A Comparative Study on IoT-Based Smart Health Monitoring Systems Using Machine Learning and Deep Learning Approaches

[1]Pranali Chavhan, [2]Dr. C. M. Jadhao
[1]Research Scholar, Electronics and Telecommunication Engineering, Mauli Group of Institution's, College of Engineering and Technology, Shegaon, Maharashtra, India
[2]Principal, Mauli Group of Institution's College of Engineering and Technology, Shegaon, Maharashtra, India
pranalichavhan750@gmail.com

* Corresponding Author: Pranali Chavhan

Abstract:

The present literature reviews comparative study on IoT-based Smart Health Monitoring Systems in association with Machine Learning (ML) and Deep Learning (DL) for providing patient care in real-time and remote fashion. With the advent of IoT technology, patients are equipped to have continuous monitoring of the vitals such as body temperature, blood pressure, oxygen saturation, etc., for sharp observation by means of wearable and connected devices. The innumerable data and variety formed from the healthcare system now require a system to analyze fully and accurately, be predictive and diagnostic. In this case, effective classification and early disease detection are given to ML algorithms like Decision Trees, Support Vector Machines, and Random Forest. DL frameworks, such as ConvNets and RNNs alike, provide a great performance in managing the large-scale, unstructured medical data. Analyze and compare different ML and DL-based IoT healthcare models based on key performance metrics such as accuracy, precision, recall, computational complexities, and scalability. According to this study, while ML methods own computational efficiency and are suitable to be run in resource-constrained IoT environments, DL approaches have greater accuracy and are more efficient in the extraction of features in complex health data situations. Further, when the benefits of integrating edge computing with cloud platforms are brought to bear, this can seriously enhance the responsiveness of the system, which will allow the processing of data more efficiently as well. Literature also covers various challenges such as data privacy, security vulnerabilities, and interoperability in IoT healthcare systems and associated issues of energy consumption. Areas for future research are suggested, such as combining hybrid models with federated learning and real-time analytics to further enhance the reliability and efficiency of smart health monitoring systems.

Keywords: *IoT-based Healthcare, Smart Health Monitoring, Machine Learning, Deep Learning, Wearable Sensors, Predictive Analytics*

I. INTRODUCTION

The healthcare sector has undergone a tremendous transformation with the advent of rapid digital technologies, paving the way for intelligent and interconnected real-time patient monitoring systems. Among these, Internet of Things (IoT) has emerged as an innovative frontier that seamlessly connects medical devices, sensors, and healthcare systems for continuous collection, transmission, and analysis of patient data. IoT-based intelligent health-monitoring systems are not just beneficial but vital in offering the best healthcare services since they facilitate remote patient monitoring, timely diagnosis, and intervention. They are of high value and can help in management of chronic diseases, geriatric care, and emergency situations along with continuous monitoring of physiological measurements [1]. Traditional healthcare systems still rely heavily on periodic checks and manual monitoring, leading often to delays in either diagnosis or treatment. This is where the internet of things (IoT) steps in, as it offers designs enabling proper monitoring both continuously and in real time to ensure vital changes can get picked up with a beat. For a start, you have heart rate, body temperature, blood pressure, oxygen saturation, and electrocardiogram (ECG) signals. The real-time monitoring systems tend to gather data via wearable devices, smart sensors, and wireless communication technology, all for the patient's good and requiring help from the cloud for further analytics. The continuous data flow ensures better care freelance of any need for hospital visits, increase of healthcare costs, and the probability that professional health workers take on increased burden [2].

The Internet of Things (IoT) in healthcare has its share of advantages. Nevertheless, the incredibly large quantity of resulting data presents substantial challenges for its storage, processing, and analysis. This is where Machine Learning (ML) and Deep Learning (DL) techniques aid significantly. ML algorithms, which are exceptionally adept at handling large datasets so as to search for patterns, detect anomalies, and predict future data based upon historical data. Techniques such as decision trees, support vector machines, k nearest neighbors, or random forests have been widely applied to IoT-based healthcare for disease diagnosis and classification [3]. These methods work fairly well with structured data and smaller datasets. Deep Learning, a subset of Machine Learning, on the other hand, has gained immense attention due to its automatic extraction of complex features from unstructured large data sources. Models within DL, namely CNNs, RNNs, and LSTM de blur profound outcomes in analyzing health information, viz., both image data and signal data in time-series. Severally and altogether, these sorts of models give finesse to applications like ECG signal analaysis, medical image classification, and real-time health prediction that might otherwise be skipped by conventional ML procedures. Moreover, with the integration of DL into IoT systems, their health monitoring systems can further benefit in terms of being able to handle data analysis in a more accurate and efficient manner [4]. Figure 1 illustrates the overall architecture of the diet and fitness recommendation system, showing how user data is collected, processed, analyzed, and used to generate personalized health recommendations.

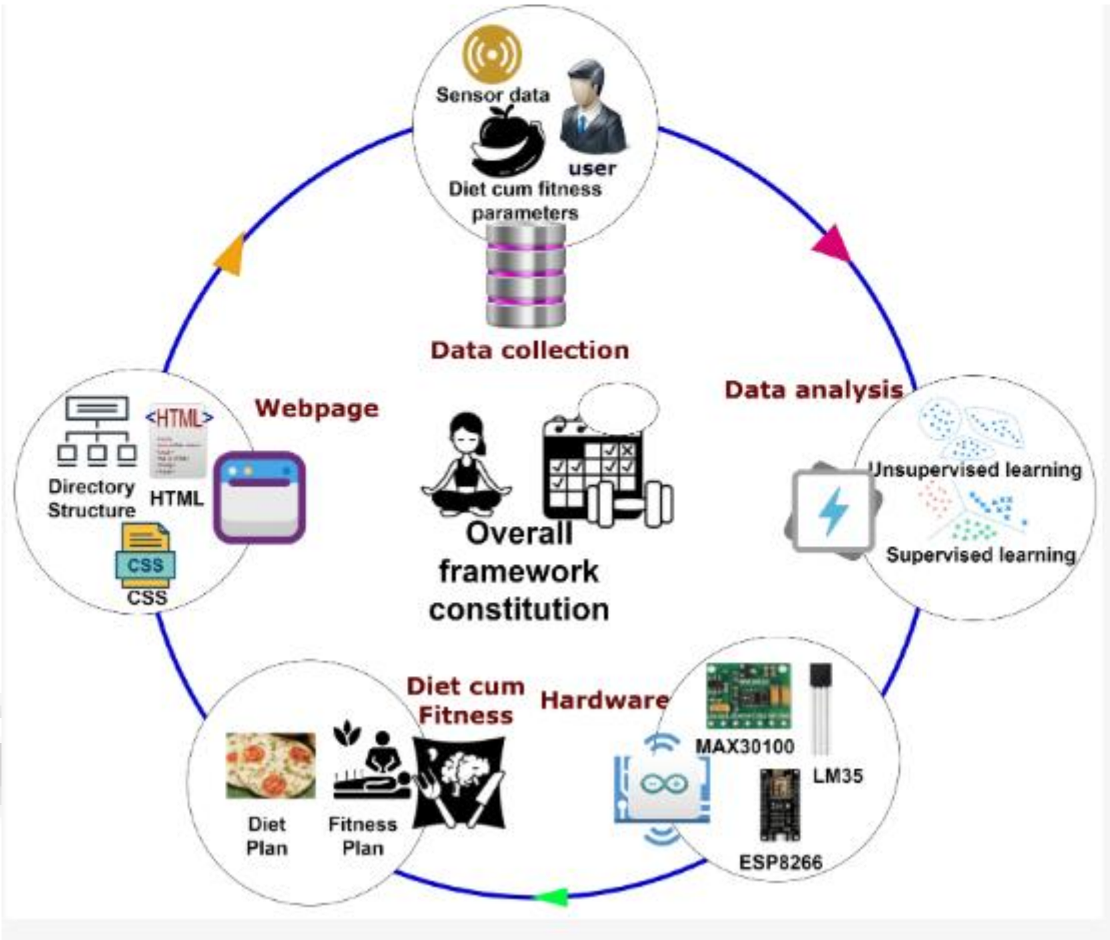

Figure 1: Overall Framework of the diet and fitness recommendation system [5].

To enhance healthcare IoT systems through integrating ML and DL for improved performance, hybrid models have been developed by researchers focusing on using the text of both paradigms. They reconcile the disadvantages by providing the opportunity to use the strengths for the ultimate benefit, thus raising the bar in terms of the accuracy and generalizability of the models and in reducing processing time. Moreover, the efficiency of IoT-based health monitoring systems has been highly enhanced as a result of the IoT paradigm caused through cloud computing, edge computing, and fog computing-real-time data processing and latency reduction. Substantial progress has been made in overcoming obstacles; nonetheless, there are challenges and restrictions that persist [5]. Patient privacy and data security are main concerns as they transmit patient-sensitive information through networks and store it in cloud ecosystems. Ensuring a secure communication framework while combating cyber threats to patient-related data would play an important role in the mass adoption of IoT-embedded healthcare systems. Data linkages and exchangeability mechanisms and system scalability are also associated with integration and frictionless operation. Machine learning (ML) and deep learning models are also subject to reliability and accuracy, depending on the quality and quantity of data, which is known to exhibit a wide amount of variation across healthcare applications.

It is arduous to determine the computational complexity and resources needed to onboard DL models to IoT devices which could in turn restrict their potential widespread usage. To mend this, researchers are amending light-weight models and edge-based processing techniques accommodated to analyze data as closely to the data source possibly. Thus, reducing latency also reduces reliance on central cloud computing as an architecture.[6] On one level, interpretability of ML and DL models is crucial in healthcare. In healthcare, especially where transparency and explain ability constitute the basics, the model needs attention to truly gain the support of medical professionals and patients. It becomes necessary to assess various existing approaches effectively in light of the rapidly changing scene of IoT-based smart health monitoring systems. This review gives an evaluation and a comparative analysis of all relevant systems that could prominently embody the use of IoT in health care. Here, Machine Learning, Deep Learning, and IoT-based healthcare systems are the focus. Performance evaluation of the various methodologies will be emphasized for pros and cons, which will provide insights on the most effective approaches for differing healthcare applications. The paper will also provide insights into the latest developments, emerging trends, and recommendations for potential research initiatives in this realm [7].

The study also approached to determine the major factors involved in performance evaluation on these systems like data pre-processing techniques, feature extraction methods, model selection, and system architecture. By contrasting ML and DL approaches, the objective of this research is to illustrate which techniques are better suited for specific health scenarios and how hybrid models could potentially augment the system performance [8]. The review results can be beneficial to academics, professionals, or healthcare professionals in designing and implementing efficient, reliable IoT-based smart health monitoring systems. In emergence of IoMT with Machine Learning and Deep Learning paves the way for advanced systems for "smart healthcare" that can monitor patients in real-time, with precision and efficiency. The significant progress that has been made needs to be supported by further long-term research to tackle the apparent challenges and improve system performance. This review paper adds to this developing body of knowledge by doing a detailed comparative analysis of ML and DL-based technologies for IoT healthcare that will drive future innovations of smart healthcare technology.

II. OVERVIEW OF IOT-BASED SMART HEALTH MONITORING SYSTEMS

Internet of Things(IoT) has transformed the health sector by making possible a variation of smart health monitoring systems; today these systems offer anything from continuous, real-time patient care to remote monitoring of the patient. These systems are really cracking up with a variety of advanced sensors, networks of communication, and data analytics in order to monitor parameters of a patient's health, thereby augmenting timely medical decision. The smart health monitoring systems based on IoT will enhance patients' outcomes, minimize costs for healthcare, and improve the efficiencies in medical services. At the heart of these systems is a network of connected devices that sense and communicate medical data pertaining to a patient [9]. These devices include wearable sensors, implantable devices, and ambient sensors. It keeps an eye on vitals like heart rate, body temperature, blood pressure, glucose level, oxygen saturation (SpO_2), and ECG signals. Devices such as smartwatches and fitness bands have become quite favored because they keep good watch over various health markers easily and continuously while being very affordable and portable. They facilitate preventive healthcare by detecting abnormalities early and also provide chronic disease management. The IoT-based health monitoring system architecture is a multi-layered one; each layer is responsible for a specific function. The sensing layer, otherwise known as the perception layer, is responsible for the data acquisition of sensors and medical devices. During data transmission, the network layer embodies communication technologies such as Wi-Fi, Bluetooth, Zigbee, and cellular network. The processing layer, mostly supported through cloud or edge computing, takes care of storing, processing and analyzing the data. The application layer, on the other hand, offers the healthcare professionals and patients user interfaces for visualization and alerts, thereby providing decision assistance.

The data gathered from IoT devices is transferred to centralized and distributed platforms for analysis. Cloud computing is doing a commendable job in effortlessly storing large amounts of healthcare data and enabling scalable processing. Although beneficial in some aspects, cloud-based systems may introduce issues related to latency and bandwidth, chiefly in real-time applications. As a practical response to those problems, edge and fog computing paradigms have been proposed to make data processing near the information origin [10]. These significantly reduce latency, response time, and enhance system efficiency, making them suitable for real-time health monitoring applications. One crucial asset of IoT-based smart health monitoring systems is supporting remote patient monitoring (RPM). The RPM enables physicians to monitor patients outside of conventional clinical settings, such as in their homes or in rural areas. The elderly and patients with chronic illnesses such as diabetes, cardiovascular diseases, and respiratory problems are the main beneficiaries. As patient health data are continuously recorded, the detection of any potential health concerns and the subsequent decrease in hospital readmissions is expedited.[11]

In addition, telemedicine services are provided by IoT-based systems via remote monitoring. Integration with mobile applications and web platforms now allows patients to remotely consult with healthcare providers, share data, and receive personalized treatment recommendations. This, currently, is especially pertinent in situations where access to healthcare facilities is restricted by disease pandemics or remoteness. The usefulness of the IoT-based health-monitoring systems fundamentally depends upon the organization and analysis of the data. The data rawly collected from the sensors is often noisy and requires many preprocessing techniques like filtering, normalization, and feature extraction. When this preprocessed data is further brought into ML and DL algorithms, they are capable of searching for patterns, detecting anomalies, and predicting health conditions. Such intelligent systems enhance decision-making metrics and enhance the accuracy of diagnosis [12]. A few of the pertinent considerations for IoT-based healthcare systems are security and privacy. Patient data transmitted and stored over networks is highly sensitive and thus sometimes at the risk of data breaches and cyber-attacks. Hence, encryption technologies, proper authentication deeds, and secure data communication procedures are put to service. Moreover, conformity to healthcare rules and standards ensures patient data is protected and trust is maintained within the confines of such systems.

In spite of the multiple advantages, a number of challenges that IoT-based smart health monitoring systems have been facing include interoperability within the various platforms, a considerable challenge as devices from different manufacturers often use incompatible standards. Another concern would be that scalability is again disturbed in places where mostly thousands of devices will be deployed [13]. Besides that, the constraint of power consumption and battery-line constraints in wearable devices must be pragmatically assessed relative to system performance and user experience. Sustainable research and creativity in hardware design, protocol-based communication, and other integration efforts can pave the way to a bright future. Acceptance by user and usability are still an important area regarding these systems. For wide usage, IoT-based healthcare solutions must be user-friendly, reliable, and cost-effective. Both patients and consequently healthcare providers should interact easily with the system and visualize the given information in an understandable manner with less technical knowledge. It is necessary to design an intuitive interface and hereby provide actionable insights to improve user engagement, and system efficacy [14].

In recent years, the developments in AI, big data analytics, and mobile communications have still provided further strength in the IoT-based designs for care. The integration of 5G networks has increased data speed and reliability, and the real-time monitoring and quicker response to critical situations have been enabled. Similarly, it is considered to be concerned that blockchain technology will enhance data security and ensure transparency in health data management. IoT-based intelligent health monitoring systems are a crucial next step in making intelligent and connected healthcare ecosystems a reality, which improves patient care and allows customized, proactive health care solutions to thrive. With an evolution in technology, IoT integrated with advanced analytics and communication technologies is going to altogether transform the healthcare field. Table 1 presents the key components of IoT-based smart health monitoring systems and summarizes their respective roles in data collection, transmission, processing, analysis, and secure user interaction [15].

Table 1: Components and Functions of IoT-Based Smart Health Monitoring Systems

Component	Description	Examples
Sensing Layer	Collects physiological data using sensors and medical devices	Heart rate sensor, ECG sensor, temperature sensor
Network Layer	Transfers data from sensors to processing units	Wi-Fi, Bluetooth, Zigbee, 4G/5G
Processing Layer	Stores and analyzes data using cloud/edge computing	Cloud platforms, edge devices
Application Layer	Provides interface for users and healthcare providers	Mobile apps, web dashboards
Data Analytics	Processes data using ML/DL algorithms for prediction and diagnosis	Disease prediction models
Security Mechanisms	Ensures data privacy and secure communication	Encryption, authentication protocols

III. MACHINE LEARNING TECHNIQUES IN HEALTHCARE MONITORING

The field of IoT-based smart health monitoring system research has witnessed significant growth in the last few years with researchers exploring various Machine Learning (ML) and Deep Learning (DL) techniques in order to enhance system performance, accuracy, and reliability. Reference [1] introduces an IoT-supported health-care platform where wearable sensors and cloud computing are integrated to monitor patient vitals in real time, displaying a better efficiency in remote health tracking and early disease detection using popular machine learning (ML) classifiers such as Decision Trees and Support Vector Machines. Ref [2] presents another integrated health monitoring model that utilizes the Random Forest and K-Nearest Neighbors algorithms to predict diseases, thus obtaining high accuracy. This study emphasizes the importance of feature selection and proper data preprocessing in the IoT scenarios for improved model performance. The work in [3] demonstrates the new cloud-assisted IoT-based system for health care, focusing on the usefulness of integrating deep learning models, specifically Convolutional Neural Networks (CNNs), for ECG analysis. It demonstrates immense improvement in detecting cardiac abnormalities than the classical ML methods. Again, [4] briefly presents a hybrid IoT-monitored system using both ML and DL; in it, ML methods are responsible for feature extraction whereas the classification is operated by deep neural networks to lead to higher prediction accuracy and minimized false positives in medical diagnoses.

According to [5], the usefulness of edge computing in the IoT-based healthcare system is well emphasized. This scheme has foundations in the fact that it works to handle data using lightweight ML models at the local data level, and in the process, reduce latency and bandwidth overheads, and in so doing, make real-time response or health emergency monitoring a possibility. Long Short Term Memory (LSTM) networks in IoT-based systems for time-series health data analyses, especially for chronic disease prediction, are discussed in [6], and the time at the beginning is placed higher. [7], which was devoted to a wearab1e IoT device tied to a mobile application for continuous health monitoring, uses ML algorithms for the purpose of anomaly detection and alert generation, which enhances extreme patient safety and can therefore provide timely medical intervention. [8] performs an exhaustive comparison of various ML algorithms in an IoT healthcare framework. The algorithms of this new gradient class, as well as Naïve Bayes, Decision Trees, and Random Forest, are discussed and their performances are discussed. This study concludes that ensemble methods are better than individual classifiers in terms of accuracy and stability.

Moreover, [9] suggests deep learning-based IoT system for multihorizon health monitoring using a merger of CNNs and RNNs to look into spatial and temporal features simultaneously within the model, with an excellent classification of diseases and prediction of their status. [10] resolves various security issues in healthcare regarding IoT by using blockchain. These days, ML-based monitoring systems are both lossless and trickle down the user's system for fast and efficient data security. The solutions in [11] provide several procedures for data variations and the noncompatibility of IoT-based systems and design a standardized framework that combines ML techniques to support the incorporation of multiple sources of data to improve system compatibility and performance. [12] digs deep into real-time patient monitoring using IoT devices and DL models, establishing the real practice of capture and HSV experiments in fully automating large-dimensional space extraction processes around big and wild data, especially for applied scenarios in critical care.

Hybird ML/DL Approaches for Accurate Disease Prediction are proposed by the authors for IoT-Based Healthcare System applications [13]. In that work, ML algorithms work in the first place to filter the data and in the later step select for the multi-level introfication of the DL models for feature learning. This schemes result in a better performance of the overall system. In order to support a health management system based on IoT, [14] introduced the concept of the fog architecture, thus distributing data execution and reducing poor reliance on centralized cloud architecture for the sake of improving system stability and responsivity. The discussions in [15] provide a good survey of IoT-based intelligent healthcare systems, discussing various ML and DL approaches and highlighting the hurdles of data privacy, scalability, and computational complexity, along with potential research directions, such as the possibility of lightweight models and models with improved security mechanisms.

All analyzed and reviewed literature impeccably imparted that the change in IoT-based smart health monitoring systems evolved with the integration of up-to-date ML and DL techniques. In fact, ML leverages data and the computation of structured data while DL models prove to perform considerably better in the analysis of data which is complex and unstructured. In fact, hybrid methods and emerging technologies such as edge computing, fog computing, and blockchain further strengthen system capabilities. However, challenges such as data security, interoperability, and resource constraints still hold essential areas for future studies. This comparative analysis of existing studies signifies the need that we desire something capable of strengthening IoT-based healthcare solutions to reach the security and scalability in talking to both ML and DL abilities as far as patient care and the making of medical decisions are concerned.

Table 2: Summary of Literature Review on IoT-Based Smart Health Monitoring Systems

Ref. No.	Methodology/Technique	Key Contribution	Findings/Outcome	Limitations
[1]	IoT + ML (DT, SVM)	Real-time monitoring using wearable sensors	Improved early disease detection	Limited accuracy with complex data patterns
[2]	IoT + ML (RF, KNN)	Disease prediction with feature optimization	High accuracy in classification	Computational cost increases with large datasets
[3]	IoT + DL (CNN)	ECG analysis using deep learning	Accurate cardiac abnormality detection	Requires large labeled datasets
[4]	Hybrid ML + DL	Combined feature extraction and classification	Reduced false positives	Increased system complexity
[5]	IoT + Edge + ML	Edge-based real-time processing	Low latency and bandwidth usage	Limited processing power at edge devices
[6]	IoT + DL (LSTM)	Time-series prediction for chronic diseases	Better temporal analysis	High training time and resource usage
[7]	IoT + ML	Wearable-based anomaly detection	Real-time alerts and monitoring	Sensor reliability and noise issues
[8]	IoT + ML (NB, DT, RF)	Comparative ML algorithm analysis	Ensemble methods perform better	Overfitting in some models
[9]	IoT + DL (CNN + RNN)	Multi-parameter monitoring system	High prediction accuracy	Complex model tuning required

[10]	IoT + ML + Blockchain	Secure data transmission framework	Enhanced privacy and security	Increased computational overhead
[11]	IoT + ML	Interoperability framework	Improved scalability	Standardization issues across devices
[12]	IoT + DL	Real-time monitoring with DL models	Efficient handling of big data	High hardware requirements
[13]	Hybrid ML + DL	Multi-stage prediction system	Improved performance	Integration complexity
[14]	IoT + Fog Computing	Distributed processing system	Faster response time	Infrastructure cost and maintenance
[15]	Review (ML + DL)	Comprehensive survey	Identified research gaps	Lacks experimental validation

IV. DEEP LEARNING APPROACHES FOR SMART HEALTH SYSTEMS

The rapid evolution of IoT, ML (Machine Learning), and DL (Deep Learning) technologies have considerably revolutionized the smart healthcare systems ensuring intelligent real-time and remote patient monitoring solutions. Recent research has been focused on integrating these key technologies with biosensors, wearable devices and advanced analytics to enhance diagnostic accuracy, patient care, and system efficiency. Consequently, the following section focuses on compiling a comparative review of recent case studies (e.g. the studies [16]–[30] with the methodologies, contributions, and limitations pertaining to the domain of smart health monitoring systems, based on IoT certainties.

According to [16], some trends in modern biomedical technology, with AI merged with biosensor techniques, are under evaluation, with the purpose of providing improvement in patient clinical diagnostics via better care provision. Advanced biosensor systems have an admirable potential to pick up fine-grained physiological signals that, when analyzed by AI, might be said to be instrumental in reaching a more accurate and timely diagnosis. They can provide continuous monitoring at the bedside for supportive decision-making in a clinical setting. They can be used to work on personalized treatment, and by using the patient's own data pattern, diagnostics can be made supportive. The article continued as more diagnoses were being eliminated because of the interlinking between bio-sensor and AI systems for diagnostics. However, challenges did surface in processes such as system integration and data heterogeneity. The research corroborates the strong potential of AI and biosensor-driven systems for the healthcare of tomorrow.

In the study [17], the authors proposed an AI-assisted remote monitoring system specifically designed for hand surgery application. The system employs IoT devices and ML models to monitor patient recovery and rehabilitation. This method has reduced the number of patient visits, thereby ensuring comfort to patients. The system analyzes motion data to ascertain transgressions in the trajectory of wound healing. Instantaneous feedback drives better clinical decision-making. It is pertinent to acknowledge that while there are many advantages to the system, data privacy and dependency on hardware accuracy are the major concerns. This study is a proof of the AI-enabled monitoring system's effective application in specialized healthcare.

Earlier studies emphasized on detecting behavioral and psychological symptoms of dementia using wearable devices in combination with machine learning techniques [18]. The system is designed to continuously monitor individual activity and behavioral patterns based on sensor data. By using ML algorithms and differential technology, dementia precursors, yet not cognitive decline is detected at an occult stage. This approach mainly supports the willing caregivers through rapid alerts and an alert to act on. The study further posits that continuous monitoring of the dementia patient is still meaningful. Some of the challenges concerning data credibility and patient compliance should be addressed, although specific points do warrant further discussion. An ML-based wearable system is conceivable to have a positive impact on a disposition related to dementia treatment.

This paper addresses the crisis of deep learning by implementing an Internet of Things (IoT) based health system for an in-depth understanding of patient health, diagnosis, and treatment. Integrating IoT sensor data in healthcare with deep learning models such as Convolutional Neural Networks will predict diseases accurately. The study aims to handle a vast volume of complex healthcare data and extract intricate patterns within the datasets. Better results from diagnoses with reduced interference for manual intervention are expected. However, cloud enablement will necessitate the entire infrastructure on the entire fog. We agree that computation is high; latency causes a major concern for this model. With this background, we can confirm the results in this study that highlight the benefits of using deep learning to improve IoT-based healthcare systems.

A novel contactless health monitoring system that uses CSI and ML technology was designed. Such a system uses the signal variations in the RF environment to monitor the vital signs without sensors that were attached to the body. The ML models analyze the signal patterns to detect changes in physiological parameters. Theoretically, such an application could be favorable in critical care and remote monitoring environments. Moreover, the study states that the system shows a high accuracy in the detection of health parameters. However, an environment where noise and signal interference may bring poor performance. This application could reduce dependency on wearable devices; hence, it is capable of alerting predictions for non-invasive health care monitoring.

In [21], an IoT-based healthcare system integrated with deep learning technology for continuous monitoring of patient health has been proposed by the authors. The system programs real-time data collection via sensors and curves it through DL models for disease prediction. This is an improved form of monitoring for early detection purposes of patients suffering from critical conditions. The architectural structure is cloud-based for data storage and processing. The authors scrutinized the enhanced scalability and efficiency of the system while focusing on the various issues posing around data security and latency. The study advocates that the role for DL in intelligent healthcare systems has grown significantly.

A research paper by [22] demonstrates the application of a wearable sensing system powered by a triboelectric nanogenerator and machine learning. The friction-activated device supports the system, making it self-sustainable, ideal for sustained health monitoring, and able to track gait data and analyze for various conditions with the assistance of machine learning algorithms. The system is very effective in motion detection and health analysis. The use of energy harvesting promotes sustainability. However, calibration issues and environmental factors act as a bottleneck. The present work proposes something new in wearable healthcare technology. An improved machine learning algorithm is proposed in [23] for predicting disease risk factors in big data healthcare systems. This approach processes immense data efficiently using state-of-the-art, ML techniques. Feature selection and model optimization enhance prediction accuracy. The software system supports strategies to diagnose and intervene in the early course of disease. It boasts improved scalability and performance. The flip side, however, lies with the computational complexity. The study underscores the importance of big data analytics in healthcare applications. In [24], the author is discussing the application of machine learning and deep learning methods for fault diagnosis. The signals vibrating and streaming are physical sensors being utilized for the majority of the case attributes; however, it is possible beyond that. Thus, comparison based on performance factors accuracy and computational speed has been revealed. Where DL models have emerged as the best performers beyond traditional ML-based technologies in the context of pattern recognition, the DL and ML machines to a great extent depend on each other. However, model complexity and data dependency do limit the forces by which they could bid other models good. But research basically proposes a flexibility of ML's extension into many areas. It proposes some opportunities for healthcare monitoring systems.

A combination of deep learning methodologies has been proposed in order to go a step further in securing the healthcare IoT and enhancing its performance. Combining deep learning methodologies with security frameworks also ensures secure data communication. This has the advantage of providing system reliability while protecting personal data. This study has shown improvements in performance and system robustness, although computational overhead poses a challenge. The study on healthcare IoT security responds to the biggest real-world issues, suggesting a better way forwards to an efficient yet challenging-scale solution. Research works [26] on ECG arrhythmia classification using deep learning and transfer learning methods. Besides the use of pre-trained models to elevate the classification accuracy, the system can competently understand biomedical signals and detect cardiac-related abnormalities. Transfer learning proves to be sufficient even with relatively small datasets. Nevertheless, these algorithms are highly accurate and efficient models; their drawback remains their high interpretability. It is necessary to revolutionize monitoring of cardiac related challenges such as this. Thus, that will enhance the use of DL in the area of medical diagnostics.

Fuzzy ensemble-based federated learning in [27] was suggested for emotion recognition from EEG, IoMT systems. Such a system will utilize fuzzy logic with federated learning to help in strengthening the models by preserving data privacy. There was the demonstration of an improved recognition rate of emotions. However, there are problems in communication and system complexity. It generally supports systems designed for privacy with limited healthcare. It thus shows the importance of decentralized learning approaches.

There is a need to develop decentralized secure patient monitoring. In order to meet this need, the paper about FFL in Telehealth emerges. This study covers FFL in monitoring individuals. It is expected to enable being employed in sensors integrated within clothes and shoes. While data are provided, privacy and security are guaranteed, thus improving operational visibility. This offers time-saving, responsiveness, and the power to react in healthcare delivery. The path to develop an asynchronous system is very bumpy because it lays heavily on network access. This work is moving forward in the development of decentralized healthcare architectures. An interesting concept is the secure floating of IoT-based information. The authors described how machine learning models such as XGBoost, LightGBM and Random Forest are used for predictive analysis in [29]. While they have applied these methods to environmental hazard assessment, not healthcare forecasting, the methodologies are just as applicable to the latter. The study comparatively analyzes the performance of the models used and, among others, highlights the apparent effectiveness of ensemble techniques. While, naturally, higher accuracy and efficiency could be reached, the method's inherent changeability and data dependency seem to reject these. This work underscores the potential flexibility of ML techniques. The study suggests the approach for healthcare data analysis. Finally, in [30] presented an optimized model based on deep learning for diabetes detection using a hyperparameter-tuned Bi-directional Gated Recurrent Unit. The model essentially works with health data as time series for an accurate forecast. The time series show how optimization improves performance and reduces error rate. Thus, information derived from the data is better understood by preventive rather than reactive benefits. When compared with the most common traditional approaches, according to the outcomes, these outperformed by me. However, it is noted that although the model prediction leads to excellent outcomes, it draws heavy computational resource chains to process compared to the traditional model. This work showcased the functionalities of major chronic diseases management systems; thus valuable insight to corroborate the need for standard optimization techniques in the DL model. Table 3 highlights the key differences between Machine Learning and Deep Learning models in terms of performance, data requirements, complexity, and their suitability for IoT-based smart healthcare applications.

COMPARATIVE ANALYSIS OF ML AND DL MODELS

Table 3: Comparative Analysis of ML and DL Models in IoT-Based Smart Health Monitoring Systems

Criteria	Machine Learning (ML)	Deep Learning (DL)
Definition	Algorithms that learn patterns from structured data using statistical methods	Subset of ML that uses multi-layer neural networks to learn complex patterns
Data Requirement	Performs well with small to medium datasets	Requires large volumes of data for effective training
Feature Engineering	Manual feature extraction required	Automatic feature extraction (end-to-end learning)
Accuracy	Moderate to high accuracy depending on features	Generally higher accuracy, especially with complex data
Handling of Data Type	Best suited for structured data	Effective for both structured and unstructured data (images, signals, text)
Computational Complexity	Low to moderate	High (requires GPUs/advanced hardware)
Training Time	Faster training	Slower due to deep architectures
Model Interpretability	Easier to interpret and explain	Difficult to interpret ("black-box" models)
Examples of Algorithms	Decision Tree, SVM, KNN, Random Forest	CNN, RNN, LSTM, GRU
Performance in IoT Healthcare	Efficient for simple prediction and classification tasks	Superior for complex tasks like ECG analysis and image processing
Scalability	Limited scalability with large data	Highly scalable with big data and cloud support
Real-Time Processing	Suitable for real-time with low resources	Challenging but possible with edge optimization
Energy Consumption	Low	High due to intensive computations
Deployment in IoT Devices	Easily deployable on low-power devices	Requires optimization for edge deployment
Applications	Disease prediction, anomaly detection	Medical imaging, signal processing, advanced diagnostics
Limitations	Lower performance on complex/unstructured data	High computational cost and data dependency

V. CONCLUSION AND FUTURE WORK

The study compared and contrasted IoT-based smart health monitoring systems along with ML and DL procedure voyage. An interfacing view as described in this study focuses on the fact that IoT allows real-time data acquisition through sensor-embedded wearable devices for the purpose of remote patient monitoring, but fundamentally establishes healthcare accessibility. Methods of ML were discovered to be quite advantageous for structured yet light data processing regarding less computational requirements, while deep learning models with accuracy, studied on ECG, or medical images were found most suitable in examining the complexities and unstructured medical data. Several comparisons have been made between accuracy and accuracy. It was concluded that if the technical staff is sufficient, DL may be used for the application of big data jobs since it requires very large data sets and hardware resources to effectively support block cooperation, while ML models were considered quite fit for lightweight real-time application cases. One of the identified problems was extreme energy consumption, interoperability issues among IoT devices, and gigantic data with plenty of annotations. Very briefly, the challenges of the interpretability and complexity of DL models remain detrimental in healthcare application areas where transparency is required. Further research should concentrate on developing blended models that embrace the strengths of ML and DL for enhanced performance and efficacy.

REFERENCES

[1] Castrejón-Peralta, César, et al. "Artificial Intelligence and Deep Learning-Based Methods and Devices for Measuring Vital Signs: A Systematic Review." *Applied Sciences* 16.2 (2026): 1126.

[2] Beloualid, Siham, et al. "Autonomous Robotics Computer-Vision based Framework for Intelligent Remote Patient Monitoring in Health Care." *Results in Engineering* (2026): 109397.

[3] Melibayeva, Farog'at, and Gulnora Axmadaliyeva. "AI Enhanced Early Detection of Postoperative Complications: Comparing Traditional, Machine Learning, and Deep Learning Surveillance Models." *Journal of Clinical and Biomedical Research* 2.1 (2026): 223-230.

[4] Aparna, Mudiyala, Battula Srinivasa Rao, and Mallela Siva Naga Raju. "AI Revolution in Healthcare: Digital Health Services Empowered by Machine Learning and Deep Learning." *Digital Cities* (2026): 1-12.

[5] Alluhaidan, Ala Saleh, et al. "Revolutionizing artificial intelligence enabled predictive analytics with smart consumer electronics for real-time healthcare monitoring." *Engineering Applications of Artificial Intelligence* 167 (2026): 113712.

[6] Sharma, Kusum, et al. "Deep learning-assisted organogel pressure sensor for alphabet recognition and bio-mechanical motion monitoring." *Nano-Micro Letters* 18.1 (2026): 63.

[7] Ansari, Rayan A., et al. "Deep Learning–Based Continuous QT Monitoring to Identify High-Risk Prolongation Events After Class III Antiarrhythmic Initiation." *Circulation* 153.1 (2026): 35-46.

[8] Sadanandan, Binesh. "Multimodal deep learning for early prediction of patient deterioration in the icu: Integrating time-series ehr data with clinical notes." *arXiv preprint arXiv:2603.14719* (2026).

[9] Chandu, S., et al. "Biometric authentication using IoT devices powered by deep learning and encrypted verification." *International Journal of Computer Technology and Electronics Communication* 9.1 (2026): 87-92.

[10] Saini, Vivek, et al. "Development of a hybrid first principles-machine learning adaptive modeling framework for health monitoring of power plant boiler superheaters." *Fuel* 406 (2026): 136795.

[11] Rhaiem, Rami, et al. "Machine learning models for Disease-free survival analysis after liver resection for hepatocellular carcinoma: a multicentric French collaborative study." *Liver Cancer* (2026).

[12] Badjate, Sagarkumar, and Priyamwada Sharma. "Machine Learning-Enabled Smart Health Monitoring for Predictive Analytics." *Bioengineering and IoT*. CRC Press, 2026. 212-226.

[13] Karomo, Muzondiwa, Mainford Mutandavari, and Wilton Muzava. "Deep learning for sentiment analysis and topic extraction in health insurance." *Computer Science and Information Technologies* 7.1 (2026): 66-73.

[14] Thanekar, Gananjay Sandeep, and Swati Sayankar. "ENHANCING DIABETES DIAGNOSIS USING ADVANCED MACHINE LEARNING AND DEEP LEARNING TECHNIQUES." *Transformative Education: A Multidisciplinary Journal (TEMJ) E-ISSN: 3117-8057* 2.1 (2026): 113-118.

[15] Pabitha, C., et al. "IoT and Cloud-Enabled AI Predictive Maintenance for Manufacturing, Energy, Healthcare Systems." *Advanced Materials for Biomedical Devices*. CRC Press, 2026. 431-443.

[16] Baluta, Sylwia, et al. "Improving Clinical Diagnostics and Patient Care through Artificial Intelligence and Biosensor Technologies." ACS omega (2026).

[17] Lin, Eugenia A., and Kevin J. Renfree. "AI-Enabled Remote Patient Monitoring Systems in Hand Surgery." Hand Clinics 42.1 (2026): 75-83.

[18] Chen, Oscar Tai-Yuan, et al. "Alerting to Behavioral and Psychological Symptoms of Dementia Using Machine Learning and Wearable Devices." Management of Dementia from the Preclinical Stage: An Update. Singapore: Springer Nature Singapore, 2026. 139-161.

[19] Alharbe, Nawaf, and Manal Almalki. "IoT-enabled healthcare transformation leveraging deep learning for advanced patient monitoring and diagnosis." Multimedia Tools and Applications 84.19 (2025): 21331-21344.

[20] Khan, Muhammad Imran, et al. "Tracking vital signs of a patient using channel state information and machine learning for a smart healthcare system." Neural Computing and Applications 37.28 (2025): 23065-23079.

[21] Najim, Ali Hamza, et al. "An IoT healthcare system with deep learning functionality for patient monitoring." International Journal of Communication Systems 38.4 (2025): e6020.

[22] Parashar, Parag, et al. "Machine learning-driven gait-assisted self-powered wearable sensing: a triboelectric nanogenerator-based advanced healthcare monitoring." Journal of Materials Chemistry A 13.19 (2025): 13750-13762.

[23] Thatha, Venkata Nagaraju, et al. "Optimized machine learning mechanism for big data healthcare system to predict disease risk factor." Scientific reports 15.1 (2025): 14327.

[24] Ayankoso, Samuel, et al. "Performance of vibration and current signals in the fault diagnosis of induction motors using deep learning and machine learning techniques." Structural Health Monitoring 25.1 (2026): 196-212.

[25] Babar, Muhammad, et al. "An efficient and hybrid deep learning-driven model to enhance security and performance of healthcare internet of things." IEEE Access 13 (2025): 22931-22945.

[26] Mavaddati, Samira. "ECG arrhythmias classification based on deep learning methods and transfer learning technique." Biomedical Signal Processing and Control 101 (2025): 107236.
[27] Jiang, Weiwei, et al. "Fuzzy ensemble-based federated learning for EEG-based emotion recognition in Internet of Medical Things." Journal of Industrial Information Integration 44 (2025): 100789.
[28] Almogadwy, Bassam, and Abdulrahman Alqarafi. "Fused federated learning framework for secure and decentralized patient monitoring in healthcare 5.0 using IoMT." Scientific Reports 15.1 (2025): 24263.
[29] Yu, Tai-Kuei, et al. "Predicting potential soil and groundwater contamination risks from gas stations using three machine learning models (XGBoost, LightGBM, and Random Forest)." Process Safety and Environmental Protection 199 (2025): 107249.
[30] Rayala, Ramya Vani, et al. "Optimized Deep Learning for Diabetes Detection: A BGRU-based Approach with SA-GSO Hyperparameter Tuning." 2025 International Conference on Innovations in Intelligent Systems: Advancements in Computing, Communication, and Cybersecurity (ISAC3). IEEE, 2025.