A Novel Internet of Things-enabled Approach to Monitor Patients' Health Statistics

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***Abstract*—Leveraging Internet of Things (IoT) technology in healthcare systems improves patient care, reduces costs, and increases efficiency. Enabled by IoT, telemedicine allows remote patient monitoring, vital sign tracking, and seamless data accessibility for doctors across multiple locations. This article presents a novel IoT-enabled approach that utilizes artificial neural networks with radial basis functions to detect patients' positions. This real-time tracking mechanism operates even without cellular connectivity, providing timely diagnoses and treatments. Our research aims to develop a smart and cost-effective healthcare approach, revolutionizing patient care. Mathematical analysis and experiments confirm the effectiveness of our proposed method, particularly in predicting patient location for the upcoming smart healthcare solution.**

***Keywords*—Internet of things; healthcare; telemedicine; artificial neural network**

I. Introduction

In today's world, with the ever-increasing advancement of technologies, sharing data related to old systems is cumbersome and often weak. For example, sharing health data with others in old systems is difficult due to different formats and parameters and is not suitable for the urgent needs of modern users [1]. In addition, the relationship between healthcare experts and patients has always been a one-way path. For patients and experts, the current system is incredibly slow, inflexible, and unclear. These problems are equally evident in all stages. When a patient needs services, health plans are used to determine the amount of money they will pay. To determine this fee, as opposed to the agreement between the patient and the health plan, the health plan must validate the services received from the provider and then share the results with the provider [2]. This only happens if the application provider is online. For a provider to be considered online, a complex agreement must be negotiated, which adds significant overhead to the provider's administrative costs. Part of these costs are related to billing and insurance costs, which include activities such as updating the database and maintaining records of the services provided [3]. Normally, this whole process takes between one to two weeks if done electronically and three to five weeks if done on paper. In addition, this process is full of spots where it is possible that an error can occur. In order for sponsorship to actually take place, many people have to check multiple old agreements compared to multiple records. The result is an ineffective and unclear process that causes profiteers and patients to feel confused and pessimistic [4].

Recent advancements in wearable health technologies have opened new avenues for telemedicine and have made it possible to monitor one's health remotely and continuously. These sensors can collect a wide range of data, including heart and respiratory system data and several more vital signals. Using artificial intelligence and signal processing techniques, these signals can be automatically analyzed and categorized. In the event of detecting unusual signal patterns, notifications are promptly sent to both patients and doctors. This innovative approach to telemedicine provides a valuable and rewarding experience for individuals needing medical assistance [5]. Internet of Things (IoT), humanitarian logistics, meta-heuristic algorithms, nonlinear complementarity, silicon nanostructure arrays, machine learning, Markov-modulated regime-switching market, and artificial intelligence play crucial roles in the field of telemedicine, revolutionizing healthcare delivery and improving patient outcomes.

The integration of IoT in telemedicine allows for remote patient monitoring, real-time data collection, and seamless communication between healthcare providers and patients. This connectivity enhances the accessibility and effectiveness of healthcare services, especially in remote or underserved areas [6-8]. Humanitarian logistics leverages technology to optimize the delivery of medical supplies and resources during emergencies or humanitarian crises. It ensures timely and efficient distribution, minimizing supply chain disruptions and saving lives [9]. Meta-heuristic algorithms provide efficient solutions to optimization problems in telemedicine, helping healthcare providers in resource allocation, scheduling, and decision-making. These algorithms can optimize complex systems and improve the utilization of healthcare resources [10, 11]. Nonlinear complementarity and silicon nanostructure arrays are emerging technologies with potential for telemedicine. They enable advanced diagnostics, drug delivery systems, and personalized medicine, enhancing the accuracy and effectiveness of medical treatments [12, 13]. Machine learning and artificial intelligence enable predictive analytics, risk assessment, and decision support systems in telemedicine [14-16]. They can analyze vast amounts of patient data, identify trends, and assist healthcare professionals in making informed decisions [17-21]. The markov-modulated regime-switching market model provides insights into the dynamics of telemedicine markets, helping stakeholders understand market behavior and optimize healthcare service provision [22].

Furthermore, telemedicine makes medical services more available at lower costs by using modern communication tools. Additionally, telemedicine virtually provides easy access to medical services for people in rural areas [23]. This easy access cannot be limited to just one country, and different people in different countries can use these medical services. Doctors and

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patients can communicate with each other online using computers or smartphones. Doctors can check the patient's file and test results remotely. Patients also visit their doctor at their homes and receive diagnoses and treatment through telemedicine software without waiting for an appointment. Easy and reliable use, smart characteristics, no time loss, high security, and low cost are some advantages of telemedicine [24]. Although telemedicine is still a new concept for users and doctors, advances in technology and medical innovation have expanded its use. Despite the provision of many advantages through this technology, its use is expected to increase in the coming years. “Telemedicine” includes maintenance, care, diagnosis, consultation, and treatment, while at this stage, the focus is on transferring medical data and educational goals. Also, in a more comprehensive and complete view, it can be said that, in general, “telemedicine” is the use of medical and communication technologies to exchange any data, including data, voice or video communications between a doctor and a patient or a doctor and healthcare experts in separate geographical locations as well as creating the possibility to exchange medical, healthcare, research and educational concepts [25].

The convenience of using remote medical services, low waiting time, high-quality medical diagnosis and treatment, and cost reduction are among the advantages of this technology. Also, the presence of the patient's medical record online makes it possible to diagnose and treat the disease more accurately and with higher quality. Another advantage is the lower costs of telemedicine compared to the traditional method. With this method becoming common, insurance companies also will include telemedicine services in their insurance plans, and this process will lead to a reduction in the costs of telemedicine services. Telemedicine services only require a webcam (or smartphone) and a secure online system to connect the patient with the doctor and store medical records. In addition to ensuring the patient's privacy and safe keeping of medical records, the professional competence of doctors should also be ensured through the examination of documents [26]. Moreover, the challenges facing the current medical care system, which is often accompanied by cumbersome laws that slow down medical services, can include data dispersion in the health system, patient disobliging, misdiagnosis, and false medical data, security risks for patient data, and lack of transparency. Researchers and healthcare professionals are faced with a number of new challenges as they attempt to understand and utilize new developments in the field of information technology. Wireless communication platforms and their application to the development and interconnection of smart devices have revolutionized the landscape where the first electronic healthcare systems were conceived. The use of network-enabled devices has become widespread, covering a wide range of items from household items and cars to health and care management systems in what has been referred to as IoT [27].

The purpose of modern information and communication technologies (ICTs) in the healthcare system is traditionally to provide promising solutions that facilitate the efficient delivery of healthcare services, referred to as e-health, including personalized diagnostic, telemedicine, and electronic record tools. In the developed world, however, the rapid increase in longevity has led to the fact that an increasing proportion of the population is over the age of 80. Consequently, traditional healthcare systems need to be designed and developed in a more cohesive and ubiquitous manner in order to provide excellent patient-centered services [28]. In recent years, the emergence of wearable gadgets and smartphones has enabled IoT technology to revolutionize healthcare by changing a traditional hub-based model to a personalized one. With the effective implementation of IoT into customized healthcare services, preventive care becomes timelier and safer, costs are reduced, and patient-centered care is improved. As IoT becomes increasingly prevalent, highly customized healthcare services will be able to provide enhanced and customized access to extensive healthcare information and facilitate clinical decision-making for each patient through the use of unobtrusive, continuous monitoring and sensing [29]. We conduct research on the remotely monitored healthcare system as it plays a vital role in the medical field. A change in lifestyle is also leading to new diseases appearing in the modern age. Further, the COVID-19 epidemic shows the global community our deficiencies regarding healthcare services. A large number of people need health care services at the same time, and adequate resources, equipment, and space are required. Remote health monitoring offers several advantages for elderly and ill patients who are unable to visit medical facilities for periodic checkups. This will ultimately improve the efficiency of the entire healthcare system and allow critical patients to receive the necessary care. The main contributions of the paper are centered around addressing the energy efficiency and decision problems related to location tracking for remote health monitoring. The specific contributions can be summarized as follows:

- Problem identification and analysis: The paper identifies and analyzes the energy efficiency and decision challenges associated with location tracking in the context of remote health monitoring. By understanding these challenges, the researchers lay the groundwork for developing solutions that optimize energy consumption and improve decision-making processes.
- Development of a location tracking system: The researchers design and develop a system that is capable of collecting patients' location data for remote health monitoring. This system incorporates a mobility management model to efficiently track the patients' movements and gather relevant location information.
- Feature extraction based on movement: In order to accurately predict the patients' location, the paper introduces a novel approach for feature extraction. By analyzing the movement patterns of the patients, relevant features are extracted from the location data. This step is crucial for improving the accuracy of location prediction.
- Utilization of radial basis function neural network: The paper proposes the use of radial basis function neural network as a learning algorithm to process the extracted features and predict the patients' location.

- Enhanced prediction of patient location: The combination of the mobility management model, feature extraction, and radial basis function neural network learning enables an efficient and accurate prediction of patients' locations. This advancement in location tracking facilitates seamless information gathering of patients' health data in remote monitoring scenarios.

II. Related Work

A mobility-aware, IoT-enabled healthcare security framework has been proposed by Moosavi, et al. [30]. The system consists of three main components: interconnected gateways that provide robust mobility, an ad-hoc protocol that supports resuming sessions, and a certificate-based DTLS handshake protocol for user authentication and authorization. Smart gateways serve as an intermediary computing layer between cloud services and IoT devices. With the computing layer, there is no need to reconfigure the device for ubiquitous mobility. The framework is demonstrated using simulations and a full prototype of both hardware and software. Compared to existing approaches, this framework significantly reduces the delay between end users and smart gateways by 17% and the amount of communication overhead by 25%.

Data generated by medical devices with sensors is often referred to as big data, which is a combination of structured and unstructured data. The complexity of the data makes it difficult to analyze and process big data in order to find relevant information to aid decision-making. Security of data is an essential requirement for healthcare big data systems. This issue was addressed by Manogaran, et al. [31] by creating a new architecture for incorporating the IoT into healthcare for storing and processing scalable sensor data (big data). The suggested architecture is based on two main underlying models, namely Grouping and Choosing (GC) and Meta Fog-Redirection (MFR). MFR collects and archives sensor data (big data) generated by a variety of sensors. The proposed GC architecture integrates fog computing and cloud computing. MapReduce-based prediction models are also used to predict heart disease. Based on performance measures such as f-measure, precision, robustness, and efficiency, the proposed architecture and prediction model are evaluated.

Pal, et al. [32] have proposed an IoT-based system for controlling access to constrained healthcare resources. Using this approach, trusted users will have access to the services while unauthorized users will not be able to access valuable resources. The authorization design utilizes attributes, roles, and capabilities in a hybrid manner. Role membership is assigned based on attributes, and permissions are evaluated based on attributes. Capabilities are granted by membership in roles. User capabilities may be granted according to additional attributes when accessing specific services provided by IoT devices. Consequently, the number of policy instances necessary for specifying access control criteria is significantly reduced. It is implemented and evaluated based on an initial proof-of-concept. There was minimal additional overhead associated with this approach when compared to other solutions that incorporate access control functions within the Internet of Things.

IoT technology has revolutionized the healthcare industry, resulting in smart medical applications. A system for monitoring urine-based diabetes (UbD) at home has been presented by Bhatia, et al. [33]. In order to predict and monitor diabetes-related urinary tract infections, a four-layer system is proposed. Diabetes measures are regularly tracked and a prediction procedure is conducted to enable precautionary steps to be taken at an early stage of the disease. Furthermore, a Recurrent Neural Network (RNN) was used to obtain a probabilistic measure of UbD monitoring by calculating the Level of Diabetic Infection (LoDI), a measure of diabetes infection. Simulation results demonstrated that the proposed system was more accurate, robust, and consistent than state-of-the-art decision-making techniques.

In the design of any information and communication technology (ICT) infrastructure, interoperability and connectivity play an important role. By integrating IoT technologies into medical systems, people will be able to receive timely, cost-effective, and ubiquitous healthcare services. Currently, a complex ecosystem of devices, databases, and communication technologies provides a wide range of healthcare services. Healthcare information systems must integrate and collaborate with these technologies and resources to ensure that healthcare is provided efficiently. By providing connectivity for billions of devices worldwide, IoT technology improves healthcare delivery and quality. The potential benefits of IoT-based connectivity for healthcare are discussed by Zeadally and Bello [34]. An overview of recently implemented IoT-based healthcare systems is provided. Lastly, they discuss the potential uses of the IoT for enhancing healthcare solutions.

A new IoT-based reliable healthcare monitoring approach was proposed by Jacob, et al. [35]. To collect vital parameters, such as deviations in body temperature, multiple sensor nodes are implanted into the body of a patient as a first step. After preprocessing the dataset in order to eliminate redundant and irrelevant attributes, the normalization procedure is applied. Cancers are classified based on their features using a convolutional neural network (CNN). Based on sensor input, the CNN model calculates the cancer risk of a patient. Once the results have been received by the hospital management, they are analyzed. Rivest-Shamir-Adleman (RSA) encryption is primarily used in this study in order to achieve high assurance security, simplicity of deployment, and simplicity of use. A modified version of the RSA algorithm, utilizing the double encryption-decryption process and n prime numbers, is presented in this paper. Based on experimental results, the proposed method demonstrated superior performance when compared to other approaches.

III. Proposed Method

A. Network Model

System performance and network architecture are critical to the success of an IoT-based healthcare system. The ability to process large amounts of data quickly and accurately is essential for IoT-based healthcare systems to work properly and provide accurate diagnoses and treatments. Additionally, the network architecture of an IoT-based healthcare system must be robust enough to handle the large amounts of data being transferred between various devices and systems. By placing sensors in the patient's body and transmitting the data to the monitoring end, various processes are undertaken, which require careful observation of the locations of the sensors, the hardware configurations, and the control of the energy usage of the monitoring devices. An industry-specific IoT environment incorporating significant parameters was used to design the network architecture for optimal data transmission and energy consumption according to the patient or node locations. Assumptions and approximations are outlined below.

- Sensor nodes operate continuously and communicate via cellular networks.
- According to the Rayleigh distribution, the signal magnitude varies randomly or fades.
- Rayleigh fading channels are considered throughout the communication process.
- Continuous sensing, transmission, and reception are characteristics of sensing operation.
- Patients' bodies are continuously monitored by heterogeneous sensors that collect data such as temperature, blood sugar, etc.
- Patients are equipped with sensors, and they are mobile.

As illustrated by Fig. 1, the present design comprises a mobility management strategy for collecting location information, followed by a radial basis function neural network-based learning method used to predict the node's location to ensure uninterrupted communication. Fig. 2 illustrates the network architecture. In this system, mobility management is used to determine the patterns of movement of nodes as a set of locations. As shown in Fig. 2, these data are used to train the proposed model with location feature maps for each time instant. Based on the training output, nodes or patients' positions are predicted and localized. Localized nodes collect observations estimated from the previous data gathered over time.

B. Mathematical Modeling

The proposed system begins with tracking patient location information. Thus, a patient movement scheme is designed to estimate at first the positions of N patients based on their movements. The number of locations (n) is assumed to be fixed in proximity to the individual's residence or the locations he/she frequently visits. It is also assumed that there are m unknown places that must be investigated to determine how patients move two-dimensionally. Throughout the range of transmission radius R, sensing devices can communicate omnidirectionally with each other. The direction and speed experienced by a patient from any fixed position can be used to determine their relative locations. Sensor location changes over time are primarily a function of rapid node movements, and displacement is measured as a Gaussian random variable with mean 0 and variance 1. The following equations can be used to illustrate the randomness of the movement:

$$|u(r)| = \eta|u(r-1)| + (1-\eta)\phi_{|u|} + \gamma|u|\sqrt{1-\eta^2}h_{|u(r-1)|} \tag{1}$$

$$d(r) = \eta d(r-1) + (1-\eta)\phi_d + \gamma d\sqrt{1-\eta^2}h_{d(r-1)} \tag{2}$$

In the above Equations, u(r) represents time-dependent displacement, whereas d(r) represents displacement direction concurrent with the movement of the sensor nodes. In this situation, the probability of the sample depends on η ranging from 0 to 1 and on the proportional average speed based on the scale factor of r→∞.

C. Pattern Definition and Feature Assignment

The random movement of patients makes it difficult to recognize certain patterns. Patients move from one location or provider to another, and their care may be fragmented, making it hard to determine a consistent care pattern or evaluate the effectiveness of interventions. Additionally, patients may not have the same healthcare access, making it difficult to identify patterns. However, using historical location records, relationships are formed, and feature mapping is conducted. This feature mapping can then be used to identify potential gaps in care and areas where healthcare providers can intervene to improve patient outcomes. It can also help reduce the burden of fragmented care by helping providers identify the most effective treatments. In a high-dimensional space, locations of patient i can be mapped at different time intervals t, as follows:

$$L_{x_i} = \{x_i(1), x_i(2), \dots, x_i(r)\}$$

$$L_{y_i} = \{y_i(1), y_i(2), \dots, y_i(r)\} \tag{3}$$

In a g-dimensional space, patients' positions can be mapped separately in the x- and y-axes. By plotting points on the graph in the x- and y-axes, it is possible to map out the position of each patient within the given space. This allows for more accurate tracking and analysis of the patient's movements over time. Thus, both feature spaces can be expressed as follows:

$$W_{x_i} = \left\{W_{x_i}(1), W_{x_i}(2), \dots, W_{x_i}(v), \dots, W_{x_i}(r-g+1)\right\}$$

$$W_{y_i} = \left\{W_{y_i}(1), W_{y_i}(2), \dots, W_{y_i}(v), \dots, W_{y_i}(r-g+1)\right\} \tag{4}$$

The feature vectors assigned to each patient are bound in the g dimension and stored in feature spaces WXi and WYi, respectively. These features provide sensor movement characteristics and can be used as training data for predicting a sensor's future location.

D. Feature Learning

Machine learning techniques are the most effective in terms of optimizing and approximating functions accurately, making them a valuable tool for prediction. Among the various machine learning approaches used to train systems, the radial basis function neural networks are unique in their ability to approximate functions and classify them. As shown in Fig. 3, radial basis function neural networks are able to linearize nonlinear data.

Fig. 3 illustrates an architecture in which three layers are present: input, hidden, and output. The input layer takes the input data and passes it on to the hidden layer. The hidden layer processes the input data with mathematical operations and passes the processed data to the output layer. The output layer produces the desired output, such as a prediction or classification. A radial basis function is used in the hidden layer to convert the nonlinear to linear data. In most cases, nonlinear kernels are used as Gaussian kernels in radial basis function neural networks based on Euclidean distance. The radial basis function neural network is trained to learn the input characteristics in the form of $v = 1, 2, \ldots, (r - t(g-1))$, which are output components to be $Q_{X_i(v)}$ and $Q_{Y_i(v)}$.

E. Place Estimation

The last step in our approach involves obtaining predictions based on our assumptions. The predicting procedure is initiated, and the position is estimated if the mobility management solution cannot identify the point of interest because of excessive communication interference. At first, the model considers the initial coordinates of the last place and searches for the next possible location. During the prediction process, this assumption was based on the non-availability of the model for mobility management. According to our assumptions, m is the predicted number of locations or steps associated with our experiment and $V_P(p)$ denotes an input vector for (p = 1, 2, . . ., m). Suppose that the output results for (P = X, Y) during the prediction will be $S_P(p)$. Therefore, it can be calculated as follows:

$$S_P(p) = \sum_{j=1}^{z} k_j . \phi(V_P(p), c_j) \quad (5)$$

In other words, with respect to $S_P(p)$, the anticipated position ith individual can be shown by:

$$\hat{L}_i(r+p) = \hat{x}_i(r+p), \hat{y}_i(r+p) \quad (6)$$

In this manner, the latest position corresponds to the following location on the axis of $\hat{x}_i(r+p)$, $\hat{y}_i(r+p)$. Neurons are updated periodically in order to predict future locations in accordance with certain rules. The incoming points for the pth vector are expressed matrixial in the following way.

$$V_X(p) = \begin{bmatrix} x_i(r - t(g-1) & \ldots & x_i(r)) \\ \hat{x}_r & \ldots & \hat{x}_i(r+p) \end{bmatrix} \quad (7)$$

$$V_Y(p) = \begin{bmatrix} y_i(r - t(g-1) & \ldots & y_i(r)) \\ \hat{y}_r & \ldots & \hat{y}_i(r+p) \end{bmatrix} \quad (8)$$

This is our setup for converting high-dimension states into low-dimension ones in order to predict them. The prediction outcome is as follows:

$$\hat{L}_i = \{\hat{L}_i(r+1), \hat{L}_i(r+2), \ldots, \hat{L}_i(r+p), \ldots, \hat{L}_i(r+m)\} \quad (9)$$

In order to determine the prediction error, the actual number of patient places traveled by the mobility management scheme can be compared to the prediction error. According to the prediction-based algorithm, known locations can be expressed as follows:

$$L_i^0 = \{L_i^0(r+1), L_i^0(r+2), \ldots, L_i^0(r+p), \ldots, L_i^0(r+m)\} \quad (10)$$

In this regard, the expected error value can be calculated as follows:

$$e(p) = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(L_i^0 - \hat{L}_i)^2} \quad (11)$$

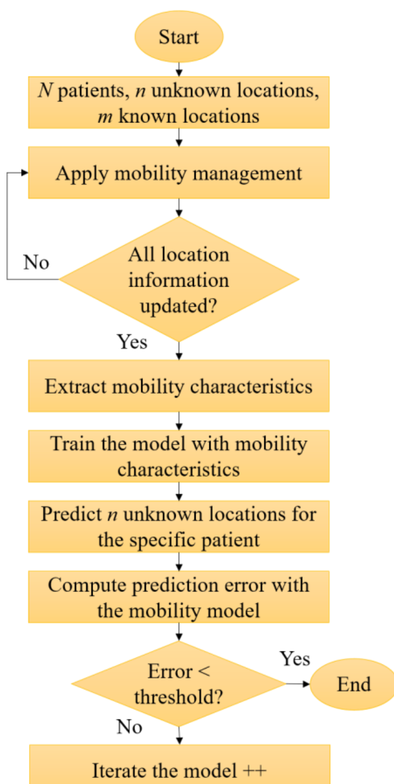

Fig. 1. Flowchart of the proposed method.

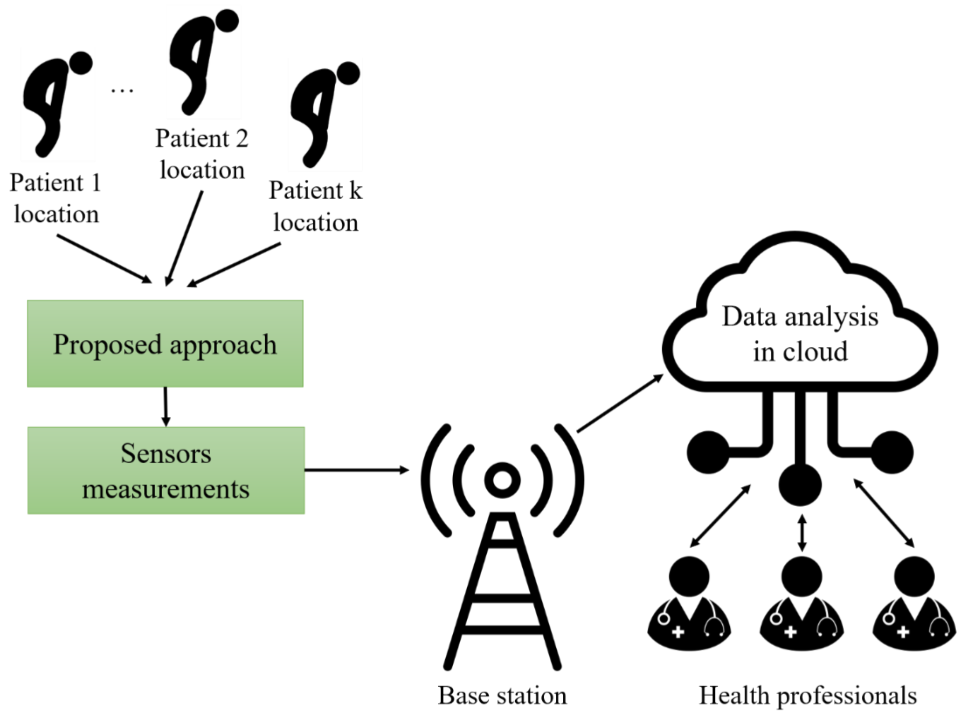

Fig. 2. .Architecture of the proposed method.

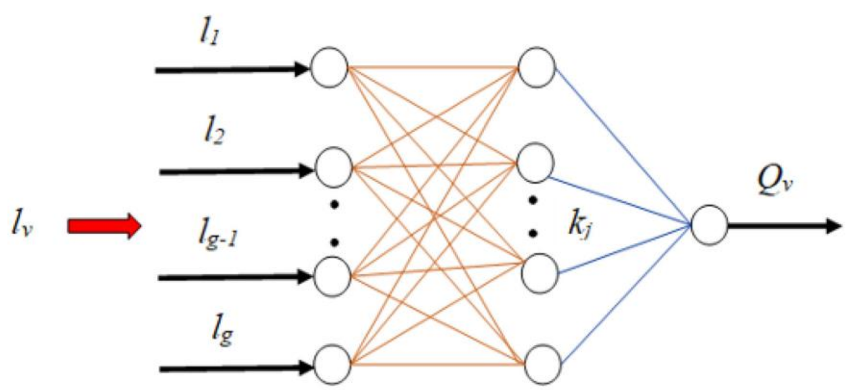

Fig. 3. Overview of radial basis function neural networks.

IV. Experimental Results

This section presents the numerical analysis and provides a detailed analysis of the experimental findings to evaluate the effectiveness of the proposed mechanism. The experiments were conducted using a MATLAB simulator, and Table I outlines the parameters used for the simulation tests. The dataset consisted of 2400 data points, capturing position information for 600 locations over different time periods, which were used for both training and testing purposes. To assess the accuracy of the suggested technique, an average error was calculated, as depicted in Fig. 4. In the traditional method, a simple range error is employed as the basis for the mobility management model. As the number of prediction steps increases, the average error becomes more pronounced. The error rate rises when the number of prediction steps is reduced and when an individual remains outside the range of the cellular network for an extended period. However, our proposed method demonstrates fewer errors compared to conventional methods. Unlike the traditional approach, which relies on a fixed number of prediction steps and exhibits increased error rates when the patient is out of range for longer durations, our method leverages machine learning algorithms to better predict the patient's movements, resulting in a reduction in the average error rate.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Network dimensions	80 × 80 m2
Number of simulations	500
Simulation time	1000 seconds
Number of prediction steps	20
Range of sensors	30m
Locations for training	500 locations

Furthermore, the proposed method is compared to a conventional mobility management model in Fig. 5. The primary objective of our research is not only to predict patients' locations but also to monitor their health with precision. Therefore, it is crucial to verify that the developed system can obtain accurate and timely patient data to a significant extent. Fig. 5 illustrates that our prediction model provides additional data and information compared to traditional approaches. As a result, the proposed approach enables more accurate and real-time prediction of patient positions.

Additionally, Fig. 6 shows the minimal response time achieved by our proposed algorithm compared to the conventional method [36]. The results demonstrate that our algorithm can handle a greater number of requests in less time. This improved performance is attributed to the efficient utilization of resources and optimal request routing. The use of at least 10 prediction steps and a minimum time interval of one second between locations contribute to the algorithm's superior performance. It is important to note that modifying these parameters may result in a smoother transition between the performance of the proposed method and the traditional approach.

The experimental results provide quantitative evidence of the proposed mechanism's effectiveness in terms of efficiency, accuracy, and response time. The findings highlight the superiority of our approach over conventional methods, emphasizing the potential impact and benefits it can offer in the field of healthcare monitoring and patient management.

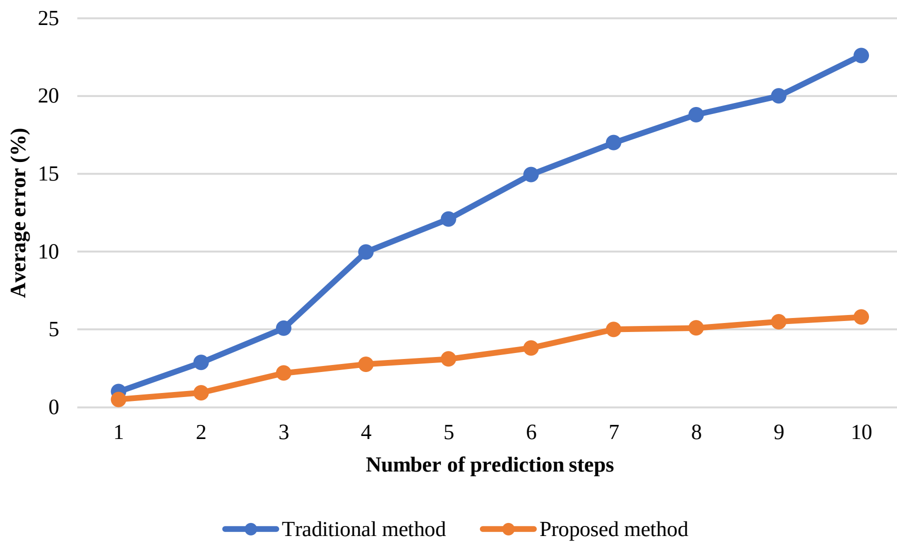

Fig. 4. Average error comparison.

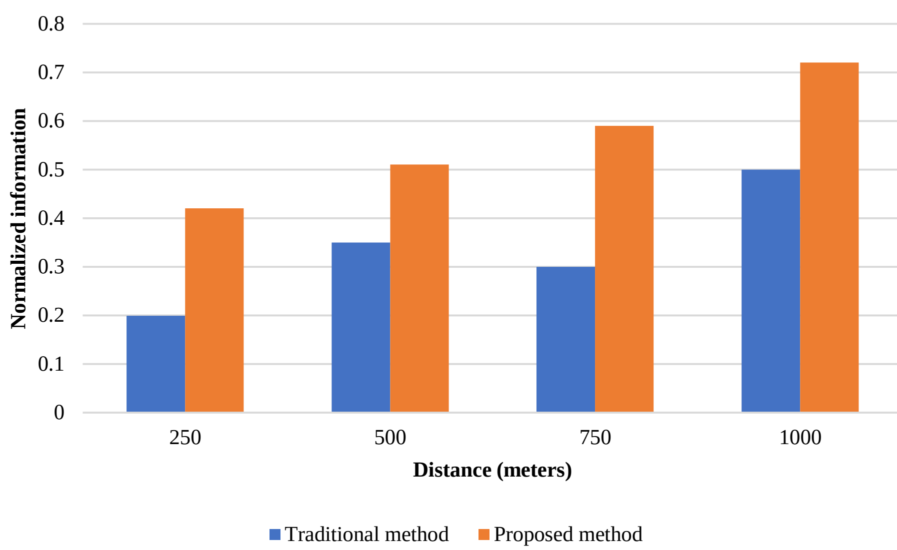

Fig. 5. Data collection comparison.

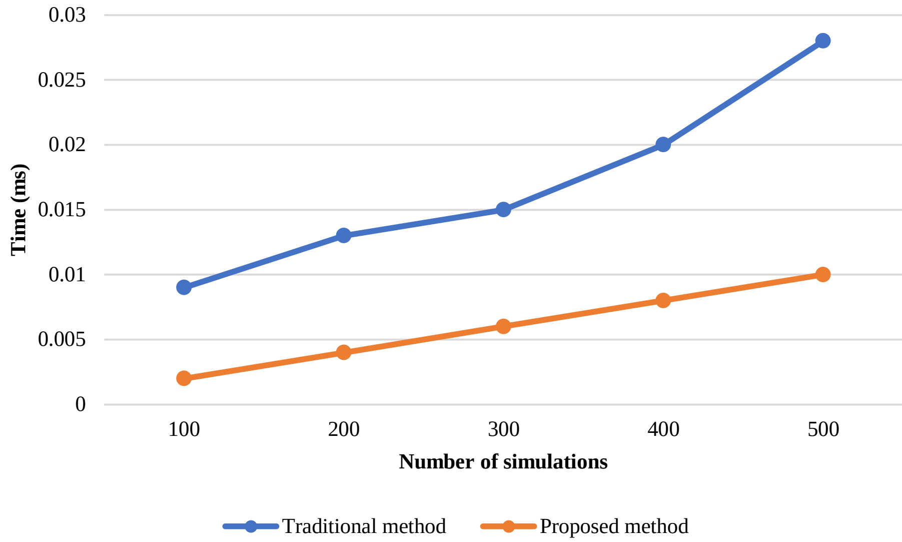

Fig. 6. Response time comparison.

V. Conclusion

In this paper, a neural network-based radial basis function algorithm is presented for the prediction of a patient's location in a remote healthcare system. The movement characteristics of the patients are trained using a radial basis function neural network, and their locations are predicted whenever they move outside of their range of cellular devices. The training of the system is based on a mobility management model. Simulated results indicate that the proposed method is faster and consumes less energy than the existing method. Also, the proposed work shows good results regarding the average error for predicting the position. As a result, the proposed system can reliably and accurately track the locations of patients while maintaining low energy consumption and fast response times. This makes the proposed system an ideal choice for applications in healthcare and monitoring patient mobility, as it offers optimal performance. While radial basis function neural networks have faster training times, their classification process can be slower compared to multilayer perceptron networks. This is primarily due to the computation of the radial basis function in each node of the hidden layer before the input sample vector can be classified. To overcome this limitation and enhance the system's ability to learn new categories and update the classification system in real-time, we propose incorporating transfer learning in future work. Transfer learning is a technique that utilizes pre-trained models as a starting point for learning new features while preserving the existing knowledge. By leveraging transfer learning, we intend to take advantage of the knowledge acquired by the back-end network of the radial basis function neural network. This approach allows for a more efficient adaptation of the network to new categories without disregarding the valuable information that has already been learned.

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