A Machine Learning-based Sentiment Analysis for Assessing the Effectiveness of Social Media Posts.

Surekha M N V
Computer Science and Engineering
Sri Vasavi Engineering College
Tadepalligudem, India
Surekhamnv.cse@srivasaviengg.ac.in

Priyanka Irrinki
Computer Science and Engineering
Sri Vasavi Engineering College
Tadepalligudem, India
irrinkipriyanka75@gmail.com

Sai Maheswari Ganuboina
Computer Science and Engineering
Sri Vasavi Engineering College
Tadepalligudem, India
saimaheswari2002@gmail.com

ManojKumar Sandramalla
Computer Science and Engineering
Sri Vasavi Engineering College
Tadepalligudem, India
manojkumarsandramalla@gmail.com

S S V Snehitha Ramadugula
Computer Science and Engineering
Sri Vasavi Engineering college
Tadepalligudem, India
snehitharamadugula@gmail.com

M Vamsi sai Rakurthi
Computer Science and Engineering
Sri Vasavi Engineering College
Tadepalligudem, India
mohanvamsisai6033@gmail.com

Abstract— **Analyzing sentiment On social media involves extracting opinions and emotions from user-generated content. This project outlines a study of using machine learning techniques to understand sentiment patterns across diverse social platforms. Through advanced algorithms, the project scans and analyzes a vast amount of Social media posts, extracting and interpreting textual data to discern sentiments such as positive, negative, and neutral. It highlights the significance of feature selection and model training for accurate sentiment classification. The study leverages large datasets spanning various domains to enhance model generalization. Additionally, it investigates the impact of linguistic expression. The findings contribute insights into sentiment dynamics, aiding in the development of robust sentiment Analysis tools for Social media monitoring and understanding user attitude, The project relies on the labeled datasets to rain models, addressing challenges such as noisy data and the dynamic nature of online language. Successful implementation allows for real-time monitoring and interception of user sentiments, contributing to a nuanced grasp of the digital community's attitude and preferences.**

Keywords—*Sentiment Analysis, Machine Learning, Linguistic Expression, labeled datasets, Supervised Learning.*

Introduction

In the contemporary era, the sheer volume of data inundating social media platforms daily is staggering. Among these platforms, Twitter stands out as a prominent social networking platform where individuals can openly share their their views, opinions, thoughts, and feelings on a myriad of subjects. To navigate and analyze this vast reservoir of data, a machine learning approach is adopted, employing classifiers within a supervised learning framework. This machine learning endeavor delves into linguistic expressions within the data, aiming to decipher the sentiments conveyed by users. The project heavily relies on labeled datasets to train models, addressing formidable challenges such as noisy data and the dynamic nature of online language. Noisy data, comprising irrelevant or erroneous information, poses a significant hurdle, necessitating robust strategies to ensure accurate analysis. Moreover, the ever-evolving landscape of online language demands adaptable methodologies to effectively capture sentiment nuances.

To facilitate sentiment analysis, various machine learning algorithms are enlisted, including Support Vector Machine (SVM), Naive Bayes, Decision Trees, and logistic regression. Each algorithm brings its unique strengths to the fore, enabling nuanced interpretations of sentiments expressed across Twitter. The input data, in the shape of plain text, encapsulates current trending topics, providing a rich tapestry for sentiment analysis.

Sentiments are categorized into three classes: positive, negative, and neutral, enabling a comprehensive understanding of user sentiments on diverse subjects. Through meticulous training and forecasting, the system endeavors to unveil insights into prevailing sentiment trends, offering valuable perspectives on public opinion dynamics. In essence, this project harnesses the power of machine learning to navigate the vast expanse of social media data, offering invaluable insights into the sentiments permeating through the Twitter-verse.

RELATED WORKS

This project undertakes an extensive exploration of sentiment analysis, utilizing machine learning techniques to discern and categorize sentiments present in user-generated content across diverse social media platforms. Key components of the research include a thorough investigation into feature selection methods and model training approaches, pivotal elements that directly influence the accuracy and dependability of sentiment classification. By employing large-scale datasets spanning various domains, the study aims to bolster the generalization capabilities of the models, ensuring their effectiveness in capturing sentiment nuances across different contexts and communities.

A crucial dimension of the project involves delving into the intricacies of linguistic expression within social media data. The research acknowledges the significance of understanding how subtle language nuances impact the accuracy of sentiment analysis. By scrutinizing the diverse ways in which users express their emotions and opinion online, the study seeks to enrich the comprehension of sentiment dynamics in the digital realm.

Moreover, the project extends its focus to the application-oriented domain, aspiring to contribute tangible solutions for social media monitoring and user sentiment analysis.By aligning research endeavors with real-world applications, the project aims to foster the development of robust sentiment analysis tools specifically tailored for understanding user attitudes and preferences across a diverse array of social platforms. The assimilation of insights garnered from related work in these areas informs the project's methodology, ensuring a holistic and effective approach to unraveling sentiment patterns in the dynamic and multifaceted landscape of social media communication.

MOTIVATION

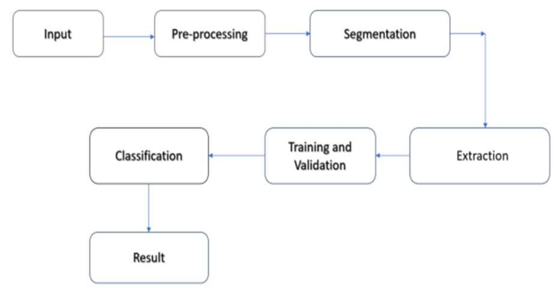
In today's world, lots of people share their thoughts and feelings on Twitter. This project is all about using computer programs for understanding what people are saying and how they feel om platforms like Facebook or Twitter. By doing this, we can learn about trends, spot new issues, and figure out the overall mood of the online world. This project is driven by the idea of using advanced computer techniques to got through the huge amount of social media posts and figure out what sentiments or feelings are being expressed. By looking at big sets of data from different areas, the goal is to make sure the computer can understand sentiments across various topics and communities. The project also wants to explore how the way people use language online affects this sentiment analysis, giving us an improved knowledge of the complex ways people express themselves.

In simple terms, the project aims to use smart computer tools for understanding what people are saying and feeling on social media. The hope is that this will help us keep track of trends, respond quickly to important things happening online, and better understand how people communicate in the digital world.

PROPOSED SYSTEM

The envisioned sentiment analysis system for social media is designed to harness cutting-edge machine learning algorithms to decode and classify sentiments embedded within the vast landscape of user-generated content on various social platforms. By adopting a sophisticated and adaptable framework, the proposed system aims to process substantial volumes of textual data efficiently, categorizing sentiments into positive, negative, or neutral categories. The emphasis will be placed on real-time processing capabilities, enabling prompt and dynamic insights into evolving public sentiments. The system may explore the integration of ensemble methods, leveraging the collective intelligence of diverse algorithms to enhance accuracy and robustness. The primary objective is to furnish businesses, researchers, and stakeholders with a nuanced understanding of the prevailing sentiment trends across social media, empowering them to formulate informed strategies, engage effectively with their audience, and respond proactively to emerging patterns and sentiments. Through this proposed system, we aspire to contribute to a more insightful and responsive approach to social media analytics.

Fig. 1. Architecture of Proposed System



SENTIMENT ANALYSIS

Sentiment analysis focuses on analyzing a large amount of text data to understand the sentiments expressed within it. The primary purpose is to train models on extensive datasets so that they can precisely identify and categorize sentiments in new, unseen text. This process helps in making sense of the emotions and opinions conveyed through the textual content.

A. Data Gathering

Social Media sites such as Twitter uses a source of text.To get sentiment analysis data from Kaggle, go to the Kaggle website and sign up. Find datasets related to sentiment analysis, like "Sentiment Analysis" or "text Classification". Kaggle has various datasets on topics such as movie reviews and social media sentiments.

Choose a dateset that suits your project, download it from the datasets page, and check for any provided documentation. This information may consists of details about the datasets structure and sentiment labels. Explore Kaggle kernels and discussions for insights from others who have used the dateset.

Remember to comply wit the datasets license and usage terms. Kaggle is a great resource for sentiment analysis datasets, supporting collaborative learning in language processing and machine learning.

B. Pre-Processing

After gathering textual data from Kaggle about Twitter, the next step involves pre-processing, a task accomplishes through Python. The pre-processing steps involves:

i. Conversion to Lowercase:

Transforming all uppercase letters letters to lowercase.

ii. Tokenization:

It involves removing hash tags, converting text to tokens, and eliminating elements like numbers, URLs and targets(@).

iii. Removal of Non-English Words:

Since our project focuses on English sentiments, we exclude non-English words, ensuring a streamlined analysis.

iv. Emotion Replacement:

Assessing user sentiments requires handling emotional terms. Therefore, we substitute emotional terms with their respective polarities by referencing a dictionary of emotions.

v. Removal of Stop Words:

It is crucial to eliminate stop words(“a”,”an”,) that don’t contribute significantly to sentiment analysis.

C. Feature Extracting:

Feature Extraction in sentiment analysis means picking out the important words or aspects from a user’s tweet.After preparing the Twitter data through pre-processing steps like making it lowercase, breaking it into words, and removing unnecessary words, we focus on identifying key features.These features are the words that are vital for understanding the sentiment, like “excellent” or “disappointed”. These selected words become the input for sentiment analysis models, helping them better recognize and categorize sentiments for more accurate results.

D. Feature Selection:

It plays a crucial role in defining relevant attributes and improving the accuracy of classification in machine learning.

E. Classifying Methods:

There are several Machine Learning Classifying methods we will apply here are: Random Forest, Support Vector Machine.

A. ALGORITHMS

Sentiment analysis algorithms for social media typically employ machine learning techniques to classify user-generated content into positive, negative, or neutral sentiments. These algorithms often use supervised learning with labeled datasets, where the model learns patterns and associations between words and sentiments. Pr-processing steps, such as ionization and removing stop words, enhance the efficiency of these algorithms. Lexicon-based approaches, revenue for analysis. Advanced models like deep learning-based neural networks, including recurrent neural networks (RNs) or transformer architectures such as the BERT, are increasingly utilized for their ability to capture contextual nuances. Continuous training and adaptation are crucial to keeping these algorithms effective, especially in the dynamic and evolving landscape of social media language.

The envisioned sentiment analysis system for social media is designed to harness cutting-edge machine learning algorithms to decode and classify sentiments embedded within the vast landscape of user-generated content on various social platforms. By adopting a sophisticated and adaptable framework, the proposed system aims to process substantial volumes of textual data efficiently, categorizing sentiments into positive, negative, or neutral categories. Emphasis will be placed on real-time processing capabilities, enabling prompt and dynamic insights into evolving public sentiments. The system may explore the integration of ensemble methods, leveraging the collective intelligence of diverse algorithms to enhance accuracy and robustness. The primary objective is to furnish businesses, researchers, and stakeholders with a nuanced understanding of the prevailing sentiment trends across social media, empowering them to formulate informed strategies, engage effectively with their audience, and respond proactively to emerging patterns and sentiments. Through this proposed system, we aspire to contribute to a more insightful and responsive approach to social media analytics.

1. RANDOM FOREST

Random Forest emerges as a potential tool in the realm of sentiment analysis, a process involving the determination of sentiment in text, such as discerning whether a review carries a positive or negative tone. Its effectiveness lies in its ability to navigate complex relationships within data while mitigating the risk of over fitting, a common challenge in machine learning. In sentiment analysis, each text is transformed into features, often based on word frequencies or other relevant characteristics. Random Forest takes advantage of this by constructing numerous decision trees during training, each on a random subset of both the data and features. This diversity within the ensemble of trees allows the model to capture various facets of sentiment patterns, enhancing its ability to generalize well to different contexts.

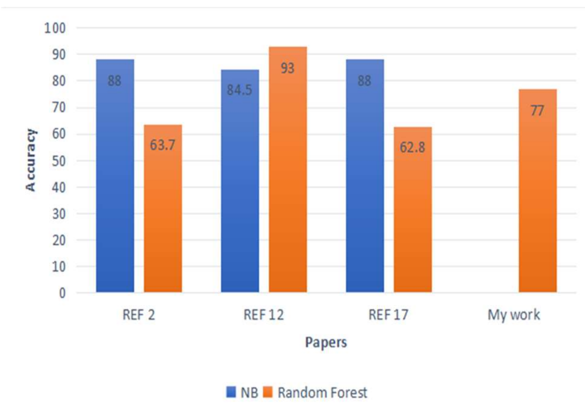
During the prediction phase for a new document, the Random Forest model aggregates the votes from the ensemble of trees to determine the sentiment. This ensemble approach imparts robustness to the model, making it less susceptible to over fitting and increasing its reliability in making predictions on unseen data. Furthermore, Random Forest excels in handling non-linear relationships within the data, a common characteristic of natural language, making it particularly well-suited for sentiment analysis tasks. It goes beyond mere prediction by providing insights into feature importance, enabling the identification of crucial words or phrases that significantly contribute to sentiment expression. This flexibility, accuracy, and interpretability make Random Forest a versatile and powerful tool for sentiment analysis in the broader field of natural language processing.

```
Accuracy:  0.7784338098197638
Classification Report:

              precision    recall  f1-score   support

        -1.0       0.87      0.47      0.61       767
         0.0       0.73      0.93      0.82      1088
         1.0       0.79      0.83      0.81      1363

    accuracy                           0.78      3218
   macro avg       0.80      0.74      0.75      3218
weighted avg       0.79      0.78      0.77      3218
```



2. SUPPORT VECTOR MACHINE(SVM)

Support Vector Machines(SVM) stand out as intelligent classifiers frequently employed in sentiment analysis, a field focused on determining the sentiment conveyed in textual content, such as discerning whether a review express positivity, negativity, or neutrality. SVM excels in finding the optimal way to draw a line or boundary between different sentiments, making it particularly adept at handling situations where sentiments are nuanced or not entirely clear-cut. This capability is crucial in the realm of sentient analysis, where the language can be intricate, and sentiments may manifest in subtle ways.

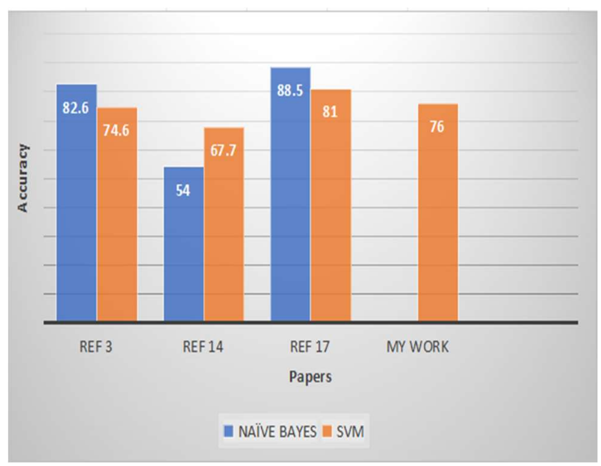
SVM's strength lies in its proficiency with words, even in situations involving a multitude of them. It can effectively navigate the complexity of language, making it a valuable tool for processing diverse and lengthy textual data, common in sentiment analysis tasks. What sets SVM apart is its ability to ,learn from examples, enabling it to adapt and understand new textual data. After being trained with labels examples, SVM can rapidly classify new texts, providing quick and accurate assessments of whether the sentiment is positive, negative, or falls somewhere in between. This adaptability and efficiency make SVM a favored choice in sentiment analysis applications, particularly SVM for its reliability in handling linguistic complexity and delivering dependable predictions in sentiment -related tasks.

```
Accuracy:  0.7641392169049099
Classification Report:

              precision    recall  f1-score   support

        -1.0       0.83      0.52      0.64       767
         0.0       0.72      0.87      0.79      1088
         1.0       0.78      0.82      0.80      1363

    accuracy                           0.76      3218
   macro avg       0.78      0.74      0.74      3218
weighted avg       0.77      0.76      0.76      3218
```



EXISTING SYSTEM

Sentiment analysis systems for social media combine natural language processing (NLP) and machine learning techniques to interpret and categorize sentiments expressed in user-generated content. They start by preprocessing text data, including cleaning and tokenization, to prepare it for analysis. Machine learning models, from traditional algorithms to advanced deep learning architectures, are then trained on labeled datasets to classify sentiments as positive, negative, or neutral. These systems also utilize sentiment lexicons and real-time updates to capture evolving language nuances and sentiments on social media platforms.

These systems are useful for businesses, researchers, and organizations as they provide insights into public opinions, brand sentiment, and emerging trends. By automating the analysis of social media data, they enable informed decision-making, help tailor strategies, improve customer relations, and stay responsive to online conversations.

METHODOLOGY

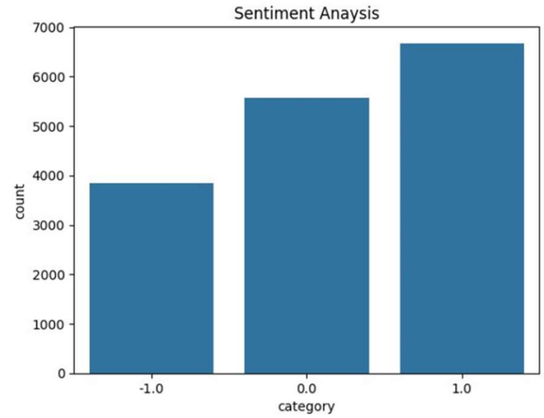
The project is centered around a meticulous process that begins with comprehensive data collection from the Twitter platform. To ensure the reliability of the sentiment analysis, a rigorous preprocessing stage is implemented to handle noise and eliminate irrelevant information. This involves cleaning and organizing the data to enhance its quality and relevance. Feature selection criteria are then defined to optimize the accuracy of sentiment classification. Thoughtful consideration is given to the selection and tuning of machine learning models to achieve optimal performance in accurately categorizing sentiments. Th experimental results, including accuracy matrices and confusion matrices, serve as tangible evidence of the effectiveness of the approach, proving a quantitative measure of the models performance.

The subsequent discussion segment of the project investigates into the implications of linguistic expression on sentiment dynamics, contributing to a more nuanced understanding of user attitudes on the Twitter platform. This analysis aims to uncover how language nuances impact sentiment classification accuracy, adding depth to the interpretation of the results. The project concludes by summarizing key findings and highlighting potential applications of the research outcomes. Additionally, it identifies areas for future research, indicating a commitment to ongoing exploration and improvement in the field of sentiment analysis on social media platforms like Twitter.

GRAPHICAL REPRESENTATION

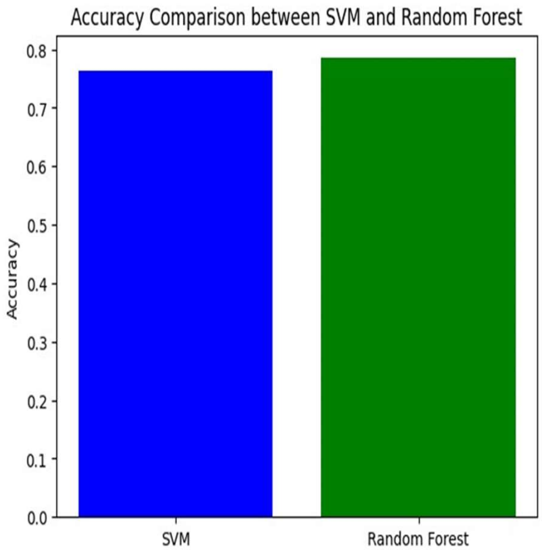
There are various great packages or libraries which used for graphical representation such as: pie chart, line chart, column chart, histogram and so on:

In this system, Bar chart or we can call it histogram has been used for graphical representation of the sentiment classification as shown:



RESULTS AND ANALYSIS

The result analysis of this project encompasses a multifaceted evaluation of its machine learning-driven sentiment analysis approach. Key considerations include assessing the accuracy of sentiment classification achieved by the trained models, including precision, recall, and F1-score metrics across positive, negative, and neutral sentiment categories. Feature importance and selection methods are scrutinized to understand the most influential factors in sentiment prediction, while also exploring how different features impact model performance. The project's ability to generalize across diverse domains is examined by testing model performance on datasets spanning various topics and contexts. Additionally, the study delves into the impact of linguistic nuances on sentiment classification accuracy, elucidating the models' proficiency in interpreting subtle linguistic expressions such as sarcasm and irony. Evaluation also extends to the real-time monitoring and interception capabilities, assessing the system's speed and efficacy in capturing evolving sentiment trends on social media platforms. Insights gleaned from the analysis contribute to the development of robust sentiment analysis tools, providing valuable insights into sentiment dynamics and user attitudes across digital communities.



CONCLUSION

The result analysis of this project encompasses a multifaceted evaluation of its machine learning-driven sentiment analysis approach. Key considerations include assessing the accuracy of sentiment classification achieved by the trained models, including precision, recall, and F1-score metrics across positive, negative, and neutral sentiment categories. Feature importance and selection methods are scrutinized to understand the most influential factors in sentiment prediction, while also exploring how different features impact model performance. The project's ability to generalize across diverse domains is examined by testing model performance on datasets spanning various topics and contexts. Additionally, the study delves into the impact of linguistic nuances on sentiment classification accuracy, elucidating the models' proficiency in interpreting subtle linguistic expressions such as sarcasm and irony. Evaluation also extends to the real-time monitoring and interception capabilities, assessing the system's speed and efficacy in capturing evolving sentiment trends on social media platforms. Insights gleaned from the analysis contribute to the development of robust sentiment analysis tools, providing valuable insights into sentiment dynamics and user attitudes across digital communities.

FUTURE WORK

Looking ahead, our project on understanding feelings on Twitter media plans to make our machine learning methods even better at figuring out what people think on the Twitter platform. We want to use smarter techniques like deep learning and teamwork between models to improve how accurate and quick our systems are. We're also looking into keeping up with how people talk online, including emojis and pictures, and making sure our tools are fair and respectful to everyone. We're not just focusing on words- we want to get the whole picture of what users are expressing. Additionally, we are thinking about how our tools can work in real time and handle a lot of information efficiently. We're mindful of the impact our work might have, so we're looking into ethical considerations and trying to avoid any unfair biases. Our goal is to help social media companies and users with better insights into sentiments, contributing to making online experiences more enjoyable and meaningful for everyone.

REFERENCES

[1]V. Prakruthi, D. Sindhu and D. S. Anupama Kumar, "Real Time Sentiment Analysis Of Twitter Posts," *2018 3rd International Conference on Computational Systems and Information Technology for Sustainable Solutions (CSITSS)*, Bengaluru, India, 2018, pp. 29-34, Doi: 10.1109/CSITSS.2018.8768774.

[2] M. Khurana, A. Gulati and S. Singh, "Sentiment Analysis Framework of Twitter Data Using Classification," *2018 Fifth International Conference on Parallel, Distributed and Grid Computing (PDGC)*, Solan, India, 2018, pp. 459-464, Doi: 10.1109/PDGC.2018.8745748.

[3] L. Mandloi and R. Patel, "Twitter Sentiments Analysis Using Machine Learning Methods," *2020 International Conference for Emerging Technology (INCET)*, Belgaum, India, 2020, pp. 1-5, Doi: 10.1109/INCET49848.2020.9154183.

[4] S. A. El Rahman, F. A. Alotaibi and W. A. AlShehri, "Sentiment Analysis of Twitter Data," *2019 International Conference on Computer and Information Sciences (ICCIS)*, Sakaka, Saudi Arabia, 2019, pp. 1-4, Doi: 10.1109/ICCISci.2019.8716464.

[5] C. Kariya and P. Khodke, "Twitter Sentiment Analysis," *2020 International Conference for Emerging Technology (INCET* Belgaum, India, 2020, pp. 1-3, Doi: 10.1109/INCET49848.2020.9154143.

[6] A. S. Al Shammari, "Real-time Twitter Sentiment Analysis using 3-way classifier," *2018 21st Saudi Computer Society National Computer Conference (NCC)*, Riyadh, Saudi Arabia, 2018, pp. 1-3, Doi: 10.1109/NCG.2018.8593205.

[7] R. S. Karan, K. K. Shirsat, P. L. Kasar and R. Chaudhary, "Sentiment Analysis on Twitter Data: A New Approach," *2018 International Conference on Current Trends towards Converging Technologies (ICCTCT)*, Coimbatore, India, 2018, pp. 1-4, Doi: 10.1109/ICCTCT.2018.8551169

[8] M. F. Çeliktuğ, "Twitter Sentiment Analysis, 3-Way Classification: Positive, Negative or Neutral?" *2018 IEEE International Conference on Big Data (Big Data)*, Seattle, WA, USA, 2018, pp. 2098-2103, Doi: 10.1109/BigData.2018.8621970.

[9] S. Naz, A. Sharan and N. Malik, "Sentiment Classification on Twitter Data Using Support Vector Machine," *2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI)*, Santiago, Chile, 2018, pp. 676-679, Doi: 10.1109/WI.2018.00-13.

[10] P. Harjule, A. Gurjar, H. Seth and P. Thakur, "Text Classification on Twitter Data," *2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE)*, Jaipur, India, 2020, pp. 160-164, Doi: 10.1109/ICETCE48199.2020.9091774.

[11] M. I. Zul, F. Yulia, and D. Nurmalasari, "Social Media Sentiment Analysis Using K-Means and Naïve Bayes Algorithm," *2018 2nd International Conference on Electrical Engineering and Informatics (ICon EEI)*, Batam, Indonesia, 2018, pp. 24-29, Doi: 10.1109/ICon-EEI.2018.8784326

[12] Y. Indulkar and A. Patil, "Comparative Study of Machine Learning Algorithms for Twitter Sentiment Analysis," *2021 International Conference on Emerging Smart Computing and Informatics (ESCI)*, Pune, India, 2021, pp. 295-299, Doi: 10.1109/ESCI50559.2021.9396925.

[13] S. Al-Hadhrami, N. Al-Fassam and H. Benhidour, "Sentiment Analysis Of English Tweets: A Comparative Study of Supervised and Unsupervised Approaches," *2019 2nd International Conference on Computer Applications & Information Security (ICCAIS)*, Riyadh, Saudi Arabia, 2019, pp. 1-5, Doi: 10.1109/CAIS.2019.8769550.

[14] J. Ramteke, S. Shah, D. Godhia and A. Shaikh, "Election result prediction using Twitter sentiment analysis," *2016 International Conference on Inventive Computation Technologies (ICICT)*, Coimbatore, India, 2016, pp. 1-5, Doi: 10.1109/INVENTIVE.2016.7823280.

[15] S. Dhar, S. Pednekar, K. Borad and A. Save, "Sentiment Analysis Using Neural Networks: A New Approach," *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*, Coimbatore, India, 2018, pp. 1220-1224, Doi: 10.1109/ICICCT.2018.8473049.

[16] H. Parveen and S. Pandey, "Sentiment analysis on Twitter Dataset using Naive Bayes algorithm," *2016 2nd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT)*, Bangalore, India, 2016, pp. 416-419, Doi: 10.1109/ICATCCT.2016.7912034.

[17] M. Khurana, A. Gulati and S. Singh, "Sentiment Analysis Framework of Twitter Data Using Classification," *2018 Fifth International Conference on Parallel, Distributed and Grid Computing (PDGC)*, Solan, India, 2018, pp. 459-464, Doi: 10.1109/PDGC.2018.8745748.

[18] G. Shetty, A. Nair, P. Vishwanath, and A. Stuti, "Sentiment Analysis and Classification on Twitter Spam Account Dataset," *2020 Advanced Computing and Communication Technologies for High-Performance Applications (ACCTHPA)*, Cochin, India, 2020, pp. 111-114, Doi: 10.1109/ACCTHPA49271.2020.9213206.

[19] K. Chakraborty, S. Bhattacharyya, and R. Bag, "A Survey of Sentiment Analysis from Social Media Data," in *IEEE Transactions on Computational Social Systems*, vol. 7, no. 2, pp. 450-464, April 2020, Doi: 10.1109/TCSS.2019.2956957.

[20] R. I. Permatasari, M. A. Fauzi, P. P. Adikara and E. D. L. Sari, "Twitter Sentiment Analysis of Movie Reviews Using Ensemble Features Based Naïve Bayes," *2018 International Conference on Sustainable Information Engineering and Technology (SIET)*, Malang, Indonesia, 2018, pp. 92-95, Doi: 10.1109/SIET.2018.8693195.

[21] P. Karthika, R. Murugeswari and R. Manoranjithem, "Sentiment Analysis of Social Media Network Using Random Forest Algorithm," *2019 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS)*, Tamil Nadu, India, 2019, pp. 1-5, Doi: 10.1109/INCOS45849.2019.8951367.

[22] R. Wagh and P. Punde, "Survey on Sentiment Analysis using Twitter Dataset," *2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, Coimbatore, India, 2018, pp. 208-211, Doi: 10.1109/ICECA.2018.8474783.

[23] S. Dhawan, K. Singh and P. Chauhan, "Sentiment Analysis of Twitter Data in Online Social Network," *2019 5th International Conference on Signal Processing, Computing and Control (ISPCC)*, Solan, India, 2019, pp. 255-259, Doi: 10.1109/ISPCC48220.2019.8988450.

[24] G. Gupta and P. Gupta, "Twitter Mining for Sentiment Analysis in Tourism Industry," *2019 Third World Conference on Smart Trends in Systems Security and Sustainability (WorldS4)*, London, UK, 2019, pp. 302-306, Doi: 10.1109/WorldS4.2019.8903940.

[25] K. AbdulSattar, Q. Obeidat, and M. Akour, "Towards harnessing based learning algorithms for tweets sentiment analysis," *2020 International Conference on Innovation and Intelligence for Informatics, Computing and Technologies (3ICT)*, Sakheer, Bahrain, 2020, pp. 1-5, Doi: 10.1109/3ICT51146.2020.9311990.

[26] N. Alduaiji and A. Datta, "An Empirical Study on Sentiments in Twitter Communities," *2018 IEEE International Conference on Data Mining Workshops (ICDMW)*, Singapore, 2018, pp. 1166-1172, Doi: 10.1109/ICDMW.2018.00167.

[27] S. Roy, S. Sehgal and S. Agrawal, "An Approach to Sentiment Analysis of Twitter Data on the Goods and Services Tax," *2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN)*, Greater Noida, India, 2018, pp. 32-36, Doi: 10.1109/ICACCCN.2018.8748822.

[28] M. R. Hasan, M. Maliha and M. Arifuzzaman, "Sentiment Analysis with NLP on Twitter Data," *2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2)*, Rajshahi, Bangladesh, 2019, pp. 1-4, doi: 10.1109/IC4ME247184.2019.9036670.

[29] R. R. Dalvi, S. Baliram Chavan and A. Halbe, "Detecting A Twitter Cyberbullying Using Machine Learning," *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2020, pp. 297-301, doi: 10.1109/ICICCS48265.2020.9120893.

[30] M. E. M. Abo, N. A. K. Shah, V. Balakrishnan, and A. Abdelaziz, "Sentiment analysis algorithms: evaluation performance of the Arabic and English language," *2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE)*, Khartoum, Sudan, 2018, pp. 1-5, doi: 10.1109/ICCCEEE.2018.8515844.