Optimized EEG-Based Emotion Recognition with FFT and Hyperparameter-Tuned Machine Learning Classifiers

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Abstract. Emotions play a critical part in everyday life since it affects decision-making, behavior, and human interactions with systems. As a result, emotion recognition has become an important topic in affective computing. Among various physiological signals, electroencephalography (EEG) is widely used for emotion recognition because it directly captures brain activity with high temporal resolution and is less susceptible to conscious manipulation than facial expressions or speech, thereby supporting more objective emotion detection. In this study, EEG-based emotion classification was performed using the Fast Fourier Transform (FFT) to extract frequency-domain features from EEG signals. FFT was selected because it efficiently represents spectral characteristics associated with emotional states across EEG frequency bands. Three machine learning classifiers: K-Nearest Neighbor (KNN), Random Forest (RF), and Support Vector Machine (SVM) were employed to classify emotional states. To enhance classification performance, Optuna was applied in the hyperparameter optimization process. Experimental results show that the Optuna consistently improves the performance of all models compared to the default configuration. Among the evaluated models, SVM achieved the best performance with an accuracy of 0.9174, outperforming both KNN and RF. These findings imply that the combination of FFT as feature extraction and hyperparameter optimization using Optuna effectively enhances the performance of EEG-based emotion classification.

Keywords: EEG · Emotion Recognition · FFT · Machine Learning · Hyperparameter Optimization · Optuna.

1 Introduction

Emotion is a fundamental aspect of human experience that profoundly influences cognition, behavior, and social interaction [1]. The ability to accurately recognize and classify emotional states has become increasingly important for a wide range of applications, including mental health monitoring, human-computer interaction, and affective computing [2]. However, traditional emotion recognition methods based on self-reporting or facial expression analysis are inherently

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subjective and susceptible to deliberate concealment, limiting their reliability in practical settings [3].

Electroencephalography (EEG) offers a promising alternative for objective emotion detection, as it directly captures the brain's electrical activity and reflects the underlying neurological processes associated with emotional states [3]. EEG is suitable for detecting emotions since the biological signals associated with emotions are naturally generated by the nervous system and represent emotional states [4]. Unlike behavioral indicators, EEG signals are difficult to consciously manipulate, and therefore provide a more reliable and objective data source for emotion recognition [5]. EEG data is generally represented as multichannel time-series signals that are random, spatially discrete, and temporally non-stationary, in which emotional states manifest as distinct patterns across the delta, theta, alpha, beta, and gamma frequency bands .

Despite its considerable potential, previous research on EEG-based emotion recognition has faced several notable limitations. The difficulties lie in the high complexity and non-stationary nature of EEG signals, rendering feature extraction a complex process and the task of accurately capturing neural patterns daunting.[6]. In previous studies, feature extraction was commonly accomplished using the Fast Fourier Transform (FFT) [7]-[11] and the Discrete Wavelet Transform (DWT) [13]-[15]. Compared to DWT, which decomposes multiresolution and sensitively detects local changes in the signal, FFT provides a more relevant representation of the global spectral distribution for emotion recognition, as emotional states are generally reflected through changes in activity across EEG frequency bands [16]. Furthermore, machine learning classifiers such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF) have been widely employed in this domain [10]-[14], [17]-[19]. RF and SVM classifiers achieved an accuracy of 0.975 on the DEAP and SEED datasets [13], while KNN achieved an accuracy of 0.8333 on the primary dataset recorded from 50 participants [11]. Although these classifiers have demonstrated reasonable performance, their effectiveness depends heavily on the quality and discriminability of the extracted features, and they may struggle to generalize across subjects [17] [18]. Optimization strategies can be leveraged to improve a model's robustness and generalization ability by selecting the most appropriate hyperparameter configuration. Optimal hyperparameter selection can enhance accuracy by tailoring the model's behavior to the characteristics of the data [11] [18]. The Optuna algorithm is an optimization method that adaptively explores the search space through sampling and pruning to efficiently identify more optimal hyperparameter combinations.

However, most existing studies employ classification with default or manually tuned hyperparameters, without systematic optimization tailored to the characteristics of EEG spectral features. This results in significant untapped potential for classification performance. No previous study has investigated the combined effects of FFT-based feature extraction and automatic hyperparameter optimization using Optuna for emotion classification. To address these limitations, this study proposes an EEG-based emotion recognition system that combines

FFT-based feature extraction with optimized hyperparameter machine learning classification. FFT provides a straightforward and computationally lightweight method for transforming raw EEG signals into informative spectral representations. FFT is employed to decompose EEG signals into their constituent frequency components: delta, theta, alpha, beta, and gamma bands, which are well-established correlates of distinct emotional states [5]. Given the structured and relatively low-dimensional nature of frequency-domain EEG features, machine learning approaches are expected to perform robustly while maintaining computational efficiency and interpretability [17] [18]. KNN, RF, and SVM have shown promising performance have been widely validated in biosignal classification tasks. This study also provides a reproducible benchmarking comparison with previous studies on the same dataset, showing that the proposed approach consistently outperforms existing methods under equivalent experimental conditions.

2 Material and Method

This section describes the approach taken in this study, covering each stage of the proposed workflow, starting from data preprocessing through to final classification. As depicted in the graphical abstract in Figure 1, the overall workflow consists of four main steps: data collection using GAMEEMO dataset [14], feature extraction using FFT, hyperparameter tuning using Optuna, and classification using three machine learning models: KNN, RF, and SVM. Each stage plays a specific role in transforming raw EEG signals into discriminative features and optimizing model performance for binary emotion classification. Detailed implementations of each step are presented in the subsections below.

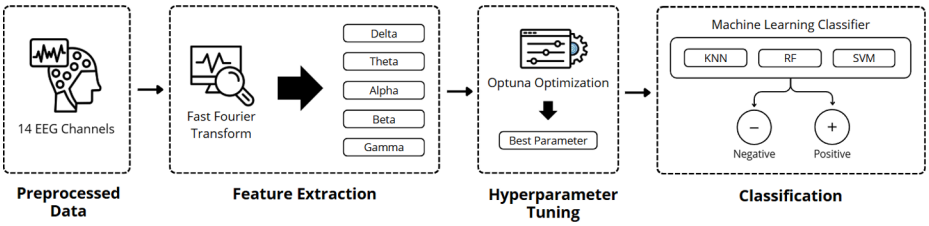


Fig. 1. Graphical Abstract

2.1 Dataset

The publicly available GAMEEMO dataset employed in this study consists of 28 subjects recorded across 14 channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. Signal acquisition was conducted at sampling rate of 128

Hz over a bandwidth of 0.16–43 Hz, encompassing delta, theta, alpha, beta, and low gamma signals. The signals were filtered using a built-in 5th-order sinc filter integrated into the device to remove frequency components above and below the cutoff limits without disturbing the relevant frequency information [14]. This filter is applied to reduce artifacts caused by hand, head, and arm movements, thereby ensuring the acquired EEG signal is more stable and representative for subsequent analysis [20].

2.2 Feature Extraction

Feature extraction is a crucial step in extracting information from raw signals, structuring the data, and making it representative for the classification process. Data originally in the time domain is first segmented into 1-minute intervals, and then each segment is transformed into the frequency domain using the Fast Fourier Transform (FFT), giving a clearer view of the signal's oscillation patterns and frequency component distribution [21]. The EEG signal is subsequently decomposed into 5 distinct signals based on their frequencies [7]: delta (0.16–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–43 Hz) [14]. Features are extracted from each EEG channel into 5 distinct frequency bands [22]. Consequently, the final processed dataset consisted of 448 samples with 70 extracted features.

2.3 Classification

The features obtained through the extraction process were used as input for three machine learning models: KNN, RF, and SVM. KNN determines class labels based on the majority of the k nearest neighbors [23], RF utilizes a set of decision trees, randomly selecting a subset of features at each split to improve model generalization [24], while SVM works by separating classes using the hyperplane with the largest margin to obtain an optimal solution [25]. These three models are then compared to evaluate the best classification performance.

Hyperparameter Tuning To improve classification performance, hyperparameter tuning was used to find the optimal hyperparameter combination. This tuning process leveraged Optuna, working using adaptive search approach via trial-based optimization and each trial evaluated a specific combination of hyperparameters based on a predetermined objective function value [26]. In the optimization process, Cross Validation (CV) is also applied to evaluate the performance of each hyperparameter combination more robustly across multiple data splits, ensuring that the selected parameters are not only optimal for a specific subset but also exhibit better generalization capabilities [21]. Hyperparameter optimization was performed with 150 optimization trials. During the optimization process, model performance was evaluated using 5-fold stratified cross-validation on the training set. Optuna and CV were implemented to find the best hyperparameter combinations for KNN, RF, and SVM. The hyperparameter values tested for KNN, RF, and SVM are shown in Table 1.

Table 1. Tested Hyperparameter for Each Model

Model	Hyperparameter	Tested Value
KNN	neighbors	3 – 15
	weight	uniform, distance
	metric	euclidean, manhattan, minkowski
	p	1 – 3
RF	n_estimators	100 – 500
	max_depth	5 – 30
	min_samples_split	2 – 10
	min_samples_leaf	1 – 5
	max_features	sqrt, log2
SVM	C	1e-2 – 1e2
	Gamma	1e-4 – 1e-1
	Kernel	rbf, linear, poly, sigmoid

2.4 Evaluation

The data was divided into training and test sets in an 80:20 ratio. The training data was used during the hyperparameter optimization process using Optuna with CV. The best model was then evaluated on the test data, which had never been used during either the training or hyperparameter optimization processes. KNN, RF, and SVM were compared and evaluated, both with and without hyperparameter tuning. Each scenario was evaluated using the accuracy metric to measure overall classification performance. The precision, recall, and F1-score metrics were likewise employed to provide a more in-depth analysis of prediction quality, particularly in identifying missed classifications. This combination of evaluation metrics is useful for assessing model performance more comprehensively, not only based on overall accuracy but also on the model's ability to minimize prediction errors.

3 Result and Analysis

The comparison of KNN, RF, and SVM accuracy using default and tuned hyperparameters is presented in Table 2. Without tuning, RF outperformed the other two models. These results suggest that RF, with its ensemble approach that combines multiple decision trees, is more robust to data variations and thus has better generalization capabilities even with default parameters. The SVM accuracy is slightly below that of the RF. The generated hyperplane is quite effective at separating classes but is not fully optimal with default parameters. Meanwhile, KNN yields the lowest accuracy and indicating suboptimal class separation, particularly with the default parameters which may not be optimal during learning.

The classification performance of KNN, RF, and SVM with default and tuned hyperparameters is presented in Table 3. With default parameters, RF and SVM show higher precision than recall for Class 1, meaning that both models make

Table 2. Accuracy Comparison on Tuning Hyperparameters

Model	Accuracy	
	Default	**Tuned**
KNN	0.6333	0.8000
RF	0.7889	0.8333
SVM	0.7667	**0.8889**

relatively accurate Class 1 predictions but miss some actual Class 1 samples. For Class 2, both models obtain higher recall than precision and allowing them to identify more actual Class 2 samples but with some Class 1 samples being classified as Class 2. KNN shows a more balanced precision and recall across the two classes, but its lower F1-scores indicate weaker performance than RF and SVM. After hyperparameter tuning, all three models achieve higher accuracy than their default configurations. For Class 1, KNN and RF obtain higher recall than precision, whereas SVM achieves higher precision than recall. For Class 2, KNN and RF show higher precision than recall, while SVM shows the opposite pattern, with higher recall than precision. Overall, SVM achieves the highest F1-score and accuracy after tuning, while the small performance gap between the two classes reflects its consistent classification performance and lowest misclassification rate.

The best hyperparameter combinations obtained through Optuna for each model are presented in Table 4. KNN achieved its best configuration using distance-weighted neighbors with the Manhattan metric, while RF performed best with a moderate tree depth and `sqrt` feature selection. In contrast, SVM achieved its best performance with a polynomial kernel that enable nonlinear separation of the frequency-domain EEG features. This configuration makes SVM to better capture the complex relationships among features extracted from different EEG channels and frequency bands. Compared with KNN which relies mainly on local neighborhood relationships, and RF which separates the feature space through hierarchical decision tree splits, SVM was able to model the overall structure of the feature space through its decision boundary. The optimized kernel and regularization parameters further provide a suitable balance between

Table 3. Classification Report with Default and Tuned Hyperparameters

Class	Model	Precision		Recall		F1-Score	
		Default	**Tuned**	**Default**	**Tuned**	**Default**	**Tuned**
1	KNN	0.6304	0.7755	0.6444	0.8444	0.6374	0.8085
	RF	0.8095	0.8261	0.7556	0.8444	0.7816	0.8352
	SVM	0.8000	0.9070	0.7111	0.8667	0.7529	0.8864
2	KNN	0.6364	0.8293	0.6222	0.7556	0.6292	0.7907
	RF	0.7708	0.8409	0.8222	0.8222	0.7957	0.8315
	SVM	0.7400	0.8723	0.8222	0.9111	0.7789	0.8913

Table 4. Best Hyperparameter Combination

Model	Hyperparameter	Best Value
KNN	neighbors	4
	weight	distance
	metric	manhattan
	p	2
	leaf_size	48
RF	n_estimators	106
	max_depth	19
	min_samples_split	3
	min_samples_leaf	1
	max_features	sqrt
SVM	C	81.7986
	gamma	0.0085
	kernel	poly

fitting the training data and maintaining generalization, which may explain the stronger performance of SVM on the FFT-based EEG features.

The Optuna optimization history for KNN, RF, and SVM is presented in Figure 2. For KNN, the objective value increases substantially during the early trials and reaches a stable level after approximately 20 trials, with subsequent trials producing only minor improvements. RF shows a similar pattern, with rapid improvement during the initial trials and gradual stabilization at higher objective values. SVM reaches a high objective value within the early trials and remains relatively stable throughout the remaining optimization process. Compared with KNN and RF, SVM shows a more gradual improvement in the later trials before reaching its final objective value. Additional trials in SVM contributed to further refinement of its hyperparameter configuration.

Given the exact same data, the proposed SVM model outperforms previous studies, as shown in Table 5. Through FFT, spectral patterns that were previously difficult to observe in the time domain become clearer and more structured in the frequency domain, making them easier for the model to capture. Additionally, hyperparameter optimization with Optuna and cross-validation helps

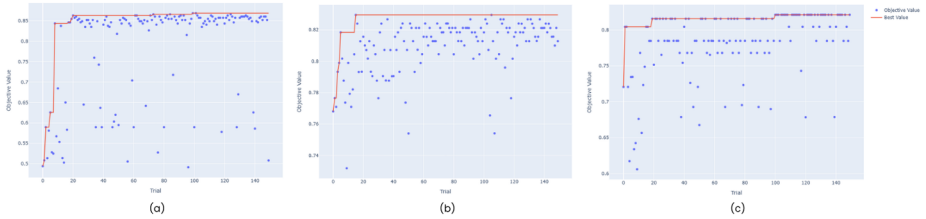


Fig. 2. Optimization Accuracy History of (a) KNN, (b) RF, and (c) SVM

identify the best parameter combination adaptively and objectively, ensuring the model not only performs optimally on the training data but also generalizes well to new data. The SVM emerges as the best-performing model because it can construct a hyperplane with the largest margin that most effectively separates emotions into positive and negative categories.

Table 5. Model Comparison

Reference	Model	Accuracy
[14]	KNN	0.6600
	SVM	0.7250
[15]	BiLSTM	0.7693
This Study	KNN	0.8000
	RF	0.8333
	SVM	**0.8889**

4 Conclusion

Emotion classification using EEG signals demonstrates that the FFT is an efficacious feature-extraction method for generating informative feature representations across five brainwave frequency bands. The classification results show that hyperparameter optimization using Optuna generally improves model performance compared with the corresponding default configurations. The optimized models achieving higher classification accuracy after selecting suitable parameter combinations and SVM emerged as the best-performing model with an accuracy of 0.8889. Despite these promising results, the study is limited to binary emotion classification based on positive and negative valence, while the consistency of the proposed method across individual participants has not yet been evaluated. Future work will therefore focus on more complex multi-class emotion classification and subject-wise performance analysis to further assess the robustness and generalizability of the proposed approach.

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