Research Paper

Single-Channel EEG Classification for Motor Tasks via Bayesian-Optimized Lightweight 1D CNN

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***Abstract*—Electroencephalogram (EEG) monitoring enables the capture of brain activity and provides insights into motor tasks with applications in rehabilitation, prosthetic control, and Brain-Computer Interfaces (BCI). Traditional classification approaches often rely on complex architectures, limiting usability in resource-constrained settings. This study introduces a 1-dimensional Convolutional Neural Network (1D CNN) optimised using Gaussian-based Bayesian optimisation for classifying single-channel EEG signals. While existing models are deep, requiring extensive pre-and post-processing, the proposed model achieves a trade-off between computational efficiency and classification accuracy. Trained exclusively on a private dataset of 27 individuals performing motor tasks, the model achieved a promising accuracy of 81.82%, demonstrating its potential for practical deployment. The proposed model also outperformed complex pre-trained architectures such as VGG-16 and GoogLeNet by achieving significantly fewer parameters and lower computational demand, making it particularly suitable for resource-limited environments. As an early investigation, this work explores the feasibility of single-channel approaches using lightweight architectures for real-time EEG classification in resource-constrained environments.**

Keywords— EEG, Signal Classification, Motor Imagery, 1D CNN, Bayesian Optimisation, Assistive Technologies, Single-Channel, Resource-Constrained Environments.

I. INTRODUCTION

Electroencephalogram (EEG) signal monitoring offers significant potential in rehabilitation, prosthetic control, Brain-Computer Interface (BCI) research, and accessibility for individuals with disabilities. EEG signals such as frequency bands and artefacts are essential for understanding brain function and assisting with neurological conditions diagnosis. However, existing single-channel deep learning (DL) -based classification methods require extensive data processing, making them resource-intensive and time-consuming [1]. Innovative methods such as Independent Component Analysis (ICA) addressed some challenges, but issues such as longer training times, high computational resources demand, and lack of standardisation persist [2, 3, 4, 5]. Recent advances in machine learning (ML) and DL have introduced more efficient solutions, with 1-dimensional Convolutional Neural Networks (1D CNNs) notable for their capability to capture temporal relationships while reducing computational complexity and address signal variability and low amplitude [6, 7, 8]. These models have been utilised effectively in epileptic seizure detection [9], heart sound classification [10], and emotion recognition [11], though they still encounter some challenges related to data variability and computational demands [9, 10, 11, 12]. To address these issues, this study investigates using a lightweight 1D CNN optimised via Gaussian Process-based Bayesian Optimisation (GP-BO) for single-channel EEG signal classification. With reduced computational requirements and good classification accuracy, the paper seeks to provide further insights for resource-efficient EEG classification models.

II. RELATED WORKS

Existing techniques for EEG signal classification have been explored, focusing on feature extraction and classifiers. Ref [13] used the wavelet-transform-based feature extraction, getting an accuracy of 98.00% with classifiers like SVM, MLP, and KNN. However, this approach faces challenges such as the wavelet basis function sensitivity, high computational cost, and overfitting. Ref [14] proposed pe-trained with VGG-16 on Short-Time-Fourier-Transformed (STFT) EEG signals to address these limitations, achieving 74.20% accuracy. Generalisation, edge effects, and high resource requirements were observed in [14]. Similarly, Ref [15] applied GoogLeNet but faced limited model expressiveness and detection of out-of-distribution data, which negatively impacted practical use. Ref [16, 17, 18] used complex pre-processing with MATLAB toolboxes, limiting their applicability in real-time scenarios. Long Short-Term Memory (LSTM) networks [19, 20] showed improvements in capturing temporal dependencies but did not solve the issues of high computational complexity, long training times, and overfitting. Single-channel EEG studies, Ref [21] transformed signals into a 2D frequency representation, thereby increasing computational demands and interpretability challenges. Ref [22] employed template matching for finger movement classification, while Ref [23] used MLP with backpropagation. Both approaches were limited by dependency on representative templates, scalability issues, and local minima problems [39]. These works highlight the necessity for efficient solutions to solve computational resource demand and long training time challenges. This study proposes a low-resource-demanding 1D CNN capable of processing raw EEG signals without extensive pre-processing. The approach aims to simplify single-channel EEG signal classification while maintaining accuracy and efficiency, validated through experiments on a private dataset.

III. CONTRIBUTIONS

This study presents a novel approach for classifying single-channel EEG signals related to finger movements to reduce computational complexity, minimise training time, and simplify pre-processing. The proposed 1D CNN optimised using Gaussian Process-based Bayesian Optimisation, balances efficiency and performance in resource-constrained environments [24, 25]. With significantly fewer parameters than pre-trained architectures like VGG-16 and GoogLeNet [14, 15], the model achieves 81.82% accuracy on a private dataset of 27 participants performing four limb movement tasks without relying on complex feature extraction.

IV. PROPOSED METHOD

A. Data Collection

This study collected EEG signals from 27 healthy volunteers performing four limb movement tasks: finger open, finger close, wrist clockwise, and wrist counterclockwise. Each participant executed movements in a relaxed state, with recordings lasting 60 seconds per movement. Signals were collected using the 10-20 electrode placement system, explicitly targeting motor-relevant channels (C3, C4, CZ, FZ, and PZ). Among these, the C4 channel, exhibiting the highest signal variation, was selected for further analysis due to its strong relevance to limb motor tasks. Data was acquired using an RMS kit with a 100-foot transmission range and a signal sampling rate of 8–13 Hz, corresponding to alpha band frequencies. Artefacts were carefully removed during preprocessing, and participants adhered to standardised protocols to ensure consistent and high-quality recordings. Using a relatively small private dataset allowed for a focused exploration of lightweight single-channel EEG classification. The dataset enables efficient model development and optimisation by ensuring high-quality signals and task relevance. Though larger datasets may have improved generalisability, this initial investigation prioritises iterative refinement, intending to establish a foundation for future validation and broader applications. This approach supports the in-depth exploration of computational tradeoffs and accuracy, making it highly suitable for real-world deployments in resource-constrained environments.

B. Gaussian process model-based Bayesian optimisation for hyperparameters

This study employs Bayesian Optimisation (BO) to efficiently optimise a base 1D CNN model for EEG signal classification by searching for the optimal hyperparameters in a pre-determined search space. Using a Gaussian Process (GP) as a surrogate function and an acquisition function, BO systematically explores the hyperparameter space, reducing computational costs associated with tuning [24, 25]. The process, implemented via the Optuna library, included 200 exploratory trials to identify hyperparameter importance and 2000 trials to optimise the 1D CNN architecture [24]. Key parameters such as layer depth, kernel size, number of filters, activation functions, learning rate, and dropout rates were evaluated. The optimisation identified a network depth that balanced feature extraction and overfitting prevention while a carefully chosen kernel size captured critical temporal EEG patterns. Efficient use of computational resources was achieved through optimised filter numbers, stable learning rates ensured convergence and dropout regularisation enhanced generalisability. These refinements resulted in a lightweight, high-performing model suitable for resource-constrained environments. See Fig. 1 for the BO flowchart.

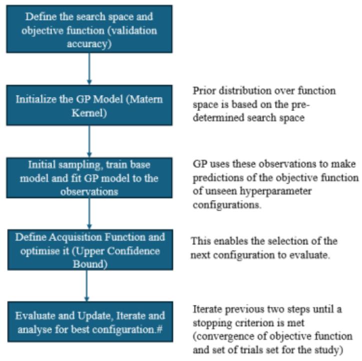

Fig 1. Flow chart of the optimisation process

C. 1D CNN Network architecture

The proposed 1D CNN model sequentially combines convolutional and dense layers to classify EEG signals efficiently. The first convolutional layer applies filters of size 3 to extract salient feature maps; the next is a max-pooling layer to reduce dimensionality. Two convolutional layers process higher-level features are added, with their output further refined by another max-pooling layer. The input is shaped into a 1D vector, passing through dense layers to enhance representation learning for discriminative features [27]. Dropout is applied to prevent overfitting, and the final dense layer outputs multi-class predictions based on a Softmax function. ReLU activation functions are used in hidden layers to allow backpropagation [28]. Compared to pre-trained models like VGG-16 and GoogLeNet [14, 15], the proposed architecture addresses challenges such as excess computational resource needs, information loss and excessive dimensionality reduction due to network depth. The design includes a kernel size of 3, a pooling size of 2, and a dropout rate of 0.4. Table 1 shows a detailed layerwise summary of our ID CNN model. N is the batch size dimension. The pooling size is 2.

TABLE 1: LAYERWISE SUMMARY OF THE PROPOSED MODEL

Layer (Type)	*Output Shape*	*Learnable Parameters*
conv1d_6(Conv1D)	(N, 1022, 32)	128
max_pooling1d_4(MaxPooling1D)	(N, 511, 32)	0
conv1d_7 (Conv1D)	(N, 509, 16)	1552
conv1d_8 (Conv1D)	(N, 507, 16)	784
max_pooling1d_5 (MaxPooling1D)	(N, 253, 16)	0
reshape_1 (Reshape)	(N, 4048)	0
flatten_2 (Flatten)	(N, 4048)	0
dense_4 (Dense)	(N, 128)	518272
dropout_2 (Dropout)	(N, 128)	0
dense_5 (Dense)	(N, 4)	516
Total Parameters	521,252	

Table 1 shows a detailed layerwise breakdown of the proposed model's architecture, including the total number of learnable parameters. There are 521,252 parameters, ensuring a lightweight design suitable for resource-constrained environments.

V. RESULT AND ANALYSIS

A. Results

The experiment used a Python 3 Google Compute GPU Engine on Google Colab. The dataset was split into 80% training and 20% testing to ensure unbiased evaluation. A 5-fold cross-validation was implemented to enhance robustness, and online data augmentation techniques, such as random scaling and shuffling, were applied to improve generalisation [29]. Training checkpoints were utilised.

TABLE 2: COMPARISON OF PROPOSED MODELS AND RECENT WORKS ON THE EEG SIGNAL CLASSIFICATION

Model	**Accuracy (%) (Testing)**	**Memory Usage / Training Time (s)**	**No. of Parameters**
Proposed 1D CNN	81.82 ± 0.08	413.44 KB / 31.11s	521,252
VGG-16 [14]	69.65 ± 0.06	2249.43 MB / 283.74s	17,926,596
GoogLeNet [15]	57.56 ± 0.02	3441.68 MB / 214.57s	28,322,596
Linear Discriminant Analysis (LDA)	75.56 ± 0.07	2285.87 MB / 2.47s	602,116

This is further visualised in Fig 2.

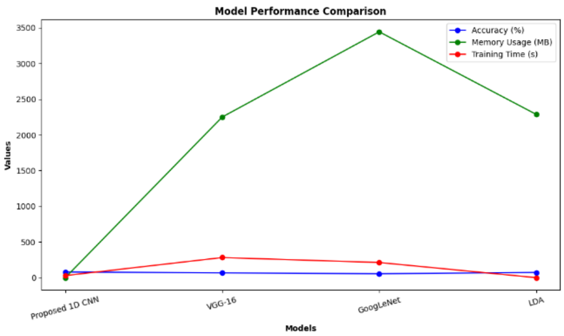

Fig 2. Performance Comparison Chart

B. Result Comparison

Our proposed 1D CNN model achieves a balanced tradeoff between accuracy, computational efficiency, and memory usage, specially designed for single-channel EEG classification. It achieved an average accuracy of 81.82% ± 0.08, effectively demonstrating its ability to discriminate EEG signal classes while maintaining a lightweight design. In contrast, while requiring less training time, the statistical model, Linear Discriminant Analysis (LDA), lacked the scalability and robustness necessary for intricate EEG signal patterns. Our proposed model significantly reduced computational resource demands compared to commonly used pre-trained architectures such as VGG-16 and GoogLeNet, which contain millions of parameters and exhibit higher memory usage. With trainable 521,252 parameters, it showed minimal memory usage (413.44 KB) during training and efficient training times (31.11 seconds). This lightweight design makes the proposed 1D CNN highly effective when deployed in resource-limited environments, where a balance of accuracy and efficiency is a priority. These results reinforce the adaptability of the 1D CNN in handling single-channel EEG classification, offering a practical solution for real-time applications while overcoming the limitations of computationally intensive models.

C. Biomedical Engineering and Clinical Significance

DL-based methods offer faster, more consistent, cost-effective, and more accurate EEG signal evaluations than human interpretation, transforming applications within the biomedical industry. For single-channel EEG classification, advances in hardware, such as optimised electrodes, improve noise management and user comfort for DL algorithms [33]. Furthermore, multi-modal sensors enhance EEG signal classification accuracy by fusing supplementary physiological data [34], while standardised quality metrics support device performance reliability in noisy environments [35]. The proposed Bayesian-optimized 1D CNN is a significant step forward in single-channel EEG signal classification. Its lightweight architecture, combined with the computational resource and accuracy trade-off, makes it suitable for real-time applications in rehabilitation, prosthetic control, and assistive technologies. This capability is beneficial for individuals with severe motor impairments, including those affected by spinal cord injuries or strokes. By directly communicating with prosthetics or wearable devices, these individuals can significantly improve their quality of life and regain autonomy [36].

VI. CONCLUSION

This study highlights the potential of an efficient, low-resource DL model for single-channel EEG classification, showcasing its ability to enhance biomedical device reliability and patient outcomes. The proposed Bayesian-optimized 1D CNN refined using a Gaussian process model estimator, achieves a balance between computational efficiency and performance. While the use of a small private dataset provided a focused and controlled environment for model optimisation, it represents a limitation in terms of generalisability. The proposed 1D CNN model is optimized for sequential data, offering computational efficiency and performance trade-off tailored to the dataset. Comparisons with VGG and GoogleLeNet focus on evaluating their pre-trained feature extraction capabilities rather than fine-tuned performance, providing insights into their baseline effectiveness. Additionally, the 600K parameter count for LDA reflects the complexity of projecting high-dimensional features while preserving class separability, an aspect clarified in our revision. Support Vector Machines (SVM) and other traditional ML methods were not used due to their limitations in handling high-dimensional feature spaces and sequential data. Future work should include larger, more diverse datasets to validate the model and enhance its applicability across broader conditions and populations. Despite these limitations, the study demonstrates the feasibility of deploying lightweight models for real-time applications in rehabilitation, prosthetic control, and assistive technologies, particularly in resource-constrained environments.

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