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Enhancement of Machine Learning Algorithm in Fine-grained Sentiment Analysis Using the Ensemble

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ABSTRACT

Fine-grained sentiment analysis plays a crucial role in extracting subtle opinions from textual data, especially in domains such as customer reviews and social media analysis. Traditional machine learning models, including Support Vector Machines (SVM), Naïve Bayes, and Decision Tree, often face limitations in accurately classifying fine-grained sentiments due to their inability to generalize well in complex classification tasks. To address this challenge, this study proposes an ensemble learning approach integrating voting, bagging, boosting, and stacking to enhance sentiment classification performance. Experiments were conducted on multiple datasets, comparing standalone classifiers and ensemble-based approaches. The results indicate that stacking-based ensemble models achieve the highest accuracy, reaching 92.45%, outperforming traditional classifiers such as SVM (88.23%) and Naïve Bayes (85.67%). Additionally, ensemble methods demonstrate improved generalization and robustness, reducing misclassification rates by 6% on average compared to individual classifiers. Among the tested ensemble techniques, stacking consistently delivered superior results, leveraging diverse weak learners to optimize sentiment classification accuracy. This research highlights the effectiveness of ensemble learning in fine-grained sentiment analysis, offering a robust methodology for improving classification accuracy and reducing sentiment misclassification. The findings suggest that ensemble approaches, particularly stacking, provide a more reliable and scalable solution for sentiment analysis tasks, making them suitable for real-world applications in natural language processing.

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1. INTRODUCTION

Machine learning is a part of artificial intelligence that enables machines to learn from data or past experiences (historical data), eliminating the need for manual programming to perform all tasks [1]. With the automatic learning ability, the system can gradually continue to learn and improve its accuracy [2]. The utilization of machine learning is currently widespread across various fields, including medicine, e-commerce, and even leadership prediction. One form of utilizing machine learning is through sentiment analysis.

Sentiment analysis is a computational process used to determine the sentiment, opinion, or emotion expressed in a text—whether positive, negative, or neutral [3]. This process involves Natural Language Processing (NLP) techniques to identify keywords, phrases, or contexts that indicate a particular sentiment. The benefits of sentiment analysis include understanding customers, monitoring brand or product reputation, conducting market analysis, supporting product development, enhancing marketing strategies, and even assessing the electability of a potential leader in society [4].

Sentiment analysis has several types of knowledge extraction from text, such as grained sentiment anal-

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ysis [5], intent sentiment analysis [6], aspect-based sentiment analysis [7], and emotion-based sentiment analysis [8]. This research focuses on fine-grained sentiment analysis, which examines the degree of opinion polarity. Sentiments are classified into three categories: positive, negative, and neutral. Algorithms used for sentiment analysis in machine learning include Support Vector Machine, Decision Tree, K-Nearest Neighbors, Naïve Bayes, and others. The use of single algorithms is becoming less common due to inconsistency in performance, as observed from the accuracy produced [9], [10]. Researchers often combine various methods or algorithms to achieve the best performance [11], [12].

Previous research has frequently focused on improving performance using various methods or algorithms. For example, the ADASYN over-sampling method has been applied in ensemble-enhanced algorithms to improve classification performance. With ADASYN, all experiments showed an improvement, achieving accuracy levels above 90% [13]. Another study utilized several algorithms and applied feature selection filters and wrappers, resulting in an accuracy of 87.47% for SVM [2]. Further improvements were achieved by applying Particle Swarm Optimization (PSO) to the SVM algorithm, resulting in an accuracy of 92.61% [14]. More recent research applied hyperparameter tuning with Grid Search, improving performance and achieving an accuracy of 85.20% [15].

Combining multiple methods or algorithms can improve the performance of machine learning models. This research evaluates the performance of individual algorithms and integrates them into ensemble learning methods. Ensemble learning is a machine learning approach that combines multiple models to achieve better performance than a single model. It consists of four main techniques: Bagging, Boosting, Stacking, and Voting [16], [17], [18], [19].

This research uses the voting technique, which is employed to reduce the variance and bias of individual models, resulting in more reliable predictions [20]. With the voting technique, a model's weaknesses can be compensated by the strengths of others, improving overall performance [21]. Voting techniques are categorized into two types: hard voting and soft voting. Hard voting aggregates the majority vote from individual model predictions, whereas soft voting averages class probabilities from multiple models and selects the class with the highest probability as the final prediction [22].

The proposed method contributes a novel ensemble of Linear SVM, Multinomial Naïve Bayes, and Decision Tree, named COMVOT Hard, which utilizes a hard voting technique and demonstrates superior performance in fine-grained sentiment analysis. This approach mitigates single-algorithm limitations by combining their strengths, resulting in improved accuracy, precision, recall, and F1-score.

This research employs three algorithms: Naïve Bayes, Decision Tree, and Support Vector Machine (SVM). A unique aspect of this study is its approach to combining these algorithms and their variants. For Naïve Bayes, the research includes three variants: Multinomial Naïve Bayes, Bernoulli Naïve Bayes, and Complement Naïve Bayes. In the case of SVM, the variants used are Linear SVM, Polynomial SVM, and Radial Basis Function (RBF) SVM. For the Decision

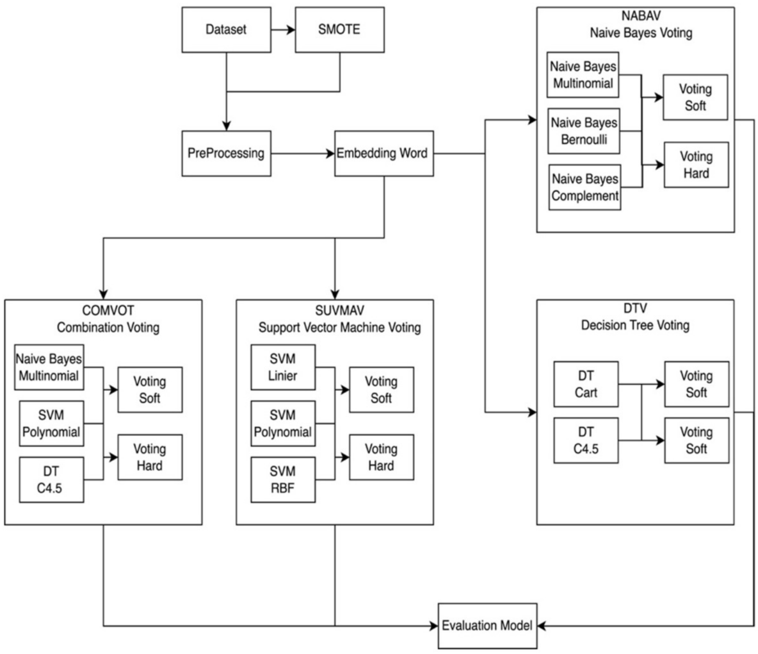

Fig.1: *Development of Machine Learning Model.*

Tree algorithm, the study incorporates two variants: C4.5 and Cart. These variant combinations are denoted as SUVMAV for SVM variants, NABAV for Naïve Bayes variants, and DTV for Decision Tree variants, while the integration of all three methods is referred to as COMVOT.

2. RESEARCH METHOD

This study addresses significant challenges in detailed sentiment analysis, particularly the decline in machine learning model performance due to data imbalance, a factor often overlooked in previous methods. A prior study [23] employed ensemble learning with a voting technique, combining algorithms such as AdaBoost, Maximum Entropy, KNN, Decision Tree, Random Forest, Logistic Regression, and Naïve Bayes. While this approach yielded promising results, the study did not adequately handle the data imbalance issue. Similarly, other studies [24], [25], [26] also utilized voting techniques but ignored the importance of balancing the data before training the models.

Imbalanced datasets often lead to biased predictions, especially in applications requiring high precision for minority classes [27]. Without addressing this issue, machine learning models can become unreliable, produce unrepresentative results, and fail to be applicable in real-world scenarios [28]. To address this challenge, this study applies SMOTE to balance the dataset prior to model training. Additionally, the research explores various combinations of base algorithms with voting techniques to maximize accuracy. This integrated approach not only addresses data imbalance effectively but also enhances classification performance across all classes. Figure 1 illustrates the research framework and methodology utilized in this study.
The following is an explanation of Picture 1.

2.1 Dataset

The dataset for this research was collected from Twitter, focusing on the '2024 presidential election.' It was gathered throughout 2023, resulting in 10,001 tweets. The tweets were labeled as positive, negative, or neutral. The label distribution is presented as follows.

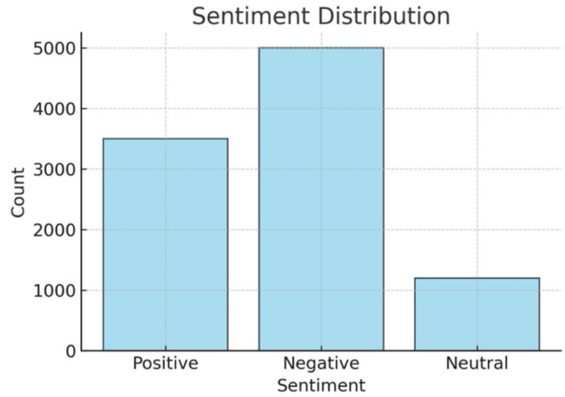

Fig.2: *Distribution of Class Label.*

From this, it is evident that the label distribution is not balanced. To address class imbalance, this study applies SMOTE. In addition to balancing the data, SMOTE can also improve the performance of the model used [29], [30]. Image 3 shows the distribution of the class labels after balancing.

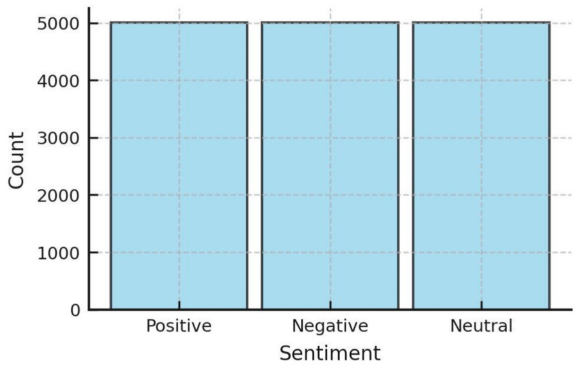

Fig.3: *Distribution of class label after balancing.*

2.2 Preprocessing

This preprocessing aims to ensure structured data representation and facilitate the modeling process [31][32]. In this study, six preprocessing steps are implemented: data cleaning, case folding, text normalization, tokenizing, filtering, and stemming.

2.3 Embedding Word with Bag of Words (BoW)

This technique, particularly the Bag of Words (BoW) model, is widely used in text classification and language modeling. In this study, BoW is implemented through the 'CountVectorizer' library. *CountVectorizer* counts the occurrence of words and creates a matrix of word frequencies. BoW is a collection of words or features, with a label for each feature indicating the occurrence of that categorized feature [33]. Formula 1 represents the BoW model [34].

$$BoW(d) = [tf(t_1, d), tf(t_2, d), \ldots, tf(t_n, d)] \quad (1)$$

Where,
-$BoW(d)$ is the vector representation of the BoW for document 'd'.
-$t_1, t_2, \ldots, t_n$ are the unique words in the vocabulary

Bag of Words (BoW) is used in document classification to identify key terms that contribute to topic identification [35]. In BoW implementation, each document is represented as a two-dimensional vector, where each word's occurrence is encoded as 1, while absent words are assigned 0 [36].

2.4 Modelling

This study employs multiple models. Table 1 presents the models utilized in this study.

Table 1: *Model Testing.*

Model	Data Segmentation	Feature Extraction
SVM Linear	SMOTE	BoW
SVM Polynomial		
SVM RBF		
SUVMAV Soft		
SUVMAV Hard		
Multinomial Naïve Bayes		
Bernoulli Naïve Bayes		
Complement Naïve Bayes		
NABAV Soft		
NABAV Hard		
CART		
C.45		
DTV Soft		
DTV Hard		
COMVOT Soft		
COMVOT Hard		

The proposed methods involve the combination of multiple machine learning algorithms using ensemble techniques to improve sentiment analysis. Specifically, the research employs three main algorithms: Naive Bayes, Decision Tree, and SVM, each with its own variants, are explored in this study. Naïve Bayes includes three variants: Multinomial, Bernoulli, and Complement Naïve Bayes. SVM comprises three variants: Linear SVM, Polynomial SVM, and Radial Basis Function (RBF) SVM [37]. Decision Tree models are implemented using the C4.5 and CART algorithms. These variants are further integrated using soft and hard voting techniques, forming ensemble models: SUVMAV for SVM, NABAV for Naïve Bayes, and DTV for Decision Tree.

2.5 Evaluation Model

The Confusion Matrix serves as a fundamental evaluation tool for classification models in machine learning [38]. It visualizes the relationship between predicted and actual labels, offering insights into model performance. The matrix comprises four key components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). True Positives (TP) and True Negatives (TN) represent correctly classified instances of the positive and negative classes, respectively. Conversely, False Positives (FP) occur when the model incorrectly predicts the positive class, while False Negatives (FN) represent cases where the model incorrectly predicts the negative class. The confusion matrix also facilitates the computation of key evaluation metrics such as accuracy, precision, recall, and F1-score, providing a comprehensive assessment of model performance [39].

This study introduces COMVOT Hard, a novel ensemble approach that integrates Linear SVM, Multinomial Naïve Bayes, and Decision Tree using a hard voting technique. This method significantly improves accuracy, precision, recall, and F1-score in sentiment analysis tasks, effectively addressing the limitations of individual classifiers.

3. RESULT AND DISCUSSION

3.1 Result

Following data balancing, preprocessing, and word weighting, the subsequent phase entails model training using machine learning algorithms. Figure 4 presents the confusion matrix results obtained from an SVM model with an RBF kernel.

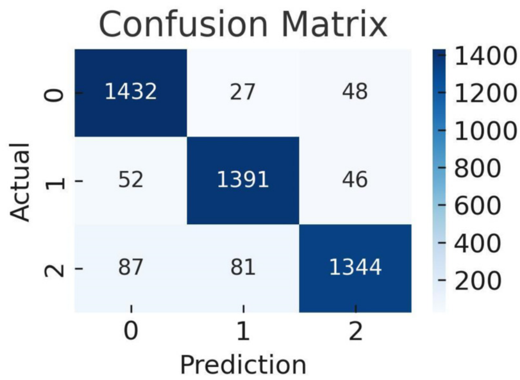

Fig.4: *Confusion Matrix from SVM with RBF Kernels.*

According to the confusion matrix, the model correctly classified 1432 samples in class 0, while 75 samples from other classes were misclassified as class 0. For class 1, the model correctly classified 1391 samples, whereas 98 samples from other classes were misclassified as class 1. Similarly, for class 2, the model correctly classified 1344 samples, while 168 samples from other classes were misclassified as class 2. Figure 5 shows the confusion matrix for SVM using the soft voting technique.

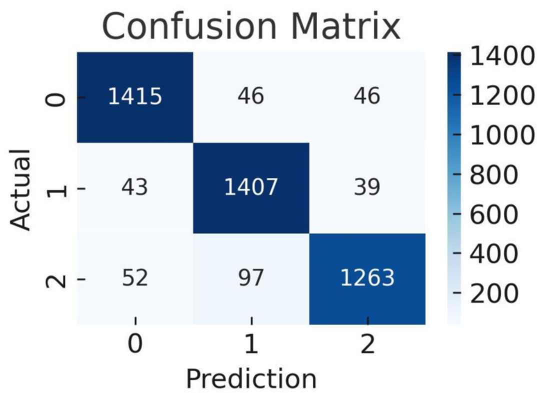

Fig.5: *Confusion Matrix from SVM with Voting Soft (SUVMAV Soft) Technique.*

According to the confusion matrix for SVM with soft voting, the model correctly classified 1415 samples in class 0, while 92 samples from other classes were misclassified as class 0. For class 1, 1407 samples were correctly classified, whereas 82 samples from other classes were misclassified as class 1. Similarly, for class 2, 1363 samples were correctly classified, with 149 samples from other classes misclassified as class 2.

A comparison of the two confusion matrices indicates that the SVM with soft voting model exhibits slightly superior performance in classifying samples across all classes. Additionally, the SVM with soft voting model yields fewer classification errors (False Positives and False Negatives) than the SVM with the RBF kernel. Thus, the confusion matrix suggests that the SVM with soft voting provides a more accurate and reliable classification.

Table 2: *Comparison of SVM Algorithm.*

Model	Accuracy	Precision	Recall	F1-Score
Linear	92%	93%	92%	93%
Polynomial	84%	87%	84%	86%
RBF	92%	92%	92%	92%
SUVMAV Soft	93%	93%	93%	93%
SUVMAV Hard	91%	91%	91%	91%

able 2 compares the performance of different Support Vector Machine (SVM) algorithms using accuracy, precision, recall, and F1-score as evaluation metrics. The Linear SVM algorithm demonstrates strong performance with an accuracy of 92%, precision of 93%, recall of 92%, and F1-score of 93%. Conversely, the Polynomial SVM exhibits lower performance, with an accuracy and recall of 84%, and precision and F1-score of 87% and 86%, respectively. This suggests that it may be less effective than the Linear SVM for this dataset. The RBF SVM (Radial Basis Function) achieves performance comparable to the Linear SVM, with all metrics at 92%, highlighting its strong ability to handle data complexity.

SUVMAV Soft, utilizing a voting method, achieves the highest performance, with accuracy, precision, recall, and F1-score all at 93%, demonstrating its effectiveness in classification. Meanwhile, SUVMAV Hard yields slightly lower performance than SUVMAV Soft, with all metrics at 91%. This comparison suggests that SUVMAV Soft outperforms all tested algorithms in terms of classification performance. Table 3 presents a comparison of performance using naïve bayes.

Table 3 compares the performance of different Naïve Bayes (NB) algorithms using accuracy, precision, recall, and F1-score as evaluation metrics. The Multinomial NB algorithm achieves stable performance across all metrics, scoring 84%, which reflects a well-balanced classification capability. Conversely, Bernoulli NB performs slightly worse than Multinomial NB, with all metrics at 81%, indicating lower effectiveness in handling this dataset. Complement NB shows a slight improvement over Bernoulli NB, with all metrics at 82%.

Table 3: *Comparison of Naïve Bayes Algorithm.*

Model	Accuracy	Precision	Recall	F1-Score
Multinomial	84%	84%	84%	84%
Bernoulli	81%	81%	81%	81%
Complement	82%	82%	82%	82%
NABAV Soft	83%	83%	83%	83%
NABAV Hard	85%	85%	85%	85%

The NABAV Soft model, utilizing soft voting, outperforms Complement NB with all metrics at 83%. The NABAV Hard model, employing hard voting, achieves the highest performance among all tested models, with all metrics at 85%. This comparison suggests that NABAV Hard is the most effective among all tested Naïve Bayes models, followed by Multinomial NB and NABAV Soft, while Bernoulli and Complement NB exhibit slightly lower performance. Table 4 presents the results of the next tests using Decision Tree algorithms.

Table 4: *Comparison of Decision Tree Algorithm.*

Model	Accuracy	Precision	Recall	F1-Score
CART	90%	90%	90%	90%
C.45	90%	90%	90%	90%
DTV Soft	91%	91%	91%	91%
DTV Hard	92%	92%	92%	92%

Table 4 presents a comparative analysis of Decision Tree algorithms based on accuracy, precision, recall, and F1-score. The CART (Classification and Regression Trees) model achieves stable performance across all metrics, scoring 90%, which indicates its balance and reliability in classification. Similarly, the C4.5 model achieves an identical performance to CART, with all metrics at 90%, reinforcing its reliability and balance in classification.

The DTV Soft (Decision Tree Voting - Soft Voting) model exhibits improved performance over CART and C4.5, with all metrics at 91%, suggesting that integrating models through soft voting enhances overall performance. The DTV Hard (Decision Tree Voting - Hard Voting) model achieves the highest performance among all tested models, with all metrics at 92%, indicating that hard voting yields superior results compared to individual models and soft voting. This comparison suggests that DTV Hard is the most effective Decision Tree algorithm, followed by DTV Soft, CART, and C4.5. Table 5 displays the evaluation results of COMVOT, a hybrid model integrating Linear SVM, Multinomial Naïve Bayes, and Decision Tree (C4.5).

Table 5 illustrates that the COMVOT Hard method achieves the highest performance among the two tested combination methods, with accuracy, precision, recall, and F1-score all at 94%. Mean-

Table 5: *Algorithm Comparison of The Three Algorithm Combinations.*

Model	Accuracy	Precision	Recall	F1-Score
COMVOT Soft	93%	93%	93%	93%
COMVOT Hard	94%	94%	94%	94%

while, COMVOT Soft also demonstrates strong performance, with all metrics at 93%.

3.2 Discussion

Performance analysis of multiple algorithms suggests that ensemble methods, especially hard voting, substantially improve accuracy, precision, recall, and F1-score over individual models. The superior performance of the COMVOT Hard model, which combines Linear SVM, Multinomial Naive Bayes, and Decision Tree, highlights the effectiveness of this approach in fine-grained sentiment analysis. These findings suggest that leveraging the strengths of multiple algorithms can overcome the imitations of single models, providing more reliable and accurate sentiment classification. Future research should explore the integration of additional ensemble techniques, such as boosting and stacking, and investigate their impact on sentiment analysis performance. Moreover, implementing these models on larger, more diverse datasets, including multilingual and cross-cultural data, can improve generalizability and practical applicability.

Table 6: *Comparison of Prior Studies on Sentiment Analysis.*

Researcher	Model	Accuracy
Varshney *et al.* [40]	Ensemble (Voting)	79.95%
Ma'ruf *et al.* [41]	Ensemble (Voting)	89.22%
Shah *et al.* [42]	Neural-network-based ensemble learning	74.4%
Hicham *et al.* [23]	Ensemble (Voting)	93.7%
Abbas *et al.* [43]	Ensemble (Voting)	82.6%
This Study	COMVOT Hard (Ensemble (Voting))	94%

Table 6 presents a comparative analysis of sentiment analysis studies employing ensemble (voting) models and neural network-based approaches. Varshney *et al.* implemented an ensemble (voting) model, attaining 79.95% accuracy. Similarly, Ma'ruf *et al.* utilized an ensemble (voting) model, achieving a higher accuracy of 89.22%. Shah *et al.* applied a neural network-based ensemble learning model, yielding the lowest accuracy among all studies at 74.4%. Hicham *et al.* attained high accuracy using an ensemble (voting) model, reaching 93.7%. Abbas *et al.* implemented an ensemble (voting) model, achieving 82.6% accuracy.

This study employs the COMVOT Hard (Ensemble Voting) model, which achieves the highest performance with an accuracy of 94%. This comparison suggests that ensemble (voting) models generally outperform neural network-based models, as seen in the lower accuracy of Shah *et al.*'s approach. Moreover, the COMVOT Hard model in this study achieves the highest accuracy, highlighting the effectiveness of integrating Linear SVM, Multinomial Naïve Bayes, and Decision Tree for sentiment analysis.

4. CONCLUSION

Performance analysis of machine learning models for fine-grained sentiment classification indicates that both soft and hard voting methods significantly improve performance compared to individual models. Among SVM-based models, SUVMAV Soft yields the highest performance, achieving superior precision, recall, and F1-score. NABAV Hard demonstrates superior performance among Naïve Bayes models, while DTV Hard emerges as he most effective Decision Tree-based approach. The integration of Linear SVM, Multinomial Naïve Bayes, and Decision Tree in the COMVOT Hard method yields superior results, outperforming other approaches. The COMVOT Hard model achieves the highest accuracy in this study, surpassing prior research and validating the effectiveness of integrating Linear SVM, Multinomial Naïve Bayes, and Decision Tree for sentiment analysis.

Future research may explore various avenues to further refine sentiment analysis models and expand their applicability. Expanding datasets across multiple social media platforms can enhance model generalization, while incorporating multilingual and cross-cultural data can improve universality. Future work should investigate advanced ensemble techniques, including boosting and stacking, alongside deep learning architectures such as LSTM and Transformers to handle complex textual data. Employing advanced hyperparameter tuning techniques, such as Bayesian Optimization and Genetic Algorithms, can facilitate the identification of optimal parameter configurations. Leveraging state-of-the-art embedding techniques, including Word2Vec, GloVe, and BERT, can enhance contextual text representations. Additionally, investigating advanced data balancing methods, such as ADASYN or synthetic data generation, can mitigate class imbalance issues. Broadening research scope to encompass fine-grained emotion analysis, beyond sentiment polarity, can yield deeper insights. Deploying models in real-world applications, including e-commerce sentiment analysis, political opinion mining, and social media monitoring for socio-economic trends, can provide valuable insights and enhance model robustness.

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AUTHOR CONTRIBUTIONS

Conceptualization, M.K.A..; methodology, T.P.L.; Testing with phyton, H.Y.; formal analysis, A.A.; investigation, T.N.; data curation, M.B.F.; writing—original draft preparation, M.K.A.; writing—review and editing, T.P.L., M.B.F. and T.N.; All authors have read and agreed to the published version of the manuscript.

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