COMMUNICATIONS IN SCIENCE AND TECHNOLOGY
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Optimization of electromyography (EMG) signal parameters for assistive device control using a convolutional neural network (CNN)

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Article history:
Received: 30 July 2025 / Received in revised form: 3 December 2025 / Accepted: 12 December 2025

Abstract

Facial Electromyography (EMG) signals offer a promising modality for intuitive human-machine interfaces (HMIs). The development of robust control systems, however, remains challenging in view of the inherent complexity, noise susceptibility, and significant inter-subject variability of EMG signals in the facial region. This study addresses these technical challenges by developing and validating an optimized Deep Learning framework for facial gesture recognition. The primary objective of this study is to create a reliable classification model for five essential facial movements: 'Rest', 'Smile', 'Eyebrow Raise', 'Right Lip Movement', and 'Left Lip Movement'. The model will serve as precise control inputs for assistive devices. The proposed methodology employs a systematic workflow comprising signal preprocessing (filtering, normalization, and segmentation) followed by the automated hyperparameter optimization of a one-dimensional (1D) Convolutional Neural Network (CNN). The experimental results demonstrate that the optimized model achieved a classification accuracy of 90% on internal test data, with the learning rate identified as the most critical hyperparameter influencing performance. Furthermore, validation of the model on entirely new participants yielded an accuracy of 71%. While this result underscores the persistent challenge of generalizing across different users, it establishes a reliable baseline. Ultimately, this work provides a validated, optimization-based framework that utilizes low-cost instrumentation, thereby offering a substantial pathway towards more accessible and personalized hands-free assistive technologies to restore autonomy for individuals with severe motor impairments.

Keywords: Assistive device control; deep learning; facial EMG; neural networks; hyperparameters

1. Introduction

As reported by the World Health Organization (WHO) and the World Bank, over one billion individuals globally face significant challenges due to disabilities [1]. Within this demographic, individuals suffering from severe motor impairments caused by stroke, amyotrophic lateral sclerosis (ALS), or muscular dystrophy frequently experience the loss of the ability to use their upper and lower limbs. For these individuals, standard assistive interfaces (such as joysticks) are considered ineffective. Consequently, facial gestures present a vital, hands-free alternative modality for controlling assistive devices, offering the potential to restore autonomy and improve psychological well-being [2–6].

While various biosignals such as electroencephalography (EEG) have been explored for such applications, electromyography (EMG) signals particularly from facial muscles offer a higher signal-to-noise ratio and a more direct correlation with motor intent [7,8]. However, the development of robust facial EMG-based control systems is impeded by several distinct technical and scientific challenges. Facial muscles are characterized by their small size and closely grouped, leading to signal crosstalk where the activity of one muscle group interferes with the sensors of another. Furthermore, EMG signals are inherently non-stationary and susceptible to artefacts, which makes precise gesture classification difficult using conventional processing methods [9].

Existing studies have previously employed a variety of classification techniques to address these issues. However, many researchers rely on manual feature extraction or standard architectures that may not be optimally tuned for the specific characteristics of facial EMG data. The need for a system capable of automatically learning complex features from raw or minimally processed signals while managing the variability inherent in biological data is indisputable.

The objective of this study is to address these gaps by developing and validating a facial movement classification system using a Deep Learning approach. In particular, this research focuses on the facial region for the purpose of classifying five essential gestures intended for device control. The primary contribution of this work is the implementation

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https://doi.org/10.21924/cst.10.2.2025.1758

of a systematic hyperparameter optimization workflow for a 1D Convolutional Neural Network (CNN). By experimentally tuning the model architecture, this study seeks to maximize classification accuracy and investigate the model's generalization capability when applied to new users. Furthermore, this research utilizes a low-cost biosignal instrumentation system to demonstrate that high-performance control can be achieved on a wide scale, thereby enhancing its accessibility.

The remainder of this paper is organized as follows: Section 2 provides the preliminaries and reviews related works in EMG processing. Section 3 details the methodology, including data acquisition, preprocessing, and the CNN optimization process. Section 4 presents the experimental results and discussion with a focus on model performance and validation. Finally, Section 5 concludes the study and outlines future research directions.

1.1. Biosignal-based control systems

In the domain of Human-Machine Interfaces (HMI), biosignals serve as a bridge between biological processes and external devices. Early research extensively explored Electroencephalography (EEG) in relation to this purpose. For instance, studies by Manik et al. [4], Rosemari et al. [5], and Utari et al. [6] successfully utilized EEG signals in combination with classifiers such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Bidirectional LSTM (Bi-LSTM), and Gated Recurrent Units (GRU). While being effective for cognitive-based control, EEG systems frequently are cumbersome and susceptible to environmental noise. In contrast, Electromyography (EMG) signals offer a distinct advantage for motor control tasks due to their ability to directly reflect muscle activation intensity, rendering them more dynamic and suitable for precise gesture recognition [7–9].

1.2. Challenges in facial EMG processing

Previous studies have extensively explored EMG applications for prosthetic control and assistive devices [10], [12–14], [15–22]. However, the application of EMG to the facial region introduces more specific challenges in comparison to limb muscles. The primary technical challenges pertain to the "crosstalk" effect and the similarity of frequency components across various facial gestures [12,15,16,18].

To address this issue, conventional approaches rely heavily on manual feature engineering. Researchers have investigated various time-domain and frequency-domain features, including Root Mean Square (RMS), Power Spectral Density (PSD), Mean Absolute Deviation (MAD), and Variance (VAR) [13,18]. These features are typically fed into conventional algorithms such as K-Nearest Neighbors (KNN), SVM, and Multilayer Perceptron (MLP) [13,18,23,25]. Although methods such as SVM [10] and Fuzzy C-Means [15] have demonstrated potential, their performance relies heavily on the quality of the pre-selected features. The variability in reported accuracies suggests that handcrafted features may fail to capture the complex, non-linear patterns of facial muscle activation across different users [13].

1.3. Deep learning and system optimization

To overcome the limitations of manual feature extraction, machine learning paradigms have shifted towards Deep Learning. It has been demonstrated that neural networks are capable of demonstrating superior capabilities in recognizing complex patterns within biological signals and possess a higher tolerance for noise [26,32–37]. The landscape of EMG processing now includes diverse approaches, such as Radial Basis Networks (RBN) [38], Decision Trees [38,55,56], Wavelet-Based Neural Networks (WNN) [39], Fuzzy Systems [40–42], and various implementations of SVM [38,43–52].

In addition, hybrid systems that integrate multiple algorithms or use classifier fusion have been proposed to enhance robustness [43–45,53,54]. In the pursuit of enhancing system performance, a range of techniques have been explored, including Genetic-Based Machine Learning (GBML) [34,44], multivariate discriminant analysis, and statistical pattern recognition [57,58].

Despite this progress, a significant gap remains: many deep learning models in EMG studies are designed with manually fixed architectures, potentially leading to suboptimal performance. There is a paucity of studies systematically optimizing the hyperparameters of Convolutional Neural Networks (CNN) specifically for facial EMG tasks. This study addresses this limitation by focusing on the automated hyperparameter tuning of a CNN model to effectively handle the complexity and variability of facial EMG signals for assistive device control.

2. Materials and Methods

2.1. Research design and ethics

This study employed an experimental laboratory design focused on the acquisition and classification of facial electromyography (EMG) signals. The protocol involved ten participants, referred to as P1 through P10, who were selected based upon inclusion criteria: aged between 18 and 38 years, in good health, and without a history of neuromuscular disorders.

The research protocol adheres to strict ethical standards involving human subjects. Ethical clearance was granted by the Medical and Health Research Ethics Committee, Faculty of Medicine, Universitas Islam Indonesia, under the approval number 13/Ka.Kom.Et/70/KE/I/2025 on January 24, 2025. All participants provided written informed consent prior to data collection.

2.2. Data acquisition setup

Electromyography (EMG) signals were recorded using an OpenBCI biosensing board. The electrode placement strategy was focused on the facial region to capture distinct muscle activities corresponding to specific commands. As detailed in Table 1, electrodes were positioned on the frontalis and zygomaticus muscles. The data acquisition protocol (visualized in Fig. 1) required each participant to perform the five gestures in a sequence: 15 seconds of active holding, followed by 30 seconds of relaxation, repeated for a duration of 4 minutes for each gesture. The total duration of the recordings was approximately 30 minutes per participant. The research stages comprised the following:

a. Preparation (4 minutes): This protocol involved checking the OpenBCI device, cleaning the participant's skin, and placing electrodes on the forehead, temples, cheeks, and behind the ears according to the specified channel configuration.
b. Gestures 1–5 (4 minutes/gesture): The participants were instructed to perform specific facial gestures: raising both corners of the lips upward for 'Forward'; raising both eyebrows for 'Backward', maintaining a relaxed state for 'Stop'; raising the right lip corner and eyebrow for 'Turn Right'; and raising the left lip corner and eyebrow for 'Turn Left'.
c. Removal (2 minutes): The final stage of the procedure involved the careful removal of the device. Electrodes were detached from the skin, and the corresponding areas were cleansed to remove any conductive gel residue.

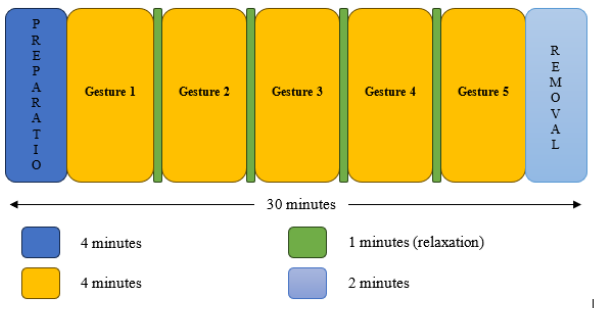

Fig. 1. Data acquisition protocol

Table 1. Gesture input patterns and sensor locations

Command	Gesture	Sensor Placement
Forward	Smile	Forehead, right temple, right cheek, left cheek, and behind both ears
Backward	Eyebrow Raise	
Stop	Rest	
Turn Right	Right Lip Movement	
Turn Left	Left Lip Movement	

2.3. *Proposed methodology and system framework*

To ensure robust classification, this study proposes a systematic pipeline consisting of four main stages: (1) Signal Preprocessing, (2) Data Segmentation, (3) Automated Hyperparameter Optimization, and (4) Model Evaluation. In contrast to conventional methods that are dependent upon fixed architectures, this framework dynamically searches for the optimal CNN configuration.

Raw EMG signals are inherently contaminated by noise and artifacts. The preprocessing workflow, implemented in Python, involves the following steps:

2.3.1. *Filtering*

A 50 Hz notch filter is applied to eliminate power-line interference. Subsequently, a fourth-order Butterworth bandpass filter with a frequency range of 20–120 Hz is employed. The selection of this frequency range is intended to isolate the predominant energy derived from facial muscle activity while removing motion artifacts (<20 Hz) and high-frequency noise (>120 Hz).

2.3.2. *Normalization*

To mitigate amplitude variability between subjects, the filtered signals are normalized using the Z-score method (StandardScaler), thereby transforming the data to have a mean of 0 and a standard deviation of 1.

2.3.3. *Labeling and segmentation*

Continuous signals are labeled based on the timing protocol. The transitional states (also referred to 'Relaxation') are discarded, retaining only the five active classes. The data is then segmented using a sliding window technique employing a window size of 20 samples and a step size of 5 samples (75% overlap). This overlap serves as a data augmentation strategy to enhance model translation invariance.

The core classification engine is a one-dimensional Convolutional Neural Network (1D-CNN), selected for its capacity to automatically extract spatial-temporal features from time-series data. To address the challenge of determining the optimal architecture, this study employed Bayesian Optimization via the Keras Tuner library. The optimization process searches for the best combination of the following hyperparameters: convolutional layers, number of filters (range: 32–128) and kernel size. To prevent overfitting, regularization and dropout rates (range: 0.1–0.5) were employed. The learning rate values of 0.01, 0.001, 0.0001 are to be considered for the optimization algorithm. The term of Dense Layer Units denotes the size of the fully connected layer prior to the output. The objective function for the optimizer is to maximize the validation accuracy over a defined number of trials (40 trials).

The dataset was divided into a training set (80%) and a testing set (20%) using stratified sampling to maintain class balance. The model's performance was evaluated using (1) Internal Testing with the metrics of accuracy, precision, recall, and F1-Score on the held-out test set from familiar participants (P2-P10). (2) External Validation (Generalization): A crucial step in this methodology was the evaluation of the optimized model on data from a completely new user (P1) who was excluded from the training phase. This procedure was employed to assess the system's robustness against inter-subject variability.

3. Results and Discussion

3.1. *Verification of signal preprocessing*

The integrity of the EMG data is paramount for the success of deep learning models. Prior to feed the data into the neural network, the efficacy of the preprocessing pipeline was subjected to rigorous validation. As illustrated in Fig. 2, a segment of the raw EMG signal was captured during the execution of 'Smile' gesture. As expected, the raw signal contained meaningful muscle bursts; however, these were obscured by artifacts and baseline wander.

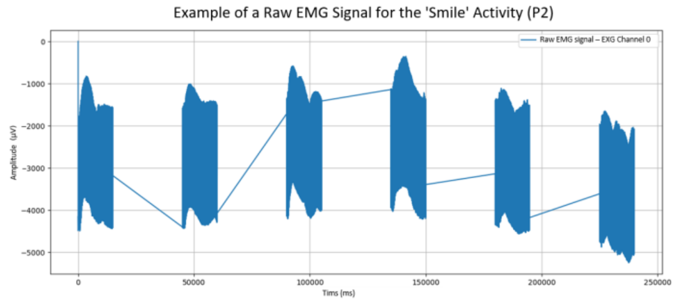

Fig. 2. Example of a raw EMG signal for the 'Smile' activity

The impact of the digital filtering stage was best analyzed in the frequency domain. Fig. 3 presents a comparison of the spectrogram and frequency spectrum between the raw and filtered signals. The analysis revealed a significant artifact in the raw signal: a persistent high-magnitude spike at 50 Hz, indicative of power-line interference. Following the application of the Notch and Bandpass filters, this interference was completely attenuated (red line), while the frequency components relevant to facial muscle activity (20–120 Hz) were preserved. This process of spectral cleaning ensures that the CNN model learns from biological signals rather than environmental noise.

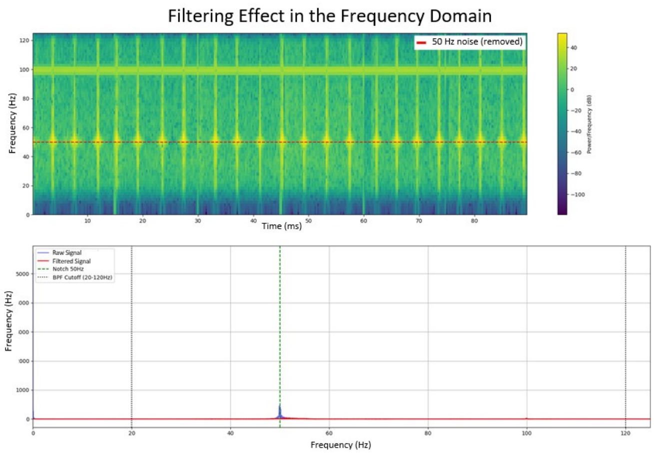

Fig. 3. Filtering effect in the frequency domain

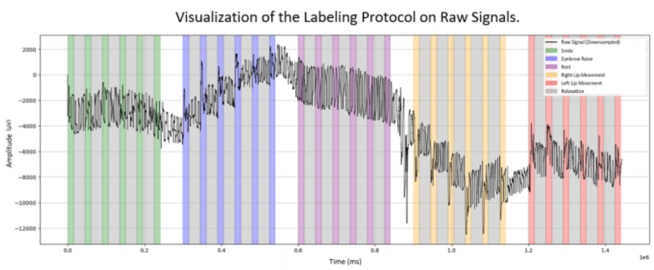

Fig. 4. Visualization of the labeling protocol on raw signals

Moreover, the automated labelling protocol based on the relative time axis successfully categorized the signals. As visualized in Fig. 4, distinct morphological changes in amplitude correspond precisely with the labeled active regions (e.g., 'Eyebrow Raise') versus the relaxation states, thereby confirming the synchronization between the recording protocol and the acquired data.

3.2. Dataset characteristics and normalization

A prevalent challenge encountered in classification tasks is class imbalance, which is potential to introduce bias in the model. The data selection process employed in this study resulted in a highly balanced dataset. As demonstrated in the class distribution analysis (Fig. 5), the five active classes ('Smile', 'Eyebrow Raise', 'Rest', 'Right Lip', 'Left Lip') each contained approximately 35,000 to 36,000 segmented samples. This uniform distribution is imperative in ensuring that accuracy metrics reported subsequently are reliable indicators of model performance, not artifacts of majority class prediction.

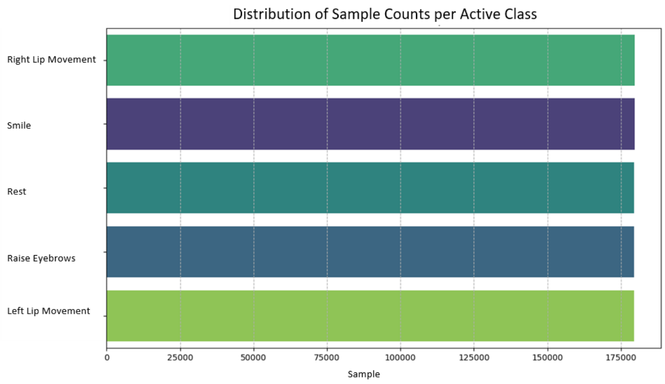

Fig. 5. Distribution of sample counts per active class

Furthermore, the impact of Z-score normalization is critical for model convergence. As illustrated in Fig. 6 the signal undergoes transformation; while the temporal morphology of the muscle activation remains intact, the amplitude scale is standardized. This standardization enables the CNN to assign equal weighting to inputs from both sensor channels, thus preventing channels with inherently higher impedance or amplitude from dominating the learning process.

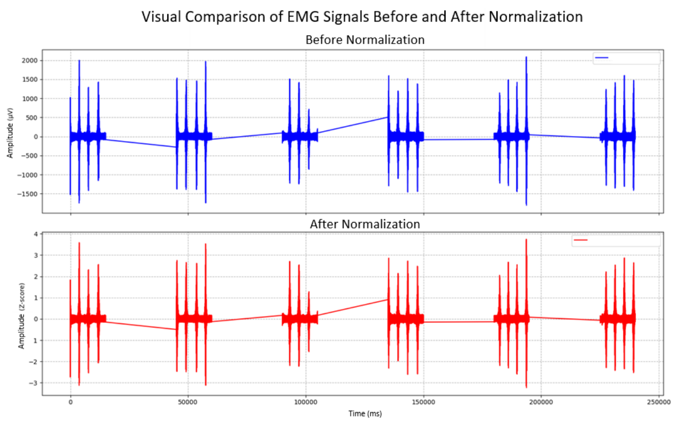

Fig. 6. Visual comparison of EMG signals before and after normalization

3.3. Analysis of hyperparameter optimization

One of the primary contributions of this study is the identification of an optimal CNN architecture through the utilization of Bayesian Optimization. The search process, conducted over 40 trials using Keras Tuner, provided significant insights into the sensitivity of the model to various hyperparameters.

The analysis identified the learning rate as the most dominant factor influencing model performance. As depicted in Fig. 7, trials utilizing a learning rate of 0.001 (represented by the cluster of high-accuracy points) consistently achieved validation accuracies above 85%. Conversely, learning rates that were excessively low resulted in slow convergence, while excessively high rates caused unstable training dynamics, leading to significantly lower accuracy.

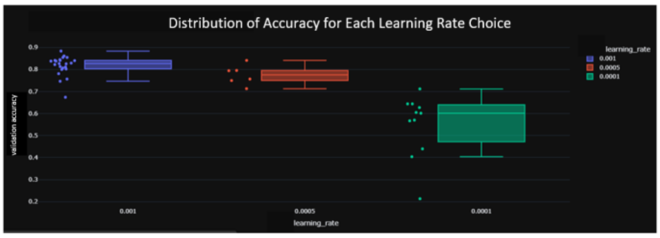

Fig. 7. Distribution of accuracy for each learning rate choice

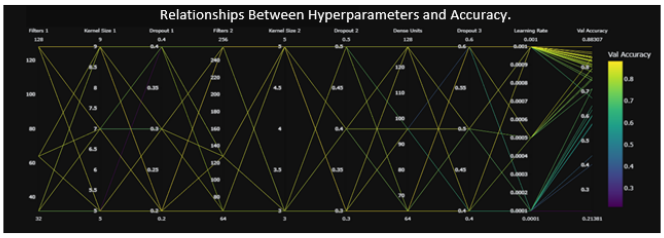

Fig. 8. Plot of relationships between hyperparameters and accuracy

Table 2. Optimal hyperparameters from the keras tuner search

Best hyperparameter results	
filters_1	128
kernel_size_1	9
dropout_1	0.2
filters_2	256
kernel_size_2	5
dropout_2	0.3
dense_units	64
dropout_3	0.6000000000000001
learning_rate	0.001

The relationship between hyperparameters was further visualized in the parallel coordinates plot (Fig. 8). The optimal configuration path (highlighted in yellow) suggests a specific structural preference for facial EMG signals:

a. Filter Complexity: The model benefits from a higher number of filters (128) in the initial convolutional layers to capture diverse feature maps.
b. Regularization: A moderate rate of dropout (0.2) in the early layers is preferred. This finding indicates that while some noise suppression is necessary, excessive dropout at the input stage might result in the loss of subtle information contained within the transient EMG signals.

The most effective trial (Trial 36) resulted in a validation accuracy of 88.31%, as outlined in Table 2, serving as the blueprint for the final model training.

3.4. Internal model performance evaluation

Following the training phase, the final model architecture was evaluated on the held-out test set (20% of the internal dataset). The model achieved a test accuracy of 89.81% with a low-test loss of 0.2536, indicating high confidence in its predictions.

To address the concern regarding reliance on accuracy metrics alone, a comprehensive performance analysis was conducted using Precision, Recall, and F1-Score, as summarized in the classification report (Table 3).

Table 3. Classification report of the model on test data

Final Model Evaluation on Test Data				
Test Accuracy	0.8981			
Loss Test	0.2536			
1122/1122	3s 2ms/step			
Classification Report				
	Precision	Recall	F1-score	Support
Still	0.94	0.94	0.94	7179
Right Lip Movement	0.88	0.87	0.88	7187
Left Lip Movement	0.87	0.89	0.88	7175
Raise Eyebrows	0.95	0.86	0.90	7177
Smile	0.86	0.93	0.89	7186
Accuracy			0.90	35904
Macro avg	0.90	0.90	0.90	35904
Weighted avg	0.90	0.90	0.90	35904

Precision vs. Recall: The model demonstrates exceptional precision for the 'Eyebrow Raise' gesture (0.95), suggesting a low false-positive rate for this command. Conversely, the 'Smile' gesture exhibits high recall (0.93) but slightly lower precision (0.86). Overall Reliability: The Weighted Average F1-Score is 0.90. Given the balanced nature of dataset, this metric confirms that the model performs consistently across all five gestures and is not biased towards any specific class. This reliability is of crucial for assistive devices, where misinterpretation of a 'Stop' or 'Turn' command could have safety implications.

3.5. External validation and inter-subject variability

A critical limitation inherent in many EMG studies is the absence of testing on unseen subjects. To evaluate generalization, this present study validated the trained model on Participant 1 (P1), whose data had been entirely excluded from the training process.

The external validation yielded an accuracy of 70.90%. While being lower than the internal accuracy, this result is significant as it exceeds the chance level (20% for 5 classes) by a substantial margin, proving that the CNN has learned fundamental generalized muscle patterns.

However, the decline in performance highlights the challenge posed by inter-subject variability. A thorough examination of the Confusion Matrix for the new user (see Fig. 9) reveals particular misclassification patterns:

a. Smile vs. Eyebrow Raise: The most significant confusion occurred between 'Smile' and 'Eyebrow Raise'. This finding suggests the presence of a physiological "crosstalk" or similarity in signal activation patterns for this specific user. It is possible that when P1 smiles, there is unintentional co-activation of the forehead muscles, or that their specific "smile" intensity differs from that of the training group (P2-P10).
b. Implications for Control: The model successfully recognized 'Left' and 'Right' movements with higher degree of stability. The observed confusion regarding the 'Smile' gesture indicates that future systems may require a brief calibration phase (transfer learning) for new users to adapt the model to their specific muscle topology.

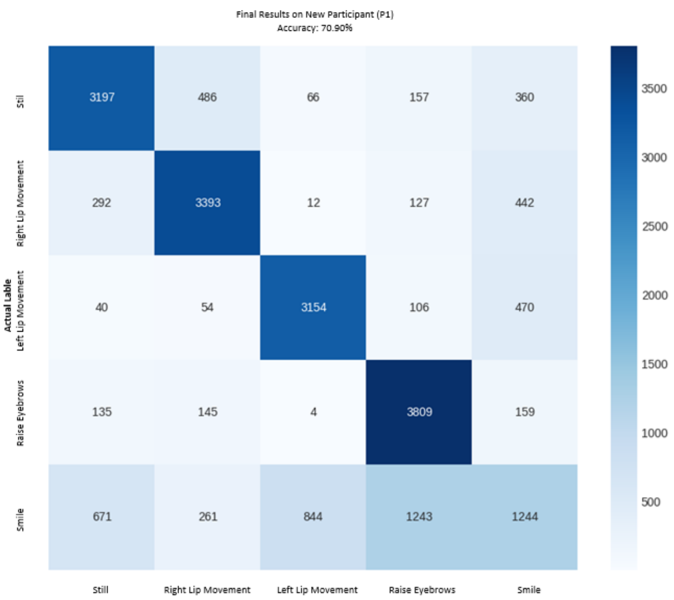

Fig. 9. Confusion matrix of the final model on the new user's test data

3.6. Discussion on deep learning advantages and comparative analysis

The experimental results emphasized the efficacy of the proposed Deep Learning framework in comparison to conventional EMG processing pipelines. In conventional studies as reviewed in the preliminary section, classifiers such as SVM and KNN typically rely on handcrafted features such as Root Mean Square (RMS) or Mean Absolute Value (MAV). While these features are computationally affordable, they frequently discard valuable temporal information and are highly sensitive to amplitude variations caused by electrode shift or skin impedance changes.

The superiority of the optimized 1D-CNN over traditional approaches aligns with findings by Ang et al. [18] and van den Broek et al. [13], who noted that manual feature extraction (such as RMS or MAV) frequently fails to capture the full temporal dynamics of complex signals. While previous studies that employed SVM [10], [43] achieved satisfactory accuracy, they required extensive noise filtering and feature engineering. In contrast, our CNN model demonstrated an ability to learn robust features directly from minimally processed data. This capability of CNNs to extract meaningful patterns without manual intervention is consistent with recent findings in other signal processing domains, as demonstrated by Firdousi & Ahmad [61], who demonstrated that concise CNN architectures can outperform traditional models by effectively learning from raw data characteristics.

In contrast, the optimized 1D-CNN model developed in this study operated directly on the raw (filtered) signal segments. The high internal accuracy of 90% validates that the CNN's convolutional layers successfully learned hierarchical feature representations, automatically identifying complex, non-linear patterns of muscle activation that are difficult to define mathematically. Specifically, the model's capacity to maintain high F1-scores across all five classes indicates that it can effectively distinguish subtle differences between spatially adjacent muscle groups (e.g., differentiating 'Right Lip Movement' from 'Smile'), a common failure point in simpler linear classifiers due to crosstalk.

The internal accuracy achieved at 90% was competitive when compared to similar facial EMG studies, such as the 88% accuracy reported by Hamedi et al. [60] using hybrid neural networks. However, the CNN model optimized by the present study offers simpler end-to-end architecture without the need for complex basis function transformations.

Furthermore, the hyperparameter optimization process revealed that the model requires a specific architectural balance favoring a larger number of filters (128) in the early layers. This finding suggests that facial EMG signals contain a rich variety of low-level features (such as motor unit action potential shapes) that need to be captured before high-level decision-making. The robustness of the model is also attributed to the use of Dropout regularization, which prevents the network from memorizing noise patterns, a critical advantage given the low signal-to-noise ratio of facial biosignals.

Despite a decline in the performance of the new users to 71%, this benchmark remains pivotal. It highlights that, while Deep Learning is capable of achieving effective generalization within a known population distribution, the physiological differences between individuals (e.g., muscle size, skin thickness, and expressive style) introduce a "domain shift."

The decline in performance observed in the new user (70.90%) highlights the persistent challenge of domain shift in biosignal processing. As discussed extensively by Gohel and Mehendale [9], EMG signals are inherently non-stationary and susceptible to physiological variations such as muscle fatigue and skin impedance. The present findings confirm the limitations noted by Hamedi et al. [12], [20], who posited that inter-subject variability significantly alters signal distribution, causing generic models to struggle with new users. This finding indicates that future iterations of this system should incorporate adaptive strategies, such as Transfer Learning or Domain Adversarial Neural Networks (DANN), to align the feature space of a new user with the pre-trained model. This necessity has also been emphasized in recent rehabilitation robotics studies [24].

4. Conclusion

This present study successfully developed and validated a facial EMG-based gesture classification system intended for assistive device control. The implementation of a systematic hyperparameter optimization workflow using Bayesian Optimization, has enabled the identification of an optimal 1D-CNN architecture which is capable of distinguishing five distinct facial movements with a high internal accuracy of 90.0%. The rigorous analysis of classification metrics, including a weighted average F1-score of 0.90, confirms the model's reliability and its capacity to mitigate class bias within a balanced dataset. However, the external validation conducted on an unseen participant revealed a performance decrease to 70.90%, with specific misclassifications observed between the 'Smile' and 'Eyebrow Raise' gestures. This finding quantitatively exposes the challenge of inter-subject variability as the primary bottleneck in EMG-based HMI systems. It demonstrates that, while a generic model can learn fundamental muscle patterns, individual physiological differences significantly impact signal morphology. Future works will focus on the improvement of cross-subject generalization through transfer learning–based domain adaptation, advanced temporal modeling architectures, and expanded participant diversity.

Acknowledgements

The authors would like to express their gratitude to the Islamic University of Indonesia for their provision of support and resources that facilitated the execution of this research. The Electrical Innovation Laboratory at the Islamic University of Indonesia is to be commended for its provision of facilities and equipment that were instrumental in facilitating the efficient process of data acquisition, processing, and analysis. Finally, the authors express their sincere gratitude to the participants who voluntarily dedicated their time and effort to the data collection process. Their contributions made by these individuals were a vital component of the success of this study.

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