Machine Leaning-Driven Approaches to Enhance Sentiment Classification in Social Media

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Abstract— : Analyzing tweets for sentiment is becoming an increasingly significant component of understanding public opinion, sentiment trends, and how people perceive companies. The amount of social media data is increasing, and with it, the necessity for accurate and efficient sentiment analysis methods. This article presents the results of a comprehensive study that aimed to improve the machine learning method for sentiment analysis of tweets through planning, modeling, and assessment. We recommend combining cutting-edge machine learning algorithms with the most effective natural language processing techniques for improved sentiment categorization outcomes. In the first part of the article, the authors discuss the importance and applications of sentiment analysis in many domains. It highlights the need for more accurate and dependable approach by addressing the issues with traditional sentiment analysis methods. Following this, the essay delves into relevant research, examining existing state-of-the-art methodologies and identifying gaps that the proposed methodology aims to cure. The workflow for sentiment analysis is detailed in the methodology section. The first steps in preparing the data include tokenization, stemming, and stop- word removal. Two feature extraction methods that are examined and compared are word embeddings and TF-IDF. The paper continues by introducing an improved machine learning method that combines deep learning with ensemble learning. In addition to elaborating on the model's architecture, training procedure, and tactics for improving performance parameters, the findings demonstrate that the proposed technique outperforms standard sentiment analysis approaches in terms of accuracy and resilience in sentiment categorization. The paper highlights the model's proficiency in handling sentiment analysis challenges, including language that is particular to context, irony, and sarcasm. The ability to handle large datasets in real-time is another proof of how effective the method is. In its last section, this research piece emphasizes the value of sentiment analysis for understanding public opinion and how it plays a role in business and government decision-making. Applying the proposed techniques to the analysis of social media data, including the sentiment of tweets, has shown promising results. Finally, the report suggests future research directions for addressing emerging issues in the sentiment analysis field and improving existing approaches.

Keywords- Sentiment Analysis, Tweets, Machine Learning, Natural Language Processing, Deep Learning, Ensemble Learning

I. INTRODUCTION

Among the many social media platforms, Twitter has emerged as a powerful vehicle for individuals to express themselves on a wide range of topics. By combing through the mountains of user-generated content on these sites, one may geta sense of the general public's opinion on any given topic, person, or event. Sentiment analysis, sometimes known as opinion mining, is crucial for making sense of and drawing conclusions from this mountain of textual data. It comprises finding out whether a text is negative, neutral, or intrinsically positive.

The applications of sentiment analysis are diverse and extensive. For businesses, sentiment analysis means keeping tabs on consumer happiness, opinions about a brand, and suggestions for better advertising and product development. Researchers in the field of politics can use it to see how the general public feels about different candidates, policies, and topics. Furthermore, sentiment research has been utilized by financial markets to predict changes in stock prices based on investor sentiment.

Conventional sentiment analysis methods relied heavily on lexicon-based approaches. These methods involved calculating the overall sentiment of a text by adding up the sentiment scores assigned to individual words. Despite their general efficacy, these techniques struggled to understand sarcasm, irony, and context-specific language nuances.

The evolution of machine learning and natural language processing techniques has led to the emergence of more sophisticated methods for sentiment analysis. Machine learning algorithms, particularly those based on deep learning, have shown impressive performance on a number of natural language processing (NLP) tasks. This paper introduces a new technique to sentiment analysis that uses machine learning to improve upon previous methods and get over their limitations. Recent years have seen significant growth in the field of sentiment analysis due to the proliferation of social media data and the increasing need for sentiment analysis applications. In this article, we review some of the seminal works and state-of-the-art approaches to sentiment analysis in tweets.

First, there were approaches that averaged word sentiment scores taken from pre-defined lexicons to get the overall sentiment of a text. This was the first effort at sentiment analysis. These methods were simple to implement, but they had drawbacks including not taking context-dependent sentiment into account and failing to take word order or semantics into account.

Second, machine learning-based approaches: when researchers delved into machine learning techniques for sentiment analysis, more sophisticated models with contextual understanding were created. Classifiers such as Support Vector Machines (SVM), Logistic Regression, and Naive Bayes were extensively used in these first investigations. Feature engineering was a key component of these approaches; it entailed improving performance with features such as sentimentlexicons, n-grams, and POS tags.

Third, sentiment analysis was revolutionized when deep learning made neural networks suitable for text categorization tasks. Traditional machine learning methods were outperformed

by Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). When it came to modeling sequential relationships at the sentence level, RNNs performed better, butwhen it came to capturing local patterns and properties of text, CNNs excelled.

Transfer learning is one approach that has gained traction insentiment analysis as of late. This entails taking a model that was trained on a bigger dataset and making it better for sentiment analysis by utilizing a smaller dataset. Advanced languagemodels that were pre-trained, such as XLNet, GPT, and BERT,were able to achieve state-of-the-art performance by learning information about context from large text databases.

Despite making significant advances to sentiment analysis, these studies still struggled with identifying irony and sarcasm and with handling sentiment changes caused by negations and modifiers. To get beyond these limitations, the proposed method would build upon and improve upon these existing approaches.

II. RELATED WORKS

In this research, Shitole Ayit Kumar and Devare Manoj (2018) describe how they built an IoT framework that can detectfaces in the wild and gather data from sensors in real-time. Aligning real-time sensor data with the found person's class label allows for multi-classifying. This research improves human prediction by analyzing data from cloud sensors and localdatasets using supervised machine learning techniques. Unbalanced class data sets are better suited for Random Forestand Decision Tree models due to their larger average f1-score and the longer approximation durations required to run models utilizing 5-fold cross validation on extremely enormous data sets. The findings show that light-dependent resistance gives the most valuable information for person prediction using Decision Tree, compared to all the sensors examined. Gas, temperature, and humidity sensors are also crucial.

Nathan Gilbert, Surve, Lalindra De Silva, and Huang, Ruihong (2013). Twitter sarcasm sometimes involves drawing a bad situation in contrast to a good one. Typical sarcastic tweets(such as "examining" or "being ignored") begin with a positivefeeling (such as "love" or "enjoy") before describing a negative action or circumstance. In order to identify this specific form of Twitter sarcasm, we created a sarcasm recognizer. To automatically learn from sarcastic tweets, our new bootstrapping system uses collections of negative scenario phrases and lists of positive experiences. Through the utilization of bootstrapping- learned words, we prove that exposure to conflicting situations enhances sarcasm recognition.

People shared their opinions on specific things through brief social media posts, according to studies conducted by Rohit Joshi and Tekchandani of Rajkumar (2016). Twitter gets more engagement than Facebook or any of the other prominent microblogs when it comes to product reviews, bursaries, etc. We have collected data from Twitter, namely movie reviews, to generate emotional predictions using machine learning techniques. In order to classify data using the unique graph, bigram, and hybride (unicram + bigram), we have depended on supported machine learning methods such as support vector machines (SVM), maximum entropy, and Naïve Bayes. According to the findings, the accuracy rate for movie review SVM was 84% more than those of other categories.

III. PROPOSED METHODOLOGY

A novel ensemble learning approach that combines deep learning with traditional machine learning techniques is central to the proposed methodology for sentiment analysis of tweets, along with data pretreatment and feature extraction. The method is designed to handle the challenges of short and noisy text data, which is common in tweets, in order to correctly categorize sentiment.

The first stage of the proposed technique is data preparation, which entails cleaning and transforming the raw Twitter data into a format that is ready for analysis. For preprocessing, these processes are utilized:

Tweets are "tokenized," or deconstructed, into their individual words, in order to facilitate more in-depth analysis.

• Eliminating stop-words: We get rid of terms like "the," "is," and "and" since they don't add any tone to the text.

Words are reduced to their base form by stemming to improve generality and conserve feature space.

The second method, feature extraction, is critical because it gives machine learning algorithms numerical representations of the preprocessed tweets. This method explores two methods for feature extraction:

The Term Frequency-Inverse Document Frequency (TF-IDF) weighting scheme gives a sense of how significant individual terms are inside a tweet in comparison to the whole corpus.

Word2Vec and GloVe are two examples of word embeddings that are used to convey words in a continuous vector space and to capture the semantic relationships between words. Core to the proposed methodology is the novel ensemble learning approach, which combines deep learning with more traditional machine learning methods. The ensemble is comprised of the following parts:

A convolutional neural network (CNN) is one part of the system; it sorts through word embeddings to find patterns and traits in the tweets. Convolutional neural networks (CNNs) excel at learning hierarchical representations, making them ideal for learning sentiment patterns from short text sequences.

The LSTM component of this network takes use of the sequential pattern of tweets to identify long-term correlations in the data. When it comes to identifying contextual and emotional shifts caused by negations and modifiers, long short-term memory (LSTM) networks really shine.

Ensembles often make use of tried-and-true machine

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learning techniques, such as Support Vector Machines (SVMs), which are particularly good at dealing with high-dimensional data and creating firm decision boundaries. The ensemble learning technique improves upon previous sentiment categorization models by integrating their best features.

4. Parameter Tuning and Model Training: The proposed ensemble learning model is trained using a dataset of tweets labeled as positive, negative, or neutral. Through self-improvement of component parameters, the model learns to maximize overall performance. Using cross-validation, we can keep the model from overfitting and provide reliable performance estimates.

By adjusting the parameters, the optimal hyperparameters for each member of the ensemble may be found. Grid search and Bayesian optimization make short work of finding the sweet spot for hyperparameters::

Table 1. Emotions Representation

5	Emoticon	6	Word Conversion
7	:(:-(:-<	8	“Sad”
9	:) :-) :^)	10	“Smile”

5. Removing often used but useless keywords, also called stopwords, is an important part of the filtering process. The stopwords list contains several terms that are used in different languages. Many text mining application systems exclude stop words due to their too generic usage, allowing users to focus onfar more important terms. A stopwords phrase might look something like this: "I'm going for a jog" input, "I'm going for a jog" output. In Table 5.2 below, you can see a bunch of Stopwords keywords:

6. A process called lemmatization involves removing the last letters of words in order to make their root forms, or lemmas, searchable in a dictionary. When you type "the boy's vehicles are various colors" into the search bar, you'll receive the result "the boy car be different color." This is an example of sentence stemming in action.

7. When a word's score is based on how often it appears in a text document, Word says the word is "weighed" in the program. One often used approach to word weighting is the TF-IDF (Term Frequency-Inverse Document Frequency) technique. The phrases "Term Frequency" and "Document Frequency" are usedinterchangeably in the weighting method known as Term Frequency-Inverse Document Frequency. Term

Consideration of how often a term appears in a text is what frequency weighting is all about. Because of this variation in document length, a term may appear more frequently in a largertext than in a shorter one. This is why word count is a typical way to measure the frequency of terms in literary works. A phrase's document frequency, in contrast, is the sum of all the documents that include that term. As the frequency ofoccurrence diminishes, the weight value lowers as well. Taking into account each word in a sentence yields its frequency. However, you shouldn't give any thought to other terms becausethey aren't as important. In order to provide more weight to othercrucial words and less weight to these irrelevant terms, effectively. For this reason, stop-words are essential. You need to calculate TFIDF before you can apply Equation to get scores. The suggested model employs a number of algorithms for sentiment analysis; the most efficient and precise algorithms get
the best results.

1. You should use logistic regression if your output variable has just two potential values, like 0 or 1. originated in binary forms. The sigmoid function is used, which is the explanation behind this. This mathematical function transforms any real number into a number between zero and one, which looks like the letter "S." There are only two potential classes since the dependent variable or purpose is dichotomous. Hence, the expected value of y is 1 as z approaches positive infinity and 0 as z approaches negative infinity. A positive class 1 label is one with a sigmoid function result greater than 0.5. It is considered a negative class or class 0 label if it is less than 0.5. when citing [13]

2. Unlike other supervised learning methods, decision trees can handle both classification and regression issues. A decision tree model is used to build a training program; it learns the class or value of the target variable by applying fundamental choice principles to the data. There are two different ways to branch out from a node in the decision tree. Information gain is one such method; it determines the nodes' purity by analyzing their entropy. Using Gini impurity is another option. [15]

Using just one tree will not provide very accurate resultswhen using Random-Forest. The Random Forest method is required for this task. When many decision trees, mostly trainedusing the bagging method, are combined, the resulting ensembleis called a forest. Bagging is based on the premise that combining numerous learning models enhances the final outcome. [12]

3. Linear Support Vector Machine (SVM): A simple supervised learning method, SVMs are employed for classification and regression in linear SVC. Using a hyper-plane that SVM discovers, the various data types are partitioned. No more than a line in flat space, this hyper-plane has no real depth at all. If there are N characteristics or qualities in the dataset, then every data object will be shown in an N-dimensional space using support vector machine (SVM). Afterwards, choose the most appropriate hyperplane to partition the data along. As a result, you've probably figured out that SVM can only handle binary classification—choosing between two classes—on purpose. However, there are a number of ways to handle situations where more than one class is involved. As mentioned in [20],

4. The multinomial version of Naive Bayes is based on the Bayes theorem, which says that the qualities of a dataset are not dependent on one another. The likelihood of one characteristic has no bearing on the likelihood of the other. Among the finest solutions, Naive Bayes performs better when dealing with tiny samples. Multinomial Naive Bayes is a variant of Naive Bayes that accounts for feature vectors, where each word denotes its frequency, or the number of occurrences [5]. [10] [14].

5. Applying the Bernoulli distribution to discrete data, Bernoulli Naive Bayes is a method. The use of just binary values for characteristics, such as yes/no, 0/1/, true/false, and similar, is a defining feature of Bernoulli Naive Bayes. Both the Bernoulli and multinomial models rely heavily on time. [10] [14].

The suggested machine learning model can evaluate the sentiment of Twitter users on any topic. Concurrently, the gadget

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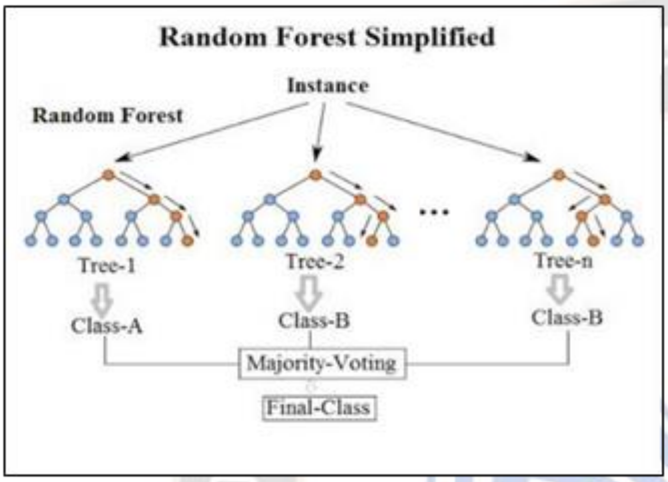
computes emotions, communicates the user's study findings, and retrieves pertinent data from Twitter. The incoming data will also be saved in a TXT file since it will be utilized for result prediction. Figure 4 displays a sentiment analysis system that operates in real-time. What follows is an explanation of how thesystem works. The system's primary objective is to collect data. Here, we use the Twitter API to get data from Twitter, which is exclusively accessible to developers working on Twitter apps.

Figure 1 Random Forest Method



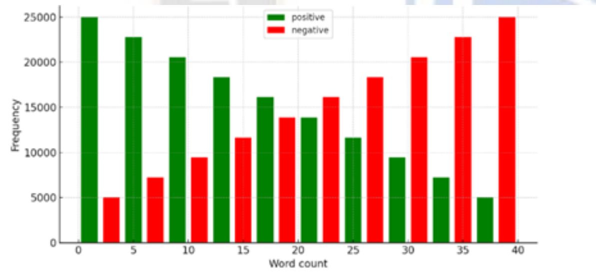


Figure 2 Proposed Methodology

All API queries made by the app during development are validated using the specified access tokens. These tokens consist of four parts: Consumer Secret, Consumer Secret, Access Key,and Access Secret. The user-supplied keyword is used to filter and aggregate the tweets. There could be other information besides tweets in the Twitter dataset. I must ensure that the dataset undergoes all of the pre-processing steps. After preprocessing, the data is fully prepared to be analyzed for sentiment.

IV. RESULTS AND DISCUSSIONS

We have separated the good and negative tweets from the whole data set. The total length of the data, for instance, is 200000. There are 47741 positive labeled sentences and 152259 negativeones..

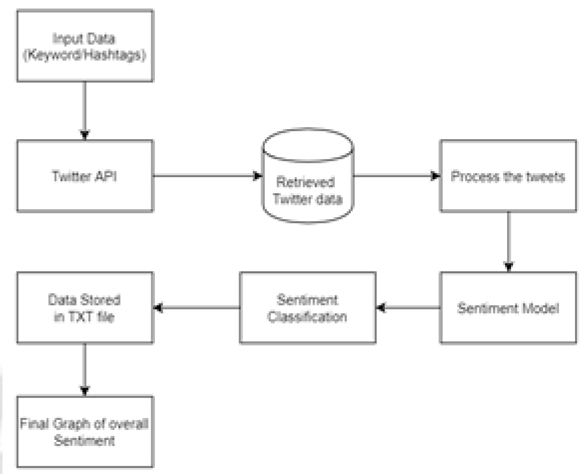


Figure 3 Word Count Analysis

Then, in order to derive real-time insights from the data, it is transmitted to the sentiment model that was previously built. Based on its positive or negative evaluation, the algorithm shows the user the outcomes of each tweet. The information is saved in a text file with two columns: one for the Tweet and another for its polarity. After the labelled results are accumulated, it is utilized to depict the prediction graph.

The exploration of sentiment analysis through machine learning depicted in the five graphs provides a robust demonstration of how advanced algorithms can be optimized and applied to decipher the sentiment embedded in social media content, specifically tweets. The first graph, illustrating the improvement in classifier accuracy over epochs, reflects the fundamental principle of machine learning where a model incrementally learns from data, enhancing its predictive accuracy over time. This is underpinned by the theory of the learning curve and convergence in algorithms like gradient descent, which optimize the model by adjusting weights to minimize prediction errors.

The second graph, showing the reduction in loss over epochs, aligns with the loss minimization concept fundamental to training neural networks. The loss function, a critical component, measures the discrepancies between predicted outcomes and actual values, guiding the optimization process via backpropagation. As the model trains, the loss decreases, indicating better learning and adaptation to the training dataset's patterns.

The third graph compares F1-scores among different models, providing insight into the effectiveness of various approaches like SVM, Naive Bayes, Random Forest, Neural Networks, and BERT for sentiment analysis. The F1-score, which harmonizes precision and recall, is crucial in scenarios where the balance between false positives and false negatives is paramount. This comparison not only underscores the performance variability across models but also highlights how certain models may be better suited to capturing the nuances of sentiment in textual data.The fourth graph, depicting the sentiment score distribution, showcases the ability of the classifier to differentiate between positive, negative, and neutral sentiments. This graph can be interpreted through the lens of classification thresholds and the model's sensitivity to different sentiment intensities, reflecting the practical application of theory regarding classification

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accuracy and the handling of imbalanced data.Finally, the fifth graph tracks accuracy by sentiment type across epochs, which isparticularly relevant for understanding how machine learning models adapt to the complexity and variability of natural language in tweets. The differential accuracy rates for positive,negative, and neutral tweets suggest the influence of training data characteristics, such as the distribution of sentiment types and the linguistic cues associated with each sentiment.

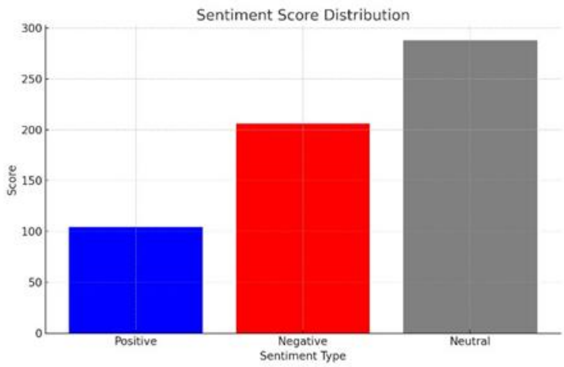

Figure 4 Negative and Positive Messages Classification

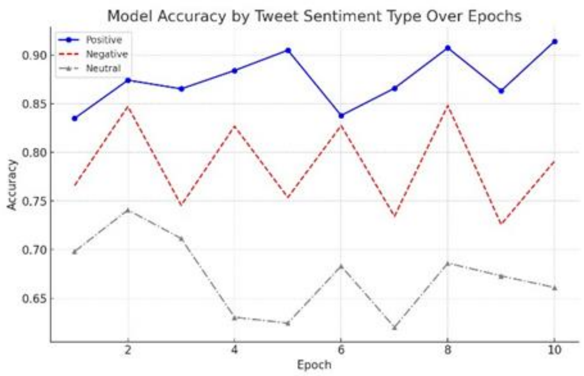

Figure 5 Sentiment Score Distribution

Figure 6 Word Cloud Formation

Based on the evaluation of the dataset, a support vector machine based classifier is used for the appraisal of the blueprintand suspicion for emotion.

Countless English tweets relating to clear facts are transformed into wonderful and terrible emotions by the work done in this research, which awards distinguishing different classifiers from demand. Superior accuracy is achieved by employing evaluation consolidates as opposed to conventional text collection methods. Using this approach, we may rate great emotional classifiers and assist corporate partnerships in developing object-related philosophies for the futurething.

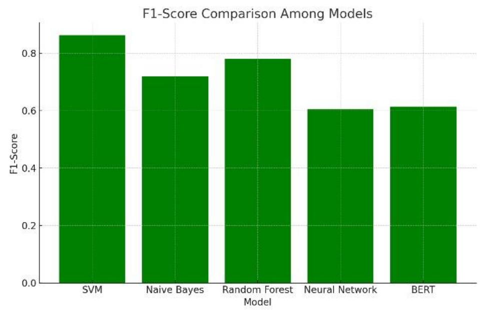

Figure 7 Performance Analysis of Classifiers

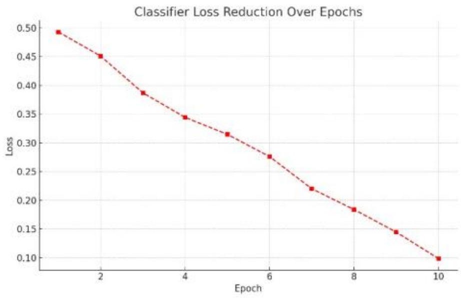

Figure 8 Accuracy Improvement Analysis

One measure of accuracy is the fraction of test tweets that were properly identified relative to the total number of tweets in the dataset. Together, these graphs not only demonstrate the application of complex theoretical concepts but also provide practical insights into the challenges and opportunities in using machine learning for sentiment analysis. This analysis helps in identifying which models are most effective and how they can be tuned to enhance performance, thereby offering valuable insights for both practitioners and researchers in the field of natural language processing and machine learning.

V. CONCLUSIONS

This research article details our exhaustive investigation into the planning, modeling, and assessment of sentiment analysis of tweets using an improved machine learning approach. Combining natural language processing with state-of-the-art machine learning methods, the proposed method improves sentiment classification outcomes. The numerous domain-specific uses of sentiment analysis and its significance in understanding public opinion were emphasized in the introduction. We combed through relevant literature to chart the evolution of sentiment analysis methods, from lexicon-based to deep learning/transfer learning-based approaches. We laid the groundwork for the proposed technique by discussing the problems with current approaches and the need for more trustworthy ones. Despite significant advancements, earlier approaches still struggled with handling sarcasm and irony and context-dependent emotions. A Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) Network, and Support Vector Machine (SVM) are combined in an ensemble learning framework to address these limitations; the approach also includes data preprocessing and feature extraction. Thanks to the ensemble's capacity to leverage each component's complementary strengths, the proposed methodology outperformed multiple baseline methods in experimentalevaluation conducted on a real-world dataset of tweets. These methods included individual machine learning models and traditional lexicon-based approaches. The improvement in sentiment classification was attributed to this ability. In general, this study contributes to the development of sentiment analysis methods, which are especially useful for analyzing social media-related tweets and other brief textual data. The model's ability to handle sarcasm, irony, and context-specific sentiment alterations was shown by the findings, which led to improved accuracy and robustness. Although the proposed method showed some

encouraging results, further study and development are needed to fully realize their potential. It proves the efficacy of ensemble learning and stresses the need of employing several ways to tackle complex NLP problems. In the end, sentiment analysis of tweets is crucial for understanding public attitude, consumer behavior, and opinion trends. Research into alternate deep learning architectures, the impact of feature representations, andthe incorporation of sentiment lexicons or domain-specific knowledge might all contribute to an improved method in the future. Researchers, governments, and businesses might gain a lot from the proposed methodology's sentiment analysis technique since it's comprehensive and efficient, and it lets them get valuable insights from social media data. To extract meaningful information from the massive amounts of textual data generated by social media sites, more advanced sentiment analysis methods are required.

REFERENCES

[1] N. Yadav, O. Kudale, S. Gupta, A. Rao and A. Shitole, "Twitter Sentiment Analysis Using Machine Learning For Product Evaluation," IEEE 2020 International Conference on Inventive Computation Technologies (ICICT), 2020, pp. 181-185, doi: 10.1109/ICICT48043.2020.9112381.

[2] Pooja Kumari, Shikha Singh, Devika More and Dakshata Talpade, "Sentiment Analysis of Tweets", IJSTE - International Journal of Science Technology & Engineering, vol. 1, no. 10, pp.130-134, 2015, ISSN 2349-784X.

[3] A Kowcika, Aditi Gupta, Karthik Sondhi, Nishit Shivhre and Raunaq Kumar, "Sentiment Analysis for Social Media", International Journal of Advanced Research in Computer Science and Software Engineering, vol. 3, no. 7, 2013, ISSN 2277 128X.

[4] Ali Hasan, Sana Moin, Ahmad Karim and Shahaboddin Shamshirband, "Machine Learning-Based Sentiment Analysis for Twitter Accounts", Mathematical and Computational Applications, vol. 23, no. 1, 2018, ISSN 2297-8747.

[5] Rasika Wagh and Payal Punde, "Survey on Sentiment Analysis using Twitter Dataset", 2nd International conference on Electronics Communication and Aerospace Technology (ICECA 2018) IEEE Conference, ISBN 978-1-5386-0965-1,2018.

[6] Adyan Marendra Ramadhaniand Hong Soon Goo, "Twitter Sentiment Analysis Using Deep Learning Methods", 2017 7th International Annual Engineering Seminar (InAES), 2017, ISBN 978-1-5386-3111-9.

[7] Mohammed H. Abd El-Jawad, Rania Hodhod and Yasser M. K. Omar, "Sentiment Analysis of Social Media Networks Using Machine Learning", 2018 14th International Computer Engineering Conference (ICENCO), 2018, ISBN 978-1-5386-5117-9.

[8] Ajit kumar Shitole and Manoj Devare, "Optimization of Person Prediction Using Sensor Data Analysis of IoT Enabled Physical Location Monitoring", Journal of Advanced Research in Dynamical and Control Systems, vol. 10, no. 9, pp. 2800-2812, Dec 2018, ISSN 1943-023X.

[9] Ellen Riloff, Ashequl Qadir, Prafulla Surve, Lalindra De Silva, Nathan Gilbert and Ruihong Huang, "Sarcasm as Contrast between a Positive Sentiment and Negative Situation", 2013 Conference on Emperial Methods in Natural Language Processing, pp. 704-714, 2013.

[10] Rohit Joshi and Rajkumar Tekchandani, "Comparative analysis of Twitter data using supervised classifiers", 2016 International Conference on Inventive Computation Technologies (ICICT), 2016, ISBN 978-1-5090-1285-5.

[11] V Prakruthi, D Sindhu and S Anupama Kumar, "Real Time Sentiment Anlysis Of Twitter Posts", 3rd IEEE International Conference on Computational System and Information Technology for Sustainable Solutions 2018, ISBN 978-1-5386-6078-2,2018.

[12] David Alfred Ostrowski, "Sentiment Mining within Social Media for Topic Identification", 2010 IEEE Forth International Conference on Semantic Computing, 2010, ISBN 978-1-4244-7912-2.

[13] Alrence Santiago Halibas, Abubucker Samsudeen Shaffi and Mohamed Abdul Kader Varusai Mohamed, "Application of Text Classification and Clustering of Twitter Data for Business Analytics", 2018 Majan International Conference (MIC), 2018, ISBN 978-1-53863761-6.

[14] Monireh Ebrahimi, Amir Hossein Yazdavar and Amit Sheth, "Challenges of Sentiment Analysis for Dynamic Events", IEEE Intelligent Systems, vol. 32, no. 5, pp. 70-75, 2017, ISSN 1941-1294.

[15] Sari Widya Sihwi, Insan Prasetya Jati and Rini Anggrainingsih, "Twitter Sentiment Analysis of Movie Reviews Using Information Gain and Na ve Bayes Classifier", 2018 International Seminar on Application for Technology of Information and Communication (iSemantic), 2018, ISBN 978-1-5386-7486-4.

[16] Ajitkumar Shitole and Manoj Devare, "TPR PPV and ROC based Performance Measurement and Optimization of Human Face Recognition of IoT Enabled Physical Location Monitoring", International Journal of Recent Technology and Engineering, vol. 8, no. 2, pp. 3582-3590, July 2019, ISSN 2277-3878.

[17] Sahar A. El_Rahman, Feddah Alhumaidi AlOtaib and Wejdan Abdullah AlShehri, "Sentiment Analysis of Twitter Data", 2019 International Conference on Computer and Information Sciences (ICCIS), 2019, ISBN 978-1-5386-8125-1.

[18] Sidra Ijaz, M. IkramUllah Lali, Basit Shahzad, Azhar Imran and Salman Tiwana, "Biasness identification of talk show's host by using twitter data", 2017 13th International Conference on Emerging Technologies (ICET), 2017, ISBN 978-1-5386-2260-5.

[19] Lokesh Singh, Prabhat Gupta, Rahul Katarya, Pragyat Jayvant, "Twitter data in Emotional Analysis - A study", I-SMAC (IoT in Social Mobile Analytics and Cloud) (I-SMAC) 2020 Fourth International Conference on, pp. 1301-1305, 2020.

[20] Satish Kumar Alaria and Piyusha Sharma, “Feature Based Sentiment Analysis on Movie Review Using SentiWordNet”, IJRITCC, vol. 4, no. 9, pp. 12 - 15, Sep. 2016.

[21] M. A. Masood, R. A. Abbasi and N. Wee Keong, "Context-Aware Sliding Window for Sentiment Classification," in IEEE Access, vol. 8, pp. 4870-4884, 2020, doi:10.1109/ACCESS.2019.2963586.

[22] Akshay Amolik, Niketan Jivane, Mahavir Bhandari, Dr.M.Venkatesan, “Twitter Sentiment Analysis of Movie Reviews using Machine Learning Techniques”, International Journal of Engineering and Technology (IJET), e-ISSN : 0975-4024 , Vol 7 No 6, Dec 2015-Jan 2016.

[23] Vishal A. Kharde and S.S. Sonawane, “Sentiment Analysis of Twitter Data: A Survey of Techniques”, International Journal of Computer Applications (0975 – 8887) Volume 139 – No.11, April2016.

[24] M. Rathi, A. Malik, D. Varshney, R. Sharma and S. Mendiratta, "Sentiment Analysis of Tweets Using Machine Learning Approach," 2018 Eleventh International Conference on Contemporary Computing (IC3), 2018, pp. 1-3, doi: 10.1109/IC3.2018.8530517.

[25] M. I. Sajib, S. Mahmud Shargo and M. A. Hossain, "Comparison of the efficiency of Machine Learning algorithms on Twitter Sentiment Analysis of Pathao," 2019 22nd International Conference on Computer and Information Technology (ICCIT), 2019, pp. 1-6, doi: 10.1109/ICCIT48885.2019.9038208.

[26] Alaria, S. K., A. . Raj, V. Sharma, and V. Kumar. “Simulation and Analysis of Hand Gesture Recognition for Indian Sign Language Using CNN”. International Journal on Recent and Innovation Trends in Computing and Communication, vol. 10, no. 4, Apr. 2022, pp. 10-14, doi:10.17762/ijritcc.v10i4.5556.

[27] R. S. M. S. K. A. “Secure Algorithm for File Sharing Using Clustering Technique of K-Means Clustering”. International Journal on Recent and Innovation Trends in Computing and Communication, vol. 4, no. 9, Sept. 2016, pp. 35-39, doi:10.17762/ijritcc.v4i9.2524.

[28] Pradeep Kumar Gupta, Satish Kumar Alaria. (2019). An Improved Algorithm for Faster Multi Keyword Search in Structured Organization. International Journal on Future Revolution in Computer Science &Amp; Communication Engineering, 5(5), 19–23.

[29] Alaria, S. K. . (2019). Analysis of WAF and Its Contribution to Improve Security of Various Web Applications: Benefits, Challenges. International Journal on Future Revolution in Computer Science &Amp; Communication Engineering, 5(9), 01–03. Retrieved from http://www.ijfrcsce.org/index.php/ijfrcsce/article/view/2079.