A SURVEY ON AI ALGORITHMS FOR PREDICTION OF CVD ABNORMALITIES BASED ON SMART WEARABLES

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Abstract
Although all the enhancements in science, medical Science, healthcare, and the healthcare engineering, cardiovascular disease (CVD) remains one of the leading causes of morbidity and mortality in India and globally. The main reasons are the lack of precautionary health services and delayed in diagnosis due to the growing population, the failure of physicians to apply guide-based treatments, the lack of continuous patient follow-up, and the low observance of patients with doctors' recommendations. The proposed survey of Artificial intelligence (AI) Algorithms that supports complex decision-making processes using AI techniques such as data examination, insights, and optimization. These study mainly focuses on AI Algorithms for prediction of CVD abnormalities based on smart wearables, which plays main role in patient care by providing more accurate solution and personalized information to healthcare professionals in risk assessment, diagnosis, treatment optimization, and monitoring and early warning of CVD. However, for these systems to be fully Non-invasive, reliable, portable and cost-effective, they need to be trained with accurate data and carefully evaluated by medical professionals.
Keywords: *Artificial intelligence (AI), Cardiovascular diseases (CVDs), Survey, Prediction, Algorithms.*

1. Introduction

Cardiovascular diseases (CVDs) are one of the leading causes of death in India. Approximately 18 million deaths each year are accounted for CVDs. Delayed identification and poorly controlled capabilities are not sufficient to recognize them at early stage. To overcome this, there is a pressing need for real-time monitoring technologies that can monitor heart activity. Appropriate monitoring technology and real-time examination is very important in the treatment of heart problems in the early stages. Early detection can not only help prevent severe cardiac events but also improve patient care. Traditional methods like electrocardiography (ECG) lacks convenience and portability. With the recent advancements that have happened over the years, Photoplethysmography (PPG)-based solutions have emerged as reliable tools for monitoring CVDs. These are lightweight and wearables. On the other hand, Artificial intelligence (AI) based algorithms have capability to enhance the performance of these tools to deliver efficient and promising predictions.

The integration of AI Algorithms and Photoplethysmography (PPG) has recently revolutionized the analysis of CVDs. The market is flooded with smart wearables that are capable of giving clinical-grade insights, thus enabling personalized healthcare. The proposed research, a survey on AI algorithms based on health care that mainly focuses on different kinds of AI algorithms which is used for prediction of Heart Rhythmic anomalies. This would serve as a guide to researchers in the field of advanced real-time monitoring systems using AI algorithms for cardiac events.

2. Background

Photoplethysmography (PPG) is easily accessible method for monitoring Heart Rhythm (HR), which is applicable for rhythmic analysis and finding abnormalities. This non-invasive technique is an optical instrument that is used to measure blood volume changes. This is typically done using light-emitting diodes and photo detectors. When light falls on skin, some quantity gets absorbed and the remaining gets reflected to the Photodetector. The quantity of light reflected depends on the pulses of blood flow, thus creating a waveform as shown in Figure 1. A cycle of PPG waveform has two peaks, the taller one being systolic, and the smaller one being diastolic. These peaks have a diastolic notch in between.

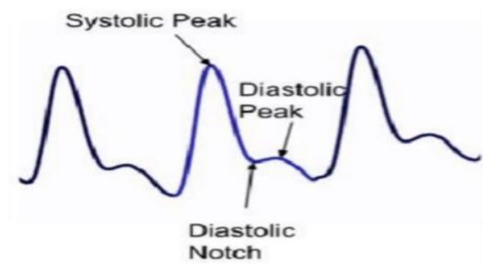


Fig.1 *A typical PPG signal. The signal has two peaks, the taller one being systolic, and the smaller one being diastolic. These peaks have a diastolic notch in between.*

a. CVD ABNORMALITIES

This PPG signal convey vital information regarding various CVD-related abnormalities. These abnormalities may include

i. Arrhythmia: This means irregular rhythm of heartbeats, which can be detectable by pulse interval variability.
ii. Bradycardia: This in contrast represents lower than normal heart rate, that can be observed from longer intervals between peaks in the PPG signal.
iii. Tachycardia: This indicates abnormally high heart rate, that can be identifiable by consistently short inter-beat intervals.
iv. Atrial Fibrillation (AF): This is determined by irregular pulse patterns and inter-beat interval variability, which can be detected using AI algorithms.

b. PPG and AI

The algorithms available in the literature can detect these abnormalities using PPG and AI algorithms. There are several machine Learning (ML) and deep Learning (DL) techniques that can be used for automated detection, classification, and prediction of CVD anomalies using PPG data. Some of these techniques are

i. Support Vector Machines (SVM): These are usually used for binary classification of normal vs. abnormal waveforms using any reliable signal features.
ii. Convolutional Neural Networks (CNN): These are neural networks that can automatically extract spatial features from PPG signals or their equivalent transforms, useful in detecting arrhythmias.
iii. Long Short-Term Memory Networks (LSTM): These are used for modeling temporal dependencies in sequential PPG data, ideal for rhythm-based predictions.
iv. Random Forests, k-NN, and Decision Trees: These are used in ensemble or hybrid models for quick, interpretable decision-making.
v. Auto encoders and GANs: These are useful for denoising and augmenting PPG signals during training.

One of the major problems in wearable health monitoring is to deal with the trade-off between real-time prediction and time for analysis. Real-time prediction demands very low-latency processing, using light computations. These systems use edge AI to reduce dependency on cloud networks. These features are essential for applications including cardiac emergency and continuous monitoring. Other challenges in real-time deployment include data latency, battery constraints, memory usage, and real-time execution speed, as these systems heavy libraries like TensorFlow Lite, Edge Impulse, and TinyML on OS like Android, RTOS, and Wear OS etc. A typical block diagram for CVD detection using PPG and AI is shown in Figure 2.

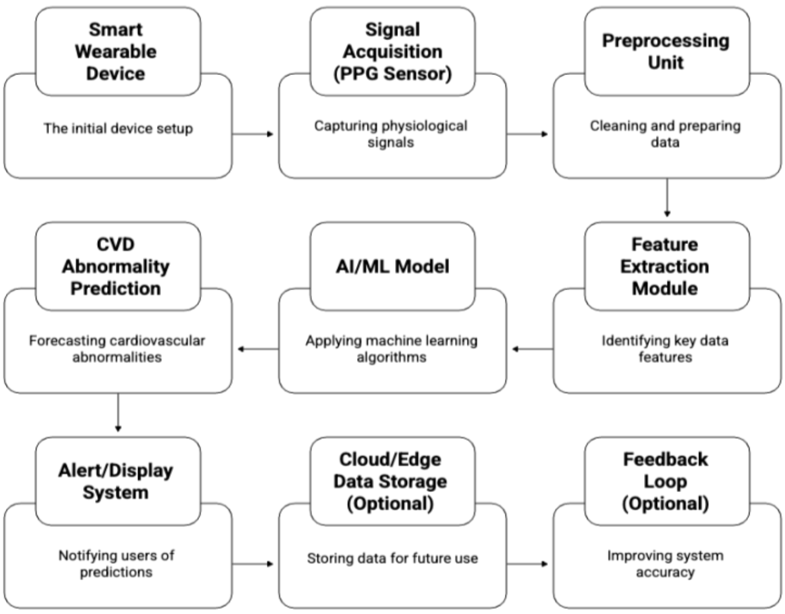


Fig.2 *A typical block diagram of system to detect CVD using PPG and AI. The system consists of major blocks like smart wearable device, signal acquisition system, preprocessing unit, feature extraction module, AI/ML model, CVD abnormality prediction, alert/Display System, cloud/edge data storage, and feedback loop.*

3. Study Of AI Algorithms

These study focuses on survey of Artificial intelligence (AI)-based Algorithms for prediction of CVD abnormalities based on smart wearables, that help healthcare professionals in the diagnosis, treatment, and management of CVD. These system is used to analyze large amounts of data, helping users to create accurate and informed decisions. At the same time, Artificial intelligence-based Algorithms provide an important support to health professionals in the early diagnosis of CVD, treatment planning, and patient management., who bear the ultimate responsibility for decisions. In this paper, we tried to summarize the status and usage areas of AI-based algorithms in different areas of CVD. Artificial Intelligence (AI) has become a transformative device in the analysis, prediction, and supervision of cardiovascular diseases (CVDs). Various AI algorithms are being employed to analyze medical data such as electrocardiogram (ECG), photoplethysmogram (PPG), echocardiogram, and electronic health records (EHRs) to detect abnormalities and assess cardiac risk with high accuracy.

Traditional machine learning algorithms like Logistic Regression, Support Vector Machine (SVM), k-Nearest Neighbors (kNN), Random Forest, and Naïve Bayes have been widely used for early prediction and classification of heart diseases. Logistic Regression and Naïve Bayes are preferred for their simplicity and interpretation, used for predicting the risk of heart attacks, hypertension, or stroke based on clinical and demographic data. SVMs are particularly used for classifying arrhythmias and myocardial infarctions from ECG signals due to their high precision. Random Forest and Gradient Boosting models such as **XGBoost** are used for handling large, heterogeneous clinical datasets, offering robust and accurate predictions of heart failure, mortality risk, and coronary artery disease.

Furthermore, Reinforcement Learning (RL) have notable impact in cardiac care for personalized cure and therapy optimization. By taking data from patient-specific and clinical feedback, RL systems can help in adjusting drug dosages, optimizing treatment plans, or supports in robotic-assisted surgeries. Hybrid and collective AI systems, combining multiple algorithms (e.g., CNN + LSTM or Random Forest + ANN), are developed to improve diagnostic precision and combine data from multimodal sources such as imaging, signals, and clinical records. Overall, AI algorithms have significantly enhanced cardiovascular disease detection and prediction by providing early, accurate, and automatic analysis. Deep learning models like CNN and LSTM currently best traditional methods, for personalized cardiac healthcare. Following table shows AI Algorithms used for healthcare, that mainly focuses on CVD anomalies based algorithms.

Table1: *Study of AI algorithms used for healthcare that mainly focuses on CVD anomalies based algorithms.*

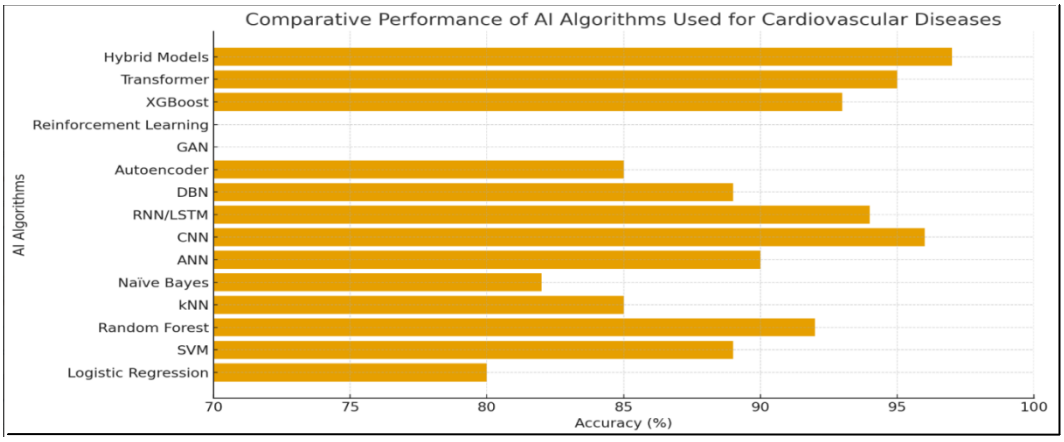
Sr. No.	Algorithm / Model	Type of AI / Approach	Data Used	Main Application in CVDs	Key Advantages	Performance / Accuracy
1	**Logistic Regression**	Machine Learning (Supervised)	Clinical and demographic data	Risk prediction of heart attack, stroke, or hypertension	Simple, interpretable, fast training	70–85%
2	**Support Vector Machine (SVM)**	Machine Learning	ECG / PPG / heart sound signals	Classification of arrhythmia and myocardial infarction	High precision, effective with small datasets	85–93%
3	**Random Forest (RF)**	Ensemble Machine Learning	ECG, EHR, blood pressure data	Prediction of heart disease and cardiac mortality	Robust to noise, handles nonlinear data	88–95%
4	**K-Nearest Neighbors (kNN)**	Machine Learning	ECG features	Detection of normal vs abnormal heartbeats	Non-parametric, easy implementation	80–90%
5	**Naïve Bayes (NB)**	Probabilistic Model	EHR, patient symptoms	Probabilistic classification of heart disease	Fast computation, interpretable	75–88%
6	**Artificial Neural Network (ANN)**	Deep Learning	ECG, echocardiogram, EHR	Predicting heart disease severity and presence	Learns complex nonlinear relationships	85–94%

7	**Convolutional Neural Network (CNN)**	Deep Learning (Image-based)	ECG images, echocardiogram, CT / MRI scans	Automated detection of arrhythmia, coronary artery disease	Extracts deep features automatically, high accuracy	90–98%
8	**Recurrent Neural Network (RNN / LSTM)**	Deep Learning (Sequential)	ECG, PPG, time-series signals	Real-time rhythm monitoring and irregular heartbeat detection	Captures temporal signal patterns	88–96%
9	**Deep Belief Network (DBN)**	Deep Learning	ECG signals	Multilayer feature learning for cardiac classification	Captures hidden complex features	85–92%
10	**Autoencoder**	Unsupervised Deep Learning	ECG / PPG data	Noise removal, feature extraction, dimensionality reduction	Efficient compression and pattern learning	80–90%
11	**Generative Adversarial Network (GAN)**	Deep Learning (Generative)	ECG / MRI data	Synthetic data generation, rare disease data augmentation	Improves data diversity for training	Quality-dependent
12	**Reinforcement Learning (RL)**	Learning by Interaction	Treatment and patient response data	Personalized treatment optimization, therapy adaptation	Learns from clinical feedback, adaptive	Task-specific accuracy
13	**Gradient Boosting (XGBoost / LightGBM)**	Ensemble Learning	Clinical and lab data	Early prediction of heart failure and mortality risk	Efficient, high predictive accuracy	90–96%
14	**Transformer Models (BioBERT / ECG-BERT)**	Deep Learning (NLP / Sequential)	ECG sequences, medical text	ECG interpretation, report summarization	Context-aware learning, state-of-the-art in NLP	92–97%
15	**Hybrid / Ensemble Models**	Combined ML + DL	Multimodal (ECG, EHR, imaging)	Integrated heart disease diagnosis and monitoring	Combines strengths of multiple algorithms	95%+

Table2: *Summative based study on AI algorithms For prediction of Heart rhythmic abnormalities:*

CVD Focus Area	**Effective AI Algorithms**	**Application Purpose**
Arrhythmia Detection	CNN, LSTM, SVM	Detection of irregular heartbeats from ECG / PPG
Heart Disease Prediction	Random Forest, XGBoost, ANN	Prediction of coronary artery disease and heart failure
Blood Pressure / PPG Analysis	LSTM, Autoencoder	Continuous monitoring and abnormality detection
Echocardiogram / Image Analysis	CNN, Transformer	Structural heart abnormality and artery blockage detection
Cardiac Risk Assessment	Logistic Regression, Gradient Boosting	Prediction of heart attack or stroke risk
Personalized Treatment Optimization	Reinforcement Learning	Dynamic therapy adjustment, treatment planning

Fig.3 *Graphical representation of AI Algorithms used for Cardiovascular Diseases*



We can clearly see that **CNN,** Transformer models, and Hybrid systems achieve the highest accuracy (95–97%), followed by LSTM, Random Forest, and XGBoost**,** which are also strong performers for ECG and EHR-based diagnosis.

4. Conclusions

In this paper, we presented a survey on AI Algorithms for prediction of CVD abnormalities based on smart wearables. These survey offered **CNN,** Transformer models, and Hybrid systems achieve the highest accuracy (95–97%), followed by LSTM, Random Forest, and XGBoost**,** which are also strong performers for ECG and EHR-based diagnosis. These AI algorithm based devices have delivered significant statistics in detecting conditions like arrhythmia, tachycardia, and bradycardia, using various AI techniques. These advances can enhance the accuracy and patient-specific monitoring, to create a smart, continuous, and overall cardiovascular health assessment.

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