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Design of an IoT-based smart healthcare eco system for precise ageing illness detection and prognosis

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Abstract

The article aims to provide a comprehensive review of the current state of smart healthcare systems, focusing on important topics such as the use of wearables and smartphones for health monitoring, the application of AI and machine learning for illness detection, and the integration of assistive frameworks like social robots for ambient-supported living. One of the key aspects discussed in the study is the software integration architectures required for the development of smart healthcare systems and the seamless integration of data. Analytics and various AI technologies are utilized in conjunction to create these systems. The article examines the different approaches employed in the development of these systems,

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highlighting the contributions of each framework, the overall functioning methodology, performance outputs, and comparative advantages and limitations. Moreover, the article also addresses current research challenges and identifies prospective future directions. It emphasizes the shortcomings of existing smart healthcare systems and proposes strategies for introducing innovative frameworks to overcome these limitations. The analysis aims to provide detailed insights into recent advancements in smart healthcare systems, enabling specialists to contribute to the field with their expertise. Overall, the article serves as a valuable resource for understanding the current landscape of smart healthcare systems, shedding light on recent breakthroughs, and encouraging further research and development in this rapidly evolving field.

Subject Classification: *Primary 68T05, Secondary 68U35.*

Keywords: *Smart healthcare, Internet of Things, Artificial intelligence, Machine learning, Early detection, Disease detection.*

1. Introduction

The healthcare sector has recently embraced information technology to create cutting-edge apps and improve diagnostic and treatment procedures. Scientific theories and technological procedures are the primary drivers of massive amounts of digital data. Furthermore, innovative clinical applications have recently been developed via information technology [1]. Elderly living alone attracts the development of a model for the improvement of aged home-care service[2]. Liu et al [3] analysed the impacts of influenza vaccination policy for the elderly and the SARS epidemic on influenza-like illness in Taiwan. Kumari and Singh [4] analyzed the impact of counseling on psychological health during the hard days of Covid-19 lockdown. Advanced healthcare apps are supposed to be simple, elegant, and multifunctional. Embedded systems based on the Internet of Things (IoT) are being turned into networked smart devices with sensors. Smart device use was difficult owing to limited storage space and processing power, but cloud computing remedied these issues by offering high-level processing and storage capabilities [5]. A smart healthcare setup necessitates the integration of IoT sensors with cloud computing [6][7]. The smart healthcare system includes real-time monitoring. It is important to use deep learning and artificial intelligence (AI) to keep an eye on patients and provide high-quality, timely care at a fair price. AI and the IoT-cloud architecture provide real-time smart healthcare systems and better decision-making skills. When smart mobile devices are connected to sensors in a smart healthcare setting, medical personnel may be alerted instantly. For patients in intensive care, prompt reaction, adequate monitoring, and urgent care are critical. Medical professionals are in short supply in hospitals. A smart framework is necessary to address these difficulties in healthcare systems. Machine learning is frequently employed in the field of healthcare informatics [8]. The use of machine learning and Blockchain technology in medical data analysis and security gives a variety of useful techniques for intelligent and secure data analysis[9]–[12]. Modern hospitals have well-equipped monitoring and data-collecting equipment because huge information systems combine and store data. According to one study, machine learning is an excellent method for assessing health-related data. Clinical data is accessible in hospitals for correct diagnosis; patient data must be input into computer software with appropriate diagnostic values. Patients who have previously been treated automatically submit information on the clinical diagnosis. ML is firmly embedded in many aspects of healthcare, including illness diagnosis, patient health monitoring and management [13]. The issue with ML is that it is prone to mistakes and requires enormous datasets for training. Module transferability and reusability are also key issues with ML approaches. In order to overcome this challenge, DL models are utilized in this study to predict illnesses using gathered and accessible datasets. An updated GAN model is presented as part of this model, and many sensors are employed to monitor the patient's health. The proposed model is validated using known DL classifiers".

Methods are exhausting. Efficient facilities are required to reduce the excessive strain on physicians and hospital employees while decreasing health monitoring expenditures. Because of IoT, smart, networked gadgets and wearables with sensors have spread, allowing for remote monitoring

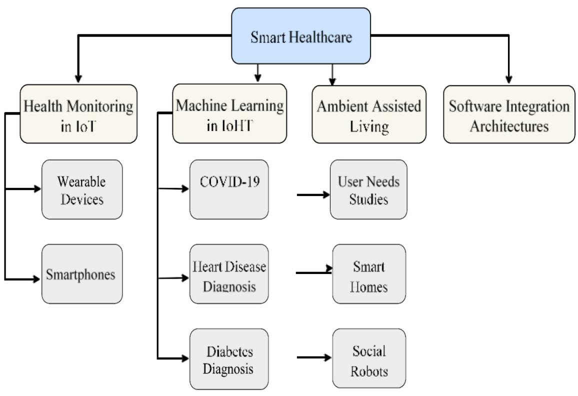

Figure 1

Overall workflow of the reviewed systems of smart healthcare

of heart disease patients. Wearable blood pressure monitors and ECG monitors with medical sensors are examples of IoT for healthcare monitoring [14]. Thus, healthcare IoT collects and sends crucial patient data to the Cloud for storage, advanced deep learning analytics, and preceding electronic clinical records. IoT devices may instantly alert physicians and caregivers about a patient's status. Clinicians can make better judgments for individuals and the public by evaluating patients' likelihood of contracting a disease.

Incorporating social robots into residential spaces. This document helps in the following areas: Give a comprehensive overview of current research in smart medical devices, machine learning for illness prediction, AAL, and software architectures [15]. Comparing methods to each problem, emphasizing their benefits and drawbacks, and recommending further research. Present a comprehensive review of the smart healthcare industry to clearly grasp how technology from many fields might be used to advance smart healthcare. Figure 1 depicts the entire workflow of the systems under consideration. The Figure divides AAL into three primary categories": health monitoring, illness diagnosis, and supporting devices. This review also includes a discussion of software integration architectures [16]. Wearable gadgets and cell phones are classified based on their ability to monitor one's health.

1.2 *Contribution*

The following are the key findings of this study project:

1. Data collected from IoT sensors for heart disease risk prediction are subjected to pre-processing tasks such as data cleaning and filtering at the Cloud layer;
2. The resulting data are sent to the fuzzy information system (FIS) for the initial classification task;"
3. Finally, the "proposed Bi-LSTM model accurately predicts patients' risk of heart disease.

2. Literature Review

Recent years have seen the "development of diverse systems for predicting heart disease. The deployment of several ensemble classifiers enhances the accuracy of heart disease risk prediction to 85.4% . The chaos firefly algorithm combined with an interval type-2 fuzzy logic system for diagnosing heart disease demonstrates an accuracy of 86% [17]. In a

Table 1

Summary of the Smart Health Monitoring System Based on smart phone

Authors	Year	Signs	Sensors	Smartphone	Number of participants	Video length	Sampling rate	Comments
"Zhang et al.	2020	Glucose level	Camera	iPhone 6s Plus	80	60 s	30 Hz	The performance of the developed system is relatively low.
Nemcovaa et al.	2020	HR, BP, SpO2	The rear camera, microphone	Honor 7 Lite, Apple iPhone SE, Lenovo Vibe S1	22 (13 F, 9 M)	20 s	30 Hz	The synchronization between PPG and PCG signals is not handled, although there are different time bases.
Alafeef and Fraiwan	2020	Respirator rate	Camera	Samsung Galaxy S6	15	30 s	30.30 fps	The system did not consider temperature and skin colour as well as the condition.
Tabei et al.	2020	BP	Camera	iPhone X	6	120 s	30 fps	The derivation of pulse transit time from two sides of the arterial is not mentioned.
Dey et al.	2018	BP	Heart rate sensor	Samsung Galaxy S6	205 (90 M, 115 F)	15 min	125 Hz	The results do not satisfy the precision in terms of standard value.
Wang et al.	2017	BP	Rear camera, accelerometer	N/M	9	N/M	N/M	The prototype is not able to monitor blood pressure continuously.
Alafeef	2017	HR	Camera	Samsung Galaxy	19	Few seconds	30.30 fps	The duration of the video is relatively low.
Lomaliza And Park	2017	HR	Rear camera	Pantech Vega Racer 3, Samsung Galaxy S2, LG G3, HTC Desire HD	5 (3 M, 2 F)	10 s	10 fps	The proposed system ignores the effects of different camera modules of different smartphones."

machine learning hybrid model to predict heart disease, random forest (RM) and linear method (LM) approaches are combined to achieve an accuracy of 88.7%. An integrated decision support system for predicting the risk of heart failure combines a fuzzy analytic hierarchy process and artificial neural network for feature weighting and classification tasks," respectively, achieving 91.0% accuracy. "Our smart system employs a dual statistical model and a deep neural network for feature refinement and classification tasks, respectively. The model has a 91.57% accuracy rate, a 93.12% specificity rate, and an 89.78% sensitivity rate [18]. Ghose [19] created an ML method that detects and analyses cardiac illness using the Naive Bayes (NB) algorithm and the SVM; several ML approaches are applied. +e authors proposed an ML system that predicts diabetes diseases using NB[20] and DT [21]. Kumar and Batra[22] worked on breast cancer disease prediction proposed Stacked Generalized Ensemble algorithm that classifies the images into benign and malignant.

The encryption/decryption processes are based on alternative quantum walks that have been measured. +e simulation results suggest that the picture encryption strategy is sound and well-organized for safeguarding patients' privacy. Soni et al[23] in their study investigated the concerns of the general public, perceived risks and attitudes towards the spread of COVID 19 and to understand the perception of the people in a populated region during the initial spread of the novel Coronavirus. Another Computational Intelligence and Neuroscience 3 healthcare monitoring system based on lightweight sensor-enabled wearable devices was presented in [1]. ML algorithm classification and regression tree (CART) to aid in diagnosing diabetes. Thyroid disorders are also forecasted using ML algorithms. SVM and DT are used as classification methods, utilizing data from the UCI repository. Fuzzy maps and data mining algorithms are used in advanced approaches for thyroid illness diagnostics presented in [24]. Table 1 depicts the summary of the existing smart health monitoring system based on smart phone In a wireless body sensor network (WBSN)-enabled IoT healthcare system was presented. It employs a wireless body network of tiny, lightweight sensor nodes to track the patient.

3. Materials and Methods

IoT technology is an important acquisition component for many real-time applications that enhance object-individual interaction [25]. The enormous volume of data created by IoT devices presents a tremendous challenge to the healthcare system regarding data processing, storage, and administration".

3.1 *Layer of Data Acquisition/Collection*

A suggested healthcare system gathers information from two key sources. A patient's normal health monitoring provides the following physiological data: blood pressure (BP), heart rate, blood sugar/glucose level, respiration rate, blood oxygen, cholesterol level, activity, electrocardiogram (ECG), electromyogram (EMG), and electroencephalogram (EEG) (EEG). The data is sent through Bluetooth/ Zigbee to remote gateway devices and ultimately to the cloud data centre, where it is pre-processed, and illness predictions are created. In addition to the electronic clinical data (ECD), the patient's medical history (including smoking and diabetes history), observation reports, and comprehensive clinical (lab) reports are stored in a cloud database and provide valuable disease prediction information.

3.2 *Data Pre-Processing Layer*

Because of data pre-processing, ML algorithms are prone to being unstable, incomplete, and noisy. Missing data must be processed, standardized, and characteristics picked to forecast heart disease from the heart disease dataset properly. Data from wearable sensors can be influenced by signal anomalies such as missing values and noise, which might undermine prediction accuracy or lead to incorrect conclusions". By using Kalman filtering [26], "we effectively eliminate duplicate records, noise, and discrepancies from the data. It requires low computational effort due to its basic nature [27]. Unsupervised filtering techniques handle large amounts of sensor data in real-time and provide results near the sensor readings while removing noise.

Furthermore, we employ two other unsupervised filters in the data filtering deleting unnecessary values and substituting missing values. The first filter eliminates unnecessary features with an additional 90% of maximum variance. The second filter replaces the mean and median values of the existing data for any missing values in the structured dataset.

3.3 *System model*

This section describes a novel smart healthcare framework that leverages edge technology and employs different AI techniques, such as DRL. As shown in Figure 2, the proposed system model has three main layers: a sensor layer, an edge layer, and a cloud layer. An end user in this model can be a patient at a smart home who is remotely monitored, a patient in a health institute, an older adult, or even a healthy individual who monitors his/her fitness. A health professional, a hospital, a mobile ambulance, a family member, or a pharmacy can provide care. In order to facilitate smart healthcare services, various AI techniques, including DRL, are distributed from sensors to the cloud [19]. The proposed framework is flexible enough to define a solution map for any issue encountered automatically. As a result, the system can accomplish processes on sensors and edge layers. Depending on the end user's request, results can be stored temporarily on edge or permanently in the cloud. Depending on the current healthcare issue, the system can choose where to host DRL's input and output layers. By compressing data in the sensor layer, we believe the system can reduce overall latency, network congestion, and computation complexity at the edge.

Sensors can be equipped with lightweight AI techniques such as CS to compress data. AI techniques are hosted on edge devices and edge servers in the edge layer. In smart healthcare, AI and edge technology have been extensively researched. However, some challenges remain unresolved. In order to train DL algorithms, for example, a large amount of data is needed. However, in some cases, such as tele surgery, there is insufficient data to train. DL data trained for a specific illness cannot be used for another similar illness; therefore, the data should be retrained.

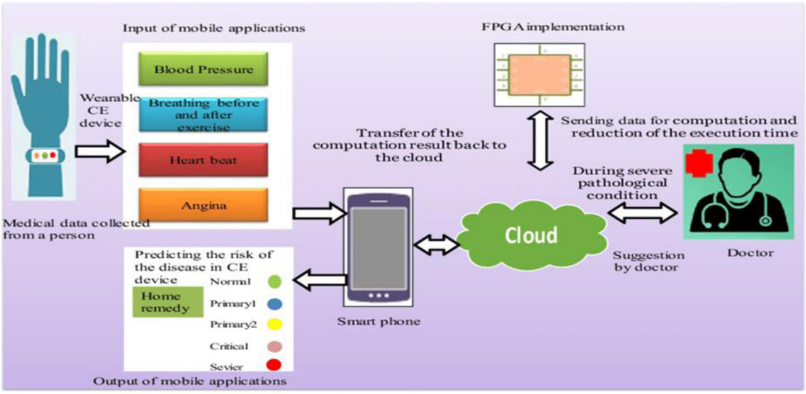

Figure 2

Proposed system model

RL, as an autonomous self-training system, should make several small decisions to achieve a sophisticated goal. A complicated decision with many states, such as monitoring a mobile patient with a chronic disease, may have countless states because the context information of a moveable patient is unstable [28]. Because the RL algorithm cannot be controlled to learn from all states and regulate the reward path, it may not be able to handle the problem." In order to overcome these limitations, "an AI technique that uses both estimation and mapping can be considered. The proposed framework can use a real-time self-training model or training from datasets depending on the circumstances.

A corresponding alert would be sent instantly to the caregiver, end user, or both after making a decision, allows them to prevent a potential catastrophe by taking action in time. The proposed model can provide an automated smart healthcare system that can function even without human interaction by utilizing self-training AI methods based on edge technology [20]. As a result of the vulnerability of IoT devices and medical data to hackers, security and privacy management should also be considered vital concerns in smart healthcare systems. As a result, automated AI techniques such as DRL can manage security and privacy at different levels, from the sensor to the cloud, preventing unauthorized access. With sensors, the proposed system model collects real-time health data related to patients while fully integrating with physical items. The cloud-based system that connects all the components collects and processes sensor data. The proposed system model can be viewed as a digital twin system using edge intelligence and wireless communication to simulate real-world and real-time data. It can calculate the best way to set up a procedure to achieve better outcomes in disease prevention or life-saving in emergency situations. Three problems are regarded as non-technical, the others as technical. The most crucial aspect of sensor uptake is patients' comfort with their use. Sensors that can be worn or implanted are both options. The use of wearable technology may be challenging for elderly people. Others might not accept the implanted sensors. This challenge also indicates a personal comfort zone; what one patient may find comfortable may not be comfortable for another. How dependable and responsive family members, trusted relatives, and carers are in responding to alerts is the main worry when sending them.

5. Conclusions

The article introduces a novel smart healthcare framework that leverages various AI techniques in a parallel mode, utilizing edge technology. This framework distributes processes from sensors to cloud servers. By employing lightweight AI techniques on sensors, latency, complexity, and network load can be minimized. Additionally, parallel processing on the edge layer and flexible AI methods further reduce latency, enable swift response and decision-making, and facilitate real-time alerts to caregivers. These aspects are crucial in providing efficient smart healthcare services. The proposed model also takes into consideration security and privacy requirements for the entire smart healthcare system, including sensitive medical data, network connections, and user access. Protecting these aspects is essential for maintaining the integrity and confidentiality of the system.

However, while the proposed system model addresses some limitations of previous smart healthcare frameworks, there are still other challenges that need to be addressed. Two significant challenges mentioned in the article are data loss and autonomous network management. These issues require further attention and innovative solutions to ensure seamless operation and optimal performance of smart healthcare systems.

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