The Place of Artificial Intelligence Based Biomedical Signal Processing and Its Impact on Medical Diagnostic Systems

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Abstract: Today, artificial intelligence (AI) and data analytics have gained a significant position in the field of engineering for solving complex problems, especially in the medical domain. In particular, machine learning techniques such as artificial neural networks (ANN), Bayesian learning, and clustering algorithms have demonstrated remarkable results in classification and prediction tasks. These methods are increasingly applied in biomedical applications, enhancing the accuracy of diagnostic systems and enabling the effective analysis of large and complex datasets. As a result, biomedical data can now be accessed and processed more efficiently.Biological signals such as motor imagery (MI), electroencephalography (EEG), electrocorticography (ECoG), and electrocardiography (ECG), which play a critical role in clinical decision making, are now analyzed using machine learning algorithms. This integration enables more accurate and rapid decision making processes, particularly in areas such as brain signal classification, epileptic seizure detection, cardiac arrhythmia identification, and early breast cancer diagnosis — all of which are vital for human health.In addition, AI based approaches are being utilized in security and biometric identification systems, which are critical components of healthcare services, achieving high levels of accuracy. In light of these advancements, AI powered classification and prediction systems continue to make a profound impact in both the medical and engineering fields.This study reviews various biomedical signal processing studies conducted using AI based machine learning techniques. The selected studies were examined in terms of the materials used, methodologies applied, domains from which the data were obtained, and their reported performance metrics. The scope was limited to academic research published over the past 15 years. Furthermore, the practical use of these systems in clinical diagnosis is also discussed.

Keywords: Machine Learning; Medical Diagnosis; Health Informatics

1. Introduction

In recent years, artificial intelligence (AI) technologies, which have shown remarkable progress in the scientific community, have brought about significant transformations across various domains. Particularly in the field of healthcare an area of critical importance to human life AI has contributed substantially to the detection and resolution of medical problems. Today, AI plays a pivotal role in healthcare services, especially in biomedical signal processing and consequently in disease diagnosis and classification processes. AI based systems are capable of performing computational operations at speeds and levels of precision beyond human perception, enabling the detection of subtle signal characteristics such as noise, artifacts, and high dimensional data complexity. Biomedical signals are generally classified as electrocardiogram (ECG), electroencephalogram (EEG), and electromyogram (EMG). These signals reflect the dynamic changes in human physiology and play an essential role in the monitoring, classification, and prognostic assessment of both chronic and acute diseases. Through the intelligent processing and analysis of these data, artificial intelligence provides accurate, scalable, and automated solutions, thereby offering efficient and reliable decision support mechanisms in the field of health informatics and biomedical information systems.
In particular, when examined from the perspectives of machine learning and deep learning models, artificial intelligence has produced promising results in the classification of biomedical signals, anomaly detection, and early diagnosis tasks (Alqudah & Moussavi, 2025). The AI assisted analysis of signals that play a crucial role in the cardiovascular system, such as the electrocardiogram (ECG), photoplethysmogram (PPG), and phonocardiogram (PCG), significantly enhances diagnostic accuracy. During these analytical processes, the preprocessing stages, including noise reduction, normalization, and artifact mitigation—are of critical importance in terms of overall system performance and diagnostic reliability (Jia et al., 2024).

On the other hand, inadequate data presents a significant problem in the healthcare sector for diseases related to the nervous system. Synthetic data generation methods are often employed to address this issue. In this context, Generative Adversarial Networks (GAN) and Temporal GAN transfer learning techniques are widely used. Studies that have increased model accuracy and sensitivity by augmenting epileptic seizure data, and also achieved low false alarm rates in tests with real data (Rasheed, et al., 2020), and synthetic data have increased model sensitivity and overall accuracy in situations with limited SEEG (stereo EEG) resources (Ganti, Chaitanya, Balamurugan, Nagaraj, Balasubramanian, & Pati, 2022) serve as examples of these issues.

From a theoretical perspective, AI based biomedical signal processing systems are expected to have a profound impact on various aspects of medical science. This impact can be categorized under three main dimensions: early diagnosis and classification capability, generalizability and model reliability, and interpretability and clinical transparency. The first dimension, early diagnosis and classification capability, refers to the system's ability to detect time frequency patterns that are often imperceptible to the human eye (Diogo et al., 2023). The second dimension, generalizability and model reliability, emphasizes the system's capacity to maintain consistent performance across different patient groups, datasets, and clinical conditions (Loh et al., 2022). The third dimension, interpretability, pertains to the transparency of model decisions, enabling clinicians to use AI driven systems with confidence—an essential factor for clinical acceptance and regulatory compliance (Amann et al., 2020; Abgrall et al., 2024). Furthermore, AI driven biomedical systems hold considerable potential in improving the accessibility of healthcare services. In regions with limited medical resources, mobile health (mHealth) applications and wearable sensor technologies enable local analysis of physiological signals, facilitating decentralized diagnostic support (Vaquerizo Villar & Barroso García, 2025). However, translating these theoretical advantages into practical clinical deployment remains challenging due to several technical and ethical constraints. Among the major limitations are variability in data quality, sensor placement artifacts, lack of labeled datasets, risk of overfitting, real time processing constraints, as well as ethical, privacy, and regulatory approval issues (Nazir et al., 2023).

This study presents various disease prediction approaches by employing multiple variants of supervised machine learning algorithms, along with a comparative analysis of their diagnostic performance metrics. In recent years, such approaches have gained considerable attention within the domains of disease prediction, medical informatics, and data science. This growing interest has been driven by the widespread adoption of computer based technologies in the healthcare sector and the increasing availability of medical datasets for research and model development purposes. The research primarily focuses on machine learning algorithms such as Support Vector Machines (SVMs), Logistic Regression (LR), and Artificial Neural Networks (ANNs), which are typically utilized within a supervised learning framework. The main objective is to identify which methods in the current literature demonstrate superior performance in AI driven biomedical signal processing. Moreover, the study discusses the limitations of these systems and their potential impact on clinical diagnostic processes.

2. Literature Review

AI based biomedical signal processing has led to a significant transformation in clinical diagnostic systems in recent years. Within this context, ten academic studies were examined in detail. These studies were analyzed based on their subject focus, the type of disease related data used, and the machine learning algorithms applied. The review revealed that in the analysis of EEG, ECG, and ECoG signals, both time–frequency domain and nonlinear analytical methods were prominently utilized (Gajic et al., 2015; Iscan, Dokur & Demiralp, 2011). In the classification of electrocardiographic signals, innovative approaches such as the integration of learning vectors with spectral information yielded promising results (Dutta, Chatterjee & Munshi, 2011). Moreover, Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) were frequently employed particularly in motor imagery classification tasks achieving high accuracy when combined with diverse feature extraction techniques (Siuly, Li & Wen, 2014; Rathipriya, Deepajothi & Rajendran, 2013). Additional studies demonstrated the effectiveness of

AI in technical applications such as system fault detection (Rahmatian et al., 2013) and its potential use in security domains like biometric authentication via brainwave analysis (Blondet et al., 2014). Comprehensive reviews on the implementation of deep learning architectures in healthcare data analysis have also been published, highlighting the expanding role of these models in medical informatics (Alqudah & Moussavi, 2025; Sbrollini & Saibene, 2025). Research focusing on signal preprocessing and noise reduction emphasized that these stages are determinant factors affecting the final classification accuracy (Jia et al., 2024). Furthermore, it has been stated that the success of automated diagnostic systems depends not only on the architecture of the algorithm itself but also on the accuracy of error correction mechanisms and decision support frameworks (Belciug & Gorunescu, 2014; Ltifi et al., 2012). Finally, several studies have underscored the necessity of addressing both technical advancements and decision reliability simultaneously in the development of AI driven biomedical signal processing systems (Belciug et al., 2010).

3. Materials and Methods

In the field of artificial intelligence, a wide range of algorithms are utilized for biomedical signal processing. An examination of the literature indicates that while some algorithms are frequently employed, others are used less commonly depending on the specific application context. In general, the frequency of algorithm usage is strongly influenced by their performance metrics. Therefore, performance comparison studies based on different algorithms are frequently conducted, both to achieve accurate diagnostic outcomes and to ensure computational efficiency. In this study, various research works focusing on biomedical signal processing and their corresponding performance evaluations were analyzed. Table 1. presents a summary of the reviewed studies, including details about the signal types, materials, and methods utilized in each work.

Table 1. Signal type, materials and methods of studies in the field of biomedical signal processing

Source	Signal Type	Material	Method
Gajic et al. (2015)	EEG	EEG recordings (neurological patterns)	Time frequency analysis, wavelet transform, feature extraction, and classification
Iscan, Dokur & Demiralp (2011)	EEG	EEG data (cognitive state detection)	Nonlinear analysis, chaotic measures, and classification using Artificial Neural Networks (ANN)
Dutta, Chatterjee & Munshi (2011)	ECG	ECG recordings including cardiac arrhythmia	Spectral feature supported learning vectors, classification via SVM
Siuly, Li & Wen (2014)	EEG	EEG motor imagery datasets	Time frequency feature extraction, classification using SVM and ANN with high accuracy
Rathipriya, Deepajothi & Rajendran (2013)	EEG	EEG data (motor imagery)	Noise reduction, multi feature sets, comparative analysis using SVM and ANN
Rahmatian et al. (2013)	Technical / Medical Signal	Technical signals from medical equipment	Fault detection and system behavior analysis using Artificial Neural Networks
Blondet et al. (2014)	EEG	Subject specific EEG recordings	Biometric analysis for identity authentication, feature extraction, and classification
Sbrollini & Saibene (2025)	ECG / EEG	Large scale biomedical datasets	Deep learning based review focusing on classification and segmentation

Jia et al. (2024)	EEG / ECG	High noise clinical signals	Preprocessing techniques (filtering, ICA), noise reduction, and classification performance analysis
Belciug & Gorunescu (2014)	Clinical data / signals	Clinical decision support datasets	Error correction strategies, classification modeling with decision support architectures
Ltifi et al. (2012)	Clinical data / signals	Patient records and signal based datasets	Decision trees and probabilistic classification methods
Belciug et al. (2010)	Biomedical signals	Various biomedical signal datasets	Reliability analysis of AI based decision models with multi validation strategies

The information presented in Table 1. corresponds to studies conducted in this field between 2010 and 2025. An examination of the table indicates that the most frequently utilized type of biomedical signal is the Electroencephalogram (EEG). In addition to EEG, Electrocardiogram (ECG), clinical data and signals, as well as various technical or medical signal types and health related datasets have also been employed in computational analyses. A review of recent studies reveals a growing preference for EEG and ECG data in biomedical signal processing research. Given the prevalence of EEG data, it is particularly important to examine these signals in greater depth. EEG recordings are widely used for the detection of epileptic seizures. However, manual analysis of EEG recordings is often time consuming, labor intensive, and prone to human error. Therefore, there is a strong need for automated and efficient methods to identify such activities accurately. Figure 1. illustrates an example flow diagram depicting the sequential steps involved in such an automated detection methodology.

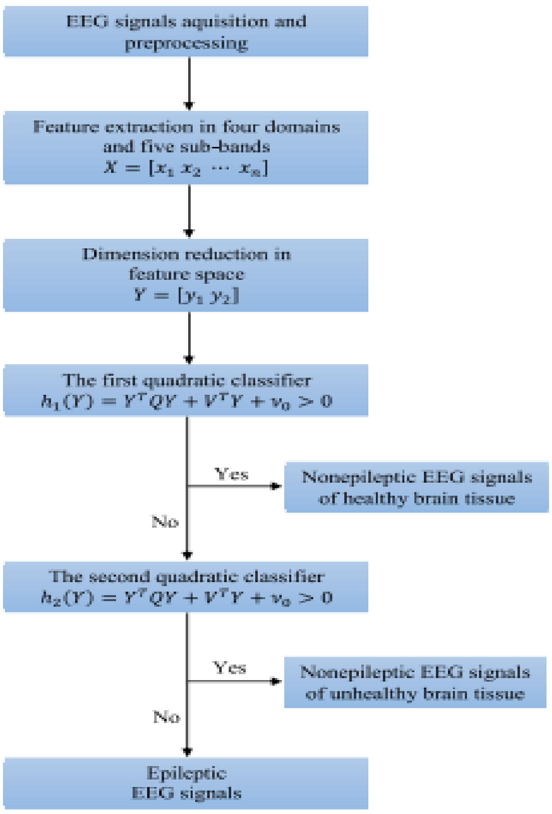

Figure 1. Structure of the new technique, preprocessing, feature extraction, dimensionality reduction and classification (Gajic, D. et al., 2015).

The diagram is derived from a study focusing on EEG signal processing. In this framework, the process begins with signal acquisition followed by a preprocessing stage. In the second stage, feature extraction is performed across four frequency domains and five sub bands. The third stage involves dimensionality reduction, while the fourth stage introduces the first classifier. At this point, non pathological EEG signals representing healthy brain activity are separated from the dataset, and a secondary classification step is applied to the remaining pathological EEG signals. In the subsequent phase, non epileptic abnormal EEG signals are classified into one group, while epileptic EEG signals are categorized into another, thereby completing the classification pipeline. This technique, unlike conventional methods used in similar research domains, demonstrates the ability to detect epileptic seizures more rapidly and accurately (Gajic et al., 2015). It also holds strong potential for real time seizure detection in future studies. Furthermore, applying this method across different experimental conditions and diverse patient groups could enhance its generalizability and clinical robustness.

4. Findings

The previous section examined the disease, algorithms used, and performance data of the studies. The results of the analysis are presented in Table 2.

Table 2. Diseases studied and algorithms used in the presented articles.

No	Author (Year)	Disease / Application	Algorithm Used	Performance
1	Gajic et al. (2015)	Epileptic activity (EEG)	Time–frequency analysis, nonlinear methods	98.7%
2	Dutta et al. (2011)	ECG beat classification	Cross spectrum + Learning Vector Quantization (LVQ)	95.24%
3	Iscan et al. (2011)	EEG signal classification	Time–frequency features + Artificial Neural Network (ANN)	90%
4	Siuly et al. (2014)	Motor imagery (EEG/BCI)	Modified CC LR algorithm + three feature sets	93.4%
5	Rahmatian et al. (2013)	Transformer insulation fault detection	ANN + k NN regression	97%
6	Rathipriya et al. (2013)	Motor imagery (ECoG/BCI)	Support Vector Machine (SVM)	95.72%
7	Blondet et al. (2014)	Identity authentication via EEG	Two different approaches (unspecified)	90%
8	Belciug & Gorunescu (2014)	Automated medical diagnosis	Error corrected ANN + Bayesian approach	>95%
9	Sbrollini & Saibene (2025)	Deep learning for classification/segmentati on	Deep learning (classification, segmentation, review)	Review study
10	Jia et al. (2024)	Enhancement of noisy EEG/ECG signals	Preprocessing techniques (filtering, ICA), classification analysis	Comparative study
11	Belciug et al. (2010)	Breast cancer recurrence	Clustering based approach	84.07%, 66.48%, 79.04%, 78.10%
12	Ltifi et al. (2012)	Decision support system	Bayesian Networks	74%

The table presents the performance metrics of twelve studies that were previously examined in the materials and methods section. An analysis of these values indicates that each study achieved an accuracy rate of at least 70% or higher, with the majority reporting performance levels exceeding 90%. The classification models that predominantly utilized EEG and ECG signals demonstrated notably high performance outcomes. In addition, the reviewed studies highlight the feasibility of developing biometric authentication systems, artificial neural network–based models, and dynamic decision support systems using AI driven biomedical signal processing approaches. These advancements suggest that the integration of such intelligent systems into medical practice has the potential to significantly enhance the overall quality and efficiency of healthcare services.

5. Discussion and Conclusion

The utilization of artificial intelligence (AI) and machine learning (ML) techniques in medical diagnosis and the analysis of biomedical signal data has begun to establish a fundamental role within the healthcare domain. These technologies enable the generation of more accurate and rapid clinical outcomes while simultaneously minimizing diagnostic errors. Moreover, AI and ML facilitate the implementation of critical applications in both healthcare delivery and security systems. The applicability of biometric authentication, artificial neural networks, and dynamic decision support systems within the medical field holds significant potential for enhancing the quality and reliability of healthcare services. Particularly, the processing of brain related signals such as electroencephalogram (EEG) and electrocorticogram (ECoG) data, which represent vital neurological activity has yielded promising results in early disease detection and the development of innovative technologies such as brain–computer interfaces (BCIs). These advancements mark a transformative step toward more intelligent and adaptive healthcare systems.

An examination of the reviewed studies reveals that time frequency based analyses and nonlinear methods used for the detection of epileptic seizures achieve remarkably high accuracy rates, with reported performances reaching up to 98%. Similarly, EEG classification methods based on motor imagery tasks have demonstrated accuracy levels exceeding 90%, highlighting their critical role in the development of brain–computer interface (BCI) systems. In particular, approaches employing Support Vector Machines (SVMs) and cross correlation techniques have yielded strong results, underscoring the potential applicability of such systems in clinical rehabilitation processes. From a healthcare perspective, EEG signals have also been utilized in biometric security systems for clinical validation purposes. These signals are individual specific, allowing the constructed systems to achieve high levels of security and robust identity verification. Studies have reported accuracy rates of up to 90%, demonstrating that these AI driven biometric frameworks offer safer and more tamper resistant alternatives compared to traditional authentication methods. Consequently, such systems represent a promising direction for integrating secure and intelligent biometric authentication into future medical and healthcare infrastructures.

Furthermore, the integration of methods such as Artificial Neural Networks (ANNs), Bayesian learning algorithms, Support Vector Machines (SVMs), and clustering techniques into medical diagnostic processes has produced successful results in the detection of various diseases, including breast cancer, cardiovascular disorders, and diabetes. Among these, ANN architecture enhanced with error correction mechanisms have demonstrated improved reliability and robustness in diagnostic decision making. In addition, k means and other clustering based approaches have been effectively utilized to predict disease recurrence, thereby enhancing the predictive performance of healthcare data analytics and supporting clinical decision making. These findings indicate that AI and ML algorithms are not confined to theoretical exploration but are increasingly contributing to the practical enhancement of healthcare services through real world diagnostic and prognostic applications.

In conclusion, the application of machine learning (ML) and artificial intelligence (AI) based methods to biomedical data has enabled revolutionary advancements in healthcare by making medical diagnostic systems more accurate, rapid, and reliable. The studies presented in the literature suggest that, with the integration of larger datasets and more sophisticated algorithms, these approaches can contribute even more substantially to clinical practice in the future. In particular, models developed for the processing of EEG and ECoG signals in the early diagnosis of neurological disorders have demonstrated high accuracy and effective performance. Similarly, deep learning based approaches applied to motor imagery classification show significant potential for use in Brain Computer Interface (BCI) systems designed to assist individuals with impaired motor functions. Moreover, EEG based biometric systems, leveraging the individual specific nature of brain signal patterns, are increasingly being employed in secure identity verification applications. The integration of Bayesian learning, Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs) into medical diagnostic workflows has contributed to reducing error rates and enhancing system reliability. Additionally, clustering based approaches aimed at predicting disease recurrence have facilitated the development of early warning mechanisms within healthcare data systems, supporting proactive and data driven medical decision making.

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