it comes to tracking public trends and making sound analytical decisions. However, it is very difficult to process this tremendous amount of information and, especially, to perceive sentiments expressed in tweets. Sentiment analysis, which is an important component of NLP, aims at classifying the emotions from a particular text. While in the context of the context of Twitter, sentiment analysis aims at categorising the posts into positive, negative or neutral. Analysing sentiments of text messages on Twitter remains a daunting challenge yet very important when analysing informal language, short messages containing hashtags and other microblogging tools [2]. It also allows organisations to evaluate consumer's opinions on some matters, determine the mood of society concerning products, services, or events, or even forecast the market trend through the analysis of the opinions. The incorporation of NLP coupled with sentiment analysis on Twitter data has laid the foundation for better and faster solutions [3]. Text mining, or using NLP to map human language onto computation, focuses on turning text data into usable information [4]. One of these is the process of data collection, sentiment identification, feature extraction, classification and determination of the sentiments' polarity. Many components of sentiment analysis involve natural language processing techniques in extracting sentiment-carrying words and phrases and the overall sentiment of the tweet.

It has been seen that in recent past there is an increase in research work focused on applying ML and AI for sentiment analysis. The use of AI models results in better capturing the various structures in the use of the Twitter platform and better prediction of the sentiment. To generate predictions on unseen data, these models need a lot of labelled data to understand the link between the text and sentiment [5]. Furthermore, they enable sentiment classification to be done in real time by using machine learning algorithms, which makes them highly useful in use cases such as market analysis, customer support and looking at the political climate in various countries [6]. The use of NLP, AI, and ML makes the sentiment analysis of Twitter data a strong framing feature that enables understanding of the information drawn from large volumes of unstructured texts [7]. Sentiments identified in tweets can, therefore, appropriately be classified and used by organisations affecting decision-making, customer relationships and future trends.

A. Motivation and Contributions of the Study

The reason for carrying out this study stems from the fact that there is difficulty in attributing appropriate sentiments to tweets, particularly because Twitter data is unstructured and constantly evolving. Currently, they are used to classify sentiment for different domains such as politics, customer feedback and health to address issues of public opinion, trends and sentiments. Common approaches for sentiment analysis are not successful in handling Twitter data that consists of unbalanced classes, temporal-sensitive data and a large number of tweets. Consequently, the purpose of this research is to improve the precision of sentiment analysis by using state-of-the-art ML models and NLP methods.

The key contributions of this study include:

- ✓ Collection of a Twitter dataset consisting of 1.2 million tweets with annotated sentiments (positive, negative, neutral).
- ✓ Application of data preprocessing techniques, including stopword removal, URL filtering, and number elimination to enhance data quality.
- ✓ To transform textual information into numerical forms, feature extraction employs the Bag of Words (BOW) technique.
- ✓ Implementation of ML models such as KNN, LR, and SVM for sentiment classification.
- ✓ Finding the best sentiment analysis classifier by comparing models using F1-score, recall, accuracy, and precision.

B. Structure of the Paper

Presented below is the paper's outline: Section II delves into the study of sentiment using Twitter data. Data collecting, preprocessing, feature extraction, and model selection are all covered in Section III, which lays out the technique. Section IV presents the results of the tests conducted with several ML classifiers. Finally, Section V concludes with a summary and some suggestions for further research.

II. Literature Review

The literature review highlights advancements in sentiment analysis of Twitter data. However, the review identifies persistent challenges such as real-time processing, multilingual analysis, and nuanced sentiment detection.

Some reviews are:

In this study, Rane and Kumar [8] evaluated the sentiment of six major US airlines' tweets using multi-class sentiment analysis. The study included seven different classification algorithms: DT, RF, SVM, KNN, LR, GNB, and AdaBoost. The classifiers were trained using 80% of the data and then tested using the remaining 20%. Whether the sentiment of the tweets is positive, bad, or neutral is the outcome of the test set. The aggregate emotion count was visualised by merging all six airlines, and the accuracy of each categorisation method was compared based on the findings [8]. This study, Çeliktuğ [9] primary objective is to categorise three (3) annotated Twitter datasets into negative, positive, and neutral methods. In dataset-2 experiments, the baseline is attained. Experiments on dataset 1 showed an overall accuracy of 88%, which is better than the previous paintings. Overall accuracy and class-based accuracy balance have been significantly impacted by Unigram features [9].

In this research, Fitri et al. [10] there are several steps involved in sentiment analysis, including gathering sentiment data using Twitter's API. Following the processing of raw initial data in the preprocessing step, the NBC approach is used for classification, POS tagging, and word weighting with TF-IDF computation. On average, the study's results show a 94.5 percent precision rate, 93.3 percent recall, and 99.0 percent accuracy [10]. In this study, Amjad et al. [11] concentrate on analysing the mood of Urdu-language news tweets from Pakistan's main news outlets. They gathered data from Twitter for 10 months in order to create an Urdu sentiment lexicon. 77% accuracy is attained by our sentiment analysis technique. In addition, they conducted perspective analysis, and with 77.45% accuracy, they calculated the bias in news reporting on the government via tweets [11].

In this study, Ibrahim and Yusoff [12] there were twenty-seven trainers present. 25 tweets containing each keyword were given to each trainer to categorise in terms of emotion. The NB approach was then used to ask the trainers to verify the sentiment classification findings. In terms of the overall number of correctly identified tweets, the study's accuracy is 90%±14% [12]. In this study, Sahu et al. [13] provide a fresh method for sentiment analysis on Twitter. Following this first preprocessing, the ML techniques (Maximum Entropy and SVM) are used. To measure the sentiment's degree, they also provide a cutting-edge sentiment scoring system. Our method has an 80% accuracy rate in identifying tweet sentiments [13].

Table 1 summarises key studies on sentiment analysis of Twitter data, highlighting various methodologies such as machine learning classifiers, sentiment lexicons, and novel preprocessing techniques.

Table 1. Summary of literature review on sentiment analysis using machine learning methods and technique.

Author	Data	Methodology	Findings	Limitation/future work
Rane and Kumar [8]	Tweets from 6 major US airlines	Preprocessing, Doc2Vec for phrase-level analysis, 7 classification strategies (Decision Tree, SVM, etc.)	Accuracies compared for different classification approaches, visualised sentiment counts across airlines	Limited to US airlines, real-time processing and multilingual analysis not addressed
Çeliktuğ [9]	Three annotated Twitter datasets	Oversampling, unigram features, classification accuracy evaluation	88% overall accuracy in dataset-1, significant effect of unigram features on accuracy and class balance	Further exploration of feature engineering and class balancing required
Fitri, et al. [10]	Twitter data via	Preprocessing, POS tagging, TF-IDF	94.5% precision, 93.3% recall, 99.09%	Improvements in real-time classification and

	API	weighting, Naive Bayes Classifier (NBC)	accuracy in sentiment classification	scalability needed
Amjad et al. [11]	Urdu language news tweets from Pakistan	Sentiment lexicon creation, cumulative sentiment score-based classification	77% accuracy in sentiment classification, perspective analysis on bias in news reporting	Focus on other languages, more extensive dataset needed for better accuracy
Ibrahim and Yusoff [12]	27 trainers classifying 25 tweets each	Naive Bayes classification, trainers validate sentiment classification	90%±14% accuracy measured by total correct classifications	Limited to trainer participation, more diverse validation needed
Sahu, et al. [13]	Twitter data	Novel spell-checking algorithm, disjoint compound word handling, emoticons replaced by emotion words, SVM and maximum entropy classifiers	80% accuracy in sentiment classification, novel sentiment scoring mechanism	Need for improvement in sentiment detection accuracy and feature handling

III. Methodology

The aim of this study is to classify sentiments in Twitter data using machine learning models. The research methodology follows the steps outlined in Figure 1. Initially, a dataset of 4500 tweets containing various fields like "text," "user ID," "date," and "tweet URL" is collected, with the tweets classified into positive, negative, and neutral categories. Next, data preprocessing steps were performed to improve data quality. This included URL removal, stop word elimination, number removal, and stemming to refine the content. Textual input was transformed into numerical features appropriate for ML models using feature extraction employing the BOW approach. Subsequently, the preprocessed dataset was split into test set (25 percent) and training set (75 percent). In the present study, dataset was used to train different types of ML models such as KNN, LR & SVM. Then finally, all the models for the sentiment analysis are compared using the accuracy, precision, recall, and F1-score. The results showed that SVM was the best model overall. This process helps to sort the tweets into a sentiment type to draw conclusions on opinions of the general public on some product, an event or a brand for instance.

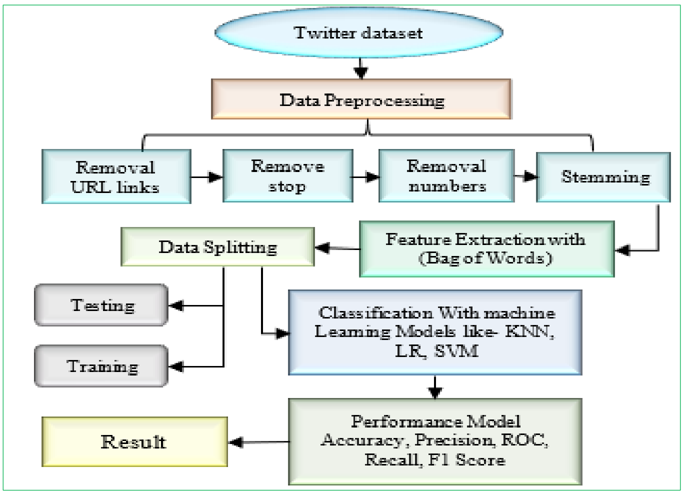

Figure 1. Flowchart for sentiment analysis.

A following provides a quick explanation of each phase in a data flow diagram:

A. Data Collection

This study used the Twitter dataset. Twitter was used to get 4500 Twitter data points for this investigation. Nearly 1.2 million tweets discussing diverse viewpoints and ideas on the furniture company were included. It featured many fields, including "text," "user ID," "date," and "tweet URL," which held the primary review. Out of all the tweets gathered and annotated, 1680 were classified as neutral, 1220 as affirmative, and 1600 as negative. The following analysis and visualisation of Twitter data are given below:

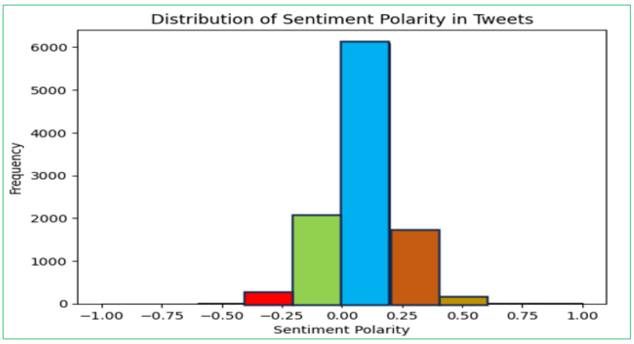

Figure 2. Histogram for distribution of sentiment polarity.

Figure 2 shows a right-skewed distribution of tweet sentiment, with a mode around 0.25, indicating more positive than negative tweets. The sentiment range spans from -1 to 1, with a few outliers on the negative side. This provides a quick insight into the sentiment distribution, highlighting overall positivity and some extreme negatives.

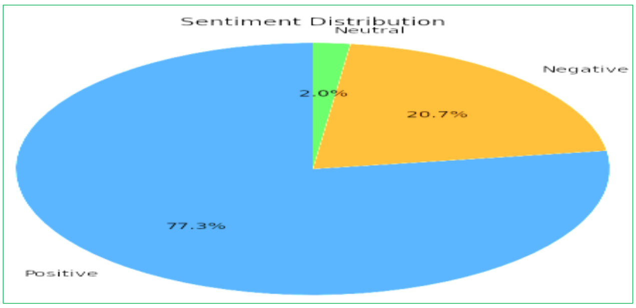

Figure 3. Pie chart for sentiment distribution.

The pie chart in Figure 3 shows that 77.3% of the dataset expresses positive sentiment, while 20.7% is negative, and only 2.0% is neutral. This indicates that the content being analysed is largely viewed favourably, with a small but notable portion expressing negative sentiment, suggesting some areas of concern. The low neutral percentage may reflect a general lack of ambiguity or strong opinion in the data.

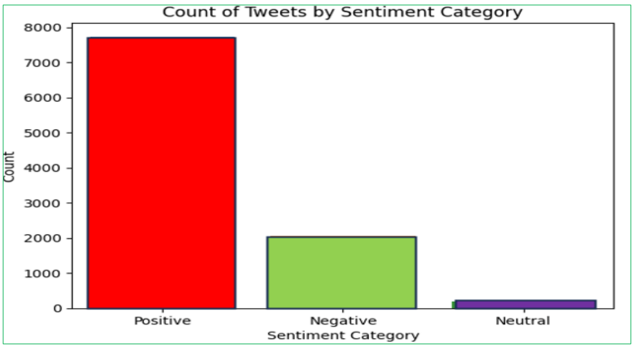

Figure 4. Count plot for tweet category.

Figure 4 shows the count plot for the tweet category. Twitter sentiment is shown on the x-axis as positive, negative, or neutral, and a y-axis as a number of tweets falling into each category, ranging from zero to eight thousand.

B. Data Preprocessing

The polarity of the raw data makes it very prone to duplication and inaccuracy [14]. The findings are impacted by the data quality; hence, the raw data is pre-processed to enhance its quality. In order to make the data more efficient, it handles the preparation that eliminates redundant words and punctuation. Here are the main stages of the pre-processing:

Removal of URL Links: The first step is to tokenise Twitter and convert its short URLs to full URLs [15]. After that, to improve the tweets' content, take out the URL that matches the tokens.

Remove Stop Words: Words that, when deleted from a phrase, have no impact on the data being analysed are called stop words [16]. They employed a list of stop words from the NLTK library in this training model, including I, me, myself, we, they, you, and so on.

Removal Numbers: A numbers are often removed by tweets to improve the tweet content since they lack sentiment information [17], making them ineffective for gauging sentiment.

Stemming: The process of text standardisation, also known as stemming, follows the elimination of stop words. In stemming, the word is reduced to its most fundamental root or base form [18]. The only drawback to this procedure is that stemming can cause the phrase or content to lose some of its meaning.

C. Feature Extraction Techniques

The goal of feature extraction is to help ML models better interpret textual input by creating relevant features or vectors from the data [19]. Text features may be built using a variety of approaches, including BoW [20]. BoW is a simple method for turning tokens into a collection of attributes by using words [21, 17]. The BoW model is used for document categorisation and uses each word as a feature to train the classifier.

D. Data Splitting

The preprocessed data is split into a training set and a testing set. In this research, the data is divided as follows: 75% is utilised for training the models, and 25% is used for testing them.

E. Classification with Support Vector Machine

The SVM-supervised learning method is rooted in the statistical learning theory that has been augmented by the structural risk minimisation principle [22]. The SVM maps the training data into a high-dimensional feature space from the original input space while choosing tan implicitly. Then, in the feature space, maximise the margins of the class borders to get the best hyperplane [23, 24]. Maximising the margin among the data and the separating hyperplane is one way the SVM aims to minimise an upper limit of a generalisation error. The training regions that are most perpendicular to the optimal hyperplane are called support vectors [25]. The objective of SVM classification is to find the optimal separation hyperplane that can distinguish between the two classes (landslides and no landslides) in the training data set. SVM modelling for discriminant-type statistical issues is based on two primary concepts. One of these ideas is a linear separation hyperplane that effectively divides data patterns [26]. The second approach is to use kernel functions to linearly separate the high-dimensional feature space from the original nonlinear data patterns. An essential SVM requirement for a situation with linear separability:

Where $||w||$ shows a typical hyperplane, b is a scalarbase, and $(\cdot)$ displayed the action of the scalar product. The cost function may be defined using the Lagrangian multiplier in the following way (1):

$$y_i((\omega.x_i) + b) \geq 1 \quad (1)$$

$$L = \frac{1}{2}\|\omega\| - \sum_{i=1}^{n} \lambda_i (y_i((\omega \cdot x_i) + b) - 1) \quad (2)$$

Where λ_i is a Lagrangian multiplier. Equation (3) may be solved by dual minimisation with regard to w and b employing conventional methods.

$$y_i((\omega.x_i) + b) \geq 1 - \xi_i \quad (3)$$

The introduction of slack variables ξ_i allows for the modification of the constraints in the non-separable scenario.

F. Performance Matrix

The findings are analysed using performance metrics that are well-known in academia and centre on the use of the confusion matrix. There are four main qualities that display the result data in the matrix, which is the combination of results from classifications.

The fundamental parameters are:

TP (True Positive): A quantity of positively anticipated situations that were accurate.
TN (True Negative): A quantity of negative instances that were accurately anticipated.
FP (False Positive): A quantity of negative instances that were mistakenly forecast as positive.
FN (False Negative): A quantity of positive instances that were mistakenly forecast as negative.

Accuracy: The most common measure of an evaluation's efficacy is its accuracy, which indicates the percentage of times the tested technique produced the expected result [27]. It is determined by dividing the total number of forecasts by the sum of the correct predictions In Equation 4.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Precision: The precision measures the accuracy of a procedure and is determined by dividing the total number of positive predictions by a ratio of positive occurrences that were really positive, Equation 5.

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

Recall: Recall, also known as sensitivity, is the percentage of positive instances that were really expected to be positive. Equation 6 is used to calculate it.

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

F1-Score: Recall and precision calculations are often insufficient. It is more suitable to use a mix of the two to assess the strategies' effectiveness [28]. A measure that integrates recall and precision is the F-score In Equation 7.

$$F - score = 2 \cdot \left(\frac{Precision \cdot Recall}{Precision + Recall}\right) \quad (7)$$

ROC Curve: This is a probability curve that represents several classes. It provides insight into the model's performance in classifying inputs.

IV. Result Analysis and Discussion

This study's experiments were conducted on a desktop computer with a 64-bit version of Windows 11, 16 GB of RAM, a 1 TB hard drive, and an Intel(R) Core (TM) i7-8750H CPU operating at 2.20GHz and 2.21GHz. In this section, the findings of the sentiment classification on Twitter data using multiple ML models are analysed, for sentiment classification apply SVM model that compare with KNN [29], LR [30]. The models were trained on dataset of 1.2 million tweets which were further categorised into–positive, negative and neutral. The performance of the models was measured in terms of F1-score, recall rate, accuracy and precision. The SVM model has the greatest accuracy, as seen in Table 2.

Table 2. Outcome of SVM model for sentiment analysis on the Twitter dataset.

Performance matrix	**Support vector machine (SVM)**
Accuracy	89
Precision	85
Recall	82
F1-Score	84

Table 2, present the outcome of the SVM model for sentiment analysis on the Twitter dataset. An average accuracy of 89% in classifying the attitudes of the dataset is an indication of high performance of a model. As can be seen, the model is 85% accurate in its positive sentiment predictions and forecasts. The proposed SVM model provided promising sentiment classification results for this dataset with the 82% recall value and 84% F1-score meant to reflect that the model was able to recognise the significant portion of the inherent positive sentiment [31-44].

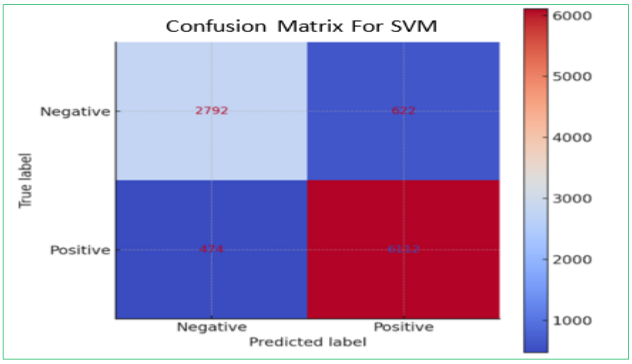

Figure 5. Confusion matrix for SVM model.

The model's performance is visualised by the confusion matrix in Figure 5, which displays the number of TP (6112), TN (2792), FP (622), and FN (474). A confusion matrix is used to enhance clarity, with higher counts in deeper colours and lower counts in lighter shades. This matrix helps evaluate the accuracy, precision, recall, and overall classification performance of the model.

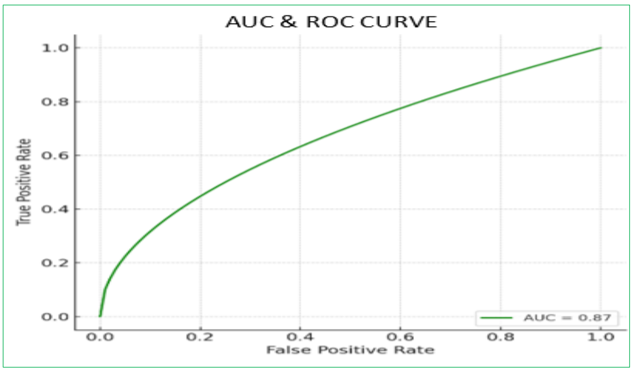

Figure 6. AUC and ROC curve for SVM.

Figure 6 depicts the ROC curve plots of the TPR (sensitivity) against the FPR. The AUC value of 0.87 indicates good model performance, where the closer a value is to 1, the better the classification. The curve demonstrates how well the model distinguishes between classes.

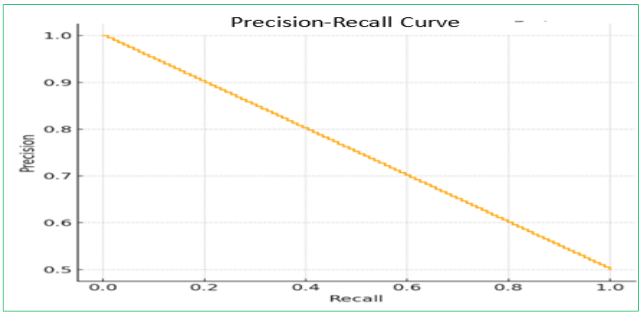

Figure 7. Precision-recall curve for SVM.

At various thresholds, the precision-recall curve of SVM assesses the trade-off between the two variables (Figure 7). The model's capacity to maximise true positives while minimising false positives is seen by the curve. It is particularly useful for imbalanced datasets, as it focuses on positive class performance.

Table 3. Comparative analysis for sentiment classification on Twitter data.

Model	Accuracy	Precision	Recall	F1-score
KNN	80.80	83	75	79
LR	62.42	62.1	62.4	62.1
SVM	89	85	82	84

Table 3 examines the F1-score, recall, accuracy, and precision of three different neural networks trained on Twitter data: KNN, LR, and SVM. SVM emerged the best model with the highest accuracy of 89%, precision of 85%, recall of 82%, and the F1-score of 84%, proving the model competitiveness in handling large data sets. KNN provided a moderate set of results and had 80.80% accuracy and 79 F1-score; however, LR showed the lowest accuracy, 62.42%. The findings show that the specific sentiment classification is best addressed by SVM due to the successful performance of this model.

V. Conclusion and Future Scope

Sentiment analysis has become an essential method for gleaning insights from user-generated material due to the fast growth of social media sites such as Twitter. To capture knowledge from customers by classifying feelings as positive, negative or even neutral, businesses and researchers can obtain many-sided outlooks to take into account and utilise in their decision-making processes. This research shows that sentiment categorisation on Twitter data may be effectively done using NLP and ML models. The study demonstrates that the SVM model outperforms KNN and LR in sentiment classification of Twitter data, with SVM achieving an accuracy 89%, precision of 85%, recall of 82% and F1-score of 84%. In comparison, KNN achieved an accuracy of 80.80%, precision of 83%, recall of 75%, and F1-score of 79%, while LR performed the weakest with an accuracy of 62.42%, precision of 62.1%, recall of 62.4%, and F1-score of 62.1%. These results confirm that SVG is a tool suitable for sentiment analysis of large text data sets from social media. However, there are some limitations in the study: For example, using conventional machine learning algorithms and the data is confined to Twitter only. It is possible to work on extending future work in relation to the use of deep learning models, for example, recurrent neural networks (RNN) and transformer models like BERT, which are appropriate for sequential and contextual data. Additionally, addressing class imbalance and incorporating hybrid approaches could further enhance the model's robustness and accuracy in sentiment classification across diverse platforms.

Declarations

Acknowledgments: We gratefully acknowledge all of the people who have contributed to this paper.

Author Contributions: All authors have contributed equally to the work.

Conflict of Interest: The authors declare no conflict of interest.
Consent to Publish: The authors agree to publish the paper in International Journal of Recent Innovations in Academic Research.
Data Availability Statement: The data presented in this study are available upon request from the corresponding author.
Funding: This research received no external funding.
Institutional Review Board Statement: Not applicable.
Informed Consent Statement: Not applicable.
Research Content: The research content of manuscript is original and has not been published elsewhere.

References

1. Goel, V., Gupta, A.K. and Kumar, N. 2018. Sentiment analysis of multilingual twitter data using natural language processing. In: 2018 8th international conference on communication systems and network technologies (CSNT) (pp. 208-212). IEEE.
2. Wagh, R. and Punde, P. 2018. Survey on sentiment analysis using twitter dataset. In: 2018 second international conference on electronics, communication and aerospace technology (ICECA) (pp. 208-211). IEEE.
3. Kumar, V.V., Pandey, M.K., Tiwari, M.K. and Ben-Arieh, D. 2010. Simultaneous optimization of parts and operations sequences in SSMS: A chaos embedded Taguchi particle swarm optimization approach. Journal of Intelligent Manufacturing, 21: 335-353.
4. Kanavos, A., Nodarakis, N., Sioutas, S., Tsakalidis, A., Tsolis, D. and Tzimas, G. 2017. Large scale implementations for twitter sentiment classification. Algorithms, 10(1): 33.
5. Mozetič, I., Torgo, L., Cerqueira, V. and Smailović, J. 2018. How to evaluate sentiment classifiers for twitter time-ordered data?. PloS One, 13(3): e0194317.
6. Patra, G.K., Kuraku, C., Konkimalla, S., Boddapati, V.N. and Sarisa, M. 2021. An analysis and prediction of health insurance costs using machine learning-based regressor techniques. International Journal of Computer Engineering and Technology, 12(3): 102-113.
7. Boddapati, V.N., Galla, E.P., Sunkara, J.R., Bauskar, S.R., Patra, G.K., Kuraku, C. and Madhavaram, C.R. 2021. Harnessing the power of big data: The evolution of AI and machine learning in modern times. ESP Journal of Engineering and Technology Advancements, 1(2): 134-146.
8. Rane, A. and Kumar, A. 2018. Sentiment classification system of twitter data for US airline service analysis. In: 2018 IEEE 42nd annual computer software and applications conference (COMPSAC) (Vol. 1, pp. 769-773). IEEE.
9. Çeliktuğ, M.F. 2018. Twitter sentiment analysis, 3-way classification: Positive, negative or neutral?. In: 2018 IEEE international conference on big data (big data) (pp. 2098-2103). IEEE.
10. Fitri, F.S., Nasrun, M. and Setianingsih, C. 2018. Sentiment analysis on the level of customer satisfaction to data cellular services using the naive bayes classifier algorithm. In: 2018 IEEE international conference on internet of things and intelligence system (IOTAIS) (pp. 201-206). IEEE.
11. Amjad, K., Ishtiaq, M., Firdous, S. and Mehmood, M.A. 2017. Exploring twitter news biases using Urdu-based sentiment lexicon. In: 2017 international conference on open source systems and technologies (ICOSST) (pp. 48-53). IEEE.
12. Ibrahim, M.N.M. and Yusoff, M.Z.M. 2015. Twitter sentiment classification using naive bayes based on trainer perception. In: 2015 IEEE conference on e-learning, e-management and e-services (IC3e) (pp. 187-189). IEEE.
13. Sahu, S., Rout, S.K. and Mohanty, D. 2015. Twitter sentiment analysis-a more enhanced way of classification and scoring. In: 2015 IEEE international symposium on nanoelectronic and information systems (pp. 67-72). IEEE.

14. Sarisa, M., Boddapati, V.N., Patra, G.K., Kuraku, C., Konkimalla, S. and Rajaram, S.K. 2020. An effective predicting e-commerce sales and management system based on machine learning methods. Journal of Artificial Intelligence and Big Data, 1(1): 75-85.
15. Gollangi, H.K., Bauskar, S.R., Madhavaram, C.R., Galla, E.P., Sunkara, J.R. and Reddy, M.S. 2020. Exploring AI algorithms for cancer classification and prediction using electronic health records. Journal of Artificial Intelligence and Big Data, 1(1): 65-74.
16. Sarisa, M., Boddapati, V.N., Patra, G.K., Kuraku, C., Konkimalla, S. and Rajaram, S.K. 2020. Navigating the complexities of cyber threats, sentiment, and health with AI/ML. Journal of Recent Trends in Computer Science and Engineering, 8(2): 22-40.
17. Akram, W. and Kumar, R. 2018. A study on positive and negative effects of social media on society. International Journal of Computer Science and Engineering, 5(10): 350-351.
18. Kumar, V., Mishra, N., Vishwa, V.K., Felix, T.S.C. and Gnanasekar, B. 2010. Warranty failure analysis in service supply chain: A multi-agent framework. In: 2010 8th international conference on supply chain management and information (pp. 1-6). IEEE.
19. Gollangi, H.K., Bauskar, S.R., Madhavaram, C.R., Galla, E.P., Sunkara, J.R. and Reddy, M.S. 2020. Unveiling the hidden patterns: AI-driven innovations in image processing and acoustic signal detection. Journal of Recent Trends in Computer Science and Engineering, 8(1): 25-45.
20. Gollangi, H.K., Bauskar, S.R., Madhavaram, C.R., Galla, E.P., Sunkara, J.R. and Reddy, M.S. 2020. Echoes in pixels: The intersection of image processing and sound detection through the lens of AI and ML. International Journal of Development Research, 10(08): 39735-39743.
21. Sarisa, M., Boddapati, V.N., Patra, G.K., Kuraku, C., Konkimalla, S. and Rajaram, S.K. 2020. The power of sentiment: big data analytics meets machine learning for emotional insights. International Journal of Development Research, 10(10): 41565-41573.
22. Reddy, M.S., Sarisa, M., Konkimalla, S., Bauskar, S.R., Gollangi, H.K., Galla, E.P. and Rajaram, S.K. 2021. Predicting tomorrow's ailments: How AI/ML is transforming disease forecasting. ESP Journal of Engineering and Technology Advancements, 1(2): 188-200.
23. Madhavaram, C.R., Galla, E.P., Reddy, M.S., Sarisa, M. and Nagesh, V. 2021. Predicting diabetes mellitus in healthcare: A comparative analysis of machine learning algorithms on big dataset. Global Journal of Research in Engineering and Computer Sciences, 1(1): 1-11.
24. Kolluri, V. 2016. A pioneering approach to forensic insights: Utilization AI for cybersecurity incident investigations. IJRAR-International Journal of Research and Analytical Reviews, 3(3): 919-922.
25. Jianqiang, Z., Xiaolin, G. and Xuejun, Z. 2018. Deep convolution neural networks for twitter sentiment analysis. IEEE Access, 6: 23253-23260.
26. Kumar, V.V. and Chan, F.T. 2011. A superiority search and optimisation algorithm to solve RFID and an environmental factor embedded closed loop logistics model. International Journal of Production Research, 49(16): 4807-4831.
27. Hasan, M.Z., Fink, R., Suyambu, M.R. and Baskaran, M.K. 2012. Assessment and improvement of intelligent controllers for elevator energy efficiency. In: 2012 IEEE international conference on electro/information technology (pp. 1-7). IEEE.
28. Kumar, V.V. 2014. An interactive product development model in remanufacturing environment: A chaosbased artificial bee colony approach. Masters Theses 7244. https://scholarsmine.mst.edu/masters_theses/724
29. Kolluri, V. 2016. An innovative study exploring revolutionizing healthcare with AI: Personalized medicine: Predictive diagnostic techniques and individualized treatment. Journal of Emerging Technologies and Innovative Research, 3(11): 218-222.

30. Kumar, V.V., Liou, F.W., Balakrishnan, S.N. and Kumar, V. 2015. Economical impact of RFID implementation in remanufacturing: a chaos-based interactive artificial bee colony approach. Journal of Intelligent Manufacturing, 26: 815-830.

31. Zhang, Y., Jin, R. and Zhou, Z.H. 2010. Understanding bag-of-words model: A statistical framework. International Journal of Machine Learning and Cybernetics, 1: 43-52.

32. Tarafdar, R. and Han, Y. 2018. Finding majority for integer elements. Journal of Computing Sciences in Colleges, 33(5): 187-191.

33. Hasan, M.Z., Fink, R., Suyambu, M.R., Baskaran, M.K., James, D. and Gamboa, J. 2015. Performance evaluation of energy efficient intelligent elevator controllers. In: 2015 IEEE international conference on electro/information technology (EIT) (pp. 44-49). IEEE.

34. Kolluri, V. 2014. An in-depth exploration of unveiling vulnerabilities: Exploring risks in AI models and algorithms. International Journal of Research and Analytical Reviews, 1(3): 910-913.

35. Kolluri, V. 2016. Machine learning in managing healthcare supply chains: How machine learning optimizes supply chains, ensuring the timely availability of medical supplies. Journal of Emerging Technologies and Innovative Research, 3(6): 282-286.

36. Lee, S., Hong, S.M. and Jung, H.S. 2017. A support vector machine for landslide susceptibility mapping in Gangwon Province, Korea. Sustainability, 9(1): 48.

37. Anuprathibha, T. and Selvib, C.S.K. 2016. A survey of twitter sentiment analysis. IIOAB Journal, 7(9): 374-378.

38. Giachanou, A. and Crestani, F. 2016. Like it or not: A survey of twitter sentiment analysis methods. ACM Computing Surveys (CSUR): 49(2): 1-41.

39. Huq, M.R., Ahmad, A. and Rahman, A. 2017. Sentiment analysis on twitter data using KNN and SVM. International Journal of Advanced Computer Science and Applications, 8(6): 19-25.

40. Pagolu, V.S., Reddy, K.N., Panda, G. and Majhi, B. 2016. Sentiment analysis of twitter data for predicting stock market movements. In: 2016 international conference on signal processing, communication, power and embedded system (SCOPES) (pp. 1345-1350). IEEE.

41. Patra, G.K., Rajaram, S.K. and Boddapati, V.N. 2019. AI and big data in digital payments: A comprehensive model for secure biometric authentication. Educational Administration: Theory and Practice, 25(4): 773–781.

42. Kuraku, C., Gollangi, H.K. and Sunkara, J.R. 2020. Biometric authentication in digital payments: Utilizing AI and big data for real-time security and efficiency. Educational Administration: Theory and Practice, 26(4): 954-964.

43. Galla, E.P., Madhavaram, C.R. and Boddapati, V.N. 2021. Big data and AI innovations in biometric authentication for secure digital transactions. Educational Administration: Theory and Practice, 27(4): 1228–1236.

44. Sunkara, J.R., Bauskar, S.R., Madhavaram, C.R., Galla, E.P., Gollangi, H.K. 2021. Data-driven management: The impact of visualization tools on business performance. International Journal of Management, 12(3): 1290-1298.

Citation: Suneel Babu Boppana, Chethan Sriharsha Moore, Varun Bodepudi, Krishna Madhav Jha, Srinivasa Rao Maka and Gangadhar Sadaram. 2021. Sentiment Classification on Twitter Data Using Artificial Intelligence and Natural Language Processing. International Journal of Recent Innovations in Academic Research, 5(12): 76-87.