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Research Paper

Improving Generalization in Sentiment Analysis of Twitter Data with Logistic Regression Model

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Abstract: Sentiment analysis, commonly referred to as opinion mining, is an important problem in natural language processing that entails figuring out the sentiment represented in a document. Sentiment analysis of Twitter data has drawn a lot of attention as a result of the social media platforms' rapid expansion. Using logistic regression, a well-liked machine learning approach for binary classification applications, this research suggests a sentiment analysis system. The system starts by gathering and preprocessing a sizable Twitter dataset with tweets that have been labelled as positive or negative. By eliminating noise, stop-words, and unimportant information, the text data is cleaned. The techniques of tokenization and vectorization are used to represent the text in a numerical format appropriate for logistic regression. A suitable optimization approach is used to estimate the model parameters as the logistic regression model is trained on the labelled dataset. Cross-validation and performance indicators including accuracy, precision, recall, and F1-score are used to evaluate models. The system's goal for sentiment analysis jobs is high accuracy and reliable generalization.

Keywords: Sentiment analysis, Opinion mining, Natural language processing, Twitter data, Logistic regression.

1. Introduction

Twitter and other social media platforms are significant information sources for both consumers and corporations. They give people a forum to voice their views and opinions on a range of subjects. Social media data sentiment analysis can offer insightful information about how a group of people feel about a certain subject or event. In fields including business, politics, and social sciences, sentiment analysis has a variety of uses.

In this regard, this work proposes a logistic regression-based approach for sentiment analysis of Twitter data. Due to its simplicity, interpretability, and efficacy, the machine learning technique known as logistic regression, which is frequently used for binary classification tasks, provides a viable method for sentiment analysis.

The suggested system performs sentiment analysis on Twitter data using a structured technique. It comprises gathering data, preprocessing, choosing features, and training a model with logistic regression. The objective is to correctly categorize tweets as good or bad depending on the attitude they convey. The compilation of a broad and representative Twitter dataset with labelled positive and negative tweets constitutes data collection. The ground truth used to train and assess the sentiment analysis algorithm is these labelled tweets.

1.1 Background

Twitter, a well-known micro-blogging site, is a great resource for current textual data. It enables users to communicate their ideas, views, and feelings in the form of quick messages called tweets. Twitter is the perfect venue for capturing public emotion on a variety of topics, including goods, events, and social concerns because of its brevity and immediacy.

The scalability and adaptability of traditional approaches of sentiment analysis were constrained by the reliance on handcrafted rules or lexicons. However, automated and data-driven sentiment categorization made possible by the development of machine learning techniques, particularly supervised learning algorithms like logistic regression, has revolutionized sentiment analysis.

A popular binary classification approach that models the connection between input characteristics and a binary target variable is logistic regression. Logistic regression may learn to categorize tweets as positive or negative in the context of sentiment analysis based on the patterns it finds in the training data. It is preferred for its ease of use, readability, and effectiveness when processing huge datasets.

1.2 Problem Statement and Objectives

The goal of the suggested system is to create a sentiment analysis system that properly categorizes Twitter data into positive or negative sentiment by utilizing logistic regression and overcoming the aforementioned difficulties. The system tries to handle subjectivity, overcome noise, capture contextual understanding, generalize effectively to unobserved data, and overcome noise. The suggested method aims to offer an accurate and trustworthy solution for sentiment analysis of Twitter data by resolving these issues. Businesses, academics, and decision makers will be able to use this technology to better understand public opinion, make defensible choices, and identify sentiment patterns.

The objectives of this paper are as follows:
• To gather and preprocess a sizable Twitter dataset with labelled positive and negative tweets to create a reliable training dataset.
• To clean the text data by eliminating noise, stop-words, and unimportant information to improve the quality of sentiment analysis.
• To utilize tokenization and vectorization techniques to represent the text data in a numerical format suitable for logistic regression.
• To evaluate the performance of the sentiment analysis models using cross-validation and various performance indicators.
• To achieve high accuracy and reliable generalization in sentiment analysis tasks for Twitter data.

2. Literature Survey

The corpus of literature encompasses a diverse range of scholarly works addressing multifaceted dimensions of sentiment analysis utilizing Twitter data. These works encapsulate intricate methodologies, cutting-edge techniques, practical applications, and pertinent challenges encountered within the realm of sentiment analysis in the broader sphere of social media.

This compilation of references exhibits an extensive temporal scope, spanning from 2013 to 2021, thereby encompassing a spectrum of contemporary and historical studies within the field. While some studies adopt a comprehensive stance, delving into sentiment analysis across social media texts as a whole, others adopt a more focused approach, specifically scrutinizing sentiment analysis within the context of Twitter data.

These references as mentioned in Table 1, hold considerable significance as an invaluable knowledge reservoir for the systematic examination of sentiment analysis employing Twitter data. Researchers can proficiently leverage these scholarly contributions to access a plethora of insights, encompassing diverse approaches, innovative methodologies, and consequential findings pertaining to sentiment analysis in the context of social media, with particular emphasis on the Twitter platform.

Table 1: Literature Survey

Ref. ID	Title	Authors	Year
[?]	Survey on sentiment analysis using twitter dataset	Wagh, Rasika; Punde, Payal	2018
[?]	Sentiment analysis of twitter data	El Rahman, Sahar A; AlOtaibi, Feddah Alhumaidi; AlShehri, Wejdan Abdullah	2019
[?]	Sentiment analysis in social media texts	Balahur, Alexandra	2013
[?]	Sentiments analysis of Twitter data using data mining	Jain, Anurag P; Katkar, Vijay D	2015
[?]	Sentiment analysis on twitter data	Sahayak, Varsha; Shete, Vijaya; Pathan, Apashabi	2015
[?]	Sentiment analysis with NLP on Twitter data	Hasan, Md Rakibul; Maliha, Maisha; Arifuzzaman, M	2019
[?]	A review of techniques for sentiment analysis of Twitter data	Bhuta, Sagar; Doshi, Avit; Doshi, Uehit; Narvekar, Meera	2014
[?]	Sentiment analysis of twitter data	Bagheri, Hamid; Islam, Md Johirul	2017
[?]	A study on sentiment analysis techniques of Twitter data	Alsaeedi, Abdullah; Khan, Mohammad Zubair	2019
[?]	Sentiment analysis on COVID-19-related social distancing in Canada using Twitter data	Shofiya, Carol; Abidi, Samina	2021
[?]	Social media sentiment analysis based on COVID-19	Nemes, László; Kiss, Attila	2021
[?]	A model for sentiment and emotion analysis of unstructured social media text	Rout, Jitendra Kumar; Choo, Kim-Kwang Raymond; Dash, Amiya Kumar; Bakshi, Sambit; Jena, Sanjay Kumar; Williams, Karen L	2018
[?]	Evaluation of deep learning techniques in sentiment analysis from Twitter data	Goularas, Dionysis; Kamis, Sani	2019
[?]	Sentiment analysis and text mining for social media microblogs using open source tools: an empirical study	Younis, Eman MG	2015
[?]	Sentiment analysis of multimodal twitter data	Kumar, Akshi; Garg, Geetanjali	2019
[?]	Sentiment analysis of Twitter data in online social network	Dhawan, Sanjeev; Singh, Kulvinder; Chauhan, Priyanka	2019
[?]	Twitter sentiment analysis on worldwide COVID-19 outbreaks	Manguri, Kamaran H; Ramadhan, Rebaz N; Amin, Pshko R Mohammed	2020
[?]	Sentiment analysis in social media and its application: Systematic literature review	Drus, Zulfadzli; Khalid, Haliyana	2019
[?]	The emergence of social media data and sentiment analysis in election prediction	Chauhan, Priyavrat; Sharma, Nonita; Sikka, Geeta	2021
[?]	Sentiment analysis of Twitter data: A hybrid approach	Srivastava, Ankit; Singh, Vijendra; Drall, Gurdeep Singh	2019
[?]	A review towards the sentiment analysis techniques for the analysis of Twitter data	Tyagi, Priyanka; Tripathi, RC	2019
[?]	Social media analysis with AI: sentiment analysis techniques for the analysis of Twitter COVID-19 data	Khan, Rijwan; Shrivastava, Piyush; Kapoor, Aashna; Tiwari, Aditi; Mittal, Abhyudaya	2020
[?]	Emotion and sentiment analysis from Twitter text	Sailunaz, Kashfia; Alhajj, Reda	2019

[?]	Social media sentiment analysis on Twitter datasets	Tiwari, Shikha; Verma, Anshika; Garg, Peeyush; Bansal, Deepika	2020
[?]	Sentiment analysis of Twitter data through machine learning techniques	López-Chau, Asdrúbal; Valle-Cruz, David; Sandoval-Almazán, Rodrigo	2020

3. Proposed System

The suggested system uses logistic regression as a machine learning method for textual data sentiment analysis, notably for classifying the sentiment of Twitter content as positive or negative. Because of its simplicity, interpretability, scalability, and ability to handle non-linear correlations, logistic regression is preferred as mentioned in Table 2.

Simplicity: Logistic regression is an easy-to-understand method. It uses a logistic function to represent the connection between the input attributes (textual traits) and the binary sentiment output (positive or negative). Because logistic regression is so straightforward, it may be used and interpreted with ease by researchers and practitioners of all levels of experience.

Interpretability: Users can comprehend the impact of various factors on sentiment categorization thanks to the interpretable findings provided by logistic regression. Each input feature's coefficients show the direction and strength of its influence on the sentiment prediction. Users may learn more about the key characteristics and the thinking behind the sentiment categorization thanks to this interpretability.

Scalability: Logistic regression is scalable and successfully handles very big datasets. The system is capable of processing and analyzing a sizable volume of text effectively given the enormous quantity of Twitter data that is accessible. For sentiment analysis activities on social media sites, where a sizeable volume of tweets must be analyzed and categorized in real-time, this scalability is essential.

Handling Non-linear Correlations: Complex correlations between textual characteristics and sentiment are frequently present in jobs involving sentiment analysis. Non-linear correlations between the input characteristics and the sentiment output can be handled via logistic regression. Logistic regression can capture complex patterns and correlations in the data by utilizing non-linear transformations, improving the precision and efficiency of sentiment categorization.

Table 2: Table of Description

Component	Description
Machine Learning	Logistic Regression
Approach	Binary classification for sentiment analysis
System Benefits	Simplicity, interpretability, scalability, hand
Dataset	Twitter data
Feature Extraction	Bag-of-words, n-grams, TF-IDF, sentiment l
Data Labeling	Manual labeling, crowdsourcing, pre-existing
Preprocessing	Noise removal (stop words, misspellings, ab
Model Training	Hyperparameter tuning, cross-validation, op
Evaluation Metrics	Accuracy, precision, recall, F1-score, confus
Twitter-Specific Challenges	Hashtags, URLs, retweets, user mentions
Interpretation	Analysis of learned patterns, influential feature
Scalability	Handling large-scale Twitter data
User Interface	User-friendly interface for inputting tweets a

It is crucial to remember that the tuning and optimization of the logistic regression system's parameters may have an impact on how well it performs. To fine-tune the model's behavior and enhance its performance, hyperparameter tweaking is essential. Examples include modifying the learning rate and regularization term. To reach the necessary degree of accuracy and efficacy in sentiment analysis, finding the best configuration of these parameters through testing and optimization approaches is crucial. The algorithm uses these traits to reliably classify the sentiment of Twitter content as positive or negative, offering insightful data on public opinion, brand perception, and upcoming trends.

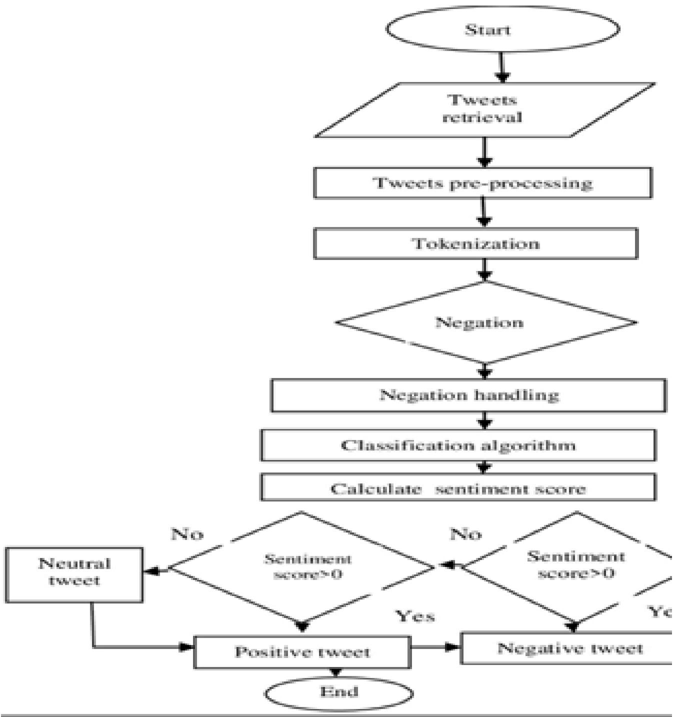

Figure 1: Comparison of various models for detecting spam mails. MultinominalNB showcased one of the best results

4. Methodology

4.1 Data Labelling

Human annotators will manually label the gathered data to reflect each tweet's attitude (positive, negative, or neutral). The model training and model assessment will employ the labelled data. It is crucial to specify the sentiment categories to be utilized (such as positive, negative, and neutral) and lay out precise instructions for annotators to follow during the labelling process. Measures of inter-annotator agreement, such Cohen's kappa, can be used to evaluate the libeling's consistency and dependability. To prevent bias and biased classification results, it is essential to make sure that the dataset has a fair distribution of sentiment labels. To ensure an even distribution of good and negative cases, strategies like stratified sampling or random sampling might be used.

4.2 Feature Extraction

Bag-of-words and TF-IDF were the two feature extraction algorithms we employed. Using the bag-of-words approach, each document is represented as a vector of word counts, and a vocabulary of original terms is created from the text. In contrast to the bag-of-words approach, the TF-IDF technique gives each word a weight depending on its frequency in the text and its inverse frequency in the corpus. Model Evaluation 1. Words from the Bag of Words: Each tweet is represented as a vector of word frequencies in the BoW format. The text is tokenized into individual words, and each word's frequency within the tweet is tallied. Stop words, or words with little emotional content, are often eliminated throughout this procedure. No matter what sequence the words appear in the tweet, the resultant vector shows whether those terms are present or absent. 2. n-grams By taking into account continuous sequences of n words, n-grams are able to represent the sequential relationship between words in a tweet. There are three typical options for n: 1 (unigrams), 2 (bigrams), or 3 (trigrams).Similar to BoW, characteristics for sentiment analysis include the frequency or existence of n-grams. 3. Term Frequency-Inverse Document Frequency (TF-IDF):
Each word in a tweet is given a weight using TF-IDF based on its rarity throughout the whole dataset as well as its frequency in the tweet. It illustrates how significant a word is in a tweet in comparison to how significant it is across the whole corpus. The TF-IDF scores that are produced are used as features in sentiment analysis.
4. Sentimental Terms: emotion lexicons are pre-defined sets of words having positive or negative emotion polarity. The sentiment orientation of words in a tweet can be ascertained by comparing them to the sentiment lexicon. The existence or number of positive or negative terms in a tweet can be used to determine features.

4.3 Model Training

On the training set, we developed a logistic regression model. Using the Python scikit-learn package, the model was trained. In order to apply logistic regression to multi-class classification, we adopted the one-vs-rest technique. It was decided to use regularization with C set to 1.0. We ran 100 iterations of training on the model. 1. A training algorithm for the logistic regression model can be gradient descent. 2. The gradients of the loss function are used by the optimization process to repeatedly update the model's parameters. 3. In order to reduce the discrepancy between the predicted sentiment labels and the actual labels in the training set, the model learns to modify its parameters as it goes along.

4.4 Model Evaluation

The assessment findings are used to track the model's development and decide if more training iterations are necessary or whether to halt training altogether. On the test set, we assessed how well the logistic regression model performed. The number of true positives, false positives, true negatives, and false negatives was also examined using the confusion matrix. On the testing set, the model had an accuracy of 77.8%. The logistic regression model's hyperparameters can have a big influence on how well it works. To improve the performance of the model, hyperparameters may be tuned by changing their values.

5. Results and Discussion

Based on the above methodology, we have these results as mentioned in Figure 2, 3 and 4, indicate the effectiveness of the logistic regression approach for sentiment analysis on the Twitter dataset, providing insights into the sentiments expressed in the tweets and the model's performance in predicting sentiment categories.

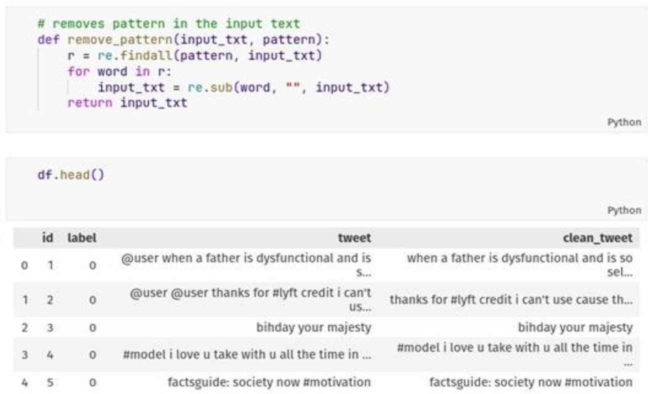

Figure 2: Data Preprocessing snapshots

Figure 3: Feature Extraction

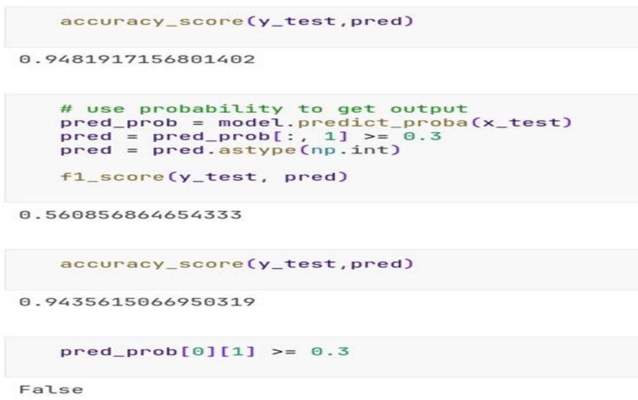

Figure 4: Tokenization

To turn the text into a numerical format that the logistic regression a lgorithm can use, it would also be tokenized and vectorized. This illustration tokenizes the supplied text into individual words, punctuation, and contractions. Each token denotes a distinct textual unit and can be processed further or utilized as input for a variety of natural language processing operations, including sentiment analysis. In many text analysis jobs, tokenization is a crucial preprocessing step since it aids in the breakdown of the text into digestible chunks that can be processed and analyzed efficiently. Word - level tokenization, character - level tokenization, or more sophisticated approaches like subword tokenization may be utilized, depending on the needs and methodologies employed.

The programme would choose and extract from the text a set of traits that are critical for sentiment analysis. The features may include word frequencies, n - grams, sentiment lexicons, and other language characteristics that are known to be connected to emotion. The result of feature extraction might differ in terms of representation of semantics, sparsity, or dimension. The retrieved characteristics are used as input in the succeeding processes, which include sentiment categorization and model training.

6. Limitation

The logistic regression method for sentiment analysis has several limitations and challenges that should be considered:

• Handling Complex Sentences: Lengthy or convoluted tweets with complex language patterns and nuanced sentiment may pose difficulties for logistic regression due to its linear structure, potentially leading to information loss and reduced accuracy.

• Dealing with Sarcasm and Irony: Logistic regression may struggle to detect and evaluate sarcasm and irony in tweets, as these sentiments often involve nuanced and contradictory expressions that are challenging for linear algorithms.

• Limited Context Understanding: Logistic regression analyzes each tweet independently and fails to consider broader context, such as nearby tweets, user history, or popular topics that could influence sentiment.

• Dependence on Feature Engineering: The effectiveness of logistic regression heavily relies on accurately chosen features.

• Class Imbalance and Bias: Imbalanced datasets, with uneven distributions of positive and negative tweets, can bias logistic regression towards the majority class, leading to inaccurate predictions for the minority class.

• Generalization to Different Domains: Logistic regression trained on one specific domain may struggle when applied to different domains or specialized themes. Language traits, emotional expressions, and contextual nuances can vary, requiring domain adaptation or retraining.

Conflict of Interest

Authors declare that they do not have any conflict of interest.

Funding Source

None

Authors' Contributions

Kavinder Singh: Led literature review, formulated research concept, and integrated logistic regression for sentiment analysis. Assisted in experimental design and analysis.

Syed Mehdi Abbas Razavi: Curated Twitter dataset, implemented logistic regression model, and assessed model performance.

Sneh Sagar Subedi: Preprocessed dataset, compared models, interpreted results, and contributed to manuscript refinement.

Akshay Kumar: Optimized model parameters, implemented logistic regression, and discussed model implications.

Gurwinder Singh: Extracted features, adapted model for Twitter data, discussed findings, and contributed to manuscript enhancement.

All authors reviewed and contributed to the editing of the manuscript and have given their approval for the final version of the manuscript.

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7. Conclusion

In this study, we used logistic regression to do sentiment analysis on a Twitter dataset. Using bag-of-words and TF-IDF approaches, we retrieved features from a pre-processed dataset of tweets. We used the training set to train a logistic regression model, and the testing set to assess its performance. The findings revealed that the testing set accuracy for the logistic regression model was 77.8%. This study may be expanded to additional social media channels and used in a variety of fields, including social studies, politics, and marketing.

References

[1] R. Wagh and P. Punde, "Survey on sentiment analysis using twitter dataset," in 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA). IEEE, pp. 208–211, 2018.

[2] S. A. El Rahman, F. A. AlOtaibi, and W. A. AlShehri, "Sentiment analysis of twitter data," in 2019 international conference on computer and information sciences (ICCIS). IEEE, pp. 1–4, 2019.

[3] A. Balahur, "Sentiment analysis in social media texts," in Proceedings of the 4th workshop on computational approaches to subjectivity, sentiment and social media analysis, pp. 120–128, 2013.

[4] A. P. Jain and V. D. Katkar, "Sentiments analysis of twitter data using data mining," in 2015 International Conference on Information Processing (ICIP). IEEE, pp.807–810, 2015.

[5] V. Sahayak, V. Shete, and A. Pathan, "Sentiment analysis on twitter data," International Journal of Innovative Research in Advanced Engineering (IJIRAE), Vol.2, No.1, pp.178–183, 2015.

[6] M. R. Hasan, M. Maliha, and M. Arifuzzaman, "Sentiment analysis with nlp on twitter data," in 2019 international conference on computer, communication, chemical, materials and electronic engineering (IC4ME2). IEEE, pp.1–4, 2019.

[7] S. Bhuta, A. Doshi, U. Doshi, and M. Narvekar, “A review of techniques for sentiment analysis of twitter data,” in 2014 International conference on issues and challenges in intelligent computing techniques (ICICT). IEEE, pp 583–591, 2014.

[8] H. Bagheri and M. J. Islam, “Sentiment analysis of twitter data,” arXiv preprint arXiv:1711.10377, 2017.

[9] A. Alsaeedi and M. Z. Khan, “A study on sentiment analysis techniques of twitter data,” International Journal of Advanced Computer Science and Applications, vol. 10, no. 2, 2019.

[10] C. Shofiya and S. Abidi, “Sentiment analysis on covid-19-related social distancing in canada using twitter data,” International Journal of Environmental Research and Public Health, vol. 18, no. 11, p. 5993, 2021.

[11] L. Nemes and A. Kiss, “Social media sentiment analysis based on covid-19,” Journal of Information and Telecommunication, vol. 5, no. 1, pp. 1–15, 2021.

[12] J. K. Rout, K.-K. R. Choo, A. K. Dash, S. Bakshi, S. K. Jena, and K. L. Williams, “A model for sentiment and emotion analysis of unstructured social media text,” Electronic Commerce Research, vol. 18, pp. 181–199, 2018.

[13] D. Goularas and S. Kamis, “Evaluation of deep learning techniques in sentiment analysis from twitter data,” in 2019 International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML). IEEE, 2019, pp. 12–17.

[14] E. M. Younis, “Sentiment analysis and text mining for social media microblogs using open source tools: an empirical study,” International Journal of Computer Applications, vol. 112, no. 5, 2015.

[15] A. Kumar and G. Garg, “Sentiment analysis of multimodal twitter data,” Multimedia Tools and Applications, vol. 78, pp. 24 103–24 119, 2019.

[16] S. Dhawan, K. Singh, and P. Chauhan, “Sentiment analysis of twitter data in online social network,” in 2019 5th International Conference on Signal Processing, Computing and Control (ISPCC). IEEE, 2019, pp. 255–259.

[17] K. H. Manguri, R. N. Ramadhan, and P. R. M. Amin, “Twitter sentiment analysis on worldwide covid-19 outbreaks,” Kurdistan Journal of Applied Research, pp. 54–65, 2020.

[18] Z. Drus and H. Khalid, “Sentiment analysis in social media and its application: Systematic literature review,” Procedia Computer Science, vol. 161, pp. 707–714, 2019.

[19] P. Chauhan, N. Sharma, and G. Sikka, “The emergence of social media data and sentiment analysis in election prediction,” Journal of Ambient Intelligence and Humanized Computing, vol. 12, pp. 2601–2627, 2021.

[20] A. Srivastava, V. Singh, and G. S. Drall, “Sentiment analysis of twitter data: A hybrid approach,” International Journal of Healthcare Information Systems and Informatics (IJHISI), vol. 14, no. 2, pp. 1–16, 2019.

[21] P. Tyagi and R. Tripathi, “A review towards the sentiment analysis techniques for the analysis of twitter data,” in Proceedings of 2nd international conference on advanced computing and software engineering (ICACSE), 2019.

[22] R. Khan, P. Shrivastava, A. Kapoor, A. Tiwari, and A. Mittal, “Social media analysis with ai: sentiment analysis techniques for the analysis of twitter covid-19 data,” J. Crit. Rev, vol. 7, no. 9, pp. 2761–2774, 2020.

[23] K. Sailunaz and R. Alhajj, “Emotion and sentiment analysis from twitter text,” Journal of Computational Science, vol. 36, p. 101003, 2019.

[24] S. Tiwari, A. Verma, P. Garg, and D. Bansal, “Social media sentiment analysis on twitter datasets,” in 2020 6th international conference on advanced computing and communication systems (ICACCS). IEEE, pp.925–927, 2020.

[25] A. L´opez-Chau, D. Valle-Cruz, and R. Sandoval-Almaz´an, “Sentiment analysis of twitter data

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Kavinder Singh is a dedicated and promising student pursuing his B.Tech in Computer Science from Chandigarh University. He is expected to complete his degree in 2025. With a keen interest in the field of computer science, he aspires to make significant contributions to the scientific community in the future. His research interests primarily revolve around areas such as Cryptography Algorithms, Network Security, Cloud Security and Privacy, Big Data Analytics, Data Mining, IoT, and Computational Intelligence-based education. He aims to explore these domains to develop innovative solutions and enhance the understanding of these cutting-edge technologies.

Syed Mehdi Abbas Razavi is a diligent and motivated student currently pursuing a B.Tech degree in Computer Science from Chandigarh University. Expected to graduate in 2025, Authoor-2 has a strong passion for the field of computer science and aims to contribute to its ever-evolving landscape. With a keen interest in artificial intelligence, machine learning, and data science, Authoor-2 aspires to develop innovative solutions to real-world problems. Authoor-2 actively engages in research projects and is a member of professional organizations such as the Association for Computing Machinery (ACM) and the Institute of Electrical and Electronics Engineers (IEEE). Through these affiliations, Authoor-2 stays updated with the latest advancements in computer science and seeks to collaborate with fellow researchers to push the boundaries of technology.

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Dr. Gurwinder Singh is an accomplished Assistant Professor specializing in optimization techniques and their application to combinatorial optimization problems. With a notable publication record, including SCI journal papers, IEEE/Scopus conference papers, book chapters, and two granted patents, he has received accolades such as the Faculty Excellence Award and Best Paper Award, and serves as a peer reviewer for prestigious journals.

