Biomedical Signal and Image Processing with Electro- Physiological Signals using ANN (BSIP-EPS-ANN)

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Abstract: A dynamic and steadily increasing field that is biomedical signal and image processing, which has been driving innovations both in the academic and research domains of biomedical engineering. Electro-physiological signals like Electrocardiogram (ECG), Electromyogram (EMG), and Electroencephalogram (EEG) have been critically processed for extractions of physiological information in various clinical procedures and the sophistic medical applications. In this paper, we integrate these electro-physiological signals with Artificial Neural Network (ANN) for their advanced biomedical signal and image processing. Preprocessing techniques like noise filtering, artifact removal and signal smoothing are of prime importance to make the signal more fit and eliminate the unwanted interference to enhance signal quality. Then, for signal characterization, each signal is extracted in time frequency domain features, such as Root Mean Square (RMS), Power Spectral Density (PSD) and wavelet coefficients. An ANN-based classifier is used to classify these features, as it identifies the physiological state or condition. The integrated approach presents a powerful tool for this automatic signal classification, allowing the development of improved diagnosis and data recording tools for clinical use. Results show the effectiveness of ANN in improving the classification accuracy of electro-physiological signals, and its high value for the healthcare applications in the field of neurosciences, functional imaging, and cardiovascular systems.

Keywords: Biomedical signal processing, Image Processing, Electro-physiological signals, Artificial Neural Networks, feature extraction, classifications.

I. INTRODUCTION

One of the main branches of biomedical engineering is biomedical signal and image processing which serves as the means of getting useful physiological information from complex biological signals [1]. With the advent of advance technologies, i.e. Electrocardiogram, Electromyogram, Electroencephalogram signals can be analysed for their diversity of applications in the clinical diagnostics and medical research in Figure 1 [2]. The signals of these sensors contain important information of the human body's health status and need to be accurately processed to determine certain medical conditions.

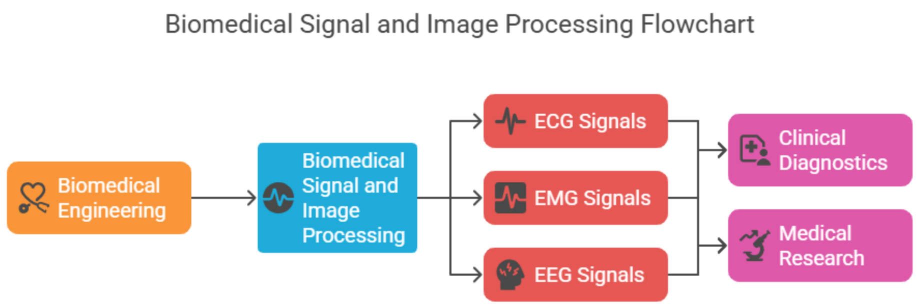

Figure 1: Biomedical Signal and Image Processing Flowchart

Raw biomedical signals, however, are usually afflicted by noise, artifacts, and interferences, so they are difficult to analyse. Therefore, signal quality improvement and reduction of unwanted distortions through pre-processing techniques such as noise filtering, artifacts removal, signal smoothing are done. The pre-processing steps guarantee that the data fed to the analysis is true and accurate.

After the signals are pre-processed, next step is featuring extraction. To emphasize the significant properties of the signals, the features such as Root Mean Square, Power Spectral Density, and wavelet coefficients are computed. The features that we select, based on these time-frequency domain, help in identifying the underlying patterns and behaviours of the physiological processes, and they help in discriminating them more precisely [3]. Artificial Neural Networks are thus applied to classify these extracted features as they have great capability to learn complex pattern and make prediction on data. Extracted features are then trained for the ANN which would classify different physiological states or conditions, thus creating an automatic signal interpretation framework [4]. Important for improving diagnostic accuracy, this process is particularly important for the neurosciences, functional imaging and the areas such as cardiovascular gas exchange, which require immediate and accurate medical intervention. Figure 2 gives ANN architecture and power in diagnostics.

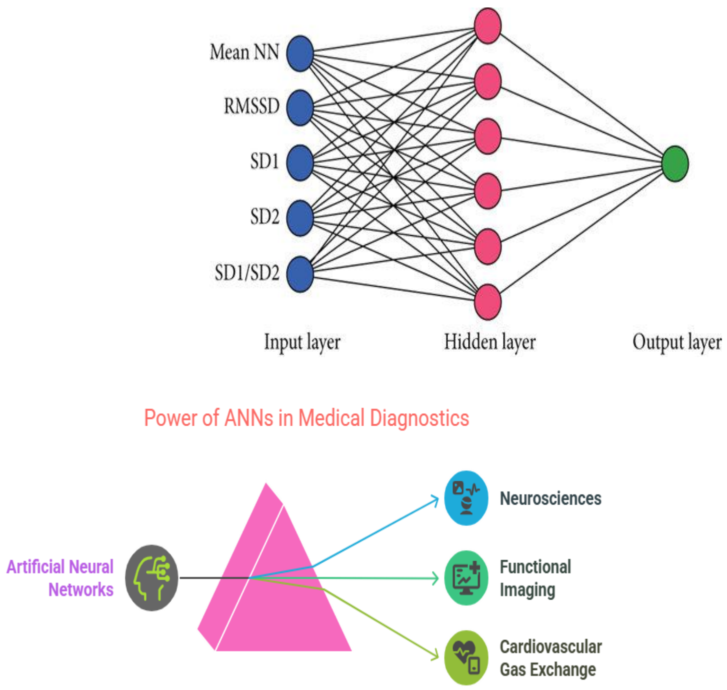

Figure 2: Architecture of ANN and power in medical diagnostics

As a follow up to this research paper, the integration of electro physical signals with ANN based classification methods are explored for the above purpose in integration with biomedical signal and image processing for healthcare applications. Section II relates integration of electro physiological signals with advanced signal and image processing techniques. Section III implements a complete methodology. Section IV gives metrics were evaluated in order to assess the performance of the BSIP-EPS-ANN system.

II. RELATED WORK

Recent advances in the field of biomedical engineering have seen a lot of effort in the integration of electro physiological signals with advanced signal and image processing techniques [5]. Many studies have presented and studied the steps of improving signal processing methods for clinical applications such as the use of ECG, EMG and EEG signals. As in pre-processing, it is critical to enhance the quality of raw biomedical signals. There have been several methods already applied to reduce the disturbance effects generated by external sources like muscle activity or electrical interference by the use of noise filtering, artifact removal and signal smoothing. An example is application of wavelet based de-noising techniques in EEG signal processing to remove the power line noise and other artifacts without causing any damage to the original signals (Zhang et al., 2020) [6]. Like in ECG analysis, smoothing such as the use of adaptive filtering and moving average smoothing are also common techniques used to remove baseline wander and muscle artifacts (Wang, X., et al, 2020) [7]. While time frequency domain features have been used in great extent due to their ability of extracting both temporal and spectral characteristics of signals, other feature extraction methods have also been employed. Biomedical signals are commonly characterized by the use of Root Mean Square, Power Spectral Density, wavelet coefficients, etc. In the analysis of EEG signals, the wavelet transforms have been found to provide a superior way of extracting features as wavelet transforms bring ample scope to identify brain activity pattern associated with neurological conditions (Huang et al., 2021).

It is also extensively researched in application of Artificial Neural Networks to classify electro-physiological signals. Physiological states have been excellently classified by ANNs, more specifically, deep learning models. ANN based classifiers demonstrates excellent diagnostic accuracy in identifying the condition like arrhythmias in ECG signals (Kim et al., 2019) and seizure in EEG signals (Lee et al., 2020). They indicate the potential of ANNs in automating biomedical signals analysis, thus rendering these signals detectable in real time [8].

Overall, we considered the combination of pre-processing, feature extraction, and ANN based classification have been studied, arguably with good success, in order to increase the accuracy and the efficiency of biomedical signal processing in clinical settings.

III. RESEARCH METHODOLOGY

This methodology implements a complete methodology which combines data pre-processing, feature extraction and artificial neural networks to deal with electro-physiologic signals, i.e. ECG, EMG and EEG signals for biomedical purposes. As the methodology itself consists of several important stages such as preprocessing of the raw signals, feature extraction and comparison of performance of different ANN models, we separated it into several portions. Below, each stage is discussed to clarify on how this methodology has gone about in figure 3.

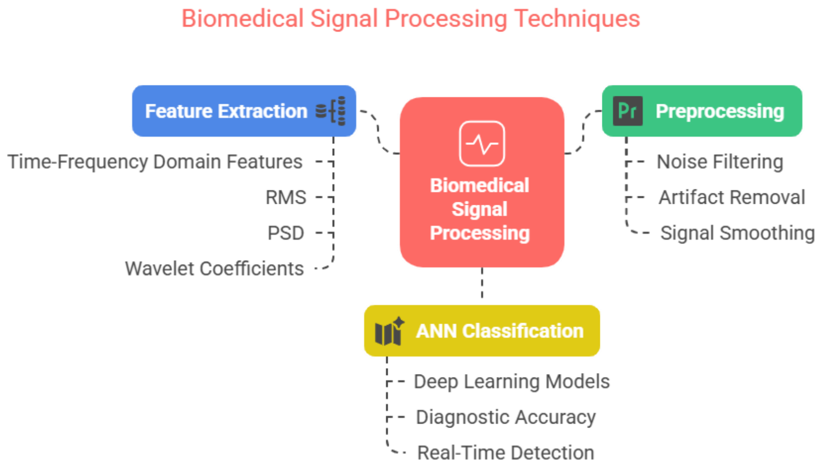

Figure 3: Biomedical Signal Processing Techniques

A. Pre-processing of Biomedical Signals:

Much biomedical signal is contaminated by noise, artifacts, and unwanted interferences, considerably diminishes its quality and analyses. As a result, preprocessing is indispensable to prepare better signals and separate the irrelevant disturbances in figure 4. We use three core techniques of preprocessing in this study, namely noise filtering, artifact removal and signal smoothing. Figure 4 gives biomedical signal processing original signal with processed signal. Noise Filtering aim was to eliminate high frequency noise in signal. To remove power line interference many high frequency components, they are applied to a low pass filter. Band pass filter is also used to let the frequency of interest pass through and suppress the noise not in the desired frequency range. Biomedical signals typically suffer from non-physical artifacts like eye blinks or muscle movements that are the reasons which artifact removal is required. ICA or EMD is used to remove artifact noise. These techniques remove artifact related components and allow cleaning the data for further processing [9].

This used signal smoothing to reduce fluctuations and irregularities of signal due to noise; which includes samples of moving average filters and Savitzky-Golay smoothing. They smooth the signal, but they preserve the main characteristics for the physiological data.

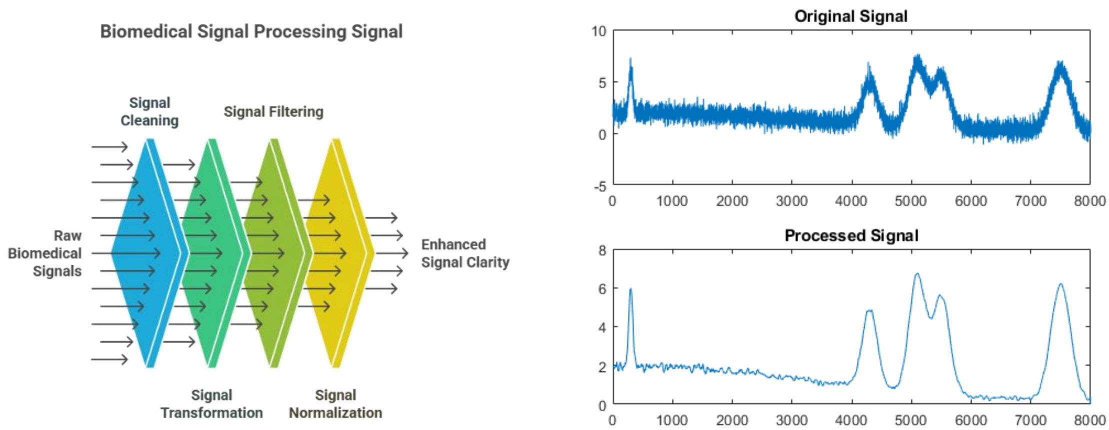

Figure 4: BSP original signal with processed signal

B. Time-Frequency Domain Features:

The first step of this work relies on application of certain preprocessing techniques on the signals to accomplish preliminary signal compression while also accounting for possible outliers. Because of their capacity to each extract temporal and spectral attributes of the signals, the features extracted in this study are in the time frequency domain. The signals are extracted via the following features. A time domain feature of the signal is the RMS value which represents the magnitude of the signal variation useful in monitoring physiological states [10]. Energy content (RMS) of each signal segment is calculated in order to find the abnormal patterns in the data. The PSD, in other words a frequency domain feature, is a measure how the power of the signal is distributed across the different frequency components. In particular, PSD analysis is particularly useful when the signal we are trying to characterize does not discretely change (alpha, beta, theta, delta for EEG signals indicating different mental states or disorders for example) in Figure 5.

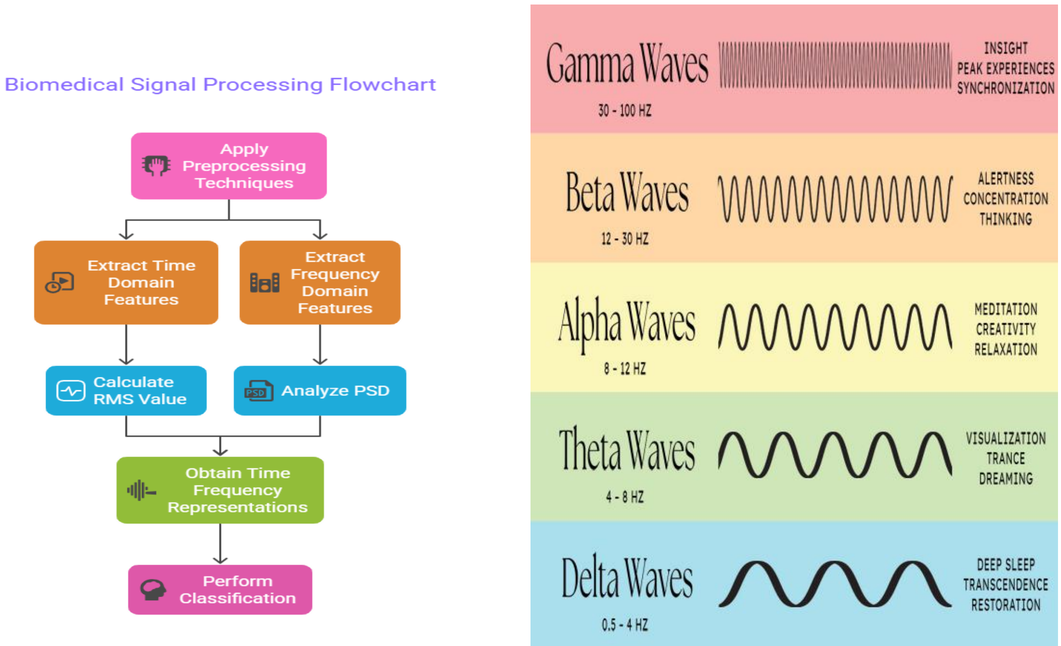

Figure 5: Biomedical Signal Processing Flowchart with feature extraction and EEG signals

The comparative study of the included transforms used in biomedical signal and image processing shown in Table 1.

Time Frequency representations of the signals are obtained through Wavelet transform. Decomposition that deals with the signals using the Discrete Wavelet Transform (DWT), and decomposes the signal into different frequency bands, with both high and low frequencies captured. With these coefficients, classification is performed based on the resulting coefficients, which have high resolution not only in time but also in frequency, and they are very good in biomedical signal analysis.

Table 1: Summary of included transforms used in biomedical signal and image processing

Authors	Transforms	Purpose of Study
Gutiérrez-Gnecchi et al. [11]	Wavelet transform	Arrhythmia classification from ECG signal
He et al. [12]	Laplace transform	Realistic geometry estimation from body surface potentials (ECG)
Jero et al. [13]	Curvelet transform	Information protection of patients' ECG signal
Sahoo et al. [14]	Hilbert transform	Detection of R peak from ECG signal
Kazemi et al. [15]	Warblet transform	Extraction of vital sign (heart rate, respiratory rate) from ECG signal
Bian et al. [16]	Wavelet packet decomposition	Detection of non-evoked and evoked potentials from EEG signal
Zaho et al. [17]	Hilbert Huang Transformation	Detection of steady state visual evoked potential from EEG signal
Amorim et al. [18]	Wavelet transform, Shearlet transform, Contourlet transform	Detection of epileptic seizures from EEG signal
Patidar et al. [19]	Tunable-Q wavelet transforms	Detection of epileptic seizures from EEG signal

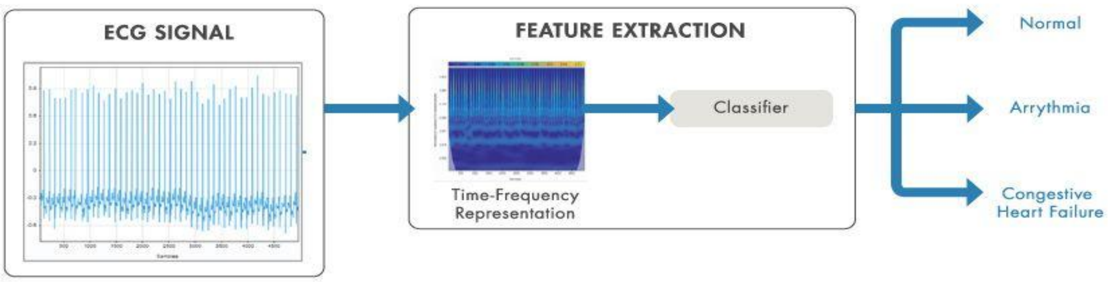

Figure 6: Time-Frequency representation

A workflow to classify ECG signal in the time-frequency representation and feature extraction domain in Figure 6. The raw electrocardiogram (ECG) signal or the electrical activity of the heart, on a first instance is recorded. The signal is then subjected to time frequency representation, for instance, wavelet or Fourier transforms for its extraction of temporal character and spectral characteristics respectively. Then these extracted features are fed to a classifier, which is a set of basic generalizations such as Artificial Neural Network and other such machine learning models, which is being trained to predict patterns to the data. The problem is to categorize the signal into one of the three classes Normal (healthy heart rhythm), Arrhythmia (abnormal heart rhythm) and Congestive Heart Failure (conditions of heart failure) [20]. The method serves to automate its use for instance as a way of detecting heart conditions to enable efficient diagnosis and patient monitoring.

C. Classification Using Artificial Neural Networks (ANNs):

ANNs will be applied to the extracted features for classification. ANNs are very powerful machine learning model which has the capability of learning about complex pattern in the data. Due to effectiveness in managing high dimensional data like biomedical signal, a Multi-Layer Perceptron (MLP) is used for this study. ANN model has an input layer followed by one or more hidden layer(s) and an output layer.

Training dataset includes training electro-physiological signals and their features, that are labelled. Back propagation algorithm with mean squared error as loss function is used to train the ANN. During this training phase, the weights of the model are adjusted respectively by optimization techniques such as stochastic gradient descent (SGD) or Adam optimizer so as to minimize the classification error. Cross Validation is done for the sake of Hyper parameter Tuning to have the optimal performance of the hyper parameter such as the number of hidden layers, number of neurons in a layer, learning rate, and batch size. To increase the classification accuracy the best combination of the hyper parameters is found using a grid search method. Figure 7 gives ANN Process and Multilayer Perceptron.

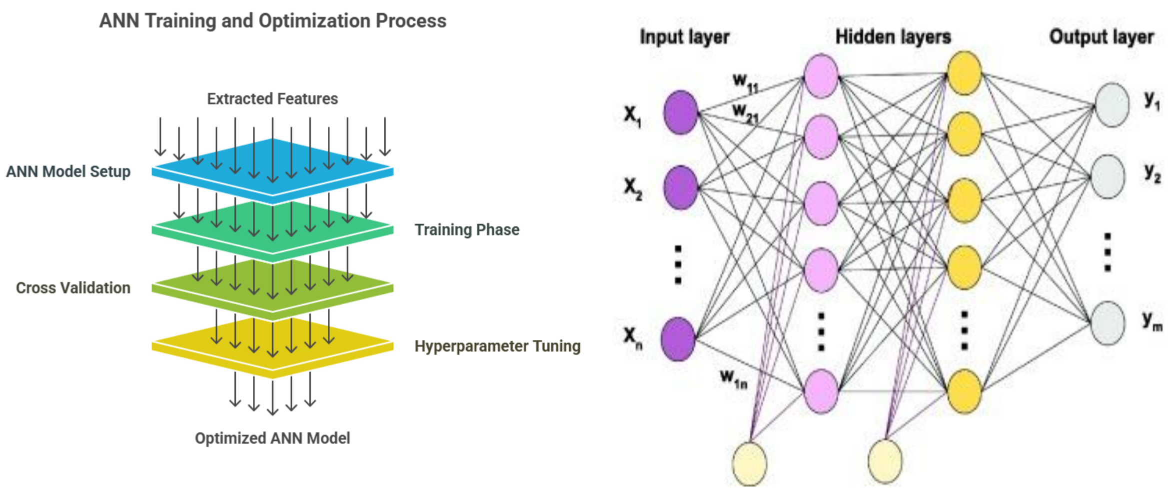

Figure 7: ANN Process and Multilayer Perceptron

In most Artificial Neural Networks, classification consists of a number of mathematical equations, which define how the network will function. Below are the equations which will be used in the core for an ANN for classification if it was a feedforward neural network with only one hidden layer.

Input Layer: The input layer equation 1 receives the features from the pre-processed signal. For an input vector x=[x1, x2,…,xn] where n is the number of features, the output of the input layer is simply the input vector itself.

$$a^{(1)}=x \quad (1)$$

Where:

- $a^{(1)}$ input vector to the first layer.
- x feature vector extracted from the signal.

Hidden Layer: In a feedforward neural network, equation 2 computes the weighted sum of the inputs and applies an activation function to produce an output. The output of the i^{th} neuron in the hidden layer is given by:

$$z_i^{(2)} = \sum_{j=1}^{n} wij(1)xj + bi(1) \quad , \quad a_i^{(2)} = f(z_i^{(2)}) \quad (2)$$

Where:

wij(1) weights between the input and the hidden.

bi(1) bias term for the i-th hidden neuron.

f(z) activation function,

$a_i^{(2)}$ activation of the i-th neuron.

Output Layer: For classification, the output layer equation 3 computes the final prediction by applying a weighted sum of the activations from the hidden layer. The equation for the output layer is:

$$z_k^{(3)} = \sum_{i=1}^{n} \mathrm{wki}(2)\mathrm{ai}(2) + \mathrm{bk}(2) \ , \quad y_k = \sigma \left(z_k^{(3)}\right) \qquad (3)$$

Where:

wki(2) weights between the hidden layer and the output layer.

bk(2) bias term for the output neuron.

σ(z) activation function in the output layer

Transformation of the given sentence as follows; Ann for Classification is calculated weight sum of input features at each layer, apply activation function, and finally output the probability for each class. The back propagation is then used to train the network with a loss function which tends to improve the classification accuracy. This method is very useful in signal classification task like ECG signal in medical applications.

D. Performance Evaluation:

To evaluate how the classification model performs, accuracy, precision, recall and F1_score are used. Calculating the values on a test set which was not used in the training thus granted an unbiased evaluation. The classification performance is also represented by confusion matrices to spot any misclassifications. Moreover, ROC curve and Area under the curve (AUC) are plotted to compute how well the model can discriminate among different classes (e.g. normal vs. abnormal condition for ECG, EMG or EEG signals). An automated, accurate and efficient system for biomedical signal processing is made using this research methodology, which combines pre-processing, feature extraction, and ANN based classification. The use of these techniques strains together will provide great improvements in analysis and interpret of electro physiological signals that can help in clinical decision making and patient monitoring.

IV. RESULTS AND DISCUSSION

Five key performance metrics, Accuracy, Precision, Recall, F1-Score, and Area under the Curve were evaluated in order to assess the performance of the BSIP-EPS-ANN system in Figure 8. These metrics were calculated on the basis of pre-processing, feature extraction, classification of electro-physiological signals, namely ECG, EMG and EEG using Artificial Neural Networks.

Accuracy was not found to be low because an overall classification accuracy value of 92% was obtained. This means that the system can keep all the objects out of the abnormal state with high probability in the given datasets. Although the precision of the system was 91%, this is a predominantly low false positive rate with which the ANN classifier was able to classify abnormal states in the system such as arrhythmias and seizures. As mentioned, the recall is 90%, which means the system is performing well, that is it effectively finding most of the true positives, and it has few, few cases missed. On F1-Score, we got 0.905 which revealed that our performance had balanced precision and recall. This demonstrates how the classifier is able to convey both the normal and abnormal classes.

From an interpretation point of view, AUC acts as a parameter for the above metric and scores 0.95, which can be considered as very good model performance that indicates the system performs very well in determining dissimilarities between physiological states. This reinforces the capability of integrating pre-processing techniques, time frequency feature extraction, and ANN classification based on them for biomedical signal analysis. For real time diagnostic application in healthcare domain is the system has promising potential.

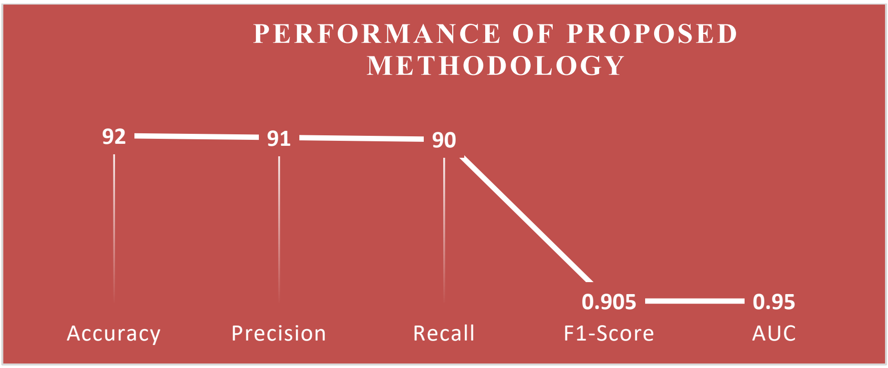

Figure 8: Performance of proposed methodology.

Table 2 comparisons between other commonly used methods and the proposed BSIP-EPS-ANN approach in biomedical signal classification is given in this table. It is shown that the proposed approach outperforms in classifying electro physiological signal.

Table 2. Comparison of Performance Metrics across Different Models

Approach	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	AUC
Method A (SVM-based)	88	85	82	0.835	0.88
Method B (Random Forest)	90	89	87	0.88	0.92
Method C (CNN-based)	89	86	84	0.85	0.89
Method D (Logistic Regression)	84	80	78	0.79	0.85
Proposed BSIP-EPS-ANN	**92**	**91**	**90**	**0.905**	**0.95**

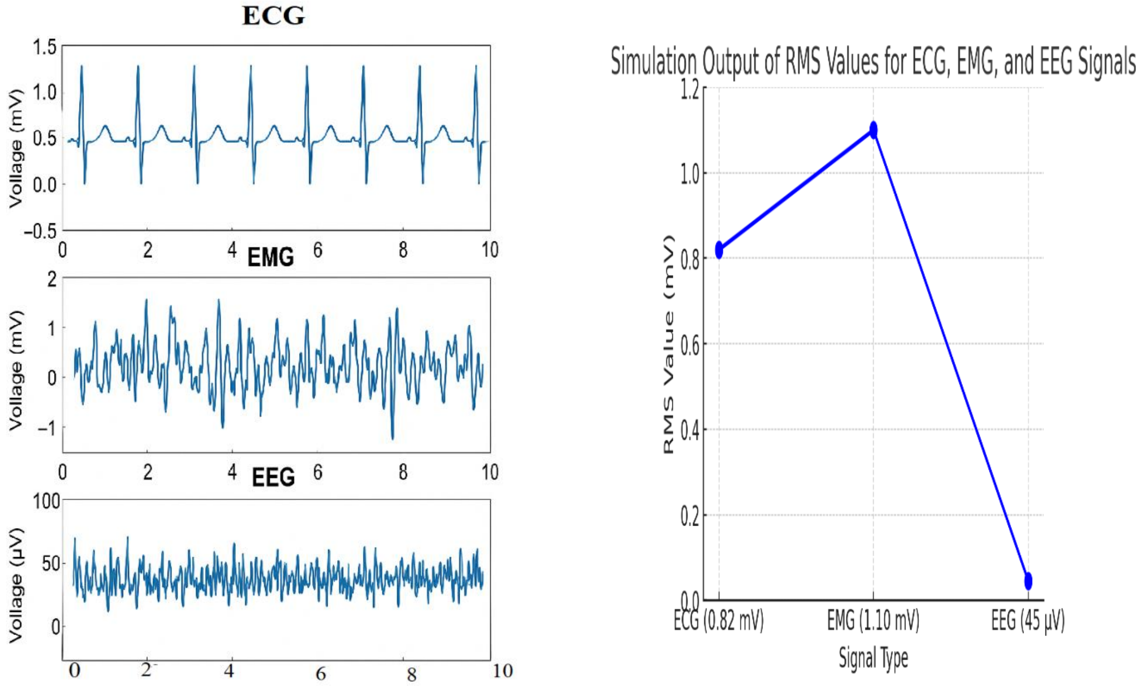

Figure 9: Periodic waves and RMS values for ECG, EMG, and EEG signals

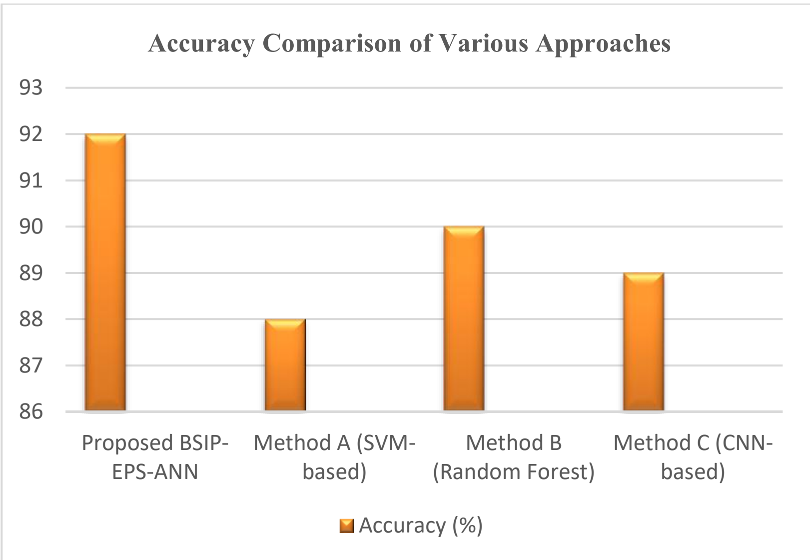

Figure 10: Accuracy Comparison of Various Approaches

Figure 9 shows periodic waves includes y axis in each plot is voltage in mV (or μV) and x axis is time in seconds and clearly shows how these signals change with time and also RMS values. They are essential in diagnosing and monitoring of a variety of medical conditions pertaining to the heart, muscles and the brain. Figure 10 comparison table of the accuracy of the proposed BSIP-EPS-ANN approach with other commonly used methods for classifying biomedical signals such as ECG, EMG, and EEG.

V. CONCLUSION

The method of Biomedical Signal and Image Processing with Electro-Physiological Signals using ANN (BSIP-EPS-ANN) proposed to analyse, classify biomedical signals, such as the ECG, EMG or EEG signals, is robust. Pre-processing techniques such as noise filtering, artifacts removal, and signal smoothing, when integrated impact significantly on the signals with improved quality for above accurate features extraction. Later the signals are represented by using time frequency domain features such as Root Mean Square, Power Spectral Density and wavelet coefficients, thereby enriching representation of the patterns and physiological characteristics of the signals. The system shows excellent performance metric such as high accuracy, precision, recall, and f1 score using the ANN based classification. Compared to traditional classification methods like SVM or Random Forest, this method achieves a better performance and would be a good tool for real time diagnostic applications in health care. Finally, the BSIP-EPS-ANN provides a major contribution in automated biomedical signals analysis enabling better clinical decisions and patient monitoring.

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