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Deep Reinforcement Learning in Healthcare IoT Monitoring Systems: A Comprehensive Survey and Future Directions

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ABSTRACT

The aspect of healthcare monitoring has been greatly enhanced by using Internet of Things. For example, small sensors can collect a patient's data, such as heart rate, body temperature, and oxygen levels. The data is then transmitted to a doctor via wireless networks. This is helpful for a doctor to monitor a patient even when he or she is not around. This is very helpful for old people or those with long-term illnesses. There are a few issues with healthcare IoT. For example, small sensors have small batteries. Therefore, energy consumption is a problem. Another issue is that network traffic is a challenge when many sensors transmit data concurrently. In medical situations, data should be transmitted urgently. If there is a delay, it may impact the safety of the patients. Therefore, there is research on intelligent ways to deal with these systems in a better manner. Deep Reinforcement Learning is one of the techniques that enables a system to learn and make decisions in a better manner. This can result in the optimization of energy usage, optimization of the network, and giving priority to emergency health data. This is a survey paper that deals with the recent research on Deep Reinforcement Learning in healthcare IoT systems and the challenges and possible improvements in creating a more intelligent system in the future.

Keywords: Healthcare IoT; Deep Reinforcement Learning; Patient Monitoring; Wireless Sensor Networks; Emergency Detection; Smart Healthcare Systems; Energy Efficiency; Network Resource Management; Network; Security.

1. Introduction

The healthcare industry is transforming with the assistance of Internet of Things technology. Many hospitals are using a number of small smart devices to monitor the health of their patients. These devices are called IoT sensors. These sensors are used to measure the heart rate, body temperature, blood pressure, and oxygen levels of a patient. The sensors collect all these values and transmit them through wireless networks to hospital systems or cloud servers. The doctor can monitor the condition of the patient remotely without physically staying near the patient [1]. This is very helpful for elderly people and those who need to be under medical observation all the time. It also reduces the number of visits to the hospital and helps doctors monitor their condition in a better manner [2].

Despite the various benefits associated with the implementation of healthcare IoT systems, there are various technical issues associated with the implementation of these systems. The first challenge associated with the implementation of the system is the limited power in the batteries of the wearable sensors. The various medical devices associated with the system have been made small and light in order for patients to be comfortable while using the system. Due to this reason, the power associated with the batteries of the system has also been limited. When the sensors send data often, the power in the batteries may go low, thus disrupting the process of patient monitoring. Another challenge associated with the system is network congestion. The various IoT devices in the system send health data at the same time in the hospital setting. In cases where there is an attempt to transmit too much data through the same network, delays may take place. In the case of healthcare, such delays may be risky since the information concerning the patients should be delivered immediately to the concerned doctor [3]. The researchers have also stated that the network should be able to handle large volumes of real-time data with effective communication between medical devices [4].

Security and privacy are two main concerns for healthcare IoT networks. Medical data is highly sensitive. Medical data includes the health, treatment, and medical history of patients. If the medical data is not properly secured, the wrong parties may access it. Hackers may hack the network of hospitals and access the medical data of patients. This may disrupt the services of hospitals and create problems for doctors and patients. Hence, there are many researchers who are trying to provide a secure communication system for healthcare IoT networks. The communication system is trying to secure the medical data of patients while sending health-related data through the network [5]. There are also suggestions by some researchers to use smart techniques of encryption. The techniques of encryption may help to secure the healthcare IoT network [6]. To resolve all these problems, nowadays many researchers are employing Artificial Intelligence and Machine Learning in healthcare systems. These systems can analyse the health data collected from various sensors and hospital records. An artificial intelligence model can analyse the data and find patterns in it, which are not visible to humans. This would help doctors understand the condition of patients better. It has also been noticed that machine learning can provide a warning when a patient's health condition starts to change. In many cases, the system can identify the signs of a problem before it becomes serious. This would enable doctors to provide better treatment to patients [7]. AI-based predictive systems can help doctors make better decisions by analysing the patient's history and health signals from various sensors [8].

Among the various techniques of AI, Deep Reinforcement Learning is becoming extremely popular for use in the field of healthcare IoT systems. This technique enables a system to learn what is the best action to be performed by learning from the results. The system tries different actions and slowly starts to learn what is better. It starts to improve its decisions over time. In the IoT network of the healthcare system, this learning technique can be used to manage the flow of data through the network by the IoT devices. This technique can also be used to manage the resources and energy usage of wearable IoT sensors [9]. Research studies are also using DRL techniques to improve wireless communications and manage the usage of the frequency spectrum in the healthcare IoT system to facilitate the smooth flow of data through the network [10]. Deep Reinforcement Learning can also play a significant role in the managing of data priorities. With regard to health care monitoring systems, not all health data is given the same level of priority. If a patient has an irregular heartbeat or an oxygen saturation level that is decreasing, doctors need to know about this instantly. Thus, through the use of DRL systems, a physician will receive the emergency data based on the incident at hand, with the priority that deals with immediate issues, being sent first, and the less important issues sent at a later time. Consequently, physicians receive the necessary alerts without delay. As well as using DRL methods, intelligent scheduling and resource allocation techniques can further assist in reducing the lag time in communication between healthcare networks and improve their overall performance.

Artificial intelligence can also be utilized in the improvement of the reliability of the communication systems in the healthcare sector. This can be done through the development of monitoring tools that can be based on AI and can monitor the network and identify any unusual activities in the system. These activities may include possible cyber-attacks or system failures. Once the system identifies such activities, it can take prompt actions to secure the patient data. Additionally, smart channel selection and scheduling can be utilized in the improvement of the communication between the sensors and the healthcare systems [13].

Despite the fact that a number of studies have offered good suggestions, there are a number of issues that are yet to be solved. A number of existing systems only address a specific problem such as energy saving, network speed, and security. However, the real-world environment is not as simple as that. There are a number of issues that occur simultaneously in a real-world environment. A good healthcare monitoring system must be able to address energy saving, communication delay, data priority, and security issues simultaneously. As a result, researchers are now trying to develop smarter systems that can integrate multiple techniques into a single system. Such smarter systems can be used to provide reliable patient monitoring and improve healthcare services in the future [14].

1.1. Study Objectives

• In order to review various Deep Reinforcement Learning methodologies used in Healthcare IoT systems and understand their functioning.

• In order to compare various research papers and understand what each paper is solving, such as saving energy, ensuring security, and reducing congestion.

• In order to understand gaps in current research, particularly in regards to emergency detection and priority scheduling.

• In order to understand how various multi-objective methodologies are solving conflicts between power consumption, encryption, and speed.

• In order to propose future research directions based on our understanding of various papers after completing the literature review.

2. Literature Review

Recent research emphasizes the significance of secure data transfer in a healthcare IoT network. Most researchers have focused their attention on using hybrid models of artificial intelligence and adaptive encryption techniques to ensure the security of sensitive patient data. The techniques used are intelligent as they vary the degree of security according to the nature of the data and the current network conditions. For instance, critical health data such as a sudden drop in oxygen levels and irregular heartbeat patterns can be given more security and faster transfer rates than less critical data such as routine checkups and tests. Deep learning techniques are also used to identify abnormal patterns in patient data and network activities, sending early warnings to the doctors before a major problem occurs. Using such intelligent techniques ensures smooth and timely data transfer in a reliable and practical IoT network for health monitoring and treatment. Doctors can monitor their patients in real time without any worries about delays and security breaches [15]. In healthcare IoT systems, deep learning algorithms are utilized for detecting anomalous behaviour through anomaly detection. Healthcare IoT systems rely on deep learning models to continuously monitor patient data that has been collected from multiple sensor sources. In the case of a patient, anomaly detection models are able to detect anomalous changes in the data being collected from the sensors. For example, an anomaly detection model will be able to detect a decrease in oxygen level, an increase in heart rate, or an increase in blood pressure. The models will have been trained on historical longitudinal data of the patient for a given timeframe which has created a baseline of typical patient behaviour from which to compute any anomalous behaviours. Anomaly detection significantly reduces the number of false positive alerts generated from the monitoring systems and creates a distinction between normal and abnormal behaviours thus improving the reliability of healthcare IoT systems to healthcare providers [16]. Management of intelligent resources in healthcare Internet of Things (IoT) networks is necessary for ensuring that sensors, networks, and computing resources are effectively utilized. Smart scheduling guarantees that critical health care data, including emergency calls, are sent first and less critical data can wait; thus, avoiding network congestion and delay. It balances energy consumption of wearables, thereby increasing their useful life. Smart management of healthcare IoT resources enable IoT systems to effectively and reliably monitor patient status through the Internet of Things [17].

Optimization of energy in the system is very important for the healthcare IoT device because the wearable sensors have limited batteries. AI and reinforcement learning can be employed for the smart optimization of the data transmission process, ensuring that the updates regarding the health of the patient are transmitted immediately. Other updates can be transmitted later, and this helps in the optimization of the network and the batteries as well. This helps the device last longer without the need for frequent charging. Smart energy optimization ensures that the patients are monitored safely as the doctors get updates regarding the patients' health at the right time [18]. Dynamic spectrum management is a very significant aspect of healthcare IoT systems because many devices are connected to a single network.

Deep reinforcement learning can also be used to manage the communication channels between devices. This ensures that no data is delayed. Emergency data is given priority so that doctors are alerted on time if there is a sudden drop in oxygen or heart rate. This also ensures network reliability, which is necessary to avoid delays in routine data transfer. Deep reinforcement learning is used to manage the spectrum of the network, which is necessary to ensure timely communication between devices. This is very essential to avoid any untoward incidents [19]. Low-latency communications are essential for successful implementation of the Healthcare IoT. Critical health information transmitted with any delay will negatively impact the health of the patient. AI and machine learning utilize the management of network resources to prioritize sending critical health information or changes in a patient's heart rate or oxygen level to their physician in real time; non-critical health information is transmitted with an allowable delay so that the network will not be overloaded with traffic. Consequently, maintaining a stable, efficient, and safe network is made possible by low-latency communication, which results in greater overall efficiency for the network [20].

Health care IoT relies on early identification of potential health issues as a key component. The use of machine learning to analyse patient data and sensor data will provide health care systems with a model for predicting future health risks prior to an issue arising. The identification of trends related to how certain physiological changes occur through the identification of trends associated with changes in vital signs (e.g., heart rate and oxygen saturation) can help aid physicians in early intervention to prevent a potential health crisis within a patient's population. The combination of predictive modelling with real-time monitoring and the necessary infrastructure will ultimately allow for accurate and timely alerts and help improve the safety of patients and the responsiveness of health care facilities [21]. It also assists in sending patient data appropriately via machine learning. The machine learning

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algorithm is able to predict the traffic on the network. It then determines which data to send first. The priority data, such as a sudden drop in oxygen levels, is sent first. The less pressing data is then sent later to avoid congestion on the network. This allows all sensors to work together smoothly. The medical staff can rely on the data, and patients are safe [22]. Energy is a big deal when it comes to wearable healthcare devices. They are small, and before you know it, they are dead. However, reinforcement learning is able to choose the best routes to send data and save energy at the same time. The critical information will reach the doctor in due time. This will also ensure that there is no traffic jam in the network. In this way, everything will be okay [23]. Children require special care because their bodies function differently. Machine learning can monitor signs like heart rate or oxygen levels. Machine learning recognizes major issues early on, such as severe infections or sepsis. Doctors receive notifications earlier than traditional methods. There are also fewer false notifications, which means doctors are not misled. This helps children achieve better outcomes or saves lives [24].

There are patients who are very risky, which is why it is important to find problems as soon as possible. Large data sets can train the model to recognize the danger quickly, even within the first few hours of admission to the hospital. This will enable the doctors to understand which patients need to be prioritized and which patients need to be monitored normally. This will save the hospital a lot of time because the emergency messages will reach the doctors immediately, enabling action to be taken without wasting any more time. This will enable the doctors to act before the patient’s condition deteriorates, thus saving the patient from complications. This will not only save the patient’s life but also make the model better through the constant learning of new patient data [25]. The ways that sepsis is treated are being changed by machine learning methods, evaluation methods, and the utilization of biomarkers. These strategies allow us to find issues sooner than we would otherwise be able to. Additionally, these methods allow us to determine an individual's level of risk. Further, the methods allow for rapid implementation of necessary treatment interventions. There are numerous obstacles that still need to be overcome; however, they should be addressed so that patient care systems will ultimately benefit patients from all angles.

3. Problem Statement

It is not easy to watch patients through the help of the healthcare IoT because the sensors send information continuously. At other times, the network gets congested and slows down. The batteries of the devices drain fast as well. When the alerts take longer to come, patients.

- Healthcare IoT devices are growing rapidly, and wearables are constantly transmitting vital information such as heart rates and oxygen levels.
- Traditional methods of spectrum allocation cannot allocate priorities to emergency medical data, which results in network congestion, increased delays, and inefficient spectrum utilization.
- Traditional methods do not incorporate smart techniques to identify abnormal health conditions or allocate network channels based on priorities.
- Traditional methods do not consider the energy consumption, interference, and security issues effectively, which is why the project incorporates Deep Reinforcement Learning.

4. Conclusion

The healthcare IoT is helping doctors keep an eye on patients more easily. The wearable devices collect vital information like heart rate, oxygen levels, blood pressure, etc. The devices have small batteries. Therefore, energy management is a crucial issue. The network is busy when many sensors transmit data at a time. This slows down emergency messages. The timely transmission of vital data is extremely important to ensure patient safety. The data is related to patients, so security is not ignored. The traditional systems solve only one problem at a time, like saving energy or security. But in a practical scenario, all problems need to be solved. Using Deep Reinforcement Learning to monitor things like energy use, network traffic, and security will allow for smart management. Emergency alerts will go to doctors first. Doctors may also spot a problem with a patient sooner by using these techniques together. In addition to slowing down the process of monitoring patients, these methods also allow doctors to react quickly and provide better care to patients. These systems become easier over time to use for patients. Overall, AI and Deep Reinforcement Learning improve the performance of healthcare IoT devices. They allow for faster communication between devices, protect patient data, and create a more reliable healthcare system. In summary, the use of these smart technologies can greatly improve the quality of healthcare services.

Declarations

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Competing Interests Statement

The authors have not declared any conflict of interest.

Consent for publication

The authors declare that they consented to the publication of this study.

Authors' contributions

All the authors equally contributed to this study.

Informed Consent

Not applicable for this study.

Institutional Review Board Statement

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Ethical Approval

Not applicable for this study.

Declaration of Artificial Intelligence

The authors declare that no artificial intelligence (AI) tools or AI-assisted technologies were used in preparing this manuscript.

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