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Development of EEG based Schizophrenia detection System using CNN Models and Raspberry Pi

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Abstract - *This study presents the development of a portable and real-time EEG-based schizophrenia detection system implemented on a Raspberry Pi 4 platform. Unlike conventional approaches that depend on high-performance computing infrastructure, the proposed system emphasizes low-cost, energy-efficient, and edge-based deployment suitable for clinical and remote healthcare environments. The system acquires EEG signals, preprocesses them to eliminate noise and artifacts, extracts discriminative temporal, spectral, and spatial features, and classifies the signals using lightweight deep learning models. Three convolutional neural network (CNN) architectures—Temporal CNN, Dual-Branch CNN, and Triple-Branch CNN—were implemented and evaluated using publicly available EEG datasets. Experimental results demonstrate that the Triple-Branch CNN model, which integrates temporal, spectral, and spatial representations, achieves superior classification accuracy and improved generalization performance compared to the other architectures. Feature extraction techniques, including Fast Fourier Transform (FFT) for spectral analysis and grid mapping for spatial representation, further enhanced the learning capability of the models. Additionally, deployment using TensorFlow Lite confirmed that advanced deep learning algorithms can be efficiently executed on low-power Raspberry Pi hardware. The proposed system demonstrates the feasibility of integrating multi-feature deep learning with edge AI for accessible neurological disorder detection and highlights its potential for point-of-care diagnosis and remote mental healthcare applications. Future work will focus on validating the system using real-time EEG acquisition in practical clinical settings.*

Key Words: Raspberry Pi 4, Schizophrenia detection, EEG, CNN models, real-time system

1. INTRODUCTION

According to the World Health Organization, schizophrenia affected approximately 23 million individuals worldwide in 2025, corresponding to nearly 1 in 345 people (0.29%) [1]. Schizophrenia is a chronic psychiatric disorder characterized by disturbances in cognition, perception, emotional regulation, and social functioning. In recent years, electroencephalography (EEG) has emerged as a valuable neurophysiological tool for schizophrenia detection, owing to its ability to capture abnormal brain electrical activity associated with the disorder. Previous studies have reported reduced long-range temporal correlations (LRTC) within alpha and beta frequency bands, indicative of cortical hyperexcitability, as well as elevated delta and theta band activity linked to atypical dopaminergic function.

Despite its clinical relevance, EEG analysis remains challenging due to the high dimensionality of the recorded signals and the subtle nature of schizophrenia-related neural alterations. Furthermore, raw EEG data typically require extensive preprocessing procedures, including filtering, artifact removal, and feature extraction, all of which demand significant computational resources and domain expertise. Nevertheless, the integration of machine learning and deep learning methodologies with EEG analysis has demonstrated considerable promise for automated schizophrenia detection, particularly given the increasing availability of high-quality open-access EEG datasets [2].

Most existing EEG-based diagnostic frameworks rely heavily on high-performance computing platforms, thereby limiting their applicability in portable and resource-constrained environments. Consequently, there is a growing demand for low-cost, real-time, and portable diagnostic systems suitable for both clinical and remote healthcare settings. In this context, the present work proposes the development of a real-time EEG-based schizophrenia detection system implemented on the Raspberry Pi 4 platform, with emphasis on computational efficiency, portability, and practical deployment. The proposed framework is designed to acquire EEG signals, perform preprocessing for noise and artifact reduction, extract discriminative features, and classify the signals using lightweight artificial intelligence algorithms. Such a system could facilitate early diagnosis, support remote patient monitoring, and contribute toward the advancement of accessible and scalable mental healthcare technologies.

2. LITERATURE REVIEW

Electroencephalography (EEG) signals are inherently complex, nonlinear, and high-dimensional, rendering manual analysis both challenging and time-intensive. Conventional

machine learning techniques have attempted to address these challenges through the extraction of handcrafted features from EEG recordings. However, such approaches are often limited in their ability to effectively capture the intricate spatial and temporal dependencies embedded within neural signals. EEG-based schizophrenia detection has long been recognized as an established neurodiagnostic approach, complementing other imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and functional magnetic resonance imaging (fMRI), owing to its accessibility, cost-effectiveness, and superior temporal resolution. Nevertheless, the interpretation of EEG signals remains difficult because schizophrenia-related neural alterations are subtle and often concealed within high-dimensional signal patterns. Recent advances in machine learning and deep learning techniques, combined with their capability to process large-scale EEG datasets, have significantly enhanced the potential of EEG as a reliable tool for automated schizophrenia detection [3,4].

Recent studies have demonstrated the effectiveness of convolutional neural network (CNN) architectures for schizophrenia classification. For instance, Latreche et al. proposed a multilayer CNN framework capable of automatically extracting discriminative features from multichannel EEG signals through convolutional, pooling, and fully connected layers, thereby improving classification accuracy [5]. Similarly, Norouzi and Ghasemi demonstrated that CNN-based approaches can effectively detect schizophrenia at both subject-level and single-trial-level EEG analyses, highlighting their ability to identify subtle neural abnormalities [6]. More advanced architectures have integrated CNNs with temporal models such as Long Short-Term Memory (LSTM) networks to better capture temporal dependencies within EEG signals, further enhancing diagnostic performance.

In addition, Sharma et al. proposed an EEG-based schizophrenia detection framework utilizing power spectral density features extracted from multiple EEG frequency bands. Their model employed machine learning classifiers to distinguish schizophrenia patients from healthy individuals, demonstrating that spectral characteristics provide meaningful insights into abnormal neural activity patterns [7]. Signal transformation techniques such as Fast Fourier Transform (FFT) [8], Short-Time Fourier Transform (STFT) [9], and Discrete Wavelet Transform (DWT) [10,11] have also been extensively applied in EEG signal processing for clinical diagnosis. Furthermore, Ranjan et al. reviewed several deep learning methodologies, preprocessing strategies, EEG databases, and architectural design trends relevant to effective schizophrenia detection systems [12].

A notable contribution was presented by V. Rajangam et al., who proposed a bifurcated deep learning framework known as BEFRNet. The architecture combined spatial-temporal EEG features with scalogram-based representations generated using Continuous Wavelet Transform (CWT). The proposed model employed parallel feature extraction mechanisms, integrating CNN-GRU networks for spatial-temporal feature learning alongside a ResNet-based architecture for scalogram image analysis. The extracted features were subsequently fused to form a comprehensive representation, resulting in improved classification performance. The study reported an accuracy of 98.81%, demonstrating that multimodal feature integration can significantly reduce misclassification rates and improve the robustness of schizophrenia detection systems [13]. Additionally, Bandopadhyay et al. conducted a comparative evaluation of multiple deep learning architectures, including DenseNet, ResNet, MobileNet, NasNet, EfficientNet, ConvNeXt, Xception, InceptionV3, and InceptionResNetV2, against state-of-the-art deep neural network models for EEG classification tasks [14].

Despite these advancements, the majority of EEG-based schizophrenia detection frameworks are implemented on high-performance computing platforms, thereby restricting their applicability in real-world and resource-constrained environments. To address this limitation, Sajja and Rooban developed a field-programmable gate array (FPGA)-based system for real-time monitoring and prediction of seizure patterns from EEG signals [15]. Similarly, R. Ranjan et al. proposed a Raspberry Pi-based attention deficit hyperactivity disorder (ADHD) detection system utilizing pretrained deep learning models, which demonstrated promising classification accuracy [16].

The increasing demand for portable, low-cost, and real-time healthcare technologies has motivated the exploration of edge-computing platforms for EEG analysis. The Raspberry Pi 4, characterized by its compact size, low power consumption, and computational efficiency, represents a suitable platform for deploying lightweight deep learning models in edge environments. Its capability to execute optimized CNN models enables localized EEG signal processing, thereby reducing computational latency and minimizing dependence on cloud-based infrastructures. Motivated by these considerations, the present study proposes a Raspberry Pi-based EEG schizophrenia detection system employing a lightweight CNN architecture for efficient and real-time classification.

3. METHODOLOGY

EEG signals utilized in this study were obtained from publicly available datasets, including Kaggle and OpenNeuro [17,18]. These datasets comprise EEG recordings from both healthy individuals and patients diagnosed with schizophrenia, thereby providing diverse data for robust model training and evaluation. Each EEG recording contains multiple channels; however, eight common channels were selected to ensure consistency across datasets. The OpenNeuro dataset provides EEG recordings in ".set" format accompanied by subject-wise labels stored in participant ".tsv" files, where individuals are categorized as either healthy controls or schizophrenia patients. In contrast, the Kaggle dataset contains EEG recordings in CSV format, with subject labels derived from associated demographic files.

To facilitate model training, continuous EEG recordings were segmented into fixed-length windows consisting of 1024 samples with overlapping intervals to preserve temporal continuity. Furthermore, a controlled number of segments per subject were selected to maintain class balance and minimize potential bias. The resulting pre-processed dataset enabled effective extraction of temporal, spectral, and spatial characteristics essential for schizophrenia detection.

Following segmentation, the EEG data underwent a multi-modal feature extraction process. Temporal features were derived directly from the raw EEG signals, while spectral features were obtained using the Fast Fourier Transform (FFT) to capture frequency-domain information. Spatial features were generated by mapping EEG electrode positions onto a structured grid representation. The integration of these complementary feature domains enhances the model's capability to learn complex neural patterns associated with schizophrenia.

Three deep learning architectures were investigated in this study:

1. Temporal CNN Model
2. Dual-Branch CNN Model
3. Triple-Branch CNN Model

3.1 Temporal CNN Model

The Temporal CNN model was designed to learn discriminative patterns directly from raw EEG signals in the time domain. The model accepts input data with dimensions corresponding to 1024-time steps and 8 EEG channels. The architecture consists of sequential one-dimensional convolutional layers that capture temporal variations in brain activity.

The first convolutional layer employs 8 filters with a kernel size of 7 to identify fundamental signal characteristics, followed by a max-pooling layer for dimensionality reduction and salient feature selection. A second convolutional layer with 16 filters and a kernel size of 5 extracts higher-level temporal representations. Subsequently, a global average pooling layer compresses the extracted feature maps into a compact representation, thereby reducing model complexity and mitigating overfitting. A dropout layer with a rate of 0.5 is incorporated to improve model generalization during training. Finally, a fully connected dense layer with sigmoid activation generates the binary classification output, indicating whether the EEG segment corresponds to a healthy subject or a schizophrenia patient. Owing to its relatively simple architecture and computational efficiency, this model serves as a baseline for comparison with more advanced architectures.

3.2 Dual-Branch CNN Model

The Dual-Branch CNN model was developed to simultaneously extract spectral and spatial characteristics from EEG signals. In the spectral branch, EEG signals are transformed into the frequency domain using FFT, resulting in feature representations of dimension 64 × 8. These spectral features are processed through one-dimensional convolutional layers, followed by max-pooling and global average pooling operations to extract informative frequency-domain patterns associated with abnormal brain activity.

Concurrently, the spatial branch converts EEG channel information into a 5 × 5 grid structure that preserves the relative spatial arrangement of scalp electrodes. This representation is processed using two-dimensional convolutional and pooling layers to capture inter-regional spatial dependencies across brain areas.

The outputs from both branches are concatenated and forwarded through fully connected dense layers with dropout regularization to improve robustness and reduce overfitting. The final classification is performed using a sigmoid activation function. Compared with the temporal-only model, the Dual-Branch architecture provides improved performance by jointly learning frequency-based and spatially distributed neural representations.

3.3 Triple-Branch CNN Model

The Triple-Branch CNN model represents the most advanced architecture investigated in this study, integrating temporal, spectral, and spatial EEG representations for comprehensive schizophrenia detection. The model accepts three parallel inputs: raw EEG signals for temporal analysis, FFT-transformed signals for spectral analysis, and spatial grid representations of EEG electrode positions.

Within the temporal branch, one-dimensional convolutional layers with progressively increasing filter sizes ranging from 128 to 1024 are utilized alongside batch normalization and max-pooling operations to capture complex temporal dynamics of brain activity. Similarly, the spectral branch processes frequency-domain features through a sequence of convolutional layers to learn discriminative spectral characteristics of EEG signals.

In the spatial branch, two-dimensional convolutional layers analyse the spatial distribution of EEG activity across different scalp regions using the 5 × 5 electrode grid representation. The outputs from all three branches are subsequently concatenated and passed through multiple dense layers incorporating batch normalization and dropout regularization for effective feature fusion and overfitting prevention. The final layer employs sigmoid activation to produce binary classification outputs.

By integrating temporal, spectral, and spatial perspectives of EEG signals, the Triple-Branch CNN model enables comprehensive feature learning and enhanced discrimination between healthy individuals and schizophrenia patients.

The proposed hardware implementation follows a complete end-to-end processing pipeline that transforms raw EEG recordings into clinically meaningful predictions using deep learning models deployed on an edge-computing platform. The performance of each model was evaluated using

standard classification metrics derived from true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). Overall detection accuracy was subsequently computed to assess the effectiveness of schizophrenia classification relative to healthy control subjects.

4. IMPLEMENTATION STEPS USING HARDWARE AND SOFTWARE PLATFORMS

The proposed schizophrenia detection system was developed and evaluated using both software and hardware platforms. In the software environment, the three deep learning models were initially implemented using Python version 3.14 [19]. Model development and experimentation were performed within the Python Integrated Development Environment (IDE) using several scientific and machine learning libraries, including NumPy for numerical computations, Pandas for data handling, MNE for EEG signal processing, TensorFlow and Keras for deep learning implementation, Matplotlib for graphical visualization, and TensorFlow Lite for model conversion and deployment in the Raspberry Pi environment. The implementation was carried out on laptop systems operating under both Microsoft Windows and Linux platforms for algorithm development and embedded deployment, respectively. Various file formats, including .npy, .npz, .h5, .tflite, .csv, and .set, were utilized throughout the data preprocessing, training, and deployment stages.

On the hardware side, the implementation employed the Raspberry Pi 4 Model B as the primary embedded processing platform [20]. The hardware configuration included a 16 GB microSD card for operating system and project file storage, a 5V/3A power supply, USB keyboard and mouse peripheral, a display monitor, and an external USB storage device for EEG dataset management. This setup enabled the realization of a portable and dedicated schizophrenia detection system suitable for edge-based healthcare applications.

Initially, all three CNN-based models were developed and validated within the Python IDE environment using EEG datasets obtained from Kaggle and OpenNeuro. Subsequently, the trained models were converted for deployment within the Raspberry Pi environment using TensorFlow Lite. Due to hardware constraints associated with the computational complexity of CNN architectures, including limited processing capability, memory resources, and execution speed of the Raspberry Pi platform, only ten EEG datasets could be processed simultaneously during experimental evaluation.

The overall algorithm development and testing methodology is illustrated in the flowchart presented in Figure 1. Initially, the raw EEG datasets obtained from OpenNeuro and Kaggle were cleaned and standardized by selecting only relevant numerical channels and restricting the recordings to eight common EEG channels. The continuous EEG recordings were then segmented into overlapping windows of 1024 samples with an overlap of 512 samples. This segmentation strategy increased the effective number of training samples while enabling the models to learn localized temporal patterns within brain activity signals.

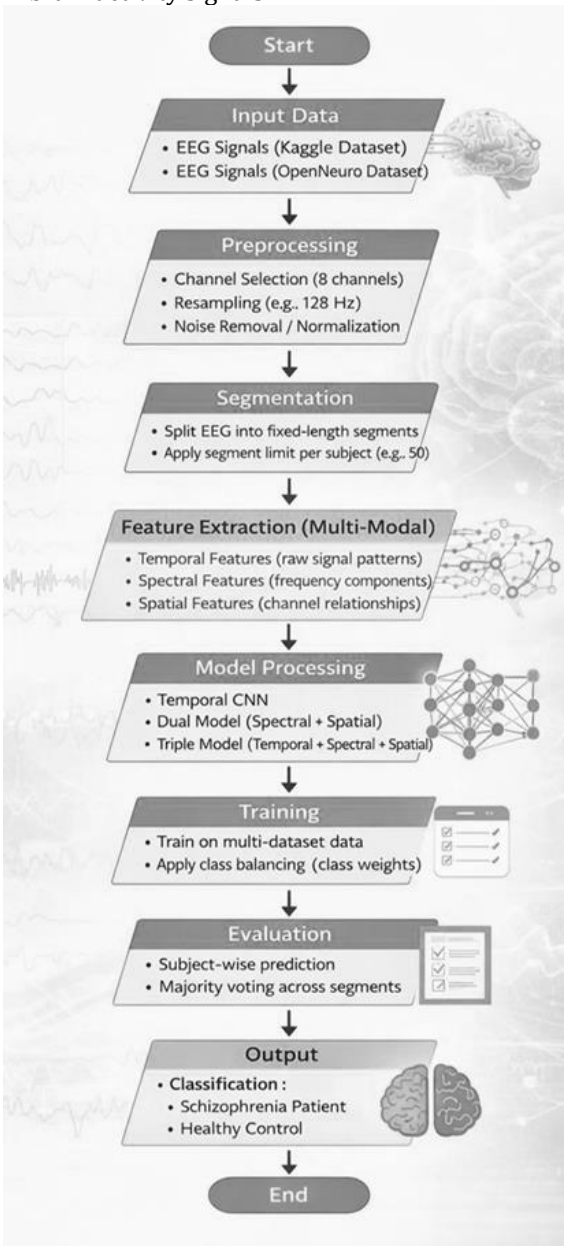

Fig-1: Flow chart of the Raspberry Pi based schizophrenia detection system

From each segmented EEG window, three distinct categories of features were extracted. Temporal features were directly obtained from the raw EEG signals to preserve time-domain information. Spectral features were generated using the Fast Fourier Transform (FFT), which transformed the signals into the frequency domain to capture discriminative brain-wave characteristics. Spatial features were derived by mapping EEG electrode channels onto a 5 × 5 grid structure representing the spatial organization of scalp regions.

Subsequently, all extracted features were normalized using the mean and standard deviation computed from the training dataset. This normalization ensured a consistent data distribution and improved training stability and convergence. The same normalization parameters were applied during testing and deployment phases to maintain consistency across the complete processing pipeline.

During the training phase, the three proposed models were trained using the processed EEG data. The training process employed the Adam optimization algorithm together with binary cross-entropy loss for binary classification. To address class imbalance, class-weighting techniques were incorporated during training. Furthermore, early stopping criteria were utilized to minimize overfitting and preserve the best-performing model parameters.

Following training, all models were evaluated using independent test datasets and performance metrics such as classification accuracy and loss values were computed and comparatively analysed. The training outputs of the three proposed models are illustrated in Figures 2–4, while the overall testing performance is presented in Figure 5. A comparative analysis of the classification accuracies achieved by the proposed models is shown in Figure 6, and the corresponding inference results are summarized in Table 1.

The trained models were initially stored in the .h5 format and subsequently converted into TensorFlow Lite (.tflite) format [21]. This conversion significantly reduced model size and optimized execution efficiency for deployment on resource-constrained embedded platforms such as the Raspberry Pi. The generated TensorFlow Lite models, together with preprocessing parameters including normalization statistics, were transferred to the Raspberry Pi system. Model execution on the embedded device was performed using the TensorFlow Lite runtime interpreter, enabling efficient on-device inference.

During the inference stage, incoming EEG samples underwent the same preprocessing operations used during training, including segmentation, normalization, FFT transformation, and spatial mapping. The processed inputs were then provided to the TensorFlow Lite models for real-time or near real-time classification. Finally, the system generated output predictions indicating either “Healthy” or “Schizophrenia Risk,” accompanied by an associated confidence score. Additionally, predictions from multiple models could optionally be combined using ensemble techniques such as majority voting or probability averaging to improve overall classification reliability and robustness.

5. RESULTS AND DISCUSSION

Initially, the system loads and displays dataset information, including participant metadata such as subject identification number, subject group (patient or healthy control), session details, gender, and age. A total of 81 subjects were included in this study, comprising 60 subjects for training and 21 subjects for testing. Following segmentation, the dataset produced 1240 training segments and 360 testing segments, where each segment possessed dimensions of (1024, 8), corresponding to temporal samples and EEG channels, respectively.

Analysis of the dataset revealed class imbalance between schizophrenia patients and healthy controls. To mitigate this issue, class-weighting techniques were incorporated during model training to ensure balanced learning across both categories. During each training epoch, performance metrics including training accuracy, validation accuracy, and loss values were computed and displayed within the processing interface for monitoring model convergence and generalization.

Each proposed model was trained for a maximum of 30 epochs using a batch size of 16, while validation was performed using the independent test dataset. Upon completion of training, the trained models were stored in .h5 format for subsequent conversion into TensorFlow Lite format suitable for embedded deployment. The performance of the three proposed architectures—Temporal CNN, Dual-Branch CNN, and Triple-Branch CNN—was evaluated to assess their effectiveness in detecting schizophrenia from EEG signals.

The training and testing performance curves of the Temporal CNN, Dual-Branch CNN, and Triple-Branch CNN models are illustrated in Figures 2–4, respectively. Figure 5 presents a comparative analysis of all three models along with their corresponding classification accuracies.

The Temporal CNN model, which utilizes only raw time-domain EEG signals, served as the baseline architecture. This model achieved moderate classification performance by learning fundamental temporal patterns associated with brain activity. The Dual-Branch CNN model demonstrated improved performance by integrating spectral and spatial representations of EEG signals. By incorporating frequency-domain characteristics together with spatial relationships among brain regions, the model was able to learn more discriminative neural representations compared with the temporal-only architecture.

Among the evaluated models, the Triple-Branch CNN architecture achieved the highest classification accuracy. This superior performance can be attributed to its ability to simultaneously integrate temporal, spectral, and spatial EEG features, thereby leveraging complementary information from multiple feature domains. The combined feature fusion strategy enabled the model to learn more comprehensive and discriminative representations of schizophrenia-related EEG patterns. Comparative analysis of the three architectures revealed a progressive improvement in performance from the Temporal CNN model to the Dual-Branch model and ultimately to the Triple-Branch model. These findings demonstrate that multimodal feature integration significantly enhances the accuracy and robustness of EEG-based schizophrenia detection systems. Overall, the experimental results confirm that the Triple-Branch CNN architecture provides the most effective

framework for schizophrenia classification in the proposed system.

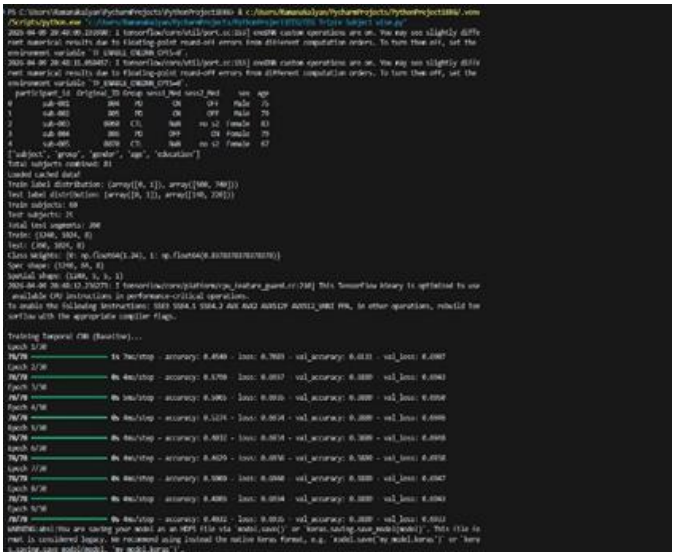

Fig-2: Temporal model output

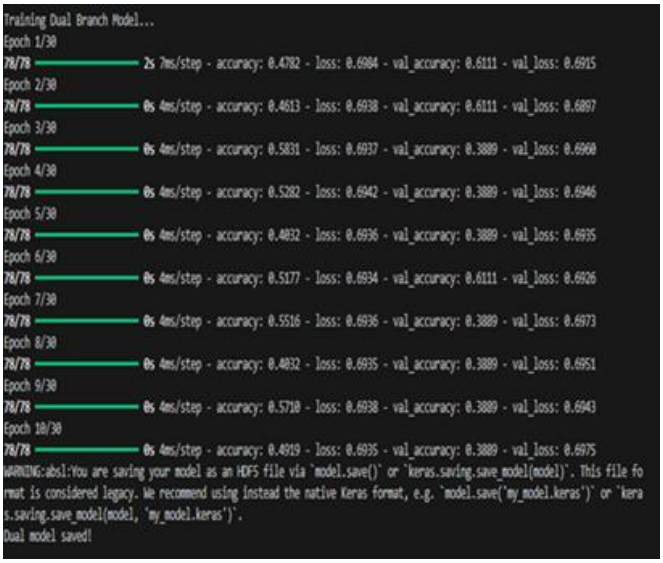

Fig-3: Dual Branch model Output

Fig-4: Triple Model Output

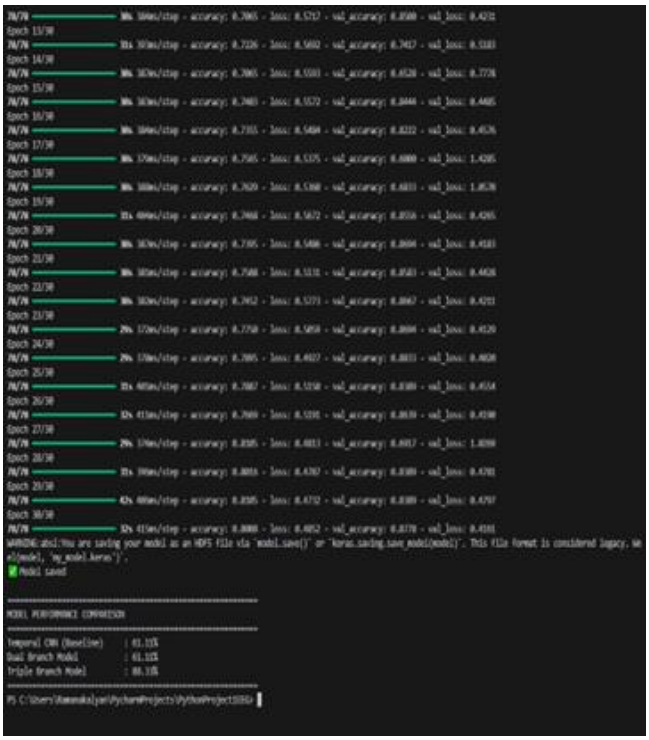

Fig-5: Testing output of all the three models

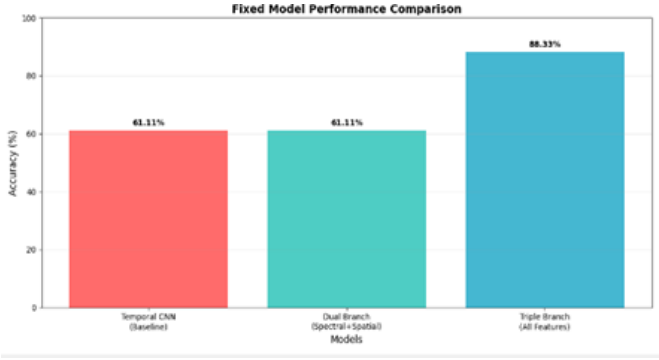

Fig-6: Accuracy Comparison of the proposed models

Table 1: Performance Comparison of the proposed models

Name of the model	Features	Accuracy (%)	Description
Temporal CNN (Baseline)	Temporal features (raw EEG signals)	61.11%	This model analyzes only time-domain EEG signals. It provides basic performance but lacks deeper insights from frequency and spatial information.
Dual Branch Model	Spectral + Spatial features	61.11%	This model combines frequency-domain (FFT) and spatial channel relationships. However, it does not significantly improve accuracy compared to the baseline.
Triple Branch Model	Temporal + Spectral + Spatial features	88.33%	This model integrates all three feature types, capturing complete EEG information. It achieves the highest accuracy, showing the effectiveness of multi-modal learning.

For embedded deployment evaluation, the trained models and associated script files were transferred to the Raspberry Pi 4 platform and tested using 10 EEG samples belonging exclusively to the schizophrenia patient class. The comparative inference outputs are shown in Figure 7, highlighting the differences in prediction confidence among the three architectures.

The experimental results demonstrated an overall classification accuracy of 100% for all three models on the selected test samples, indicating that all 10 EEG samples were correctly classified as "RISK" (schizophrenia cases). However, a detailed analysis of the confidence scores revealed substantial differences in prediction reliability among the models.

The Temporal CNN model correctly classified all samples but generated confidence scores of approximately 51% for every prediction. These results indicate that the model predictions were only marginally above the binary decision threshold, reflecting significant uncertainty and limited reliability when relying solely on temporal EEG information. Similarly, the Dual-Branch CNN model, which combines spectral and spatial representations, also produced confidence scores close to 51% despite correctly identifying all samples. This suggests that the integration of spectral and spatial features alone may not provide sufficiently robust discriminative information for highly confident schizophrenia classification. In contrast, the Triple-Branch CNN model demonstrated significantly improved confidence levels, with prediction confidence values ranging from 66% to 75% across the evaluated samples. These results clearly indicate that the simultaneous integration of temporal, spectral, and spatial EEG representations provides substantially stronger evidence for classification, thereby enabling more reliable and confident predictions. The observed improvement confirms that multimodal feature fusion enhances the discriminative capability of the deep learning framework and improves the robustness of schizophrenia detection in practical deployment scenarios.

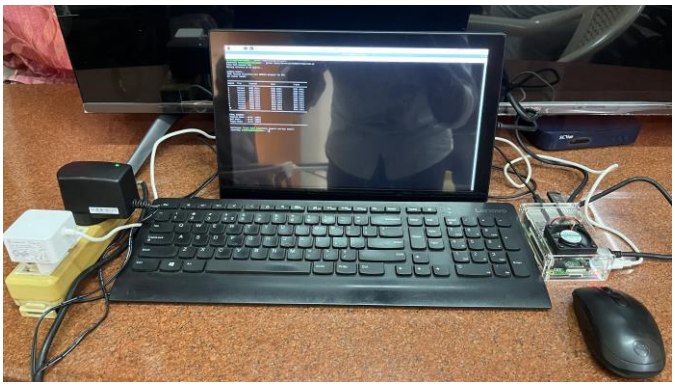

Fig-7: Output of the three proposed models in the Raspberry Pi 4 system

6. CONCLUSION

This study successfully presents a deep learning-based framework for schizophrenia detection using EEG signals implemented on a Raspberry Pi 4 platform. By utilizing publicly available EEG datasets together with a low-cost and energy-efficient embedded hardware system, the proposed approach demonstrates the feasibility of developing a portable and practical schizophrenia detection system based on conventional EEG recordings.

The proposed framework incorporates and evaluates three convolutional neural network architectures, namely the Temporal CNN model, the Dual-Branch CNN model, and the Triple-Branch CNN model. Experimental results demonstrate that the Triple-Branch architecture, which integrates temporal, spectral, and spatial EEG features, achieves superior classification performance and improved generalization capability compared with the other proposed models. The integration of complementary EEG representations enables the model to learn more

discriminative neural patterns associated with schizophrenia.

Furthermore, the incorporation of feature extraction techniques such as Fast Fourier Transform (FFT) for spectral analysis and spatial grid mapping for electrode representation significantly enhances the effectiveness of the learning process by providing richer information from EEG signals. The successful deployment of the trained deep learning models on the Raspberry Pi platform using TensorFlow Lite further demonstrates that computationally efficient deep learning solutions can be executed effectively on low-power edge devices.

The proposed system offers several practical advantages, including portability, low cost, reduced computational requirements, and suitability for real-time healthcare applications. Overall, this work highlights the significance of multimodal feature learning and edge artificial intelligence technologies in advancing neurological disorder detection systems. Future work will focus on validating the proposed framework using real-time EEG acquisitions and extending the system toward point-of-care deployment in remote and resource-constrained healthcare environments.

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Dr. Nedumaran Damodaran retired as Professor and Head of the Central Instrumentation and Service Laboratory at University of Madras. His research interests include biomedical signal and image processing, biometric image processing, and NEMS and MEMS sensor design.