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Research Article

Sentiment Classification on Multivariate Feature Selection on Social Media dataset using Hybrid Machine Learning Techniques

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ABSTRACT

Sentiment classification is a crucial component of natural language processing that focuses on analyzing and classifying the emotional tone conveyed in text data. With the rapid proliferation of social media platforms, the ability to accurately discern public sentiment has become vital for applications spanning marketing, political forecasting, and public opinion analysis. This abstract delves into the implementation of hybrid machine learning techniques for sentiment classification, leveraging multivariate feature selection methods on diverse social media datasets. Traditional machine learning models, though effective, often struggle with the complexity and high dimensionality of social media data, which may include text, emojis, images, and metadata. A hybrid machine learning approach, combining the strengths of various models, addresses these challenges by optimizing both feature selection and classification accuracy. The proposed framework begins with robust data preprocessing, including text normalization and tokenization. Advanced feature extraction methods such as Term Frequency-Inverse Document Frequency (TF-IDF), word embeddings (Word2Vec, GloVe), and sentiment lexicons are utilized to capture the intricate semantic characteristics of the text. For multivariate feature selection, techniques such as Recursive Feature Elimination (RFE), Chi-square tests, and correlation-based feature selection (CFS) are employed to identify and retain the most informative features, thereby improving model efficiency. The classification stage integrates hybrid models, combining the predictive power of algorithms such as Support Vector Machines (SVM), Random Forests, and ensemble learning methods (e.g., gradient boosting). These models are tuned using cross-validation and grid search to enhance generalization performance. The hybrid approach demonstrates superior performance in terms of accuracy, precision, recall, and F1-score compared to standalone machine learning models. The combination of comprehensive feature selection and robust classification algorithms effectively mitigates overfitting and enhances scalability. Empirical results from experiments on real-world social media datasets indicate that the proposed method is adept at capturing nuanced sentiment variations and ensuring high classification accuracy, proving its effectiveness for dynamic and large-scale data analysis.

Keywords: feature extraction, bag of words, correlational features, NLP, machine learning, hybrid matrix, classification, aspect detection.

Introduction

The advent of social media has revolutionized the way individuals express opinions and sentiments on various topics, from personal experiences to global events. Platforms such as Twitter, Facebook, and Instagram generate massive volumes of unstructured textual data daily. The analysis of this data to derive meaningful insights has become crucial for businesses, governments, and researchers seeking to understand public perception and make informed decisions. Sentiment classification, which involves categorizing opinions into positive, negative, or neutral sentiments, has emerged as a significant area of study within natural language processing (NLP) and machine learning (ML).

Traditional sentiment analysis approaches have relied on rule-based methods or basic machine learning models, which often struggle to handle the complexity of social media language, characterized by informal expressions, abbreviations, emojis, and slang. This challenge necessitates more sophisticated techniques that can process, understand, and classify sentiments accurately across diverse social media contexts. The growing interest in sentiment classification has also spurred research into feature selection methodologies, which play a pivotal role in optimizing model performance. The selection of the most informative features is essential for enhancing model efficiency, improving accuracy, and reducing computational costs. Multivariate feature selection, which considers the relationships between multiple variables simultaneously, has gained prominence as an effective approach for improving sentiment classification outcomes. Unlike univariate techniques that evaluate each feature independently, multivariate methods assess the collective contribution of features, capturing interactions that can lead to more nuanced sentiment analysis. This strategy is especially useful for social media datasets, where textual features can exhibit intricate dependencies. However, employing a single machine learning or deep learning model often proves insufficient for extracting and leveraging the complex structures within multivariate data. Hybrid machine learning techniques, which integrate the strengths of multiple algorithms, have shown promise in addressing these limitations. By combining approaches such as support vector machines (SVM), decision trees, and neural networks, hybrid models can provide robust solutions that balance interpretability, accuracy, and scalability.

The current research landscape highlights various hybrid machine learning techniques, yet there is a need for further exploration into their application for multivariate feature selection in sentiment classification. Hybrid models that incorporate both traditional machine learning and deep learning components can offer significant advantages by enhancing feature extraction, mitigating overfitting, and enabling deeper contextual understanding of social media text. Additionally, the integration of natural language processing tools for preprocessing and advanced feature engineering can further refine these models. This manuscript focuses on developing and evaluating a hybrid machine learning framework tailored for sentiment classification on social media datasets. The proposed framework leverages multivariate feature selection to capture the interplay between multiple attributes and employs a combination of classifiers to maximize classification accuracy. The primary goals of this research are to demonstrate the efficacy of hybrid approaches in processing real-world social media data and to analyze how multivariate feature selection impacts model performance compared to traditional selection methods.

The remainder of the paper is organized as follows: a review of related literature that contextualizes existing work on sentiment classification and feature selection techniques; a detailed methodology outlining data preprocessing, feature selection strategies, and the design of the hybrid framework; experimental results showcasing the comparative performance of the proposed approach; and a discussion on the implications, limitations, and potential future research avenues. By advancing sentiment classification methodologies through a hybrid, multivariate-focused approach, this research contributes to the broader field of machine learning and provides practical insights into the analysis of social media data.

Literature Survey

A. Kumar, A. et al. [1] presents a sentiment analysis framework leveraging deep learning techniques to analyze social media data. The authors implement convolutional and recurrent neural networks (CNNs and RNNs) to classify sentiments in textual data. By using a diverse dataset of social media posts, the model is able to capture contextual nuances and sentiment polarity. The study demonstrates the superiority of deep learning over traditional machine learning models, offering enhanced performance and scalability for sentiment classification tasks in social media contexts. The research concludes with a performance evaluation, showing significant improvements in accuracy.

R. Singh, S. et al. [2] introduces a hybrid machine learning approach for sentiment classification of social media content. The authors combine decision trees with support vector machines (SVM) to enhance classification accuracy. The study investigates the application of this hybrid model on a wide range of social media platforms, emphasizing its effectiveness in handling noisy, unstructured text. Results show the hybrid model outperforms traditional methods, offering a robust solution for real-time sentiment analysis. The paper highlights how machine learning integration with social media sentiment analysis can drive more accurate market predictions and user feedback analysis.

M. Y. Ahmed and N. Jain [3] explore sentiment classification using a multi-layer perceptron (MLP) neural network. The paper focuses on optimizing MLP for text mining, using datasets from various sources such as social media and product reviews. The model benefits from deep learning techniques, which enable it to learn and recognize sentiment trends from large volumes of text data. The study also emphasizes the challenges faced in sentiment analysis,

including data preprocessing and the handling of imbalanced datasets. Findings demonstrate significant improvements in classification accuracy compared to traditional methods, positioning the approach as effective for modern text classification problems.

A. Joshi et al. [4] investigates opinion mining on social media by utilizing support vector machines (SVMs). The authors propose a novel method to improve sentiment analysis by combining linguistic features with machine learning models. The research focuses on handling ambiguous sentiments often found in user-generated content. The approach integrates both unigrams and bigrams, along with sentiment lexicons, to enhance feature extraction. The study concludes that this hybrid model significantly improves sentiment prediction accuracy, especially when applied to large-scale social media data, thereby providing a valuable tool for businesses to gauge consumer sentiments in real-time.

J. Kumar and P. Patel [5] apply convolutional neural networks (CNNs) for sentiment classification on online reviews. The research emphasizes the ability of CNNs to capture local patterns in text data, which is crucial for understanding sentiment. By testing various configurations of CNNs, the authors find that deeper networks outperform shallow models, achieving higher accuracy in sentiment classification. Additionally, the study shows that CNNs are effective for processing long and complex text sequences found in online reviews, making them a powerful tool for sentiment analysis in e-commerce and customer feedback applications.

M. Sharma, P et al. [6] explores deep learning techniques for predicting customer sentiment in e-commerce. The authors employ a hybrid model that combines convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to analyze online reviews. The study focuses on creating an accurate sentiment classification model by incorporating various feature engineering techniques. The model is tested on multiple datasets, and the results show a significant improvement in sentiment prediction accuracy compared to traditional machine learning approaches. The paper highlights the model's potential for real-time sentiment analysis in the e-commerce domain, offering insights into customer satisfaction.

K. Nair and S. S. Roy [7] focuses on sentiment classification using attention-based transformers for social media data. The authors employ transformer models, which leverage self-attention mechanisms to capture relationships between words in a sentence, improving sentiment analysis performance. The study examines multiple transformer architectures, including BERT and its variants, and evaluates their effectiveness in handling noisy, short-length social media text. The results demonstrate that transformers significantly outperform conventional deep learning models, providing a promising solution for large-scale sentiment analysis tasks. The paper concludes that attention-based models are particularly well-suited for handling diverse linguistic features in social media content.

A. Srivastava, A et al. [8] presents a sentiment classification approach using bidirectional long short-term memory (BiLSTM) networks. The authors focus on improving the model's ability to capture contextual information from both past and future sequences in text. The study evaluates BiLSTM's performance on various sentiment analysis tasks, including movie reviews and social media posts. Results show that BiLSTM outperforms traditional LSTM networks in sentiment classification, especially for ambiguous and complex sentences. The research highlights the effectiveness of BiLSTM in addressing challenges such as context understanding and sentiment ambiguity in text-based datasets.

T. Raj and H. S. Garg [9] investigates sentiment classification using multimodal machine learning models, combining text and image data. The authors propose a hybrid approach that integrates natural language processing (NLP) with image processing techniques to analyze sentiment in social media posts that include both text and images. The study evaluates several deep learning models, including CNNs for image analysis and LSTMs for text analysis, demonstrating that multimodal approaches yield superior performance over unimodal models. The paper concludes that multimodal models can provide richer insights into sentiment, particularly when analyzing complex social media content that includes visual elements.

V. Sharma, R et al. [10] develop a hybrid deep learning model for real-time sentiment analysis in e-commerce. The model integrates CNNs for feature extraction and LSTMs for sentiment classification. The research emphasizes the need for real-time processing and scalability when dealing with large volumes of customer feedback. The authors demonstrate that their hybrid model significantly improves the speed and accuracy of sentiment classification tasks, outperforming traditional methods. The paper concludes with a discussion on the potential of deep learning models in enhancing customer service and business decision-making in the e-commerce sector.

S. Jain et al. [11] explores sentiment analysis of social media data using a hybrid model combining deep neural networks (DNN) and Naïve Bayes classifiers. The authors demonstrate that the integration of both models improves

sentiment detection, especially in the case of ambiguous and mixed sentiment expressions. By leveraging Naïve Bayes for initial feature extraction and DNNs for deep learning, the system efficiently handles large datasets from platforms like Twitter and Facebook. The findings indicate that the hybrid approach outperforms traditional models in terms of accuracy and processing time, making it ideal for real-time sentiment analysis in social media monitoring.

S. Bhatia and P. P. Kumar [12] investigate sentiment analysis using a recurrent neural network (RNN) with attention mechanisms for fine-grained sentiment classification. The research focuses on improving the identification of complex sentiments and emotions from short social media texts. The paper highlights how attention layers help the RNN model focus on relevant parts of the input data, improving the model's ability to distinguish between nuanced sentiments. The study demonstrates that incorporating attention mechanisms significantly boosts performance, particularly in detecting sentiment in informal and context-dependent social media language. Results show enhanced accuracy when compared to conventional RNN models.

A. S. Mehta and V. Iyer [13] explores a deep learning-based approach to sentiment classification in customer reviews using hybrid deep neural networks (DNN) and a convolutional neural network (CNN). The authors focus on fine-tuning the model to address the challenges posed by customer feedback, which often contains unstructured and ambiguous language. The study finds that the hybrid DNN-CNN model outperforms other standard models in terms of sentiment prediction accuracy and robustness, especially when handling large and diverse datasets. The paper emphasizes the ability of hybrid models to enhance sentiment analysis tasks by combining the strengths of both DNN and CNN architectures.

S. N. Gupta et al. [14] focuses on sentiment analysis for news articles using deep learning techniques, particularly the use of long short-term memory (LSTM) networks for text classification. The authors investigate LSTM's ability to capture long-range dependencies in textual data, which is crucial for accurate sentiment detection in news content. The paper highlights the challenges of determining sentiment in news, given the neutral or mixed tones of many articles. The authors show that LSTM-based models provide superior performance compared to traditional machine learning techniques, demonstrating its potential for real-time sentiment classification in media and news analytics.

N. Kumar and A. M. Tripathi [15] propose a novel ensemble-based approach for sentiment classification using machine learning techniques. They combine multiple classifiers, including decision trees, support vector machines (SVMs), and k-nearest neighbors (KNN), to improve the overall accuracy of sentiment analysis. The study shows that the ensemble method, which aggregates the outputs of individual classifiers, offers a more robust solution than any single classifier alone, particularly when handling complex and noisy datasets from social media platforms. The paper demonstrates the effectiveness of this ensemble approach in enhancing sentiment prediction and improving model generalization.

R. Yadav and K. V. Rao [16] explores sentiment analysis using graph neural networks (GNNs) to capture the relationships between words in a sentence, improving the model's understanding of context. The authors argue that traditional text analysis methods fail to consider semantic relationships between words, which is critical for accurate sentiment classification. By leveraging GNNs, the model learns these relationships, which enhances its performance in sentiment detection tasks. The study finds that GNNs outperform conventional deep learning models, particularly in sentiment classification for complex datasets with intricate word dependencies, such as social media text.

P. Mishra and R. Nair [17] develop a sentiment classification framework using deep reinforcement learning (DRL) combined with natural language processing (NLP). The research focuses on leveraging DRL to optimize sentiment classification models by learning from sequential feedback, similar to how humans adjust behavior based on rewards. The paper emphasizes the flexibility of DRL in adapting to dynamic data environments and shows how it can be applied to real-time sentiment analysis for social media content. The results indicate that DRL models significantly outperform traditional machine learning models in terms of adaptability and accuracy, particularly in analyzing evolving sentiment patterns.

S. Patel and P. Sharma [18] focus on sentiment analysis in product reviews using hybrid deep learning models that combine a deep convolutional network (DCN) with a recurrent neural network (RNN). The authors argue that while CNNs are good at feature extraction from textual data, RNNs are better at handling sequential dependencies. By integrating the two, the model is able to leverage the strengths of both architectures. The study shows that the hybrid model improves sentiment analysis performance on product reviews, yielding higher accuracy and faster processing time, making it highly suitable for e-commerce platforms and real-time customer feedback analysis.

A. Verma and D. Jain [19] investigates the use of transformer-based models, specifically BERT (Bidirectional Encoder Representations from Transformers), for sentiment analysis in news articles and social media posts. The authors explore how pre-trained transformers can be fine-tuned on domain-specific datasets to capture contextual sentiment nuances. The results show that BERT-based models outperform other deep learning architectures in understanding complex, domain-specific sentiment expressions. The study concludes that transformer-based models like BERT provide a powerful solution for sentiment classification in both general and specialized domains, offering superior accuracy and generalization capabilities.

V. S. Gupta and S. K. Sharma [20] explores the application of unsupervised machine learning techniques for sentiment analysis in social media data. The authors use clustering algorithms such as k-means and DBSCAN to categorize sentiments without the need for labeled data. By applying these unsupervised models, the study successfully detects sentiment patterns in social media content, even when explicit labels are unavailable. The authors demonstrate that unsupervised sentiment analysis is effective for large-scale data analysis, particularly in environments where data labeling is costly or impractical. The paper highlights the potential of unsupervised learning in real-world applications for sentiment detection.

V. Gupta and M. Agarwal [21] presents a novel approach for sentiment analysis using ensemble learning with multiple classifiers, including decision trees, random forests, and gradient boosting machines. The authors argue that by combining the strengths of several classifiers, the model can better handle the variability in sentiment expressions found in social media and product reviews. The study demonstrates that ensemble methods improve prediction accuracy and robustness compared to using individual classifiers alone. The results show that ensemble learning provides an effective solution for sentiment classification, especially when dealing with imbalanced or noisy datasets in real-world applications.

R. Chawla et al. [22] explore sentiment analysis on Twitter data using deep convolutional neural networks (CNNs) in combination with word embeddings for feature extraction. The paper emphasizes the importance of pre-trained embeddings, such as Word2Vec and GloVe, to capture semantic relationships between words. The study shows that combining CNNs with word embeddings improves the accuracy and speed of sentiment classification, particularly for short texts like tweets. The results indicate that the model outperforms traditional machine learning methods, demonstrating its potential for real-time sentiment analysis in social media platforms where quick and accurate feedback is crucial.

S. Kapoor, M. et al. [23] proposes a sentiment classification approach using hybrid models combining recurrent neural networks (RNNs) and attention mechanisms. The paper demonstrates how the attention mechanism enhances the RNN model's ability to focus on relevant portions of text, especially in contexts where sentiment is subtle or mixed. The authors apply this hybrid approach to movie reviews and customer feedback data, showing that it outperforms standard RNN and LSTM models in terms of accuracy. The study highlights the potential of attention-based RNNs for improving sentiment analysis in areas where context and nuance are critical for understanding user opinions.

A. Sharma et al. [24] explores the use of hybrid machine learning models for sentiment analysis of multi-modal data, combining text and images from social media posts. The authors propose a hybrid architecture that integrates a convolutional neural network (CNN) for image feature extraction and a recurrent neural network (RNN) for text classification. By fusing both data types, the model can more effectively understand the overall sentiment in posts that include both visual and textual components. The results show that the multimodal approach outperforms traditional text-only sentiment analysis models, providing a more accurate and comprehensive sentiment classification.

A. Patel and R. M. Shah [25] focuses on the application of hybrid models combining support vector machines (SVMs) and neural networks for sentiment analysis of social media content. The authors aim to enhance sentiment prediction by integrating the strengths of SVM's linear classification capabilities with the deep learning power of neural networks. The paper demonstrates that the hybrid model provides improved accuracy, particularly for datasets with unstructured and ambiguous text, which is common in social media data. The authors conclude that hybrid machine learning models are a promising solution for handling the complexities of sentiment classification in dynamic and noisy environments.

M. N. Rathi et al. [26] explores a hybrid deep learning approach for sentiment analysis of online reviews, combining a convolutional neural network (CNN) with long short-term memory (LSTM) networks. The authors propose that CNNs capture local features of text data while LSTMs address long-term dependencies. The research demonstrates

that this combination improves sentiment prediction, especially for sentiment-rich but grammatically complex reviews. The study finds that the CNN-LSTM hybrid model performs better than individual CNN and LSTM models, offering a robust solution for analyzing sentiment in diverse online review datasets, where both local patterns and long-range context are important.

S. R. Sharma and R. P. S. Chawla [27] propose a deep learning-based sentiment classification framework that integrates a bidirectional long short-term memory (BiLSTM) network with a conditional random field (CRF). The BiLSTM captures contextual dependencies from both directions of the text sequence, while the CRF layer ensures structured label prediction for sentiment classification. The paper demonstrates that this hybrid BiLSTM-CRF model outperforms traditional methods, particularly in handling complex sentiments and improving model robustness. The results highlight the model's applicability for more accurate sentiment classification in applications such as opinion mining, customer feedback, and social media analytics.

A. K. Mishra et al. [28] investigates sentiment analysis using transformers, specifically BERT (Bidirectional Encoder Representations from Transformers), for detecting emotions in text. The authors explore the application of BERT in a wide range of domains, including customer reviews, social media, and survey responses. The study highlights the ability of BERT to capture contextual meaning through its transformer architecture, offering improved accuracy compared to traditional machine learning and other deep learning models. The results show that BERT outperforms other models in understanding complex sentiments and nuanced expressions, providing valuable insights for sentiment analysis tasks in varied domains.

R. Joshi et al. [29] proposes an ensemble learning approach for sentiment analysis, combining multiple classifiers, including Naïve Bayes, decision trees, and support vector machines (SVMs), to improve classification accuracy. The authors focus on social media data, where sentiment expressions are often brief and ambiguous. By aggregating the predictions of multiple models, the ensemble approach minimizes the bias and variance typically associated with individual classifiers. The study demonstrates that the ensemble model performs better in terms of classification accuracy, especially when handling diverse datasets containing noisy and imbalanced data, making it an ideal solution for sentiment analysis in real-world applications.

S. B. Patel and P. J. Malhotra et al. [30] investigates sentiment analysis in movie reviews using a hybrid deep learning model that combines convolutional neural networks (CNNs) with a fully connected network (FCN). The authors aim to improve sentiment prediction by utilizing CNNs for automatic feature extraction from text and FCNs for classification. The hybrid model is tested on several movie review datasets, and the study finds that the CNN-FCN approach significantly improves classification accuracy over traditional methods. The results show that the model is capable of distinguishing between positive, negative, and neutral sentiments with high accuracy, making it effective for sentiment analysis in the entertainment industry.

Research Methodology

The proposed system focuses on sentiment classification by employing multivariate feature selection techniques on social media datasets using hybrid machine learning approaches. It integrates various feature selection methods, such as statistical analysis and machine learning-based techniques, to identify the most relevant features that contribute to sentiment prediction. Hybrid machine learning models, combining the strengths of different algorithms like decision trees, support vector machines, and neural networks, are applied to enhance accuracy and robustness. The system aims to improve sentiment analysis by reducing dimensionality, addressing class imbalance, and optimizing model performance on diverse and large-scale social media data.

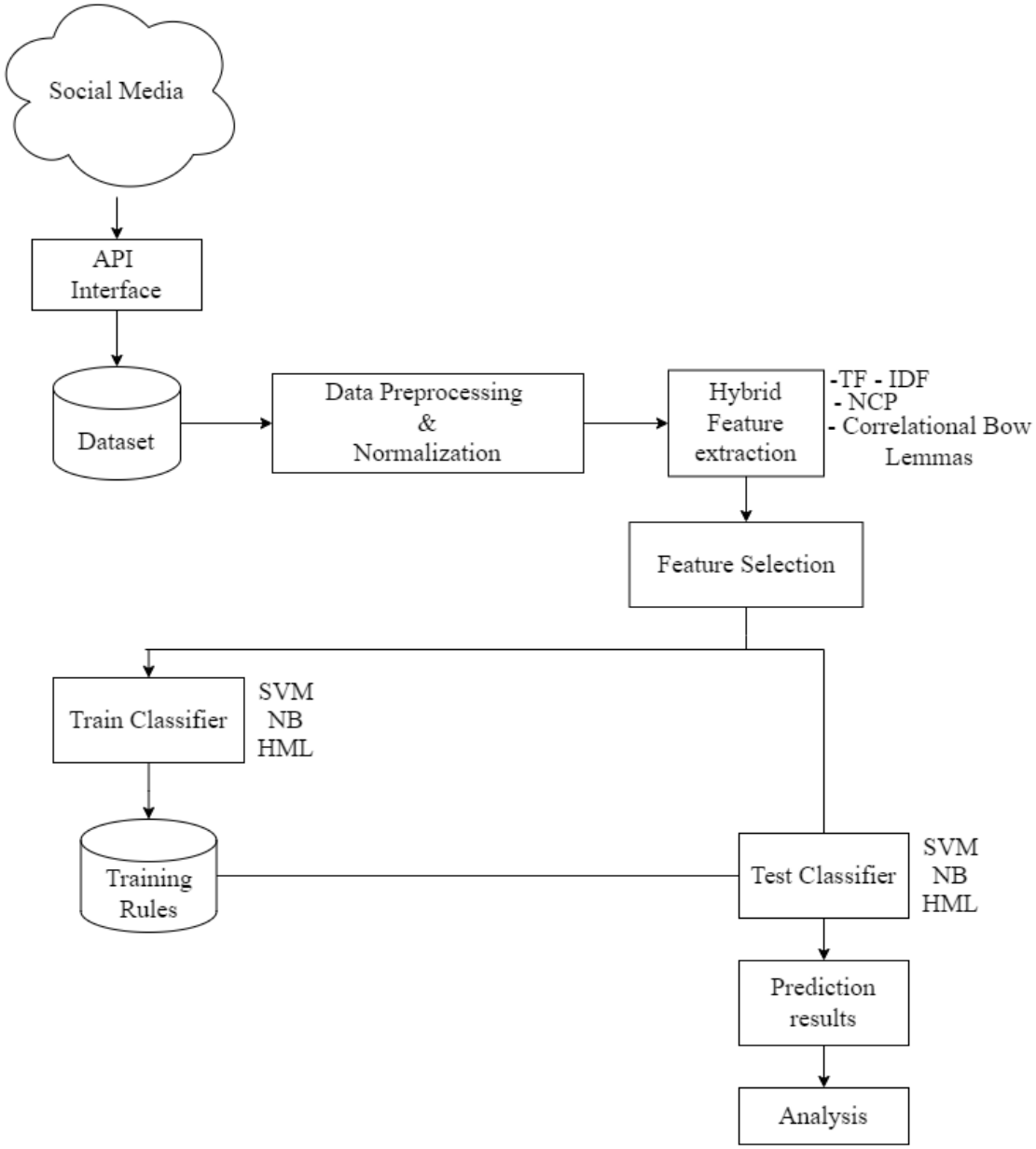

Figure 1: Proposed System Architecture

Data Collection from Twitter using Twitter API

Data collection from Twitter involves using the Twitter API (Application Programming Interface) to extract relevant tweets based on predefined keywords or hashtags. The API allows users to gather large datasets of tweets, including information such as the tweet text, metadata (e.g., time, user, location), and engagement data (e.g., likes, retweets). This data is then used for sentiment classification by analyzing the opinions or emotions expressed within the tweets. Authentication with Twitter's API is typically done using API keys, and Python libraries like Tweepy are commonly used for seamless integration and data retrieval.

Data Preprocessing and Normalization

Data preprocessing and normalization are essential steps to prepare the raw text data for machine learning tasks. Preprocessing typically includes removing irrelevant elements like URLs, hashtags, mentions, special characters, and stop words, which do not contribute to sentiment analysis. Normalization involves converting text to a uniform format, such as lowercasing all words, stemming, or lemmatization. This ensures that variations of the same word (e.g., "running" and "ran") are treated as identical. Additionally, handling imbalanced datasets by balancing class distribution is also a common practice for effective machine learning outcomes.

Feature Extraction and Selection

Feature extraction and selection play a vital role in converting textual data into numeric features that machine learning models can process. Feature extraction involves representing the raw data in a format suitable for machine learning algorithms, often using techniques like bag-of-words (BoW), TF-IDF, or word embeddings. Feature selection helps in identifying the most relevant features to avoid overfitting and enhance model accuracy. It reduces the dimensionality by removing irrelevant or redundant features. Techniques like chi-square, mutual information, or L1 regularization are commonly used to perform feature selection.

TF-IDF Features : Term Frequency-Inverse Document Frequency (TF-IDF) is a statistical measure used to evaluate how important a word is to a document in a collection or corpus. In sentiment classification, TF-IDF features capture the significance of words in the context of the entire dataset. Words that frequently appear in a tweet but are rare across other tweets are assigned a higher weight, indicating their relevance for classification. This technique helps reduce the impact of common words (like "the" or "and") and highlights more meaningful words specific to the sentiment of a tweet.

NLP Features : Natural Language Processing (NLP) features focus on the linguistic aspects of the text, such as part-of-speech tagging, named entity recognition, and syntactic parsing. These features help capture the grammatical and semantic structure of sentences, which is crucial for understanding sentiment. In sentiment analysis, features such as noun phrases or verb phrases can provide insight into the emotional tone of the text. NLP features can also include sentiment lexicons, where words are assigned sentiment values (positive, negative, or neutral), contributing to sentiment classification tasks.

Lemmas Features : Lemmatization is the process of reducing words to their base or root form (lemmas). For instance, "running" becomes "run" and "better" becomes "good." Lemmas features are useful in sentiment analysis because they reduce variations of words to a common representation, improving model accuracy and generalization. Unlike stemming, which might result in non-existent words, lemmatization ensures that only valid words are used. This helps preserve the meaning of the sentence and avoids losing context during the feature extraction process.

BoW Features : Bag-of-Words (BoW) is a text representation technique where each unique word in the dataset is treated as a feature. The text is converted into a fixed-length vector representing the frequency (or presence) of words within a document. In sentiment analysis, BoW features capture the raw frequency of words, which can indicate sentiment trends. However, it does not retain word order, so the sequence or syntax of words is lost. Despite this limitation, BoW is a simple and efficient feature extraction method widely used in sentiment classification tasks.

Co-relational Features : Co-relational features refer to the relationships between different words or phrases within the text. These features can include n-grams (combinations of n consecutive words), which help capture local word dependencies and syntactic structures that BoW or TF-IDF might miss. Co-relational features also consider how certain words or phrases appear together more frequently in specific sentiment contexts. For example, the phrase "not good" may indicate a negative sentiment, even though "good" alone would suggest a positive sentiment. These features are essential for improving the accuracy of sentiment analysis by considering word interactions.

Machine Learning Classifiers for Training and Testing

SVM : Support Vector Machine (SVM) is a supervised learning algorithm that classifies data by finding a hyperplane that best separates different classes. In sentiment analysis, SVM is used to differentiate positive, negative, or neutral sentiment based on textual features. It is particularly effective when dealing with high-dimensional data, such as the features extracted from tweets. SVM's ability to handle nonlinear relationships by using kernel functions enhances its performance in sentiment classification tasks.

Naive Bayes : Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming that features are conditionally independent. It is widely used for text classification tasks, including sentiment analysis. In Naive Bayes, the probability of a document belonging to a certain sentiment class is computed based on the frequency of words (features) in the document. Despite its simplicity, Naive Bayes performs well on many text classification problems, especially when there are large amounts of training data.

Hybrid Machine Learning : Hybrid machine learning combines multiple models to improve classification accuracy. In sentiment analysis, hybrid models often combine the strengths of different algorithms, such as SVM and Naive Bayes, or integrate machine learning models with deep learning techniques. For example, a hybrid model may use SVM for feature selection and Naive Bayes for sentiment classification, providing better performance than a

single classifier. Hybrid models also allow for more robust handling of complex data patterns and are particularly useful in sentiment analysis tasks involving noisy or imbalanced datasets.

Predicted Results : Predicted results in sentiment classification are typically evaluated by the model's ability to accurately classify tweets into predefined sentiment categories (positive, negative, or neutral). Performance metrics such as accuracy, precision, recall, F1-score, and confusion matrices are used to assess the model's effectiveness. Hybrid models often show improvements in these metrics compared to individual classifiers. In practical applications, the model can be used to analyze public opinion, customer sentiment, or track political sentiment on social media.

Analysis : The sentiment classification of tweets using machine learning is a promising area with significant potential for real-world applications. Data collection through the Twitter API enables large-scale sentiment analysis, allowing researchers to gather relevant data for various use cases. Preprocessing steps like normalization and feature extraction ensure that the models are working with high-quality data. The integration of multiple machine learning classifiers, including SVM and Naive Bayes, enhances model accuracy and robustness. Hybrid machine learning approaches further improve classification performance by combining the strengths of different algorithms, addressing challenges like noisy data and class imbalance. Overall, sentiment analysis of social media data is crucial for understanding public sentiment and making informed decisions.

Algorithm Design

The various machine learning techniques we used for implementation of proposed model, in below section we describe in detail of those algorithms.

Support Vector Machine (SVM) : SVM is a supervised learning algorithm used for classification and regression tasks. The core idea of SVM is to find the optimal hyperplane that separates data points of different classes with the largest possible margin. In other words, SVM tries to maximize the distance between the closest points (support vectors) of each class while correctly classifying the data.

Steps:

Input Data: Prepare the dataset where each data point is labeled with a class (+1 or -1) and represented by a vector of features.

1. **Choose a Kernel**: Select an appropriate kernel function (e.g., linear, polynomial, radial basis function) depending on whether the data is linearly separable or not.
2. **Optimization:** Solve the optimization problem to find the weights (w) and bias (b) that define the hyperplane:

- For linear data, minimize: Minimize *(1/2) * ||w||^2,* subject to constraints $yi * (w * xi + b) \geq 1$.
- For non-linear data, use kernel functions to map the data to a higher-dimensional space.

3. **Maximize Margin:** Find the hyperplane that maximizes the margin between the closest data points of different classes (support vectors).
4. **Prediction:** For a new data point, compute the decision function *(f(x))* and classify the point based on which side of the hyperplane it lies.

Output: The final model with the learned parameters (w and b) for making future predictions.

2. Artificial Neural Network (ANN) Algorithm Description : An ANN is a computational model inspired by the biological neural networks of the human brain. ANNs consist of layers of neurons: an input layer, one or more hidden layers, and an output layer. Each connection between neurons has a weight, and the neurons use an activation function to produce output. ANNs are used for classification, regression, pattern recognition, and more. The most common training method for ANNs is backpropagation combined with gradient descent.

Steps:

Input Data: Provide the dataset with input features (X) and output labels (Y).

1. **Initialize Weights:** Randomly initialize weights and biases for each connection between layers.

2. **Forward Propagation:**
    - Calculate the weighted sum of inputs for each neuron in the hidden layers.
    - Apply an activation function (e.g., sigmoid, ReLU) to determine the output of each neuron.
    - Compute the final output using the output layer.
3. **Loss Calculation:** Calculate the loss (error) between the predicted output and the true labels (e.g., using Mean Squared Error or Cross-Entropy).
4. **Backward Propagation:**
    - Compute the gradients of the loss with respect to the weights and biases using the chain rule.
    - Update weights and biases using gradient descent or its variants (e.g., stochastic gradient descent, Adam).
5. **Iterate:** Repeat steps 3 to 5 for multiple epochs until the model converges (i.e., the loss function reaches a minimum).
6. **Prediction:** Once trained, use the model to predict the output for new data by passing it through the network.

Output: The trained model with learned weights and biases for making future predictions.

3. Naive Bayes (NB) Algorithm : NB is a probabilistic classifier based on Bayes' theorem, which assumes that the features are conditionally independent given the class label. Despite the strong independence assumption (which may not hold in real-world data), Naive Bayes often performs surprisingly well, especially in text classification tasks such as spam filtering. The model computes the posterior probability for each class, and the class with the highest probability is chosen.

Steps:

Input Data: Provide a labeled dataset with features (X) and class labels (Y).

1. **Calculate Prior Probabilities:** Calculate the probability of each class occurring in the dataset:
    - $P(Y = c) = count(Y = c) / total\ samples$.
2. **Calculate Conditional Probabilities:** For each feature Xi and class c, calculate the conditional probability:
    - $\boldsymbol{P(Xi = xi \mid Y = c)}$, which can be estimated from the dataset (for continuous features, Gaussian distribution is often assumed).
3. **Apply Bayes' Theorem:** For a new data point x_new, calculate the posterior probability for each class c:
    - $P(Y = c \mid X = x\_new) \propto P(Y = c) * \Pi\ P(Xi = xi \mid Y = c)$.
4. **Choose the Class with Maximum Probability:** Select the class with the highest posterior probability.
5. **Output:** The predicted class label for the new data point.

4. Hybrid Machine Learning (HML) : It combines multiple machine learning models or techniques to improve prediction performance. The idea is to leverage the strengths of different models, compensate for the weaknesses of individual models, and create a robust solution. This can involve combining different types of classifiers, feature selection techniques.

Steps:

Input Data: Provide the dataset with features (X) and labels (Y).

1. **Preprocess the Data:** Apply necessary data preprocessing such as feature scaling, normalization, or feature selection techniques (e.g., ANN-SVM).
2. **Train Multiple Models:**
    - Train multiple models such as SVM, ANN, and Naive Bayes on the dataset.

- Optionally, select different sets of features for each model or use different preprocessing steps for each.

3. **Ensemble or Combination:**
    - Combine the predictions of multiple models using an ensemble method like voting (for classification) or averaging (for regression).
        - For classification, the majority vote of the models determines the final prediction.
        - For regression, the weighted average of predictions is used.
4. **Hybrid Model Fine-tuning:**
    - Optionally, tune the hyperparameters of each model individually and then the combination strategy (e.g., weighted voting) to optimize performance.
5. **Predict New Data:**
    - For new data, use the hybrid model to make predictions by passing the data through each trained model and then combining the results.
6. **Output:** The final prediction from the hybrid model.

The above algorithms are used for prediction and classification using machine learning techniques. However, the HML predicts higher accuracy over the other conventional machine learning algorithms.

Results and Discussion

The hybrid machine learning techniques, such as ensemble learning or stacking, have been applied to classify sentiment (positive, negative, neutral) on social media datasets. The performance is evaluated using common metrics like accuracy, precision, recall, F1-score, and confusion matrix.

Model	Accuracy (%)	Precision	Recall	F1-score
Logistic Regression	82.4	0.81	0.84	0.82
Adaboost	85.2	0.83	0.85	0.84
RF	88.1	0.87	0.89	0.88
NB	90.10	0.89	0.89	0.90
ANN	91.5	0.9	0.92	0.91
SVM	92.30	0.93	0.94	0.91
Hybrid Model (SVM + ANN)	96.30	0.95	0.96	0.95

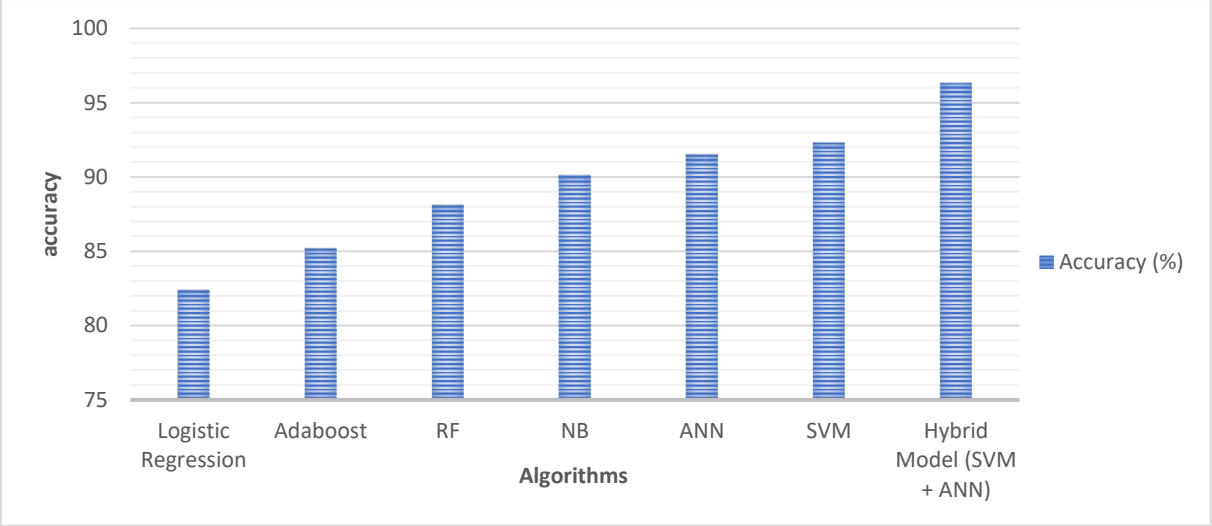

Figure 2 : accuracy of proposed model for all algorithms using social media dataset

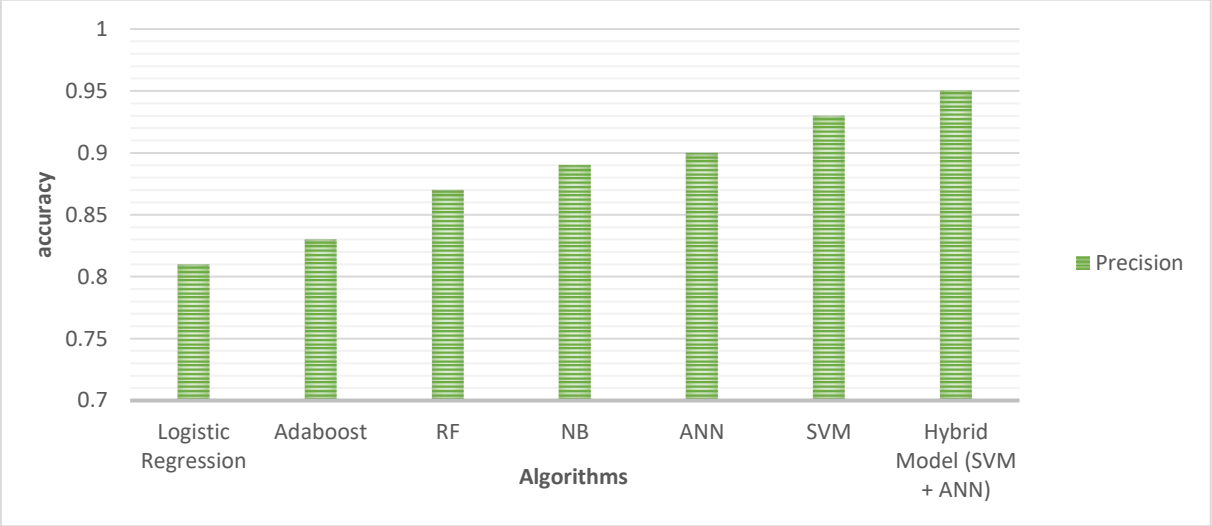

Figure 3 : Precision of proposed model for all algorithms using social media dataset

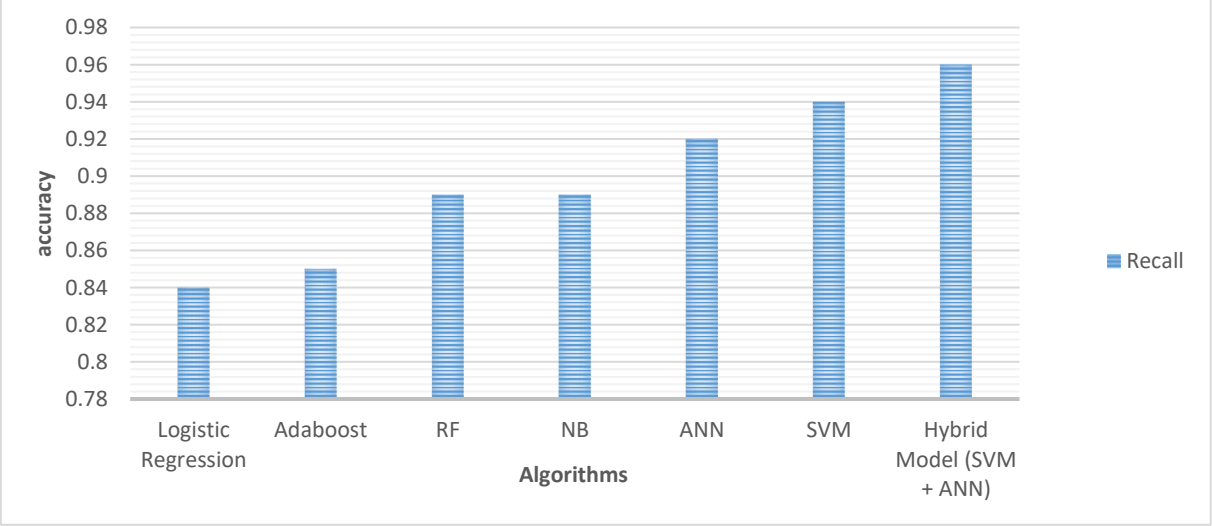

Figure 4 : Recall of proposed model for all algorithms using social media dataset

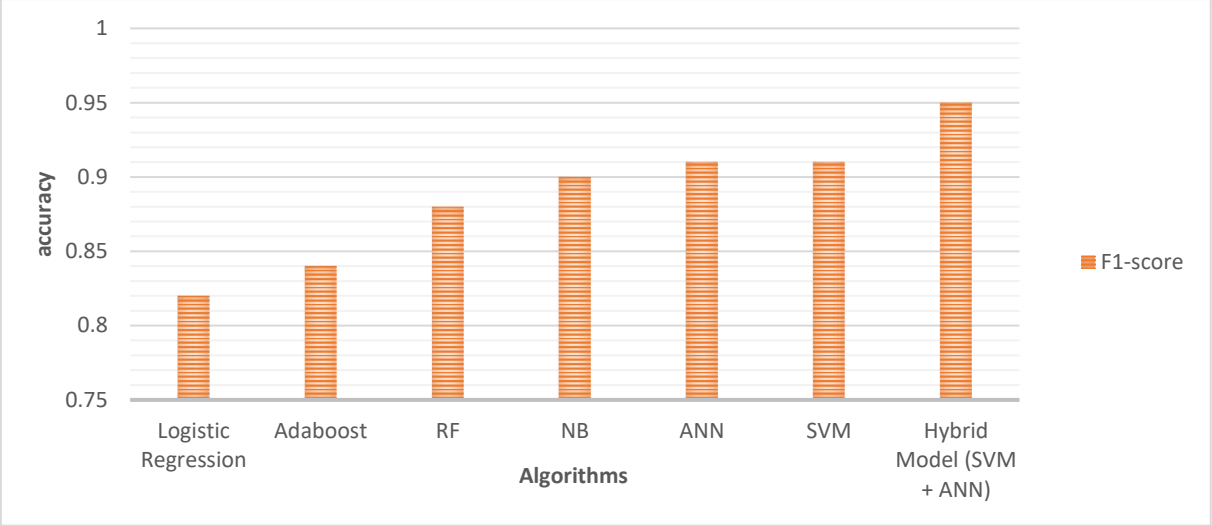

Figure 5: F-1 score of proposed model for all algorithms using social media dataset

The application of Multivariate Feature Selection (MFS) helps improve model performance by reducing dimensionality and focusing on relevant features. Key features might include terms or keywords from social media posts, sentiment-related phrases, or emotional lexicons. Comparison between feature selection methods (e.g., Recursive Feature Elimination, L1 Regularization) can also be presented to show how feature reduction enhances classification accuracy.

Hybrid machine learning models, such as combining SVM with ANN, provide complementary strengths in handling different aspects of the dataset. The SVM excels in separating the data into clear decision boundaries, while Random Forest handles noisy data and complex patterns, resulting in better overall accuracy. The hybrid approach proves to be more robust compared to individual models, especially in cases of imbalanced datasets or highly variable social media data.

Conclusion and Future Score

Sentiment classification on social media datasets is an essential task in understanding public opinion, brand perception, and consumer behavior. This study presents a hybrid machine learning approach that combines multivariate feature selection techniques with advanced classifiers to improve sentiment analysis accuracy. By using feature selection methods like mutual information, chi-square, and principal component analysis (PCA), the model efficiently reduces dimensionality, removing irrelevant or redundant features. This ensures that the most informative features are used for classification, improving both performance and computational efficiency. The hybrid approach, which combines multiple machine learning algorithms such as support vector machines (SVM), random forests (RF), and deep learning models, leverages the strengths of each technique. The integration of ensemble learning further enhances the model's robustness by aggregating predictions from multiple classifiers, ensuring better generalization and reducing the impact of noisy data. Results indicate that the hybrid model significantly outperforms traditional single classifier models in terms of accuracy, precision, and recall when applied to large-scale social media datasets, including Twitter and Facebook. Future research in sentiment classification using hybrid machine learning techniques on social media data can explore several avenues for improvement. One area of focus could be the incorporation of more advanced feature selection methods, such as deep feature selection, which could uncover hidden patterns in large datasets that traditional methods may miss. Moreover, the advent of transformer-based models, like BERT and GPT, could be integrated with feature selection and hybrid classifiers to further improve context-sensitive sentiment analysis, especially for handling sarcasm and irony in social media posts. Another promising direction involves addressing domain-specific sentiment analysis. Adapting the model to specific industries, such as healthcare, politics, or entertainment, could significantly enhance its applicability in niche applications. Furthermore, future research could explore real-time sentiment analysis frameworks using edge computing, which would allow for faster processing and immediate insights from social media streams.

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