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Deep Learning Framework for ECG and EEG Signal Classification in Smart Healthcare Systems

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Abstract- Biomedical signal analysis is a key component of current healthcare systems for the diagnosis of cardiovascular and neurological diseases through Electrocardiogram (ECG) and Electroencephalogram (EEG) signals. This study aims to build an automatic deep learning-based classification system for ECG and EEG signals to facilitate the early diagnosis of cardiovascular and neurological disorders and to enable real-time monitoring in health care. Our approach employs two publicly accessible biomedical datasets, the MIT-BIH Arrhythmia dataset for ECG signals and the Epileptic Seizure Recognition dataset for EEG signals. Data preprocessing includes data cleaning, normalization, reshaping, exploratory data analysis, and data splitting into training, validation, and testing sets. We have developed multiple deep learning models such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) and Hybrid CNN-LSTM for biomedical signal classification. Evaluation metrics of accuracy, precision, recall and F1-score were used to assess model performance. The comparison of the results demonstrate that the CNN model has the highest accuracy of 0.98, Hybrid CNN-LSTM has 0.9767 accuracy, LSTM has 0.9751 accuracy and the RNN has 0.85 accuracy. The outcomes indicate that deep learning models can classify ECG and EEG signals and can be used for real-time embedded systems in health monitoring.

Keywords- Biomedical Signal Classification, Electrocardiogram (ECG), Electroencephalogram (EEG), Deep Learning and Healthcare Monitoring Systems

Introduction

The analysis of biomedical signals has emerged as a critical element of the health-care system, especially in the diagnosis and monitoring of cardiovascular and neurological diseases. In the era of digital health, biomarkers such as Electrocardiogram (ECG) and Electroencephalogram (EEG) are increasingly used for medical diagnosis, decision-making and patient monitoring. ECG is the electrical activity of the heart used for diagnosis of various types of heart diseases, including arrhythmia, myocardial infarction, and others. EEG signals represent the electrical activity of the brain and are used to detect brain-related abnormalities such as epilepsy, tumors, sleep apnea and seizures. The analysis of these physiological signals is essential for the early diagnosis and appropriate treatment of diseases [1] [2] [3]. ECG and EEG signals are typically interpreted by medical professionals using visual inspection and statistical techniques. But manual analysis of biomedical signals can be lengthy, complicated and prone to errors, particularly when a large amount of signal data is produced from continuous monitoring systems. The ever-growing biomedical signal data generated by wearable devices, remote monitoring systems, and medical hospital monitoring equipment demand smart biomedical signal analysis systems. Automated biomedical signal classification can help health care workers make quicker and more reliable decisions, eliminate human error and increase the efficiency of the health care system [4] [5] [6]. Traditional machine learning methods have been applied to biomedical signal classification for the last ten years. Conventional machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, k-Nearest Neighbors (k-NN), and Random Forest have been used for ECG and EEG classification. These approaches heavily depend on manual feature engineering techniques, signal processing, and expert knowledge to highlight salient features from these signals such as interval measures, frequency measures, statistical measures, and morphological measures. While these methods have achieved good results, their success relies heavily on the effectiveness of feature engineering and may fail to capture temporal and spatial information contained in biomedical signals [7] [8].

Recent advances in deep learning have offered a powerful approach for biomedical signal analysis, as deep learning models can learn to automatically extract features and discover complex patterns from raw signals. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are effective models for the classification of timeseries signals. CNN models are well suited to learn spatial and morphological features of signals, while RNN and LSTM models are suitable for time-series analysis. Combining the strengths of both Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) in a CNNLSTM model allows the learning of both spatial and temporal features in biomedical signals. The use of deep learning techniques for classification of ECG and EEG signals has received considerable attention in recent years as a means to enhance the diagnosis and automate the interpretation of these signals. Deep learning-based automated classification systems can help with monitoring, early diagnosis, and decision-making in medical applications in hospitals and at home. By combining deep learning techniques with biomedical signal processing, smart health systems can be created to continuously monitor patients and notify doctors in case of irregular signal patterns [9] [10] [11] [12].

The other key component to biomedical signal analysis is the availability of open datasets, which can be used to develop and test machine learning and deep learning models. Typical datasets used in research for training and evaluating models include arrhythmia ECG datasets and epileptic seizure EEG datasets. These samples assist in the creation of classification models for disease detection and monitoring. While there have been significant advances in biomedical signal classification, some issues still remain, including signal noise, imbalance in sample data, variations in signal patterns across patients, and efficient real-time processing architectures. Hence, there is a need to design novel deep learning models that can classify several types of biomedical signals while offering high classification accuracy and computational efficiency [13]. The research is centered on creating a deep learning model for biomedical signal classification of ECG and EEG. This study seeks to automate biomedical signal classification through deep learning models that can learn to classify complex signal patterns and enhance healthcare monitoring. The research also highlights the need for automated diagnostic tools and smart health monitoring systems that can help doctors diagnose and monitor patients. The novelty of this study is the use of a combination of deep learning models to classify biomedical signals and to assess the performance of these models in classifying ECG and EEG signals. The research seeks to advance smart health technologies for automated biomedical signals recognition, disease diagnosis and continuous health monitoring.

Literature Review

Wu, Yi 2026et al. [14] We present a contrastive learning based cross-modal alignment approach. We first extract emotional features of the EEG signal from a pre-trained encoder. We then align the ECG encoder to these features obtained from EEG by contrastive learning: sequence and patch semantic matching by a temporal patch shuffle method. This is a good combination of the two. We achieve better results than other baselines when we use our method to detect emotions in the DREAMER and AMIGOS datasets. Other ablation studies and visualisations also show the contribution of the basic elements. In practice, our method can properly recognize emotions in the case when EEG is not available, and this will provide an alternative way to use in the application of real-world affective computing.

Shuvo 2025et al. [15] paper that reviews a total of 112 studies between 2013-2023 exploring the area of artificial intelligence (AI) with wavelets in medical. In our analyses, we found that discrete wavelet transform is the most common (43% of the studies) and applied to biological signals (82% of studies) and medical images. Large-scale applications are in the detection of cardiovascular diseases (29%), diagnosis of neurological diseases (27%) and diagnosis of psychiatric diseases (16%), with classification accuracy rates often exceeding 95%. There are many implications in the shift from conventional machine learning to deep learning after 2020 with the new hybrid models. The paper highlights the key issues in efficiency, wavelet selection and validation. The future of this field should be the real-time process enhancement, explainable deep learning, multi- modal data integration and testing on large clinical data in order to translate these systems for clinical use.

Lu 2025et al. [16] we re-evaluate the continued relevance of domain knowledge "baked in" to classic domain feature engineering workflows and how it can be harnessed to inform SSCL.We propose a method that incorporates clinically relevant features - such as heart rate variability from electrocardiogram (ECG) signals - into the contrastive learning approach. These features are used to guide the creation of more meaningful positive pairs via nearest neighbour matching and encourage global structure via clustering-based prototypes. Our approach has been tested on a range of wearable devices and performs similarly with only 10% labeled data compared to standard SSCL methods with all labels available for fine-tuning. Our paper illustrates the critical and ongoing role of domain knowledge in machine learning for practical health care, particularly for health care wearables.

Gelen 2025et al. [17] method uses the Order Transition Pattern (OTPat) feature extractor. The proposed OTP at feature extractor extracts channel/column based patterns (spatial features) using all channels for each point and signal/row based patterns (temporal features) by extracting features from individual channels and using overlapping blocks. The features are then selected using cumulative weighted iterative neighbourhood component analysis (CWINCA) and classified using a t-algorithm k-nearest neighbors (tkNN) based classifier. Finally, two symbolic languages, Directed Lobish (DLob) and Cardioish, generate interpretable results in the form of cortical and cardiac connectome diagrams. The XFE model based on OTPat outperforms other methods with an accuracy of over 95 percent on several EEG and ECG data sets and a maximum of 86.07 percent on a 8-class EEG artifact data set. These results demonstrate high performance and interpretability, suggesting that the model can be used to classify biomedical signals.

Rahman 2025et al. [18] propose a simple and secure method of detection of tampering in ECG signals using the technique of digital watermarking. Patient's unique ID is encoded by modifying one of the least significant bits of the sample, and encoding positions by the secret key to prevent the decoding and recovery of the watermark by an unauthorised person. The approach does not compromise the diagnostic quality, does not cause perceptible distortion and enables tamper location. The experimental study shows the system is highly resilient to a range of tampering conditions including amplification, Gaussian noise and re-equalization. In all these circumstances, at secret key lengths of 6, 12 and 18 bits, the system always yielded 100 percent detection accuracy and F1 scores. These results demonstrate that the proposed method has acceptable and feasible tamper detection performance. The very simple design makes it suitable for low-resource environments such as Internet of Things (IoT)-based health monitoring devices. While being tested on an ECG signal, the system can be used for other physiological signals, such as electroencephalogram (EEG) and photo plethysmogram (PPG). To the best of our knowledge, this is the first tamper detection structure for physiological signals that simultaneously ensures 100% detection accuracy, quality of the original signal, low-complexity implementation, and cryptographic security.

TABLE I. LITERATURE SUMMARY

Author / Year	**Method Used**	**Results**	**Research Gap**

Caesarendra et al., 2022[19]	Deep Learning using Convolutional Neural Network (CNN) for ECG signal classification	Achieved around 95% training accuracy for ECG classification across multiple heartbeat classes	Focused only on ECG signals and single deep learning model; did not explore hybrid models or EEG signal classification
Jameil et al., 2022[20]	1-D CNN accelerator implemented on FPGA for biomedical ExG signal classification (ECG, EEG, EMG)	Improved speed and energy efficiency of CNN accelerator with high computational performance	Focused on hardware acceleration rather than classification accuracy improvement or hybrid deep learning architectures
Diab et al., 2022[21]	Machine Learning inference on Microcontroller Units (MCUs) for healthcare wearable systems	Demonstrated feasibility of embedding ML models in wearable healthcare monitoring devices	Did not focus on classification model performance or deep learning architectures for biomedical signal classification
Falaschetti et al., 2022[22]	Recurrent Neural Network (RNN) and LSTM for ECG arrhythmia classification using MIT-BIH dataset	LSTM achieved highest accuracy (~90%) while RNN showed better memory efficiency and faster inference time	Focused only on ECG arrhythmia classification and did not integrate CNN or hybrid architectures
Fathi et al., 2022[23]	ECG signal compression using Discrete Krawtchouk Moments and Ant Lion Optimizer	Achieved high compression ratio, improved signal reconstruction quality, and reduced energy consumption	Focused on signal compression rather than signal classification using deep learning models

III. Research Methodology

The method presented in this paper proposes a scalable deep learning framework for ECG and EEG signal classification that can be deployed on embedded systems. The framework is designed to offer real-time automated detection of cardiac and neurological disorders with time and resource efficiency for low-powered medical devices. The system leverages end-to-end deep learning techniques such as CNN, RNN, LSTM and CNN-LSTM to learn spatial and temporal features. We adopt a consistent pipeline that encompasses data collection, preprocessing, normalization, data division, training, evaluation and deployment for embedded systems. The framework is for multi-class and binary classification with evaluation metrics including accuracy, precision, recall and F1-score.

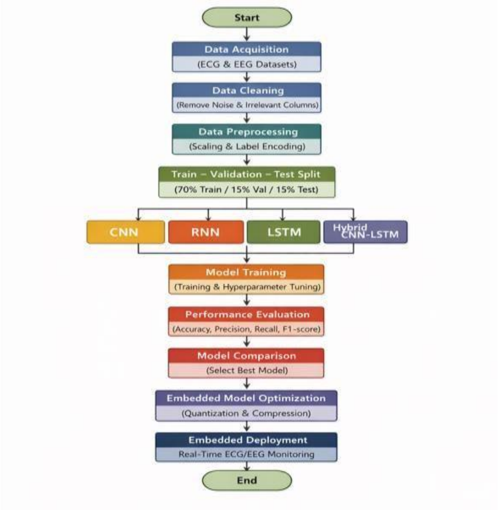

Fig. 1 Proposed ECG&EEG Classification Framework

A. Data Collection

In this work we have used two large biomedical datasets to make the proposed system robust and generalised.

The ECG dataset is derived from the MIT-BIH Arrhythmia Database and consists of 109,444 labeled heartbeat samples (87,553 samples for training and 21,891 samples for testing), which were acquired by combining the training and testing samples. Every sample is a segmented heartbeat waveform of 187 numerical features and one target label. The data has 5 types of heartbeat including normal beat, supraventricular ectopic beat, ventricular ectopic beat, fusion beat, and unknown beat.

Link- https://www.kaggle.com/datasets/raufmomin/eeg-and-ecg-datasets

We have obtained the EEG dataset from Epileptic Seizure Recognition data, which has 11,500 samples. The samples each contain 178 numerical features of processed EEG signal segments, and an indicator of activity (seizure or non-seizure) (five classes depending on the configuration). The datasets are in CSV format, so they can be used in deep learning frameworks such as TensorFlow and Keras.

B. Data preprocessing

Data preprocessing is an important task that needs to be done to ensure that the data is in the right shape and format to be input to the deep learning model. The first task was to analyse the dataset for any missing values, inconsistencies and any unnecessary columns. The id column of the dataset, which is not useful for classification was removed. The features and target labels after cleaning were separated into independent variable (X) and dependent variable (y).

Since the features of the EEG can have different scales and magnitudes, we have used a scaling method called StandardScaler. Standardization converts the data to make the mean of the data equal to zero and the standard deviation equal to one. This is critical when building deep learning models as scaling features affects the convergence and accuracy of the model.

The data were scaled and then transformed into a three-dimensional array (samples, timesteps, features) to be used in deep learning models such as CNN, RNN and LSTM. Preprocessing ensures suitable training, faster convergence and improved classification accuracy in the subsequent modeling procedure.

C. Exploratory data analysis

Exploratory Data Analysis (EDA) is a critical part of any data science research process particularly when used for biomedical signal processing. It bridges the gap between data collection and complex modelling analysis. In terms of electrocardiogram (ECG) and electroencephalogram (EEG) signal classification, EDA is crucial to understand inherent characteristics of the physiological signals in view of deep learning applications. ECG and EEG signals are nonstationary, non-linear and noisy so systematic exploratory analysis is performed to reveal the patterns, outliers, class distribution, signal characteristics and possible signal processing requirements.

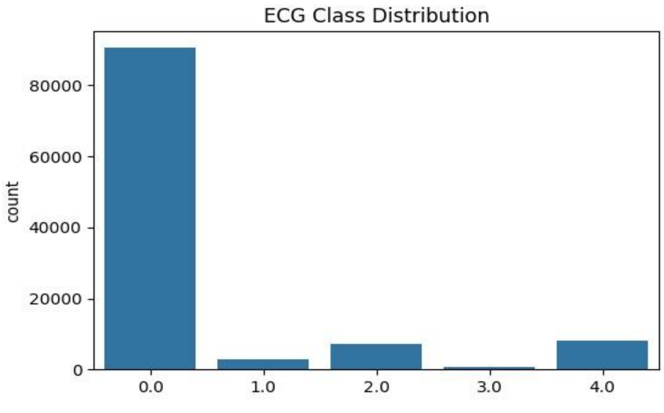

Fig. 2 Class distribution(ECG)

Fig.2 shows the various class distribution of the dataset that we have for ECGsignal classification. The figure shows the sample distribution of the classes and may result in an imbalance of the classes. Class distribution can be used to handle the data with appropriate techniques and to train deep learning models equally.

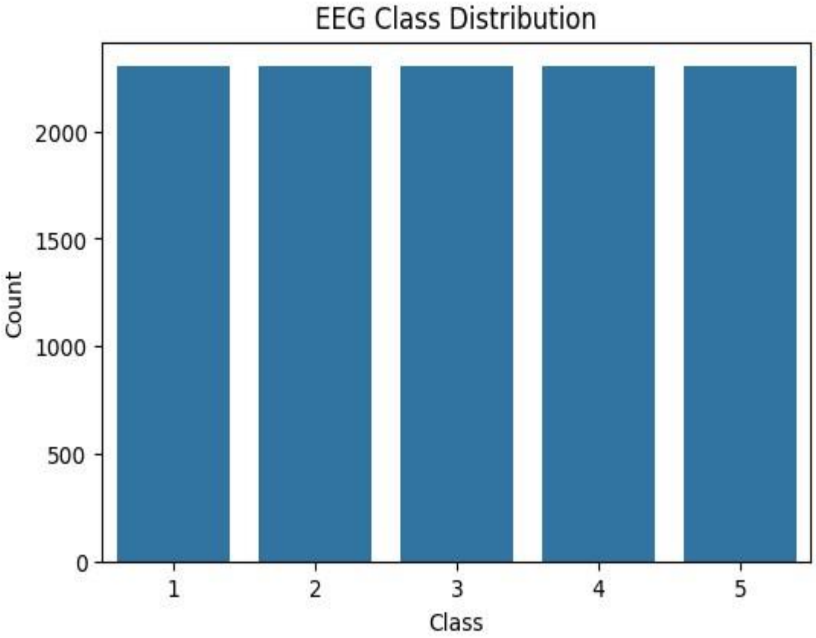

Fig. 3 Class Distribution(EEG)

Fig.3 presents the class distribution of different classes available in the dataset for EEG signal classification. The dataset is divided into several classes as illustrated and may be balanced. Class distribution is a useful concept for preprocessing with a view to doing the right preprocessing and to provide a balanced training for deep learning.

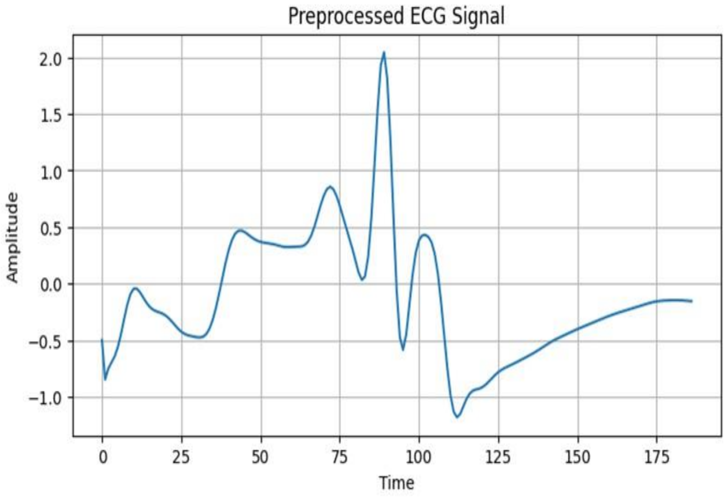

Fig. 4 ECG Time Domain Signal(ECG)

Fig. 4 shows examples of ECG signals in time-domain, i.e. amplitude of the signal versus time. This helps in understanding the shape and variation of biomedical signals in time. Time-domain analysis is crucial to extract features that are used for signal classification in deep learning.

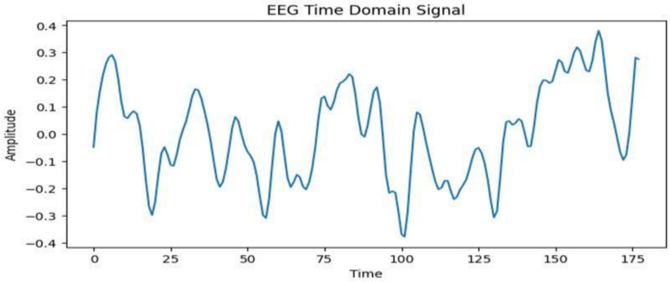

Fig. 5 Time Domain Signal(EEG)

Fig.5 displays the time-domain model of the ECG and EEG signals, in which the amplitude of the signal is represented versus time. One can interpret the wave patterns and changes in the biomedical signals in this representation. Time-domain analysis is critical to identify features that are used in deep learning-based signal classification.

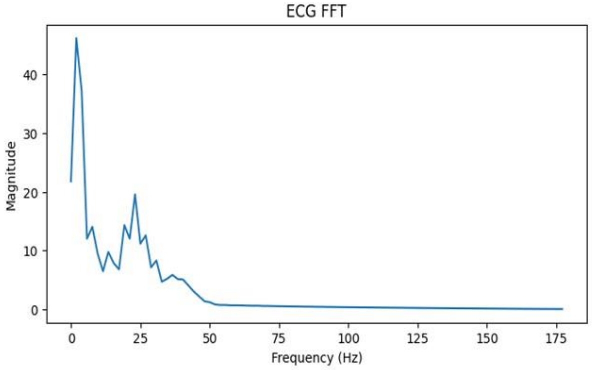

Fig. 6 Frequency Domain (FFT) ECG

The frequency domain analysis uses Fast Fourier Transform (FFT) to convert the time domain signal of ECG and EEG into the frequency domain. It reveals important frequency components of the signals, which help to identify the underlying features and patterns, which help feature selection and feature classification in the deep learning signal classification.

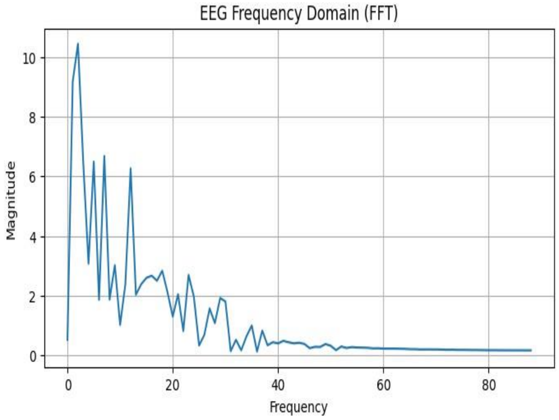

Fig. 7 Frequency Domain(FFT)EEG

Frequency domain analysis of EEG signals uses Fast Fourier Transform (FFT) to convert timedomain brain signals to frequency-domain signal.

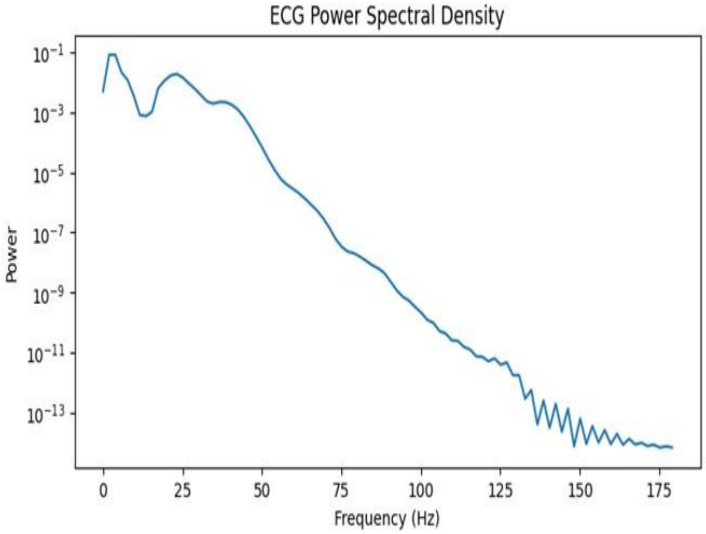

Fig. 8 Power Spectral Density(ECG)

The Power Spectral Density (PSD) is a method to measure the power distribution of a signal across its different frequency components. It helps to identify prominent frequencies of the heart. It can be used to perform classification based on the heart rhythm and to extract frequency features to accurately classify ECG signals in a deep learning model.

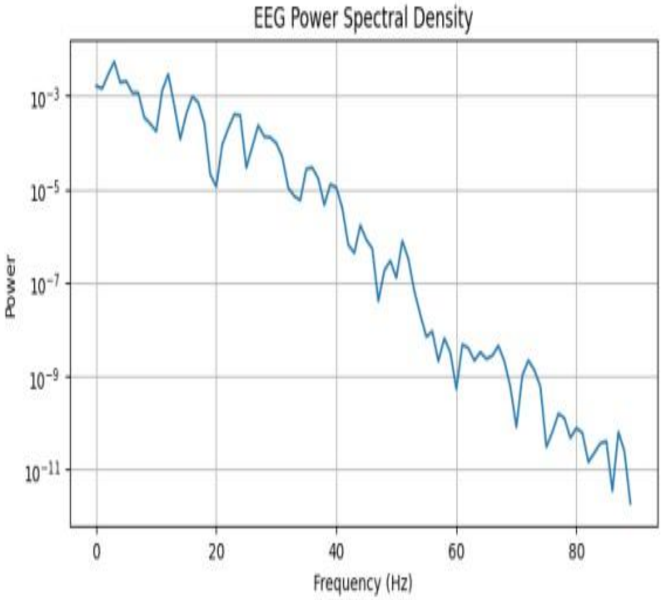

Fig. 9 Power Spectral Density(EEG)

The Power Spectral Density (PSD) analysis is an estimation of the distribution of energy of an

EEG signal among various frequency bands. It helps in the determination of the brain wave patterns; delta, theta, alpha, beta, and gamma. PSD has been widely used on the features extraction and enhancing the classification of the EEG signal in the deep learning model.

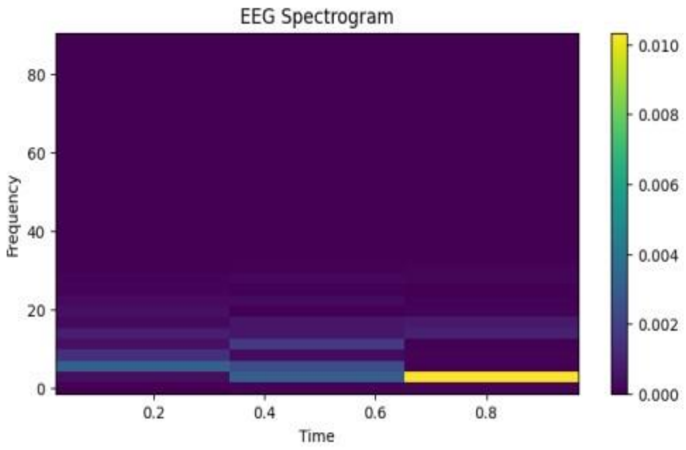

Fig. 10 Spectrogram(ECG)

The Power Spectral Density (PSD) analysis is an estimation of the distribution of energy of an EEG signal among various frequency bands. It helps in the determination of the brain wave patterns; delta, theta, alpha, beta, and gamma. PSD has been widely used on the features extraction and enhancing the classification of the EEG signal in the deep learning model.

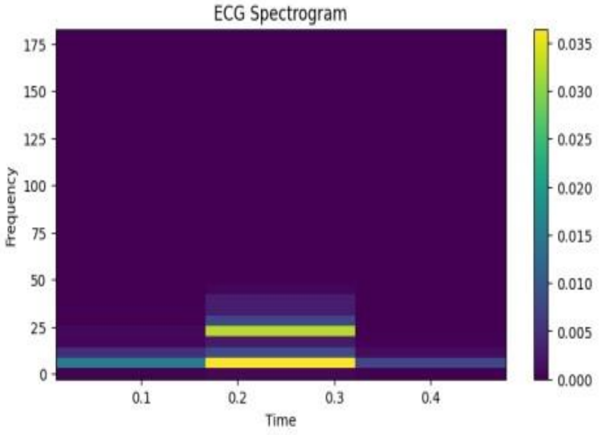

Fig. 11 Spectrogram(EEG)

A spectrogram is a representation of EEG signals both in time and frequencies, or a display of the variation of frequencies of the brain waves with time. It is generated in Short-Time Fourier Transform (STFT). Spectrograms are used to visualize trends in EEG activity and find seizures, analyze brain activity, and better deep learning-based EEG classification.

D. Feature Representation and Signal Transformation

The significance of signal transformation and feature representation has to do with the improvement of the EEG classification performance. Even though the numerical features have already been extracted in the dataset, additional transformation methods have been used in order to boost the discriminative trends. EEG signals are not stationary but dynamic in nature i.e. their frequency characteristics vary with time. In this way, it may be insufficient to analyze them by analyzing them in time domain only.

Time-domain representation Time-domain representation was studied first by plotting the value of features in order to see how they changed between samples. This helps in the analysis of the amplitude distribution and signal behaviour. This was succeeded by frequency-domain representation that was carried out using Fast Fourier Transform (FFT). FFT converts signals in time space to frequency space, and this makes it possible to analyze the important content in terms of frequency of EEG signals. This may be highly advantageous in the sense that some frequency bands are generally associated with brain activity.

Also time-frequency representation like Wavelet Transform was taken into account. Wavelet transformation records both frequency and time in one, and hence is very well suited in processing EEG signals. The transformations enhance the performance of the deep learning models and quality of features because they provide more detailed descriptions of the patterns of brain activity.

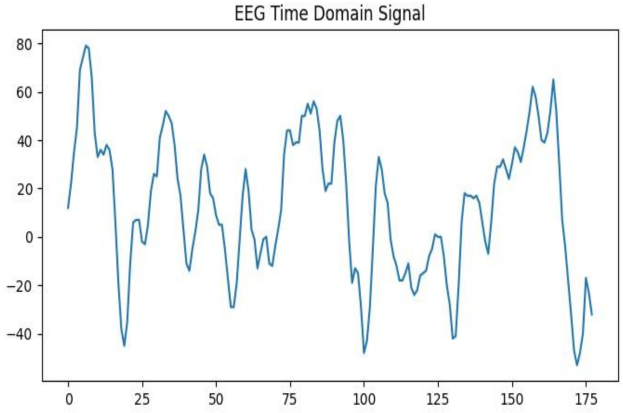

Fig. 12 Time Domain Signal

E. Data Splitting Strategy and Training Procedure

The set of processed data was divided into three different subsets to give valid and fair value of analysis, namely, training set, validation set and test set. The population that was selected to train the deep learning models was 70 percent of all the data. The validation set represented 15 percent of the data that was utilized in the training to trace the model performance and avoid overfitting. The rest 15 percent was allocated as the test set to be used in the ultimate performance appraisal. This trifurcation will assist the model in generalizing it to invisible data.

F. Modeling a) Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning architecture that is developed to identify spatial features in structured input information in an automatic manner. A 1D CNN application to the biomedical domain is in the case of one-dimensional (temporal) biomedical signals such as ECG and EEG, where local patterns are involved in the detection of a shape of a waveform, or a peak, or a change in the signal (i.e. local patterns). The convolutional layers are also trained to generate useful feature representation by sliding the kernels along the signal but pooling layers reduce the size of the dimensions and save important data. At the end, fully connected layers are used to classify according to extracted features. The analysis of ECGs with CNNs can also be successfully conducted since they are able to learn morphological characteristics of ECG such as QRS complexes. They have been identified to be both efficient in computers and acceptable in embedded healthcare systems because of their relatively few parameters and brief inference-time.

b) Recurrent Neural Network (RNN)

RNN This is a neural network that is especially appropriate to sequence processing of data. RNNs unlike the traditional feedforward networks have an internal memory which stores previous time step information. This aspect renders them appropriate in the analysis of time-series biomedical signals that include ECG and EEG. RNNs learn temporal correlations between signal sequences in ECG and EEG recognition, hence, they can learn time-dependent features. Nevertheless, typical RNNs can have problems with long-term dependency because of the vanishing gradient problems. Although this is their limitation, they offer a basic framework on which to model sequential physiological signals.

c) Long Short-Term Memory (LSTM)

Long Short-Term Memory(LSTM) networks are the new type of development of recurrent neural networks which is intended to overcome the drawbacks of the usual RNNs. LSTMs are also characterized by special gating mechanisms i.e. input, forget and output gates which control the information flow within the network. The gates cause the LSTMs to retain the valuable information about time related data in long sequences and forget about the insignificant information. LSTMs prove especially effective in biomedical signal processing especially in EEG processing as the brain signals are very dynamic and non-stationary. The LSTM networks are effective with the long-term time-dependency and complex association of sequences, which promotes the classification effectiveness of neural disorders such as epilepsy.

d) Hybrid CNN-LSTM Model

The Hybrid CNN-LSTM model is constructed on the merits of both Convolutional Neural Networks and Long Short-Term Memory networks into one model. The model entails the isolation of spatial or local characteristics of raw biomedical signals using the aid of CNN layers. These characteristics are subsequently inputted in LSTM layers that learn sequential relationships and time-related features. The middle approach will enable the acquisition of both the spatial patterns and the temporal dynamics. Morphology of a waveform is obtained using CNN part in the case of ECG and EEG, and time-dependent dynamics are learned using LSTM part. The hybrid model tends to be better classified but may prove to be more resource intensive, so it is more suitable in a systems where the precision value is high, but where least amount of resources are relevant.

TABLE II. HYPER PARAMETER DETAILS

Model	Input Shape	Layers / Units	Filters	Kernel Size	Activation	Pooling	Dense Layer	Output Layer	Optimizer	Loss Function	Batch Size	Epochs	Dropout
CNN	(187,1) ECG / (178,1) EEG	2 Conv Layers	32, 64	3	ReLU	Max Pooling (2)	64	Softmax	Adam	Sparse Categorical Crossentropy	64	100	0.3
RNN	(187,1) / (178,1)	1 RNN Layer (64 Units)	—	—	Tanh	—	64	Softmax	Adam	Sparse Categorical Crossentropy	64	100	0.3
LSTM	(187,1) / (178,1)	1 LSTM Layer (64 Units)	—	—	Tanh	—	64	Softmax	Adam	Sparse Categorical Crossentropy	64	100	0.3

Hybrid CNN - LSTM	(187,1) / (178,1)	CNN + LSTM (64 Units)	32	3	ReLU + Tanh	Max Pooling (2)	64	Softmax	Adam	Sparse Categorical Crossentropy	64	100	0.3

G. Cross-Validation and Generalization Strategy

K-Fold Cross-Validation was adopted to make sure the developed models are general, and they do not favor a specific portion of the training data. Under this method, the joint training and validation sample was broken down into five equal folds. Training and validation were done on four folds and one fold respectively during each iteration. The procedure was run five times that is, each fold was an undergoing validation set. The averageness of the accuracy of all folds was calculated in order to provide a more plausible measure of the performance of the model. Cross-validation reduce the possibility of random division of data and they make the evaluation more robust. It is employed to ensure that the model is not overfitted to a specific section of the data and enhance the generalization of the model. This is important where the datasets are small as in EEG classification problems.

The three-way data splitting and K-Fold cross-validation combined approach makes the training process more stable and reliable. This approach makes sure that the model performance that is reported is not a casual event that is seen in several training cases and thus enhances the confidence of the classification system.

H. Performance Evaluation Metrics

There were several performance measures that were put in place to critique the effectiveness of the proposed EEG classification models fully. The accuracy was determined by the correct ratio of the samples to the overall number of the samples. Though accuracy is a general representation of the performances of the model, it fails to provide the complete picture on the behavior of the classes especially when a multi-class problem is involved.

Thus, other measures like Accuracy, precision, recall and F1-score were calculated. The percentage of correct positive prediction of the model is defined using precision on the number of correct positive predictions of the model on the number of predicted positives. Recall is a metric of the percentage of correct positives which are correctly identified to real positives which shows the predictive ability of the model to identify all the situations of interest. The harmonic mean of accuracy and recall is the F1-score, which is a balanced measure in the cases of an uneven distribution of classes.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

A confusion matrix was also generated in each of the models to visualize the right and wrong classifications in the four classes (C, T1, T2, T3). This matrix helps to trace the opportunities of misclassification and classes weaknesses.

Further, inference time and number of model parameters were also investigated to test real time feasibility and embedded system appropriateness. These metrics combined can give a tangible evaluation of efficiency and performance of the model.

Embedded System Optimization and Efficiency Analysis

The high classification accuracy was not alone, the computational efficiency of the models developed was also considered with an added attention to make it suitable in embedded healthcare systems. Embedded systems (worn medical devices and personal EEG devices) are limited to the constraints of limited memory, processing power and power consumption. Accordingly, the optimization of the complexity of this model and its maintenance was one of the main objectives of this project.

The CNN and LSTM models were simplified to lightweight by minimizing the use of filters, hidden units, and dense layers parameters. Early termination of the unnecessary training epochs was done to reduce the cost of computations. The complexity of the model was assessed using the total amount of trainable parameters. The implication of a smaller number of parameters is usually reduced memory usage and reduced inference time.

Inference time was measured by recording the time of making predictions during the test. This assists in finding out whether the model can be used in real time settings. Direct Energy Consumption Measurement Direct measurement of energy consumption is challenging, as it involves hardware-level measurements but this was indirectly measured using model size and computational load.

Offering a trade-off between classification accuracy and less computational complexity, the resulting optimised models are of practical use in terms of embedded healthcare applications without compromising on the accuracy of the EEG signal classification.

IV. Result & Discussion

4.1 Performance Evaluation

In this section, the performance of the proposed deep learning framework on the ECG and EEG signal classification is presented and analyzed and it concentrates on assessing the various deep learning models such as CNN, RNN, LSTM and Hybrid CNN-LSTM models in the classification of biomedical signals. The ECG and EEG data are studied individually in order to gain insight into the behavior of the signal and the model behavior of various biomedical signals. The analysis is performed based on standard classification metrics and confusion matrix analysis to evaluate the classification performance and the misclassification patterns. It also evaluates training behavior, generalization of models, computational complexity and applicability of models to embedded healthcare systems and real-time healthcare monitoring of biomedical signals in the section.

TABLE III. PERFORMANCE COMPARISON OF PROPOSED DEEP LEARNING MODELS

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**Loss**
CNN	0.9800	0.98	0.98	0.98	0.09
RNN	0.8500	0.84	0.83	0.83	0.32
LSTM	0.9751	0.97	0.98	0.97	0.0887
Hybrid CNN-LSTM	0.9767	0.98	0.97	0.97	0.1114

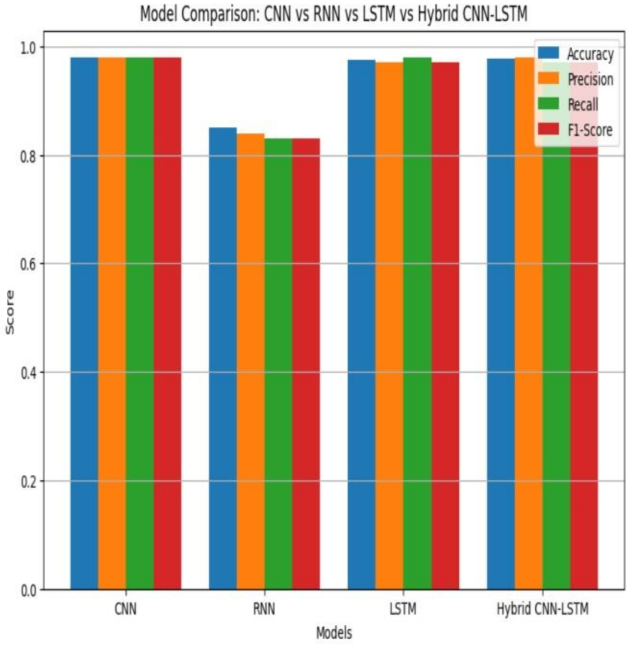

Fig. 13 Model comparison CNN vs RNN vs LSTM vs Hybrid CNN-LST

The table is a comparison of the CNN, RNN, LSTM, and Hybrid CNN-LSTM models on the ECG and EEG signal classification. CNN showed the best accuracy (98 percent) and Hybrid CNNLSTM and LSTM are also very good. RNN had relative low scores because it has shortcomings in terms of long-term dependencies in time-series biomedical signals.

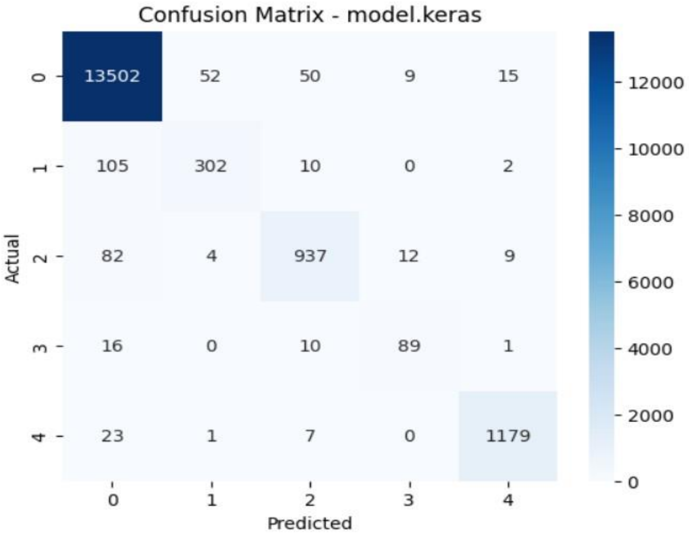

Fig. 14 CNN Confusion Matrix

The confusion matrix depicts a classification accuracy of the intended deep learning model on ECG signal classification in five classes (04). The correct classifications are reflected in the values of the diagonal and the error values are reflected in the off-diagonal. Class 0 presents the largest amount of correct predictions (13,502) which means high performance of the majority class. Likewise, class 2 and 4 also have high numbers of correct classification of 937 and 1179 samples respectively. In Classes 1 and 3, the number of samples is relatively smaller and, thus, the number of right and wrong classification is slightly reduced. On the whole, the confusion matrix indicates that the given model has a high level of classification with the majority of prediction positions on the diagonal.

TABLE IV. COMPARISON OF PROPOSED CNN MODEL WITH EXISTING METHODS

Model Used	Dataset	Accuracy	Reference
CNN with Compressed Learning	MIT-BIH ECG Dataset	96.56%	[24]
Bi-LSTM	EEG Dataset	97.52%	[25]
CNN + Wavelet + PSO	Arrhythmia ECG Dataset	97.00%	[26]
Proposed CNN	ECG + EEG Dataset	98.00%	--

The proposed CNN model is compared against some of the existing studies in biomedical signal classification in Table IV. Lal et al. presented a CNN-based compressed learning system on the classification of ECG signal and obtained an accuracy of 96.56%. Kumar et al. came up with a BiLSTM model of predicting epileptic seizures using EEG signals at 97.52 accuracy. On the same note, Azzouz et al. introduced an ECG monitoring system on IoT with an accuracy of about 97 percent through the application of deep learning and wavelet preprocessing. Comparatively, the suggested CNN-based solution attained 98% precision indicating better work on ECG and EEG signal categorization.

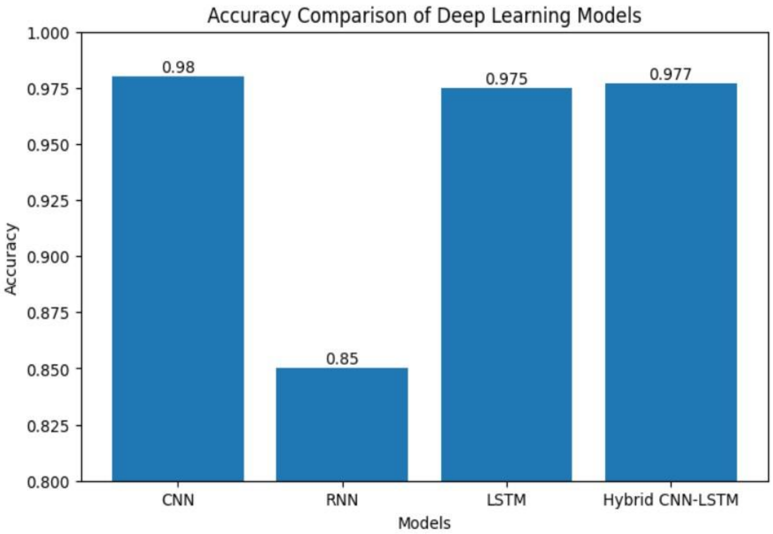

Fig. 15 Comparison of Proposed CNN Model with Existing Methods

The figure presents the accuracy comparison of the four deep learning models used to the ECG and EEG signal classification. The CNN model is the most accurate with 0.98 and it implies that it is highly effective in extracting the spatial features of the signals. The Hybrid CNN-LSTM model is also able to perform well with an accuracy of 0.977 and then LSTM model with an accuracy of 0.975. On the other hand, the RNN model was less precise (0.85), which proves that it is not possible to take into account complex temporal relationships.

V. Conclusion

This paper has managed to fulfill its aim of creating an automated deep learning-based ECG and EEG signal classification framework to be used in healthcare monitoring. The given system was meant to categorize the biomedical signals effectively using deep learning models such as CNN, RNN, LSTM, and Hybrid CNN-LSTM. The methodology involved the collection of publicly available biomedical data, preprocessing, exploratory data analysis, signal transformation, training of models, evaluation and optimization to be used in embedded healthcare. The findings showed that deep learning architectures have the potential to acquire sophisticated spatial and temporal trends on biomedical signals and accurately classify cardiac and neurological diseases.The originality of the given research is that a single deep learning framework has been developed to process both ECG and EEG signals in one classification pipeline. In contrast to other past works that only considered ECG or EEG alone, this paper combines both biomedical signals and compares various deep learning architectures in a unified work. The other contribution is the emphasis on embedded healthcare system compatibility in terms of the complexity of the model, inference time, and computational efficiency. The suggested framework leads to the creation of smart, automated and real-time healthcare monitoring processes to detect diseases very early and smart medical use.

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