Intelligent Healthcare System for Predicting Cardiac Diseases

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Cardiovascular diseases (CVD) are amongst the leading causes of death worldwide. Modern medical milestones are represented by 5G systems, internet services, artificial intelligence (AI), microelectronics, big data, cloud computing (CC), and smart bioengineering. These techniques are employed at every stage of sophisticated medicine. The Internet of Things (IoT)', given its capacity to assist in solving diverse health-related problems in a highly efficient manner, has attracted the attention of scientists desirous of contributing to this domain.

Keywords: smart healthcare system ; cardiovascular disease ; CVD

1. Introduction

Cardiovascular diseases or diseases of the heart and circulatory system are a leading cause of severe illness and death worldwide. Diseases of the cardiovascular system manifest as cardiovascular events, which are a disruption of the circulatory system presenting as myocardial infarction, stroke, dizziness, etc. [1]. A number of risk factors, such as diabetes, high blood pressure, and high cholesterol, have been identified to contribute to cardiovascular diseases. In spite of technological advancements, it is challenging to detect early stage cardiac diseases in most settings [2]. The occurrence of a cardiac disease has the potential to drastically limit a person's productivity and well-being [3]. Cardiac arrest can manifest as sudden collapse of the patients. Medical tools, such as defibrillators, help provide a high-energy shock to the heart during cardiac arrest aiding the reactivation of the normal heart activity and recovery of the patients [4]. The World Health Organization (WHO) reports that chronic diseases have significantly increased in wealthy nations in the past few decades. This has been mainly attributed to lifestyle diseases and the ageing population. Comorbidity, or multiple illnesses in the same person, is another crucial factor complicating the management of such patients [5][6][7][8]. Comorbid conditions in the elderly are a matter of greater concern [9]. Newer technology has been increasingly utilized in the prevention and management of such diseases in recent decades.

Modern medical milestones are represented by 5G systems, internet services, artificial intelligence (AI), microelectronics, big data, cloud computing (CC), and smart bioengineering. These techniques are employed at every stage of sophisticated medicine [4]. The Internet of Things (IoT)', given its capacity to assist in solving diverse health-related problems in a highly efficient manner, has attracted the attention of scientists desirous of contributing to this domain [10]. Examples of intelligent healthcare that can profit from the IoT include elderly care, remote patient monitoring, wellness treatment, chronic disease control, and supported accommodation [9][11]. Medical devices with sensors are referred to as smart gadgets. The IoT has been shown to lower equipment costs and increase human lifespans with the help of healthcare providers [12]. The IoT enables more effective scheduling of scarce resources, facilitating the monitoring of a greater number of patients [9]. Remote healthcare monitoring can be used to predict and identify the condition early, and people's clinical records can be stored within the database for future use. With the use of such technology, patients can have easy and timely access to their health records [5].

When required, patients can monitor their health using portable or wearable devices. They can utilize remote facilities to control their homes and as virtual aids to obtain medical advice. Experts in medicine believe that highly developed clinical decision-support tools could be used to guide and improve medical testing. An innovative concept called the "Internet of Medical Things" (IoMT) has emerged due to the widespread acceptance and implementation of modern clinical instruments and support hardware for healthcare providers [13]. The healthcare industry and the prevalence of IoT-enabled medical devices have undergone significant transformations, offering new opportunities for healthcare professionals and researchers [11]. These advancements allow investigators to monitor a user's activities through various means, including portable sensors, ingestible devices, and embedded sensors, as well as tracking smartphone usage and gadget patterns. With the wealth of data collected, modern technologies like artificial intelligence (AI) and deep learning (DL) can be harnessed to gain insights into an individual's health status [1]. Machine learning (ML) techniques, particularly deep learning, have shown promise in population-based research for assessing cardiovascular risk, predicting cardiac events, and identifying valuable biomarkers such as ECG signals [14].

Although several machine learning-based methods for predicting and diagnosing cardiac diseases have emerged in recent times, there are notable limitations. Existing intelligent frameworks often struggle to effectively utilize data from multiple sources, especially when dealing with high-dimensional datasets [15]. Furthermore, traditional algorithms typically select features from a dataset and compute their overall significance, which does not always lead to improved accuracy in diagnosing cardiac diseases.

2. Intelligent Healthcare System for Predicting Cardiac Diseases

The field of predicting cardiovascular diseases has seen various techniques and models developed over time, each with its own set of limitations. The need for the suggested model arises from these limitations, and it aims to address these issues. In the medical domain, knowledge is derived from data and experiences of medical professionals. The human body is highly complex and susceptible to various factors, making modeling its functions and dysfunctions a challenging and time-consuming process.

Machine learning techniques have become instrumental in using medical data for diagnosing and forecasting various illnesses, playing a vital role in e-health systems. For instance, in a previous study [4], Mansour et al. introduced the Crow Search Optimization-based Cascaded Long Short-Term Memory (CSO-CLSTM) framework, which leverages AI and convergence methodologies to identify illnesses. The CSO-CLSTM model demonstrated strong classification rates and specificity. However, it faced challenges related to the complexity and intricacy of the proposed system.

Another approach, as seen in the work of Kumar and Gandhi [3], involved a scaled three-tier system for managing a large volume of wearable sensor data. Tier 1 focused on data collected from IoT wearable sensor devices, Tier 2 employed Apache HBase to store data from integrated IoT devices within the cloud, and Tier 3 used Apache Mahout to create a probabilistic linear extrapolation heart disease prediction model. However, this approach could be computationally demanding due to its sequential nature.

These examples highlight the ongoing efforts to improve disease prediction models aims to contribute to this area by addressing specific limitations and providing a novel approach to predicting cardiovascular diseases. Mohan et al. [2] used machine learning techniques to design a novel strategy for detecting essential traits and enhancing cardiovascular illness prediction accuracy. The prediction model is developed with different combinations of attributes and well-known methods to obtain higher performance. The revolutionary techniques proposed here are simple and efficient, improving heart disease prediction while lowering costs. Nevertheless, feature selection methods are needed to obtain a broader view of the critical information to enhance the accuracy of heart disease prediction.

Dami and Yahaghizadeh et al. [1] created a deep learning strategy using 5 min (ECG) recordings. They retrieved the time–frequency characteristics of electrocardiogram data to predict vascular catastrophes a few days before the occurrence. The Long Short-Term Memory (LSTM) neural net was used to investigate the prospect of learning long-term connections in the ability to detect and prevent these events swiftly. The fact that there must be defined criteria for experimentation and evaluation since the topic is unique, however, serves as one of the research's shortcomings.

Basheer et al. [5] developed a hybrid fuzzy-based tree-based method for the early diagnosis of cardiac diseases using a constant and remote patient monitoring program. The mixed fuzzy-based decision tree method successfully detects cardiac disorders compared to previous classification methods. However, there is no fixed system or set of IoT implementation standards. It cannot be utilized everywhere and needs to offer adequate solutions to the issues. Kaur et al. [6] developed a healthcare system based on the IoT and a Random Forest classifier. The developed approach improves interactivity between patients and doctors. However, developing and deploying a healthcare system via cell phones involves several challenges. A deep learning-based IoT health surveillance system has been introduced by Wu et al. recently [7]. This method might help identify dangerous disorders amongst athletes such as tumors, heart issues, cancers, etc.

On the other hand, the classifier that was used to build the model can result in overfitting, complexity, and high processing costs. For example, an Internet of Things peripheral heart rate monitoring intelligent sports wristband system was created by Xiao et al. [8] to track changes in patient's heart rate while engaging in athletics. The physiological parameters in the constructed model focus primarily on the heart rate. Critical metrics, such as blood pressure, need to be addressed, which is significant or a flaw in the method. **Table 1** summarizes predicting cardiovascular disease using a Predator Crow Optimization-tuned deep neural network for an intelligent healthcare system.

Table 1. Summary of surveys from the literature.

Refs.	Technique	Findings	Advantages	Disadvantages
[1]	**Long Short-Term Memory (LSTM) neural net**	**Mean accuracy**	**The accuracy is good**	**Non-continuous feasible monitoring**
[2]	**Revolutionary methods**	**Accuracy**	**The cost is low**	**Increases computational time**
[3]	**Scaled three-tier system**	**Sensitivity specificity**	**The technique is simple**	**Difficult to interrupt**
[4]	**Crow Search Optimization-based Cascaded Long Short-Term Memory (CSO–CLSTM) framework**	**Accuracy**	**High sensitivity**	**Low recall**
[5]	**Hybrid fuzzy-based tree-based method**	**Sensitivity, specificity, and accuracy**	**Recall is higher**	**When using large datasets, the training time is extended**
[6]	**Random Forest classifier**	**Maximum accuracy**	**F1-score is higher**	**Difficult to interrupt**
[7]	**Deep learning-based IoT**	**Precision and F1**	**Decreases computational time**	**The weights of the variables are not constant**
[8]	**The smart sports wristband system**	**Accuracy**	**Higher accuracy**	**Low-dimensional data**
[16]	**MSSO with Random Forest model**	**Accuracy and efficiency**	**Greater accuracy, and high classification efficiency**	**Depends on the database's quality**
[17]	**Correlation-based feature selection and hyperparameter optimization**	**Accuracy, AUC**	**Increased classification accuracy**	**Limitation to transferability, and generalizability**
[18]	**Smart healthcare system based on Bi-LSTM**	**Sensitivity, specificity, accuracy, and f-measure**	**Ability to control sequential healthcare database**	**High computational time and demands more resources**
[19]	**Cluster-based BiLSTM**	**F-measure, sensitivity, and accuracy**	**Robustness and transferability**	**Instability**
[20]	**Computational method based on CNN**	**Accuracy**	**Enhanced accuracy**	**Depends on the consistency and quality of the input images**

Cenitta et al. [16] presented an integrated cardiac disease prediction model using the modified squirrel search optimization (MSSO) and the machine learning model. This approach incorporated the MSSO with the Random Forest algorithm for optimal feature extraction and selection. This helps minimize the number of attributes and records in the classification process. This model was evaluated with the ischemic heart disease database, and the implementation results demonstrate that the designed model attained greater efficiency in disease identification. However, the model's reliability depends on the image dataset's quality. Reddy et al. [17] designed an effective heart disease identification model using the optimization and principal components. This method concentrates on feature extraction and selection. Initially, the feature extraction was performed to track the principal elements, and then the feature selection was carried out to choose the optimal principal element in the heart database. Further, an ensemble classification module and hyperparameter optimization was designed for classification purpose. Optimization integration enhances the accuracy and area under the curve (AUC) of the system. However, this method is restricted to generalizability and transferability.

Challenges

- Heartbeat and Pulse Rate Monitoring: The use of a 650 nm green LED as a light source for pulse rate monitoring is common, allowing light to penetrate various tissues. However, the output current from photosensitive elements is typically low, making them susceptible to external electromagnetic interference. Additionally, the electrical signal generated by photoelectric conversion may be weak, which can pose challenges in capturing accurate pulse information [8].

- Data Preprocessing and Feature Extraction: To ensure the quality of telemedicine data and avoid data duplication, extracting meaningful features from raw data using deep learning and machine learning algorithms is essential. This process helps filter out duplicate, noisy, and inaccurate data before storage in remote cloud data centers, thus optimizing resource utilization and avoiding potential negative health-related consequences [7].

- Real-Time Health Surveillance: Contemporary health surveillance systems rely on real-time analytics to provide critical information swiftly and improve response times. However, challenges may arise due to unstable network connections and inconsistent data flows from remote sensors, potentially affecting the efficiency of these systems [7].

- Deep Learning Model Complexity: Increasing the number of hidden units in a deep learning model can lead to improved accuracy in training and testing procedures. However, it also introduces challenges such as higher processing costs, increased model complexity, and the risk of vanishing gradient problems, which can hinder the training process [7].

- These points highlight some of the technical and practical considerations in health monitoring and data analysis, particularly in remote or telemedicine applications. Addressing these challenges is crucial for enhancing the accuracy and reliability of health-related systems and ensuring they deliver meaningful results.

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