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Research article

# Optimization of resources in intelligent electronic health systems based on internet of things to predict heart diseases via artificial neural network

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ABSTRACT

As a paradigm shift in tandem with the expansion of ICT, smart electronic health systems hold great promise for enhancing healthcare delivery and illness prevention efforts. These systems acquire an in-depth understanding of patient health states through the real-time collection and analysis of medical data enabled by the Internet of Things (IoT) and machine learning. With the widespread use of cutting-edge artificial intelligence and machine learning techniques, predictive analytics in medicine can assist in making the shift from a reactive to a proactive healthcare strategy. With the ability to rapidly and precisely evaluate massive amounts of data, draw intelligent conclusions, and solve difficult issues, artificial neural networks could revolutionize several industries. Two cardiac illnesses were assessed in this study using a multilayer perceptron artificial neural network that incorporated a genetic algorithm and an error-back propagation mechanism. The ability of artificial neural networks to handle consecutive time series data is crucial for optimizing resources in smart electronic health systems, especially with the increasing volume of patient information and the broad use of electronic clinical records. This requires the creation of more accurate predictive models. Through the use of Internet of Things (IoT) sensors, the proposed system gathers data, which is then used to do predictive analytics on patient history-related electronic clinical data saved in the cloud. A smart healthcare system that uses Mu-LTM (multidirectional long-term memory) to accurately monitor and predict the risk of heart disease has a coverage error of 97.94 %, an accuracy of 97.89 %, a sensitivity of 97.96 %, and a specificity of 97.99 %. In comparison to other smart heart disease prediction systems, the F1-score of 97.95 % and precision of 97.71 % is very good.

## 1. Introduction

There have been numerous opportunities in the eHealth area brought about by the substantial advancements in ICT, particularly the Internet of Things (IoT), in the last several decades [1–3]. Electronic health systems have been able to advance and improve thanks

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to these advancements, despite obstacles including data management, privacy protection, and information security [4–6]. The prevention of cardiovascular illnesses is a hotly debated topic in this domain because it is one of the leading causes of death worldwide [7,8]. One promising approach in this area is the use of machine learning for resource optimization in smart electronic health systems with the purpose of predicting cardiac illnesses [9,10]. Machine learning, a subfield of AI capable of analyzing massive amounts of data and making predictions about their future trends, is the ideal tool for enhancing IoT-based electronic health systems [11–13].

Modern apps and improved diagnostic and treatment processes have been developed in the healthcare sector using information technology in recent years [14–16]. Excessive volumes of digital data are mostly produced by sophisticated methods and scientific theories. Then, new forms of information technology have given rise to sophisticated clinical applications [17]. It is also believed that modern healthcare has applications that are multifunctional, attractive, and straightforward [18]. Clinical model development, information development changes, expansion of clinical management, and reforms from prevention and treatment are all part of these reforms [19–21]. These changes include moving the focus from disease treatment to a preventive medicine system, expanding clinical management from general management to personal management, and changing the focus from medical data to regional medical data [22]. Therefore, in order to boost health care abilities, which in turn enhances health service knowledge and necessitates the construction of smart medicine's future, the following adjustments are centered on meeting people's basic demands [23,24].

Many different parties are involved in providing high-quality medical care, including doctors, patients, and hospitals, clinics, and universities [25,26]. It is important to think about several aspects, including health decision making, medical research, clinical management, disease monitoring and prognosis, therapy and clinical outcomes [27–29]. Some examples of what are often considered to be the defining features of contemporary healthcare include intelligent biotechnology, mobile internet, cloud computing (CC), big data, 5G systems, microelectronics, and artificial intelligence (AI) [30]. At every level of modern medical treatment, these techniques are utilized. From the perspective of the patient, they can track their health status anytime it's needed with wearable or portable equipment. Through virtual help, they can access clinical supervision, and through remote facilities, they can manage their houses from anywhere. Intelligent clinical decision support systems can help doctors with diagnosis by guiding and improving the process.

Chronic diseases, such as hypertension, put a lot of people at risk for cardiovascular disease. There is a growing epidemic of chronic heart disease among the world's aging population. Timely treatment is necessary in the event of variations in vital signs, which necessitates continuous real-time monitoring of both home care recipients and hospitalized patients. Although traditional approaches to long-term health monitoring are time-consuming and laborious, they help save healthcare costs and improve the quality of life for the elderly. In order to minimize the expense of health monitoring while reducing the excessive workload of doctors and hospital staff, effective facilities are necessary. With the rise of sensor-equipped wearables and smart, linked devices made possible by the ubiquitous Internet of Things, cardiac patients can now be monitored remotely. Wearable electrocardiogram (ECG) monitors, smart health watches, and blood pressure monitors are all examples of IoT devices used for healthcare monitoring. With the help of the healthcare IoT, vital patient data can be securely stored in the cloud. Advanced deep learning algorithms, in conjunction with historical electronic clinical records, can then accurately diagnose cardiac risk. Internet of Things devices can swiftly notify medical professionals and caregivers of the patient's status. By assessing the likelihood of patients having a specific cardiac disease, their prognosis for a specific condition, and the treatment that corresponds, this enables doctors to make timely decisions for both individuals and the overall community. Here is a brief overview of the key findings from this study.

In order to estimate the likelihood of cardiovascular disorders, data gathered from Internet of Things (IoT) sensors is processed, cleaned, and filtered on the cloud. The future data is forwarded to the FIS for preliminary classification. Lastly, patients' risk of heart disease is accurately predicted using the suggested Mu-LTM model. The rest of the article is organized as follows. Section 2 reports challenges, approaches and results obtained from previous works. In section 3, the proposed model is described in detail. Evaluation and simulation are given in section 4 and finally section 5 reports the conclusion and future works.

## 2. Related works

The World Health Organization reports that cardiovascular disorders account for the majority of fatalities on a global scale. It has been demonstrated that cardiovascular illnesses account for almost 30 % of all fatalities [31–33]. Therefore, it is crucial to find ways to identify the early warning signals of cardiac disorders so that people all over the world can live healthy lives. Analyzing the data generally is challenging at the moment because of the large diversity of cases in medical data and the relevant disorders and symptoms. Both the heavy workload and unequal qualifications of doctors are well-known facts [4,5]. Because of this, it's more difficult to reliably interpret the data that is available and draw useful conclusions from historical examples in order to improve diagnosis and treatment. As a result, medical decision support systems have been utilized to extract reliable information from specific datasets, thereby aiding doctors in making informed decisions [34,35].

Smart automated systems that aid in disease prediction and diagnosis through the IoT have been developed as a result of tremendous advancements in deep learning. Thus, an EDCNN, an advanced deep learning-assisted convolutional neural network, is suggested as a tool to aid in and enhance cardiac illness prognosis. Using regularization learning techniques as an overlay on top of the multilayer perceptron model, the EDCNN model aims for a deeper architecture. In addition, both the full and minimized versions of the system's features are tested to ensure their performance [36]. Because of this, the mathematical analysis of the test data shows that feature reduction impacts the classifiers' efficiency in terms of processing time and accuracy. Using EDCNN, doctors may quickly and accurately diagnose cardiac patients' data stored on cloud platforms all over the globe through the Internet of Medical Things (IoMT) platform's decision support tools.

A smart healthcare system that uses AI and the Internet of Things for disease diagnostics is presented in Ref. [37]. This paper's primary objective is to provide a model for the diagnosis of cardiovascular disease and diabetes by combining approaches from the fields of artificial intelligence and the Internet of Things. Data collection, pre-processing, classification, and parameterization are all components of the given model. Internet of Things (IoT) devices, like sensors and wearables, make data collecting easy, while artificial intelligence (AI) methods exploit data for illness detection. For medical condition identification, the suggested approach employs the cascading short-term memory model (CSO-CLSTM) built on the crow search optimization algorithm. Applying CSO to fine-tune the CLSTM model's "weight" and "bias" parameters leads to improved medical data classification. Furthermore, outliers have been removed from this study using the isolation forest technique (iForest). The CLSTM model's diagnostic performance is greatly enhanced when CSO is utilized. Medical records served as validation for the CSO-LSTM model's efficacy.

The primary objective is a machine learning-based healthcare model that can accurately and early forecast the onset of different diseases [38]. The aim of this study is to forecast the occurrence of nine deadly diseases, including cardiovascular disease, breast cancer in diabetics, hepatitis, liver disorders, skin, surgical data, thyroid, and cardiac aspects, using seven machine learning classification algorithms: decision tree, support vector machine, simple Bayes, adaptive reinforcement, random forest (RF), artificial neural network, and K-nearest neighbor. Four performance metrics (including accuracy, sensitivity, specificity, and area under the curve) are utilized to assess the efficacy of the suggested model. A model for predicting a patient's chronic health state (such as renal or heart illness) is suggested in Ref. [39]; it is an optimized lightweight EO automated modulation classification network called EO-LWAMCNet. The data can be collected by a sensor implanted in the patient's body, which then uses a gateway to send the data to the cloud. Based on the acquired sensor data, the EO-LWAMCNet model starts the classification process to predict chronic disease [40]. Currently, this model is being trained and tested. This illness is foreseen by analyzing CKD and HD records. In this case, the training step makes use of the pre-processed data for categorization. Once training is over, the data collected by the cloud server's sensors is evaluated for abnormalities and categorized as normal or abnormal, indicating conditions like heart or renal problems. If a result is out of the ordinary, the doctor will get a warning message to help them treat the patient. Machine learning, optimization, and fuzzy algorithms are some of the most current AI applications that he discussed in Ref. [41]. Furthermore, we look into the possibility of using big data analysis for IoMT-based cardiac disease prediction. This paper presents a case study of cardiovascular disease prediction using rule-based classification models and tree-based homogenous ensemble methods on a new dataset. With a prediction accuracy of 73 % and an area under the curve (AUC) of 0.78, preliminary testing results demonstrated that rule-based models from JRIP and PART are useful in identifying cardiac disorders. A framework based on big data analysis and heterogeneous ensemble techniques is proposed for the diagnosis of heart diseases. When it comes to diagnosing cardiac disorders like CVD, this framework can help with real-time monitoring and individualized healthcare.

To forecast diseases based on biosensor estimates of patients' limitations, a cloud-based database based on the Internet of Things is suggested in Ref. [42]. Furthermore, a novel approach to optimizing ant milk classification is suggested, which combines regression law with generalized fuzzy intelligence (GFIbALO) for precise disease prediction. Before processing the data according to the suggested GFIbALO method for illness classification, the dataset is filtered and features are extracted using the regression law. Furthermore, in the event that the patient is ill, the warning signal is communicated to them via SMS or another means, allowing them to seek medical care from professionals. The GFIbALO classifier is implemented using the MATLAB program.

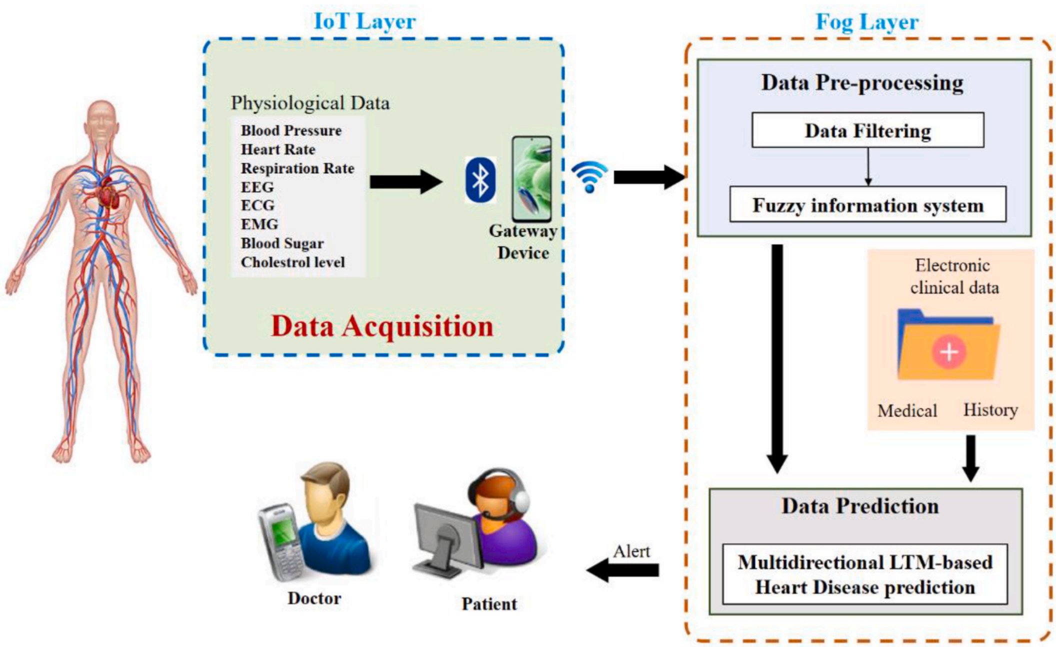



**Fig. 1.** Block diagram of the proposed approach in intelligent e-health systems based on the Internet of Things to predict heart diseases.

## 3. Proposed method

Internet of Things (IoT) technology is an essential building block for innumerable real-time applications that facilitate interaction between humans and inanimate objects. When it comes to collecting, storing, and managing the vast amounts of data produced by Internet of Things devices, the healthcare system faces considerable obstacles. Some of the components of the suggested AI healthcare system for predicting the likelihood of cardiovascular illness are as follows: (1) a data gathering and acquisition layer; (2) data preparation. and (3) the layer for illness prediction that is depicted in Fig. 1.

### 3.1. *Collecting the data set*

The current study's target sample is comprised of 794 patients with heart attacks and congestive heart failure who were included through a hospital census in Germany in 1998. Out of this group, 524 individuals had heart attacks and 571 individuals had congestive heart failure. In order to enhance the prediction accuracy, this study employed a genetic method to tune the weights of an artificial neural network. We used Matlab 2022b confusion matrix and ROC diagram to compute and compare the outcomes after we built the prediction model. Fig. 2 shows that we used the minimum and maximum method to transform our input data to a zero and one range after collecting data from 794 cardiac patients at Hanover Hospital in Germany. The following stage involves obtaining the necessary neural network parameters via trial and error. These parameters include the number of intermediate layers, the transfer function selection for each layer, and the overall architecture of the neural network. According to Table 1, the outcomes of choosing the transfer functions for the neural network layers are correct.

In order to make predictions about the likelihood of heart disease, researchers looked at quantitative and qualitative variables found in the medical records of people who had suffered a heart attack or congestive heart failure. They started by recording 25 characteristics, but after consulting with an expert in internal medicine, they eliminated those that didn't significantly affect the likelihood of heart disease. 19 features from Table 2 were chosen as the most effective features for heart disease diagnosis; the features are listed in the order they appeared in Table 2. This ensures that the neural network will only use these features. A total of 497 cardiac patients had their values extracted from their medical records; 257 of those patients suffered a heart attack, and 240 had congestive heart failure. Normalizing data before utilizing it in the model is an important consideration during neural network training. When the range of input changes is large, the indicated action assists in training the model better and faster.

This study makes use of normalization, which allows for easier data comparisons and yields results according to formula (1) in light of the aforementioned circumstances and the reality that entering data in raw form decreases the network's speed and accuracy.

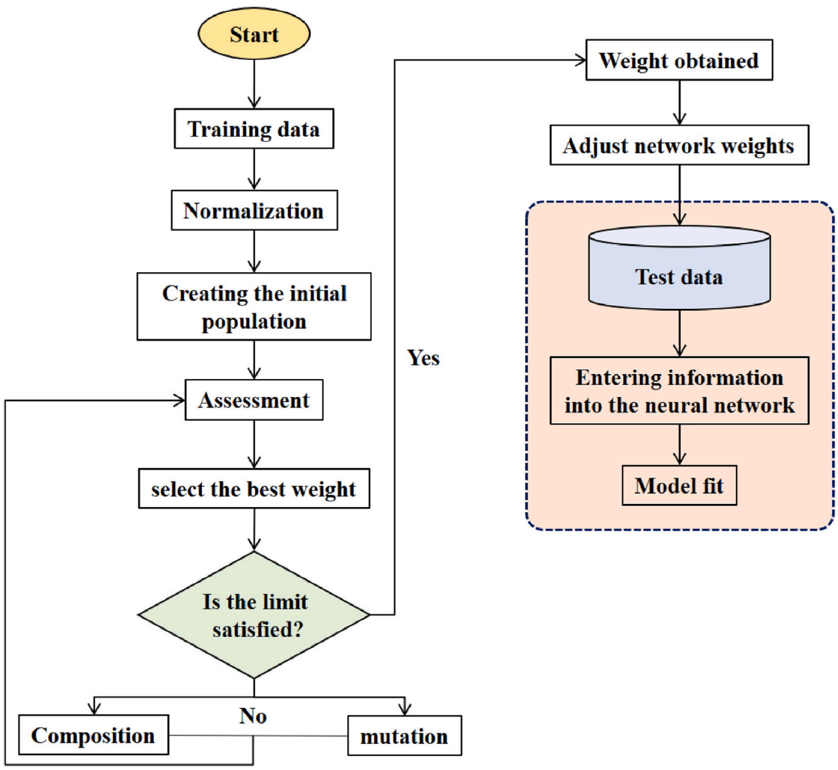



**Fig. 2.** Model design steps.

**Table 1**
Transfer functions used in neural network.

| First layer transfer function | Second layer transfer function | MSE |
|---|---|---|
| Sigmoid tangent | Sigmoid tangent | 0.06 |
| Sigmoid tangent | Sigmoid logistic | 0.04 |
| Sigmoid logistic | Sigmoid tangent | 0.05 |
| Sigmoid logistic | Sigmoid logistic | 0.25 |

**Table 2**
Features used in this study.

| Characteristic | Description |
|---|---|
| target | With 0 being no and 1 being yes, this is the expected status of CVD |
| thal | A normal score is 4, a fixed score is 7, and a reversible score is 8 |
| Age | Year of patient's birth |
| CA | Major arteries colored using fluoroscopy, numbered 0–4 |
| sex | male: 1 female: 0 |
| t.halach | Peak heart rate measured |
| slope | Exercise peak slope of the T-segment (unsloping = 1, flat = 2, and down sloping = 3) |
| f.s.b | Value more than 130 mg-dL for fasting blood sugar (false:0, true:1) |
| Old.peak | Enhanced ST Depression Caused by Exercise |
| Trest.bps | Myocardial relaxation time |
| Ex.ang | Heart attack caused by physical exertion (1 = affirmative, 0 = no) |
| c.h.o.l | Value of cholesterol |

$$\text{Normalized data} = \frac{\textit{Minimum data} - \textit{amount of data}}{\textit{minimum data} - \textit{maximum data}} \tag{1}$$

The data set includes the lowest and highest values for each variable, respectively. The input of the neural network is the newly acquired values after data normalization. To determine the average error in the target network, the Mean Square Error (MSE) approach is employed. The estimate with the smallest MSE is chosen using this parameter. The first layer of the neural network transfer function employed the sigmoid tangent function, and the second layer used the sigmoid logistic function. The sigmoid and tangent functions are commonly employed in the analysis of nonlinear situations, which is why they are utilized here. It was also shown that the MSE error of the neural network with two middle layers rose during the investigation. Our neural network now contains one middle layer thanks to this study, and we trained it with a thousand EPOCHs. The electronic clinical data (ECD) is another source of information. It contains the patient's medical history, whether it's a smoking or diabetes history, as well as reports on observations and complete clinical (laboratory) tests that can help with illness prognosis and A database in the cloud holds it. The next step is to use the genetic algorithm's training to determine the network's weights; after that, the neural network is fed the weights it needs to produce the desired output. In this study, we should employ the chromosomal genes as the weights and biases of our network, since the genetic algorithm trains on chromosomes and genes [43,44]. What follows is an explanation of each of these stages. An optimization technique that makes use of neural networks is the genetic algorithm. By 1961, a more refined variant of the genetic algorithm had been developed. A variety of complicated optimization problems have been successfully solved by the genetic algorithm with only three basic genetic operations: selection, combination, and mutation [45]. Convergence probability decreases the local optimum, and the evolutionary algorithm simultaneously attends to several places in the research space. The effectiveness of a genetic algorithm is sensitive to the values of its various parameters.

#### *3.1.1. Combination*

If you combine two answers, you get a one-point combination. To begin, a random integer between 1 and the number of variables (NPar) is chosen. Then, the offspring are created in a manner that the first child receives a random number of genes from their parents while the second child receives a random number of genes from their parents.

#### *3.1.2. Mutation*

In order to generate a new population in subsequent generations, the mutation operator takes the population into account and multiplies it by the mutation probability. Afterwards, a matrix is formed at random between varmin and varmix during the mutation step. Here, he assessed the neural network using the confusion matrix; we then use this matrix to determine the specificity, sensitivity, and accuracy metrics. Here, sensitivity refers to a test's capacity to detect heart attacks, specificity to identify congestive heart failure, and accuracy to distinguish between heart attacks and congestive heart failure is the test's capacity to do just that. By combining the evolutionary algorithm with the neural network, we were able to improve the weights and achieve higher accuracy [46]. We documented the results in a table for comparison after collecting the values of sensitivity, feature, and accuracy of the neural network.

Table 3 shows that in a state with six neurons, the neural network is generally accurate, sensitive, and specific; however, when using a combination of the genetic algorithm and the neural network, the state with five neurons yields the best accuracy. The models' ability to differentiate between healthy and sick individuals was evaluated using the area under the curve and disturbance matrices.

Two metrics, specificity and sensitivity, are utilized in the area under the curve and disturbance matrix diagrams.

### 3.2. Data preprocessing layer

Due to the inherent irregularity, incompleteness, and noise in real-world data, data preparation is now an essential step in deploying artificial neural networks. Data normalization, feature selection, and missing data management are necessary for efficient cardiac disease prediction using cardiac disease datasets. When it comes to heart disease prediction, data acquired from wearable sensors might be skewed due to signal deviations including missing values and noise, which can lead to inaccurate predictions or even erroneous results. The dataset was pre-processed to improve its quality and get it ready for effective analysis before the model was trained. In doing so, we had to scale features, find and remove outliers, encode categorical variables, and reduce dimensionality using methods like principal component analysis (PCA). Furthermore, data augmentation techniques were employed to enhance the model's robustness and diversify the dataset. This research makes use of a popular data filtering technique known as the Kalman filter [47–49], which efficiently eliminates noise, inconsistencies, and duplicate entries. Its low computational requirements are a result of its simplicity [50]. This unsupervised filtering technique is designed to work with data from real-time sensors and produce noise-free results that are closer to the actual sensor readings [51]. If any values are missing from the structured data set, the second filter will fill them in using the median and mean of the available data.

### 3.3. Fuzzy inference system

The integration of a fuzzy inference system (FIS) into the prediction model improved interpretability and allowed for intelligent decision making. To better analyze the intricate correlations between input variables and heart disease outcomes, FIS use fuzzy logic to handle the inherently uncertain and ambiguous medical data. Using fuzzy rules based on expert knowledge and data-driven learning, the fuzzy inference engine is built to generate explicit predictions. The fuzzifier applies the appropriate fuzzy set to clear input; this procedure is called fuzzification. The inference engine then uses a knowledge base of fuzzy conditional rules to approximate the values of the output variable based on the specialized knowledge, translating the input variable values to linguistic values. Databases and rule bases are two components of domain information that must be utilized by the knowledge base. Linguistic control rules are stored in the database, whereas domain expertise is housed in the rule base. If numerical data output is needed in addition to linguistic values, the resultant fuzzy set can be "dephased" to include clear data. Here we describe method 1, a Fuzzy Inference System (FIS) method that uses patients' health data to classify their risk of heart disease.

***Algorithm 1: Fuzzy system optimization of patients' health data***

*Step 1: identifies the fuzzy system's inputs and matching n1 member functions.*
*Step 2: Using n1 (ECG1), n1 (MaxHeartRate1), and n1 (blood pressure 1) as n1 (normal), n1 (low), or n1 (high), determine the risk status for heart disease.*
*Step 3: If the level of health risk is n1 (high),*
*3.1 Use SPARK as the RTA to send a warning to GD*
*3.2 The state of Puid's health risk in CS*
*Step 4: If not, send CS the Puid health risk status.*
*Step 5: Complete the procedure*

The member functions take in raw data like maximum heart rate, electrocardiogram (ECG), and blood pressure and convert it into fuzzy sets with fuzzy value ranges [52,53]. The fuzzy inference system's ability to forecast cardiac illnesses is illustrated in Fig. 3. Patients' health data is used to maximize their resources through the fuzzy inference system, which takes the created fuzzy sets as input. The fuzzy inference system's language variables and fuzzy set are displayed in Table 4. Organ function and blood pressure range are displayed in Table 5.

An appropriate approximation reasoning approach is supplied in the knowledge base as fuzzy conditional rules, which are used to map the value connected to the values of the output variable's language from the input variable. Classification of the outcomes is dependent on the member functions and fuzzy rule functions that make up the rule base. Patients who are at danger receive this alert,

**Table 3**
Comparison of the confusion matrix in different modes.

| Artificial neural network | | | | Combination of genetics and neural network | | | |
|---|---|---|---|---|---|---|---|
| Nu. of neurons in the middle layer | Accuracy (%) | Specificity (%) | Sensitivity (%) | Nu. of neurons in the middle layer | Accuracy (%) | Specificity (%) | Sensitivity (%) |
| 3 | 89 | 91 | 88 | 3 | 97.5 | 98.1 | 96.8 |
| 4 | 87 | 87 | 88 | 4 | 94.5 | 92.2 | 96.9 |
| 5 | 86 | 83 | 89 | 5 | 97.7 | 97.22 | 98.5 |
| 6 | 89.5 | 90.6 | 88.3 | 6 | 95.5 | 94.2 | 96.8 |
| 7 | 85 | 83 | 88 | 7 | 95 | 95.6 | 94.3 |
| 8 | 87 | 89 | 85 | 8 | 95.5 | 93.8 | 97.3 |
| 9 | 89 | 85 | 88 | 9 | 85.6 | 94.8 | 75.6 |
| 10 | 89 | 89 | 89 | 10 | 95.2 | 96.2 | 94.2 |

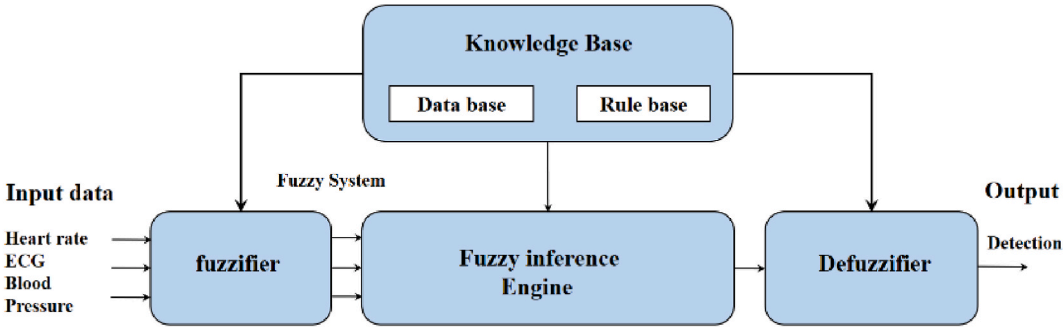



**Fig. 3.** Fuzzy inference system for predicting heart diseases.

**Table 4**
Fuzzy set and linguistic variable comprise the fuzzy inference system.

| Language Variable | Fuzzy Set |
|---|---|
| maximal heart rate | Norm. – H.risk – L.risk |
| E.C.G | Norm. – H.risk – L.risk |
| blood of pressure | Norm. – H.risk – L.risk |

**Table 5**
Organ function and blood pressure.

| Participant Role | Rate |
|---|---|
| Low | 30/85–65/110 |
| Norm | 80/110/70/130 |
| High | 100/140 and above |

and their total risk status is saved in the cloud for further evaluation. The following prediction layer does further analysis on data from patients who are deemed to be at high risk for cardiovascular disease.

### *3.4. Artificial neural networks*

Modern computing methods and systems for machine learning, knowledge presentation, and application of acquired information to forecast the output reactions of complex systems are sometimes referred to as neural networks or artificial neural networks (ANN). The core concept of these networks is based on principles that are similar to those of the biological nervous system, which processes information and data in order to learn and generate new knowledge [54]. Developing novel frameworks for the data processing system is

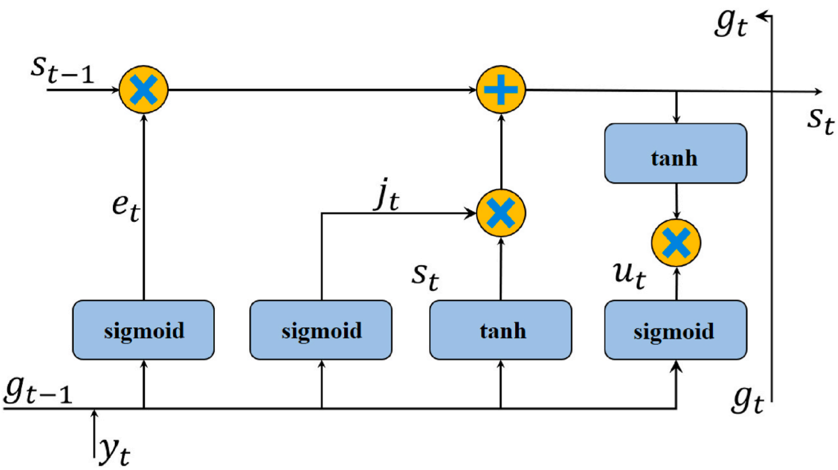



**Fig. 4.** General model of LTM.

central to this concept.

Typically, the input temporal data is too much for CNN and DNN to handle. Artificial neural networks excel in domains that deal with sequential inputs, including text, audio, and video. An integral part of artificial neural network (ANN) architecture, a cyclic connection updates the current state based on input and past states [55,56]. Recurrent cells make up ANNs' hidden or recurrent layers. The present input, which includes feedback connections and previous states, affects the feedback cells' states. It is possible to create several ANNs by arranging the recurrent layers in various ways. Thus, ANNs are distinguished by their network architecture and recurrent cells. Various cells and their interconnections impact ANNs' capabilities. Full ANNs and selective ANNs, which use traditional recurrent units like sigma cells and tanh cells, have been quite effective in certain cases. It is challenging to find meaningful information with large gaps between related input data, which is why ANNs with normal iterative cells can't manage long-term dependencies.

### 3.5. Using LTM for coronary heart disease prediction

After devoting a lot of time to studying ANNs for sequence learning, the idea of using long-term memory (LTM) to address "short-term dependence" emerged. LSTMs [57] are an improved kind of ANN that can capture long-range interdependence and nonlinear dynamics by substituting hidden layer memory cell units for recurrent units. You may see the general LTM model in Fig. 4. To further leverage the temporal relationships and sequence patterns in heart health data, a prediction model based on long-term memory (LTM) was suggested, in addition to classic neural network approaches. The LTM design takes its cues from ANNs and MENs, which are able to preserve long-range relationships through the use of memory cells. As a result, the model can better anticipate the onset of cardiac disease and account for small changes in patient health markers over time.

The ability to store and retrieve data is what makes memory cells so useful for understanding relationships between different times. There are three gates the input gate, the output gate, and the forget gate that control it, and its connections keep the network's transient state. In long short-term memories (LTMs), the efficiency of each memory cell is controlled by the gate process. The activation of the gate causes the LTM to update the state of its cells [58]. The memory cell communicates with the rest of the network using input and output gates. Additionally, the memory cell now has an amnesia gate that can transmit neuronal heavy output data. The high degree of activity of the input unit dictates the amount of data stored in memory. When it's high, the data is stored in the memory cell. Also, the next neuron receives data from an extremely active input unit. On the other hand, memory cells are used to store input data with a high weight. Like ANN, LTM activation is determined in a similar way according to Eqs. (2)–(6) [59,60].

$$e_t = \partial\left(V_e y_t + V_{ge} g_{t-1} + a_e\right) \tag{2}$$

$$j_t = \partial\left(V_j y_t + V_{je} g_{t-1} + a_j\right) \tag{3}$$

$$u_t = \partial(V_u y_t + V_{ue} g_{t-1} + a_u) \tag{4}$$

$$\check{s}_t = tan.h(V_s y_t + V_{se} g_{t-1} + a_s) \tag{5}$$

$$s_t = e_t \times s_{t-1} + j_t \times s_t \tag{6}$$

Here, e, j, u, and s stand on behalf of the input gate, the forget gate, and the vectors that activate cells, correspondingly. Their weight matrices and bias vectors are V (e, j, u, s) and a (e, j, u, s), respectively [61,62]. Hidden value is represented by g. According to Eqs. (7)–(11), the value of $y_Z$ at time t is the input to the memory cell, and s $\widetilde{Z}$ and *st* represent the units of memory, respectively.

$$e_t = s.wish\left(V_e y_t + V_{ge} g_{t-1} + a_e\right) \tag{7}$$

$$j_t = s.wish\left(V_j y_t + V_{je} g_{t-1} + a_j\right) \tag{8}$$

$$u_t = s.wish(V_u y_t + V_{ue} g_{t-1} + a_u) \tag{9}$$

$$\check{s}_t = tan.h(V_s y_t + V_{se} g_{t-1} + a_s) \tag{10}$$

$$s_t = e_t \times s_{t-1} + j_t \times s_t + tan.h \tag{11}$$

### 3.6. Multidirectional LTM-based heart disease prediction

An LTM cell's limitation is that it can only influence data from the past, not data from the future. Proposed were bidirectional recurrent neural networks with two separate LTM hidden layers that produced similar results when directed in opposite directions. In this method, the output layer makes use of both historical and prospective data. The forward direction of Mu-LTM is represented by *gi*→=(g1→,g2→,⋯, *gn* →) and the backward direction by *gt*↽=(g1↽,g2↽, …, *gn* ↽), where =(1,2, …, x*n*). The combination of *gi*→ and *gt*↽produces the final output x*Z*, and the sequence of final outputs is x=(x1,x2, …x*Z* …, x*n*). The training dynamics and task performance of deep networks are heavily impacted by the activation function that is chosen. The generic model's cell divergence problem is solved by inserting a leaky rectified linear unit after output gating and including a tan.h activation function in the cell propagation. Taken as a whole, they demonstrate the absence of negative outputs and the decrease in prediction oscillation. The suggested model's LTM cell architecture and Mu-LTM are displayed in Fig. 5. Their weight matrices and bias vectors are V (e, j, u, s) and a (e, j, u, s), respectively. Hidden value is represented by g. The input to the memory cell at time t is denoted by y*Z*, the current and previous memory cell units are denoted by s*Z*, and the final output is denoted by x*Z*.

## 4. Experimental results

The goal of this research was to assess the efficacy of sequential prediction models using heart disease datasets in conjunction with other artificial neural network models, such as the general LTM model, the fuzzy inference system, Mu-LTM, and so on. In the initial collection related to cardiovascular disease, there are 404 records with 14 features and 312 records with 13 features. To ensure the suggested neural network model could withstand the test, these records were increased in size to 200,000 records using the data generating tool Mockaroo. Based on this, the system is defined with 200,000 records, with 72 % used for training and 28 % for testing. Two hidden layers and seven units make up the four-layer neural network model suggested here. With a starting weight value ranging from 0.12 to 0.22 and a removal value of 21 %, the number of nodes is automatically determined according to accuracy standards.

Both the decay and learning rates are 0.98 and 0.18, respectively. With a batch size of 256 and a momentum value of 0.83, the number of periods can be adjusted.

### *4.1. Performance evaluation*

Previous work on patent classification has had some issues, one of which is the fact that various evaluation criteria have been employed to present classification findings. One or more labels can be applied to an output simultaneously in multi-label classification, in contrast to single-label classification. Consequently, evaluating the performance of multi-label classification becomes more challenging and complex as the number of labels increases, as is the situation with patent categorization. Additionally, there is a significant imbalance in the distribution of patent documents among the various IPC categories. Some of the earlier evaluation criteria may not have been appropriate for this particular issue. In any case, we do our best to present the assessment metrics used in earlier patent studies so that you can compare and contrast. Three distinct models, including a general LTM for disease prediction, were used to examine the following data after the first data preprocessing activities, which include data cleaning and data filtering, were completed. To maximize the resources of patients' risk status for heart disease, the second model of the fuzzy inference system uses the LTM model for prediction, while the fuzzy inference system itself optimizes the resources. In order to forecast cardiac problems identified by FMu-LTM, the third model the one that has been suggested integrates the fuzzy inference system with LTM. The accuracy, precision, sensitivity, and specificity of these three models are assessed in relation to the patient's risk status for cardiovascular disease. Consequently, the final measurement takes into account the unequal distribution of data in each label and uses weights that are different for each label. Consequently, micro F1 measurements are commonly used to assess performance in cases with imbalanced

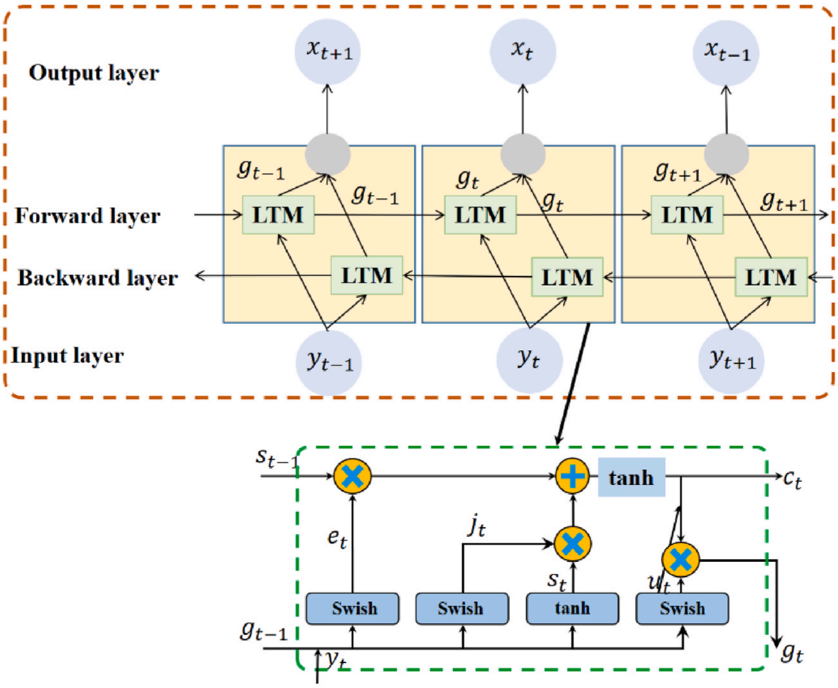



**Fig. 5.** A proposed hybrid model for cell LTM and Mu-LTM.

data [63]. Let TP, FP, TN, and FN represent the number of true positives, false negatives, and correct results, respectively, given n patents and m labels. According to Eqs. (12)–(14), This is how micro precision, recall, and measurement are computed [64].

$$Micro\ Precision = \frac{\sum_{j=1}^{m} TP_j}{\sum_{j=1}^{m} TP_j + \sum_{j=1}^{m} FP_j} \tag{12}$$

$$Micro\ Recall = \frac{\sum_{j=1}^{m} TP_j}{\sum_{j=1}^{m} TP_j + \sum_{j=1}^{m} FN_j} \tag{13}$$

$$Micro\ F1 = \frac{2 \times Micro\ Precision \times Micro\ Recall}{Micro\ Precision + Micro\ Recall} \tag{14}$$

The average number of labels in the ranking list that the estimated probabilities needed to calculate is shown by the coverage error [65]. Eqs. (15)–(17) are used to determine the direction of all positive real labels:

$$Coverage\ Error = \frac{1}{m}\sum_{j=1}^{m} \max rank_{ji} \tag{15}$$

$$rank_{ji} = [g : J_{gi} \geq J_{gi}] \tag{16}$$

$$Micro\ F1 = \frac{2 \times Micro\ Precision \times Micro\ Recall}{Micro\ Precision + Micro\ Recall} \tag{17}$$

The average accuracy score is connected with L.RAP. But rather than relying on memory and precision, it employs the idea of label ranking [66]. According to Eq. (18), it evaluates the capacity of the classifier to rank the appropriate labels associated with each sample:

$$L.R.A.P = \frac{1}{m}\sum_{j=1}^{m} \frac{1}{Li} \sum_{j:Lij=1} \frac{Lij}{rank_{ji}} \tag{18}$$

The CLEP-IP competition's assessment tools were used in some earlier studies. To clarify, for every document, you should initially forecast k labels (for example, 1, 4). Then, as seen below, you should compute the precision, recall, and F1 measure at top-k for every prediction [67]. Eqs. (19)–(22) for precision, recall, and F1 measures are reported in Label 1 above for comparative purposes.

$$Precision = \frac{correct\ predictions}{all\ predictions} \tag{19}$$

$$Recall = \frac{correct\ predictions}{all\ relevant\ documents} \tag{20}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{21}$$

$$Specificity = \frac{true\ negative}{false\ positive + true\ negative} \tag{22}$$

**Table 6**
Evaluation of the results for the performance indicators of recall, precision, and F1.

| Data (%) | F1 | | | recall | | | precision | | |
|---|---|---|---|---|---|---|---|---|---|
| | LTM | FMu-LTM | This Work | LTM | FMu-LTM | This Work | LTM | FMu-LTM | This Work |
| 10 | 89.02 | 93.21 | 93.10 | 93.01 | 93.25 | 93.74 | 93.14 | 93.27 | 93.26 |
| 20 | 89.24 | 94.41 | 95.23 | 93.18 | 94.26 | 95.46 | 93.19 | 94.76 | 95.06 |
| 30 | 89.62 | 95.23 | 95.43 | 93.24 | 95.28 | 95.87 | 93.22 | 95.36 | 95.27 |
| 40 | 89.64 | 95.51 | 96.12 | 93.32 | 95.64 | 96.03 | 93.64 | 95.48 | 96.17 |
| 50 | 89.67 | 96.20 | 96.24 | 93.46 | 96.37 | 96.24 | 93.68 | 96.31 | 96.29 |
| 60 | 89.70 | 96.32 | 96.29 | 93.51 | 96.85 | 96.59 | 93.72 | 96.39 | 96.71 |
| 70 | 89.72 | 96.45 | 97.15 | 93.56 | 96.89 | 97.26 | 93.89 | 96.48 | 97.42 |
| 80 | 89.75 | 96.48 | 97.68 | 93.74 | 96.97 | 97.52 | 93.94 | 96.58 | 97.58 |
| 90 | 90.05 | 96.64 | 97.75 | 94.21 | 96.99 | 97.89 | 94.09 | 96.89 | 97.89 |
| 100 | 90.21 | 97.03 | 97.94 | 94.36 | 97.06 | 97.98 | 94.24 | 97.28 | 97.92 |

The purpose of this experiment is to test the suggested system with various sample sizes (ranging from 10 % to 110 %) in relation to standard LTM models, fuzzy inference systems that incorporate LTM, and the suggested technique itself. Tables 6 and 7 display the results of the accuracy, precision, recall/sensitivity, specificity, and F1 score evaluations of the LTM, FMu-LTM, and suggested models, respectively.

Analyses of the Coverage Error, accuracy, precision, recall, specificity, and F1-score shown by LTM, FMu-LTM, and the suggested approaches are presented in Fig. 6. As part of the experiment, the three models under consideration had their records raised from 10 % to 100 %.

After comparing the proposed method to the LTM and FMu-LTM models using metrics like Coverage Error, accuracy, precision, recall, specificity, and F1-score, it becomes clear that the recommended model performs better. Table 8 shows a comparison of the suggested model's overall performance with that of the LTM and FMu-LTM methods.

The suggested model's performance results, based on previous evaluations, are displayed in Fig. 7.

After looking at a number of performance metrics, it's safe to say that the suggested fuzzy inference system using the FMu-LTM model does better than competing models. When there is a large gap between related input data, recurrent neural networks struggle to handle long-term reliance, but they excel at processing sequential data. The traditional ANN has its flaws, however LTM was suggested as a solution. Using a memory cell's hidden unit, LTM stores previously input data. A unidirectional long short-term memory (LTM) keeps track of previous data. Nevertheless, bilateral LTM is able to process both past and future content because it uses two hidden layers of LTM that provide similar output but in different directions. On the UCI heart disease dataset, which contains 200,000 records, experiments were carried out with several models for risk prediction of heart disease, including general LTM models, a fuzzy inference system combined with LTM, and the suggested FMu-LTM models. The combined use of LTM and the fuzzy inference system results in an accuracy of 97.98 %, surpassing the 94.57 % achieved with the general LTM model. By combining FIS with FMu-LTM, the suggested method achieves a 97.98 % accuracy rate, which is higher than the last two models. Precision, recall, specificity, and F1 score are all areas where the suggested approach outperforms the other two models. The activation function that is used has a significant impact on deep neural networks; the sigmoid and tanh functions are used in the general LTM model. With meta-parameter adjustment, the suggested approach achieves better results after modeling both LTM cells with swish and tanh activation functions.

### 4.2. *Evaluation of optimization criteria through comparative analysis*

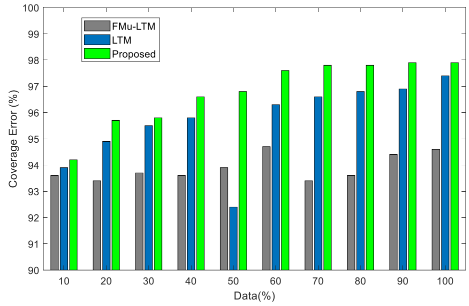
Here, we compare the Proposed Method with two similar cloud-based approaches in order to delve deeper into performance indicators. The Proposed Method is the product of our research. A solution for remote heart rate monitoring was created by researchers in Ref. [18] utilizing an agent-based Internet of Things (IoT) fog architecture. With this method, individuals with cardiovascular disease can be monitored and tracked from anywhere, which improves accessibility and convenience. The patient's heartbeat can be recorded, located, stored, and analyzed using the proposed technology. A requirement for accelerated decision-making can also arise in an emergency. Beyond the four walls of a hospital, this technology has numerous potential applications for healthcare providers. Based on five well-known supervised learning-based machine learning algorithms, an earlier work [29] suggested a cloud-based architecture for early heart illness detection. The proposed method's delay analysis and comparison with other similar approaches are shown in Fig. 8. References [18,29] use two related techniques in this investigation. It is possible to show that the Proposed Method has lower latency than the FMu-LTM and LTM approaches.

Fig. 9 shows the results of a comparison evaluation with other comparable methods and an analysis of the runtime parameter of the Proposed Method. The use of two interrelated procedures in Refs. [18,29] allows us to see that the Proposed Method outperforms the LTM and FMu-LTM techniques in terms of execution time.

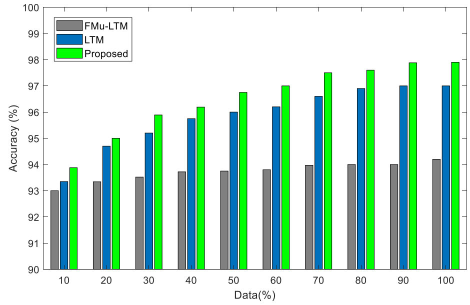
The experimental findings of the throughput parameter assessment on the Proposed technique and its comparison to other similar methodologies are shown in Fig. 10. The Proposed method outperforms the LTM and FMu-LTM approaches in terms of advanced throughput consumption, according to this study, which makes use of two interrelated methodologies [18,29].

**Table 7**
Evaluation of the results for the performance indicators of Specificity and Coverage Error.

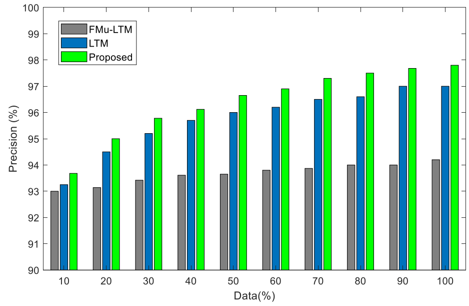
| Data (%) | Specificity | | | Accuracy | | | Coverage Error | | |
|---|---|---|---|---|---|---|---|---|---|
| | LTM | FMu-LTM | This Work | LTM | FMu-LTM | This Work | LTM | FMu-LTM | This Work |
| 10 | 90.14 | 94.33 | 94.22 | 94.13 | 94.37 | 94.86 | 94.26 | 94.39 | 94.38 |
| 20 | 90.36 | 95.53 | 96.35 | 94.3 | 95.38 | 96.58 | 94.31 | 95.88 | 96.18 |
| 30 | 90.74 | 96.35 | 96.55 | 94.36 | 96.4 | 96.99 | 94.34 | 96.48 | 96.39 |
| 40 | 90.76 | 96.63 | 97.24 | 94.44 | 96.76 | 97.15 | 94.76 | 96.6 | 97.29 |
| 50 | 90.79 | 97.32 | 97.36 | 94.58 | 97.49 | 97.36 | 94.8 | 97.43 | 97.41 |
| 60 | 90.82 | 97.44 | 97.41 | 94.63 | 97.97 | 97.71 | 94.84 | 97.51 | 97.83 |
| 70 | 90.84 | 97.57 | 98.27 | 94.68 | 98.01 | 98.38 | 95.01 | 97.6 | 98.54 |
| 80 | 90.87 | 97.6 | 98.8 | 94.86 | 98.09 | 98.64 | 95.06 | 97.7 | 98.7 |
| 90 | 91.17 | 97.76 | 98.87 | 95.33 | 98.11 | 99.01 | 95.21 | 98.01 | 99.01 |
| 100 | 91.33 | 98.15 | 99.06 | 95.48 | 98.18 | 99.1 | 95.36 | 98.4 | 99.04 |



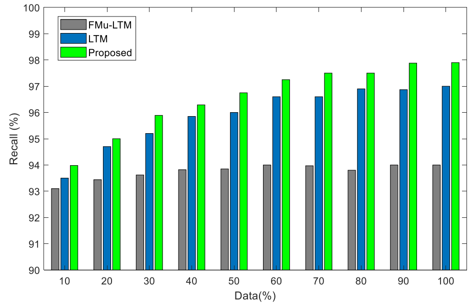

a) Evaluation results for Coverage Error index.



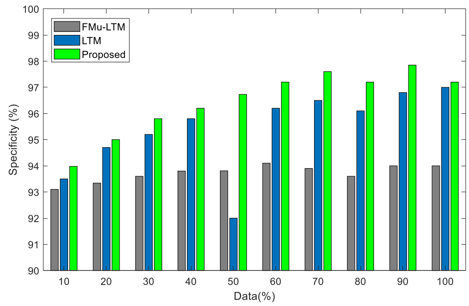

b) Evaluation results for accuracy index.



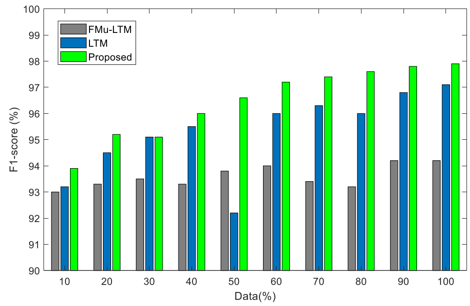

c) Evaluation results for precision index.




d) Evaluation results for recall index.




e) Evaluation results for specificity index.




f) Evaluation results for F1-score index.

**Fig. 6.** Analysis of coverage error, accuracy, precision, recall, specificity and F1 score by LTM, FMu-LTM and proposed approaches.

**Table 8**
Evaluation of the suggested system's performance in comparison.

| performance criteria (%) | LTM | FMu-LTM | This Work |
|---|---|---|---|
| Coverage Error | 96.32 | 97.04 | 99.23 |
| Accuracy | 96.31 | 97.06 | 99.27 |
| Precision | 96.35 | 97.08 | 99.65 |
| Recall | 96.38 | 97.06 | 99.28 |
| Specificity | 96.78 | 97.05 | 99.52 |
| F1-score | 96.94 | 97.08 | 99.19 |

## 5. Conclusion

With the goal of reducing medical mistakes through better prediction and decision-support system design, this study optimizes resources in IoT-based smart electronic health systems to forecast cardiac diseases using artificial neural networks. For the prediction task, it is suggested to use a Recurrent Neural Network with a Bidirectional Long Short-Term Memory (LTM) and a Fuzzy Inference System (FIS). Outperforming existing advanced models for heart disease prediction, the suggested approach achieves a precision score of 97.94 %, an accuracy of 97.82 %, a specificity score of 97.76 %, and an F1 score of 97.63 %. With the vast untapped potential of deep learning models still to be found, predictive analytics are already driving this and other areas of healthcare research. Using a patient's current health status and the advise of their cardiologist, the model can be enhanced to automatically generate dietary and activity

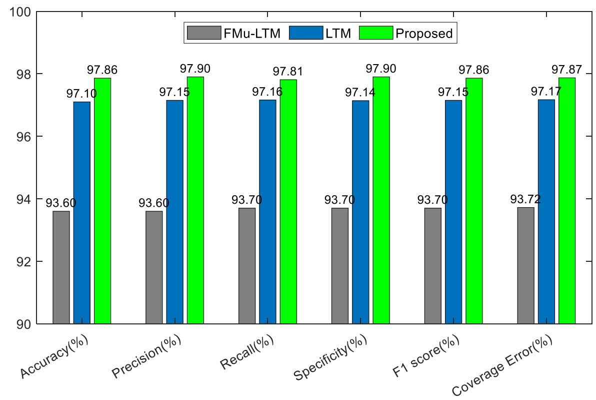



**Fig. 7.** The suggested method's overall performance outcomes.

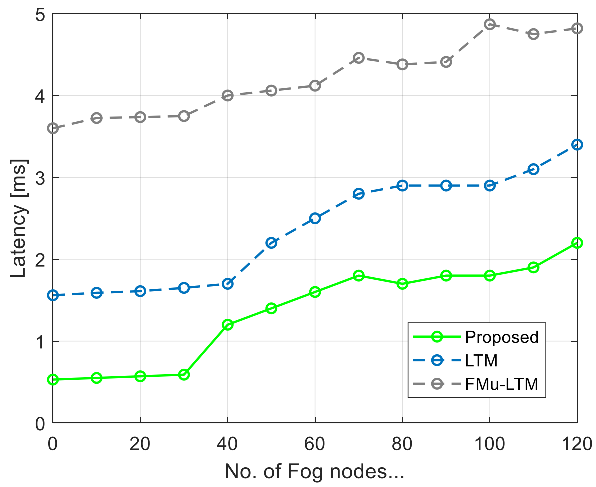



**Fig. 8.** Comparison of the delay parameter between FMu-LTM and LTM.

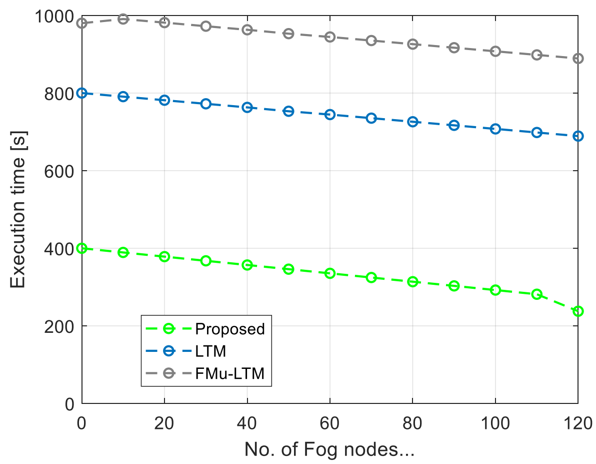



**Fig. 9.** Comparison of runtime parameters between FMu-LTM and LTM.

recommendations tailored to the patient's specific needs. Internet of Things (IoT) devices gather data for the proposed intelligent heart disease prediction system, while the cloud handles much of the other heavy lifting. Future work can expand this to fog/edge computing, which would allow for the execution of time-sensitive analytical activities in the fog/edge layers, so avoiding the cloud's

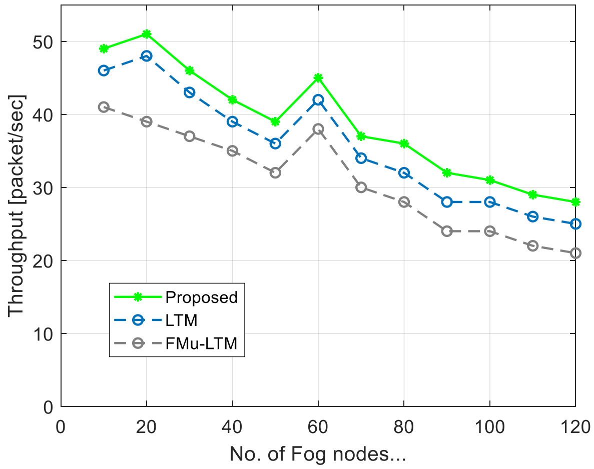



**Fig. 10.** Throughput parameter comparison using LTM and FMu-LTM.

inherent restrictions such increased latency and bandwidth utilization during Internet management. With the use of fog/edge computing, healthcare organizations can improve the quality of service they provide by making more precise and timely predictions about diseases, responding more quickly, and making more agile decisions.

## Ethics statement

Ethics committee review and/or approval was not required for this study, as no animal or human-based experiments/case studies were used.

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## Data availability statement

The authors do not have permission to share data.

## CRediT authorship contribution statement

**Yuxuan Liao:** Software, Resources. **Zhong Tang:** Writing – original draft, Software, Methodology, Formal analysis. **Kun Gao:** Writing – review & editing, Visualization, Validation, Resources, Investigation. **Mohammad Trik:** Project administration, Investigation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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