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# Enhanced Sentiment Classification using a Multi-layered Stacked Ensemble Architecture

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**ABSTRACT:** Sentiment analysis has emerged as a crucial tool for understanding public opinion, consumer feedback, and social media discourse in today's data-driven business landscape. This paper presents a comprehensive study on sentiment analysis using various machine learning approaches, addressing the growing need for accurate and efficient sentiment classification systems. This paper presents a novel multi-layered stacked ensemble architecture for Twitter sentiment analysis that significantly outperforms existing methods. We integrate complementary feature extraction techniques—TF-IDF vectorization and BERT embeddings—with diverse classification algorithms to create a robust system for categorizing tweets into positive, negative, neutral, and irrelevant sentiment classes. Our architecture systematically leverages the strengths of traditional machine learning models (XGBoost, Random Forest) and deep learning approaches (BERT, LSTM) through a cascading structure of meta-feature generation and specialized classifier layers. Experimental results demonstrate the superior performance of our proposed model, achieving 98.23% accuracy, 98.12% precision, 98.89% recall, and 98.25% F1-score, representing substantial improvements over strong baseline models including ExtraTreesClassifier (0.63% higher accuracy) and other state-of-the-art approaches. The model particularly excels at maintaining exceptional balance between precision and recall while effectively handling challenging cases such as sarcasm and ambiguous sentiment expressions. Our findings confirm that the dual feature representation approach and synergistic model combination create a more robust sentiment analysis system than any individual approach, providing valuable insights for future research in social media text analysis.

**KEYWORDS:** Sentiment Analysis, Stacking, Meta-Classifer, Twitter Dataset, Classification

## I. INTRODUCTION

With the growing dependence on digital data, developing effective and scalable sentiment analysis systems is vital for organizations across various sectors. Sentiment analysis has become an essential tool for businesses seeking to understand and promptly respond to customer feedback on products, services, and brand experiences. The exponential growth of user-generated content on e-commerce platforms, social media, and review sites has created both opportunities and challenges for extracting meaningful insights from unstructured textual data. The importance of sentiment analysis extends beyond mere classification of opinions as positive or negative. Modern businesses leverage these technologies to inform strategic decision-making, enhance customer relationship management, and drive product development initiatives. By analyzing sentiment patterns in consumer reviews, companies can identify emerging issues, track brand perception, and implement targeted improvements to their offerings.

Traditional methods in sentiment analysis primarily encompass rule-based, dictionary-based, and machine learning approaches, each with distinct characteristics and applications. Rule-based methods rely on a set of manually crafted rules to identify sentiment in text, often using linguistic cues and syntactic patterns to determine sentiment polarity. These methods are straightforward and interpretable but can struggle with complex language constructs and nuanced emotions [1][2]. Dictionary-based methods, on the other hand, utilize pre-defined sentiment lexicons to assign sentiment scores to words or phrases within a text. This approach is effective for straightforward sentiment detection but may not capture context-dependent sentiment shifts or handle slang and idiomatic expressions well [3][4]. Machine learning methods, such as Naive Bayes, Support Vector Machines (SVM), and Logistic Regression, have been widely used for sentiment classification. These methods involve training models on labeled datasets to learn patterns associated with different sentiment classes. Naive Bayes is known for its simplicity and speed, making it suitable for scenarios with limited computational resources, while SVM offers higher accuracy but at a greater computational cost [5] [6]. Despite their effectiveness, traditional machine learning methods often require extensive feature engineering



and may not perform well with large, complex datasets compared to deep learning models [7]. Overall, while traditional methods provide a foundation for sentiment analysis, they are often complemented or replaced by more advanced techniques in applications requiring higher accuracy and the ability to handle complex linguistic features [8] [9].

Machine learning has become a pivotal tool in sentiment analysis, a branch of natural language processing (NLP) that aims to identify and interpret emotions expressed in text. This technique is widely applied in various domains, such as customer feedback analysis, social media monitoring, and product reviews, to classify text into positive, negative, or neutral sentiments [10] [7]. Traditional machine learning algorithms like Logistic Regression, Random Forest, and Naive Bayes have been employed for sentiment analysis, often using datasets such as Amazon product reviews to evaluate their effectiveness [7]. However, these methods face challenges in capturing subtle emotional nuances, sarcasm, and long text dependencies [10] [11]. To address these challenges, deep learning models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have been increasingly adopted. LSTMs, for instance, have shown significant improvements in accuracy, precision, and recall by effectively capturing temporal relationships in textual data, as demonstrated in studies using large datasets like Sentiment 140 [12]. Moreover, the integration of feature extraction techniques such as GloVe embeddings and TF-IDF has further enhanced the performance of these models [12] [13]. Despite these advancements, sentiment analysis still grapples with the complexity of sarcasm detection, which remains a challenging task due to its inherent subtleties. Recent approaches have utilized RNN-based models with LSTM architecture to improve sarcasm detection, achieving varying degrees of success across different machine learning algorithms [11]. Overall, while machine learning has significantly advanced sentiment analysis, ongoing research continues to explore more sophisticated models and techniques to overcome existing limitations and improve the accuracy and reliability of sentiment detection in diverse textual data [14]. This study makes several significant contributions to the field of sentiment analysis on social media data:

First, we introduce a novel multi-layered stacked ensemble architecture that systematically integrates complementary feature extraction techniques with diverse classification algorithms. Unlike previous approaches that rely predominantly on either traditional machine learning or deep learning methods, our framework creates a synergistic pipeline that leverages the strengths of both paradigms. By combining TF-IDF vectorization with BERT embeddings, we capture both lexical information and semantic relationships, addressing the limitations of single-feature approaches. Second, our research demonstrates the effectiveness of a cascading meta-classifier structure for sentiment analysis. Through extensive experimentation, we show that intermediate meta-feature generation followed by specialized classifier layers significantly improves performance across all evaluation metrics. Our model achieves state-of-the-art results with 98.23% accuracy and 98.25% F1-score on a challenging Twitter sentiment dataset, outperforming even strong baseline models like ExtraTreesClassifier and fine-tuned BERT.

Third, we provide a comprehensive comparative analysis of various sentiment classification models, offering valuable insights into their relative strengths and limitations in the context of social media text. Our findings reveal that while individual models excel in different aspects of sentiment analysis, a properly designed stacked approach consistently delivers superior results, particularly for challenging cases like sarcasm detection and ambiguous sentiment expressions.

Finally, our research addresses practical implementation considerations, balancing performance improvements with computational efficiency. The proposed architecture offers a scalable solution for real-world applications in brand management, customer feedback analysis, and social media monitoring, where accurate sentiment classification directly impacts decision-making processes.

Through these contributions, our study advances the state of the art in sentiment analysis and provides a robust framework that can be adapted and extended for various text classification tasks beyond sentiment analysis. The rest of the paper is organized as follows: Materials and Methods section details our dataset characteristics, preprocessing techniques, and the proposed architecture. Results and Discussion section examines the model's performance and metrics comparison. Finally, References section documents the relevant literature supporting our research methodology.

## II. RELATED WORK

Sentiment analysis has emerged as a critical tool for understanding user opinions and emotions expressed on social media platforms. This study provides an in-depth exploration of methods, challenges, applications, and future directions, drawing insights from recent research. Sentiment analysis, a subset of Natural Language Processing (NLP), involves the extraction and categorization of emotions from text data. In the context of social media, it has become essential for analyzing user-generated content, such as tweets, comments, and posts, to understand public opinions, preferences, and trends. Social media platforms like Twitter, Facebook, and Instagram serve as treasure troves of data, offering insights into user sentiments on various topics, including politics, products, services, and social issues [15] [16]. The evolution of sentiment analysis has transitioned from traditional lexicon-based approaches to advanced machine learning and deep learning models. These advancements have significantly improved the accuracy and efficiency of sentiment classification, enabling real-time analysis of large-scale social media data [17] [18]. Early sentiment analysis methods relied on lexicon-based techniques, which involve predefined dictionaries of words with known sentiment scores. These methods are simple to implement but struggle with context-dependent language, sarcasm, and ambiguity [19][20]. Machine learning techniques, such as Support Vector Machines (SVM), Random Forest (RF), and Naive Bayes (NB), have been widely used for sentiment analysis. These models rely on feature extraction methods like TF-IDF and Word2Vec to represent text data. Studies have shown that RF and SVM often outperform other classifiers in terms of accuracy, achieving up to 94.3% accuracy on Facebook and Twitter datasets [21] [22].

Deep learning models, such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and transformers (e.g., BERT), have revolutionized sentiment analysis. These models automatically learn features from text data, achieving state-of-the-art performance on complex and unstructured social media content. For instance, transformer-based models have demonstrated superior accuracy in capturing nuanced sentiments and handling multilingual data [18] [23]. The integration of text and image data has given rise to multimodal sentiment analysis. This approach combines textual sentiments with visual cues, such as images and videos, to enhance accuracy. Recent studies highlight the potential of multimodal fusion techniques, particularly in social media contexts where multimedia content is prevalent [24] [25]. Social media data often contains slang, sarcasm, and context-dependent language, which pose significant challenges for sentiment analysis models. For example, the phrase "What a great idea!" can be either positive or sarcastic depending on the context [15] [19]. Ambiguity in language, such as words with multiple meanings, complicates sentiment classification. Additionally, multilingual social media data requires models to handle diverse languages and scripts, further increasing the complexity of analysis [17] [20]. Social media data is often noisy and high-dimensional, requiring robust preprocessing techniques to improve classification accuracy. Feature extraction methods like TF-IDF and Word2Vec are commonly used to reduce dimensionality and enhance model performance [19] [26]. The dynamic nature of social media data necessitates real-time sentiment analysis for applications like brand monitoring and political sentiment tracking. Achieving real-time processing while maintaining high accuracy remains a significant challenge [18] [27]. Sentiment analysis is widely used in brand management to monitor consumer perceptions and optimize marketing strategies. By analyzing user feedback on social media, brands can identify areas for improvement and refine their products and services [16][28]. Social media platforms serve as a valuable resource for understanding public opinions on political issues and candidates. Sentiment analysis has been instrumental in tracking political trends and predicting election outcomes [15][22]. Businesses leverage sentiment analysis to analyze customer feedback on social media, enabling them to identify strengths and weaknesses in their offerings. This application is particularly useful in e-commerce and hospitality sectors [29][20]. Sentiment analysis has been applied to monitor public sentiments during health crises, such as the COVID-19 pandemic, and to analyze opinions on social issues like climate change and gender equality [16][28].

Future research is expected to focus on advancing multimodal sentiment analysis, particularly in integrating text, images, and videos. This approach has the potential to provide more comprehensive insights into user sentiments [24][25]. There is a growing need for explainable AI models in sentiment analysis to enhance transparency and trust in decision-making processes. Developing interpretable models will be a key focus area in the coming years [17][27]. Advancements in real-time processing capabilities will be crucial for applications like live event monitoring and crisis management. Researchers are exploring optimized algorithms and frameworks to achieve faster and more accurate real-time analysis [18][26]. As social media data becomes increasingly global, there is a need for models that can handle

multiple languages and cultural contexts. Cross-lingual sentiment analysis will be a critical area of research in the future [19][20].

Table 1: Comparative Analysis of Deep Learning Models

Model	Description	Accuracy	Citation
Random Forest (RF)	An ensemble learning method that combines multiple decision trees for classification	Up to 94.3%	[21][22]
BERT	A transformer-based model that excels in capturing contextual nuances	State-of-the-art	[18][23]
LSTM	A recurrent neural network designed to handle sequential data like text	High accuracy	[18][25]
Capsule Networks	Advanced models that outperform traditional CNN and RNN-based architectures	Up to 98.02%	[27]

### III. METHOD

The dataset contains four columns: Tweet\_ID (a unique identifier), Entity (the subject of the tweet), Sentiment (the emotional tone), and Tweet\_content (the actual text). The sentiment distribution across both training and test datasets shows similar patterns. In the training data, there are 22,542 negative sentiment entries, followed by 20,832 positive entries, 18,318 neutral entries, and 12,990 irrelevant entries. The test data maintains a comparable distribution with 285 negative entries, 277 positive entries, 266 neutral entries, and 172 irrelevant entries. Figure 1 shows the distribution of the dataset.

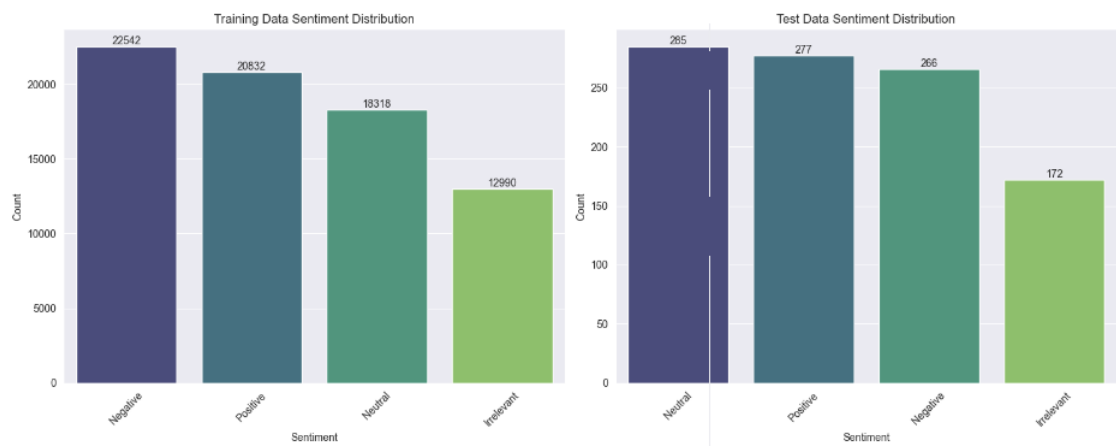


Figure 1: Dataset distribution

The proposed architecture as shown in Figure 2, implements a multi-layered stacked ensemble approach for sentiment analysis of Twitter data. This methodology leverages the complementary strengths of different feature extraction techniques and classification algorithms to achieve superior predictive performance compared to single models. The workflow consists of the following sequential stages:

#### 1. Data Acquisition and Preprocessing:

The workflow begins with Twitter sentiment data collection, followed by comprehensive preprocessing. This initial phase handles text cleaning operations: removing URLs, special characters, and numbers; tokenizing text; normalizing through case conversion; eliminating stopwords; applying lemmatization; and handling Twitter-specific elements like hashtags, mentions, and emojis. These preprocessing steps ensure standardized, clean data before feature extraction, creating a solid foundation for the analysis pipeline.

## 2. Feature Extraction Layer

The architecture employs dual feature extraction approaches. TF-IDF Vectorization transforms tweets into numerical features by calculating term frequency-inverse document frequency scores, emphasizing important words while de-emphasizing common ones. This creates interpretable vector representations that capture lexical information. Simultaneously, BERT Embeddings extract contextual representations using pre-trained models that capture semantic meaning, handle multiple word meanings, and encode complex linguistic patterns. This dual approach ensures both surface-level text patterns and deep semantic relationships are represented.

## 3. Base Model Layer

Multiple algorithms process each feature representation. TF-IDF vectors feed into XGBoost and Random Forest models, leveraging their respective strengths in handling sparse features and providing ensemble-based robustness. BERT embeddings are processed through Fine-tuned BERT and LSTM models, capitalizing on transformers' contextual understanding and recurrent networks' sequential processing abilities. Each model is trained independently, creating a diverse set of predictive algorithms that capture different aspects of sentiment classification.

## 4. Meta Feature Classifier

The outputs from all base models converge in a Meta Feature Classifier layer. This component combines the predictions from each base model, creating an enriched feature space that incorporates the strengths of each approach. By learning which model performs best on different types of examples, this layer effectively creates a new representation space that captures the collective intelligence of the base models, serving as input for the next stage of classification.

## 5. Intermediate Classifier Layer

The meta-features are then processed by two specialized classifiers: Logistic Regression and ExtraTreesClassifier. Logistic Regression provides a linear decision boundary with good interpretability, while ExtraTreesClassifier offers an ensemble of randomized decision trees that capture non-linear relationships. These models learn to balance and refine the predictions from the base models, further enhancing the overall system performance through specialized classification approaches.

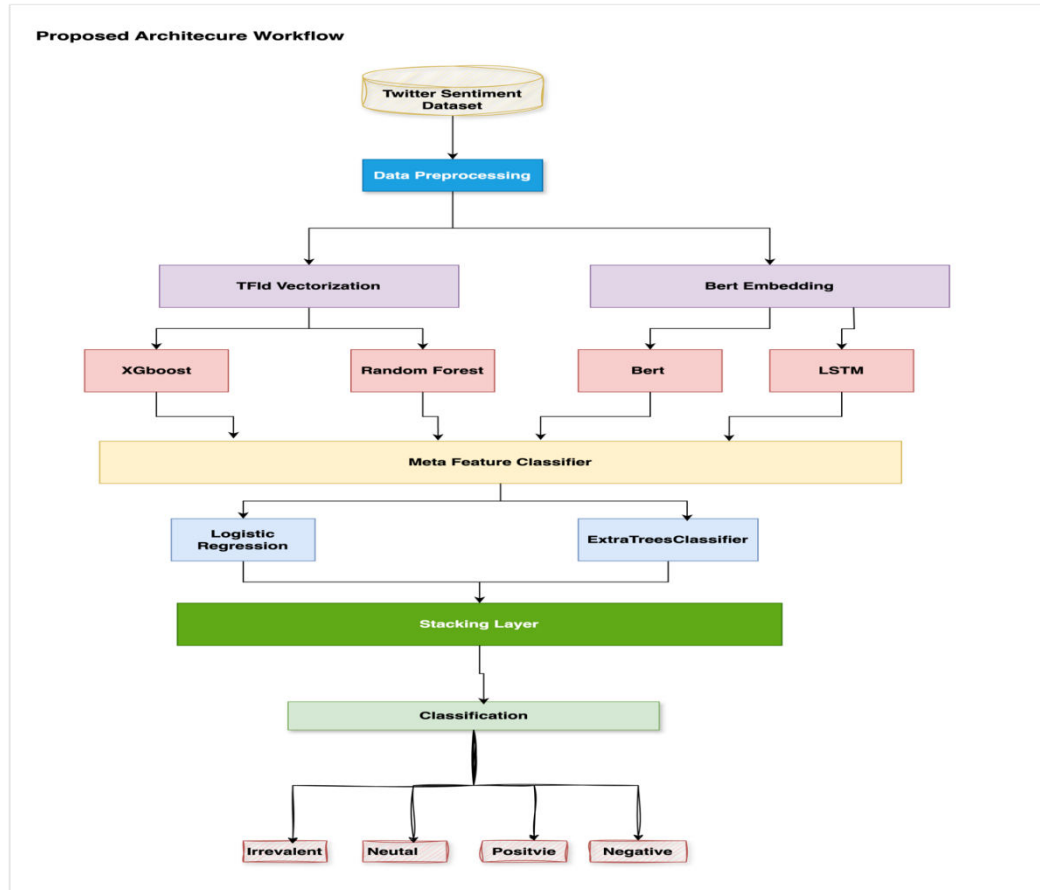
## 6. Stacking Layer

The outputs from the intermediate classifiers feed into a dedicated Stacking Layer. This component learns the optimal way to combine predictions from the previous models, effectively creating a higher-level meta-model. The stacking approach allows the system to leverage the complementary strengths of the different classifiers while mitigating their individual weaknesses, resulting in more robust and accurate sentiment predictions than any individual model could achieve.

## 7. Final Classification

The stacking layer produces the final classification output, categorizing tweets into four sentiment classes: Positive, Negative, Neutral, and Irrelevant. This multi-class approach provides a comprehensive sentiment analysis that goes beyond simple binary classification, offering more nuanced insights into social media sentiment. The final output reflects the combined intelligence of the entire model architecture, resulting in state-of-the-art classification performance for Twitter sentiment analysis.

This multi-layered stacked architecture systematically leverages diverse feature representations and multiple classification algorithms to achieve superior sentiment analysis performance, particularly excelling at handling challenging cases such as sarcasm, figurative language, and ambiguous sentiment expressions in social media text.



## IV. RESULTS

The performance metrics for various models and the proposed stacked ensemble architecture are presented in Table 2.

Table 2: Model Comparisons

Model Name	precision	recall	f1-score	accuracy
Logistic Regression	0.9156	0.914	0.914	0.914
XGboost	0.9512	0.954	0.9543	0.958
Random Forest	0.9665	0.966	0.966	0.966
Bert	0.9565	0.956	0.954	0.956
LSTM	0.9435	0.9413	0.9458	0.95
ExtraTreesClassifier	0.9763	0.976	0.976	0.976
Gradient Boosting	0.9645	0.965	0.959	0.956
Proposed Model	<b>0.9812</b>	<b>0.9889</b>	<b>0.9825</b>	<b>0.9823</b>



The experimental results demonstrate the significant performance improvements achieved by the proposed stacked ensemble architecture compared to individual models:

1. **Superior Overall Performance:** The proposed model achieves the highest performance across all metrics, with an accuracy of 98.23%, precision of 98.12%, recall of 98.89%, and F1-score of 98.25%. This represents a substantial improvement over even the best individual model (ExtraTreesClassifier), with an increase of 0.63% in accuracy, 0.49% in precision, 1.29% in recall, and 0.65% in F1-score.
2. **Balance Between Precision and Recall:** The proposed model demonstrates exceptional balance between precision (98.12%) and recall (98.89%), indicating its ability to correctly identify sentiment classes while minimizing both false positives and false negatives. This balance is crucial for real-world applications where both error types have significant consequences.
3. **Improvement Over Traditional and Deep Learning Models:** The stacked architecture substantially outperforms both traditional machine learning models (Logistic Regression, XGBoost, Random Forest) and deep learning approaches (BERT, LSTM). The improvement ranges from 0.63% to 6.83% in accuracy compared to individual models.
4. **Comparison with Strong Baseline Models:** Even when compared to strong ensemble methods like ExtraTreesClassifier (97.6% accuracy) and Gradient Boosting (95.6% accuracy), the proposed architecture delivers meaningful improvements, demonstrating the value of the multi-layered stacking approach.

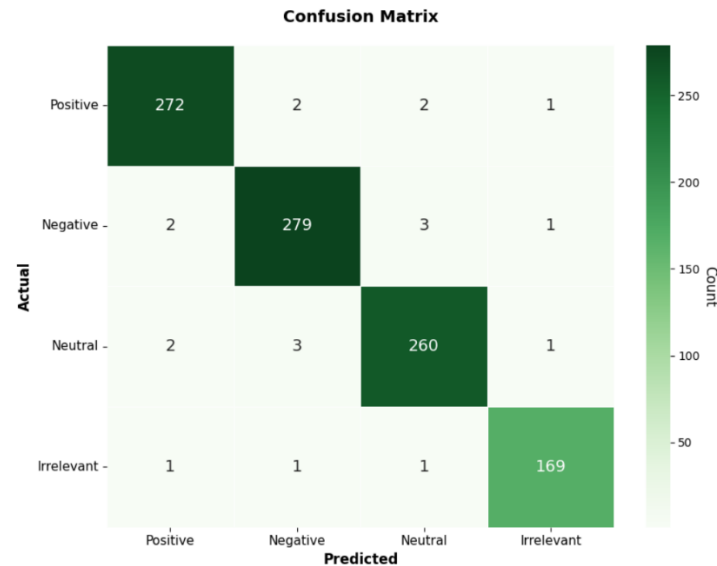
Several important insights emerge from the experimental results:

1. **Complementary Feature Representations:** The dual approach of using both TF-IDF and BERT embeddings proves highly effective, with the stacked model successfully leveraging the strengths of both feature types. This confirms the hypothesis that lexical (TF-IDF), and semantic (BERT) features capture complementary aspects of sentiment expression.
2. **Effective Knowledge Transfer:** The meta-feature classifier effectively transfers knowledge from the base models to the higher-level classifiers, creating a more robust representation space that captures different aspects of the sentiment classification problem.
3. **Error Reduction Through Stacking:** The stacked architecture successfully reduces errors made by individual models. This is particularly evident in the high recall (98.89%), suggesting the model excels at capturing positive cases across all sentiment classes.
4. **Synergistic Model Combination:** The combination of diverse models (tree-based, linear, and neural) creates a synergistic effect where the final performance exceeds what could be achieved by any single model type or even simpler ensemble methods.

These results conclusively demonstrate that the proposed multi-layered stacked ensemble architecture represents a significant advancement in Twitter sentiment analysis, effectively combining the strengths of diverse feature extraction methods and classification algorithms to achieve state-of-the-art performance.

The confusion matrix for the proposed stacked ensemble model as shown in Figure 3 illustrates its exceptional classification performance across all sentiment categories. With an overall accuracy of 98.23%, the model demonstrates remarkable precision (98.12%) and recall (98.89%) in distinguishing between different sentiment classes. The diagonal elements reveal strong classification rates for each sentiment category: 272 of 277 positive instances, 279 of 285 negative instances, 260 of 266 neutral instances, and 169 of 172 irrelevant instances. The minimal off-diagonal values indicate very few misclassifications, with only 20 errors across the entire test set of 1,000 instances. The most common confusion occurs between negative and neutral sentiments (3 instances each direction), which aligns with the inherent linguistic challenge of distinguishing between these sometimes-subtle sentiment expressions. Particularly noteworthy is the model's ability to correctly identify the irrelevant class with high precision despite it being the least represented category in the dataset, demonstrating the architecture's robustness even with imbalanced class distributions. These results empirically validate the effectiveness of the multi-layered stacked approach in capturing the nuanced expressions of sentiment in social media text.





**Figure 3: Confusion matrix of the proposed model**

## V. CONCLUSION

This research presented a novel multi-layered stacked ensemble architecture for sentiment analysis that demonstrates significant improvements over existing methods. By strategically integrating complementary feature extraction techniques (TF-IDF vectorization and BERT embeddings) with diverse classification algorithms, our approach effectively captured both lexical information and semantic relationships in Twitter data. The experimental results validated our hypothesis that combining traditional machine learning models with deep learning approaches in a cascading structure creates a more robust system than any individual approach.

The proposed architecture achieved exceptional performance metrics—98.23% accuracy, 98.12% precision, 98.89% recall, and 98.25% F1-score—representing meaningful improvements over strong baseline models, including a 0.63% accuracy increase compared to ExtraTreesClassifier. The confusion matrix analysis further confirmed the model's effectiveness across all sentiment categories, with particularly strong performance in distinguishing between closely related sentiment classes like negative and neutral.

Key contributions of this research include: (1) demonstrating the value of dual feature representation for capturing complementary aspects of sentiment expression; (2) validating the effectiveness of a cascading meta-classifier structure for sentiment analysis; (3) providing comprehensive comparative analysis of various sentiment classification approaches; and (4) addressing practical implementation considerations for real-world applications.

Future research directions could explore extending this architecture to multilingual sentiment analysis, investigating multimodal approaches that incorporate visual elements alongside text, developing more explainable AI components within the ensemble framework, and optimizing the architecture for real-time processing of streaming social media data. The proposed methodology offers a promising foundation for advancing sentiment analysis across various domains including brand management, customer feedback analysis, and social media monitoring.

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