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A HYBRID MACHINE LEARNING FRAMEWORK FOR MULTI-LEVEL TWEET MINING AND SENTIMENT CLASSIFICATION

Ravi kumar Kuchipudi [1] and **Dr V.V. Jaya Rama Krishnaiah**[2]

[1]Research Scholar, Department of Computer Science and Engineering, Acharaya Nagarjuna University, Guntur

[2]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India

Abstract

Sentiment analysis, a branch of NLP, deals with the extraction of opinion and emotional sentiment from data. Twitter is a popular data source for sentiment analysis, but its abbreviated, slang-laden, and erratic writing style makes classifying its data difficult. Many studies have analyzed how individual algorithms perform for sentiment classification, but studies that assess how the integration of multiple algorithms can elevate classification performance are few and far in between. This research establishes a hybrid model for sentiment analysis that integrates Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). An extensive data cleaning and preparation infrastructure is outlined and constructed to improve data quality from Twitter by noise elimination before any data classification is performed. The efficiency of the constructed infrastructure and model are examined, and results are reported according to the classification accuracy and F-measure metrics for each sentiment. Results from the experiments show that the performance of SVM-KNN integration is much better than that of its isolated counterparts, and it was the most optimal choice for the analysis of Twitter's data.

Keywords: A Hybrid Machine ,Learning Framework, Multi-Level Tweet Mining, Sentiment Classification

1. INTRODUCTION

Compared to earlier years, a substantial increase in user-generated content regarding consumer perceptions, emotions, and attitudes toward products, services, and social issues is occurring on social media platforms. Due to these characteristics, Twitter is a good example of a fast and easy source of real-time information [1]. The analysis of this type of data has enabled the categorization of feelings expressed in texts as neutral, negative, or positive [2], [4]. This process and categorization of text falls under the topic of sentiment analysis (SA) in the area of Natural Language Processing (NLP).

Interest in sentiment analysis has increased due to its applications within the fields of business intelligence, product evaluation, customer relationship management, political forecasting, stock market prediction and recommender systems [5], [8]. Organizations use sentiment analysis to identify customer perceptions and provide feedback for improving products and services, while policymakers and researchers use public sentiment to discover opinions on social issues and political trends. Despite these advancements, achieving sentiment extraction from Twitter data is still difficult, tweets are informal in nature containing abbreviations, misspellings, slang expressions and short number of content words [4], [7].

To overcome these problems, a number of sentiment classification techniques have been introduced based on machine learning methods, lexicon-based approaches and hybrid ones. Tweet classification is primarily performed by machine learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naïve Bayes and Decision Trees due to their capability of learning complex patterns from labeled datasets [2, 3, 11]. While supervised learning techniques provide high accuracy in general, the result is highly influenced by preprocessing and feature extraction processes [10]. In contrast, lexicon-based approaches make use of sentiment dictionaries to find the polarity of words and sentences and do not need much training data [16], [17].

In recent researches, it is shown that a good preprocessing can greatly enhance the performance in sentiment classification. We use techniques like stop-word removal, stemming, spelling correction, abbreviation expansion and handling of negation to convert the noisy Twitter text to a structured representation for machine learning models [10]. In addition, feature engineering is a crucial way to extract semantic and contextual information from tweets for classification [6], [11].

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Likewise, some researchers explore hybrid sentiment analysis frameworks that incorporate multiple classification methods to take advantage of their individual distinctiveness [11], [12]. Hybrid techniques are more robust than single classifiers and achieve less misclassification both of which create a great deal of interest in this particular area. Driven by these results, this research examines a hybrid sentiment classification framework that combines SVM and KNN classifiers for the multi-level tweet sentiment identification. Overview of proposed framework for feature generation (our framework includes some preprocessing techniques to deal with the unstructured and high noisy nature of Twitter data.)

This research addresses the question of whether, as with ensemble classifier, combining SVM and KNN will result in better sentiment classification performance than its single classifiers. Based on the proposed model, tweets are classified in positive, negative and neutral positions and evaluated using the standard metrics, such as accuracy, precision, recall and F-measure. Experimental results show that the hybrid method can successfully combine features from different domains to improve classification performance on Twitter sentiment datasets.

2. PROPOSED WORK

This work proposes a hybrid sentiment classification model due to its three-tier gain of better tweet sentiment predictions. This architecture implements state-of-the-art preprocessing, a feature generation model and a hybrid machine learning classifier in order to successfully analyze Twitter data.

Stage 1: Preprocessing and Filtration

The Stage1, Preprocessing via a Filtration and Impurity Correction (FIC) mechanism. There are some cleaning operations to be performed given that tweets have noisy and unstructured content in a lot of cases, which ultimately helps with data quality overall. Stop-word removal, spelling correction, abbreviation expansion, stemming and tokenization are few of such operations. The preprocessing step will also handle negation terms, and divide tweet materials such as work content, sentiment words, and user tags. Sentiment features: List of positive & negative opinion words are extracted and saved separately. This stage reduces the noise significantly and creates a standardized version of the raw tweets for machine learning verbose.

Stage 2: Feature Generation

The second stage is to extract both statistical and sentiment-based features from the preprocessed tweets. Both filtered training and testing datasets are vectorized into numerical feature vectors that can be processed by a machine learning model. Pos word frequency, neg word freqency,sentiment score,tag counts and net polarity are created. These features encode the typo and emotional aspects of tweets, providing input to the classification method.

Stage 3: Hybrid Sentiment Classification

The last phase uses a hybrid classification method aggregating the better aspects of Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) classifiers. The feature vectors generated are given in both classifiers as input. At each tweet instance, prediction probabilities from SVM and KNN are extracted. Finally, the sentiment label is distilled from taking whichever classifier has the confidence to make such a prediction. This proposed hybrid model combines the decision features of both algorithms in order to perform more accurate sentiment classification than using separate classifiers.

This entire framework is capable of processing twitter data efficiently and classifies tweets into sentiment categories based on the predictive power of SVM along with KNN. It can increase the classification accuracy, precision, recall and F-measure if compared with problem-oriented standalone machine learning methods.

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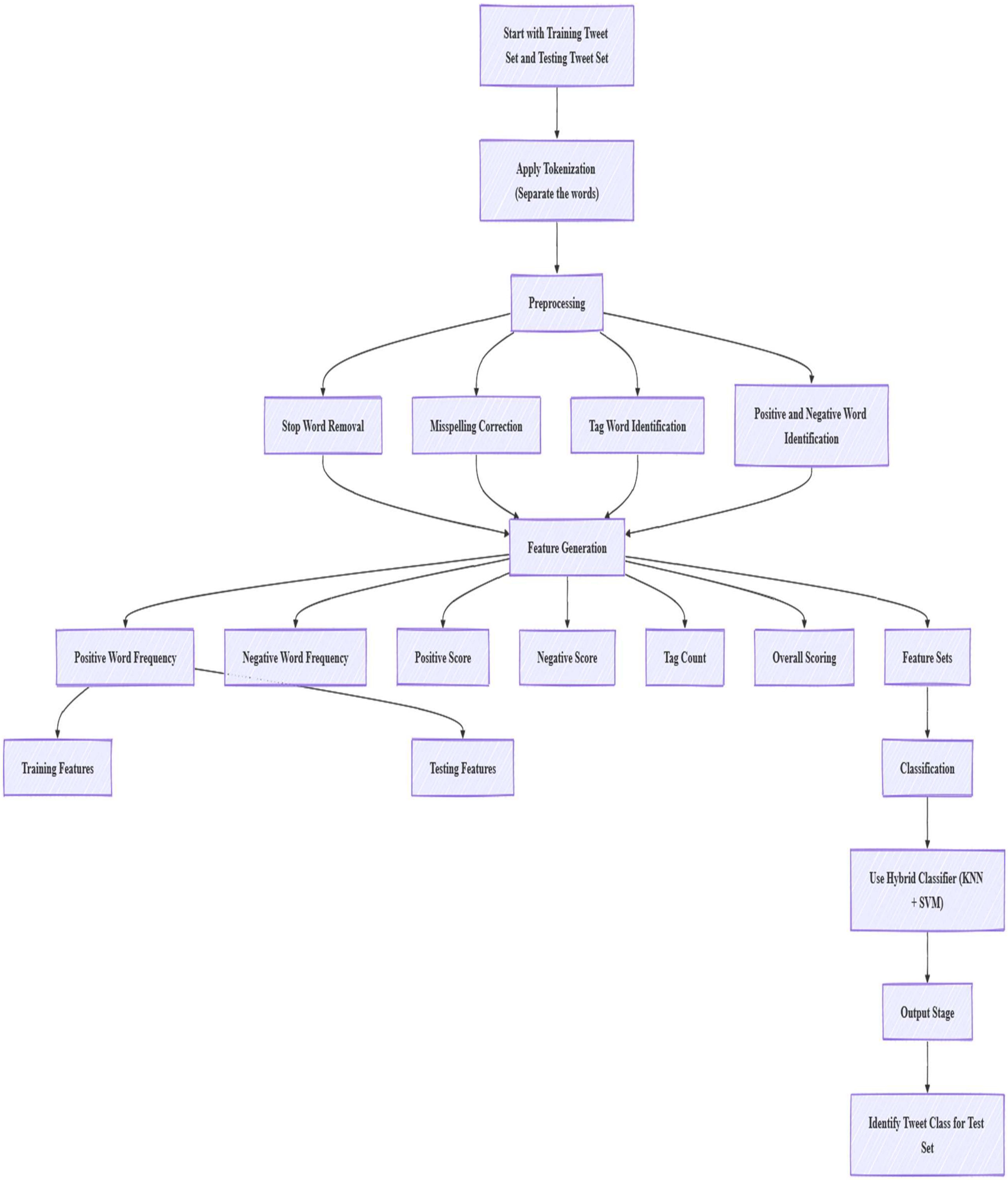

Fig 1: Framework of the Proposed functionality

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The classification algorithm is applied on the tweets taken from the website https://github.com/TharinduMunasinge/Twitter-Sentiment-Analysis. The description of dataset is given below in Table 1:

Table 1. Overview of the Twitter-Sentiment-Analysis-Finalized Dataset

Feature	Value
Dataset Name	Twitter-Sentiment-Analysis-Finalized
No. of Tweets	699
Classes	Positive Tweets, Negative Tweets, Neutral Tweets
File Type	CSV (Comma-Separated Values)
Dataset Source URL	https://github.com/TharinduMunasinge/Twitter-Sentiment-Analysis

2.1 Preprocessing

Preprocessing is a critical stage in the proposed sentiment analysis framework, as Twitter data often contains noisy and unstructured text. Raw tweets include abbreviations, misspellings, user mentions, hyperlinks, and other non-standard linguistic elements that may adversely affect classification performance. Therefore, a series of preprocessing operations are applied to transform the collected tweets into a structured format suitable for feature extraction and machine learning.

The preprocessing procedure consists of the following steps:

1. **Tokenization** – Each tweet is segmented into individual tokens or words.
2. **Stop Word Removal** – Frequently occurring words that carry little semantic value, such as articles and conjunctions, are eliminated.
3. **Negation Handling** – Negation terms are identified and processed to preserve their influence on sentiment orientation.
4. **Abbreviation Expansion** – Common internet abbreviations and slang expressions are converted into their complete forms using a predefined abbreviation dictionary.
5. **Misspelling Correction** – Spelling errors are corrected through a normalization database to improve lexical consistency.
6. **Stemming** – The Porter Stemming Algorithm is employed to reduce words to their root forms, thereby minimizing vocabulary redundancy.
7. **Sentiment Word Identification** – Positive and negative adjectives are extracted and maintained separately for each tweet.

Figure 5.2 illustrates the tweets after the preprocessing stage. To facilitate normalization, dedicated databases are maintained for stop words, abbreviation expansion, and spelling correction.

The preprocessing stage generates the following intermediate datasets:

- **Filtered List:** Contains tweets after tokenization and application of all preprocessing operations.

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- **Tag-Filtered List:** Contains processed tweets after removing user mentions (@tags). Although the tags are removed from the textual content, their count is preserved as a feature.
- **Negative List:** Stores all negative sentiment-bearing adjectives identified within each tweet.
- **Positive List:** Stores all positive sentiment-bearing adjectives identified within each tweet.

The resulting datasets provide a clean and structured representation of tweet content, enabling effective feature extraction and sentiment classification.

Figure 2. Twitter Dataset after Tokenization and Sentiment Word Identification


Data

SrNo	Tweet	Filtered List	Tag Filtere...	Negative L...	Positive List	G	H
1	@united U...	[@unit, ua...	[ua5396, ...	[crap]	[get]		
2	I hate Tim...	[hate, time...	[hate, time...	[hate, porn]	[warner, li...		
3	Tom Shan...	[tom, shan...	[tom, shan...	[]	[]		
4	Found the ...	[found, sel...	[found, sel...	[]	[]		
5	@united a...	[@unit, arri...	[arriv, ye, fli...	[miss, slow]	[]		
6	Driverless ...	[driverless...	[driverless...	[]	[]		
7	how can y...	[not, love, ...	[not, love, ...	[joke]	[love]		
8	Safeway is...	[safewai, r...	[safewai, r...	[]	[rock]		
9	RT @jquer...	[rt, @jqueri...	[rt, ultim, jq...	[]	[]		
10	I saw Nigh...	[night, mu...	[night, mu...	[]	[]		
11	Missed thi...	[miss, , ge...	[miss, gen...	[miss]	[]		
12	is being fu...	[fuck, time,...	[fuck, time,...	[fuck, suck]	[warner]		
13	I hope the ...	[hope, girl,...	[hope, girl,...	[]	[hope]		
14	@aparajul...	[@aparaju...	[good, luck]	[]	[good, luck]		
15	needs so...	[explain, la...	[explain, la...	[]	[]		
16	@united T...	[@unit, tha...	[thank, ma...	[]	[thank, get]		
17	@ontheMA...	[@onthem...	[ditto!, not, ...	[]	[good]		
18	waiting in l...	[wait, line, ...	[wait, line, ...	[]	[]		
19	OMG, I wo...	[oh my go...	[oh my go...	[died, no]	[good]		
20	Theres a g...	[there, goo...	[there, goo...	[]	[]		
21	#MBA Adm...	[mba, adm...	[mba, adm...	[]	[]		
22	am loving ...	[morn, lov...	[morn, lov...	[outlier]	[love]		
23	Goodby, Si...	[goodbi, si...	[goodbi, si...	[]	[enjoi]		
24	12 Gift Ide...	[12, gift, id...	[12, gift, id...	[]	[lover]		
25	So the #C...	[coachella...	[coachella...	[]	[]		
26	New blog ...	[blog, post...	[blog, post...	[]	[]		
27	whoever is...	[whoever, r...	[whoever, r...	[rape, out]	[warner, u...		
28	@Donnie...	[@donnie...	[tell, spoke...	[]	[right, hop...		
29	Three Chi...	[china, aer...	[china, aer...	[]	[invest]		
30	Ok, first as...	[ok, asses...	[ok, asses...	[fuck]	[ok]		
31	heyy loves!...	[heyi, love...	[heyi, love...	[kick]	[loves]		
32	@united w...	[@unit, we...	[well, john,...	[]	[well]		
33	I loved tod...	[love]	[love]	[]	[love]		
34	RT @Wate...	[rt, @water...	[rt, ca, mer...	[]	[profit, well]		

2.2 Feature Generation

After preprocessing, a set of discriminative features is generated to represent each tweet numerically for classifier training. The proposed model utilizes a sentiment lexicon containing adjectives along with their associated sentiment scores. These lexical resources assist in quantifying the polarity of tweets and enhancing classification accuracy

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Table 2. Description of Sentiment Adjective Dataset Features

Feature	Explanation
ID	A distinct numeric value used to uniquely identify each adjective entry in the dataset.
Adjective	The word or term represents a sentiment-bearing adjective.
PScore	A numerical value between 0 and 1 that reflects the degree of positive sentiment associated with the adjective.
FScore	A numerical value between 0 and 1 that indicates the level of negative sentiment expressed by the adjective.
Score	A composite sentiment measure ranging from −1 to +1, where values closer to +1 represent stronger positive sentiment, values closer to −1 represent stronger negative sentiment, and values near zero indicate neutral sentiment.

Using the processed tweets and sentiment lexicon, several features are extracted for machine learning classification. Figure 3 presents the output of the feature generation stage.

The extracted features include:

- **Word Count:** Total number of words present in a preprocessed tweet.
- **Tag Count:** Number of user mentions (@tags) contained in the original tweet.
- **Negative Word Count:** Total number of negative sentiment words identified in the tweet.
- **Positive Word Count:** Total number of positive sentiment words identified in the tweet.
- **Positive Score:** Cumulative positive sentiment score calculated from all positive adjectives present in the tweet.
- **Negative Score:** Cumulative negative sentiment score calculated from all negative adjectives present in the tweet.
- **Overall Sentiment Score:** Combined polarity measure representing the overall sentiment of the tweet.

These generated features constitute the input vector supplied to the proposed hybrid SVM–KNN classification model.

For sentiment classification, tweets are categorized into three classes:

- **Class 0 (Negative):** Tweets expressing dissatisfaction, criticism, or negative opinions.
- **Class 1 (Neutral):** Tweets that do not exhibit a clear positive or negative sentiment.
- **Class 2 (Positive):** Tweets expressing satisfaction, appreciation, or favorable opinions.

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The extracted feature set effectively captures both lexical and sentiment-oriented characteristics of tweets, thereby improving the performance of the proposed hybrid sentiment classification framework.

Data

WordCou...	FilteredW...	TagCount	Negative...	Positive...	PositiveS...	Negative...	Score	Message...
25	13	1	1	1	0.125	0.125	0.0	0
25	21	0	2	3	1.0	0.625	0.375	0
13	9	0	0	0	0.0	0.0	0.0	2
6	5	0	0	0	0.0	0.0	0.0	2
24	15	1	2	0	0.0	1.0	-1.0	0
7	4	0	0	0	0.0	0.0	0.0	0
11	6	0	1	1	-0.125	0.375	-0.5	4
7	4	0	0	1	0.375	0.0	0.375	4
8	8	1	0	1	0.375	0.0	0.375	2
20	14	0	0	0	0.0	0.0	0.0	2
20	12	0	1	0	0.0	0.25	-0.25	2
17	11	0	2	1	0.125	0.5	-0.375	0
10	5	0	0	1	0.375	0.0	0.375	2
5	3	1	0	2	1.0	0.125	0.875	4
9	5	0	0	0	0.0	0.0	0.0	0
13	9	1	0	2	0.25	0.0	0.25	4
9	6	1	0	1	0.375	0.125	0.25	4
5	3	0	0	0	0.0	0.0	0.0	2
22	10	0	2	1	0.375	0.625	-0.25	4
15	9	0	0	0	0.0	0.0	0.0	2
11	10	0	0	0	0.0	0.0	0.0	2
8	7	0	1	1	0.125	0.25	-0.125	4
8	7	0	0	1	0.375	0.0	0.375	4
13	12	0	0	1	0.125	0.0	0.125	2
6	5	0	0	0	0.0	0.0	0.0	2
10	10	0	0	0	0.0	0.0	0.0	2
24	14	0	2	2	0.5	0.5	0.0	0
26	17	1	0	5	2.375	0.0	2.375	4
18	14	0	0	1	0.625	0.0	0.625	2
9	6	0	1	1	0.375	0.25	0.125	4
19	10	0	1	1	0.125	0.375	-0.25	4
26	18	1	0	1	0.625	0.0	0.625	4
3	2	0	0	1	0.125	0.0	0.125	4
20	13	1	0	2	0.75	0.0	0.75	2

Figure 3. Computed Sentiment Metrics for Twitter Messages

2.3 Classification

After preprocessing and feature extraction, the generated feature vectors are supplied to the proposed hybrid classification model. The classification framework combines the strengths of both Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) classifiers to improve sentiment prediction accuracy. Instead of depending on single classifier, the proposed approach evaluates the prediction confidence of both models and assigns the final class label based on the classifier exhibiting higher reliability.

The dataset is initially divided into two subsets: a training set and a testing set. Features are extracted independently from both subsets using the feature generation process described in the previous section. The training feature set is utilized for learning the classification models, while the testing feature set is used for performance evaluation.

The SVM classifier is trained using the generated feature weights obtained from the training dataset. Simultaneously, the KNN classifier stores the training feature vectors for similarity-based classification. During testing, each tweet is evaluated by both classifiers, and their respective prediction probabilities are computed.

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A threshold value of 0.5 sets the classifier confidence. For each test instance, the predictive probabilities from SVM and KNN are assessed. If both classifiers show prediction probabilities that surpass the threshold, the classifier showing the higher confidence score is selected to determine the final sentiment class. If only one classifier surpasses the threshold value, it is engaged in the classification process.

The hybrid classification procedure is summarized as follows:

Algorithm 1: Hybrid SVM–KNN Classification

Input: TrainingSet, TestingSet

Output: Predicted sentiment class for each testing tweet

1. Generate feature vectors for the training dataset and create **TrainFeatureSet**.
2. Generate feature vectors for the testing dataset and create **TestFeatureSet**.
3. Train the SVM classifier using the training feature set and obtain the corresponding feature weights.
4. Train the KNN classifier using the same training feature set.
5. For each tweet in the testing dataset:
    - Compute the prediction probability using the KNN classifier (**K1**).
    - Compute the prediction probability using the SVM classifier (**S1**).
6. Define the classification threshold **Th = 0.5**.
7. If both **K1** and **S1** exceed the threshold:
    - Select the classifier with the higher prediction probability.
    - Assign the corresponding sentiment class.
8. Else if **K1 > Th**:
    - Assign the class predicted by the KNN classifier.
9. Else:
    - Assign the class predicted by the SVM classifier.
10. Store the predicted class label for the testing instance.
11. Repeat the process for all testing tweets.
12. Return the final classified testing dataset.

The proposed hybrid model leverages the margin-based learning capability of SVM and the instance-based decision mechanism of KNN. By combining the prediction strengths of both classifiers, the model reduces classification errors and achieves improved sentiment prediction performance compared with individual classifiers.

3. Experimental Results and Evaluation

The effectiveness of the proposed hybrid sentiment classification framework was evaluated using Twitter datasets containing positive, negative, and neutral tweets. The implementation was carried out using NetBeans 8.0, Weka 3.8, and MySQL. Weka was employed for data preprocessing, classification, and performance evaluation, while MySQL databases

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were used to store training datasets, testing datasets, sentiment lexicons, abbreviation dictionaries, and spelling correction resources.

The proposed model combines the predictive capabilities of Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) classifiers. Individual classifier performance was first evaluated using Weka, and the results were subsequently compared with those obtained from the hybrid SVM–KNN model. For the KNN classifier, the value of K was fixed at 15 based on preliminary experimentation.

Dataset Description

The dataset was divided into training and testing subsets. Table 3 presents the distribution of tweets used in the experiments.

Table 3. Configuration of the Experimental Dataset and Classification Models

Parameter	Description
Training Dataset	699 tweets used for model training, comprising 168 neutral, 267 positive, and 264 negative tweets.
Testing Dataset	298 tweets reserved for model evaluation, including 71 neutral, 114 positive, and 113 negative tweets.
Sentiment Classes	Three sentiment categories were considered: Neutral, Positive, and Negative.
Baseline Classifiers	Individual machine learning models employed for comparison were Support Vector Machine (SVM) and K-Nearest Neighbors (KNN).
Proposed Approach	An ensemble classification framework combining SVM and KNN was developed to improve sentiment prediction performance.

The hybrid sentiment classification approach proposed in this study combines the strengths of K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) classifiers. The detailed classification procedure is described in Section 2. To evaluate the effectiveness of the individual classifiers, the generated training and testing feature sets were imported into the Weka environment. The classification results produced by Weka were used to generate confusion matrices for both KNN and SVM classifiers.

Table 4 presents the confusion matrix obtained using the KNN classifier. The results indicate that 78 negative tweets, 47 neutral tweets, and 79 positive tweets were correctly classified. However, a number of tweets were misclassified across sentiment categories. Specifically, 18 negative tweets were classified as neutral and another 18 as positive. Similarly, 8 neutral tweets were classified as negative, while 16 were classified as positive. For the positive class, 22 tweets were incorrectly identified as negative and 15 as neutral. These observations highlight the challenges associated with distinguishing between closely related sentiment categories in Twitter data.

Table 4. Confusion Matrix Obtained Using the K-Nearest Neighbors (KNN) Classifier

Actual Class	Predicted Negative	Predicted Neutral	Predicted Positive
Negative	78	18	18

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Actual Class	Predicted Negative	Predicted Neutral	Predicted Positive
Neutral	8	47	16
Positive	22	15	79

The confusion matrix serves as the foundation for calculating performance measures such as accuracy, precision, recall, and F-measure, which are subsequently used to compare the performance of KNN, SVM, and the proposed hybrid classification model.

Table 5. Confusion Matrix of the Support Vector Machine (SVM) Classifier

Actual Class	Predicted Negative	Predicted Neutral	Predicted Positive
Negative	77	14	22
Neutral	11	47	13
Positive	16	20	78

Table 5 summarizes the classification performance of the Support Vector Machine (SVM) model through a confusion matrix. The diagonal entries indicate the number of tweets correctly assigned to their respective sentiment classes, whereas the off-diagonal values represent classification errors. The SVM classifier correctly predicted 77 negative tweets, 47 neutral tweets, and 78 positive tweets. The results indicate that the model achieved satisfactory sentiment classification performance, although some overlap among sentiment categories led to misclassifications.

Hybrid SVM–KNN Classification Results

The performance of the proposed hybrid SVM–KNN classifier was evaluated using a confusion matrix constructed from the aggregated prediction outputs of the individual SVM and KNN models. By integrating the strengths of both classifiers, the ensemble approach aims to improve the accuracy of sentiment classification across the three sentiment categories.

Table 6. Confusion Matrix of the Hybrid SVM–KNN Classifier

Actual Class	Predicted Negative	Predicted Neutral	Predicted Positive
Negative	79	11	25
Neutral	0	49	24
Positive	0	12	102

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Table 6 presents the classification outcomes obtained from the hybrid SVM–KNN model. The diagonal elements represent correctly classified tweets, while the off-diagonal values indicate misclassified instances. The model successfully classified 79 negative tweets, 49 neutral tweets, and 102 positive tweets.

A notable improvement can be observed in the classification of positive tweets, where the hybrid approach achieved the highest number of correct predictions among all sentiment categories. This enhancement suggests that combining the decision-making capabilities of SVM and KNN enables the model to capture sentiment patterns more effectively than either classifier operating independently. Overall, the ensemble classifier demonstrates improved predictive performance and contributes to more reliable sentiment analysis results.

Figure 4 illustrates the execution output of the proposed hybrid SVM–KNN sentiment analysis system. The output presents the overall classification accuracy, class-wise recognition rates, and the number of correctly classified instances for negative, neutral, and positive tweets. The results demonstrate the effectiveness of the ensemble model in accurately identifying sentiment categories within the Twitter dataset.

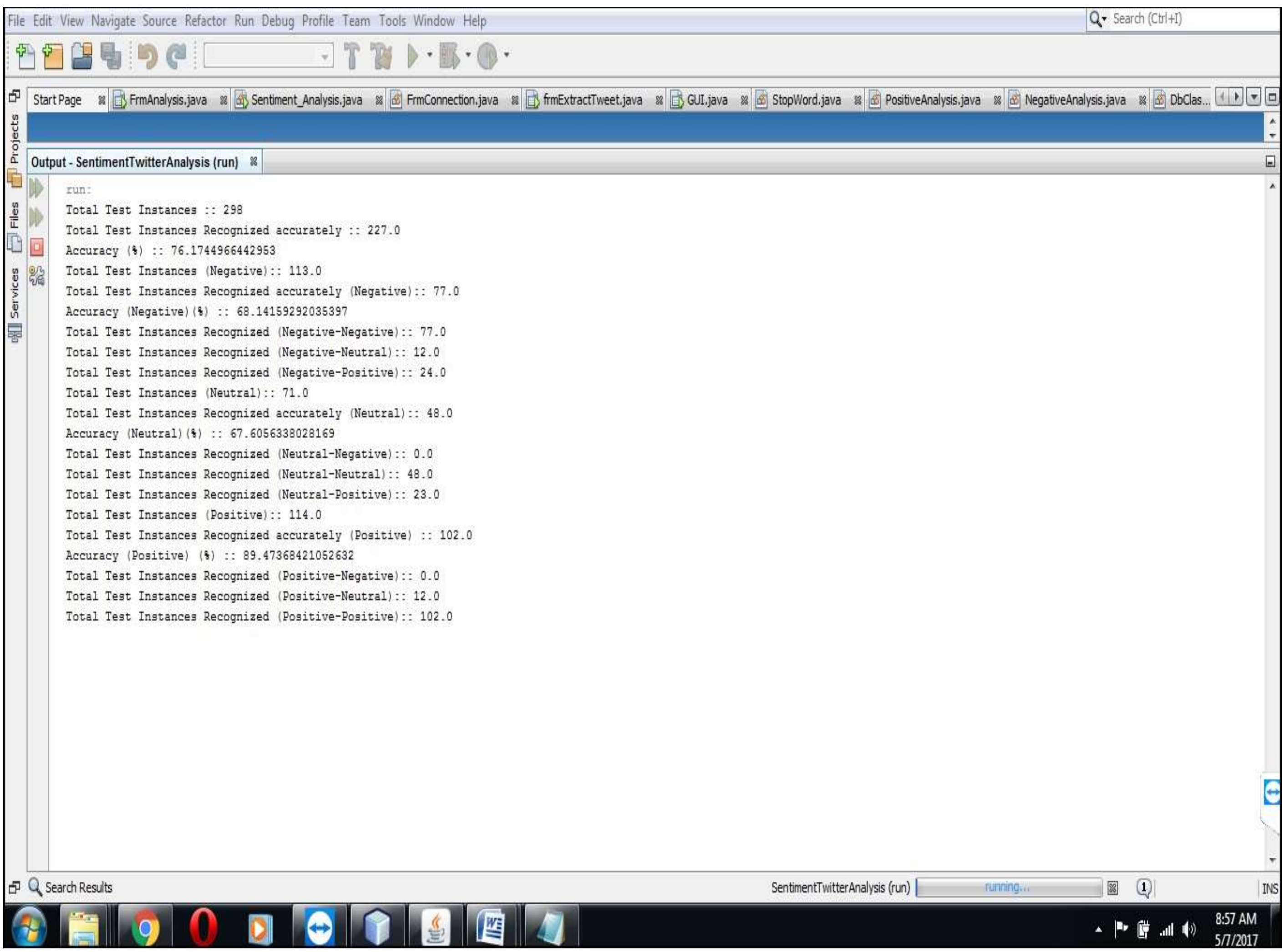

Figure 4. Performance Evaluation Results of the Hybrid SVM–KNN Sentiment Classification Model

3.1 Performance Analysis

To evaluate the effectiveness of the proposed approach, several performance measures were calculated from the confusion matrices.

3.1.1 Accuracy Analysis

Figure 5 presents the overall classification accuracy obtained by the KNN, SVM, and Hybrid SVM–KNN models. The results indicate that the proposed hybrid classifier achieved the highest accuracy of 76.17%, surpassing both the standalone KNN and SVM classifiers, each of which recorded an accuracy of 67.78%. The superior performance of the hybrid approach demonstrates the effectiveness of combining multiple classification techniques, enabling the model to leverage the strengths of individual classifiers, reduce misclassification rates, and improve the reliability of sentiment prediction.

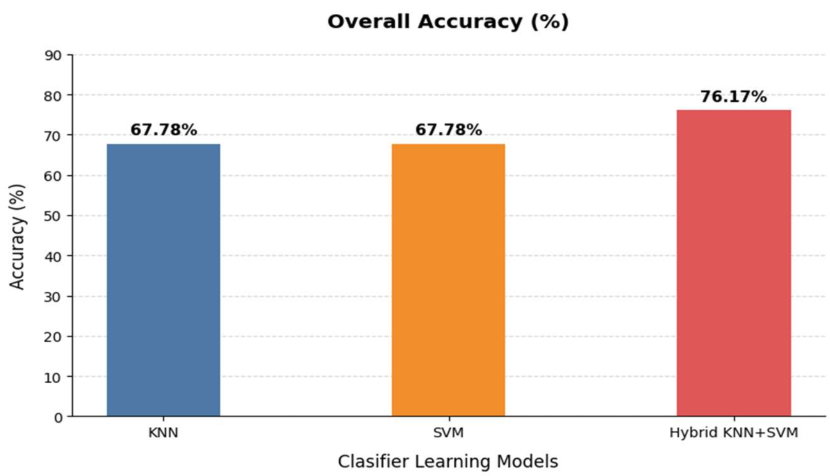

Figure 5. Comparative Accuracy of KNN, SVM, and Hybrid SVM–KNN Classifiers

3.1.2 Precision Analysis

Figure 6 presents the precision values obtained by the KNN, SVM, and Hybrid KNN–SVM classifiers across the three sentiment categories. The hybrid model achieved the highest precision for the negative sentiment class (92.0%) and demonstrated improved performance for the neutral class (62.0%) compared with the individual classifiers. Although KNN attained the highest precision for the positive class (66.5%), the hybrid approach exhibited superior overall precision performance, indicating that the integration of KNN and SVM enhances the classifier's ability to correctly identify sentiment categories while reducing false-positive predictions.

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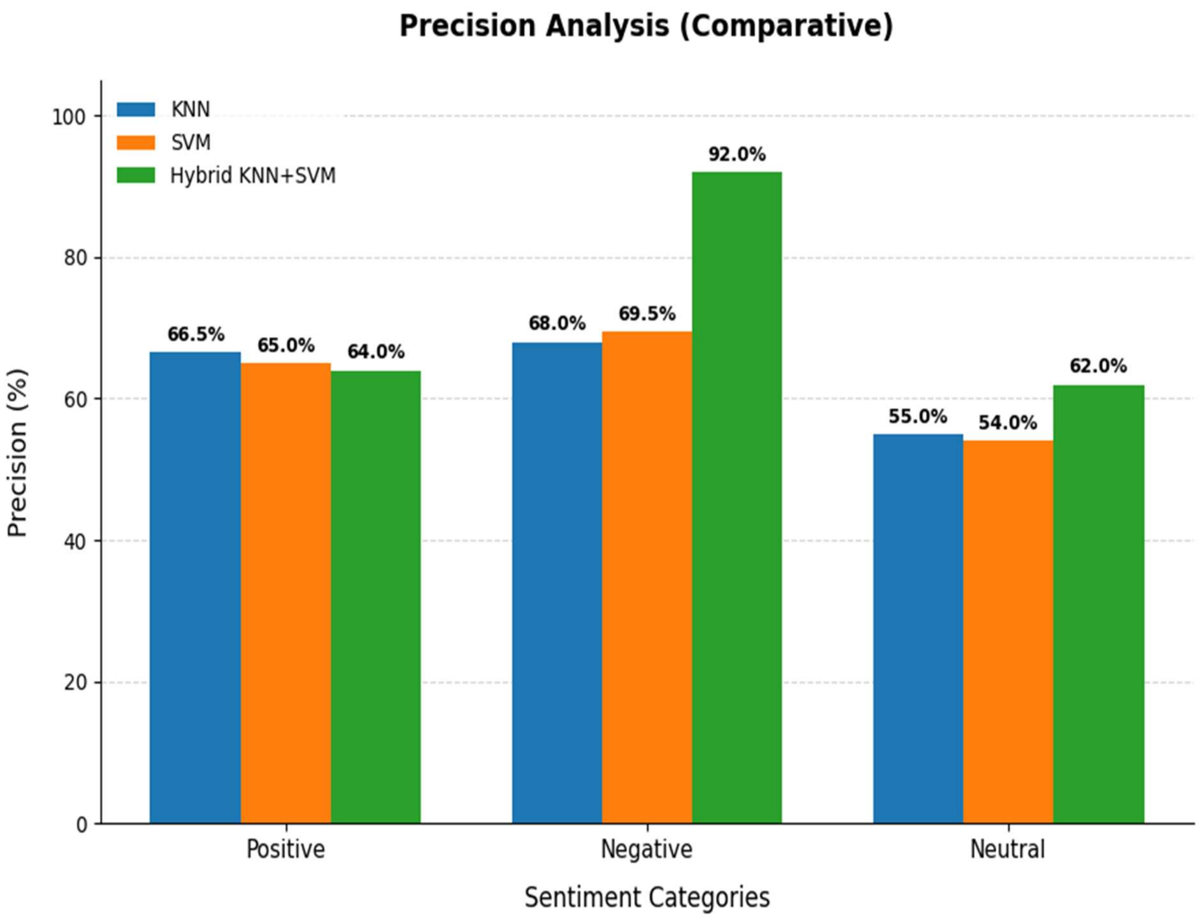

Figure 6: Comparative Precision Analysis of KNN, SVM, and Hybrid KNN–SVM Classifiers

3.1.3 Recall Analysis

Figure 7 illustrates the recall performance of the KNN, SVM, and Hybrid KNN–SVM classifiers across the positive, negative, and neutral sentiment categories. The hybrid model achieved the highest recall value for the positive sentiment class (92.0%), significantly outperforming the individual classifiers. For the neutral class, the hybrid classifier also recorded the best performance with a recall of 67.5%, while all three models demonstrated comparable results for the negative sentiment class. These findings indicate that the hybrid approach is more effective in identifying relevant sentiment instances and reducing false-negative classifications, thereby improving the overall effectiveness of sentiment prediction.

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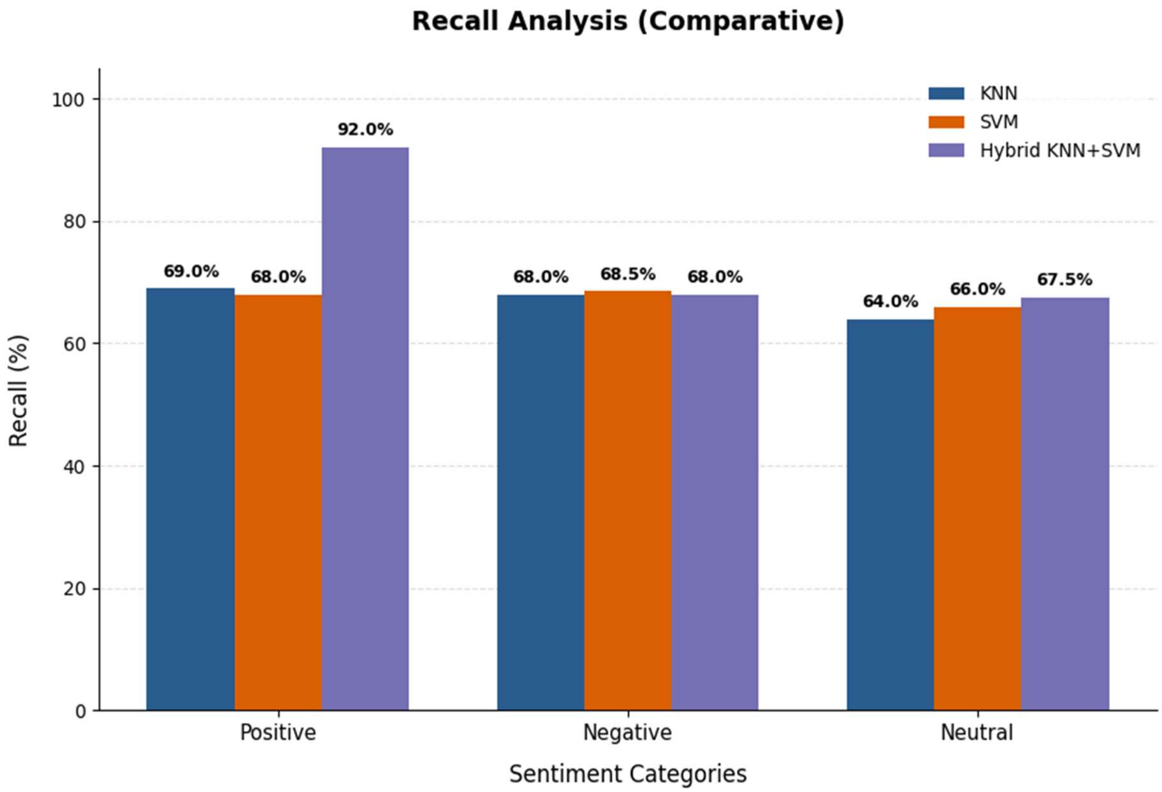

Figure 7: Comparative Recall Analysis of KNN, SVM, and Hybrid KNN–SVM Classifiers

3.1.4 F-Measure Analysis

Figure 8 presents the F-measure values achieved by the KNN, SVM, and Hybrid KNN–SVM classifiers across the positive, negative, and neutral sentiment categories. The hybrid classifier consistently outperformed the individual classifiers in all three categories, achieving F-measure scores of 76.54%, 78.43%, and 64.63% for positive, negative, and neutral sentiments, respectively. In contrast, the KNN and SVM models produced comparatively lower F-measure values. The superior performance of the hybrid approach demonstrates its ability to effectively balance precision and recall, resulting in more accurate and reliable sentiment classification outcomes.

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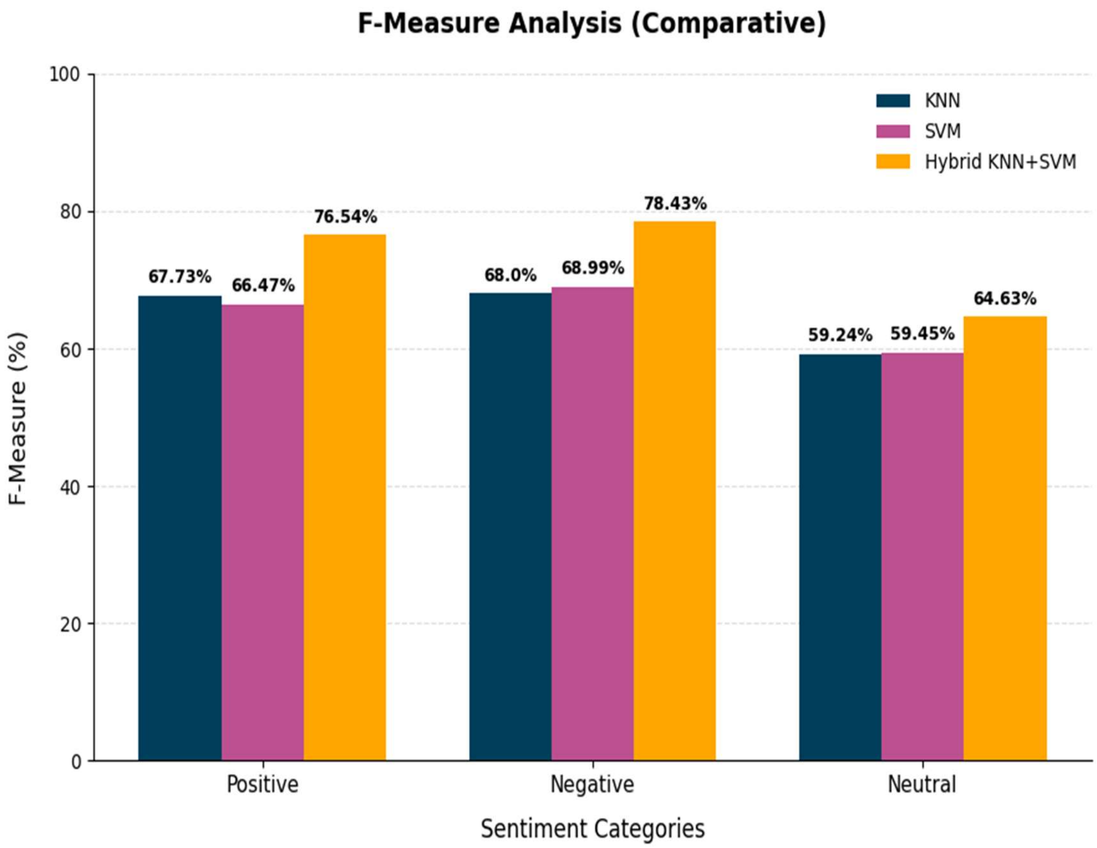

Figure 8: Comparative F-Measure Analysis of KNN, SVM, and Hybrid KNN–SVM Classifiers

3.1.5 Comparative Evaluation

The experimental analysis indicates that the proposed Hybrid SVM–KNN model delivers better performance than the standalone SVM and KNN classifiers across multiple evaluation metrics. By integrating the neighborhood-based learning capability of KNN with the robust decision boundary construction of SVM, the hybrid model is able to capture complex sentiment patterns present in Twitter messages more effectively. This complementary combination contributes to improved classification performance and enhanced sentiment prediction. To assess the effectiveness of the proposed approach, its performance was compared with several benchmark sentiment analysis datasets and previously published studies. The comparison results are presented in Table 5.7

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Table 5.7 Comparative Performance Analysis

Dataset	Average F-Measure (%) (Positive & Negative)	Average F-Measure (%) (Including Neutral)	Accuracy (%) (Positive & Negative)	Accuracy (%) (Including Neutral)
OMD [11]	65.36	–	71.63	–
Strict OMD [11]	71.81	–	84.56	–
Sanders [11]	76.25	–	86.63	–
Stanford [11]	72.23	–	79.11	–
HCR [11]	61.21	–	78.35	–
Proposed Dataset	78.28	74.22	79.81	77.27

The results demonstrate that the proposed framework achieves competitive performance when compared with established sentiment analysis approaches. In particular, the model attained an average F-measure of 78.28% for positive and negative sentiment classification, exceeding the performance reported for several benchmark datasets. Furthermore, the overall accuracy of 79.81% highlights the model's capability to effectively distinguish between different sentiment categories.

The inclusion of the neutral class introduces additional complexity to the classification task; however, the proposed method maintained satisfactory performance, achieving an average F-measure of 74.22% and an overall accuracy of 77.27%. These findings suggest that the hybrid architecture is capable of handling multi-class sentiment classification scenarios commonly encountered in social media applications.

Overall, the experimental results validate the effectiveness of the Hybrid SVM–KNN framework for Twitter sentiment analysis. The proposed model provides a reliable and efficient mechanism for identifying positive, negative, and neutral opinions, making it a suitable solution for real-world sentiment classification tasks.

4. Conclusion and Future Scope

This study developed a hybrid sentiment analysis model by combining Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms to classify Twitter posts into positive, negative, and neutral categories. The framework incorporated data preprocessing, feature extraction, and hybrid classification techniques to improve sentiment prediction accuracy. Experimental results demonstrated that the hybrid model outperformed the individual SVM and KNN classifiers in terms of accuracy, precision, recall, and F-measure. The integration of the two algorithms enabled the model to capture sentiment patterns more effectively and reduce classification errors. Comparative evaluation with existing studies further confirmed the effectiveness and competitiveness of the proposed approach for Twitter sentiment analysis.

Future research can focus on incorporating advanced linguistic, semantic, and contextual features to improve classification performance. Feature selection methods such as Information Gain, Chi-Square, Mutual Information, and Principal Component Analysis (PCA) may be employed to identify the most relevant attributes. Additionally, larger and more diverse datasets can enhance model generalization. Further improvements may be achieved by integrating deep learning techniques such as LSTM, RNN, and BERT. The framework can also be extended to multilingual sentiment analysis, aspect-based sentiment analysis, and real-time social media monitoring applications.

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