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RESEARCH ARTICLE

Enhancing the Performance of Sentiment Analysis Models Using GridSearchCV: A Case Study on Electric Vehicles in Thailand

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Abstract

This study investigates the enhancement of sentiment analysis model performance through hyperparameter tuning using GridSearchCV, with a focus on electric vehicle reviews in Thailand. To address the challenges inherent in Thai language processing, PyThaiNLP was employed for word segmentation and text preprocessing. Four machine learning models—Support Vector Machines (SVM), Multinomial Naïve Bayes, Logistic Regression, and Stochastic Gradient Descent—were implemented for sentiment classification. The hyperparameters of each model were systematically optimized to determine the configuration that maximizes accuracy, precision, recall, and F1-score. Experimental results revealed notable improvements across all models following optimization. The SVM model, identified as the best-performing classifier, achieved an accuracy increase from 75.00% to 76.69% and an F1-score improvement from 74.82% to 76.69%. The optimal SVM configuration employed a radial basis function kernel with a regularization parameter (C) of 10 and a gamma value of 0.1. These findings underscore the significance of hyperparameter optimization in improving model effectiveness and contribute to advancing sentiment analysis in linguistically complex environments such as Thai.

1. Introduction

In recent years, the adoption of electric vehicles (EVs) has surged globally, driven by the growing emphasis on sustainability and the reduction of carbon emissions. In Thailand, the transition toward EVs is gaining momentum, with increasing awareness among consumers about environmental issues and the benefits of clean energy transportation. As the market for EVs expands, understanding consumer opinions and sentiments has become crucial for manufacturers and policymakers. Sentiment analysis, a subset of natural language processing (NLP), offers valuable insights by extracting and categorizing opinions from textual data, enabling businesses to make data-driven decisions Sanguesa et al. (2021); Thananusak et al. (2017).

However, the complexity of analyzing consumer opinions is heightened by the nuances of the Thai language, such as the absence of spaces between words, tonal variations, and complex grammatical structures. These linguistic challenges necessitate advanced techniques for processing and analyzing text effectively. Machine learning models, combined with tools like PyThaiNLP and TLex+, have shown significant promise in addressing these challenges. These tools allow for the segmentation and transformation of Thai text into structured formats suitable for analysis, laying the foundation for accurate sentiment classification Netisopakul and Thong-iad (2018).

While several studies have applied machine learning for sentiment analysis in Thai, a systematic investigation into the impact of hyperparameter optimization using GridSearchCV across a range of standard classifiers (SVM, MNB, LR, SGD) for the specific, high-growth domain of EV consumer reviews has not been thoroughly explored. Existing work often focuses on a single model or does not provide a comparative analysis of performance gains from tuning. This study aims to fill this research gap by demonstrating the quantifiable benefits of a systematic tuning approach.

This research focuses on evaluating the effectiveness

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of GridSearchCV in enhancing the performance of four widely used machine learning models: Support Vector Machines (SVM), Multinomial Naïve Bayes (MNB), Logistic Regression (LR), and Stochastic Gradient Descent (SGD). The study uses consumer opinions extracted from YouTube video reviews of EVs as a case study to demonstrate the practical applications of sentiment analysis in the Thai market. By comparing model performances before and after hyperparameter tuning, this research aims to highlight the critical role of GridSearchCV in improving classification accuracy, precision, recall, and F1 scores Bowornlertsutee and Paireekreng (2022); Özçift et al. (2019). The findings provide valuable insights for leveraging machine learning in the context of Thai language sentiment analysis and contribute to the broader understanding of optimizing machine learning models in linguistically complex environments.

2. Related Work

In recent years, sentiment analysis has emerged as a vital tool for understanding and interpreting opinions expressed in textual data. The ability to categorize sentiments into positive, negative, or neutral polarities has revolutionized fields such as marketing, social media monitoring, and customer service. By leveraging advanced computational techniques, sentiment analysis enables organizations to gain actionable insights into consumer preferences, public opinion, and market trends. This section explores the key concepts, challenges, and advancements in sentiment analysis, particularly in the context of the automotive industry and the unique complexities of processing the Thai language.

2.1 Overview of Sentiment Analysis

Sentiment analysis Rabruen et al. (2025), also known as opinion mining, is the process of identifying and categorizing sentiments expressed in text to determine whether the attitude is positive, negative, or neutral. This technique has gained popularity in various industries, including marketing, customer service, and public policy, as it provides valuable insights into consumer opinions and behavior Liu (2012); Pang and Lee (2008). In the automotive industry, particularly with the rise of electric vehicles (EVs), sentiment analysis has become crucial in understanding consumer perceptions of vehicle performance, design, and affordability Sanguesa et al. (2021). The evolution of sentiment analysis from rule-based methods, which rely on lexicons of sentiment-laden words, to machine learning-based approaches has significantly improved its accuracy and scalability Feldman (2013).

2.2 Challenges in Thai Language Processing

Thai language processing presents unique challenges due to its linguistic characteristics, including the lack of spaces between words, complex tonal systems, and ambiguous sentence structures Haruechaiyasak and Kongthon (2013); Netisopakul and Thong-iad (2018). These features make tasks such as word segmentation, part-of-speech tagging, and sentiment analysis more complex compared to languages like English. Tools like PyThaiNLP and TLex+ have been developed to address these challenges Aroonmanakul et al. (2018), enabling effective segmentation of Thai text and facilitating natural language processing tasks. Despite these advancements, limited resources and datasets for Thai language processing continue to hinder progress in sentiment analysis, necessitating further research Bowornlertsutee and Paireekreng (2022). Additionally, innovative approaches such as the Replacing the English Alphabet (REA) technique have been proposed to address the challenges of segmenting misspelled or unknown Thai words, which are common in informal texts such as social media messages. This method enhances segmentation accuracy and provides a foundation for more precise sentiment analysis Vichianchai and Kasemvilas (2024).

2.3 Machine Learning Models for Sentiment Analysis

Machine learning has revolutionized sentiment analysis by offering models capable of learning from large datasets and making accurate predictions. Commonly used models include Multinomial Naïve Bayes (MNB), which is effective for text classification but assumes feature independence; Support Vector Machines (SVM), known for their robustness in separating data points with maximum margin; Logistic Regression (LR), valued for its simplicity and efficiency in binary classification tasks; and Stochastic Gradient Descent (SGD), which is computationally efficient for large-scale datasets Ren et al. (2009). These models have been widely adopted in text classification studies, but their performance is influenced by hyperparameters, emphasizing the importance of optimization techniques such as GridSearchCV Syarif et al. (2016).

2.4 Hyperparameter Optimization in Machine Learning

Hyperparameter tuning is a critical step in the machine learning pipeline, as the performance of a model is highly dependent on the choice of its parameters. Unlike model parameters that are learned during training (e.g., weights in a neural network), hyperparameters are set prior to the learning process and define aspects of the model's architecture or the training algorithm itself Li et al. (2024).

GridSearchCV (Grid Search Cross-Validation) is one of the most widely used and fundamental techniques for hyperparameter optimization. It performs an exhaustive search through a manually specified subset of the hyperparameter space of a learning algorithm. A "grid" of possible parameter values is defined, and the model is trained and evaluated for every combination of these parameters. The combination that yields the best performance on a validation set, typically measured using cross-validation, is then selected as the optimal configuration. While computationally intensive, its primary advantage lies in its completeness in exploring the specified search space, ensuring that the best combination within the grid is found.

Studies have consistently shown that hyperparameter tuning significantly improves metrics such as accuracy, precision, and F1-score, particularly for models like SVM and Logistic Regression Qaiser et al. (2021). Although more advanced methods such as Random Search and Bayesian Optimization have been developed to be more computationally efficient, GridSearchCV remains a popular and robust choice due to its simplicity, effectiveness, and exhaustive nature, making it an excellent baseline for optimization tasks Bergstra and Bengio (2012).

3. Materials and Methods

The dataset for this research was collected from YouTube video reviews of electric vehicles representing four brands within the same market segment in Thailand. Videos were selected based on specific criteria, including a minimum of 50,000 views and at least 1,000 user comments per video. The audio content of these videos was transcribed into text using the CapCut speech-to-text tool, which supports Thai language processing. This process resulted in 40 hours of video content, yielding a corpus of 35,936 sentences and 63,954 words. The data were manually labeled into three sentiment categories—positive, neutral, and negative.

Table 1. Dataset characteristics.

Category	Number of Sentences	Percentage
Positive	11,908	33.14%
Negative	11,952	33.26%
Neutral	12,076	33.60%
Total	**35,936**	**100%**

Table 1 provides a summary of the dataset characteristics.

This section describes the systematic approach undertaken to develop, implement, and evaluate the performance of machine learning models for sentiment analysis of electric vehicle (EV) reviews in Thailand. The methodology encompasses data collection, preprocessing, model development, hyperparameter tuning using GridSearchCV, and performance evaluation, as illustrated in Figure 1.

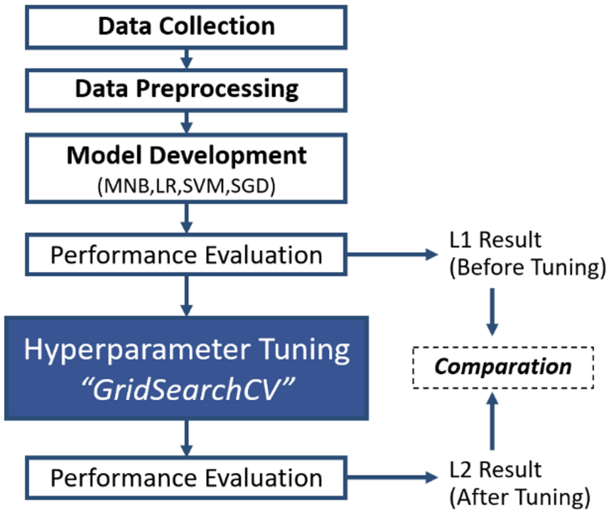

Figure 1. All operational procedures.

3.1 Data Collection

The dataset for this research was collected from YouTube video reviews of electric vehicles representing four brands within the same market segment in Thailand. Videos were selected based on specific criteria, including a minimum of 50,000 views and at least 1,000 user comments per video, ensuring relevance and diversity in the data. The audio content of these videos was transcribed into text using the CapCut speech-to-text tool, as shown in Figure 2, which supports Thai language processing. This process resulted in 40 hours of video content, yielding 35,936 sentences and 63,954 words. The data encompassed consumer opinions on key aspects of EVs, including design, performance, pricing, and safety features, providing a comprehensive foundation for sentiment analysis.

Figure 2. Pulling datasets from websites.

3.2 Data Preprocessing

The raw text data underwent a series of preprocessing steps to prepare it for analysis, as illustrated in Figure 3. Thai word segmentation was performed using two tools: PyThaiNLP, which employs the *newmm* algorithm, and TLex+, which is based on the Hidden Markov Model (HMM). Common Thai stopwords, such as conjunctions and prepositions, were removed to enhance the accuracy of the analysis. The text was then converted into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) method, which quantifies the significance of words within the document corpus. Finally, the data were labeled into three sentiment categories—positive, neutral, and negative—using AI for Thai's sentiment analysis services, ensuring that the dataset was well-structured for machine learning applications.

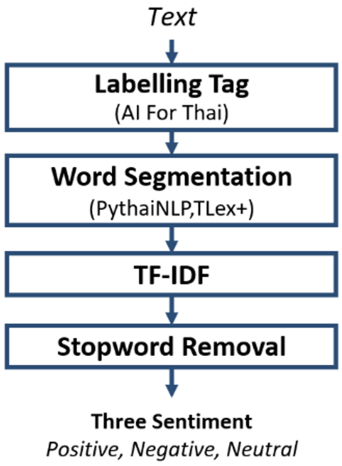

Figure 3. The process of preprocessing.

3.3 Model Development

Four machine learning models were implemented for sentiment classification (see Fig. 4). These models were chosen to represent a diverse range of well-established classification algorithms suitable for text data.

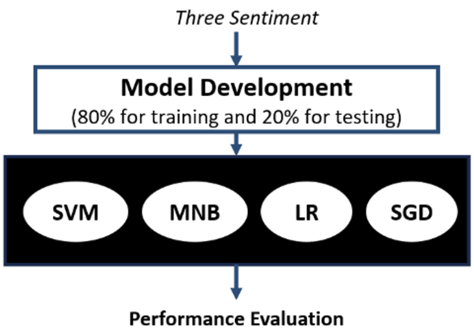

Figure 4. Data training step.

- **Support Vector Machines (SVM):** Known for their effectiveness in high-dimensional spaces, SVMs are ideal for text classification tasks where the feature set (vocabulary) can be very large.
- **Multinomial Naïve Bayes (MNB):** A strong probabilistic baseline for text classification that is computationally efficient.
- **Logistic Regression (LR):** Provides a robust and interpretable linear model for classification.
- **Stochastic Gradient Descent (SGD):** Valued for its computational efficiency and scalability with large datasets.

The dataset was split using the hold-out method, with 80% of the data used for training and 20% reserved for testing. Given the substantial size of the dataset, the hold-out method was deemed a computationally efficient yet reliable approach for model evaluation. While k-fold cross-validation is more robust for smaller datasets, the hold-out method remains a standard and acceptable practice for large-scale text classification tasks.

3.4 Hyperparameter Tuning

To enhance model performance, hyperparameter tuning was performed using GridSearchCV, a systematic approach that evaluates various combinations of parameters to identify the optimal configuration for each model. For Support Vector Machines (SVM), the parameters tuned included kernel type, regularization strength (C), and gamma for non-linear kernels. In Multinomial Naïve Bayes (MNB), the alpha smoothing parameter was adjusted to improve classification accuracy. Logistic Regression required optimization of the regularization strength (C) and penalty type, with options for L1 or L2 regularization (see Fig. 5). For Stochastic Gradient Descent (SGD), tuning focused on learning rate, the number of iterations, and regularization settings Siji George and Sumathi (2020). This process ensured that each model was fine-tuned for maximum predictive accuracy and reliability.

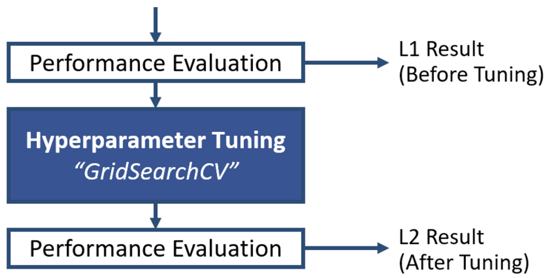

Figure 5. Parameter adjustment step.

3.5 Performance Evaluation

The performance of the machine learning models was evaluated using a set of standard metrics to ensure a comprehensive assessment of their effectiveness in sentiment classification. These metrics included accuracy, which measures the percentage of correctly classified sentiments; precision, which assesses the proportion of true positive predictions among all positive predictions; recall, which evaluates the ability of the model to identify all relevant instances; and the F1-score, which provides a harmonic mean of precision and recall, balancing both measures.

Accuracy measures how well a model classifies the data. It is calculated as the ratio of correct predictions to the total number of predictions in the dataset. A higher accuracy score indicates better overall model performance.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Precision measures a model's ability to make accurate positive predictions. It is calculated as the ratio of correct positive predictions to the total number of positive predictions made by the model. Precision is important when trying to reduce false positives.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Recall, also known as sensitivity or the true positive rate, measures a model's ability to correctly identify all positive cases. It is calculated as the ratio of correct positive predictions to the total number of true positives. Recall is valuable when trying to avoid false negatives.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

The **F1-score** is the harmonic mean of precision and recall. It provides a single metric that balances precision and recall, making it a useful measure when dealing with imbalanced datasets or when there is a trade-off between the two. Together, these performance metrics provide insight into how a model performs on a classification task, allowing a comprehensive assessment of its effectiveness Qi and Shabrina (2023).

$$F1\text{-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

where:

- **True Positives (TP):** Data points correctly predicted by the model compared to the actual labels.
- **False Positives (FP):** Data points incorrectly predicted by the model as positive when they are not.
- **False Negatives (FN):** Data points that are actual positives but were not predicted by the model.

These metrics form the basis for calculating key evaluation measures such as precision, recall, and F1-score, which are used to assess the performance of the models in this study. Each model's performance was compared before and after hyperparameter tuning using GridSearchCV, demonstrating the impact of optimized parameters on predictive accuracy. Additionally, the results of using two Thai word segmentation tools, PyThaiNLP and TLex+, were analyzed to understand their influence on model effectiveness. By comparing metrics across different models and configurations, the evaluation provided critical insights into the strengths and limitations of each approach, highlighting the most suitable methods for sentiment analysis in Thai text data.

4. Experimental Results

The experiment focused on comparing the performance of machine learning models before and after hyperparameter tuning using GridSearchCV. The results demonstrated a significant improvement in the models' performance metrics, including accuracy, precision, recall, and F1-score, after tuning. This highlights the importance of optimizing hyperparameters to achieve maximum efficiency in sentiment classification tasks.

Table 2. Comparison of model performance metrics before and after hyperparameter tuning.

Model	Accuracy (Before Tuning)	Accuracy (After Tuning)	F1-Score (Before Tuning)	F1-Score (After Tuning)
SVM	75.00%	**76.69%**	74.82%	**76.69%**
MNB	71.07%	**72.25%**	70.96%	**73.02%**
LR	73.18%	**74.02%**	73.06%	**74.04%**
SGD	71.01%	**71.76%**	61.07%	**61.76%**

Table 2 provides a comparison of the performance metrics for four machine learning models—Support Vector Machines (SVM), Multinomial Naïve Bayes (MNB), Logistic Regression (LR), and Stochastic Gradient Descent (SGD)—before and after hyperparameter tuning.

The results indicate that SVM achieved the highest improvement, with its F1-score increasing to 76.69% after tuning. This demonstrates SVM's ability to classify sentiments with superior accuracy and consistency when the optimal parameters are applied. Similarly, MNB and Logistic Regression showed considerable performance gains after tuning, reflecting the effectiveness of GridSearchCV in refining their configurations. While SGD exhibited marginal improvements, it remained less effective compared to the other models. These findings underscore the significance of hyperparameter optimization in enhancing machine learning model performance, particularly for complex tasks such as sentiment analysis of Thai text data.

5. Discussion

The findings of this study provide valuable insights into the strengths and weaknesses of each machine learning model for sentiment analysis, as well as the impact of hyperparameter tuning on their performance. Each model exhibited distinct characteristics that contributed to its overall effectiveness.

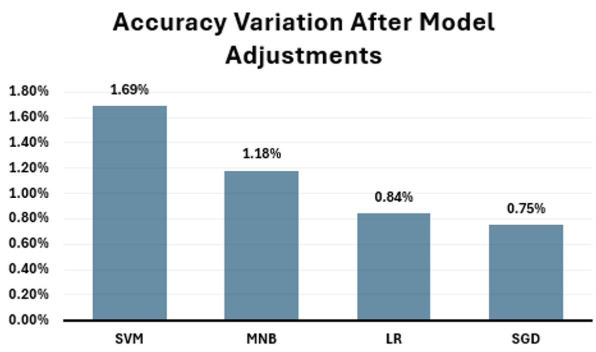

Figure 6. Accuracy variation after model adjustments.

Figure 6 highlights the percentage improvement in accuracy across four machine learning models: SVM, MNB, LR, and SGD. Among these, SVM demonstrated the most significant improvement at 1.69%, followed by MNB at 1.18%, indicating a strong positive response to the adjustments. Logistic Regression (LR) showed a moderate increase of 0.84%, while SGD exhibited the smallest improvement at 0.75%. These results suggest that the adjustments had varying levels of impact on the models, with SVM being the most responsive and SGD the least. This analysis underscores the importance of tailoring adjustments to maximize performance for specific models.

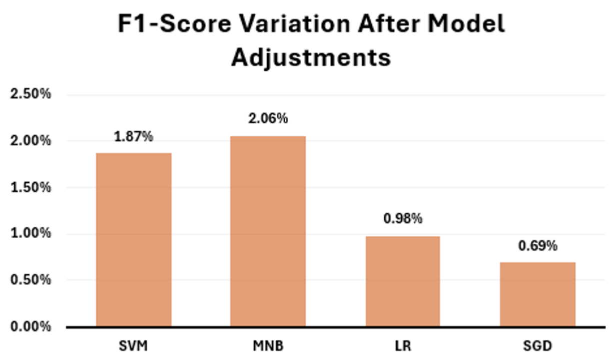

Figure 7. F1-score variation after model adjustments.

Figure 7 illustrates the percentage improvement in F1-scores for the four machine learning models following the adjustments. Among these models, Multinomial Naïve Bayes (MNB) showed the highest improvement at 2.06%, indicating its strong sensitivity to the changes. SVM followed closely with a notable improvement of 1.87%, while Logistic Regression (LR) exhibited a moderate increase of 0.98%. Stochastic Gradient Descent (SGD) showed the smallest variation, with an improvement of 0.69%. These results highlight the varied impacts of the adjustments, with MNB demonstrating the most significant enhancement in performance.

5.1 Strengths and Weaknesses of Each Model

Support Vector Machines (SVM): As noted by Syarif et al. (2016), SVM delivered the highest accuracy and F1-score after hyperparameter tuning, making it the most effective model for sentiment classification in this study. Its ability to maximize the margin between classes contributed to its robust performance. However, SVM requires significant computational resources, particularly when tuning parameters such as C, gamma, and kernel type, which can be time-consuming for large datasets.

Multinomial Naïve Bayes (MNB): According to Özçift et al. (2019), MNB demonstrated strong baseline performance and showed improvements after parameter tuning. It is computationally efficient and particularly suited for text data due to its probabilistic nature. However, MNB assumes feature independence, which might not always align with real-world data, potentially limiting its classification accuracy in complex scenarios.

Logistic Regression (LR): As reported by Ambesange et al. (2020), Logistic Regression exhibited consistent improvements after tuning and offered a balance between computational efficiency and classification accuracy. Its ability to handle both binary and multiclass classification tasks makes it versatile. However, it struggled slightly with non-linear relationships in the data, which may reduce its effectiveness compared to models such as SVM.

Stochastic Gradient Descent (SGD): As discussed in Alibrahim and Ludwig (2021), SGD is efficient for large-scale datasets and provides flexibility with a variety of loss functions. However, its performance in this study was less competitive. The model was sensitive to parameter selection, and despite tuning, the improvements were marginal compared to other models.

5.2 Impact of Hyperparameter Tuning on Model Performance

Hyperparameter tuning using GridSearchCV proved to be a critical step in maximizing model performance. However, this study has several limitations that open avenues for future research, as suggested by the peer review process.

Statistical Significance: To formally validate the impact of hyperparameter tuning, future work should conduct statistical tests, such as McNemar's test, to compare the predictions of the baseline and tuned models. This would provide statistical evidence to support the observed enhancements, a step that was beyond the scope of the current analysis.

Error Analysis: A detailed analysis of misclassification trends using confusion matrices for each model would offer deeper insights into error patterns. This analysis is a key priority for future work.

Comparison of Tuning Methods: This study was limited to GridSearchCV. Future research could compare its performance and computational cost against other optimization techniques such as RandomizedSearchCV or Bayesian Optimization to provide a more comprehensive analysis of the optimization landscape Hutter et al. (2019).

Data Imbalance and Baseline Comparison: The study did not employ specific techniques to handle the moderate data imbalance shown in Table 1. Methods such as SMOTE could be explored in the future. Additionally, a comparison with a non-machine-learning baseline, such as a lexicon-based approach, would further highlight the advantages of the trained models.

5.3 Additional Observations

While the primary focus of this study was to evaluate the performance of various machine learning models and the impact of hyperparameter tuning on sentiment analysis, additional insights emerged that further underscore the complexity of the task. These observations shed light on factors beyond model performance that contribute to the effectiveness and practicality of sentiment analysis, especially in the context of linguistically complex languages such as Thai. The findings highlight the importance of preprocessing techniques, dataset quality, and the interplay between computational efficiency and predictive accuracy.

Influence of Data Preprocessing: The preprocessing techniques employed, particularly Thai word segmentation using PyThaiNLP and TLex+, had a noticeable impact on model performance. Accurate segmentation reduced noise and improved tokenization, which is critical for models such as SVM and MNB that rely heavily on structured input data. The selection of preprocessing tools and techniques proved to be as influential as model selection and tuning in determining the success of sentiment analysis.

Practical Implications: These findings offer actionable insights for practitioners and researchers. SVM is recommended for applications requiring high precision where computational resources are not a limitation. For scenarios with limited resources, MNB and Logistic Regression are practical alternatives that still provide competitive performance. Understanding the trade-offs between accuracy, computational efficiency, and interpretability is key to selecting the most suitable model for a given task.

In summary, hyperparameter tuning proved to be a critical step in maximizing the performance of machine learning models for sentiment analysis. While SVM emerged as the most robust and accurate model, MNB and Logistic Regression also exhibited strong potential, particularly for applications where computational efficiency is prioritized. The study underscores the importance of aligning model selection, hyperparameter tuning, and preprocessing techniques with task-specific requirements, paving the way for more effective sentiment analysis in linguistically complex environments such as Thai. Future research should explore advanced deep learning techniques, real-time applications, and larger datasets to further validate and expand upon these findings.

6. Conclusion

This study explored the effectiveness of machine learning models for sentiment analysis of electric vehicle reviews in Thailand, with a focus on improving performance through hyperparameter tuning using GridSearchCV. Among the models tested, Support Vector Machines (SVM) demonstrated the highest performance, achieving an F1-score of 76.69% after tuning, making it the most suitable for sentiment classification in this context. Multinomial Naïve Bayes (MNB) and Logistic Regression (LR) also exhibited significant improvements, showcasing their viability for tasks requiring computational efficiency and robust classification. Stochastic Gradient Descent (SGD), while less effective overall, provided insights into the challenges of tuning models with high sensitivity to parameter configurations. The results highlighted the critical role of hyperparameter optimization in enhancing model accuracy and reliability, particularly when dealing with complex text data in the Thai language.

Future research could focus on incorporating advanced deep learning models, such as BERT or LSTM, to capture contextual relationships and further improve sentiment classification accuracy. Expanding the scope to include aspect-based sentiment analysis would provide more detailed insights into specific features of electric vehicles, such as performance, design, and safety. Additionally, collecting a larger and more diverse dataset from platforms such as Twitter or Pantip could enhance the models' generalizability and represent a broader range of consumer opinions. Exploring alternative hyperparameter optimization techniques, such as Random Search or Bayesian Optimization, may offer more efficient approaches to tuning. Lastly, developing real-time sentiment analysis applications could provide immediate feedback to manufacturers and policymakers, enabling informed decisions and fostering growth in the EV industry.

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Declaration of AI Use

The authors declare that AI tools were used only to assist in language refinement and content organization. All outputs generated by AI were carefully reviewed and validated by the authors to ensure factual accuracy, originality, and compliance with ethical publication standards.

Declaration of Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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