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A Systematic Review on IoT and Machine Learning Algorithms in E-Healthcare

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Abstract: In recent years, the Internet of Things (IoT) has been adopted in many applications since its usage is essential to daily life. Also, it is a developing technology in the healthcare system to provide effective emergency services to patients. In the current scenario, medical cases and diseases among people are growing enormously. Thus, it is becoming challenging to accommodate and provide healthcare services for more incoming patients in clinics and hospitals with limited space and medical resources. Hence, the integration of IoT and assistive technologies came into the healthcare sector for providing efficient healthcare services wirelessly as well as for continuous monitoring of the patients. With the help of IoT and Machine Learning technologies, healthcare providers can keep a closer eye on their patients and maintain more proactive lines of communication with them. Data collected from IoT devices can be fed to Machine Learning technologies for predicting and diagnosing diseases. Due to the severity of diseases, lack of early disease prediction methods, lack of resources, and a smaller number of specialized doctors, most of the population is dying. Hence, to address these issues in the healthcare domain, more research works are proposed based on Machine Learning and IoT-based healthcare systems. This work reviews the research works related to IoT-based healthcare systems and machine learning comprehensively.

Keywords: IoT, Machine Learning, E-Healthcare, Disease Diagnosis

1. INTRODUCTION

In this era of increasing digitization, everything is gradually transitioning into an electronic form, which involves linking to information and communication networks. Because of this, digitalization eventually made its way into the healthcare industry. E-healthcare has the potential to ease people's burdens by lowering the number of direct visits they need to make to their healthcare provisions. Additionally, it can save costs and enhance service quality.

One of the information and communication networks' fastest-growing technologies is the Internet of Things (IoT). Ashton, a computer scientist, invented the concept "Internet of Things" in 1999[1]. IoT devices make healthcare monitoring more efficient and affordable by minimizing the need for routine check-ups and providing faster test results. Remote patient monitoring is essential for continued care after discharge [1]. IoT technology enhances people's lives by improving integrated information systems' capabilities in communications, processing, and service provision. The healthcare industry demands IoT-driven technologies and applications for continuous patient monitoring and chronic disease prediction [1].

IoT healthcare solutions rely on sensors to collect crucial medical data, which are essential components for developing any IoT-based healthcare application [2]. Various sensors, including blood pressure, pulse, oxygen levels, airflow, skin response, patient position, muscle activity, and heart activity, can be used for health monitoring. This technology allows for remote surveillance of patients both within healthcare facilities and in their own homes, improving the quality of medical care while reducing costs [2].

Despite the potential of healthcare data to improve patient care, manually evaluating large datasets is challenging. Machine learning emerges as a powerful tool for analyzing and interpreting healthcare data and can be trained implicitly rather than explicitly [3]. Machine learning uses data to improve software, and it's used in many fields, including finance, retail, healthcare, and social data. It has applications in finance, retail, healthcare, and social data. The application of deep learning and machine learning methodologies is witnessing remarkable growth in the areas of health tracking and medical facilities [3]. The key findings of this study are as follows:

- Study of various IoT-based Healthcare systems using machine learning algorithms for predicting chronic diseases like diabetes, breast cancer, heart disease, etc.

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- Comparative analysis of IoT-based Healthcare Systems
- Comparative analysis of Machine Learning Algorithms in Disease diagnosis
- Identified the Open issues and challenges in Machine Learning and IoT-based healthcare systems

The subsequent sections of this work are organized as follows: Section 2 provides an overview of Machine Learning algorithms employed in E-Healthcare. Section 3 focuses on IoT-based E-Healthcare Systems. Disease diagnosis using Machine Learning Algorithms is discussed in Section 4. Section 5 explores the role of ML Algorithms in IoT-based E-Healthcare systems. Section 6 presents research findings and highlights issues identified in existing research works. Finally, the conclusion and future work are outlined in the concluding section.

2. OVERVIEW OF MACHINE LEARNING

In 1959, American computer scientist Arthur Samuel made a significant contribution to the field of artificial intelligence by coining the term 'machine learning'[4]. It is a subset of Artificial Intelligence (AI) and includes three main types: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning algorithms are used to predict outcomes when the labels are known. For continuous variables, algorithms like support vector machines, linear regression, and decision trees are used. For categorical variables, algorithms like logistic regression classifiers, support vector machines, Naive Bayes classifiers, K-nearest neighbor, and decision tree classifiers are used [3]. Unsupervised learning is used when data is unlabeled and output labels are unknown. It can be further divided into clustering and association algorithms shown in Fig.1

ML algorithms enhance diagnosis, empower self-diagnosis, lower healthcare costs, improve early intervention, and revolutionize the industry for better accessibility, cost-effectiveness, and predictive capabilities [5]. In medical applications, Machine Learning (ML) techniques have been successful in recognizing and assessing illnesses like epilepsy, dementia, autism, classification of multiclass motor imagery EEG signals, depression, stroke, Parkinson's disease, Mild Cognitive Impairment (MCI), and sudden cardiac arrest [6].

A. Supervised Machine Learning

Supervised machine learning is a technique for categorization tasks that builds a model based on labeled input data [7][8]. The technique involves splitting the data into training and testing sets, training the model on the training data, and assessing its predictive power on the testing data [6]. In healthcare, a trained model can use a person's characteristics to predict health outcomes like obesity or diabetes risk. Classification and regression are the two types of supervised algorithms used in these models [7][8].

Classification algorithms sort problems into different classes or categories using training data. The trained model is tested on unknown data. The output is a discrete class value [6]. In healthcare, classification techniques are used to diagnose diseases, such as determining if a tumor is cancerous. Common methods include K-Nearest Neighbor (KNN), Random Forest (RF), Bayesian Theorem (BT), and Support Vector Machines (SVM) [8]. Classification algorithms are key to E-Healthcare systems, enabling automated analysis of medical data for patient care and decision-making.

Classification algorithms can be used to identify diseases by analyzing patient symptoms, medical history, and test results. Learning from labeled data, they categorize new patient cases, automating the process for improved efficiency, reduced errors, and prompt healthcare interventions [9]. Algorithms like SVM, KNN, and RF were utilized by incorporating class-balancing techniques for enhanced performance in cervical cancer diagnosis [10]. Various machine learning algorithms were applied to assess cardiovascular disease risk in people over 50 years discussed in [11]. Analyzing patient data and medical guidelines can help doctors personalize treatments, improving effectiveness and patient satisfaction [12].

Real-time data analysis can improve remote patient care, prompt early intervention, and lower hospital readmissions. In [13], the authors proposed an IoT-enabled application framework called E-Healthcare Monitoring System (EHMS) that uses machine learning to create a sophisticated automation system for healthcare monitoring.

Healthcare fraud detection uses classification algorithms to spot suspicious patterns and potential fraud in billing records, claims data, and historical patterns. Common techniques involve anomaly detection, support vector machines, and ensemble approaches [14]. In [15], it was observed that the KNN algorithm outperformed other machine learning approaches in credit card fraud detection.

Regression algorithms are applied for continuous or binary output generation [6]. Utilizing training data, these algorithms predict outcomes such as life expectancy or chemotherapy tolerance. Models of patient characteristics, treatment factors, and health outcomes can be constructed using algorithms like Neural Networks, Decision Trees, and Ensemble Learning [7][8].

Regression algorithms can predict various health outcomes, including disease progression, treatment response, and patient survival. These models can estimate the likelihood of specific outcomes using patient data, which can help with treatment planning, resource allocation, and patient counseling [16]. In [17], the authors reviewed outcome prediction models designed using the data retrieved from electronic health records.

Regression algorithms can be used to assess the efficacy of various remedies or interventions. This can be done by

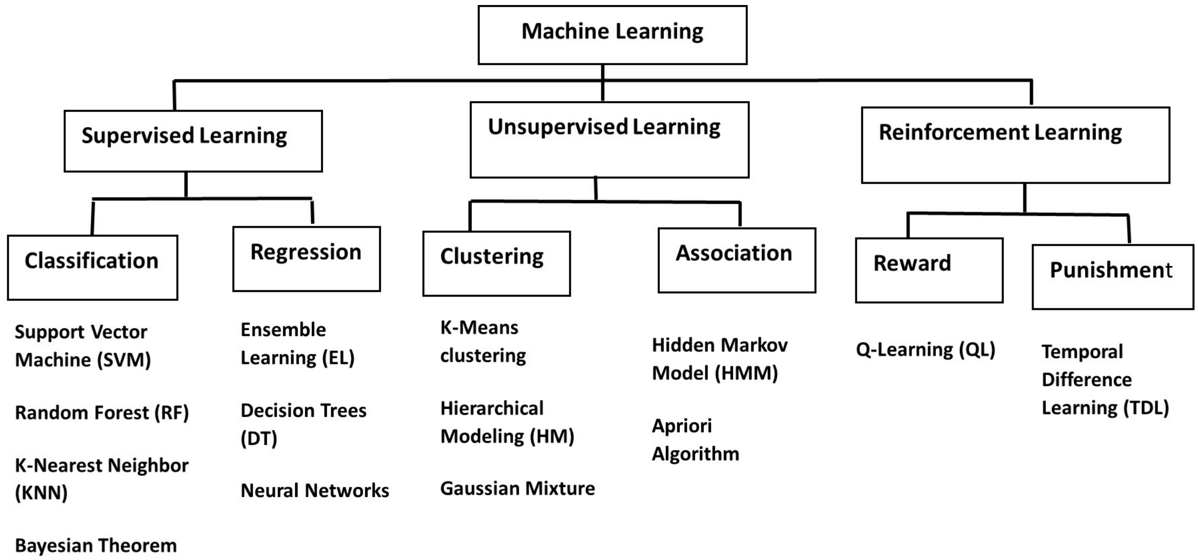

Figure 1. Classification of Machine Learning Algorithms

comparing patient outcomes before and after the treatment. This information can then be used to make decisions about treatment strategies [18]. Regarding all performance measures, the random forest method greatly assaulted logistic regression in predicting in-hospital stroke. In [18], the authors utilize machine learning to develop a predictive model for in-hospital mortality and stroke in Balloon Aortic Valvuloplasty (BAV) patients. The random forest algorithm demonstrated significantly better performance than logistic regression in predicting in-hospital stroke, as assessed by various evaluation metrics.

Regression algorithms can optimize resource allocation and predict demand in healthcare systems. By analyzing historical data, these models can forecast patient admissions, bed occupancy, and other relevant factors, helping healthcare professionals better allocate resources. Regression algorithms can also predict healthcare expenditures based on patient demographics, treatment variables, and healthcare utilization information. This helps estimate future expenses for specific patients or communities of patients and calculate costs for medical reimbursement [19].

Support Vector Machine (SVM) SVM, a robust learning method based on statistical learning theory applicable to both linear and nonlinear data [20][21][22], divides data into two groups using a hyperplane to enhance classification and prediction accuracy. However, being a binary classification scheme, it necessitates a choice between multi-class or binary classification training [21]. In Reference [22], the authors proposed a hyperparameter-tweaked assessment model for cardiac disease diagnosis. SVM's high accuracy in classification tasks suits IoT security applications like intrusion detection, malware mitigation, and smart grid attack prevention [7]. Pal's study focuses on machine learning classification algorithms such as Logistic Regression, Support Vector Machines (SVM), and Decision Trees (DT), with Decision Tree Classifiers demonstrating 95.92% accuracy and SVM showing 94.80% accuracy [23].

K-Nearest Neighbor (KNN) KNN classifier learning matches a test sample with its nearby training samples and assigns the test sample to the majority class of the nearby samples [21][22]. This algorithm finds the k most relevant training instances to a hidden sample and then predicts the sample's class as the average of the k most frequent classes in the regression [20]. Abualsaud proposed an ensemble classifier to improve categorization accuracy in noisy and incomplete data [21]. In Reference [24], the authors proposed a more accurate Multi Voter Multi Commission Nearest Neighbor (MVMCNN) model for diabetes prediction. KNN has been used as a classification algorithm for classifying diseases such as diabetes [24], cervical cancer [10], heart disease [25][26], and blood pressure [25].

Neural Networks (NN) Neural networks are inspired by the human brain and mimic its organization and function [1]. The creation of specific training algorithms facilitates learning in Neural Networks. Neural Networks can work with huge data sets [21]. NN learning mixes categories and design philosophies, occurring often in clustering, classification, and regression [7][19]. Predictive learning models use neural networks to improve accuracy in the medical field, including mental health, facial expression recognition, and sentiment analysis.

Random Forest (RF) Random Forest classifiers are suitable for classification tasks, building a forest of decision trees during training. Each node represents the class predicted by the individual trees [27]. Random Forest is different from

Decision Trees because they averages the predictions of multiple trees and uses fewer features [22]. Random forests are used in many industries, including healthcare, banking, and retail, to solve classification problems such as spam detection and disease prediction.

Decision Tree (DT) It is the most often used supervised ML approach for classifying or partitioning a data set. Decision Trees are utilized for both classification and regression models. The objective is to train a basic decision-rule-based model to correctly predict the target class label [27]. In most cases, if-then-else phrases are used to indicate the decision rules. Like a tree structure, a decision tree has nodes that stand for attribute tests, branches displaying the outcomes of those tests, and leaf nodes displaying the class labels. In practice, decision trees are constructed to comprehend and analyze the logic behind the dataset [27]. In the healthcare domain, decision trees can be used to classify breast cancers, to predict mortality based on COVID-19 symptoms, heart disease, diabetes, etc.

Bayesian theorem The Bayesian theorem relies on Bayesian probability, a theorem of statistics for learning distributions. By utilizing prior data and Bayesian probabilities, this supervised learning technique generates novel outcomes [7]. Naïve Bayes is a well-known learning algorithm that requires prior information to correctly implement Bayesian probability and forecast likely outcomes. This requirement has led to its widespread adoption. Bayesian theorem produces better accuracy than other algorithms because it considers all the features that affect the output of the model, and it works on previous data [7]. In the medical domain, it can be used to analyze the disease severity based on previous records of the patient, for analyzing Alzheimer's disease, heart disease, etc.

The development of supervised machine learning algorithms normally involves the utilization of a dataset that includes many variables as well as an outcome that is of interest. For certain jobs, like feature selectors that must process the variables (which are pixels or words) to perform image recognition or language processing. This is necessary because the variables are not fixed. A feature selector chooses distinguishable qualities from the dataset so that those characteristics can be depicted in a numerical matrix that the algorithm can comprehend [7].

B. Unsupervised Machine Learning

It does not necessitate any output training data for the variables that are provided as inputs. It does not require labeled data. Training is accomplished by finding patterns of correlation among unlabeled data to recognize and categorize the data into various groupings known as clusters [7]. There are two types of unsupervised learning: Clustering, and Association.

Clustering involves locating a set of data that does not fit into any preexisting categories based on qualities, patterns, or structures [27]. The clustering algorithms determine which data points belong to which groups or clusters. Normally, clustering algorithms like K-means clustering, Gaussian Mixture Modeling (GMM), and Hierarchical modeling are mostly used in many applications.

In e-healthcare, clustering algorithms play a vital role in identifying relevant patterns and groups within extensive healthcare information. These algorithms assist healthcare workers and researchers in understanding patient populations, disease trends, treatment efficacy, and healthcare system performance. Moreover, clustering methods support healthcare systems in optimizing resource allocation by identifying areas with similar healthcare needs, enabling more effective distribution of medical staff, equipment, and services by politicians and administrators.

Clustering algorithms aid in the identification of similar patterns among patients suffering from specific maladies or conditions. These algorithms can identify disease subtypes, risk factors, and progression patterns by analyzing Electronic Health Records (EHRs) or genomic data. Wang et al. [28], deployed unsupervised machine learning algorithms to find EHR-based latent illness clusters and patient subgroups by introducing a novel model called Poisson Dirichlet Model (PDM). The results of the experiment demonstrate the successful identification of distinct disease clusters by the proposed PDM cloud.

Clustering algorithms are capable of spotting anomalous or outlier patterns in healthcare data, such as fraud, strange patient behavior, or bad occurrences. In Reference [29], A novel clustering-based approach for detecting anomalies in multivariate time series data is introduced by the authors. The proposed framework can identify anomalies in multivariate time series, detecting abnormal patterns in both amplitude and shape across diverse application domains including healthcare, weather analysis, finance, and disease outbreak detection.

Association Hidden Markov Model (HMM) and Apriori Algorithm, enable the formation of associations between different data objects from extensive input data, commonly used in marketing to analyze buyer preferences [27]. In e-healthcare, association algorithms play a crucial role in identifying patterns and relationships in massive datasets, allowing healthcare providers to extract valuable information, make accurate predictions, and improve patient outcomes. By integrating and analyzing data from diverse sources, such as EHRs, genomics, wearable devices, and medical imaging, these algorithms offer a comprehensive view of patient health, facilitating holistic decision-making through the discovery of links and correlations across various data modalities.

Association algorithms analyze extensive healthcare data, including electronic health records and pharmacovigilance databases, to detect links between medications, adverse events, and patient characteristics. This aids in drug discovery, adverse event detection, and drug safety monitoring. In Reference [30], a systematic review revealed that textual data analysis has the potential to complement the standard pharmacovigilance approach.

K-Means Clustering Algorithm The K-Means algorithm, a clustering method, aims to minimize the squared error difference between a cluster's mean and its data points by establishing clusters in the data, where k represents the number of clusters [7][21]. The algorithm requires input data, containing features for various samples, and the user must specify the number of clusters (k) initially. Two limitations of k-means clustering are the need to predefine k and the requirement for nearly equal sample counts in each round cluster. In healthcare, k-means clustering is applied to create clusters of diseases in patient records, utilizing important features of unlabeled data. It is employed to detect conditions like Polycystic Ovary Syndrome (PCOS), diabetes, and kidney disease from patient datasets [31].

Hierarchical Modeling The hierarchical learning strategy is a top-down analytic method used by educational designers to identify fundamental prerequisites for anticipated learning outcomes in intellectual learning, also known as Deep Learning methods due to their ability to capture hierarchical performance in deep architecture [32]. In Reference [33], the authors introduced a two-stage hierarchical machine learning approach to forecast the risk of Venous Thromboembolism (VTE) in patients across different departments. In the oncology department, the proposed model outperformed both the first-stage model (AUC of 0.730) and the department-specific model (AUC of 0.787), achieving an AUC of 0.879.

Gaussian Mixture Modeling (GMM) GMM segments a dataset into k clusters, each determined by different parameters representing likelihood, average, and standard deviation at the intermediate level for each group [27]. Typically used to identify anomalies in a dataset, Wei and Zheng [34], proposed an enhanced Gaussian mixture model to reduce noise and improve image quality. Experimental results indicated that this strategy enhances picture denoising performance while preserving image detail information.

Hidden Markov Model (HMM) HMMs utilize Markov processes with hidden parameters, elegantly modeling signal sequence architectures by combining observation and hidden states, making them adaptable to various classification problems [27]. Particularly suitable for data with continuation and extension, such as time-series health checkups, HMM is a popular choice for representing health checkup data as it can express the dynamic variations in a person's health state over time [35].

Apriori Algorithm Association rules, generated from common item sets, operate on transactional databases, assessing the strength of relationships between two objects. Utilizing the Apriori algorithm and multi-level association rules, it identifies associations in health transactions, although it is time-consuming [36]. For COVID-19 prediction, Shaikh and Chitre proposed a novel Apriori algorithm based on Association Rule Mining (ARM) [37]. Zheng and Chen [38], introduced an improved Apriori algorithm comparing Chinese herbal medicine for COVID-19 treatment. In Reference [33], the authors demonstrated the Apriori method's use in examining co-morbidity or multi-morbidity in a large Electronic Medical Record (EMR) database. It reveals network correlations between illnesses from different bodily systems and highlights the impact of disease co-occurrence on prognoses, therapy efficacy, and mortality.

C. Reinforcement Learning

Reinforcement learning, the foundation of which relies on both rewards and punishments, automates systems by enabling self-education. The system learns independently, maximizing positive reinforcements and minimizing negative ones without human intervention. Noteworthy algorithms in reinforcement learning include Q-learning and Temporal Difference Learning (TDL).

Q-Learning (QL) QL is a model-free algorithm that searches for the optimal approach to accomplish a particular objective by looking for the greatest possible reward that can be anticipated. This is accomplished through participating in a diverse range of activities to gain experience with the surrounding environment and formulate sound judgments [7].

Temporal Difference Learning (TDL) TDL, a core component of RL algorithms, has garnered significant research attention over the past three decades. It is trained to perform updates based on the latest estimations while predicting a quantity dependent on the future values of a given signal. This learning process involves observing how the given signal changes over time [7].

In summary, in healthcare data processing, Decision Trees exhibit high accuracy, though they may face challenges with larger datasets. The healthcare domain explores various Machine Learning (ML) and Deep Learning (DL) algorithms, such as Naïve Bayes (NB), Support Vector Machines (SVM), Random Forest (RF), K-nearest Neighbor (KNN), and Convolutional Neural Networks (CNN), to enhance accuracy. SVM excels in non-linear classification tasks, but selecting an appropriate kernel remains challenging, and SVM models may have extended training times for larger datasets. However, SVM performs well in solving linear problems. In Reference [24], the authors introduced the Squeeze-and-Excitation Mask Region-based Convolutional Neural Network (SEMRCNN), a deep convolutional network segmentation model that is capable of precisely identifying prostate cancer lesions in Multi-parametric Magnetic Resonance Imaging (MP-MRI) images.

3. IOT-BASED E-HEALTHCARE SYSTEMS

As medical conditions multiply, patients require extended hospital stays for treatment until recovery. The surge in patients poses a challenge for hospitals, leading to increased healthcare costs [39]. The Internet of Things

(IoT) emerged as a solution, enhancing healthcare services by enabling seamless connectivity for people and devices from any network or location, thus improving healthcare delivery [10].

Kevin Ashton, a computer scientist, coined the term ”Internet of Things” in 1999 while working at Procter & Gamble. His concept involved embedding Radio-Frequency Identification (RFID) chips in items to monitor their movement within a supply chain [27]. The IoT is a network connecting electronic devices to a central server, facilitating information exchange without human intervention [21]. Recognized as a revolutionary idea, the IoT has recently spurred a technological revolution, enhancing convenience, effectiveness, and intelligence in people's lives. The adoption of IoT and sensor-based healthcare systems, such as monitoring devices, has surged globally in recent years [39]. Initial devices often use smartphones for data processing, featuring convenient voice recognition and alarm functionalities. The increasing popularity of health monitoring systems based on IoT can be attributed to ongoing technological advancements.

Fig.2 represents the architecture of IoT-based Healthcare systems. Initially, sensors that are implantable or wearable for the patients gather the data continuously and send it for Data processing and Alert System where the gathered raw data is processed and converted to meaningful information. Also, health records will be displayed and alert messages will be sent to the care takers and health care professionals when irregular data is observed. The processed data will be transmitted to the cloud server through Wireless Fidelity (WIFI) or Global System for Mobile Communications (GSM) networks. The cloud server provides a way to store the data and the tools for accessing and processing the data. From the cloud server, the patient data will be transmitted to a secure database. This stored data is fed to the ML prediction model which analyzes the data, possibly identifying patterns or anomalies. The system can then display health records (potentially to the patient, guardian, and doctor) and send alerts if it detects serious conditions. All patients' information will be stored in the secure database, and the doctor can likely access and review this data as and when needed.

In healthcare, IoT transforms the way we approach well-being by connecting stakeholders and cutting-edge technologies. It enhances personalized care through applications like living assistants, prediction systems, and remote monitoring [41]. The acute focus on health and fitness draws users to IoT devices, reducing the need for frequent hospital visits and costly consultations [42]. The challenge lies in user awareness and the intelligent use of data from a myriad of smart connected gadgets aimed at improving health and the environment [41]. The Taxonomy of IoT-based Healthcare is shown in Fig.3

IoT e-healthcare systems offer benefits but face challenges like data security, privacy concerns, interoperability, and ensuring reliable health data. Strong cybersecurity, regulatory compliance, and ethical considerations are essential to safeguard patient information and maintain confidence and confidentiality.

A. Sensors

Sensors, capable of measuring parameters such as humidity, temperature, light, pulse rate/blood oxygen, blood glucose, and electrocardiogram, can be affixed to the human body or placed in various environments [42]. For the elderly, these sensors track daily activities and share the data with caretakers, enabling them to live independently and safely. Wearable and implantable devices are commonly used in IoT-based healthcare.

Biometric Sensors

In e-healthcare, sensors play a pivotal role in gathering real-time data on diverse health parameters and environmental factors. Here are examples of sensors employed in e-healthcare:

Heart Rate Sensors: These sensors monitor a person's heart rate, giving important details about their cardiovascular health and level of exercise.

Blood Pressure Sensors: These sensors help with the detection and treatment of hypertension and cardiovascular disorders by measuring blood pressure levels.

Oxygen Saturation Sensors: These sensors can monitor respiratory problems and sleep apnea by gauging the extent to which the blood is saturated with oxygen.

Glucose Sensors: These sensors track glucose levels in the blood, which is critical information for people with diabetes to use in making treatment and lifestyle decisions [42].

Motion and Activity Sensors

Accelerometers: These sensors can detect and measure motion, which makes it possible to monitor factors such as levels of physical activity, gait analysis, fall detection, and rehabilitation assessments.

Gyroscopes: These devices measure the orientation and rotational motions of the body which help keep an eye on issues connected to mobility, posture, and balance.

Inertial Measurement Units (IMUs): These units use accelerometers, gyroscopes, and magnetometers in conjunction with one another to give full motion monitoring. This opens the door for applications such as movement analysis and virtual rehabilitation [42].

Temperature and Environmental Sensors

Thermometers: These sensors measure the temperature of the body, which assists in the diagnosis and monitoring of illnesses like as fever, infections, and other conditions

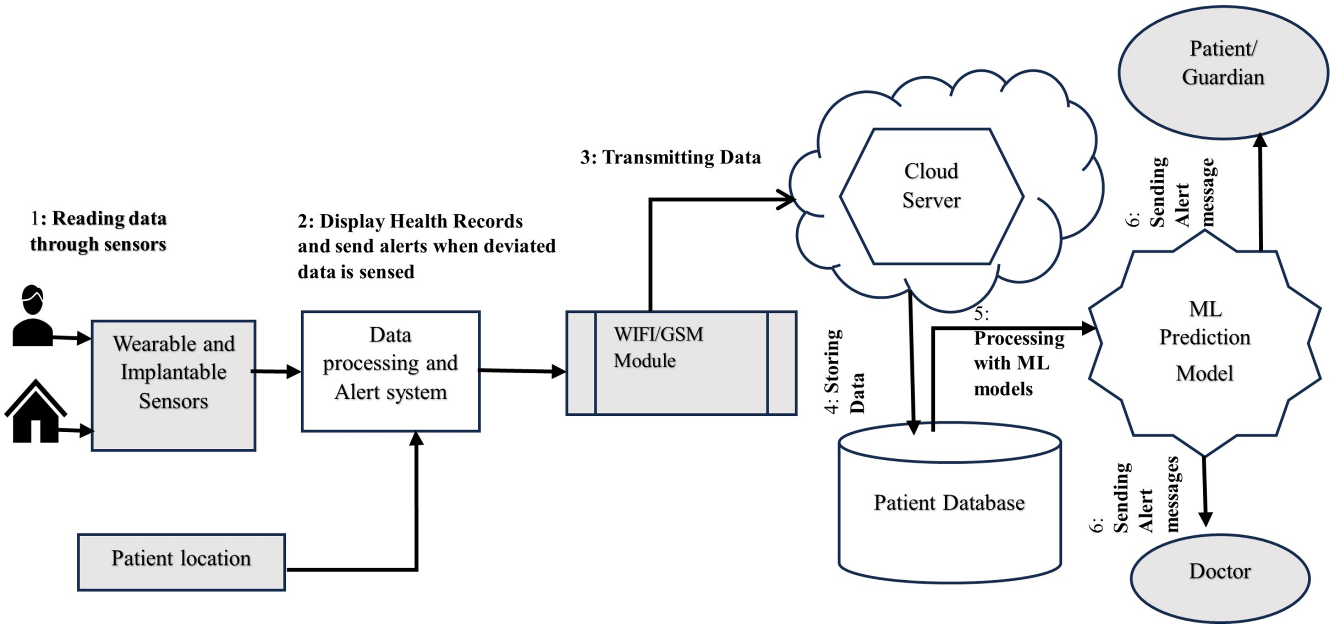

Figure 2. General Architecture of IoT-based healthcare Systems [40]

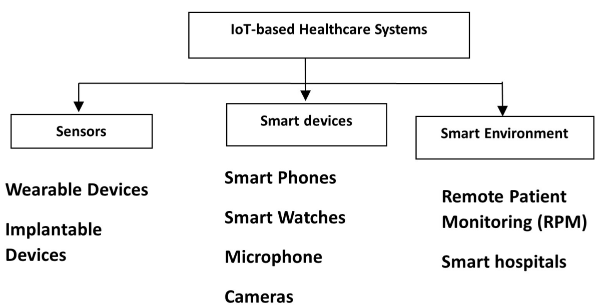

Figure 3. Taxonomy of IoT-based healthcare

connected to temperature.

Ambient Temperature and Humidity Sensors: These sensors keep an eye on the environment in hospitals and other medical facilities, checking the temperature and humidity levels to make sure they are at the ideal levels for patient comfort and safety.

Air Quality Sensors: These sensors identify contaminants and allergens in the air, which aids in the management of respiratory issues and the establishment of a healthy indoor environment [42].

Imaging and Diagnostic Sensors

Electrocardiogram (ECG) Sensors: Electrocardiogram (ECG) sensors monitor and diagnose cardiac problems such as arrhythmias and heart disease by measuring the electrical activity of the heart.

Pulse Oximeters: These sensors assess the amounts of oxygen in the blood and the heart rate, enabling them to provide insights into the state of the respiratory system and monitoring during anesthesia or sleep research.

Imaging Sensors (e.g., X-ray, MRI, CT): Diagnostic imaging, treatment planning, and illness monitoring are all made easier with the help of these sensors, which capture precise images of the inside components of the body [24].

Biosensors

Sweat Sensors: These sensors analyze the composition of sweat to detect biomarkers that are related to a person's state of hydration, electrolyte balance, and various health issues.

pH Sensors: These measure the acidity or alkalinity of bodily fluids which enables monitoring of disorders such as acidosis and alkalosis.

Chemical Sensors: The detection of compounds or biomarkers in physiological fluids using these sensors is helpful in the diagnosis and management of a variety of disorders as well as in the monitoring of drug levels [42].

In e-healthcare, the use of these sensors, in conjunction with wireless connectivity and data analytics, makes it possible to do real-time health monitoring, remote patient care, and personalized therapies. They make it possible for medical personnel to gain vital insights into the health status of their patients, facilitate the early diagnosis of anomalies, and give individuals the ability to actively control their health and well-being.

Wearable Devices

For the benefit of global health, wearable technology can be attached to the human body in products like badges, pendants, T-shirts, wristwatches, bracelets, activity trackers, glasses, smart rings, and other accessories [42]. A few of the measures which can be sensed by wearable technologies are discussed as follows.

Blood pressure: These sensors are useful for calculating the pressure that blood vessels are subjected to. These kinds of sensors are worn around the wrist, and oscillometric measurements are made of the systolic and diastolic values [31][32].

Electromyography (EMG): EMG monitoring involves tracking the electrical signals produced by muscles during use, collectively referred to as an EMG [42]. This signal is valuable for monitoring human muscle activity. In Reference [43], the authors proposed an accurate elderly care system using this sensor. Internet of Medical Things (IoMT) based emotion identification system, utilizing EMG, ECG, and other IoT sensors to collect medical data, with a Convolutional Neural Network (CNN) employed for brain state detection [44].

Electrocardiography (ECG): ECG monitors the heart signal continuously and records the heart's activity to diagnose heart disease [42]. In Reference [44], the authors proposed a technique for cardiac disease prediction by utilizing IoT-based sensors like Blood Pressure, ECG, Body Mass Index (BMI) sensors, etc. These devices collect data and send it via Bluetooth, allowing machine learning algorithms to process it for prediction and classification.

Electroencephalography (EEG): EEG shows the functions of the human brain [42]. In Reference [43], the authors made a detailed study on IoT wearable sensors and devices for elderly care. They recommended that the incorporation of these sensors and IoT devices for the elderly people, remote monitoring can be done accurately with some level of security issue due to the interconnectivity of all the network devices.

Pulse oximetry: A pulse oximeter, typically worn on a finger or earlobe, measures oxygen levels and monitors how the heartbeat affects blood in the skin [42]. Comprising a photodetector and LEDs, it gauges infrared or red light emitted or received by the body. The difference between oxygenation and deoxygenation levels indicates oxygen saturation. PhotoPlethysmoGraph (PPG) is a periodic signal used for heart rate measurement. During the Covid-19 pandemic, many used this device to periodically check their oxygen levels.

Implantable devices

Implantable medical devices are placed under the skin to assist in repairing a part or the entire biological structure of the body, particularly for monitoring heart rate [42].

Glucose Monitoring: Implanting a sensor with a multi-layered membrane embedded in abdominal tissue allows for monitoring glucose levels every thirty seconds, with data transfer occurring every five minutes [42]. Surgical implantation of these sensors enables the regulation of glucose levels through variable insulin doses.

Implantable Neural Stimulators: The treatment for chronic pain that is provided by These neural stimulators function by delivering electrical impulses directly to the spinal cord or brain of the patient.

Singh and Kumar [45] proposed an article on the latest development in an IoT-based human services framework. The framework utilizes sensors like heart rate sensors, temperature sensors, and ECG sensors. The model's software architecture offers a detailed description of patients' data journey from the cloud server to the doctor, who performs necessary activities.

B. Smart Devices

These gadgets, now encompassing personal devices like smartphones and intelligent accessories, boast advanced processing capabilities, functioning as interactive and autonomous sensors. This progress makes assistive technologies more practical for patients without the need for specialized gear [39]. The growing prevalence of e-health services relying on electronic devices and smart environments has spurred the development and deployment of assistive technologies through wireless networks and the Internet of Things [39].

Smartphones

Smarter than a regular mobile phone, a smartphone is akin to a compact computer with a virtual app store offering various features like games, browsers, maps, emails, and picture editors [46]. With advantages such as a larger display, wireless connectivity, ample memory, and a customizable operating system, smartphones surpass standard mobile phones. Equipped with sensors and health-related apps, smartphones can collect real-time vital signs and health data from patients. Medical professionals can remotely monitor patients and intervene as needed using this information [47].

In Reference [48], authors developed a cloud and IoT-based mobile app for healthcare, with the patient's end uploading data to a centralized cloud. Physicians retrieve and analyze the data for additional insights, focusing on underlying IoT theories and detailing ECG wave investigation through an Android app. The architecture is applicable beyond ECG analysis in healthcare. Reference [49] employed smartphones as a bridge to connect collected sensor data with doctors.

Smartwatches

Smartwatches continuously monitor blood pressure, sleep patterns, heart rate, and physical activity, offering insights into an individual's general health. They play a vital role in IoT-based E-Healthcare systems, providing health monitoring and improvement features. In Reference [50], the authors developed a Mobile-IoT-based healthcare system, collecting patient data from sensors and promptly notifying guardians and doctors via email and text. Smartwatches support remote patient monitoring, fall detection, medication reminders, fitness tracking, and health promotions through mobile apps or cloud platforms.

Mohammed et al. [48] employed a cloud-based IoT mobile app for healthcare, where patient data is uploaded to a centralized cloud, and retrieved by physicians for analysis. The primary focus is on underlying IoT theories. Elango et al. [49] utilized smart wearable devices for continuous monitoring.

Microphones

In IoT-based healthcare, microphones enable applications like voice-controlled medical devices, remote patient monitoring, and audio-based diagnostics. In Reference [51], the authors proposed leveraging smart homes, smart environments, and smart hospitals using modern techniques amid the impact of COVID-19. Microphone-equipped IoT devices, like smart speakers and wearables, facilitate voice-controlled interactions, allowing patients to manage medical devices, seek information, and communicate with healthcare experts. This technology supports remote patient monitoring, audio-based diagnosis, medication reminders, and daily activity tracking.

Cameras

Cameras are crucial in IoT-based healthcare, enabling visual surveillance, telemedicine consultations, gesture recognition, and security applications. In elderly care smart home setups, cameras connect to mobile or cloud platforms to monitor daily activities. Built into IoT devices or smart home systems, cameras provide visual data for remote patient examinations by capturing pictures or videos, aiding medical practitioners [43].

Table I compares a diverse range of health conditions including diabetes, emotional state, heart disease, breast cancer, sleep disorders, and general health monitoring from various existing research works based on IoT sensors and public datasets. Sensors like wearable devices, brain activity monitors, bed-based sensors, and even environmental sensors like temperature and air quality sensors will vary depending on the application. The machine learning techniques used also vary, with some research studies employing traditional methods like Support Vector Machines (SVM) and Decision Trees, while others leverage deep learning approaches like Convolutional Neural Networks (CNN). It is observed from Table I that the Deep Convolutional Neural Network (DCNN) model produces better accuracy for Diabetes, breast cancer, and heart disease diagnosis based on IoT-based data. In the case of Sleep disorder disease prediction, the wakemate sensor provides better prediction accuracy using a Feedforward artificial neural network. Moreover, Temperature sensors, Pulse sensors, ECG, Electro Dermal Activity(EDA), Room Temperature sensors, Air Quality sensors, etc. along with the ML models provide better diagnosis performance for all kinds of general health monitoring scenarios.

C. Smart Environment

Smart environments in IoT-based healthcare utilize IoT technology to create intelligent and networked healthcare ecosystems, aiming to enhance patient outcomes and reduce costs. These environments integrate various technologies, sensors, and platforms for remote patient monitoring, personalized healthcare services, and efficient healthcare operations management. Any device with a chip capable of sending and receiving data is considered part of IoT [39]. Health centers transform collected data, including passive assistive technologies, into usable information for patient observation and disease diagnosis.

Gondalia et al. [59], proposed a method for tracking the whereabouts of combatants to enhance search and rescue operations during injuries. In References [60][61][62], the authors introduced various frameworks and tools, including home-based wireless medical boxes to monitor medication intake and alert patients about pill schedules. In Reference [63], the authors suggested a healthcare framework for integrating and interpreting patient health data, offering early detection, diagnosis, cost benefits, and improved quality of life.

Remote Patient Monitoring (RPM)

RPM is a telehealth service enabling doctors to remotely monitor and care for patients using electronic medical devices, eliminating the need for patients to travel for disease diagnosis or health checks [39]. Reference [39] highlighted the benefit of avoiding potentially risky in-person interactions through smart technology. In the context of Ambient Assisted Living (AAL), smart home gadgets are typically ambient and unobtrusive. Reference [64] analyzed indoor location technologies, emphasizing biometric sensors and human activity identification.

Sheikh and Chitre [37], presented an IoT-based healthcare monitoring system using specific configurations for memory, graphic card, and Raspberry Pi connected to the Internet. Physicians receive data remotely through the IoT-based network, enabling informed judgments about the patient's health and eliminating the need for physical hospital visits. J. Mohammed et al. [48], proposed a Remote Patient Monitoring system leveraging IoT and cloud computing. Elango et al. [49], suggested IoT-based smart wearables for remote health monitoring, utilizing sensors like MPU9250, and MAX30100 for heart rate and blood oxygen levels, a 9-axis inertial measurement unit, and MLX90614 contactless temperature sensor.

TABLE I. COMPARISON OF ACCURACY IN IOT-BASED HEALTHCARE SYSTEMS

Related work	Dataset	Disease type	Sensor/Device	Technique/ Methodology	Accuracy (%)
[13]	IoT-based Kaggle dataset	Diabetes	IoT wearable devices	SVM DT KNN GB RF	80.51 70.22 71.42 77.27 79.2
[44]	Database for Emotion Analysis using Physiological Signals Dataset	Emotion Recognition	ECG, EMG, EDA	DCNN	87.5
[52]	Cleveland Heart Disease Dataset UCI Machine Learning WDBC (Wisconsin Diagnostic Breast Cancer data)	Heart Disease, Diabetic, Breast Cancer	IoT wearable devices	Deep Learning (CNN) and Fuzzy Rules	99
[53]	IoT Data	Sleep Disorder in mammals	iBrain	Brain activity monitoring	85
[54]	IoT Data	Sleep Disorder in mammals	Zeo	Brain activity monitoring	75
[55]	IoT Data	Sleep Disorder	Heally recording system Sleep Tracker Wake Mate	Feedforward Artificial Neural Network (ANN)	80 90 95-98
[56]	IoT Data	Sleep Disorder	Air cushion Emfit bed sensor	Movement and Advanced Neural Network	82.6 in Non Rapid Eye Movement(NREM) 38.3 in Rapid Eye Movement(REM)
[57]	IoT Data	Sleep Disorder	Home Health Station (TERVA)	Bed-based Sllep monitors and Classification algorithms	86-98
[58]	Polysomnography(PSG)	Sleep Disorder	SleepMinder (BiancaMed)	Bed-based Sleep monitors	78
[40]	IoT Data	Monitoring Health conditions	Temperature, Pulse, ECG, Room temperature, Air quality sensors	IoT-based Data transmission	95

Smart hospitals

Smart hospitals utilize IoT technology to enhance patient care, streamline operations, and improve efficiency through interconnected systems with various devices and sensors. Automation, real-time data analysis, and remote patient monitoring are facilitated. In Reference [65], the authors discussed the expansion of intelligent healthcare facilities in the crucial, underscoring their pivotal contribution to lessening the impact of the COVID-19 pandemic. IoT technology offers an improved solution for monitoring the elderly. Wearable and implantable devices can be attached to their bodies, collecting and monitoring data. In case of any unusual activity, alarms are sent to caretakers or hospital administrators [43].

4. MACHINE LEARNING ALGORITHMS FOR DISEASE DIAGNOSIS

Machine learning in disease diagnosis applies advanced computational techniques to analyze large medical datasets, extracting meaningful patterns. By learning from diverse data sources like patient records, lab tests, and medical imaging, machine learning algorithms identify subtle patterns beyond human perception. This allows them to classify diseases, monitor progression, predict outcomes, and suggest personalized treatments. By improving diagnostic accuracy, speeding up decision-making, and aiding in early detection, machine learning enhances patient outcomes, ensuring timely and precise diagnoses while reducing the risk of misdiagnosis.

In the optimistic era of modern healthcare data analysis, manually reviewing healthcare data remains a tedious task for practitioners [3]. Machine learning serves as a valuable resource for forecasting the future and drawing inferences from large datasets. By training a computer without individualized instruction, machine learning aims to develop data-accessible, data-using computer programs. The motivation is to create more precise predictions with an abundance of relevant data.

In Reference [10], the authors diagnosed cervical cancer using machine learning algorithms like support vector machines, logistic regression, k-nearest neighbor, Multilayer Perceptron (MLP), and Naïve Bayes. Better performance was achieved with the combination of MLP and KNN, though future applications may require more complex balancing techniques. In Reference [66], the authors conducted a study on mental health disorders using ML and DL techniques, noting that nearly all techniques, including transfer learning, exhibited good performance.

In our previous work [67], we conducted a detailed comparative analysis of ML algorithms for chronic disease prediction. This extension utilizes datasets from Kaggle repositories, Statlog, University of California Irvine (UCI) Machine Learning Repository, etc., to explore disease prediction research covering conditions like heart disease, diabetes, and chronic diseases. Researchers employed different ML techniques to formulate hypotheses and analyze datasets, revealing a range of accuracy (71 to 99) for systems dealing with smaller datasets. Despite achieving improved prediction results with various ML models, significant challenges still require attention. In Reference [68], the authors conducted a study using Naive Bayes, RF, and j48 techniques to predict diabetes prevalence.

Table II shows a comparative analysis of ML algorithms across existing research works. The observed trend indicates the widespread utilization of ML algorithms such as Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Vector Machines (SVM), Naive Bayes (NB), K- Nearest Neighbor (KNN), J48 Decision Tree (DT), C4.5 tree, and some incorporating Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), among others. Notably, the RF algorithm consistently achieved high accuracy, reaching 97.40%[69], showcasing its effectiveness. Additionally, DT demonstrated commendable performance with an accuracy of 95.92%[23], particularly suited for smaller datasets. An intriguing finding was the application of CNN with fuzzy rules, achieving the highest accuracy of 99% [52]. This exploration reveals the diverse landscape of ML algorithms in disease prediction research, with each demonstrating varying strengths and effectiveness.

5. ROLE OF MACHINE LEARNING IN IOT-BASED E-HEALTHCARE SYSTEMS

In IoT-based e-healthcare systems, machine learning plays a crucial role in managing and forecasting chronic diseases. Analyzing vast data from IoT devices and sensors, machine learning algorithms generate precise predictions, identify patterns, and provide individualized solutions. Key functions include:

Personalized Treatment and Intervention To provide personalized therapy suggestions, machine learning algorithms analyze patient-specific data, incorporating medical history, lifestyle factors, and treatment response. By considering factors like comorbidities, genetic predispositions, and pharmaceutical interactions, these algorithms optimize treatment plans, leading to improved disease management and better patient outcomes [13][41].

Data Analysis and Feature Extraction IoT devices gather diverse data, from physiological measurements to environmental and patient-reported outcomes, all processed and analyzed by machine learning algorithms. These algorithms automatically extract features for predictive models, including indices of cardiovascular health like Heart Rate Variability (HRV) from wearable device ECG signals [76][44].

Early Disease Detection IoT devices collect real-time health data, analyzed by machine learning algorithms for anomalies or early signs of chronic diseases. By monitoring vital signs, activity levels, and health factors, these algorithms detect deviations and alert healthcare professionals or patients, allowing for timely intervention and disease progression prevention. The work [25], discusses early detection of PCOS.

Predictive Modeling Training machine learning algorithms, such as logistic regression, decision trees, random forests, or support vector machines, with past patient data enables the creation of predictive models. These models predict the likelihood of developing chronic diseases based on a combination of risk factors and patient features [11]. With increasing data availability, the algorithms continually adjust and enhance their predictions over time.

Population Health Management Machine learning can analyze data from a big patient group to uncover trends in chronic diseases. This information is crucial for developing health programs and policies, guiding targeted interventions and resource allocation, and predicting population-level healthcare needs.

Continuous Monitoring and Feedback Machine learning algorithms analyze continuous data from IoT devices to of-

TABLE II. COMPARATIVE ANALYSIS OF ML ALGORITHMS

Reference	ML Model/ Techniques	Disease& Dataset	Performance (%)				Remarks
			Accuracy	Precision	F-measure	Recall	
[11]	SVM RF LR NB	Cardiovascular Disease-Kaggle Dataset	70.61 70.86 72.0 59.59	-	-	70.60 70.90 72.10 59.60	Logistic Regression classifier showed better performance
[13]	SVM DT KNN GB RF	Diabetes-Kaggle Dataset	80.51 70.22 71.42 77.27 79.2	-	0.70	0.65	• Efficient patient monitoring and alerts are generated • Diagnosis accuracy needs to be improved
[23]	SVM LR DT	Chronic Kidney Disease- UCI Machine Learning	94.80 93.28 95.92	0.96 0.96 0.99	0.96 0.96 0.98	0.96 0.96 0.98	• The early predictions are made • Help the medical practitioners and patients • Need to apply feature selection methods to increase the prediction performance
[52]	Deep Learning Approach (Convolutional Neural Networks (CNN)) and Fuzzy Rules	Heart Disease, Diabetic, Breast Cancer – Cleveland Heart Disease Dataset UCI Machine Learning WDBC (Wisconsin Diagnostic Breast Cancer data)	99 99 99	86.92 84.12 93.81	92.87 93.56 93.21	97.34 99.28 98.62	• Efficient prediction of deadly diseases was done • The Elliptic Curve Cryptography (ECC) algorithm was used to store patient data securely • Still lack efficiency
[69]	LR NB RF J48 DT	Diabetes- Telehealthcare center data	67.80-92.4 73.32-87.4 71.29-97.40 77.61-96.5	-	0.66-0.92 0.73-0.88 0.71-0.97 0.76-0.97	-	• Predicts the disease in less time and scalable • Low Computational cost • Ensures trustworthiness of the healthcare system • Needs to be refined to function for the entire system
[70]	CNN LSTM	Anorexia-Spanish Anorexia Dataset	-	88.85 89.05	90.95 90.75	93.37 92.61	• Most effective over small amounts of data • Need to apply techniques based on sentiment analysis
[71]	NB LR KNN DT RF SVM	Diabetes- Direct Survey of Patients	85 85 90 81 88 90	88 88 91 87 88 89	87 87 90 83 89 90	91 91 89 85 91 91	KNN and SVM achieved similar and superior accuracy compared to other algorithms
[72]	SVM-FCMIM LR-FCMIM	Heart Disease- Cleveland HD dataset	92.37 88.67	-	-	-	• High classification accuracy is obtained • Reduced processing time • Need to be improved for different diseases
[73]	NB RF KNN SVM MLP CNN	Cardiac Arrest (CA)- MIMIC III (Medical Information Mart for Intensive Care)	0.61 0.81 0.72 0.73 0.73 0.71	-	0.48 0.82 0.74 0.72 0.73 0.7	-	• Obtained best prediction accuracy for RF and CNN • Considered smaller data recordings only • A smaller number of features are considered
[74]	SVM (duality optimization)	Heart Failure Disease- Physio Bank databases- ECG dataset	81.3	66.1	-	89.4	• Provided a valuable means for the early identification and diagnosis of heart failure • Suggested that ECG signals can be expanded to analyze other biological signals related to chronic diseases
[75]	Ensemble Classifier(k$\bar{1}$00) C4.5 tree BNN NB	Heart Disease Diagnosis- UCI Machine Learning - Statlog (Heart) dataset	92.59 87.03 85.19 83.33	-	-	-	• Better accuracy was obtained • Further experimentation is required to identify the optimal parameter settings

fer personalized feedback, behavior change suggestions, and motivation to patients. By examining trends and patterns in health parameters over time, these algorithms promote self-management and treatment adherence [37].

By combining the power of IoT data collection and machine learning algorithms, e-healthcare systems can enhance chronic disease predictions, personalized care delivery, and proactive disease management. These systems have the potential to boost patient outcomes, cut down on healthcare expenditures, and give people more control over their health.

6. RESEARCH FINDINGS AND CHALLENGES

Despite the substantial benefits offered by e-health services, certain challenges persist. These include developing a system for early disease detection, reducing healthcare expenses, efficiently handling patient health information, ensuring patient privacy, and facilitating information exchange among different healthcare facilities in IoT-based healthcare, among other hurdles.

ML models rely on a high-quality dataset representative of the target population for effective generalization. Despite their improved performance in disease prediction, challenges persist from model development to deployment. Issues arise in dataset collection, feature selection, choice of libraries and frameworks, model evaluation, and the inherent limitation of achieving 100% accuracy in any ML application [77].

- The Issues such as High-power utilization and accessibility of fewer resources are yet to be addressed in the IoT-based healthcare field [78].
- Proving Security in IoT healthcare data is always a challenge for researchers.
- Connectivity of healthcare devices is a difficult task for IoT users.
- High-speed communication of healthcare data is needed, and it is a difficult task.
- Maintaining IoT health data in a cloud will increase the storage space, and optimizing the storage space in the cloud is a challenging task.
- The rising interconnectivity of devices, people, and the Internet in the IoT-based healthcare system creates security and privacy risks.
- Proving privacy for private data in E-Healthcare is a major challenge that needs to be addressed.
- Due to vulnerabilities in IoT devices, Denial of Service attacks and malicious attacks may arise.
- The speed and capacity of wireless data transfer are constrained.
- There exist numerous opportunities and research directions in the healthcare sector to provide enhanced hospitals and clinics working together in innovation hubs either regionally or nationally [79].
- Although machine learning and AI play an important role in e-healthcare, researchers are still working hard to increase diagnostic accuracy [67].

7. CONCLUSION

This work, conducts a comprehensive examination of current systems, exploring the integration of machine learning and IoT in E-healthcare for disease diagnosis and prediction. We provided an overview of machine learning algorithms in healthcare and compared IoT-based systems utilizing wearable and implantable devices based on prediction accuracy. Comparative analysis of ML algorithms reveals the efficacy of random forest and decision tree algorithms for small healthcare datasets, while the support vector machine excels in linear problems with high accuracy. Despite the success of existing approaches, unresolved issues persist. The research highlights findings and challenges in IoT-based healthcare systems, noting the affordability hurdle for middle and lower-class individuals in adopting IoT devices and assistive technology. However, these devices play a crucial role in enhancing healthcare monitoring and disease diagnosis.

Plans include a question-and-answer survey to gather additional insights for a more thorough analysis of IoT-based healthcare systems. Additionally, there is an intent to develop a framework that suggests medications based on predicted diseases in an IoT-based healthcare system, addressing privacy and security concerns. This research aims to contribute to the advancement of healthcare solutions.

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