A Dual-Phase Hyperparameter Tuning Approach for Emotion Detection Using Boosting-Based Machine Learning Algorithms

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ABSTRACT

The purpose of this study is to develop and evaluate a dual-phase hyperparameter tuning approach for enhancing the performance of emotion detection systems using boosting-based machine learning algorithms. The methodology involves data collection and preprocessing, feature engineering, model definition, training, and evaluation. Specifically, the study applies a two-stage optimization process in initial coarse tuning with RandomizedSearchCV followed by fine-tuning with GridSearchCV on models including XGBoost, LightGBM, CatBoost and GradientBoosting. The results showed that LightGBM achieved the highest overall accuracy of 92.20%, followed by XGBoost with 91.47%, GradientBoosting with 91.19%, and CatBoost with 88.23%. Confusion matrix analysis revealed that LightGBM and XGBoost produced more balanced and accurate classifications across the six emotion classes, while CatBoost exhibited higher misclassification rates in challenging classes. In terms of computational efficiency, LightGBM provided the best balance between accuracy and training speed, whereas XGBoost demonstrated the lowest memory usage. GradientBoosting achieved competitive performance but required significantly higher computational resources, while CatBoost achieved the fastest prediction time. Based on the findings, LightGBM was identified as the most suitable boosting algorithm for emotion classification due to its superior balance of predictive performance, efficiency, and reliability. Future studies are recommended to explore hybrid and deep learning approaches, larger datasets, and real-time implementation strategies to further improve emotion classification systems.

Keywords: Emotion Detection, Hyperparameter Tuning, Boosting Algorithms, Text Classification, Natural Language Processing.

INTRODUCTION

In an increasingly digitized and interconnected world, the ability to detect human emotions through computational methods has become critically important across a wide range of applications. Emotion detection also known as affective computing, allows machines to recognize and respond to human emotional states, enhancing user experience, and personalization. As modern societies grapple with rising mental health challenges, detecting emotions through text or social media expressions has also gained prominence in early diagnosis and intervention strategies.

Recent advancements in machine learning (ML) and natural language processing (NLP) have significantly improved the ability of systems to understand emotional cues from textual activity. Alswaidan and Menai (2020) emphasize that emotion recognition from textual data has gained momentum, particularly with the rise of social media where users frequently express emotions in short and unstructured formats. In healthcare, emotion detection is increasingly used for monitoring mental health conditions such as depression or anxiety, especially through analyzing patients' speech or online activity as explained by Prabhudesai et al. (2021). In education, emotion-aware tutoring systems can adapt to students' affective states by improving engagement and learning outcomes based on Gayed et al. (2022).

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The primary objective of this study is to develop and evaluate a dual-phase hyperparameter tuning approach to enhance the performance of emotion detection systems using boosting-based machine learning algorithms. The approach involves a twostage optimization process: coarse tuning using RandomizedSearchCV, followed by finetuning using GridSearchCV, then applied to multiple boosting algorithms such as XGBoost, LightGBM, CatBoost, and GradientBoosting. The goal is to identify the most effective tuning strategy that optimizes predictive accuracy and computational efficiency in emotion classification tasks.

This study contributes to the growing field of affective computing by introducing a dual-phase hyperparameter tuning approach that systematically enhances the performance of boosting-based machine learning algorithms for emotion detection. The proposed methodology offers a balanced and efficient framework for model optimization. The study further provides a comparative analysis of six popular boosting algorithms and demonstrating how tuning strategies impact their classification performance in emotion detection tasks. The approach offers scalability and reproducibility, making it adaptable to other NLP and text classification problems beyond emotion detection.

LITERATURE REVIEW

Review of Related Studies

In the study conducted by Alswaidan and Menai (2020) emotion recognition from textual data has gained significant attention because social media platforms allow users to express their emotions through posts and online interactions. The researchers explained that affective computing improves human-computer interaction by enabling systems to identify and respond to emotional states. Similarly, Khalil et al. (2019) discussed the effectiveness of deep learning techniques in speech emotion recognition using facial expressions, speech, and audiovisual inputs, particularly in healthcare surveillance applications. Furthermore, Yan et al. (2022) explored emotion classification using physiological signals such as EEG and ECG, emphasizing the importance of preprocessing, feature extraction, and multimodal fusion techniques in improving classification accuracy.

The study of Bischl et al. (2023) provided a comprehensive review of hyperparameter optimization methods and compared the effectiveness of RandomizedSearchCV and GridSearchCV in improving machine learning model performance. In addition, Khansa et al. (2025) applied both optimization methods to the XGBoost algorithm for Parkinson's disease classification and found that GridSearchCV achieved better predictive accuracy. Malhotra and Cherukuri (2024) also explained that hyperparameter tuning techniques significantly contribute to improving software quality prediction models by optimizing model generalization and predictive capability. These studies highlighted the importance of parameter optimization in machine learning systems.

According to Sadaf (2023) CatBoost and XGBoost algorithms achieved strong performance in phishing website detection systems by accurately classifying malicious URLs. Similarly, Kumar and Guleria (2024) utilized CatBoost and LightGBM algorithms in AI-enhanced cybersecurity datasets and reported high accuracy in detecting anomalous network traffic. The study of Athanasiou and Maragoudakis (2017) also demonstrated that GradientBoosting is effective in sentiment analysis tasks even in low-resource language environments. These studies collectively support the effectiveness of boosting algorithms in classification and sentiment analysis tasks.

Review of Related Systems

In the study conducted by Al-Zakhali et al. (2024) an XGBoost-based text classification system was developed to improve document classification performance through parallel processing and boosting tree techniques. The researchers highlighted that the system achieved efficient prediction speed and high classification accuracy when handling textual datasets. Similarly, Lokker et al. (2024) implemented a LightGBM-based classification system for biomedical research abstracts and demonstrated that the system could rapidly process high-dimensional textual data while maintaining strong predictive performance.

According to Narasamma and Sreedevi (2021) a CatBoost-based Twitter sentiment analysis system was designed to improve sentiment classification by efficiently handling textual and categorical data from social media

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platforms. In addition, Prabhakar et al. (2019) utilized AdaBoost in a sentiment analysis system for airline Twitter data, where the algorithm improved classification performance by iteratively correcting weak learnererrors. Moreover, Maftoun et al. (2024) developed a HistGradientBoosting system for malicious URL and fake news detection, emphasizing its capability to process sparse and large-scale textual features efficiently. These systems demonstrate the practical applications of boosting algorithms in natural language processing and emotion detection environments.

The study of Gayed et al. (2022) introduced an AI-based emotion-aware tutoring system capable of adapting educational content according to students' emotional states to improve learning engagement and performance. Similarly, Prabhudesai et al. (2021) developed a depression detection and analysis system using deep learning techniques to identify mental health conditions through speech and online activities. Furthermore, Yan et al. (2022) proposed an emotion recognition system using multichannel physiological signals combined with adaptive decision fusion methods to accurately classify emotional responses. These systems highlight the growing importance of emotion detection technologies in healthcare, education, and intelligent human-computer interaction systems.

METHODOLOGY

This study employed a structured machine learning pipeline to improve the performance of emotion detection using boosting-based algorithms. The methodology consisted of five main stages: data collection and preprocessing, feature engineering, model definition, hyperparameter optimization, and model training and evaluation.

Data Collection & Preprocessing

The dataset used in this study was sourced from Kaggle, a reputable platform for data science competitions and dataset sharing. It initially contained a total of 422,746 rows, each comprising two columns: one for the textual content "sentence" and another for the associated emotional label "emotion". A thorough data validation process confirmed that there were no missing values, ensuring the dataset's completeness and reliability for subsequent analysis.

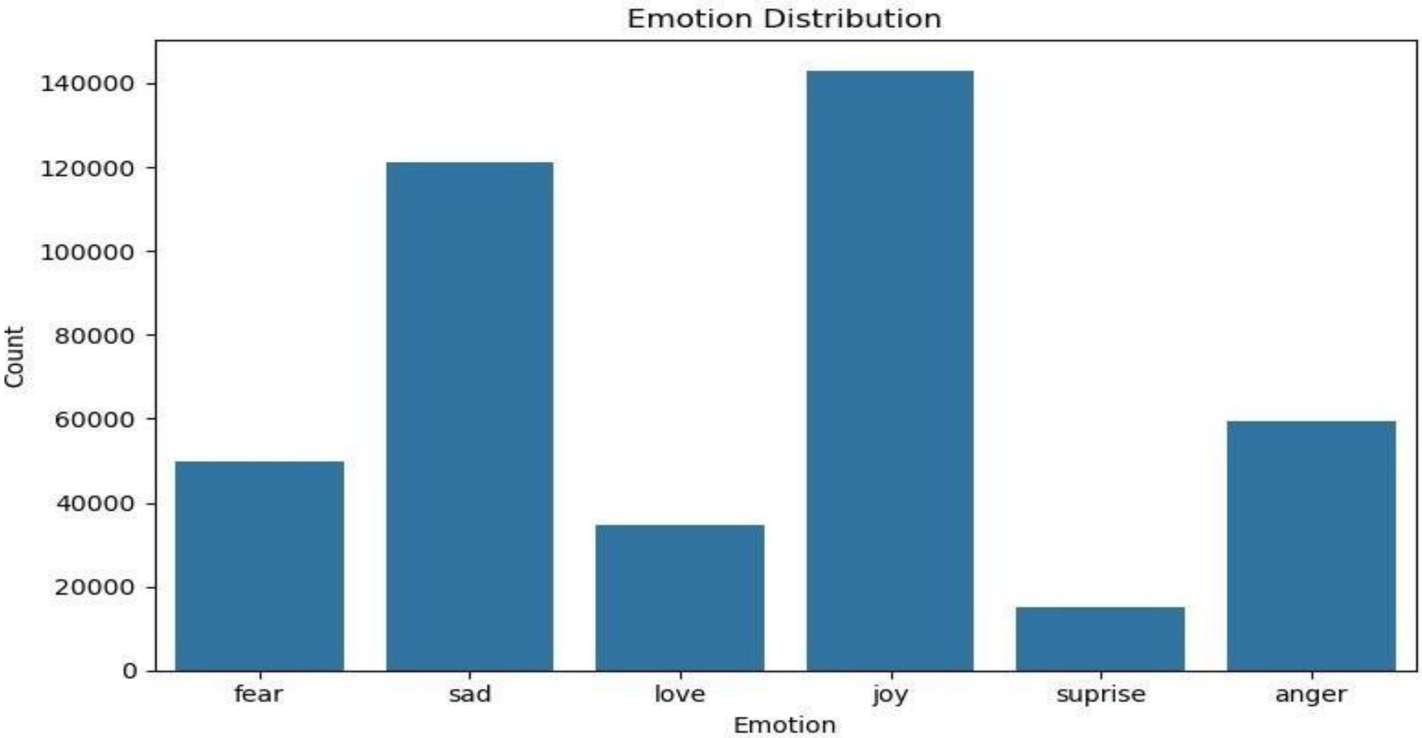

Figure 1. Emotion Distribution based on the dataset.

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As illustrated in Figure 1, the dataset exhibited a significant imbalance in the distribution of emotional categories: 'fear', 'sad', 'love', 'joy', 'surprise', and 'anger'. Most of the instances were labeled as 'joy' (143,067) and 'sad' (121,187), followed by 'anger' (59,317), 'fear' (49,649), and 'love' (34,554). The category with the fewest samples was 'surprise' (14,972). However, an imbalance was observed in the distribution of samples across these classes, which posed a risk of bias during model training.

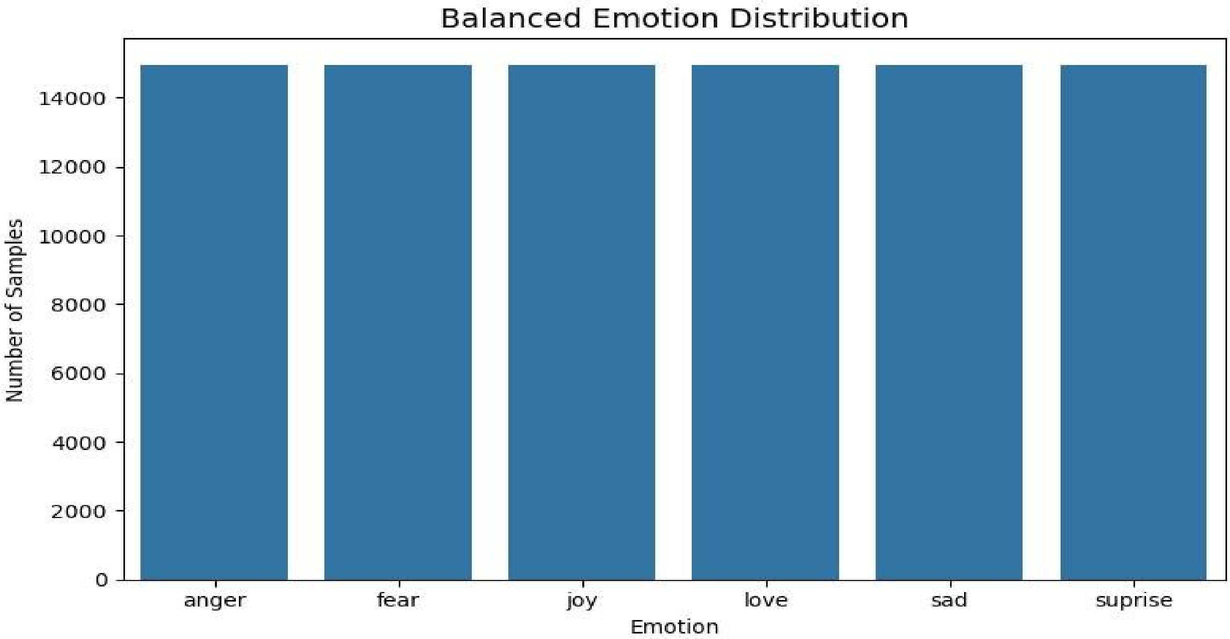

Figure 2. Emotion Distribution after balancing.

Figure 2 illustrates the transformation of the original imbalanced dataset into a balanced form by applying a down sampling technique. Initially, the dataset exhibited highly unequal class distributions, with the number of instances ranging from 14,972 ('surprise') to 143,067 ('joy'). To mitigate this imbalance and prevent model bias, the dataset was down sampled to ensure equal representation across all six emotion categories with each class containing 14,972 instances.

Feature Engineering

Feature engineering plays a critical role in transforming raw data into formats suitable for machine learning algorithms. In this phase, feature engineering involved two main steps:

1. **Target Encoding** - The categorical target variable representing discrete emotion labels was numerically encoded using label mapping. Specifically, the six emotion classes were converted into integer labels as follows: 'anger': 0, 'fear': 1, 'joy': 2, 'love': 3, 'sad': 4, 'surprise': 5. This transformation was implemented using the ‘fit_transform’ method of a label encoder which ensures that the categorical labels are represented in a format compatible with classification models.

2. **Text Vectorization** - The input feature is consisting of textual data and transformed into numerical representations using Term Frequency–Inverse Document Frequency (TF-IDF) Vectorization. According to Triana et al. (2025) the TF-IDF is a well-established technique in natural language processing that converts text into feature vectors while reducing the impact of commonly used words and highlighting more informative terms. The TF-IDF was configured with a `max_features` parameter set to 5000, thereby limiting the feature space to the top 5000 most informative terms across the sentenses.

Model Definition

This study explores the effectiveness of advanced boosting algorithms in enhancing the accuracy of emotion detection systems and occurs the following:

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1. **XGBoost** - The study of Al-Zakhali et al. (2024) applied the TF-IDF-transformed text to efficiently classify documents and leveraging its parallel boosting trees to improve prediction speed and accuracy.

2. **LightGBM** - As explained by Lokker et al. (2024) LighthGBM was employed to classifying the biomedical research abstract, demonstrating rapid training and strong performance, and high-dimensional textual data.

3. **CatBoost** – Integrated with textual features from Twitter posts to improve sentiment classification and benefiting from its native handling of categorical and textual data as mentioned by Narasamma and Sreedevi (2021).

4. **GradientBoosting** – Based on Athanasiou and Maragoudakis (2017) GradientBoosting applied to TF-IDF features for sentiment analysis in Greek, demonstrating that boosting methods remain effective even in low-resource NLP settings.

RESULTS

Hyperparameter Optimization

Phase I – Coarse Hyperparameter Optimization with RandomizedSearchCV

This study adopts a coarse-to-fine tuning strategy, where RandomizedSearchCV is initially employed as a coarse hyperparameter optimization technique. Five boosting-based algorithms were subjected to coarse hyperparameter tuning: LightGBM, XGBoost, GradientBoosting, and CatBoost. Each model was independently tuned with a defined parameter distribution and 5-fold cross-validation (CV).

Boosting Model	Best Parameters
XGBoost	subsample = 0.8, n_estimators = 200, max_depth = 3, learning_rate = 0.2, colsample_bytree = 1.0, random_state = 42;
LightGBM	num_leaves = 31, n_estimators = 100, max_depth = -1, learning_rate = 0.05, random_state=42;
CatBoost	learning_rate = 0.1, l2_leaf_reg = 1, iterations = 200, depth = 7, random_state=42;
GradientBoosting	subsample = 0.8, n_estimators = 200, max_depth = 5, learning_rate = 0.1, random_state=42;

Table 1. RandomSearchCV best parameters results.

Phase II – Fine-Tuning of Parameters with GridSearchCV

GridSearchCV is employed in the second phase for fine hyperparameter optimization. After the initial coarse search, GridSearchCV systematically evaluates combinations of hyperparameters within narrowed ranges to fine-tune model performance. Four boosting-based algorithms were subjected to fine hyperparameter tuning: LightGBM, XGBoost, GradientBoosting, and CatBoost. The tuning process was executed using 5-fold cross-validation (CV) to ensure robustness and generalization of the optimized models.

Boosting Model	Best Parameters
XGBoost	colsample_bytree = 0.9, learning_rate = 0.25, max_depth = 4,n_estimators = 220, subsample = 0.8, random_state = 42
LightGBM	n_estimators = 100, max_depth = -1, learning_rate = 0.07,num_leaves = 31, random_state=42
CatBoost	iterations = 180, depth = 7, learning_rate = 0.12, l2_leaf_reg = 0.5,random_state=42
GradientBoosting	n_estimators = 200, max_depth = 6, learning_rate = 0.08, subsample = 0.8, random_state=42

Table 2. GridSearchCV best parameters results.

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Model Training and Evaluation

XGBoost	**Precision**	**Recall**	**F1-score**	**Support**
0	0.93	0.91	0.92	4491
1	0.91	0.86	0.88	4491
2	0.9	0.87	0.89	4492
3	0.9	0.97	0.94	4492
4	0.96	0.88	0.92	4492
5	0.89	0.98	0.94	4492
accuracy			0.91	26950
macro avg	0.92	0.91	0.91	26950
weighted avg	0.92	0.91	0.91	26950

Table 3. Classification Results for XGBoost.

The XGBoost model achieved an overall accuracy of 91% after applying two-phase hyperparameter tuning using Random Search and Grid Search. The model obtained a macro average precision of 92%, recall of 91%, and F1-score of 91%, indicating strong and balanced classification performance across the six emotion categories. The results demonstrate that the model is effective and reliable in predicting emotions from the dataset.

LightGBM	**Precision**	**Recall**	**F1-score**	**Support**
0	0.91	0.94	0.93	4491
1	0.91	0.87	0.89	4491
2	0.96	0.87	0.91	4492
3	0.9	0.97	0.94	4492
4	0.96	0.89	0.93	4492
5	0.89	0.98	0.94	4492
accuracy			0.92	26950
macro avg	0.92	0.92	0.92	26950
weighted avg	0.92	0.92	0.92	26950

Table 4. Classification Results for LightGBM.

The LightGBM model achieved an overall accuracy of 92% after hyperparameter tuning. It obtained a macro average precision, recall, and F1-score of 92%, with a weighted average of 92% across all metrics. These results indicate strong and well-balanced performance across all six emotion classes, demonstrating the model's effectiveness and reliability in emotion classification.

CatBoost	**Precision**	**Recall**	**F1-score**	**Support**
0	0.92	0.88	0.9	4491
1	0.91	0.84	0.87	4491
2	0.76	0.87	0.81	4492
3	0.9	0.95	0.92	4492
4	0.95	0.77	0.85	4492
5	0.89	0.98	0.93	4492
accuracy			0.88	26950

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macro avg	0.89	0.88	0.88	26950
weighted avg	0.89	0.88	0.88	26950

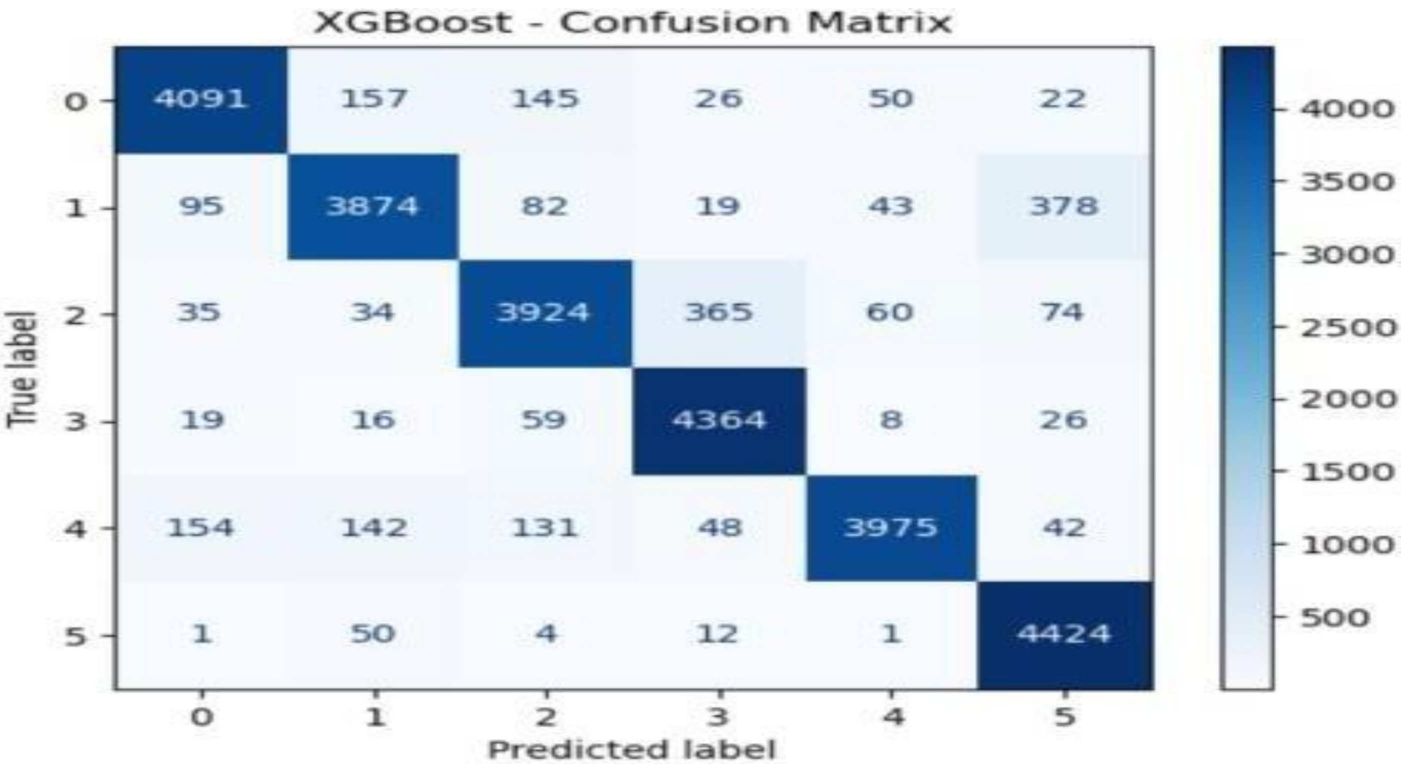
Table 5. Classification Results for CatBoost.

The CatBoost model achieved an overall accuracy of 88% after hyperparameter tuning. It obtained a macro average precision of 89%, recall of 88%, and F1-score of 88%, with similar weighted averages across all metrics. While the model shows generally good performance across the six emotion classes, its results are slightly lower and less balanced compared to XGBoost and LightGBM, particularly in some emotion categories.

GradientBoosting	**Precision**	**Recall**	**F1-score**	**Support**
0	0.92	0.91	0.92	4491
1	0.9	0.85	0.88	4491
2	0.9	0.87	0.89	4492
3	0.9	0.98	0.94	4492
4	0.96	0.88	0.92	4492
5	0.89	0.98	0.93	4492
accuracy			0.91	26950
macro avg	0.91	0.91	0.91	26950
weighted avg	0.91	0.91	0.91	26950

Table 6. Classification Results for GradientBoosting.

The GradientBoosting model achieved an overall accuracy of 91% after hyperparameter tuning. It obtained a macro average precision, recall, and F1-score of 91%, with consistent weighted averages across all metrics. The results indicate strong and stable performance across all six emotion classes, showing that the model is effective and well-balanced in emotion classification.



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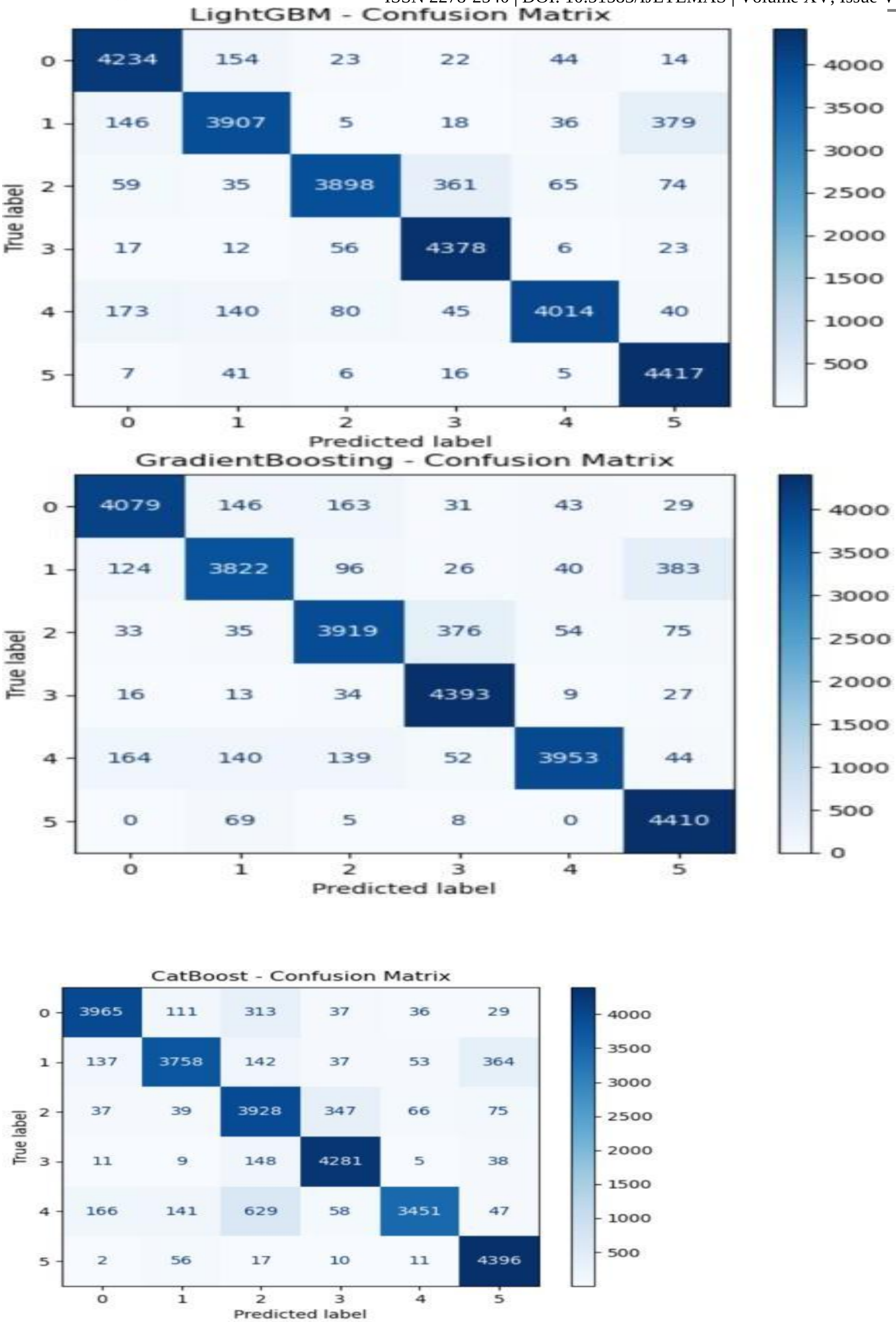

Figure 3. Confusion Matrices of Boosting Models.

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Compared to the XGBoost and LightGBM results, the CatBoost and GradientBoosting models also demonstrate strong overall classification performance, with predictions largely concentrated along the diagonal of the confusion matrices. However, the performance difference between CatBoost and GradientBoosting appears more noticeable, particularly in handling difficult class separations such as the confusion between Classes 4 and 2. While CatBoost exhibits stronger misclassification patterns in these challenging classes, GradientBoosting significantly reduces these errors and achieves more balanced predictions across multiple classes. In contrast, the comparison between XGBoost and LightGBM shows more subtle differences, where both models maintain highly similar error distributions and only slight advantages in specific emotion categories. Overall, GradientBoosting shows a clearer improvement over CatBoost, whereas XGBoost and LightGBM demonstrate more closely matched performance with only marginal differences in overall accuracy and class discrimination.

Boosting Model	**Accuracy**	**Training Time (s)**	**Prediction Time (s)**	**Peak Memory Usage (MB)**
LightGBM	0.922004	20.62865	0.561455	7.824903
XGBoost	0.914731	58.55378	0.206033	2.599951
GradientBoosting	0.911911	1307.367	1.482315	26.79842
CatBoost	0.882338	296.5523	0.069385	11.14843

Table 7. Ranking of Model by Performance Metrics.

Based on the overall performance metrics, LightGBM achieved the highest accuracy among the four boosting models at 92.20%, followed by XGBoost at 91.47%, GradientBoosting at 91.19%, and CatBoost at 88.23%. In terms of computational efficiency, LightGBM maintained a strong balance between accuracy and training speed, requiring only 20.63 seconds for training, while XGBoost required a longer training time of 58.55 seconds but achieved the lowest memory usage at 2.60 MB. GradientBoosting, although competitive in accuracy, showed the slowest performance with a significantly higher training time of 1307.37 seconds and the highest memory consumption at 26.80 MB, making it less efficient for large-scale applications. Meanwhile, CatBoost recorded the fastest prediction time at 0.069 seconds, indicating strong inference efficiency despite having the lowest accuracy among the models. Overall, LightGBM demonstrates the best trade-off between accuracy, speed, and resource utilization, while XGBoost provides a memory-efficient alternative with competitive predictive performance.

DISCUSSION

The findings of this study demonstrate that boosting-based machine learning algorithms are highly effective for multiclass emotion classification, particularly when combined with a two-phase hyperparameter optimization strategy using RandomizedSearchCV and GridSearchCV. The adopted coarse-to-fine tuning approach enabled the models to first explore a broad hyperparameter space and subsequently refine the most promising parameter combinations, leading to improved predictive performance and stronger model generalization. The use of 5-fold cross-validation throughout both tuning phases further enhanced the reliability of the results by minimizing overfitting and ensuring consistent evaluation across different data partitions.

Among the evaluated models, LightGBM achieved the highest overall performance with an accuracy of 92.20%, together with balanced macro-average precision, recall, and F1-score values of 92%. This indicates that the model was able to classify the six emotion categories consistently and effectively without favoring specific classes. The superior performance of LightGBM can be attributed to its leaf-wise tree growth strategy and efficient gradient-based optimization, which allow it to capture complex feature interactions while maintaining

computational efficiency. In addition, LightGBM achieved a relatively short training time of only 20.63 seconds, demonstrating its capability to deliver both high predictive accuracy and fast model training. These characteristics make LightGBM highly suitable for real-time emotion classification systems and large-scale applications where both speed and accuracy are critical.

XGBoost also demonstrated strong and competitive performance, achieving an accuracy of 91.47% with balanced precision, recall, and F1-score metrics. Although its predictive performance was slightly lower than

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LightGBM, the model showed strong capability in handling minority misclassification cases and distinguishing closely related emotion categories. The confusion matrix results revealed that XGBoost maintained stable classification behavior across challenging classes, indicating strong generalization capability. Furthermore, XGBoost recorded the lowest memory consumption among all models at 2.60 MB, highlighting its efficiency in resource utilization. This suggests that XGBoost remains a practical choice for deployment in environments with limited computational resources or memory constraints.

GradientBoosting achieved an overall accuracy of 91.19%, producing performance results that were close to XGBoost. The confusion matrix analysis showed that GradientBoosting significantly reduced several major misclassification cases, particularly between difficult class pairs, resulting in more balanced class predictions compared to CatBoost. However, despite its strong predictive capability, GradientBoosting exhibited the slowest computational performance, requiring more than 1300 seconds for training and consuming the highest amount of memory among the evaluated models. These findings indicate that while GradientBoosting can provide competitive classification performance, its high computational cost limits its practicality for large datasets and real-time implementations.

In comparison, CatBoost achieved the lowest overall accuracy at 88.23%, although it still demonstrated generally good classification performance across the six emotion categories. The confusion matrix revealed higher misclassification rates in certain challenging classes, suggesting that the model had more difficulty distinguishing emotions with overlapping characteristics. Nevertheless, CatBoost recorded the fastest prediction time at only 0.069 seconds, indicating excellent inference efficiency during deployment. This implies that while CatBoost may not provide the highest predictive accuracy in this study, it may still be beneficial in applications where rapid prediction speed is prioritized over maximum classification performance.

CONCLUSION AND RECOMMENDATIONS

This study successfully developed and evaluated a dual-phase hyperparameter tuning approach for emotion detection using boosting-based machine learning algorithms. The findings revealed that hyperparameter tuning has a significant but model-dependent impact on classification performance. Among the evaluated algorithms, LightGBM achieved the highest accuracy, followed by XGBoost and GradientBoosting, demonstrating their effectiveness in handling text-based emotion classification tasks. The study also confirmed that combining RandomizedSearchCV and GridSearchCV provides a systematic optimization process that improves predictive capability and model generalization. However, the results also showed that improper or excessive tuning may negatively affect performance, as observed in the CatBoost model. Overall, the study highlights the importance of selecting appropriate optimization strategies and validation techniques when developing emotion detection systems.

Based on the findings, future researchers are encouraged to apply model-specific tuning strategies and explore advanced approaches such as deep learning and transformer-based architectures to further improve emotion classification accuracy. Educational institutions, healthcare organizations, and developers may also adopt boosting-based emotion detection systems for applications in sentiment analysis, mental health monitoring, and intelligent human-computer interaction. Furthermore, future studies should utilize larger and multilingual datasets, improve preprocessing techniques, and conduct continuous testing and evaluation to ensure system reliability, scalability, and real-world effectiveness.

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Ethical Approval

This study did not get funding from any institution.

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Conflict of Interest

The author declared that there is no conflict of interest.

Data Availability

The data that support the findings of this study are available from the authors upon reasonable request.

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