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AI APPROACHES FOR EARLY DETECTION OF DISEASES IN IOT-ENABLED HEALTHCARE SYSTEMS

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Abstract

Recent developments in IoT, cloud computing, and AI have revolutionised the conventional healthcare system and set the stage for the rise of smart healthcare. Significant advancements in healthcare are possible through the combination of Internet of Things and artificial intelligence. Opportunities abound in healthcare thanks to the combination of IoT and AI. In light of this, this study presents a new approach to disease diagnosis using the intersection of AI and IoT in the context of intelligent healthcare delivery systems. The primary goal of this article is to use AI and IoT convergence techniques to create a disease diagnosis model for heart disease and diabetes. Data collection, preprocessing, classification, and fine-tuning are all parts of the proposed model. Wearables and other sensor-based IoT devices facilitate effortless data collection, which is then utilised by AI methods for disease diagnosis. Combining the Crowd Search Optimisation (CSO) algorithm with the Cascaded Long Short Term Memory (CLSTM) model, this study presents a novel approach to disease diagnosis. Applying CSO to the CLSTM model's 'weights' and 'bias' parameters improves its ability to classify health data. The isolation Forest (iForest) method is also used in the study to filter out anomalies. When CSO is incorporated into the CLSTM model, diagnostic accuracy is greatly improved. Extensive experiments were performed using healthcare data to validate the performance of the CSO-CLSTM model. The outcomes showed that the proposed model performed exceptionally well, with an accuracy of 96.16 percent for detecting heart disease and 97.26 percent for detecting diabetes. Therefore, the CSO-CLSTM model emerges as a robust and efficient instrument for disease diagnosis, amenable to incorporation in intelligent healthcare systems.

Keywords: Healthcare, Artificial Intelligence, Internet of Things, iForest, Diagnosis and Data Collection.

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1. Introduction

The healthcare industry has embraced IT in recent years, allowing for the creation of cutting-edge applications and the improvement of diagnostic and treatment procedures. Modern methods and scientific hypotheses fuel the production of enormous amounts of digital data. As a result of these innovations, cutting-edge clinical applications have emerged that are straightforward yet feature-rich[1]. There has been a shift in healthcare towards a focus on the individual patient, the integration of medical data at the regional level, the development of patient-centered clinical management, and the implementation of a preventative medical system. These alterations are meant to accommodate people's fundamental needs, raise the quality of medical care, increase our understanding of health services, and prepare the groundwork for the introduction of intelligent medicine in the future[2]. Doctors, patients, and institutions for medical research and clinical practise all have a stake in the delivery of cutting-edge healthcare. Disease prevention, diagnosis, treatment, prognosis, clinical management, health policy, and investigation are all crucial factors[3]. Key components of today's healthcare system rely on cutting-edge technologies like mobile internet, Cloud Computing (CC), big data, 5G systems, microelectronics, AI, and smart biotechnology. Wearable and portable devices allow patients to access health monitoring, virtual support for clinical guidance, and home automation from anywhere. Intelligent clinical decision support systems improve diagnostic procedures from the perspective of the treating physician. Emerging from IoT, the concept of Internet of Medical Things (IoMT) seeks to revolutionise healthcare delivery by linking together previously siloed medical tools[4]. Researchers can monitor user habits and reveal their health status by utilising cutting-edge Machine Learning (ML) or Deep Learning (DL) techniques, as well as data from mobile patterns and device usage. Applying cloud computing for big data analysis guarantees top-notch functionality across a wide range of non-safety and delay-based Internet of Things (IoT) use cases. Disconnecting from the main network or experiencing latency differences may, however, have negative consequences, especially in emergency situations where time is of the essence and resources are scarce[5]. To get around these problems, researchers are working on cloud, fog, and edge computing architectures that use edge nodes and low-level fog nodes to perform data processing, examination, correlation, and inference. There are scalability issues with this method, but it does allow for effective medical domain services[6]. Diagnostics and treatment of diseases are greatly improved by the use of artificial intelligence (AI) models, surgical devices, and mixed reality applications. Clinical Decision Support Systems (CDSS) powered by artificial intelligence are now more accurate than doctors at diagnosing diseases like hepatitis, lung tumours, and skin cancer. The accuracy of ML-based models exceeds that of highly skilled doctors, including pathologists and imaging specialists. Watson, IBM's new clinical decision support system (CDSS), features a powerful cognitive mechanism that analyses medical and literary details to provide optimal solutions[7]. As a result of CDSS's ability to improve diagnostic processes, reduce missed and incorrect diagnoses, and guarantee timely and appropriate medical treatment, doctors have seen significant improvements in their ability to identify diabetes and cancer in their patients. Smart diagnosis of the patient's health status and disease severity can accurately define treatment procedures. In this study, we present a new disease diagnosis model for intelligent healthcare systems that makes use of AI and the Internet of Things. The goal is to create a model for diagnosing diabetes and cardiovascular disease using AI and IoT convergence[8]. Data is collected, processed, classified, and adjusted for optimal performance in the proposed model's various stages. Data collection is handled by Internet of Things (IoT) tools like wearables and sensors, and analysis is performed using AI methods to diagnose diseases. The AI and IoT convergence strategy uses a Cascaded Long Short Term Memory (CSO-CLSTM) model based on the Crowd Search Optimisation (CSO) algorithm for disease diagnosis[9]. In addition, the isolation Forest (iForest) method is used to filter out anomalous data. CSO is used to fine-tune the CLSTM model's 'weights' and 'bias' parameters, leading to more accurate diagnoses. CSO is favoured because it improves the CLSTM technique's diagnostic efficacy.

1. Literature Survey

In order to evaluate critical cases and accidents, previous research has focused on creating systems that can monitor physiological variables and health indicators. Mustlag et al. used WBSN to track people's heart rates and motions even when they were in uncharted territory. Edge nodes with internet access sent notifications to loved ones about significant events like an impending fall or an abnormal heart rate (tachycardia or bradycardia). Electrocardiogram (ECG) data processing was also proposed by Villarrubia et al. for remote patient monitoring and heart rate analysis. In addition, IoT devices have been integrated into emotion-aware, connected healthcare models to collect patients' speech and visual signals in smart homes [10]. Kaur and Jasuja [8] also looked into how the Bluemix cloud method could be used to keep track of vital signs and give doctors access to that data from afar. IBM Watson IoT environment was used to visualise and process the simulated results. An integrated system that constantly monitors patients' health data was used in a case study on fever analysis by Alwan and Rao. In order to prove the efficacy of a model based on a number of activities, Satija et al. created a real-time IoT-based ECG telemetry system. Because of their use of static monitoring, they were able to cut down on the number of domain sensors required to gather contextual data and execute multimodal processing. Wearables have been used in other studies to collect data on physiological variables in addition to video, images, and audio [11]. These studies made use of ecological sensors, optitrack cameras, and smartwatch-based sensors. It has also been proposed to use deep learning techniques for pathology detection, with the goal of identifying pathogens from electroencephalogram (EEG) signals [12]. Human activities have been studied with the help of wearable sensors, Long Short-Term Memory-Recurrent Neural Network (LSTM-RNN) models, and local fog servers with GPU acceleration [13]. Movement tracking and prediction using classification techniques such as Support Vector Machines (SVM) and Random Forest (RF) have necessitated the use of additional sensors [14]. Recent models have attempted to simulate this process by utilising mobile sensors and edge machine learning techniques to simulate the analysis of physiological data. However, in an edge stream computing architecture, predicting abnormalities of physiological variables is difficult. The distributed implementation of Hierarchical Temporal Memory (HTM) has been deployed on edge nodes for inference [15]. Using Multi-Access Edge Computing, solutions for fall prediction based on LSTM-RNN methods have been proposed, implemented at the edge level, and evaluated [16]. Existing classification models like RF, Naive Bayes (NB), k-Nearest Neighbours (kNN), and decision trees were used to evaluate the effectiveness of these methods. To split up workloads between the edge, fog, and cloud, IBM developed the Hierarchical Computing Architecture for Healthcare (HiCH) and the Monitor-Analyze-Plan-Execute Plus Knowledge (MAPE-K) mechanism [17]. Using 1D and 2D convolutions to capture temporal and spatial information, CNN-based automatic EEG pathology detection models have been developed [18].

2. Proposed Method

The method proposed in this research allows users greater mobility because it makes use of wireless communications and low-power IoT devices. Smartphones, wristbands, and smartwatches, all of which are designed with the user in mind, are used. To estimate and differentiate between normal and abnormal heart rates, embedded sensors play a crucial role in performing extensive computations. The test subjects have pocketable smart devices like smartphones at their disposal. For a more complete picture of the subject's health and lifestyle, an embedded electrocardiogram (ECG) and temperature sensor are suggested. Low-power Bluetooth communication between IoT devices and smartphones transfers the collected data, which is then analysed and classified as healthy or unhealthy. Android is used for accurate diabetes prognosis and heart rate analysis. Internet-of-Things devices collect and preprocess patient data for later use[19]. This preprocessing includes things like transforming data, converting formats, and labelling classes. The iForest method is then used to clean up the patient records and get rid of any anomalies. In order to determine whether or not the disease is present in the data, the CSO-CLSTM model is used. iForest, a tree-based outlier detection method with linear time complexity and high precision, is fed the preprocessed medical data. It works well with massive data sets and high dimensions. Because data anomalies tend to be few in number and widely dispersed, they tend to exist in isolation. Records are repeatedly partitioned in data-based random trees until isolation is achieved. Short, irregular records with unusual values can be generated with the help of random partitioning. It is advised to begin the partitioning process as soon as possible [20]. Each iTree in an iForest is a representation of a binary tree.

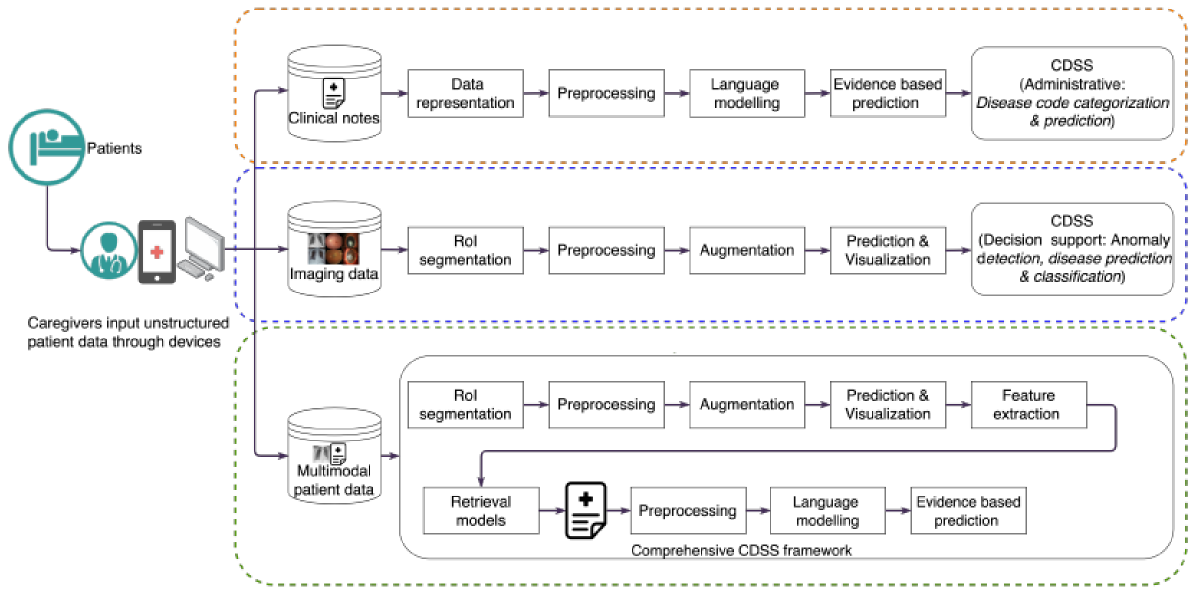

Figure.1: Proposed Healthcare Model

Clinical Decision Support System (CDSS) for multimodal healthcare data, based on artificial intelligence, illustrated by system architecture in figure.1. It's a visual representation of the system's parts and how they work together. The conceptual workflow of developing an unstructured clinical notes-based patient-centric CDSS is depicted in figure.2. Specifically addressing the issue of using unstructured clinical notes for predictive analytics, it demonstrates the sequential steps involved in creating and employing the CDSS.

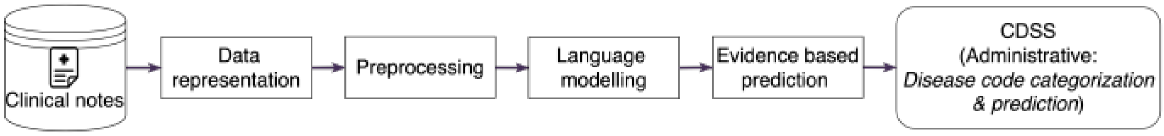

Figure.2: Predictive analytics with unstructured text data

In this scenario, IoT devices are part of a safe health monitoring system with multiple wireless interfaces for data exchange. The system uses a number of biosensors to track a patient's vitals in real time. The information gathered by these sensors is sent to a Personal Wireless Hub (PWH), where it is stored until it can be accessed by medical professionals. Connected Devices in a Healthcare Monitoring System, as Shown in Figure 3 This diagram shows the various Internet of Things interfaces found in a typical healthcare monitoring setup. Multiple biosensors built into the system allow for constant health tracking[21]. The PWH acts as a communication hub, receiving and processing data from the various sensors. The data is transferred safely from the PWH to the HDC, where it is stored until it is needed for analysis by doctors.

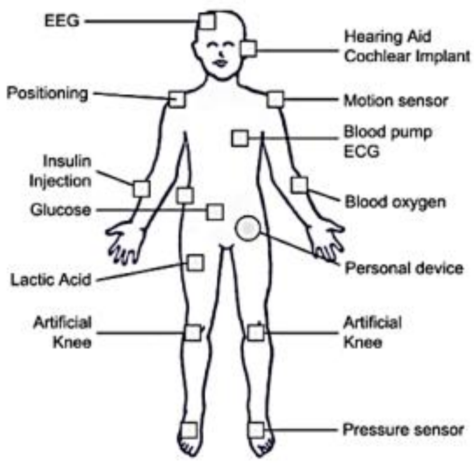

Figure.3: Deployment of Sensors for Health Monitoring

3. CSO Algorithm

In this study, the Convolutional Long Short-Term Memory (CLSTM) model's weights and bias parameters are optimised using CSO (Crow Search Optimisation). Crows, widely regarded as one of the most perceptive bird species, served as inspiration for CSO. Crows are highly intelligent and capable of solving complex problems due to their large brains in relation to their body size. Numerous studies and observations corroborate the crow's supposed intelligence. Self-awareness tests show that they do well in mirrors, and they are also adept toolmakers. Crows have the ability to recognise and remember human faces, as well as convey threats to other crows. They can also remember where food has been stashed and work together to use and share tools.

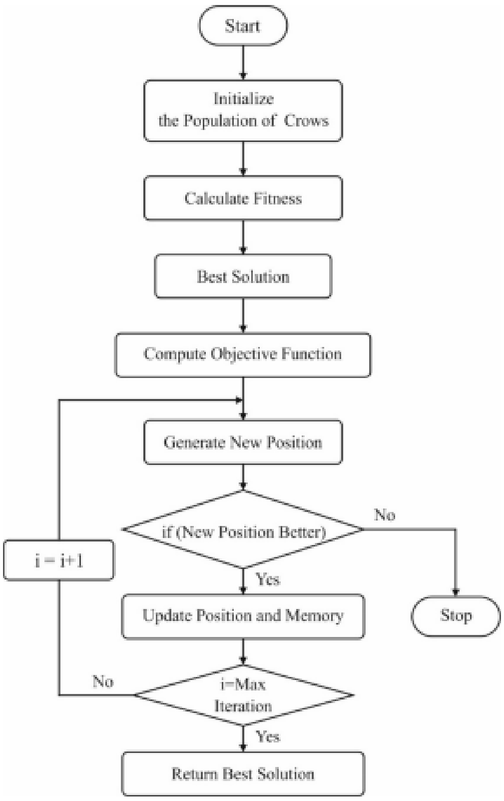

Figure.4: Flowchart of CSO algorithm.

In order to resolve optimisation issues, the CSO algorithm mimics the actions of crows. It optimises based on the idea of a thief's behaviour. CSO investigates the problem space and looks for the best possible answers, much like a crow choosing a safe method of protecting its meal. The CSO algorithm's flow chart, depicted in Figure.4, shows the various stages it goes through to achieve an optimal solution. CSO takes advantage of crows' unique traits and behaviour to fine-tune the CLSTM model's weights and bias parameters for maximum efficiency and effectiveness.

The goal of the current study is to integrate AI and IoT technologies into a disease diagnosis model for use in smart healthcare systems. Data acquisition, preprocessing, classification, and parameter tuning are all parts of the model. Wearables and sensors that are part of the Internet of Things (IoT) are used to gather patients' vital statistics. Artificial intelligence methods are then used to examine the information and make diagnoses. In order to make a correct diagnosis, the iForest method is used to filter out any anomalies in the patient's data. The CSO algorithm is used to optimise the weights and bias parameters of the CLSTM model, which is then applied to disease classification with the CSO-CLSTM model. The diagnostic accuracy of the CLSTM model is improved by this optimisation procedure. Healthcare data, including diagnoses of heart disease and diabetes, are used to assess the CSO-CLSTM model's efficacy. The experimental results show that the model is effective, with rates of accuracy of 96.16 percent for heart disease diagnoses and 97.2 percent for diabetes diagnoses. The model's performance can be enhanced in the future by implementing feature selection methods to deal with the curse of dimensionality and reduce computational complexity. Hybrid metaheuristic algorithms can be incorporated into the optimisation process to overcome the shortcomings of the CSO algorithm, such as low search precision and an increased likelihood of being stuck in local optima. The efficiency and accuracy of the disease diagnosis model will both increase as a result of these enhancements.

4. Results and Discussion

A Wireless Sensor Network (WSN) is set up in the provided health monitoring centre, with varying sensor node (SN) densities. N denotes the total number of SNs in the network, and 50, 100, 200, and 300 are all possible values for N. Each SN in the network has a set schedule for when it wakes up from sleep and when it returns to sleep, with 't' being the amount of time it is awake for and 'ts' being the amount of time it is asleep for. Each SN has its own unique schedule for when it is awake and when it is asleep. Each SN has a directional antenna with a range of Rc for sending and receiving signals. This means that within a certain range, each SN can send data to other SNs but cannot communicate with SNs outside of that range. The SNs are permanently stationed, so they cannot collide with one another. One hundred separate simulations are run to assess the system's efficiency. Each simulation runs with a different random starting time for the SNs' wake-up mode. Changing the time at which the test begins ensures that a wide variety of conditions under which the system is put to the test can occur. Researchers and system designers can learn more about how a network operates and what effects different parameters have on its performance by simulating various scenarios. It's useful for learning the strengths and weaknesses of the health monitoring center's WSN deployment.

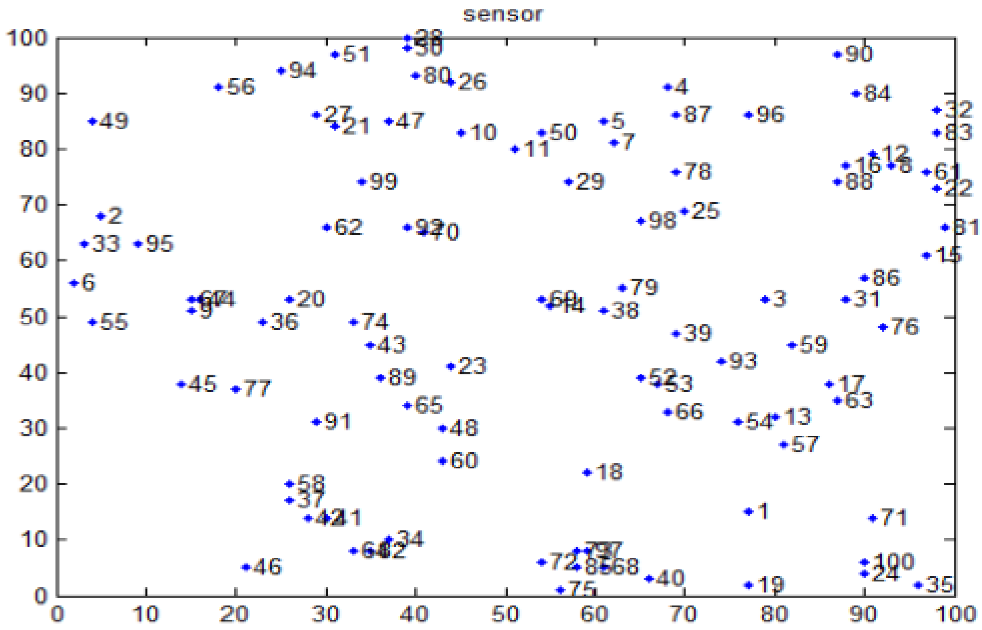

Figure.5: Allocation of 100 Sensor Nodes

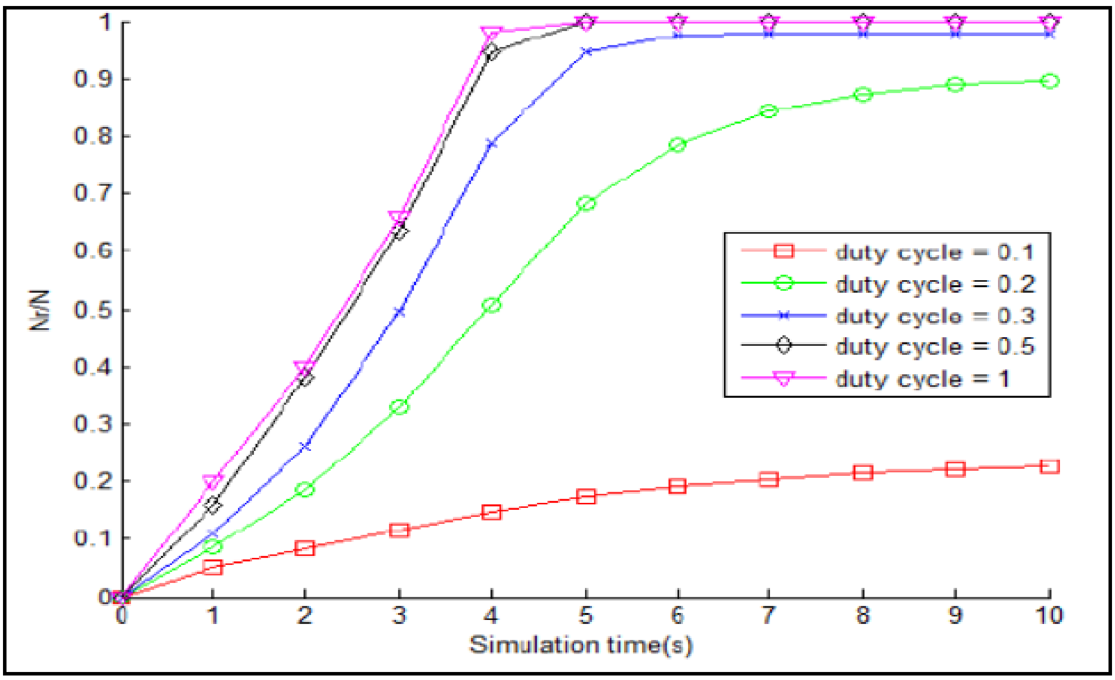

Figure.6: Average Reachability with 50 SNs

Figure 5 is a diagram showing a coverage area of 100 metres by 100 metres with a total of 100 sensor nodes (SNs). These SNs can be found transmitting at around 900 MHz. The SNs have a gearbox range of between 5.5 m and 70 m. However, the transmission range increases to 50-75 metres if the 900 MHz receiver is raised off the ground by 3-6 metres. In this example, we'll use a maximum gearbox range of 35 metres (denoted by the symbol "Rc"). For 50 SNs, with a maximum transmission range of Rc = 35 m for each SN, the average reachability impact is shown in Figure 6. Duty cycles of 0.1, 0.2, 0.3, 0.5, and 1 were selected for this example. The duty cycle of an SN is calculated by dividing the amount of time it is awake by the sum of the time it is awake and asleep. A duty cycle of 0.1, for instance, indicates that the SN is awake for only 10% of the time and is in a sleep state for the other 90%. These diagrams illustrate the configuration of the network and the effect of duty cycles on the range at which SNs can be reached. Researchers or system designers can evaluate the compromise between duty cycle and network coverage, energy consumption, and overall system performance by analysing these numbers.

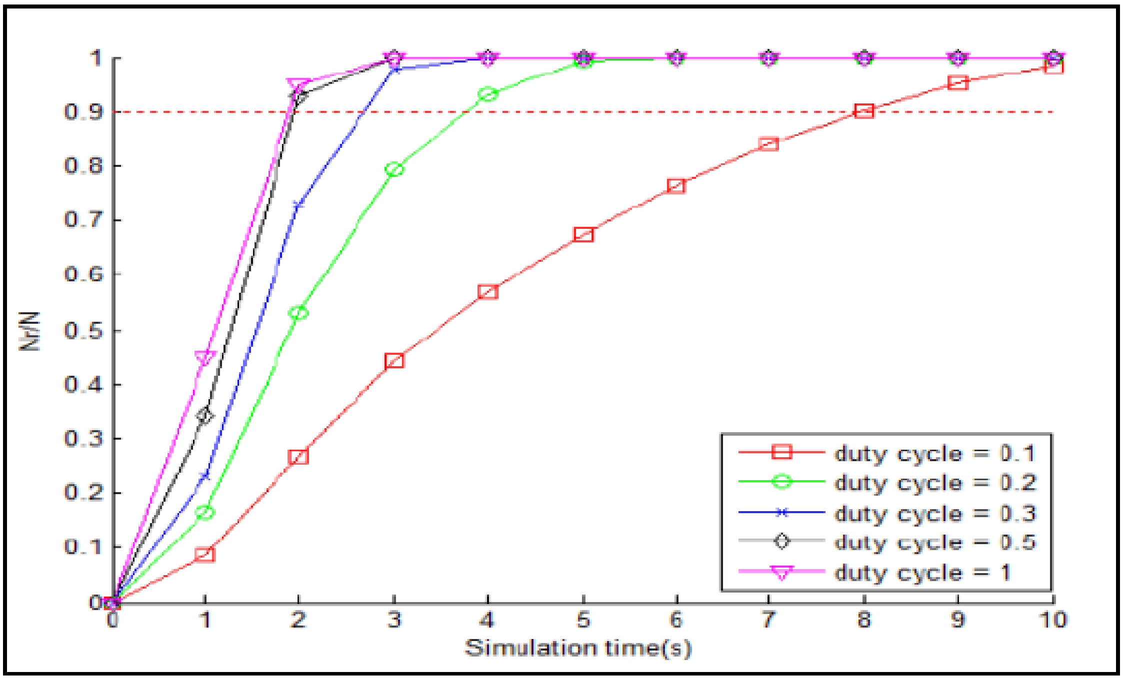

Figure.7: Average Reachability with 200 SNs

Figure.7 shows the sensor node (SN) reachability values for different duty cycles. In this case, there are 200 SNs spread out over an area of 100 m x 100 m, giving an SN density of 0.02 SNs/m2. The SNs' reachability values, which reflect their connectivity to other nodes in the network, are displayed in the figure. The effect of varying duty cycles on accessibility is explored. Duty cycle describes the fraction of each SN's lifetime that it is actually being used. Researchers or system designers can evaluate the trade-off between duty cycle settings and the network's ability to maintain connectivity and communication among the SNs by analysing the reachability values for different duty cycles.

5. Conclusion

By allowing for early intervention and individualised care, the combination of AI methods with IoT-enabled healthcare systems has the potential to revolutionise disease detection. To overcome these obstacles and guarantee the smooth incorporation of these technologies into clinical practise, however, more study is needed. The future of early disease detection in healthcare holds much promise for better patient outcomes and lower healthcare costs as AI and IoT technologies continue to advance. Several salient features characterise the proposed scheme in this setting. One of these features is the automatic updating of priorities in response to changes in the latency and reliability of individual data packets and the overall state of the network. This means that the scheme can change its priorities in real time to optimise data transmission under different network conditions. The inclusion of safety features is another distinguishing feature. The scheme incorporates mechanisms to guarantee the privacy, integrity, and accessibility of the transmitted data, taking into account the security implications of data packets. This aids in preserving the confidentiality of patients' personal data. The sensor mechanism is essential to the scheme because it keeps tabs on the patient at all times. The patient's current condition can be assessed, and future communication needs, such as bandwidth, can be predicted. The scheme is able to seamlessly communicate with the patient by anticipating the need for increased bandwidth and allocating resources accordingly.

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