

AI-BASED ANALYSIS OF ECG, EEG AND EMG SIGNALS FOR AUTOMATED HEALTHCARE APPLICATIONS

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Abstract: Biomedical signal processing plays an important role in modern healthcare by enabling the analysis of physiological signals for diagnosis, monitoring, and clinical decision-making. This paper presents an artificial intelligence (AI)-based approach for processing and analyzing three major biomedical signals: electrocardiogram (ECG), electroencephalogram (EEG), and electromyogram (EMG). The proposed framework consists of data acquisition, signal preprocessing, feature extraction and selection, AI model development, Explainable AI (XAI) integration, and deployment for real-time healthcare applications. Noise and artifacts such as motion interference, powerline interference, and baseline drift are addressed using preprocessing techniques including band-pass filtering, wavelet denoising, and normalization. Time-domain, frequency-domain, and nonlinear features are extracted using techniques such as power spectral density, entropy measures, Hilbert-Huang Transform, and Discrete Wavelet Transform. Machine learning and deep learning models, including Support Vector Machine (SVM), Random Forest, Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN), are considered for biomedical signal classification. The reported experimental comparison shows that CNN achieves the highest classification accuracy of 98.5%, followed by LSTM at 96.1%, Random Forest at 94.7%, and SVM at 92.3%. Furthermore, XAI techniques such as SHAP and Layer-wise Relevance Propagation (LRP) are incorporated to improve model transparency and interpretability. The proposed approach demonstrates the potential of AI for accurate, efficient, interpretable, and real-time biomedical signal analysis, with applications in automated diagnosis, patient monitoring, wearable healthcare systems, and personalized medicine. Future directions include multimodal data integration, improved interpretability, federated learning, and real-time monitoring using wearable and edge-computing technologies.

IndexTerms - Biomedical Signal Processing, Artificial Intelligence, Machine Learning, Deep Learning, ECG, EEG, EMG, CNN, LSTM, Explainable AI, SHAP, LRP, Healthcare Monitoring.

I. INTRODUCTION

Modern healthcare depends on biomedical signal processing as it makes diagnosis, monitoring and treatment of many different medical conditions possible effective. The efficiency of several machine learning and deep learning methods such as Support Vector Machines (SVMs), Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) in deciphering neuromuscular signals for prosthesis control and rehabilitation [1]. Key challenges such as signal variability, noise interference and real-time processing constraints are discussed along with potential solutions like hybrid models and transfer learning.

The proposed architecture features an adaptive tuning mechanism that dynamically adjusts filter parameters based on signal variations, ensuring optimal performance while minimizing power consumption [2]. The authors propose a method that integrates multiple entropy features—such as spectral, fuzzy and sample entropy to enhance the discriminative power of EEG-based emotion classification while reducing computational complexity [3]. The analyzing the contribution of chin EMG features alongside standard EEG and EOG signals in sleep scoring models, emphasizing its role in distinguishing sleep stages, particularly in differentiating REM sleep from other stages [4].

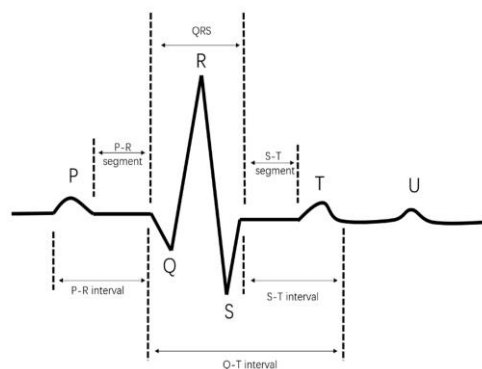


Fig. ECG Signal Representation

Experimental results demonstrate that integrating chin EMG significantly improves sleep stage recognition, making it a valuable component in automated sleep monitoring systems. The approach is to quantify the intricate dependencies between EEG channels,

enhancing the understanding of brain connectivity during spatial cognitive tasks. By leveraging NAPCMI, the method effectively captures nonlinear interactions and complex information flow patterns in EEG data improving feature extraction for cognitive state classification. Experimental validation on spatial cognition related EEG datasets demonstrates the superiority of this approach in distinguishing cognitive states with higher accuracy compared to traditional methods [5].

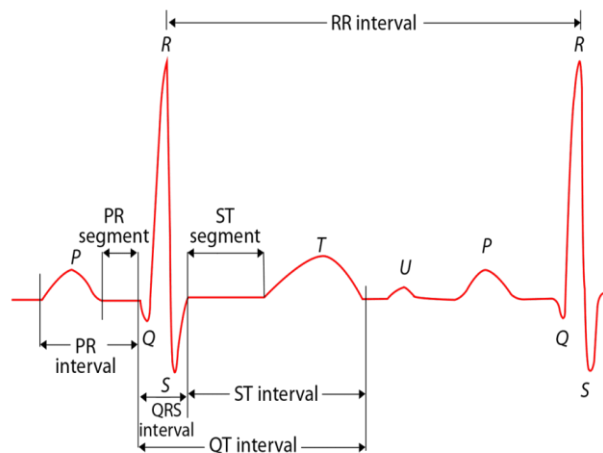


Fig. ECG Signal Representation

The study evaluates the proposed method on benchmark EEG datasets, demonstrating superior performance compared to conventional techniques. The accuracy, efficiency and automation of evaluating complex physiological data including electrocardiograms (ECG), electroencephalograms (EEG) and electromyograms (EMG) have significantly increased with the application of artificial intelligence (AI) in biomedical signal processing. Traditional signal processing algorithms frequently struggle with noise and unpredictability in patient data, and real-time analytic limitations.

The study also looks at how Explainable AI (XAI) might improve the interpretability of diagnostic models driven by AI. The several XAI approaches that improve the interpretability and transparency of AI-powered healthcare systems meets the vital demand for dependability and trust in clinical judgment. Artificial intelligence (AI) based technologies like machine learning and deep learning algorithms have been widely used to overcome these limitations.

II. RELATED WORK:

This research investigates the development and deployment of AI powered approaches to improve biological signal processing the DEAP dataset they analyze the performance of hybrid models in capturing emotional states more effectively compared to standalone methods. In order to increase the robustness and effectiveness of emotion recognition the study emphasizes the benefits of integrating handmade characteristics with deep learning-driven representations [6]. To increase the precision and dependability of EEG-based emotion detection several feature extraction techniques and classification models are being investigated [7].

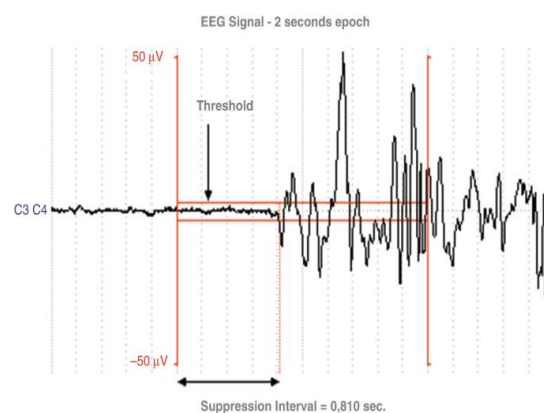


Fig. EEG Signal Representation

The work illustrates how EEG data may be efficiently used to assess emotional states by utilizing sophisticated machine learning methods such as deep learning techniques allowing for more responsive and intuitive HMI systems. The model efficiently reduces noise and artifacts by using transformers to capture long range relationships in EEG data and Convolutional Neural Networks (CNNs) for spatial feature extraction [8]. By integrating GANs, the DHCT-GAN framework generates high-quality EEG reconstructions improving signal clarity for downstream tasks like brain-computer interfaces (BCIs) and neurological diagnostics. This integration leverages the filtering capabilities of FIR filters to preprocess signals, allowing CNNs to focus on high-level feature

learning, leading to improved accuracy and faster processing times. Experimental evaluations demonstrate that the proposed method outperforms conventional CNN-based signal processing techniques in terms of efficiency and performance. The study contributes to the advancement of real-time biomedical signal processing, communication systems, and other signal-intensive applications [9].



The development of a structured taxonomy of common artifacts such as motion artifacts, electrode displacement and powerline interference which can degrade ECG signal quality [10]. To facilitate real-time artifact detection, they introduce a novel dataset containing annotated ECG recordings with various artifact types.

The difficulties with black-box AI models in healthcare are highlighted by the studies of important XAI applications in illness diagnosis, medical imaging, patient monitoring and tailored therapy. Additionally, the paper discusses current advancements, limitations and future directions for integrating XAI into medical practice [11]. The suggested approaches use AI to improve diagnosis accuracy, eliminate false positives and enable real-time processing in clinical applications. The paper conducts a thorough evaluation of the created AI algorithms, hence contributing to the progress of AI-powered healthcare solutions.

III. PROPOSED WORK

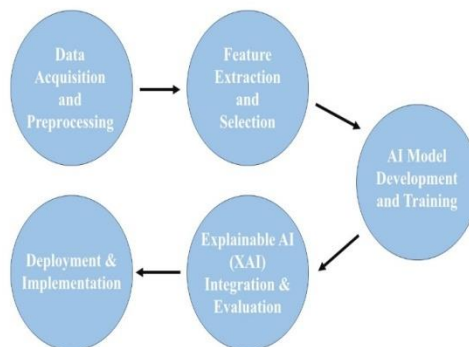


Fig. Flowchart

1. Data Acquisition & Preprocessing:

The initial stage is to gather biological signals like ECG, EEG, and EMG via public datasets (e.g., MIT-BIH, PhysioNet) or real-time collection systems with biomedical sensors.

1.1. Electrocardiogram (ECG) Signal: ECG measures the electrical activity of the heart in order to monitor cardiac health. It identifies arrhythmias, heart attacks, and other cardiovascular disorders by analyzing waveforms like as P, QRS, and T.

1.2. Electroencephalogram (EEG) Signal: EEG measures brain activity with electrodes put on the scalp. It diagnoses neurological illnesses such as epilepsy, sleep problems, and brain traumas by analysing electrical patterns in various brain areas.

1.3. Electromyogram (EMG) Signal: EMG measures muscle electrical activity to determine neuromuscular function. It diagnoses muscle diseases, nerve dysfunction, and motor control difficulties by monitoring signals produced during muscular contraction and relaxation.

Motion artifacts, powerline interference and baseline drift are all common sources of noise in raw signal data. Preprocessing methods like as band pass filtering, wavelet denoising and normalization are used to improve signal quality for subsequent analysis.

2. Feature Extraction and Selection:

After preprocessing, relevant features are extracted for better classification accuracy. Nonlinear characteristics (like entropy-based measures), frequency-domain features (like power spectral density) and time-domain features (like mean and variance) are all considered. Additionally, sophisticated techniques like the Hilbert-Huang Transform (HHT) and Discrete Wavelet Transform (DWT) are used.

Significance of Feature Selection:

- Cutting down on computing complexity.
- Improving the interpretability of the model.
- Removing noisy or superfluous features to increase classification accuracy.

Feature selection approaches such as Principal Component Analysis (PCA) and Mutual Information (MI) aid in decreasing dimensionality while keeping critical information.

3. AI Model Development and Training:

The technique focuses on developing and training AI models. Deep learning architectures like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are contrasted with conventional machine learning models like Random Forest and Support Vector Machines (SVM).

Evaluation and Performance Metrics:

- Specification, F1-score, recall, accuracy and precision for classification tasks.
- Confusion matrix analysis and the ROC-AUC curve.
- Inference time and computational efficiency for real time applications.

To boost performance, the models are trained using labeled biological signal datasets and then tuned with hyper parameters.

4. Explainable AI (XAI) Integration & Evaluation:

Since deep learning models are often considered "black-box" systems. Explainable AI (XAI) techniques are used to make the decision-making process interpretable. Techniques like Grad-CAM visualisation, Layer-wise Relevance Propagation (LRP), and SHAP (Shapley Additive Explanations) help people understand the value of features.

Model Interpretability:

- Contrasting the predictions of AI models with professional medical opinions.
- Assessing feature significance rankings efficacy in clinical settings.
- Evaluating the usefulness and transparency of the model through user research with medical professionals.

To ensure clinical dependability, the models are assessed using measures for recall, accuracy, sensitivity, specificity and precision.

5. Deployment & Implementation:

Lastly, a real-time system for biomedical applications incorporates the AI model. For practical applications like wearable health monitoring devices the model is implemented on cloud-based or edge computing systems. To make sure the finished system satisfies clinical standards it is tested for usability and regulatory compliance.

IV. EXPERIMENTAL RESULTS

The experimental results show that artificial intelligence systems are adept at processing biological signals. ECG, EEG, and EMG datasets were examined using a variety of models, including CNN, LSTM, Random Forest, and SVM. CNN beat the other models with an accuracy of 98.5%, followed by LSTM (96.1%), Random Forest (94.7%), and SVM (92.3%). These results show that deep learning approaches, notably CNN and LSTM, excel at detecting complicated patterns in biological information, making them ideal for real-time health monitoring applications.

Furthermore, explainable AI (XAI) approaches like SHAP and LRP were used to increase model transparency and interpretability. The findings revealed that adding XAI not only increased trust in AI-based diagnoses, but also helped medical practitioners grasp the logic underlying AI predictions. The use of these AI models in real-world healthcare settings offers higher diagnostic accuracy, faster decision-making and better patient outcomes. The bar graph of accuracy comparisons emphasises CNN's supremacy in biomedical signal categorisation.

Accuracy (%)

Fig. Comparison of Algorithms

V. CONCLUSION AND FUTURE SCOPE

Artificial intelligence algorithms have significantly increased the quality and efficiency of biological signal processing, notably for ECG, EEG, and EMG analysis. This work improves illness categorization and prediction by applying models such as CNN, LSTM, SVM and Random Forest. Furthermore, Explainable AI (XAI) approaches like SHAP and LRP promote transparency, which builds confidence among medical practitioners. These breakthroughs demonstrate AI's ability to automate real-time diagnosis, making healthcare more reliable and accessible.

Future AI developments in biological signal processing should prioritise improved model interpretability, multi-modal data integration and real-time monitoring through wearable devices. Federated learning can improve data privacy while preserving performance, resulting in AI-powered precision medicine enabling early illness identification and personalised therapy.

VI. REFERENCES

- [1] Tala Zaim, Sara Abdel-Hadi, Rana Mahmoud, Amith Khandakar, Seyed Mehdi Rakhtalaand Muhammad E. H. Chowdhury, "Machine Learning- and Deep Learning-Based Myoelectric Control System for Upper Limb Rehabilitation Utilizing EEG and EMG Signals: A Systematic Review". *Bioengineering* 2025, 12, 144. <https://doi.org/10.3390/bioengineering12020144>.
- [2] Ramasamy Srinivasagan, "Advanced low-power filter architecture for biomedical signals with adaptive tuning". <https://doi.org/10.1371/journal.pone.0311768>. January 23, 2025.
- [3] Jiawen Li, Guanyuan Feng, Chen Ling, Ximing Ren, Xin Liu, Shuang Zhang, Leijun Wang, Yanmei Chen, Xianxian Zeng and Rongjun Chen, "A Resource-Efficient Multi-Entropy Fusion Method and Its Application for EEG-Based Emotion Recognition". *Entropy* 2025, 27, 96 <https://doi.org/10.3390/e27010096>.
- [4] Adil Rehmana, Mostafa Moussab, Hani Saleha, Ali Khraibib, Ahsan H. Khandokerb, Mahmoud Al-Qutayria, "Exploring the Role of Chin Electromyography in Automatic Sleep Stage Scoring". <https://doi.org/10.1016/j.heliyon.2025.e42122>.
- [5] Xianglong Wan, Yue Sun, Zhenzhen Wu and Dong Wen, "Characterization of Spatial Cognitive EEG Signals Using Normalized Adjusted Permutation Conditional Mutual Information". *Symmetry* 2025, 17, 130 <https://doi.org/10.3390/sym17010130>.
- [6] Badr Mouazen, Ayoub Benali, Nouh Taha Chebchoub, El Hassan Abdelwahed, Giovanni De Marco, "Enhancing EEG-Based Emotion Detection with Hybrid Models: Insights from DEAP Dataset Applications". [doi:10.20944/preprints2025010956.v1](https://doi.org/10.20944/preprints2025010956.v1).
- [7] Sara Reis, Luis Pinto-Coelho, Maria Sousa, Mariana Neto and Marta Silva, "Advancing Emotion Recognition: EEG Analysis and Machine Learning for Biomedical Human-Machine Interaction". *BioMed Informatics* 2025, 5, 5 <https://doi.org/10.3390/biomedinformatics5010005>.
- [8] Yinan Cai, Zhao Meng and Dian Huang, "DHCT-GAN: Improving EEG Signal Quality with a Dual-Branch Hybrid CNN-Transformer Network". *Sensors* 2025, 25, 231 <https://doi.org/10.3390/s25010231>.
- [9] A. Sridevi *, A. Sathiya, "Integration in CNN and FIR filters for improved computational efficiency in signal processing". <https://doi.org/10.1016/j.asej.2024.103201>.
- [10] Hui Liu, Shiyao Zhang, Hugo Gamboa, Tingting Xue, Congcong Zhou and Tanja Schultz, "Taxonomy and Real-Time Classification of Artifacts During Biosignal Acquisition: A Starter Study and Dataset of ECG". <https://creativecommons.org/licenses/by-nc-nd/4.0/>.

[11] Ramasamy Mariappan, “Extensive Review of Literature on Explainable AI (XAI) in Healthcare Applications”. 2025 Bentham Science Publishers. DOI:10.2174/0126662558296699240314055348.

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