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A Survey on AI- Based Heart Disease Detection Using ML, DL, and IoT

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Abstract*— Cardiovascular disease are increasing rapidly, which has encouraged the development of intelligent system for early detection and continuous monitoring. Technologies like Machine Learning(ML), Deep Learning(DL), and the Internet of Things(IoT) are widely used to build such systems. This survey presents an overview of recent research focused on AI-based heart disease detection, including approaches based on symptoms, ECG signals, ECG images, and IoT-enabled monitoring devices. The studies are analyzed by grouping them according to the type of data used, such as clinical record, ECG signals, ECG images, and multisensor IoT data, along with their modeling techniques and computational methods. Traditional supervised learning models like Random Forest, Support Vector Machine and ensembles methods are commonly used for structured datasets. In contrast, deep learning models such as Convolutional Neural Networks(CNN), LSTM, and Hybrid architechtures are mainly applied to ECG based analysis for identifying abnormalities. In addition, this paper review the tools and platform used in these systems, including Python-based frameworks, MATLAB for signal processing capabilities is also provided. This analysis highlights existing challenges, such as limited integration of multiple data types, insufficient edge level intelligence and difficulties in achieving real time monitoring.
Keywords*— Machine Learning(ML), Deep Learning(DL), Electrocardiogram (ECG), Heart Monitoring System, Artificial Intelligence (AI), Internet of Things(IoT).

I. INTRODUCTION

Cardiovascular disease remain the leading cause of mortality worldwide and continue to impose a significant burden on global health systems. According to World Health Organization (WHO), approximately 17.9 million people die each year due to cardiovascular disease, accounting for nearly 32% of all global deaths. Alarmingly, above 85% of these deaths are caused by heart attacks and strokes, many of which are preventable through early diagnosis and continuous monitoring. In many countries, including india the impact of heart disease is particularly severe due to limited access to specialized healthcare services. Recent reports indicate that India accounts over 20% of global cardiovascular-related deaths, with a rising prevalence among younger age groups.Furthermore, clinical evidence shows that nearly 70-80% of premature cardiac deaths can be avoided through timely detection of risk factor like abnormal heart rhythms, hypertension and early ECG anomalies. Machine learning techniques are then applied to this data to support intelligent decision making and clinical insights [1]. As personal health is consideredas valuable as financial well-being, this has motivated the development of advanced technological solutions and innovative healthcare models. Modern e-health environments increasingly rely on a large number of electronic health sensors, commonly referred to as biosensors, which are deployed for applications such as clinical diagnosis, heart activity monitoring, sleep analysis, and smart home healthcare [2]. IoT technology has expanded across multiple domains, including smart cities, industrial automation, governance, and healthcare services. Over the past decade, rapid advancements in sensor technologies, microcontrollers, communication networks, computing capabilities, and societal demands have accelerated the adoption of IoT-based healthcare solutions [3]. IoT-enabled healthcare initiatives benefit a wide range of stakeholders, including patients, hospitals, physicians, caregivers, insurance providers, and medical professionals. Patient monitoring through IoT systems allows healthcare providers to assess treatment adherence, schedule interventions, and determine whether immediate medical attention is required [4].

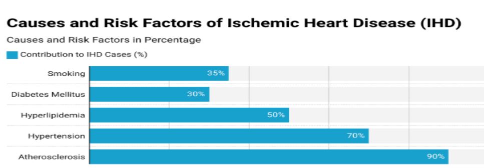

Fig. 1. Causes and Risk Factor of Heart Disease

Healthcare systems once struggled with overcrowded hospitals, long waits, and delayed diagnoses, but innovations like IoT, mobile health apps, high-speed networks, and data analytics have improved patient monitoring and early detection. However, economic constraints have reduced healthcare spending, making cost efficiency vital, and the challenge now lies in optimizing existing infrastructure while maintaining service quality in smart healthcare delivery [5].Cardiovascular disease classification can be approached using machine learning methods such as Nu-SVM, Gradient Boosting Regressor XGBoost, AdaBoost, Extra Trees, LightGBM, and SGD, with ensemble strategies like stacking to improve accuracy. These models are evaluated through metrics like precision, recall, accuracy, F1-score and the ROC curve, enabling a clear comparison of their effectiveness in distinguishing patients with and without cardiovascular disease.

II. LITERATURE REVIEW

Research on heart disease monitoring and prediction has progressed along multiple directions, including machine learning–based risk prediction, IoT-enabled health monitoring, deep learning–based ECG analysis, and edge or cloud-assisted healthcare architectures. Many early studies focused primarily on machine learning models applied to structured clinical datasets. Bhaduaria*et al.* proposed a stacked hybrid learning framework that combined classifiers such as Random Forest to enhance heart attack risk prediction accuracy. Similar data-driven approaches were adopted by Ullah *et al.* and Aashiq *et al.*, who emphasized feature optimization and explainable machine learning techniques. While these methods demonstrated promising accuracy on tabular datasets, they largely remained limited to offline analysis and did not consider ECG image interpretation or real-time sensor-based monitoring [1, 11, 12].

Another group of studies concentrated on IoT-based health monitoring systems aimed at continuous physiological data collection. Madavarapu*et al.* introduced the HOT Watch, a wearable device capable of tracking vital signs such as heart rate, oxygen saturation and temperature. Musa *et al.* designed an IoT healthcare architecture using active patch antennas to improve signal acquisition, while Shuzan*et al.* proposed an IOT assisted glucose monitoring system based on PPG and blood pressure data. Although these systems successfully demonstrated real-time data acquisition and alert generation, they lacked intelligent analytical layers for automated cardiac disease prediction [2–4].

Several researchers explored edge, fog, and cloud-enabled healthcare frameworks to reduce latency and improve responsiveness. Kumar *et al.* presented an edge-computing-based clincal decision support system , while Verma *et al.* integrated fog computing with IoT and machine learning to enhance diagnostic performance. Wong *et al.* further focused on optimizing deep learning models for edge-based cardiac detection. Despite architectural improvements, these solutions often relied on clinical-grade data or emphasized infrastructure design rather than comprehensive heart disease prediction using low-cost sensors [5, 6, 13]. Considerable attention has also been given to deep learning approaches for ECG signal and image analysis. Ramesh *et al.* proposed a hybrid LSTM–neural fuzzy interface framework for early coronary disease detection. Begum *et al.* and Meghana *et al.* employed CNN and CNN–BiLSTM architectures for ECG image classification, achieving high diagnostic accuracy. Ananthi *et al.* and Nguyen *et al.*. further investigated LSTM-based and spectrogram-based deep learning models for cardiovascular disease detection. However, many of approaches required high computational resources, large datasets, and were not designed for real time deployment on embedded or IoT platforms [7, 15–18].

Some studies focused on alternative cardiac signal modalities, such as heart sounds. Gudigar*et al.* reviewed phonocardiogram-based deep learning techniques, highlighting their potential for heart anomaly detection. Alrabie*et al.* contributed the HeartWave dataset to support AI-driven heart sound classification. While valuable, these works did not integrate ECG imaging, multi-sensor data fusion, or real-time monitoring architectures [8, 10].

Ensemble and hybrid deep learning strategies were explored by Khan *et al.*, who proposed blending-based networks for improved cardiovascular disease classification. Tayari *et al.* provided a comprehensive review of machine learning methods for heart disease detection and emphasized challenges related to heterogeneous data integration, model generalization, and system scalability. These studies reinforced the importance of combining multiple data sources but did not present unified, deployable healthcare solutions [9, 19].

Finally, Martinek *et al.* introduced a low-cost seismocardiography-based cardiac triggering system designed for MRI environments. Although the solution was practical and affordable within clinical settings, it did not address AI-based disease prediction or continuous IoT-enabled monitoring suitable for home or remote healthcare applications [20]. Overall, existing research demonstrates significant progress in machine learning, deep learning, and IoT-based cardiac healthcare. However, most studies address these components in isolation.

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The lack of a unified system that combines IoT-based real-time sensing, symptom-driven machine learning prediction, ECG image analysis using CNN, edge deployment on low-cost hardware, and cloud-based visualization highlights a clear research gap, which directly motivates the proposed work.

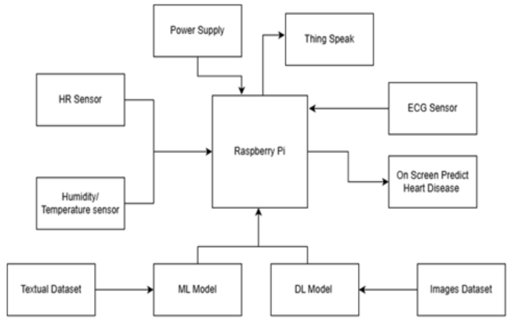

Fig.2. System Components

III. TOXONOMY OF AI HEALTHCARE SYSTEM

Concept of the IoT, originally introduced to describe interconnected physical objects capable of data exchange, has evolved into a core enabler for intelligent healthcare systems. In recent years, has gained significant attention due to its ability its ability to support continuous monitoring, early diagnosis, and remote medical supervision. In the proposed AI-powered heart monitoring and disease prediction system, IoT plays an important role in acquiring physiological data, enabling real time analysis,facilitating cloud-based healthcare services.To systematically understand such systems, a taxonomy is presented based on application domains, system components, data flow and processing pipelines, and communication technologies, aligned with the proposed implementation.

A. System Components

The IoT-assisted healthcare systems consist of multiple interconnected components that collectively enable sensing, processing, and decision making.

Biomedical Sensors: In In the proposed system, sensors form the perception layer and include ECG sensors, heart rate sensors and temperature humidity sensors. These devices capture intrinsic physiological parameters essential for cardiac assessment.

Edge Computing Device (Raspberry Pi) :Raspberry Pi acts as CPU interfacing with all sensors. It performs data acquisition, preprocessing, machine learning inference, and deep learning–based ECG analysis locally, enabling low-latency decision-making.

Gateway and Edge Learning : The Raspberry Pi also functions as an IoT gateway, aggregating sensor data and managing communication with cloud services. This edge-based architecture reduces dependency on continuous cloud connectivity.

Cloud Platform : Cloud services such as ThingSpeak are used for data storage, visualization, and remote access. Healthcare professionals can monitor patient health trends through dashboards and receive alerts during abnormal conditions.

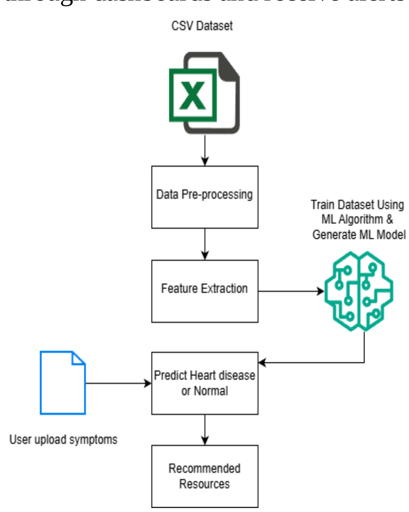

Fig. 3. Data Flow Diagram

B. Data flow and processing pipeline

Title Data creation: Physiological data is generated by IoT sensors attached to the patient signals are captured in real time and forwarded to the Raspberry Pi.

Data analysis: At the edge device, data undergoes pre processing and analysis. Machine learning models analyze structured symptom data to predict heart disease risk, while convolutional neural networks process ECG images to detect cardiac abnormalities.

Data Consumption: Processed results are presented to users, caregivers, or clinicians via cloud dashboards. Alerts are generated when abnormal cardiac patterns aredetected, enabling timely medical intervention.

IV. USING THE MACHINE LEARNING ALGORITHM IN HEALTHCARE

A. .Supervised learning

Relies on labelled datasets, where each input data instance is associated known output or class label. In healthcare applications, this approach is widely used because medical datasets often include diagnosis outcomes provided by clinicians. Supervised learning models learn the relationship between patient features—such as age, heart rate, blood pressure, ECG-derived parameters, and symptoms—and the corresponding health condition. These models are commonly applied for disease classification, risk prediction, and early diagnosis. Algorithm such as Logistic Regression, Support Vector Machines, Random Forest and k-Nearest Neighbours are frequently used in heart monitoring systems due to their ability to provide accurate and interpretable predictions based on structured clinical data.

B. Unsupervised learning

Operates on unlabelled data and also focuses on discovering hidden patterns or structures within dataset without predefined outputs. In healthcare systems, unsupervised learning is mainly used for exploratory data analysis, patient clustering, and anomaly detection. For example, clustering algorithms can group patients with similar physiological patterns, while dimensionality reduction techniques help identify abnormal variations in heart rate or ECG signals. Common unsupervised methods include K-means clustering, Hierarchical clustering, principal component analysis. Although unsupervised learning is not typically used for direct diagnosis, it serves as a supportive tool for understanding trends, identifying outliers, and enhancing preventive healthcare analysis.

A. Support Vector Machine

SVM is widely used supervisied learning algorithm for both classification and regression problems.It operates by identifying an optimal separating boundary, known as a hyperplane, that maximizes margin between different data classes. SVM is particularly effective in binary classification scenarios and high-dimensional datasets. In healthcare applications, SVM has been employed for ECG signal preprocessing and abnormality detection due to its strong generalization capability. By minimizing classification error through optimized weight and bias parameters, SVM has demonstrated reliable performance in identifying cardiac irregularities from physiological data.

C. Random Forest (RF)

RF is ensemble based supervised learning algorithm that constructs multiple decision trees using randomly selected subsets of data and features. Method combines the predictions of individual trees through majority voting, resulting in improved accuracy and reduced overfitting. Random Forest has shown strong performance across various healthcare prediction tasks due to its robustness to noise and missing values. Its ability to identify feature importance makes it particularly useful for medical decision support, where understanding influential risk factors is essential. The algorithm has been reported to outperform several traditional classifiers in health related predication scenarios.

D. Random K-Nearest Neighbours (KNN)

KNearest Neighbors is a distance-based supervised learning algorithm used for both classification and regression. The model predicts outcomes by analyzing the closest k data points to a given test sample, where k is a user-defined parameter. Classification decisions are made based on majority voting, while regression outcomes are derived from averaging neighbouring values. In healthcare systems, KNN has been applied to activity recognition, physiological data estimation, and missing data imputation. Its simplicity and effectiveness make it suitable for small-scale medical datasets, although computational complexity increases with larger data volumes.

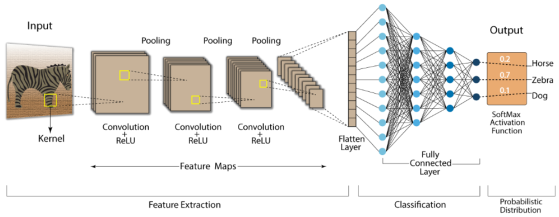

Fig.4. CNN Algorithm Processing

V. DEEP LEARNING TECHNIQUES

Deep learning techniques such as Convolutional Neural Network (CNN), Long Short term Memory and hybrid CNN LSTM models play a crucial role in (IoT-based healthcare systems by enabling effective data modeling, noise-resilient analysis, and intelligent decision-making. These techniques improve diagnostic accuracy and support real-time detection of abnormal cardiac events by learning complex patterns from physiological signals and ECG data.

A. CNN – Convolutional Neural Network

A Convolutional Neural Network (CNN) is a DL architecture designed to process image-based and spatial data efficiently. CNNs are highly effective in recognizing patterns within images and signals, which makes them suitable for medical image analysis, ECG waveform imaging, and signal-to-image transformations. In cardiac healthcare applications, CNNs automatically extract discriminative features from ECG images, enabling acuurate identification of arrhythmias and other heart abnormalities. Their ability to capture spatial correlations and morphological variations in ECG signals makes them widely adopted in heart disease detection systems [9], [13]–[16], [18]. CNN-based approaches reduce requirement for manual feature extraction and have predicated strong performance in early disease detection.

B. Long Short-Term Memory

Long Short- Term Memory (LSTM) networks are a specialized form of Recurrent Neural Network (RNNs) designed to model sequential, time-dependent data. LSTM architectures incorporate memory cells and gating mechanism input, forget, output gate to retain long-term temporal information and overcome gradient vanishing issues during training. In healthcare systems, LSTMs are primarily used for analyzing time-series physiological data like ECG signals, heart rate variability, and patient monitoring trends. Several studies have applied LSTM models to capture temporal dependencies in cardiac signals for disease prediction and abnormality detection [7], [14], [17].

C. CNN- LSTM (Hybrid Model)

Hybrid CNN - LSTM model combines all strengths of CNN and LSTM to jointly learn spatial and temporal characteristics from medical data. In such architectures, CNN layers are used for feature extraction from ECG images or transformed signal representations, while LSTM layers model temporal dependencies across consecutive signal segments. This integrated approach enables more comprehensive learning from raw cardiac data, particularly when both waveform morphology and time-based variations are important. Hybrid CNN–LSTM models have shown improved performance in cardiovascular disease detection compared to standalone models, although they often require higher computational resources [16]. This enables real-time ECG analysis without continuous dependence on cloud computation.

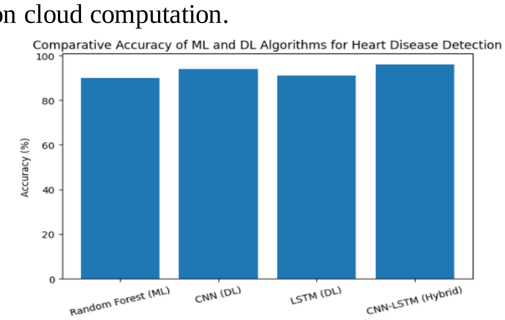

Fig. 5 Comparative Accuracy of Algorithm

Table I provides a structured overview of heart disease monitoring approaches by categorizing existing studies into IoT-based monitoring, machine learning based prediction, deep learning based ECG analysis and AI systems, highlighting their data modalities and primary healthcare objectives.

TABLE I A CLASSIFICATION OF HEART DISEASE MONITORING APPROACHES

Category	Papers	Data Modality	Primary Objective
IoT-based Monitoring	[2],[3],[5]	HR, Temp, Sensors	Continuous Monitoring
ML-based Predication	[1],[9],[12]	Clinical data	Disease Predication
DL-based ECG Analysis	[15],[16],[18]	ECG images/signals	Abnormality detection
Hybrid AI Systems	[7],[16]	ECG clinical	Improved accuracy

Table II presents a comparative analysis of widely adopted machine learning deep learning algorithm reported in the literature, highlighting their input data types, diagnostic strengths in cardiac disease analysis, and practical limitations related to model complexity, interpretability, and computational overhead. The comparison indicates that Random Forest models are highly effective for structured clinical data, while Convolutional Neural Networks demonstrate superior performance in ECG image-based cardiac abnormality detection.

TABLE II: ALGORITHM CAMPARISON ACROSS STUDIES

Algorithm	Papers	Input Type	Strength	Limitation	Suitability
Random Forest	[1], [9], [12]	Structured data	Robust, interpretable	Needs Feature engineering	Highly suitable for symptom-based heart disease prediction
SVM	[1], [11]	Clinical/ECG	High accuracy	Parameter sensitive	Moderately suitable
CNN	[15], [16], [18]	ECG images	Automatic feature learning	Computational cost	Most effective for ECG image-based abnormality detection
LSTM	[7], [17]	ECG signals	Temporal modeling	Overfitting risk	Suitable for sequential signal analysis
CNN-LSTM	[16]	ECG images	Spatial + temporal learning	High complexity	High accuracy but limited for low-cost systems

Table III summarizes the hardware platforms, software tools, and deployment strategies adopted in prior research, illustrating the transition from wearable and edge-based systems to high-performance offline environments for cardiac data analysis.

TABLE III: TOOLS, PLATFORM, DEPLOYMENT

Ref	Hardware Platform	Software Tools	Deployment Type
[2]	Wearable device	Arduino IDE	IoT cloud
[5]	Edge device	Python	Edge + cloud
[15]	GPU system	Keras, Python	Offline
[18]	High- performance system	TensorFlow	Offline

VI. CHALLENGES AND OPEN RESEARCH ISSUES

Even though IoT and AI-based cardiac healthcare systems have improved a lot, some practical challenges still remain. Medical data often comes from different sources and formats, and its quality is not always consistent, which affects reliable model performance. Many deep learning model also require high computational power, making real time use on low-cost wearable or embedded devices difficult.

Another issue is that models trained on limited datasets may not work equally good for all users, leading to scalability and retraining concerns. In addition, lack of transparency in deep learning models makes clinical interpretation harder, while data security and privacy continue to be important issues. Finally, most systems are tested only in controlled environments, and the absence of common evaluation standards slows down real-world adoption.

VII. CONCLUSION AND FUTURE WORK

Based on the performance comparison, deep learning models outperform traditional machine learning for heart disease detection. While classical ML algorithms for example Logistic Regression, Naive Bayes, kNN, and Random Forest perform well on structured clinical data, they are limited in handling complex ECG patterns. CNN-based models achieve the highest accuracy by automatically learning discriminative features from ECG images, reducing need for manual feature exctraction. Although hybrid CNN–LSTM models further enhance performance, they introduce higher computational complexity. Overall, CNN-based approaches are the most effective for ECG-based diagnosis, whereas Random Forest remains a robust choice for structured clinical data analysis. achieve the highest accuracy, making them the most effective choice for ECG image–based heart disease detection, while Random Forest remains a reliable model for structured clinical data analysis.

VIII. ACKNOWLEDGMENT

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