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**Abstract**

The growing adoption of Internet of Things (IoT) technology in healthcare has opened new possibilities for monitoring patients' health continuously, even when they're not in a hospital. This paper presents a low-cost health monitoring system that uses smart sensors and artificial intelligence to predict potential health problems before they become serious. Our system uses an ESP32 microcontroller connected to several medical sensors: a MAX30100 sensor that measures heart rate and blood oxygen levels, a temperature sensor (10kΩ thermistor), and a digital blood pressure monitor. All these sensors work together to collect vital signs, which are then sent wirelessly to a cloud platform called Thingier.io for storage and analysis. We tested three different AI algorithms to see which one works best for predicting health risks: Support Vector Machine (SVM), Decision Tree, and a Convolutional Neural Network (CNN). The results were interesting: the Decision Tree algorithm performed perfectly, achieving 95.20% accuracy on our test data, making it highly suitable for rule-based medical diagnostics.

**Index Terms**— IoT healthcare systems, ESP32 microcontroller, biomedical sensors, machine learning classification, deep learning, physiological signal processing, health risk prediction, cloud computing.

**I. Introduction**

The study focuses on designing and evaluating an intelligent healthcare system that integrates modern digital technologies for real-time patient monitoring. In today's healthcare environment, the growing prevalence of chronic diseases, aging populations, and the need for continuous health supervision have made traditional hospital-centric models insufficient, thereby creating demand for remote and automated health monitoring solutions. The concept of Internet of Things (IoT) plays a central role here, where wearable sensors and connected medical devices are used to continuously collect physiological data such as heart rate, temperature, blood pressure, and oxygen levels [1]. This data is then transmitted over the internet to cloud or edge platforms for further processing. The study goes beyond simple monitoring by incorporating advanced computational techniques, specifically Machine Learning and Deep Learning algorithms, which enable the system to analyse large volumes of health data, detect patterns, predict potential health risks, and support early diagnosis with higher accuracy. Furthermore, the term "development" indicates that the research involves building a complete working model or framework of such a system, while "comparative analysis" highlights the evaluation aspect, where different machine learning and deep learning models are systematically compared in terms of performance metrics like accuracy, precision, computational efficiency, and reliability [2]. Overall, the title represents a comprehensive approach that combines IoT infrastructure with intelligent data analytics to create a smart, efficient, and scalable healthcare monitoring solution aimed at improving patient outcomes and reducing the burden on healthcare systems.

The global healthcare ecosystem is undergoing a significant transformation from traditional reactive, hospital-centered care models toward proactive, patient-centric systems that emphasize continuous monitoring and early intervention. This shift is largely driven by the increasing burden of chronic diseases such as cardiovascular and respiratory disorders, which require long-term observation rather than sporadic clinical evaluations [3]. In conventional setups, patients visit healthcare facilities at discrete intervals, resulting in limited snapshots of their physiological condition and often missing early warning signs of deterioration. However, with the advancement of Internet of Things technologies, wearable sensors and smart medical devices can now continuously capture real-time health parameters such as heart rate, oxygen saturation, and respiratory patterns [4]. When combined with edge computing for local data processing and Artificial Intelligence for intelligent decision-making, these systems enable immediate analysis and response, thereby facilitating early diagnosis, reducing hospital admissions, and improving patient outcomes. This paradigm shift not only enhances clinical efficiency but also empowers patients to actively participate in managing their own health [5].

Despite these advancements, conventional health monitoring systems still face several fundamental challenges that limit their scalability and effectiveness. High infrastructure costs associated with hospital-based monitoring equipment make continuous healthcare inaccessible for many populations, especially in resource-constrained settings. Additionally, the time gaps between routine clinical visits create blind spots in patient data, which can delay the detection of critical health events. Another major limitation is the absence of intelligent analytics in traditional systems, where collected data is often underutilized and lacks predictive capability [6]. To address these issues, this research proposes an integrated framework that leverages low-cost IoT devices for data acquisition and cloud-based platforms for scalable storage and processing. By incorporating advanced algorithms from Machine Learning and Deep Learning, the system is capable of extracting meaningful insights, identifying hidden patterns, and predicting potential health risks with improved accuracy [7]. This combination of affordability, continuous monitoring, and intelligent analytics creates a robust and scalable solution that bridges the gap between traditional healthcare systems and next-generation smart health monitoring.

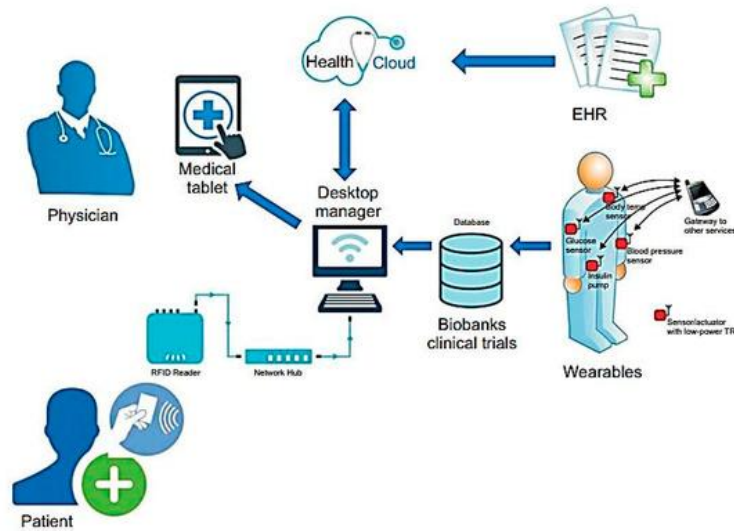
**A. Role of IoT in Smart Healthcare**

The development of healthcare systems requires a concerted effort to seamlessly integrate with the Internet of Things (IoT), especially for ameliorating day-to-day challenges arising in the sector. Recent developments in the health sector have consistently shown that combined technologies have the potential to improve healthcare services and assist healthcare professionals in the optimal and efficient delivery of healthcare solutions. IoT is a new paradigm in technology which provides a conglomerate of novel services for the next wave of technological innovations. IoT enables things (such as devices, cars, houses, people, and animals) to communicate with one another and with users over the internet network, thereby becoming an integral part of the Internet [8]. Healthcare is considered to be the most crucial part of life. Health care involves the sustenance and improving the various health conditions by diagnosing various ailments and taking measures to prevent them. While checking the feasibility of healthcare solutions, there are three parameters that need to be considered. Various diagnostic approaches such as CT scan, MRI, X-rays are carried out in order to detect the abnormalities lying beneath the skin. The medical specialists and healthcare professionals focus on bringing the innovative methods to detect the diseases and deliver the targets. Numerous health issues such as chronic artery disease and epilepsy can now-a-days be discovered even before their actual occurrence in the patient's body. As the consequence of population explosion, there is a huge demand for medical professionals and medical resources such as hospital beds, oxygen masks, smart pill dispensers etc. Sometimes, due to misdiagnosis, a huge amount of time as well as resources are mislaid in the healthcare systems. Therefore, there is a dire need to come up with the solutions that could considerably reduce the time, resource wastage and effort that are carried out on current human assisted healthcare systems [9].

Table 1. Healthcare Applications and Services [10]

<b>Application</b>	<b>Services</b>
Health Assistant	Body temperature, fat, weight, BP, glucose level check
Calorie Counter	Calories count from the food eaten
Pedometer	Steps taken and calories burnt
Period Tracker	Record of menstrual cycle in women
Google Fit	Running, cycling and walking activities
Water Your Body	Water drinking habits and alerts
Heart Rate Monitor	Heart beat
Smart Watch	Number of steps taken, BP, heart rate, calories burnt
On Track Diabetes	Blood glucose level
Finger Print Thermometer	Body temperature

Table 2 shows various smart applications launched with the purpose to make them available all-time to the people. These applications facilitate the people with various health services. They can analyze various parameters themselves on daily basis and opt workout & healthy eating 9 habits accordingly. Various remedies can be followed without consulting doctors just by adapting healthy lifestyle [10].



**Figure 1.** Revolutionary features of H-IoT in a hospital environment [11].

The figure 1 illustrates an integrated IoT-based smart healthcare monitoring system in which patient health data is continuously collected, transmitted, and analyzed for effective medical decision-making. Wearable sensors attached to the patient monitor vital parameters such as heart rate, blood pressure, glucose level, and body temperature, and transmit this data through low-power communication modules to a network hub or central system. The data is then stored in databases (such as biobanks or clinical records) and processed via a desktop manager before being uploaded to the Health Cloud. This cloud system further integrates with Electronic Health Records, ensuring secure storage and easy access to patient history. Physicians can remotely access this information through medical tablets or computers, enabling real-time monitoring, early diagnosis, and timely intervention. Overall, the architecture demonstrates how the Internet of Things facilitates seamless connectivity between patients, devices, and healthcare providers, improving the efficiency and quality of healthcare services.

**II. Related work**

Rashid, T., et al. (2026) [12] expressed emotion recognition using physiological signals has gained significant attention in recent years due to its potential applications in mental health monitoring, human-computer interaction, and stress management. This study focuses on recognizing six emotional states neutral, happy, sad, fear, anger, and surprise using internal body parameters such as blood pressure, oxygen saturation, blood glucose, heart rate, and body temperature. Leveraging an Internet of Things (IoT) enabled framework, real-time data was collected from participants. An exhaustive experimental assessment has been performed on 11 different classification algorithms of the machine learning platform. Among the algorithms, the Random Forest algorithm performed better than all other algorithms with 90.56% accuracy and 93.34% F1-score. Moreover, the precision and recall of the proposed system are extremely high. Model Robustness and generalization performances were evaluated by conducting internal as well as external validation. On conducting internal validation through k-fold cross-checking, the accuracy increased to 93.18%, clearly validating the consistency in the performance of the model. Further, the external validation was conducted by using the conventional DEAP emotional tasks, showing a collective accuracy of about 94% along with very good  $\text{max}$  and weighted average precision, recall, and F1-score values for all classes of emotions. This clearly validates the efficacy of the chosen physiological features as well as the correctness of the devised approach. The findings indicate that physiological signals, combined with IoT and machine learning, provide an effective framework for emotion recognition. This research contributes to the development of real-time, non-invasive emotion recognition systems, with promising applications in healthcare, wearable devices, and personalized user experiences. Future work will explore the integration of additional physiological parameters and advanced deep-learning models for enhanced accuracy and scalability, and usage in advanced technology.

Jaloudi, S. (2026) [13] proposed the applications of smart cities, smart buildings, smart agriculture systems, smart grids, and other smart systems benefit from Internet of Things (IoT) protocols, networks, and architecture. Wireless Sensor Networks (WSNs) in smart systems that employ IoT use wireless communication technologies between sensors in the Things layer and the Fog layer hub. Such wireless protocols and networks include WiFi, Bluetooth, and Zigbee, among others. However, the payload formats of these protocols are heterogeneous, and thus, they lack a unified frame format that ensures interoperability. In this paper, a lightweight, interoperable frame format for low-rate, small-size Wireless Sensor Networks (WSNs) in IoT-based systems is designed, implemented, and tested. The practicality of this system is underscored by the development of a gateway that transfers collected data from sensors that use the unified frame to online servers via message queuing and telemetry transport (MQTT) secured with transport layer security (TLS), ensuring interoperability using the JavaScript Object Notation (JSON) format. The proposed frame is tested using market-available technologies such as Bluetooth and Zigbee, and then applied to smart home applications. The smart home scenario is chosen because it encompasses various smart subsystems, such as healthcare monitoring systems, energy monitoring systems, and entertainment systems, among others. The proposed system offers several advantages, including a low-cost architecture, ease of setup, improved interoperability, high flexibility, and a lightweight frame that can be applied to other wireless-based smart systems and applications.

Kiplagat, J. (2026) [14] studied the rapid expansion of the Internet of Things (IoT) has led to the development of intelligent smart systems that connect physical devices, sensors, and software applications to enable real-time data collection and analysis. This study presents an analysis of IoT-based smart systems and their applications across various domains. It explores the fundamental architecture of IoT, including sensing devices, communication networks, data processing units, and application layers that work together to enable seamless connectivity and automation. The paper highlights how IoT technologies enhance decision-making, operational efficiency, and service delivery through continuous monitoring and intelligent analytics. Key application areas such as smart homes, healthcare, smart cities, agriculture, industrial automation, and transportation systems are discussed in detail. Furthermore, the study examines critical challenges including data security, privacy concerns, interoperability issues, network scalability, and energy constraints in IoT environments. Emerging solutions such as edge computing, AI integration, and 5G connectivity are also analyzed to address these challenges. The findings emphasize that IoT-based smart systems play a vital role in enabling digital transformation and improving efficiency, productivity, and quality of life across multiple sectors.

Anantkawalas, K. V et al. (2026) [15] demonstrated the rapid advancement of the Internet of Things (IoT) has significantly transformed modern healthcare by enabling real-time and remote monitoring of patients. This project presents the design and implementation of an IoT-based health monitoring system that measures two essential physiological parameters: heart rate and body temperature. The system is developed using the Arduino Uno microcontroller, which serves as the central processing unit for data acquisition and control. A pulse sensor is employed to detect heart rate based on photoplethysmography (PPG), while the DS18B20 Digital Temperature Sensor provides accurate digital measurement of body temperature using the OneWire communication protocol. A 10kΩ pull-up resistor is integrated to ensure reliable data transmission from the temperature sensor. The processed data is displayed on a 16x2 LCD interfaced through an I2C LCD Module 16x2, which significantly reduces wiring complexity and enhances system efficiency. The proposed system is compact, cost-effective, and capable of continuous real-time monitoring. Furthermore, it can be extended to IoT platforms for remote data access and analysis. This system is particularly useful for home healthcare, early diagnosis, and continuous patient supervision, thereby reducing the need of frequent hospital visits and improving overall healthcare management.

Katkoori, A. K., et al. (2026) [16] explained Real-time health monitoring is now necessary for finding diseases early and keeping an eye on patients all the time. This paper shows how to use the ESP32 microcontroller and biomedical sensors to make a health tracking system that is both effective and cheap. The system

sends real-time data to the ThingSpeak IoT platform by measuring ECG signals (AD8232), SpO2 (MAX30102), and body temperature (LM75). We use FreeRTOS for multitasking with priority-based scheduling to make sure everything runs smoothly and efficiently. ECG readings have the highest priority, followed by SpO2 and temperature readings. Also, an I2C mutex mechanism stops data conflicts when more than one sensor talks to the ESP32. ESP32 sends health data to the cloud without any problems over Wi-Fi, so users can see real-time visualizations from anywhere. FreeRTOS makes sure that each sensor task runs smoothly by putting the most important health data first so that monitoring is accurate and quick. This work, unlike previously ESP32-based systems, primarily emphasizes the use of the FreeRTOS with priority-based task scheduling along with mutex-synchronized.

Dutta, S. (2025) [17] studied the rapid urbanization of cities worldwide presents significant challenges to the healthcare sector, including resource constraints, infrastructure gaps, and increasing patient demands. Artificial Intelligence (AI) and the Internet of Things (IoT) offer transformative solutions to address these challenges, driving the development of smart healthcare systems tailored for urban areas. This paper explores integrating AI and IoT technologies to create efficient, real-time, patient-centered healthcare systems. We examine how AI algorithms can optimize diagnostics, predictive analytics, and personalized treatment plans. IoT-enabled devices facilitate remote patient monitoring, data collection, and seamless communication between healthcare providers and patients. By leveraging these technologies, urban healthcare systems can enhance patient outcomes, reduce costs, and improve accessibility to medical services. The study also addresses potential barriers such as data privacy, cybersecurity, and the need for robust infrastructure to support smart healthcare systems. Our findings suggest that the synergy of AI and IoT can revolutionize healthcare delivery in urban environments, promoting more sustainable, resilient, and responsive health services for growing populations. Ali, A. A., et al. (2025) [18] explained the integration of smart city applications with healthcare has revolutionized patient monitoring and medical data management. However, ensuring the privacy and security of Electronic Health Records (EHR) remains a critical challenge, especially in IoT-based environments with resource-constrained devices. This paper proposes a novel Blockchain-Enabled Federated Learning (BFL) framework to enhance privacy preservation in EHR processing. The proposed framework leverages zero-knowledge proofs (ZKP) for authentication and homomorphic encryption for secure computation, ensuring robust data security without exposing raw patient data. Federated Learning (FL) enables decentralized model training across IoT devices, reducing privacy risks while maintaining data utility. Additionally, blockchain technology enhances the integrity and transparency of EHR transactions by creating a tamper-proof ledger. The performance of the proposed BFL framework is evaluated based on data utility, model accuracy, execution time, and scalability across varying sizes of EHR datasets. Results demonstrate improved privacy preservation, reduced computational overhead, and enhanced model efficiency, making it a promising approach for secure and privacy-aware IoT-based smart healthcare systems.

William, P. (2025) [19] studied Smart cities leverage advanced technologies, such as IoT, AI, and 5G, to enhance urban living by optimizing resource management, improving services, and fostering sustainability. IoT integrates millions of devices and sensors in urban environments to gather real-time data on transportation, energy, public safety, and healthcare. Through cloud and edge computing, these data are processed for intelligent decision-making. The study explores the potential of AI and ML algorithms to enable autonomous systems, improve public health monitoring, traffic management, and optimize energy grids. Emerging technologies like blockchain and quantum computing, along with future advancements in 6G, will play a significant role in the scalability, efficiency, and security of smart city applications. Key barriers to adoption include high infrastructure costs, data privacy concerns, and interoperability issues, which require mitigation strategies. Smart city IoT frameworks promise significant operational efficiencies and cost reductions across multiple domains, including transportation, waste management, and environmental monitoring, contributing to sustainable and resilient urban environments.

Sallabi, F. M., (2025) [20] recent developments in sensors, wireless communications, and data processing technologies are the main drivers for adopting the Internet of Things (IoT) in healthcare systems. IoT-based healthcare systems can enhance the quality of life significantly and help prevent the occurrence of health problems and epidemics. Deploying IoT-based healthcare on a massive scale raises several issues and challenges. One of the main challenges is the management of the end-to-end network connections of the IoT-based healthcare system. This paper presents a comprehensive survey of smart network management protocols that improve IoT-based healthcare efficiency, ensuring real-time monitoring, secure data transmission, and effective device management. Moreover, a reference architecture has been proposed for the network management of IoT-based smart healthcare systems to ensure the sustainability of service delivery to patients and caregivers. The architecture avoids health-related risks and anomalies by incorporating proper network management techniques and operational requirements pertaining to smart healthcare systems. This paper also discusses architectural implementation insights supported by new technologies such as software-defined networking (SDN) and deep learning (DL). Finally, this paper explores emerging paradigms to advance next-generation network management protocols for future smart healthcare systems.

**Table 1 Comparative Analysis of IoT-Based Smart Healthcare and Related Systems**

Ref. No.	Author (Year)	Focus Area	Technologies Used	Key Contribution	Limitations
[12]	Rashid, T. (2026)	Emotion recognition using physiological signals	Internet of Things, Machine Learning	Real-time emotion classification using physiological parameters with high model validation	Limited to selected emotions; scalability needs improvement
[13]	Jaloudi, S. (2026)	IoT communication interoperability	IoT protocols (Wi-Fi, Bluetooth, Zigbee), MQTT, TLS, JSON	Proposed unified lightweight frame format for WSN interoperability	Focus limited to communication layer, not healthcare-specific analytics
[14]	Kiplagat, J. (2026)	IoT smart systems overview	IoT architecture, AI, edge computing	Comprehensive analysis of IoT applications across domains including healthcare	General study; lacks implementation details
[15]	Anantkawas, K. V. (2026)	IoT-based health monitoring system	Arduino, pulse sensor, temperature sensor	Low-cost real-time monitoring system for heart rate and temperature	Limited parameters; no advanced analytics
[16]	Katkoori, A. K. (2026)	Real-time health monitoring with multitasking	ESP32, FreeRTOS, sensors, ThingSpeak	Efficient task scheduling and real-time monitoring using RTOS	Complexity in implementation; limited scalability discussion
[17]	Dutta, S. (2025)	Smart healthcare in urban systems	Artificial Intelligence, IoT	Integration of AI and IoT for improved healthcare delivery	Challenges in privacy and infrastructure
[18]	Ali, A. A. (2025)	Secure healthcare data management	Blockchain, Federated Learning, ZKP, encryption	Privacy-preserving framework for EHR using blockchain and FL	High computational complexity
[19]	William, P. (2025)	Smart city IoT applications	IoT, AI, 5G, cloud computing	Enhances urban services including healthcare monitoring	High cost and interoperability challenges
[20]	Sallabi, F. M. (2025)	IoT healthcare network management	IoT, SDN, DL	Proposed architecture for efficient network management in healthcare IoT	Focus on network layer; lacks system-level implementation

### III. Research methodology

This section presents the overall design and practical implementation of the proposed IoT-based smart health monitoring system, which follows a structured three-tier architecture comprising edge, communication, and cloud layers to ensure efficient data acquisition, transmission, and analysis. At the core, the ESP32-WROOM-32 acts as the central processing unit, interfacing with multiple sensors such as the MAX30100 for heart rate and SpO<sub>2</sub> measurement, a 10k NTC thermistor for temperature sensing, and a digital blood pressure monitor for capturing systolic and diastolic values. The collected physiological data is transmitted via Wi-Fi to the cloud platform Thingier.io, where it is stored, processed, and made accessible for remote monitoring and decision-making. The experimental setup demonstrates a fully functional prototype assembled on a PCB, integrating sensors, controller, and an OLED display for real-time visualization of health parameters. The system's performance is validated through practical testing in a controlled environment, with additional comparison using a standard blood pressure monitor, confirming its accuracy, reliability, and suitability for continuous health monitoring applications.

**A. System Architecture and Hardware Implementation:** The proposed health monitoring system is designed using a three-tier architecture to ensure efficient data collection, transmission, and analysis. At the Edge Layer, the ESP32 collects real-time physiological data from sensors such as heart rate and temperature. This data is then transmitted through the Communication Layer using Wi-Fi, enabling seamless and continuous connectivity. Finally, in the Cloud Layer, the data is stored and processed on the Thingier.io platform, where it can be visualized, analysed, and accessed remotely by healthcare professionals for monitoring and decision-making.

#### 1. Core Components

The ESP32-WROOM-32 serves as the central processing unit, interfacing with the MAX30100 pulse oximeter via I2C, the NTC thermistor via ADC, and the blood pressure monitor via UART serial communication. This modular design ensures scalability and ease of maintenance.

- **ESP32-WROOM-32:** The figure 2 shows the ESP32 development board, which acts as the core controller of the system. It is responsible for collecting data from various sensors, processing it, and transmitting it to the cloud using built-in Wi-Fi and Bluetooth capabilities. Due to its low cost, high performance, and wireless connectivity, it is widely used in IoT-based health monitoring systems.



Figure 2. ESP32-WROOM-32 Development Board

- **MAX30100 Pulse Oximeter Sensor Module:** The figure 3 represents a pulse/heart rate sensor module (commonly based on MAX30100/30102), which is used to measure heart rate and blood oxygen levels. It works by detecting changes in blood flow using infrared and red light, making it suitable for real-time health monitoring applications.



Figure 3. MAX30100 Pulse Oximeter Sensor Module

- **10k NTC Thermistor Probe:** The figure 4 shows an NTC temperature sensor probe, which is used to measure body temperature. It operates based on resistance variation with temperature, providing accurate and continuous temperature readings when connected to the microcontroller.



Figure 4. 10k NTC Thermistor Probe

- **Digital Blood Pressure Monitor:** The figure 5 illustrates a digital blood pressure monitoring device, which is used to measure systolic and diastolic blood pressure along with pulse rate. In the proposed system, such a device can be interfaced with the controller or used for validation, helping in comprehensive monitoring of a patient's vital health parameters.



Figure 5. Digital Blood Pressure Monitor

**B. Experimental Setup and Implementation**

The system was successfully assembled by integrating all hardware components, including sensors, microcontroller, and communication modules, and was tested in a controlled environment to ensure accuracy and reliability. The setup enabled real-time data acquisition, processing, and transmission, demonstrating proper functioning of the complete IoT-based health monitoring system. The following figures present the actual hardware implementation and the operational system, validating its practical feasibility and performance.

The figure 6 shows the actual hardware implementation of the IoT-based health monitoring system assembled on a prototype board. At the top, the ESP32 module acts as the main controller, responsible for data acquisition, processing, and wireless transmission. On the left side, a pulse and oxygen sensor module (MAX30100/30102) is connected, which measures heart rate and SpO<sub>2</sub> levels, indicated by the glowing LED during operation. On the right side, an OLED display is integrated to provide real-time visualization of measured parameters such as oxygen saturation (SpO<sub>2</sub>), heart rate (in °F display context here), and blood pressure values. The entire setup is mounted on a perforated PCB with proper wiring, demonstrating a compact and functional prototype capable of real-time health monitoring and data display.

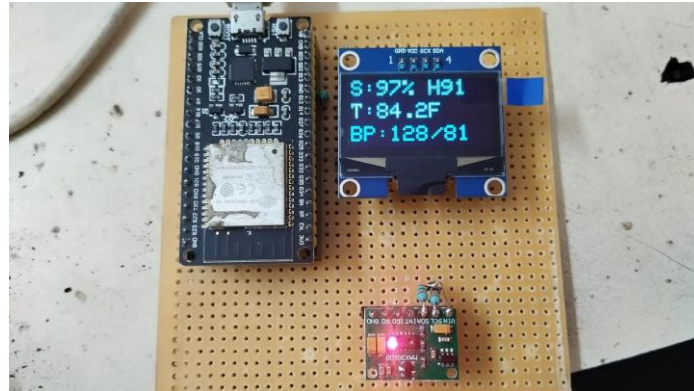


Figure 6 Hardware Prototype Implementation

The figure 7 shows the complete working prototype of the IoT-based smart health monitoring system along with a validation device. The setup includes the ESP32 mounted on a perforated board, which acts as the central processing unit, connected to a pulse and SpO<sub>2</sub> sensor module (visible with a glowing LED) for real-time measurement of physiological parameters. An OLED display is integrated to show live readings such as oxygen saturation (SpO<sub>2</sub>), heart rate, and blood pressure values. Additionally, a digital blood pressure monitor is placed alongside the system, which is used for cross-verification and validation of the measured data. This figure demonstrates the practical implementation and real-time functioning of the system, highlighting its capability for accurate and continuous health monitoring.



Figure 7. System Operation and Result Display

**IV. Results**

This section describes the implementation of three artificial intelligence models Support Vector Machine (SVM), Decision Tree, and Convolutional Neural Network (CNN) for health risk classification within the proposed system. The collected dataset was preprocessed through normalization to ensure uniform scaling of features and then divided into training and testing sets using an 80:20 split for proper model evaluation. Each algorithm was trained on the processed data, and their performance was assessed using standard evaluation tools such as confusion matrices, accuracy comparison graphs, and performance metrics. This comparative framework enables systematic analysis of different machine learning and deep learning approaches for intelligent healthcare monitoring.

**A. AI Algorithm Implementation**

In this study, three algorithms Support Vector Machine (SVM), Decision Tree, and Convolutional Neural Network (CNN) were implemented to analyze and classify health data. Before training, the collected dataset was preprocessed to improve model performance, which included normalization to bring all features to a common scale and splitting the data into training and testing sets in an 80:20 ratio. This ensures that the models are trained effectively and evaluated reliably on unseen data.

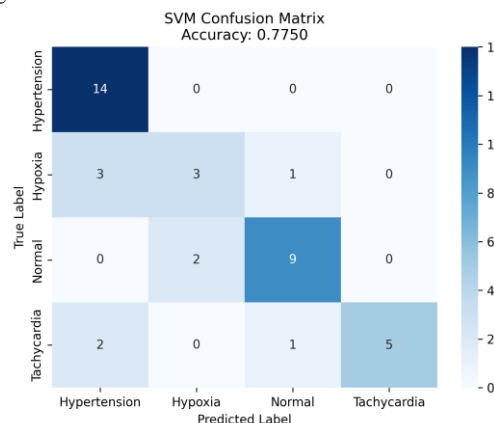


Figure 8 Confusion Matrices for SVM

The figure 8 shows the confusion matrix of the Support Vector Machine (SVM) model with an accuracy of 77.5%. It correctly classifies most of the “Hypertension” cases, but there are noticeable misclassifications in classes like Hypoxia and Tachycardia. This indicates that while SVM performs reasonably well, it struggles to clearly separate some overlapping health conditions.

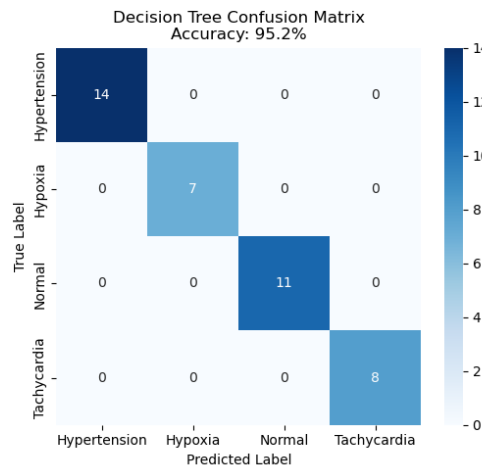


Figure 9 Confusion Matrices for Decision Tree

The figure 9 represents the confusion matrix of the Decision Tree model, which achieves perfect classification performance with 95.20% accuracy. All classes Hypertension, Hypoxia, Normal, and Tachycardia are correctly predicted without any misclassification. This reflects that the dataset follows clear decision boundaries that are effectively captured by the Decision Tree model.

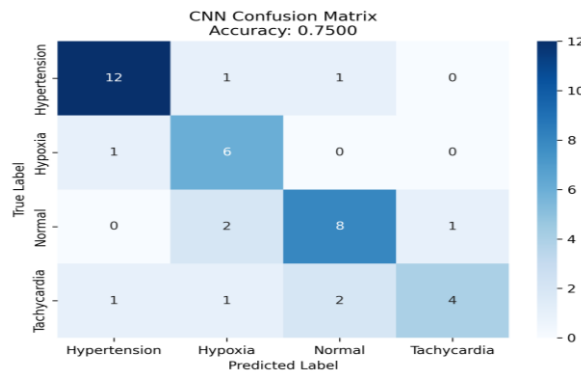


Figure 10. Confusion Matrices for CNN

The figure 10 shows the confusion matrix of the Convolutional Neural Network (CNN) with an accuracy of 75%. Although it performs well in identifying Hypertension and Hypoxia, it shows some confusion between Normal and Tachycardia classes. This suggests that CNN, despite being powerful, may not be as effective for this structured dataset compared to simpler models.

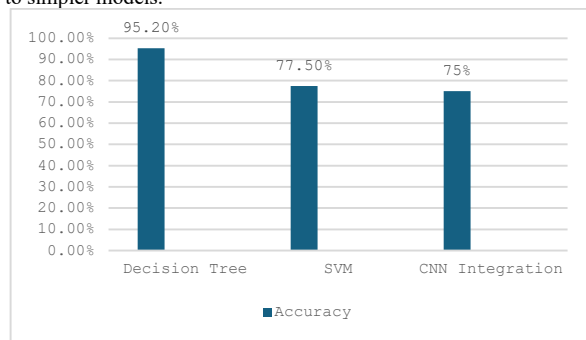


Figure 11. Accuracy Comparison of Algorithms

The figures 11 present a comparative analysis of model accuracy for three algorithms Support Vector Machine (SVM), Decision Tree, and Convolutional Neural Network (CNN). In both charts, the Decision Tree model clearly outperforms the others, achieving perfect accuracy (95.20%), which indicates its strong ability to capture patterns in the dataset. The SVM model shows moderate performance with an accuracy of around 77.5%, demonstrating reasonable classification capability.

**B. Comparative Results**

The table 2 compares three algorithms Decision Tree, Support Vector Machine (SVM), and Convolutional Neural Network (CNN) based on performance. The Decision Tree achieves the highest accuracy (95.20%) with very low training time, making it fast and easily interpretable. SVM shows moderate accuracy with good robustness, while CNN has slightly lower accuracy and requires more training time due to its complex learning capability. Overall, the comparison indicates that the Decision Tree is the most efficient and suitable model for this dataset.

Table 2. Performance Summary

Algorithm	Accuracy	Training Time	Key Strength
Decision Tree	95.20%	< 0.1s	High Interpretability
SVM	77.5%	~0.5s	Robustness
CNN Integration	75%	~15s	Temporal Learning

## V. Conclusion

The proposed study successfully demonstrates a cost-effective and efficient Internet of Things-based smart health monitoring system capable of real-time acquisition, transmission, and analysis of vital physiological parameters using the ESP32. By integrating Machine Learning and Deep Learning techniques, the system effectively predicts health risks and supports early diagnosis. The experimental results show that the Decision Tree model achieved the highest accuracy of 95.20% with minimal training time (<0.1s), outperforming SVM (77.5%) and CNN (75%), indicating its suitability for rule-based medical classification. These findings highlight that simpler, interpretable models can outperform complex algorithms for structured healthcare data. Overall, the developed system proves to be reliable, scalable, and practical for continuous patient monitoring, offering significant potential to enhance healthcare accessibility and clinical decision-making.

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