Exploring the Role of Machine Learning in Disease Diagnosis via Body Signals: An Extensive Review

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Heart disease is one of the most serious human diseases, with devastating consequences. In cardiac disease, the heart is unable to pump enough blood to the rest of the body. Accurate and timely heart disease diagnosis is critical for heart failure prevention and treatment. Traditional medical history diagnosis of heart disease has been deemed untrustworthy in several ways. Noninvasive methods, such as machine learning, are reliable and effective for classifying healthy people and persons with cardiac disease. Based on relevant research, this review covers the use of machine learning in the early detection of various diseases. The study then summarizes the most recent achievements in the field of machine learning-driven identification of diseases and Telemedicine, taking into account the algorithm, different disease categories, various body signals, numerous applications, and various assessment metrics. Finally, we summarize the key findings.

Keywords: Diagnosis, Machine learning (ML), Disease detection, Tele-medicine .

in: *Advancements in Communication and Systems*. Ed. by Ashish Kumar Tripathi and Vivek Shrivastava. Computing and Intelligent Systems, SCRS, India., 2023, pp. 185–195. DOI: https://doi.org/10.56155/978-81-955020-7-3-17

1 Introduction

The phrase "Telemedicine," which means "healing at a distance," was coined in the 1970s and refers to the use of information and communication technologies (ICTs) to enhance patient outcomes by increasing access to medical care and information. Previously, Telemedicine was divided into two categories: synchronous and asynchronous. A third type of monitoring, known as remote (tele) monitoring, has recently been recognized. This monitoring strategy involves gathering data from scattered devices such as the Internet of Things. Figure 1 is an example of a real-time health monitoring system.

In its most recent global e-health observatory survey, the World Health Organization identified four exemplary well-integrated Telehealth services: Tele-radiology, Tele-pathology, Tele-dermatology, and Tele-psychiatry. The asynchronous model is used by the first three services and the synchronous model is used by the fourth one, which shows that the replacement or enhancement of such a real-time system is impossible. The same poll also showed that over 60% of participants considered a major barrier to widespread adoption to be a lack of knowledge about clinical practices connected to telehealth.

Given this myriad of potential outcomes, an examination of the possible effects of machine learning in telehealth recently focused on four emerging themes based on different healthcare goals: patient observation, healthcare IT, intelligent aid and diagnosis, and information analysis collaboration.

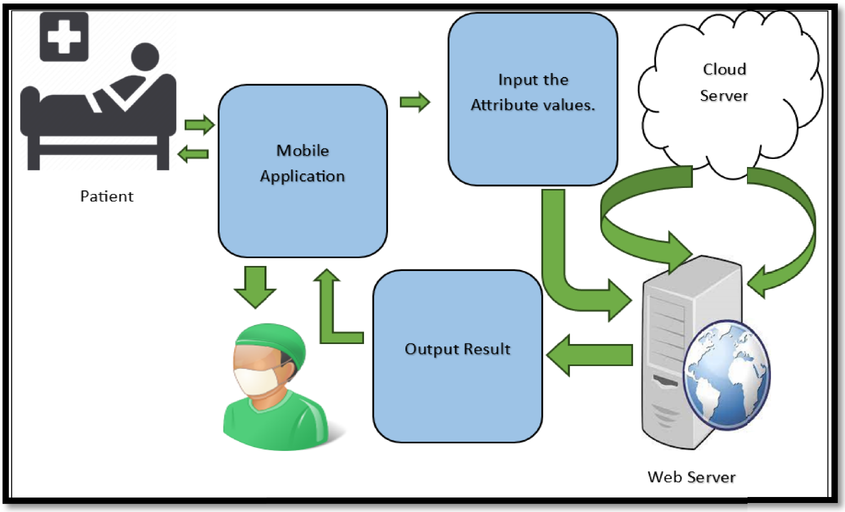

Figure 1. Real-time prediction of heart disease

Massive datasets are easily available, and computational data science (including AI-powered machine learning techniques) is fast developing, allowing for novel discoveries and useful insights that could greatly improve health outcomes. Intelligent systems with physiological signal monitoring for e-health care have arisen as a key topic of study as interest in remote healthcare systems has grown over the previous decade. The use of automated approaches in this data-rich environment enables better clinical decision-making. This research makes use of a comprehensive system that continuously monitors numerous vital signs, provides continuing medical care, and establishes a cellular link to an emergency hospital, all while transmitting all acquired data online. The study highlights how machine learning is being used to aid in the early detection of a variety of diseases.

2 Background Details

2.1 Tele-Medicine

The term telemedicine means remote transmission of medical data for patient health monitoring and remote medical care. Intelligent systems with physiological signal detection for e-health services are evolving as a result of the past decade's increased interest in remote healthcare systems. In modern India, the WHO recommends a doctor-to-population ratio of 1:1000, however, the actual ratio is 0.62:1000.

2.2 Artificial Intelligence (AI)

Artificial Intelligence (AI), which was developed in 1956, strives to duplicate and improve human intelligence.
Machine Learning (ML) – It is a Computer-based data analysis that employs statistical and automatic procedures.
Deep Learning (DL) - Multilayer and multi-neuron learning algorithms were developed, enhancing the application possibilities of ML.

According to Russell and Norvig in 1995, the AI field includes problem-solving, searching, reasoning, interpretation, strategy, pattern categorization, selection, training, interaction, vision, and automation. Medical Application - In recent years, the number of research articles incorporating machine learning in the medical field has increased (Figure 2).

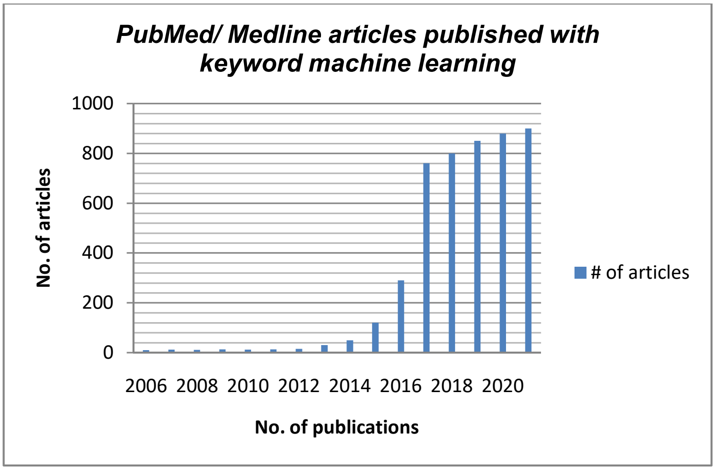

Figure 2. PubMed/ Medline articles published with keyword machine learning.

2.3 Motivation

Primary Goal- To provide current and future clinicians and researchers with knowledge of machine learning-based illness diagnosis systems. This gives them the ability to choose the finest deep learning/machine learning algorithms, boosting the chances of speedy and accurate disease diagnosis and categorization.

Secondary Goal - To identify the potential MLBDD-related studies.
Study Goal - To provide sound justification for the following inquiries:

- Identify the diseases of particular interest to academics and practitioners when assessing data-driven machine learning techniques.
- Determine the most popular MLBDD datasets.
- Explore the ML and DL methods currently employed in the healthcare industry to categorize different types of diseases.
- Investigate the frequently used neural network architecture for disease diagnosis.
- Evaluate the model's effectiveness and determine if the current assessment methods are adequate.

3 AI in Healthcare

Developed algorithms and methods to evaluate the accuracy of disease diagnosis systems. Medical diagnosis is determining the illness or illnesses that are causing a person's symptoms and indications. A patient's medical history and physical examination are typically used to make a diagnosis [1]. However, due to the vagueness of many symptoms, correct diagnosis frequently necessitates the use of skilled clinicians. This presents issues, particularly in developing countries such as Bangladesh and India, where there is a dearth of medical personnel to serve their vast patient populations [2].

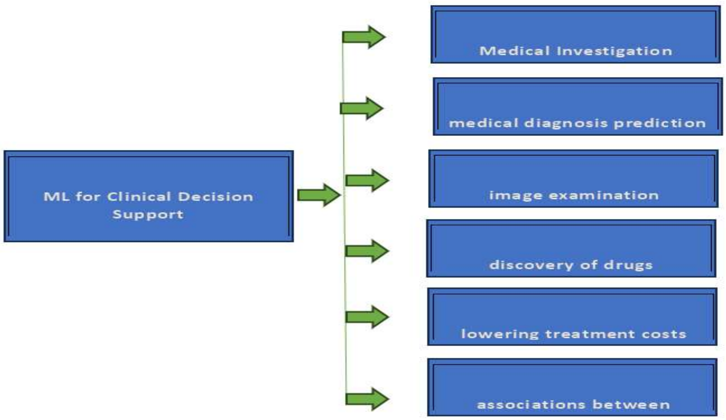

Figure 3. Machine Learning in Healthcare

Figure 3 depicts numerous applications of machine learning in the healthcare industry. Diagnostic procedures sometimes include pricey and difficult medical testing, providing a challenge for low-income persons. Human mistake contributes to overdiagnosis, which leads to unneeded therapies that harm people's health and wealth. According to a 2015 research by the National Academies of Science, Engineering, and Medicine, most people experience at least one diagnostic error in their lifetime.
Misdiagnosis can be caused by a variety of circumstances, including:

- Lack of detectable correct symptoms
- Presence of a rare disease
- Inaccurately ruling out a disease

Machine learning (ML) has a wide range of applications in modern technology including robotics, computers, mobile phones, and healthcare. The medical profession is increasingly reliant on machine learning (ML) for disease detection and safety [3]. Machine learning-based disease diagnosis (MLBD) systems are proven to be a cost-effective and time-efficient approach by researchers and practitioners [4,5].

4 Disease Diagnoses

Chatbots are used in mHealth (mobile health) applications to collect patient data such as medical history, lifestyle, and symptoms to potentially diagnose medical disorders. While the precise application of machine learning algorithms in diagnostic software is unknown, a simple implementation may include the following key steps:

- Access a comprehensive collection of patient symptoms and diagnoses that are symptom-based or symptom-verified.
- Develop a model for predicting diagnosis.
- Run the model to produce potential diagnoses for the patient in question.

Currently, radiology, pathology, ophthalmology, and dermatology are the most common medical professions that use Telemedicine diagnostics. Convolutional neural networks (CNNs) are the suggested approach for image analysis jobs. CNNs are used in a variety of computer vision applications, including object identification, image segmentation, and basic image categorization. The complete disease diagnosis system can be seen from figure 4.

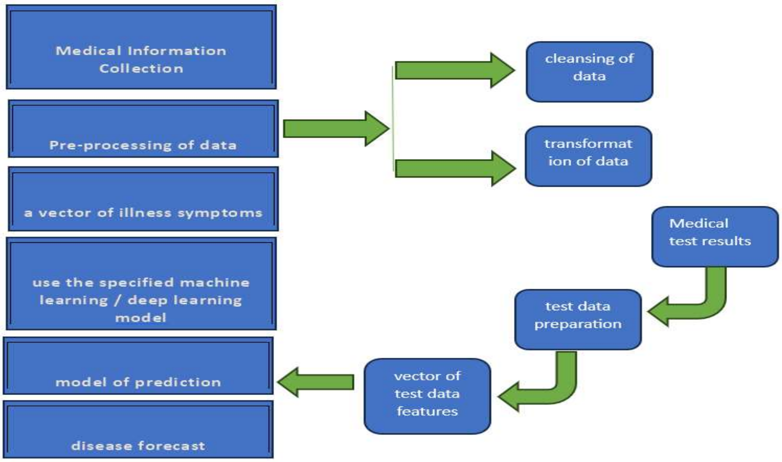

Figure 4. Disease diagnosis system

5 Literature Survey

The ECG signal processing offers a means to precisely detect the ailment contracted by any individual. The survey has been completed and is published here to provide a clear understanding of ECG signal processing.

Before dramatic outbreaks of chronic heart disease, Jeon et al. created and put into use a wearable ECG (electrocardiogram) system with cell phones for real-time monitoring, self-diagnostic, and remote diagnosis. The first attempt of its kind to address the problem was the use of a mobile phone for healthcare, but it was unsuccessful due to its restricted functionality. New research on mobile healthcare systems is being conducted by academics and businesses as a result of the recent popularity of smartphones with significantly more power.

The "Smart Patient Care System (SPaCS)" was created in June 2011 by MTM Ltd. with assistance from the Korean Ministry of Knowledge Economy [6]. The SPaCS health service, which consists of the two apps PCS and PRM, allows individuals to control their health using smartphones. Pukyong University in Korea developed the "Wearable ECG module (USN Lab ver. 2.0)" that doesn't need electrodes on the naked chest [7]. Patients may quickly put on and take off this module when it is fashioned into t-shirts, and wireless transmission of these test results to real-time devices is possible for analysis.

The UBC (University of British Columbia) medical engineering research team created a pulse-based portable oximeter called the Phone Oximeter combining mobiles and published lab-level technology [8]. These smart oximeters measure your blood o2 levels, heart rate, and breathing rate, also these measured values can be communicated to the hospital that is located far away.

In this study, the authors created and used sensor-based measurement equipment along with Android operating system-based apps. With the use of a small ECG sensor embedded in a sports shirt, patients can use this technology to monitor and instantly diagnose their heart conditions. Additionally, the application offers graphical data along with facilities for managing personal histories and an automatic emergency call system. The scientists also recommended further research and system enhancements for the system in development to use less energy and provide more precise measurements.

The experimental pilot study by Cvetkovic et al. examined at extremely low frequencies (ELF) the effects of pulsed electromagnetic fields (PEMF) concerning photoplethysmographic (PPG), electrocardiographic (ECG), and electroencephalographic (EEG) actions. The electrophysiological signals were represented using the wavelet transform (WT) as a feature extraction technique. In classifying systems like neural networks, feature extraction, and selection are crucial since classification is frequently more accurate when the pattern is simplified by representing it by crucial features. Features are the distinguishing or defining measures, transformations, or structural elements taken from the section of any pattern. To prevent the loss of critical information, features are employed to express patterns.

The amount of dimensional feature space required to convey the pattern is decreased by the feature vector, which is made up of the collection of all attributes used to characterize it. It is only possible to use the features that are contained in the feature vector out of the vast and potentially limitless collection of features that can be used to characterize a certain pattern. This is because relatively slight variations in some characteristics can be used to differentiate between various aspects. One objective of dimension reduction, in the author's opinion, is to satisfy technical specifications for the complexity of software and hardware, the expense of data processing, and the usefulness of pattern information compression. Additionally, when the pattern is clarified by focusing just on crucial traits or characteristics, the categorization frequently becomes more accurate. Methods for extracting features may be based on synthesizing syntactic descriptions or computing statistical statistics.

Alzheimer's disease (AD); is a brain condition that manifests as progressive dementia in middle-aged or old age. The diagnosis of Alzheimer's disease (AD) must be made as early and accurately as possible to have the most therapeutic benefit [9]. In this study, the author describes a technique for diagnosing AD by analyzing EEG data using a machine learning approach and demonstrates how to take data from EEG recordings and integrate them with a machine learning algorithm to create a classification model for AD. The outcomes are encouraging.

The P, QRS, and T waves on an electrocardiogram (ECG) represent the electrical activity of the heart. Most heart diseases can be diagnosed using feature extraction and segmentation from ECG data. Reviewing several machine learning algorithms for identifying arrhythmias (variations in a heartbeat), hypertrophy (increased cardiac muscle thickness), and heart enlargement is the primary objective of this research [10]. Additionally, they have discussed various machine learning strategies and contrasted various ECG analysis techniques and outcomes. The work's goal, the algorithms employed, and the results are the mixed method parameters utilized to compare and contrast the existing approaches.

Since studying ECG signal patterns for diagnosis requires a lot of time and effort, it is necessary to use automated methods for the accurate diagnosis of cardiac illnesses [11]. Following pre-processing, detection, and feature extraction from the ECG data, classification is performed using neural networks.

A diagnosis system for cardiac arrhythmias was created by utilizing an artificial neural network classifier [12]. The classifier's foundation is a Bayesian framework created using the backpropagation technique. The proposed approach has room for improvement and delivers a prediction accuracy of 90%. Additionally, the system needs modifications because it cannot be used in a real-world situation. Similar to this [13], developed an automatic Artificial Neural Network (ANN) oriented classification algorithm for cardiac arrhythmia using multi-channel ECG data.

In [14], the author has developed an ANN-based classifier for cardiac arrhythmia. Ans compared artificial Neural Networks (ANN), and Wavelets Back Propagation Algorithms using the MIT-BIH dataset.

In [15], the author compares several machine learning algorithms, including SVM, Naive Bayes, Decision Trees, Random Forest, and Gradient Boosting, to maximize the accuracy of diagnosing arrhythmia through the use of an ECG. SVM received a lot of attention among these.

The use of WPM and Internet of Things (IoT) concepts has grown quickly during the past few decades. Technology advancements in E-healthcare systems and automated smart homes make it possible to receive in-home medical care without going to the hospital. Thus, it has been recognized that the IoT could help healthcare societies by easing some of their current restrictions. Different theories and foundations in the area of e-health, mobile healthcare, and smart health services were given [16–18]. [19] carries out a thorough study of IoT applications in healthcare with a focus on issues and potential fixes.

To support people and make their lives easier, automation for smart homes is a developing area of the Internet of Things (IoT). Examples include home appliances controlled by remote control [20], energy management in the home [21], security systems [22], movement detection in the home [23], and the provision of healthcare for the elderly, the disabled, and outdoor patients [24, 25].

To monitor patients' blood pressure (BP) via mobile devices, Agarwal et al. [26] propose a healthcare monitoring system. They reasoned that systolic and diastolic pressure recorded data might be quickly sent to a cardiologist or doctor via a Web interface, where a doctor could then review them and assist the patient online. Gope and Hwang [27] have suggested a healthcare system that makes use of body sensor networks (BSN). The suggested system, also known as BSN-Care, utilizes a WPM device for measuring the physiological parameters of blood pressure and an electrocardiogram (ECG) to assess heart health. The BSN-Care server receives the data from the patient's body, which is subsequently used for evaluation. The system notifies the patient's family members and doctor in the event of an irregularity to enable quick action.

An RFID-based e-healthcare system was suggested by Chen et al. [28]. The system performs communication between the patient and the doctor as well as an evaluation of the patient's state of health. BSN may also be used to gather patient data such as blood pressure and temperature. It is also capable of preserving the patients' medical profiles and histories for use in the future. Using a smart home as a model, the author of [29] developed a health monitoring system for the remote patient monitoring of chronic patients who have high blood pressure and diabetes. The device is used to monitor the person's cholesterol and blood glucose levels at home, alerting authorized healthcare facilities or doctors or providing real-time messages in the event of any anomalies.

In [30], the author has proposed a compressed sensor-based approach to recognize PPG signals. The features extracted by scientists using the combination of discrete wavelet transform with an SVM classifier were able to achieve an accuracy of 91.31%. A short description of the literature survey can be found in Table 1.

Table 1. Summary of Literature Survey

S. No	Paper Reference	Description	Limitiations
1	[4]	This paper presents a comprehensive analysis of research in using machine learning techniques for heart disease diagnosis. The paper systematically reviews various studies, methodologies, and advancements in this field, providing valuable insights for researchers and healthcare professionals working on improving heart disease diagnostics through machine learning approaches.	ML-based heart disease detection with unbalanced data will still have many untapped elements and potentials to unlock in the future.
2	[7]	This work explores the application of time-frequency analysis techniques to study and characterize pediatric heart murmurs. The paper investigates various signal processing methods to better understand and diagnose heart conditions in children, providing valuable information for researchers and clinicians in the field of pediatric cardiology.	Deep neural networks perform well on a variety of tasks, yet they still include a number of characteristics that require further research and justification.
3	[8]	This paper introduces a novel device for getting medical images using heart sounds. The paper presents the development and application of this new device, enabling synchronization of imaging procedures with the cardiac cycle based on heart sound signals, potentially enhancing diagnostic accuracy in medical imaging.	The proposed CNN-based approach will be further examined on additional datasets and architectures in future studies.
4	[10]	This paper provides a comprehensive review of different machine-learning techniques applied to electrocardiogram (ECG) analysis. The paper explores the use of machine learning algorithms in detecting cardiac abnormalities, arrhythmias, and other ECG-based diagnostic tasks, offering valuable insights for researchers and healthcare professionals working on ECG signal processing and cardiac health assessment.	Future research will use optimization approaches like genetic algorithms and any colony optimization to address this flaw.
5	[12]	This paper presents a neural network classifier based on a Bayesian framework for identifying arrhythmias from electrocardiogram (ECG) signals. The paper discusses the use of machine learning techniques to improve arrhythmia detection and classification, providing valuable insights for researchers working on ECG-based	Because there are so many studies already done, it is necessary to do a more thorough examination to apply categorization systems practically.

		diagnostic systems with neural networks and Bayesian methods.	
6	[14]	ANN classification of cardiac arrhythmias" by Anuradha and Reddy (ARPN Journal of Engineering and Applied Sciences, 2008) investigates the use of artificial neural networks (ANNs) for classifying cardiac arrhythmias. The paper explores various ANN architectures and training techniques to improve the accuracy of arrhythmia classification, providing valuable insights for researchers and healthcare professionals working on automated arrhythmia diagnosis using machine learning.	Different arrhythmia signal types have a significant impact on the human body. These signals exhibit parameter values that vary in various ranges from those of typical signals when they are statistically processed. This clear shift in the parameters aids the classification algorithm's definition of the signal classes.
7	[15].	This paper explores the combined use of machine learning algorithms and ECG diagnostic criteria for accurate arrhythmia classification. The paper investigates the integration of machine learning techniques with established diagnostic criteria to improve the effectiveness of arrhythmia detection, providing valuable insights for researchers working on ECG-based diagnostic systems with machine learning.	This paper exhibits the anti-proliferation, anti-migration, nematicidal, and insecticidal capabilities of the latex lectin from Artocarpus altilis. The signaling pathways and mechanism of action associated with these traits will be the subject of further study.
8	[31]	In this paper, the author addresses the concern of overdiagnosis in pediatric medicine. It highlights the potential harm caused by unnecessary medical interventions and advocates for evidence-based and critical diagnostic practices to provide better care for children, minimizing the risks of overdiagnosis.	MLBDD may concentrate on multiclass classification with extremely unbalanced and missing data, explanation and interpretation of multiclass data classification using XAI, and optimization of big data that contains numerical, categorical, and picture data.

Challenges and Limitations:
Despite the promising potential of machine learning-based disease diagnosis, several challenges and limitations need to be addressed. The availability of high-quality and diverse datasets plays a critical role in training accurate machine learning models. Additionally, ethical considerations privacy concerns, and interpretability of results need to be carefully addressed to ensure the ethical and reliable use of these technologies in healthcare.

Research Gap: When the literature studies are being carried out, we can summarize that there is a need for a model that can outline the following goals:

- Offers a unique perspective on hidden patterns in the data.
- Aids in avoiding biases in people.
- The use of machine learning (ML) classifiers to categorize the illness based on user input.
- Lowers the price of medical tests.

9 Conclusion

Human healthcare is one of society's most pressing challenges, intending to identify rapid, accurate, and effective disease detection to guarantee patients receive proper care. Developing a tool for early diagnosis and successful treatment planning, however, involves major hurdles. Machine learning (ML), a subfield of artificial intelligence (AI), may be able to address some of these issues, helping researchers, medical practitioners, and patients alike. Previous studies highlighted in this article indicate how ML can be used for early disease detection. This paper provides an overview of current advances in ML-based disease identification, including techniques, disease categories, and applications. Finally, the key findings are described, followed by a prospective appraisal of possible future directions.

Machine learning-based disease diagnosis using body signals has emerged as a powerful tool in healthcare. It offers the potential for more accurate efficient and personalized diagnosis. However further research is needed to overcome the existing challenges and limitations in this field. With advancements in machine learning algorithms and data collection techniques, the future of disease diagnosis using body signals looks promising.

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