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Research Article

Mobile Cloud Healthcare Systems using Fuzzy Rules based Neural Networks Classification

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ABSTRACT

Computer systems have many advantages over traditional emergency systems, such as the ability to quickly respond to changing circumstances and the reliability of never going down if a server experiences technical Difficulties, This article will introduce the Mobile cloud computing for emergency health care model (MCCEH) with use of a cloud computing server, with the goal of reducing reaction time to save a patient's life by offering services connected to healthcare in emergency instances. When a health emergency arises or a car accident takes place, The MCCEH model will let look up the closest medical facility in their area who specializes in a certain area, and the search results will include the specialists' schedules and whether or not they are available right now. People can then make decisions about which specialist or hospital to visit based on the information they find there, as well as check reviews and ratings. Using an Internet of Things (IoT)-based body sensor database & medical sensors, a novel systematic technique is applied for the diabetic illness and the associated medical data obtained in this study. In addition, a novel classification technique, Fuzzy Rule oriented Neural Classifier, for making accurate diagnoses of diseases and their severity.

Keywords: Mobile Cloud Computing, Fuzzy Logic, Edge Devices, ANFIS, and Healthcare Systems

I. INTRODUCTION

A portable agent is a program that can easily hop from one host to another in a standardized or decentralized network to provide information to users. Numerous healthcare-related applications make use of the mobile paradigm, including those dealing with patients' medical records, the retrieval of clinical data, the incorporation of data related to their health, real-time assistance, telemedicine, the acquisition of clinical data, the management of patients, and so on [1]. The complexity and advancements in wireless agent technologies have also led to an increase in the corresponding security concerns. Since mobile agents operates in an unsecured setting, protecting their data during transmission and storage is of the utmost importance. Key security considerations with mobile agent migration include data integrity, data confidentiality, authorization, on-repudiation, disruption of service, and gaining control [2]. There are many indisputable advantages to using Mobile Cloud Computing (MCC) for healthcare already, but its expansion is being stymied by concerns about patient privacy and security. For its wide and effective use, these concerns need immediate address. Health information must be protected on a global, regional, and local scale [3]. Implementing the necessary security procedures for protection against security breaches & vulnerabilities is essential in order to make full use of health services. The suggested FSMC is studied via simulations and tests under a variety of operational scenarios to determine its viability and resilience [4]. In spite of the existence of friction torques, the findings demonstrates that the suggested FSMC with LiDAR data in feedback leads to outstanding control performance. The developed ADDMR model was also proved to be a good match for the real ADDMR model via simulations and testing. When it comes to providing healthcare, application development is often regarded as the most difficult and time-consuming stage [5]. Higher upkeep is needed because of the complexity and time commitment involved. Medical software must adhere to stringent regulations, and its potential user base, service types, and associates are all enormous. Using monolithic as well as service-oriented

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architecture (SOA) to design healthcare applications is problematic because it leads to issues with accessibility to services, remote utilization of services, service provisioning, adaptability, and healthcare system integration [6, 7]. Because of this, healthcare systems that are simpler in design and implementation, with lowerer costs associated with requirement management and agile testing, are needed. As part of the fourth industrial revolution, or Industry 4.0, the current trend in business is the digitalization of manufacturing processes utilizing contemporary information and communication technology. Particularly in demand are applications that bridge the gap between the IT and OT sectors [8]. Evidence from the field suggests that in Slovakia and neighboring countries, there is a scarcity of professionals in the labor market who are qualified to link PLCs to ICTs (cloud, online, mobile apps, etc.). However, other European nations are now seeing the effects of this issue [9]. The healthcare monitoring system may be adapted to take use of cloud computing, a relatively new and promising technology. To keep patients' protected health information and seek assistance in an emergency utilizing a cloud-based virtual server, a recent poll found that all healthcare companies require the assistance of cloud computing. Cloud-based BSN monitoring of patient health status is essential for an efficient monitoring system [10]. The cloud here functions as a virtual server, storing sensitive patient data on an external server, which poses significant security and privacy risks. The medical facility makes use of many methods for keeping an eye on cloud-based medical records. To better simplify medical data transfers between patients and healthcare providers, EHRs have increasingly being stored in mobile cloud settings, where mobile devices are connected with cloud computing [11]. This cutting-edge stratesgy makes it possible to provide healthcare at a lower operating cost, with great flexibility, and with access to electronic health records. However, questions concerning the safety of electronic health records and other sensitive information are raised by this new paradigm. The question of how to securely and reliably transfer electronic health records (EHRs) amongst mobile users in the cloud is complex [12]. The Web of Things (IoT) has expanded over the course of decades to include several sensor modalities, and it is becoming more advanced and cheaper all the time. Numerous studies have integratesd a wider range of IoT devices into cutting-edge healthcare systems to facilitate applications like activity recognition, fitness support, vital signs surveillance, daily dietary tracking, as well as sleep monitoring [13]. Both specialized health sensors and general-purpose sensors that were not developed for health monitoring may be used to implement these crucial applications for disease prevention, diagnosis, and treatment. The constant vigilance required in conventional farming may be a hassle for farmers. Using a smartphone application, farmers may track environmental conditions like humidity, heat, as well as soil moisture that influence plant development via the Internet of Things (IoT) [14]. Timer controls for pumps in traditional watering systems are also not always feasible in actual usage. The use of biological signals has been on the rise in all emerging economies, and there is potential interest in incorporating them into healthcare administration structures. Biological signals need to be categorised at suitable stages, but the current system cannot offer higher-end help with the transmission of signals utilizing a communication channel. [15].

A novel mobile medical services app for monitoring, forecasting, and diagnosing dangerous illnesses is shown here; it makes use of Cloud and IoT technologies. A new public framework is created here. Using an Internet of Things (IoT)-based body sensor database and medical sensors, a novel systematic technique is employed for the diabetic illness and the relevant medical data is generated in this study. Severely. In addition, we suggest a novel classification technique, Fuzzy Rule oriented Neural Classifier, for making accurate diagnoses of diseases and their severity.

This paper's remaining sections are structured as follows: The literature review in this field is presented in Section 2. In Section 3, we discuss the proposed system in depth and explain the architecture's functioning. The experimental findings and rationale for the advancement are presented in Section 4. In Section 5, we draw a conclusion and provide some suggestions for potential improvements.

II. RELATED WORK

The authors of [16] provide a Verifiable, Secure Mobile Agent Migrating paradigm built on two polynomials (t, n) as well as an edge secrets imparting strategy using Blowerfish encryption to ensure the secure transmission for information in clinical medical care.

Actual Modular Encryption Standard (MES) is discussed by researchers in [17] as a means to offer requirement-oriented security of medical data based on tiered modeling of the security mechanisms. Comparing the proposed work to other regularly used algorithms for health information security in the MCC context, the performance study demonstrates that the suggested work outperforms, both in terms of improved performance and supplementary qualitative security assuring measures.

The goal of the work presented in [18] was to construct trajectory-tracking of an automated dual drive mobile robot (ADDMR) in an environment of frictional torques using the proposed fuzzy sliding-mode control (FSMC). Models of the ADDMR's kinematics, dynamics, and actuators are first developed. A Bézier curves and a cubic time mapping are then used to determine the necessary route. The ADDMR's location is determined using the LiDAR point cloud data and the Monte Carlo Localization (MCL) technique. The proposed FSMC then employs fuzzy logic-inferred nonlinear sliding surfaces to eventually converge on the posture.

In [19], the authors provide a microservices architecture for building healthcare services in the cloud. Techniques based on micro services allower for loose coupling and granularity. Using the micro services approach described in this paper helps to improve productivity, scalability, and overall performance. This study establishes best practices for healthcare application cloud development and deployment. Therefore, it helps with system analysis and design. We offer quantitative and qualitative findings that demonstrates the benefits of the micro services methodology.

In order to teach students about modeling and controlling a mimicked discrete-event system with a programmable logic controller (PLC) application as well as the resulting interface to a cloud application, the study aimed to produce case studies that might be used in classrooms (see [20]). Three instances were constructed to showcase the work's objectives, which included the management of a discrete-event system through various programming methods and their interaction with the built cloud applications. These programs are for keeping an eye on data and taking action in case of an emergency in a discrete-event system. The supplied case studies are well suited for application in the realm of engineering education for the digitalization of manufacturing processes due to their features, which mix operational and informational technology. They may also be used to study the development for digital twins, which are virtual copies of physical ones.

According to the authors in [21], the purpose of this research is to have a conversation about the present approaches of using cloud computing in hospital health surveillance systems, and to provide a taxonomy of such methods. In addition, we explore the advantages and disadvantages of several healthcare monitoring system methods. Moreover, the article will shed light on data security rules, which may provide some administrators read-only access to all device settings and read-only or read-write access to a limited range of instructions. Different access profiles may be assigned to various administrators.

In [22], the authors propose a unique EHRs sharing architecture for mobile cloud computing that integrates block chain technology and its decentralized interplanetary file system (IPFS). To ensure the security of EHR transfers between patients and doctors, we develop a robust access control system using smart contracts. Using a mobile app and Amazon's cloud infrastructure, we show off a prototype of how the Ethereum blockchain may be used in a real-world data-sharing situation. The results from the field prove that our idea can be used to protect sensitive health data during transfers in mobile clouds. When compared to traditional models of data sharing, the advantages identified by the system evaluation and security analysis include a lightweight authorization architecture, decreased network latency, and increased security and privacy.

The authors of [23] compile a wide range of research on IoT-based sensor components and smart health monitoring systems. We classify and evaluate these works according to how they use data processing and classification strategies, as well as whether or not they rely on device-based approaches (i.e., usage of sensors worn or taken by the person) or device-free procedures (i.e., wireless sensors without the need to carry hardware). We focus on the innovative ways in which these methods might be combined to enable IoT networks for professional & commercial health monitoring. We also higherlight some of the gaps and possibilities that may be pursued in further studies.

In this study, we offer a framework for using sophisticated fuzzy logic to regulate the switching frequency of a pump in response to user-specified variables; sensors play a vital role in this architecture. We believe that our suggested concept has tremendous performance potential as an interface among sensors and the IoT. The suggested approach is contrasted with conventional methods of material transfer. The findings demonstrates a considerable decrease in both water use and irrigation duration [24].

In [25], the authors deal with hardware concerns by developing a four-layer approach for Hadoop-based systems. Lower-robustness Fuzzy Interface System Algorithm (FISA) is incorporatesd into the four-layer model, and transfers of reference health data acquired from different treatment facilities are performed in these layers. By including an activation function in the model's intermediate stages, this novel flanged system's performance can better account for the loss functions seen in biological data. Using a medical signal processing toolkit in MATLAB, we simulate the performance of the suggested model and find that FISA provides superior results in terms of signal quality, distance, and cost. In real-world scenarios, the suggested approach outperforms the status quo solutions by an average of 78%.

Authors' system in [26] guarantees only authorized gadgets communicate with the canonical mHealth service. To ensure the patient's privacy is maintained throughout the system, we take care of the issues associated with storing, retaining, and sharing data by leveraging blockchain. We suggest a mechanism for encrypting characteristics during the transmission, storage, or sharing of health information as an alternative to the standard blockchain's lack of privacy. The result is a system where the patient has complete control over who has access to their information and where that information remains private from beginning to finish.

Cascaded Long Short Term Memory (CSO-CLSTM) models, built on top of the Crowd Search Optimization method, were used to create a system for disease diagnosis by the group of researchers at [27]. CSO is applied to the CLSTM model's 'weights' and 'bias' parameters, allowing for more precise medical data classification. In addition, we apply the isolation Forest (iForest) method to eliminate outlier data. Incorporating CSO greatly enhances the CLSTM model's diagnostic accuracy. Medical records were used to verify the CSO-LSTM model's accuracy. Experiments showed that the described CSO-LSTM model had the highest accuracy (96.16 percentage points) in both the determination of cardiovascular disease and diabetes. As a result, the proposed CSO-LSTM model may serve as a trustworthy disease diagnosis tool in state-of-the-art healthcare networks.

According to the authors of [28], a Fuzzy Inference System (FIS-AFSA) based on the Artificial Fish Swarm Algorithm is presented as a decision maker. This method optimizes the fuzzy parameters using the AFSA algorithm. When traffic is strong, this strategy entails shifting certain delay-tolerant interconnections from a private server to a public one, which incurs costs. In terms of call blocking probability, throughput, and resource consumption, simulation results show that the proposed FIS-AFSA driven CAC scheme performs better than the Fuzzy based CAC technique.

A fuzzy rule approach is used to group researchers from [29] client systems. To guarantee security and address memory recycling concerns, the server produces an distributed common key using RSA. It improves the client's safety while using cloud storage. By using heuristic methods, it also improves the worldwide efficiency of data storage. Clients may efficiently search data stored in clusters through query using the K-nearest neighbor’s method. Power consumption and effectiveness are improved by the suggested load-balanced scheduling method. The simulation results show that the suggested system outperforms the state-of-the-art methods with regard of load balancing while maintaining a higher level of security.

Hyper ledger, the block chain technology used to create the system described in [30], offers anonymity and rapid reaction time, making it ideal for healthcare IoT settings. Utilizing fuzzy logic, this paper provides an adaptive safety system for block chain-based healthcare IoTs and networks, and gives a heuristic method to adaptive security that may be used to provide AAA services. The purpose of implementing FBASHI is to evaluate its safety and usability. In addition, we contrast this approach with other alternative block chain-based options.

III. PROPOSED WORK

A. Research Gaps

Despite the enormous number of data, machine learning techniques are playing an increasingly important part in the decision-making process. Defining data kinds like velocity, variety, and volume is an important part of adapting data analysis methodologies to unique domains. Models such as neural networks, classification trees, and clustering

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techniques are among the standbys of data analysis. It's crucial to create techniques that can deal with the data characteristics, because data may be created from a wide variety of sources, each of which has its own unique data kinds. The Internet of Things relies on massive amounts of resources to generates the required data in real time despite issues like scalability, velocity, or finding the optimal data model. All of these are among the most pressing concerns in the Internet of Things. All of these problems, meanwhile, give rise to a plethora of potential in the new innovations. In this study, we have acquired a vast amount of big data from IoT devices; this data includes a variety of formats, including images, texts, and categories. These records will be safely housed in the cloud and made available through cutting-edge healthcare apps. To move the learning process forward, we have implemented a novel machine learning algorithm that divides the data into "Usual" and "Disease Affected" categories.

B. System Model

The patient's heat, pulse rates, as well as heartbeats may all be used to inform the proposed smart health care system's decision-making. This design is also a lower-power option since it only activates sensors when necessary. The system's algorithm will regulate the sensors' use, price, and service life. The suggested solution solves the problem of remote patient monitoring by connecting them with in-hospital specialists who can provide them the care they need.

Communication channels, integrated internal and exterior sensors, an Internet of Things server, cloud storage, and a gateway are all part of the smart healthcare observation and patient administration platform described in this research. The application layer, the management layer, the network layer, and the body sensor layer are the layers at which these tasks are carried out. Figure 1 depicts the proposed system's design. Utilizing sensors and a decision support system to enhance telemedicine's effectiveness in remote locations is an innovative approach.

A. Data Collection

The suggested system will be developed to install a device in a remote clinic with the aid of IoT (Internet of things). The monitor will capture inputs such as the patient's heart rates, heat, and blood stress, and transmit that information to the attending physician at the hospital. The doctor will use the information to assess the patient's condition and then communicate those findings to the clinic staff in the outlying location.

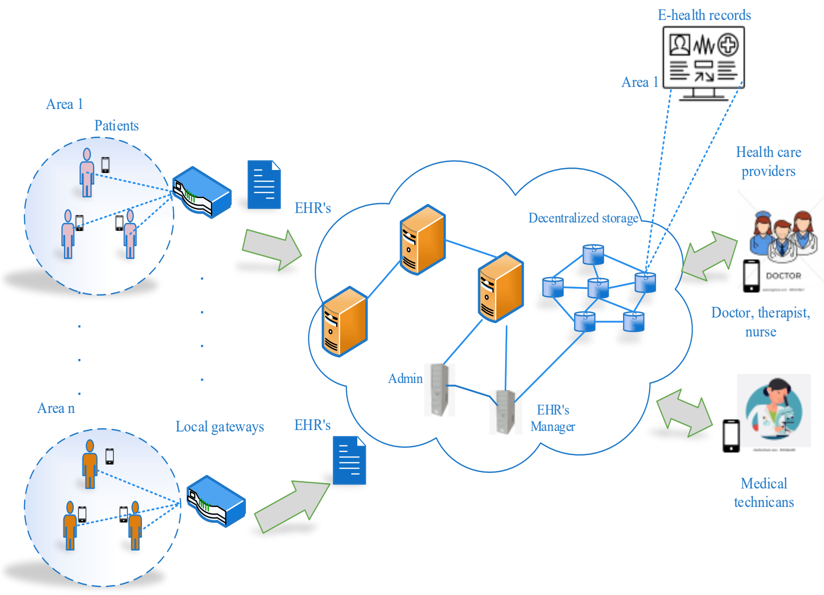

Fig.1. System Model

Figure 1 presents a physical representation of the proposed system's design, which includes all of the essential components. There are three sensors in total: one for measuring core body heat, one for measuring pulse rates, and one for measuring heart rates. The data from these three sensors is aggregated and sorted using an Arduino board. Data transport is handled via communication and networking devices. Data analytics provides the decision-making

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capabilities, and the fuzzy logic paradigm is used in this setting. With the doctor's perspective, medical professionals may check in on a patient from afar and have a two-way conversation with the patient.

B. Fuzzy System

This intelligent patient tracking and administration system incorporates a fuzzy logic method for making decisions, as will be explained in the next section. The server-based fuzzy system makes all necessary medical judgments and immediately notifies the attending physician of any urgent matters. The proposed system is described in depth, including its technical specifications, in the last section.

Because of these issues, it is sometimes necessary to merge many models into a single one. A hybrid system is what you get when you mix multiple models to solve a problem. The neural network's processing power is dedicated to pattern recognition rather than decision-making logic. Since previous information is necessary for inference rules, fuzzy logic systems excel at describing the decision-making process. Because of these restrictions, fuzzy neural network that was developed. Fuzzy-system rules are learned from the data of neural networks. The procedure that starts with "ANFIS," and the ANFIS procedure consists of the two stages listed belower: ANFIS model development (i). (ii) Creation of a model and associated technique for incorporating fuzziness within the neural network. As seen in Figure 6, a neural network receives neural inputs in order to produce neural outputs. For the purposes of making decisions and supplying the neural network with learning algorithms, the system's neural outputs serve as the connection rules used in the fuzzy interface. Since neural networks collect data through a slower propagation method, the process is tedious. It is a challenging challenge to include particular data into the network of neurons in order to explain learning approaches. Despite the difficulty of acquiring information, fuzzy systems are utilized in constrained systems because of the benefits their fuzzy rules give. Fuzzy rules are developed using numerical data to address these issues in the solution design process. Approximate Reasoning Intelligent Control (ARIC) is a neural network model that makes use of the ANFIS technology.is The ANFIS system learns from predictions made by the physical system. It regulates the database via a data-refreshing technique that allovers for fine-grained adjustments.

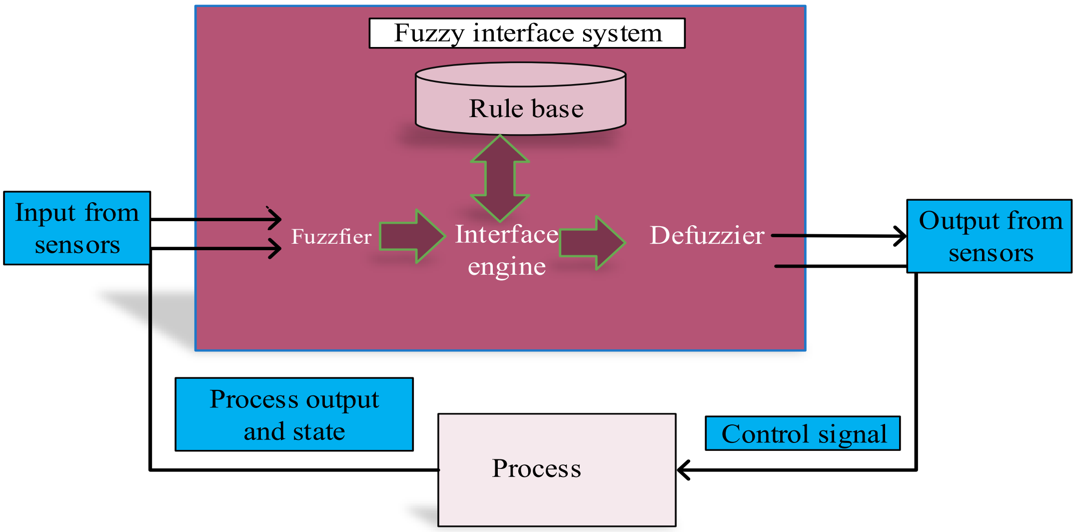

Fig.2. Fuzzy Logic Diagram

C. ANFIS Model

Combining fuzzy systems with neural networks maximizes the benefits of both approaches to decision making. The framework is able to learn, and the data used by it is of the if-then fuzzy kind. Since the rules have been predetermined and the system may be initiated independently, it learns more quickly than a conventional neural network. The INFERENCE action position of the ANFIS architecture is what's utilized to assess the data-driven network. The FUZZY operation, which is crucial in network selection, is also included in the ANFIS. The method utilizes a fuzzy control mechanism and a multilayer neural network. In the proposed system's first layer, the FUZZY element has two independent fuzzy interfaces. We use the second layer to house the neural network. Fuzzy inference helps the neural network arrive at the f[a,a+1] action. Using the length of time represented by t & the framework condition t+1, it should acquire p(a+1). The stochastic character of the modification module boosts the oversight with p(t) of fluffy component and the predicted probability regarding choices to generates the final product.

$$u'(t) = r(u(t), \mathrm{d}[t, t+1] \qquad (1)$$

Fuzzy inference's c_i subunit is set up to evaluate the fuzzy principle. An information unit, a_j, inherits a universally applicable unit, u. The activity control receives information from the unit u. The final product, known as defuzzified mixture, is the result of this procedure. Fuzzification is applied to the information level in this framework; it is monotone in character and may make use of it's parts in an ANFIS setting. Local norms are taken into account when making rules using the fuzzy tag. These criteria are used to make an educated guess as to an ancestor's enrollment status, which is subsequently replicated using load joining and the association data module. The output of this system is a quality measure. Each concealed component represents outstanding monotonic work conveying the higherest quality. The result is obtained due to the routine of this function. The contrary capability easily determines the procedure. The combination of the heaviness function and the hidden-unit linkage generates this level of respect. In the end, the weighted average approach is used to calculate the yield value.

The operators of action employed in the network evaluation that attempts to foretell the model's behavior. This system employs a standard feedforward neural network approach. The model states are gathered as data in this a feedforward neural network network through a veiled layer. As auxiliary information, it employs the physical model's error flag r. Using the results from the network & action state assessment technique, the support method controls the load variation. Post-adjustment engineering was important to the development of ANFIS. The model's understanding and its assignments are also shown to be effective.

Input neurons use real numbers, which serve as both the signals and the weights. These indicators are unaffected by the data. There is a direct correlation between the yield and the data provided. The a_i signal and the w_i load might work together to make these things.

$$d = w_i a_i,\ i = 1,2. \qquad (2)$$

In order to provide the requested details, it's necessary to assemble the input data d_i,

$$\text{net } = d_1 + d_2 = w_1 a_1 + w_2 a_2 \qquad (3)$$

Relating to the neuron. The neuron's output is determined by the f(x) exchange function, which might be sigmoidal in shape. f(x)=(1+e(-x))(-1):

$$y = f(\text{ net }) = f(w_1 a_1 + w_2 a_2) \qquad (4)$$

Multiplication, addition, and a sigmoidal function are all used in the typical neural network shown in Figure 1.

Uncertain rules were made for the medical decision support system utilized in IoT-based telemedicine. These regulations are grounded on the data and facts stated in Table 2. Some instances of fuzzy rules are shown belower.

IF (Heat == Higher) AND (Throb_Rates == Lower) AND (Blood Stress== Very Higher)

THEN Choice = Higher

IF (Heat == Higher) AND (Pulse Rates == Lower) AND (Blood Stress == Higher)

THEN Decision = Higher

IF (Heat == Usual) AND (Pulse Rates == Higher) AND (Blood Stress == Average)

THEN Choice = Lower

IF (Heat == Lower) AND (Pulse Rates == Higher)

AND (Blood Stress == Average)

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THEN Choice = Lower

IF (Heat == Usual) AND (Pulse Rates == Usual) AND (Blood Stress == Lower)

THEN Choice = Higher

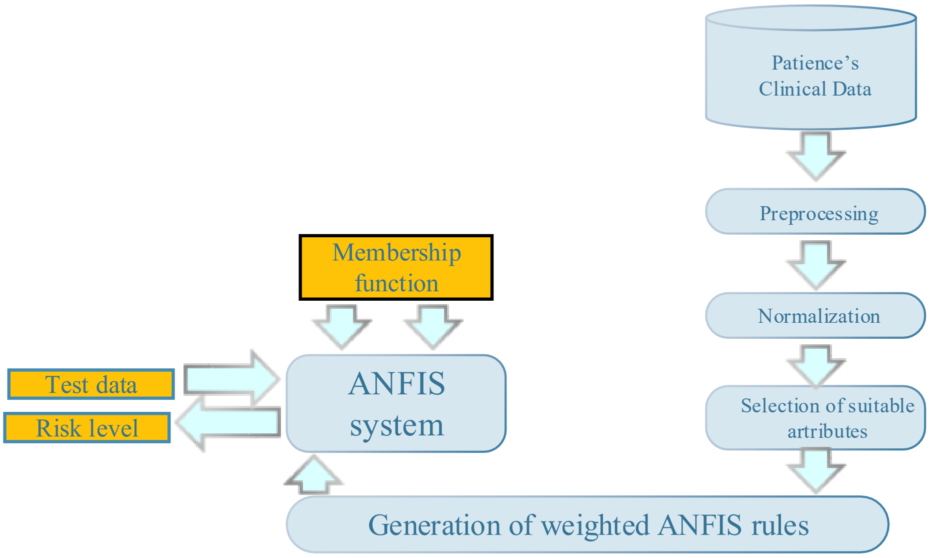

Fig.3. Proposed ANFIS Model

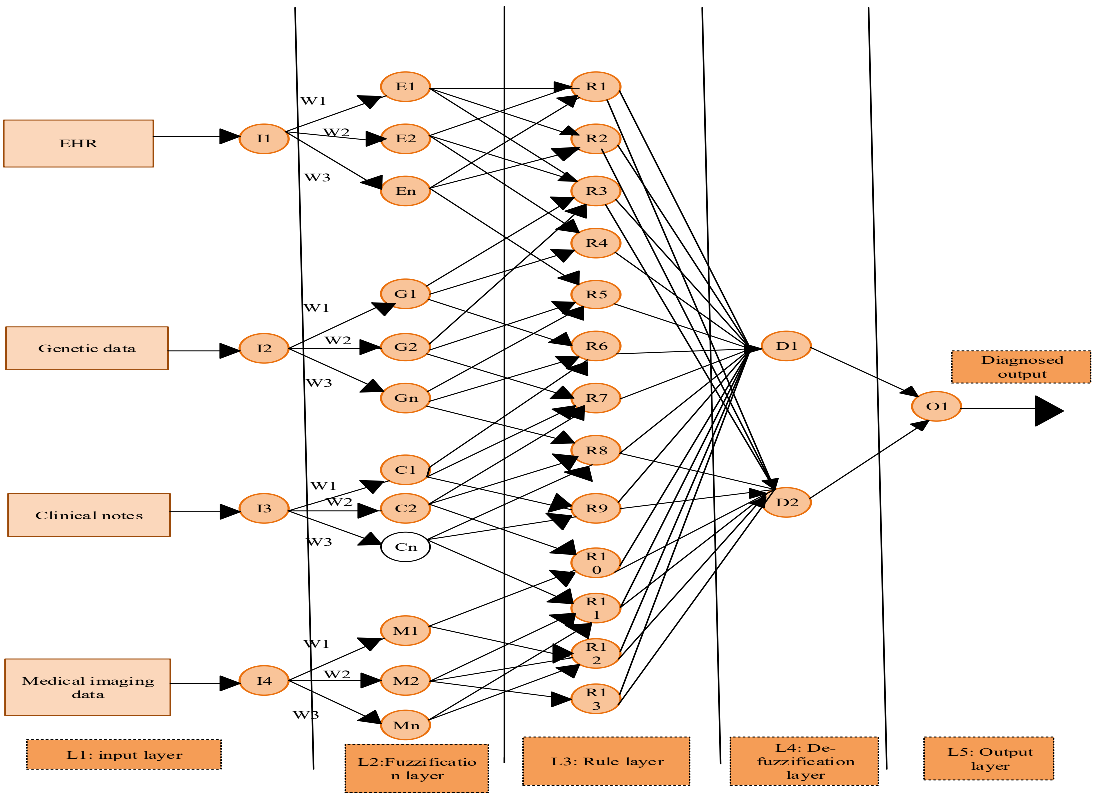

Fig.4. Proposed ANFIS (Neural Network) Diagram

IV. RESULTS AND DISCUSSION

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A. EXPERIMENTAL SETUP

We employ simulation tools to make predictions about the system's behavior in a controlled, mock environment before releasing it into the wild. To test out our suggested model, we've been utilizing the MCCSIM. This software provides a versatile simulation framework that facilitates straightforward modeling of the suggested mobile cloud models. The MCC simulator's graphical user interface also makes it simple to alter the simulation's setup settings, making it ideal for evaluating design aspects like power consumption and latency in a dynamic context. To better grasp how implementing the cloudlet affects power consumption and latency in comparison to a non-cloudlet MCC, the suggested cloudlet-based Mobile clouds computing model was simulated using the MCC SIM. Cloudlets were uniformly dispersed over the simulation environment for optimal mobile device access. Each experiment has a 500-second duration and is conducted in a 800x600-meter area with 2,000 mobile users. Using their mobile devices connected to Wi-Fi, 3G, or 4G networks, users are moving about at random at a pace of 2m/s, & transmitting packet to the cloud at a rate of 0.1Hz. Each cloudlet has a limit of 150 users who may connect to it. When simulating our new model, we took into account three different network configurations. The first is when a smartphone or tablet is linked to the company's EC through 3G. In the second case, there is just one master-Cloudlet between the mobile device and the EC. In the last possible case, the mobile device communicates with the EC by way of Cloudlets that in turn communicate with a master-cloudlet.

The intelligent system design of the healthcare patient oversight and oversight system. The suggested approach benefitted from the simplicity of a fuzzy logic decision-making system. Using sensor information as well as fuzzy based decision making, the suggested system has a novel structure. The hardware that will be needed to create this system has previously been described in detail. Sensor information was uploaded to a central database. Both the Arduino app and a web browser will display the findings. The user has the option of interacting with the system's data in several ways. The fuzzy logic system takes the three distinct sensor data kinds and converts them into an output. Table 6 displays the breakdown; temperatures from 100 to 105 degrees Fahrenheit were used to identify four distinct categories of fever severity: Usual, Mild, moderate, and Severe.

Table 7 shows the range of typical human pulse rates, from lower to Usual to higher. Pulse rates belower 60 beats per minute are regarded to be lower. A healthy pulse rate is somewhere from 60 to 100 beats per minute. Higher pulse rates are defined as those more than 100 per minute.

The range of healthy blood pressure is shown in Table 8. A blood pressure reading of 120 over 80 is considered Usual. Higher blood pressure is defined as a reading between 129 and 140 mm Hg (or 81 and 89 mm Hg). If your blood pressure is higherer than 141/91, your health may be in danger.

Sensor data from several patient measurements are summarized in Table 9. Tables 6-8 additionally provide range calibrations for the data.

Data from a heat sensor, a heart rate sensor, and a blood stress sensor all show some variance, as seen in Figure 13. Ranges in the data are additionally calibrated using Tables 6-9.

After gathering and Usualizing input data, the next phase involves using fuzzy logic to make decisions about the patient's health status. The input data and their calibrated outputs are shown in Table 10.

Accuracy, sensitivity, and specificity are three of the most often used metrics, all of which were taken into account in this study. The proportion of correct diagnoses, incorrect diagnoses, false negatives, and false positives may be used to get these numbers. Precision (TP), sensitivity (TN), sensitivity (FP), and specificity (FN) are used to characterize the results.

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \quad (5)$$

$$\text{Specificity} = \frac{TN}{(TN+FP)} \quad (6)$$

$$\text{Accuracy} = \frac{(TN+TP)}{(TN+TP+FN+FP)} \quad (7)$$

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Here, TP indicates that accurate predictions will be made for the right records, TN that inaccurate predictions will be made for the right records, FP that false records will be forecasted as a right record, and FN that false records is anticipated as a wrong record.

The system makes a call using fuzzy logic, and the quality of that call is evaluated (Figure 14). Table 10 demonstrates that the suggested approach has an accuracy of between 94% and 100%. This demonstrates that the suggested system is followering the predetermined guidelines for managing and caring for patients. Formulas in determine how well the suggested system works.

$$\text{Accuracy } = \sum \frac{\mu(\text{ai})}{n}. \qquad (8)$$

The suggested system's accuracy may be determined using the formula (5). The proportion of correct experimental data is denoted by ai in (5), and the total number of experiments is denoted by n. In this dataset, 97% accuracy has been attained on average.

The experimental findings demonstrate that the sensor oriented IoT system is practical and convenient due to intelligent as well as smart decision making. Internet of Things technique boosts system performance and throughput. The calculation for the percentage inaccuracy of the findings is given in (6). Here, the needed accuracy is the acceptable value, while the accuracy of the tests is the precision with which they were conducted.

$$\text{percent\_error } = \frac{\text{accepted\_value} - \text{experiemtnal\_value}}{\text{total\_value}} \times 100. \qquad (9)$$

Figures 15 to 16 display data demonstrating the precision and consistency of the findings.

Many sensor-based Internet of Things (IoT) systems were explored in Section 2. The suggested method is the first of its kind to employ a system of fuzzy logic to monitor and manage patient care, with the latter being used to diagnose illnesses and prescribe remedies. The tables 9 and 10 indicate that when sensors and DSSs are used in conjunction with our method, performance improves. Decisions made by the suggested system's fuzzy logic component improve its efficiency and precision. Intelligent decision making combined with a sensor and Internet of Things based technology makes this system unique. The findings demonstrate that the suggested method outperforms the alternatives in terms of accuracy, efficiency, cost, and simplicity. The followering are contributions of the proposed system. This method introduces an efficient irrigation system for underground farming for the first time.

Table 1: Heat levels

Heat (°F)	Class
< 99	No fever
$99 - 101$	Fever
$101.1 - 103$	Higher fever
> 103.1	Very higher fever

TAble 2: Classes of pulse rates

Pulse rates (BPM)
> 100 Class
61 to 100 Higher/tachycardia
< 60 Lower/bradycardia

Table 3: Classes of blood stress.

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BP(HG)	Class
$< 110/< 70$	Very lower
$120 - 110/80 - 70$	Lower
120/80	Usual
$130 - 139/80 - 89$	Higher
$> 140/> 90$	Very higher

Table 4: Sensor data for the experiments.

Sr. no.	Heat (°F)	Pulse rates (%)	Blood stress (BP-lower)	Blood stress (BP-higher)
1	200	$61 - 100$	100	181
2	104	70	88	138
3	103	111	92	142
4	103	108	81	134
5	99	107	81	123

B. Discussion

The suggested system has been tested experimentally with varying numbers of instances. In Figure 2, we can see how our suggested fuzzy classification model compares to several standard classification techniques including KNN, NB, SVM, and DT.

Results for Mild

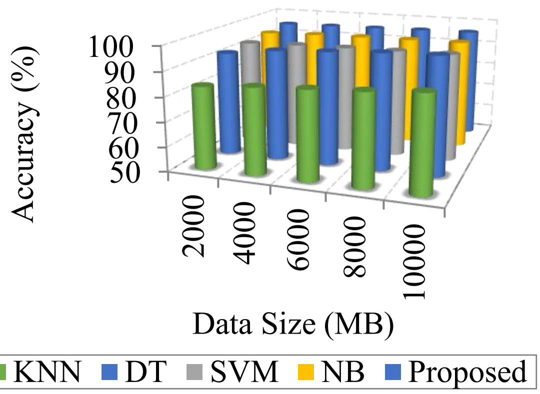

Fig.5 Accuracy vs. Data Size

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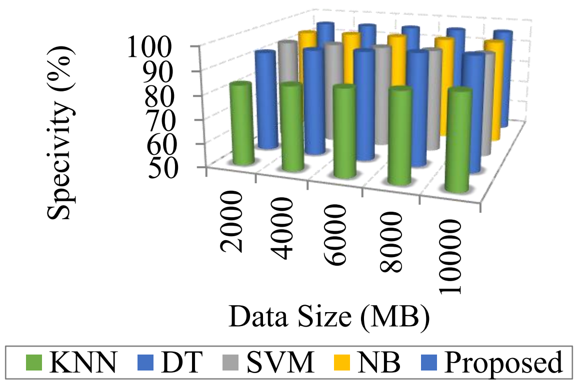
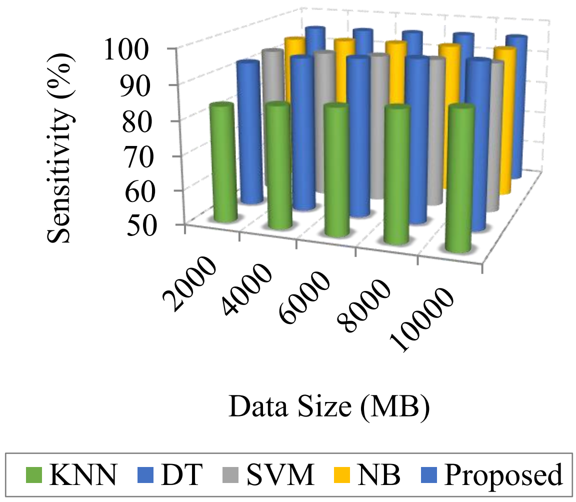


Fig.6 Specificity vs. Data Size



Results for Normal

Fig.7 Sensitivity vs. Data Size

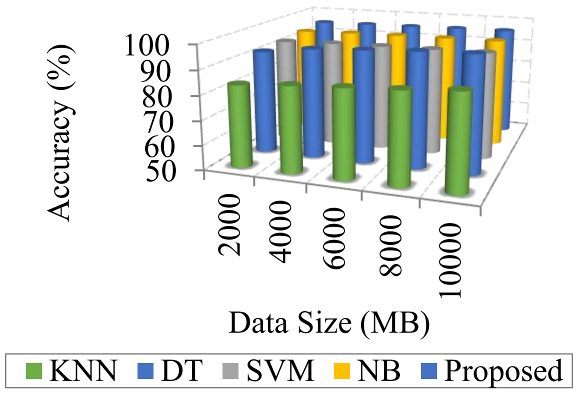


Fig.8 Accuracy vs. Data Size

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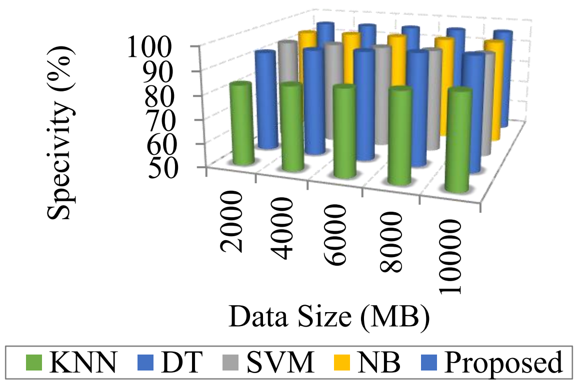

Fig.9 Specificity vs. Data Size

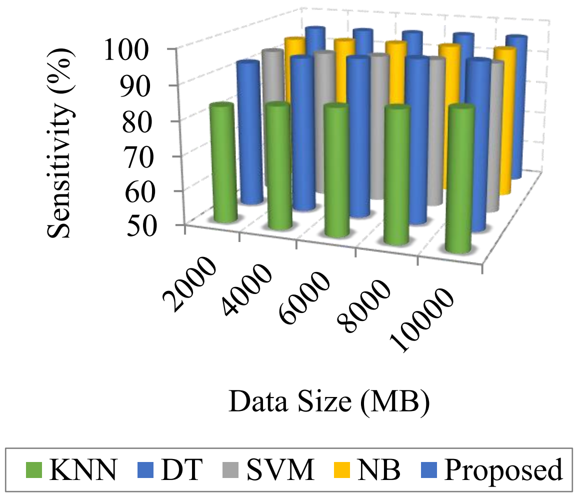

Fig.10 Sensitivity vs. Data Size

Results for Severe

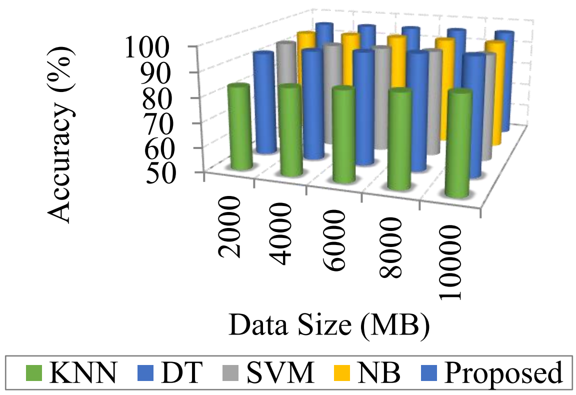

Fig.11 Accuracy vs. Data Size

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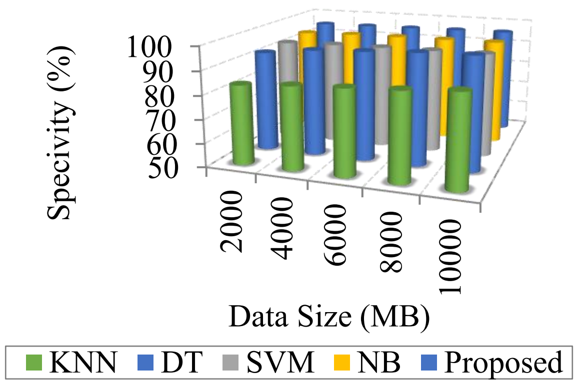

Fig.12 Specificity vs. Data Size

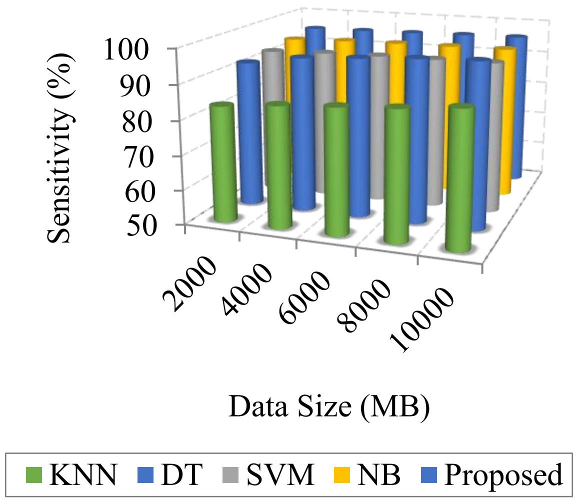

Fig.13 Sensitivity vs. Data Size

Results for Mild

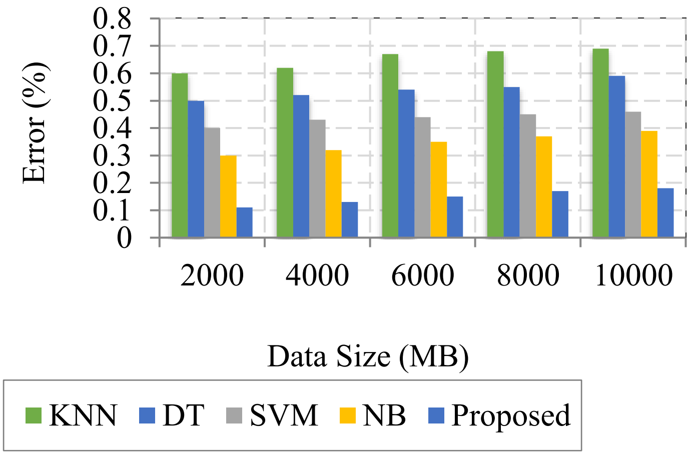

Fig.14 Error vs. Data Size

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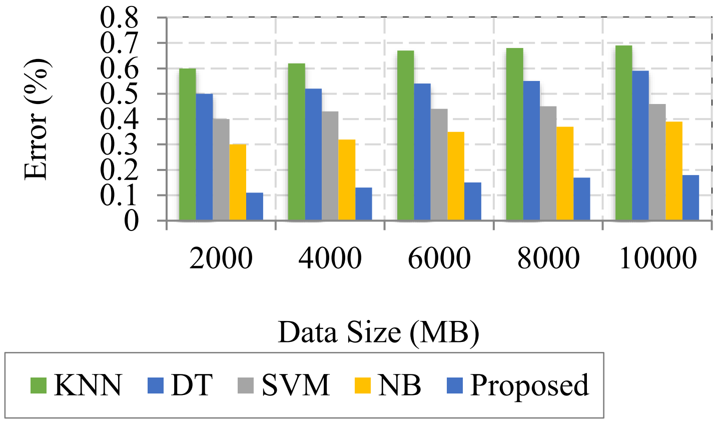

Fig.15 Error vs. Data Size

Results for Moderate

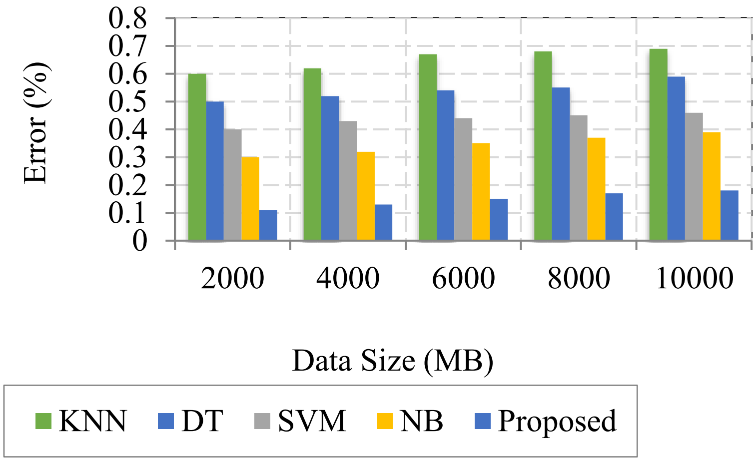

Fig.16 Error vs. Data Size

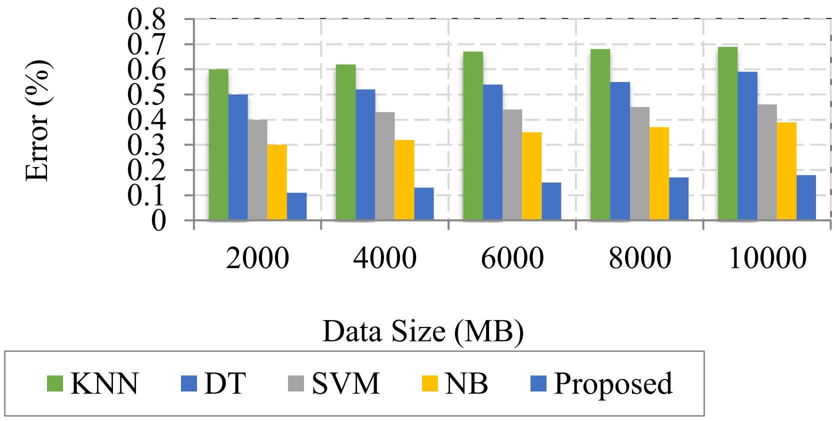

Fig.17 Error vs. Data Size

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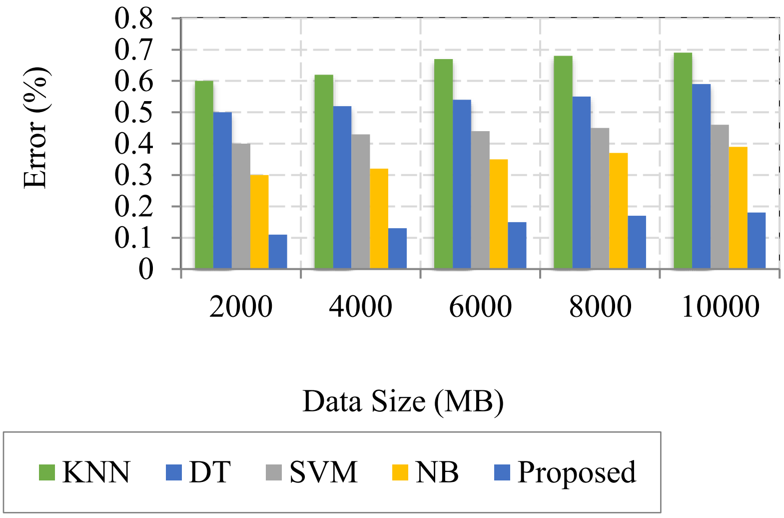

Fig.18 Error vs. Data Size

Results for Normal

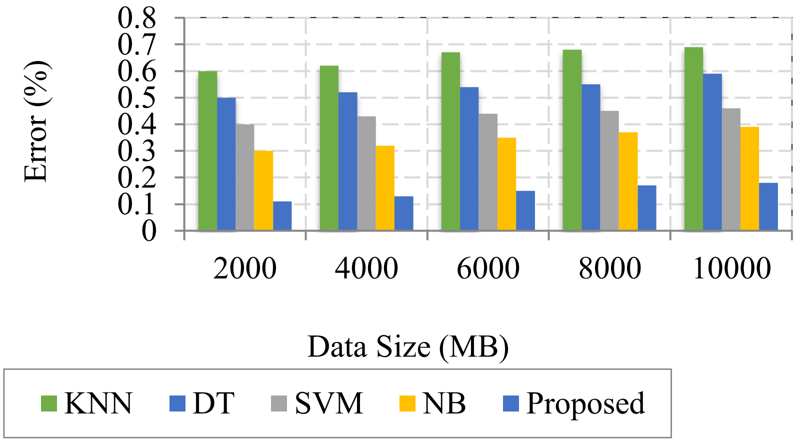

Fig.19 Error vs. Data Size

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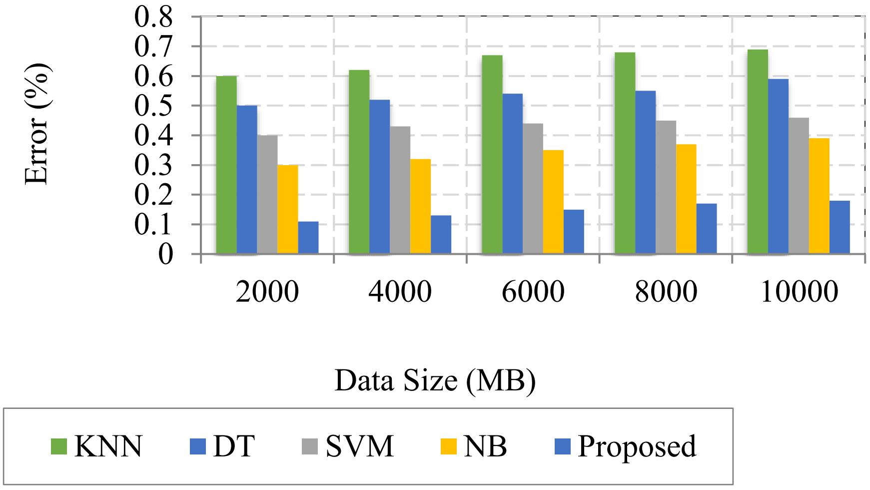

Fig.20 Error vs. Data Size

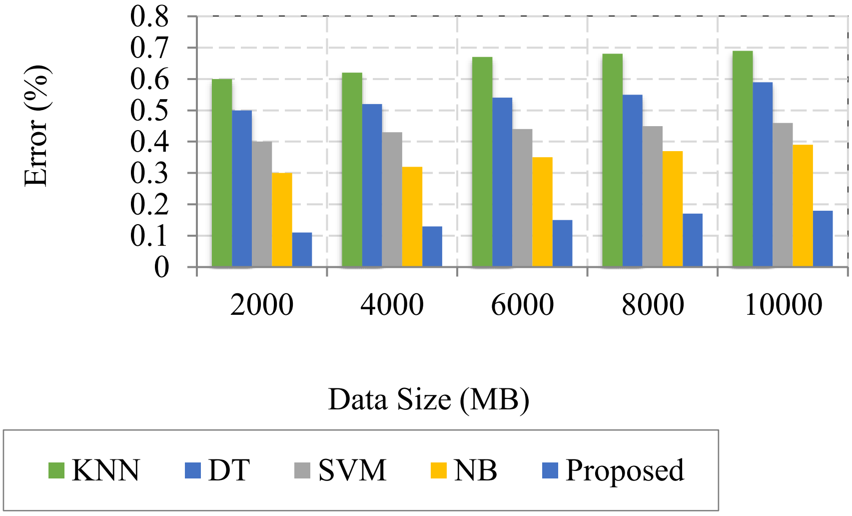

Fig.21 Error vs. Data Size

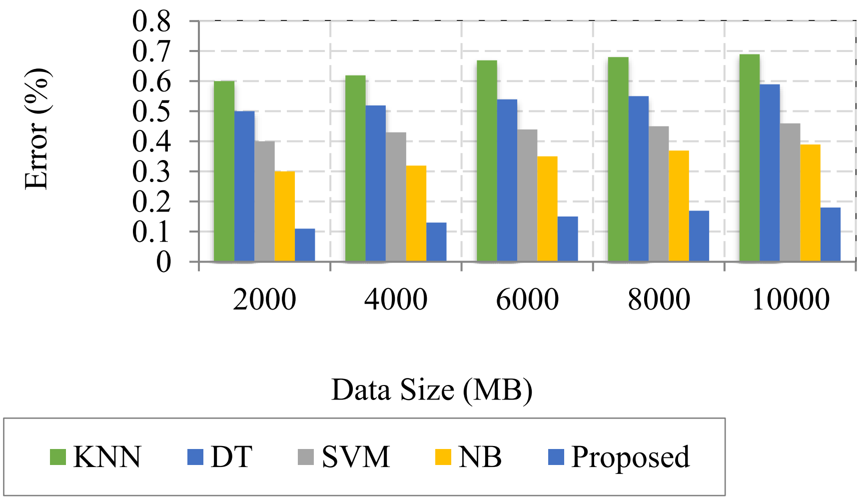

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Fig.22 Error vs. Data Size

Figure shows that the suggested fuzzy rule based neuronal classifier outperforms state-of-the-art approaches including k-NN, NB, SVM, and DT. This is because categorization takes a long time and uses fuzzy criteria. In Figure 3, we can see how the suggested fuzzy rule driven neural classifier compares to other popular classifiers as k-NN, NB, SVM, and DT in terms of specificity. Here, we've taken into account varying record sizes (2000, 4000, 6000, 8000, and 10,000) across five separate studies. Figure 3 shows that our suggested fuzzy rule oriented neural classifier outperforms state-of-the-art approaches like k-NN, NB, SVM, and DT in terms of specificity. This is because categorization takes time, therefore fuzzy criteria are often used. Comparing the suggested solution fuzzy rule based neural classifiers to other popular methods as k-NN, NB, SVM, and DT, as shown in Figure 4. In this study, we investigated five distinct record sets (2000, 4000, 6000, 8000, and 10,000) for our tests.

Table 5. Server parameters.

Server	**CPU**	**Memory**	**Bandwidth**
0	5	2049	3000
1	3	1025	4000
2	3	1025	2200
3	2	513	3500
4	2	1025	3000

Table 6 Resource allocation using different parameters for the KNN

Cloudlet ID	Performance time	Suggestion time	Final time	Target
0	42	55.5	78.5	108.6
1	72	371.5	343.5	396.6
2	86	691.5	697.5	784.6
3	84	2043.5	1237.5	1241.6
4	72	2139.5	1301.5	1273.6

Table 7 Resource allocation using different parameters for SVM

Cloudlet ID	Performance time	Suggestion time	Final time	Target
0	42	55.5	78.5	108.6
1	72	371.5	343.5	396.6
2	86	691.5	697.5	784.6
3	84	2043.5	1237.5	1241.6
4	72	2139.5	1301.5	1273.6

Table 8 Resource allocation using different parameters for DT

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Cloudlet ID	Performance time	Suggestion time	Final time	Target
0	45	56	80.5	110.6
1	74	381.5	345.5	400.6
2	88	697.5	698.5	789.6
3	86	2045.5	1240.5	1247.6
4	74	2145.5	1304.5	1278.6

Table 9 Resource allocation using different parameters for NB

Cloudlet ID	Performance time	Suggestion time	Final time	Target
0	46	58.5	79.5	107.6
1	76	372.5	345.5	398.6
2	89	695.5	700.5	789.6
3	86	2047.5	1238.5	1245.6
4	75	2140.5	1310.5	1275.6

Table 10 Resource allocation using different parameters for Proposed Methods

Cloudlet ID	Performance time	Suggestion time	Final time	Target
0	37	45.5	68.5	108.6
1	65	271.5	243.5	296.6
2	75	591.5	597.5	684.6
3	85	1043.5	1137.5	1141.6
4	78	1139.5	1201.5	1173.6

Performance time, submission time, completion time, and due date are only some of the metrics that may be used to evaluate resource allocation, which are all shown in Table 4.

Figure 4 illustrates that the suggested fuzzy rule based neuronal classifier has a higher sensitivity in comparison to the state-of-the-art approaches like k-NN, NB, SVM, and DT. This is because categorization takes a long time and uses fuzzy criteria. Comparison of the suggested fuzzy rule oriented neural classifier's reaction time to that of the state-of-the-art k-NN, NB, A-NN, and SVM classifiers is shown in Figure 5. Here, we have taken into account a wide range of response-time-analysis trials. Figure 5 demonstrates that when compared to other methods, such as support vector machines and artificial neural networks, the proposed fuzzy rule centered classifier responds much more quickly, and k-nearest neighbors. This is because appropriate choices are made at the appropriate times based on effective and intelligent principles. Figure 6 compares how long it takes for each possible combination of features in the proposed AES encryption technique.

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Table:11

Sr. no.	Heart	Pulse rates	Blood Pressure	ANFIS choice (Health state)	Accuracy (%)	Percent error (%)
1	Higher	Lower	Very higher	Severe	98.9	0.139
2	Higher	Lower	Higher	Severe	95.7	0.137
3	Usual	Higher	Average	Mild	88.9	0.132
4	Lower	Higher	Average	Mild	88.2	0.131
5	Usual	Usual	Lower	Severe	94.7	0.138
6	Higher	Higher	Average	Severe	98.7	0.13
7	Higher	Average	Average	Usual	95.6	0.130
8	Average	Lower	Average	Usual	92.6	0.14
9	Very higher	Higher	Higher	Severe	96.7	0.132
10	Average	Higher	Average	Mild	88.8	0.134

Table 12 Comparison of the detection rates of Health Disease using a variety of detection methods

Classes	Methods	Accuracy (%)
Mild	SVM	93.5
	KNN	94.3
	DT	93.6
	NB	94.6
	Proposed Method	95.3
Moderate	SVM	92.7
	KNN	90.4
	DT	93.3
	NB	94.2
	Proposed Method	96.9
Severe	SVM	92.3
	KNN	90.4
	DT	89.4
	NB	94.7
	Proposed Method	95.8

Table 13 Comparison of the detection error Health Disease using a variety of detection methods

Classes	Methods	Error Rate (%)

Mild	SVM	0.4
	KNN	0.5
	DT	0.52
	NB	0.48
	Proposed Method	0.13
Moderate	SVM	0.41
	KNN	0.514
	DT	0.53
	NB	0.47
	Proposed Method	0.12
Severe	SVM	0.35
	KNN	0.45
	DT	0.47
	NB	0.57
	Proposed Method	0.12

V. CONCLUSION

The severity of diseases may now be tracked and diagnosed in real time with the help of a brand new mobile health care software built on Cloud and IoT technologies. In this case, a new model has been made available to the general public. The UCI Repository database & the medical sensors are utilized to create the relevant medical data needed in this study to forecast the patients who have been seriously impacted by diabetes. The condition may be diagnosed and its severity mitigated with the use of a novel classification technique called Fuzzy Rule driven Neural classifier. IoT dataset and actual health information from several hospitals have been used in the studies. The experimental results demonstrate the superiority of the proposed approach over current illness prediction methods. Improved protection for healthcare records stored in the cloud might be the result of future efforts to develop and use innovative cryptographic methods. In future, offloading idea is introduced for healthcare applications.

Authors Contribution: Each author contributed equally in each part.

Data Availability Statement: The data used to support the findings of this study are available from the corresponding author upon request.

Ethical Approval: This article does not contain any studies with human participant and Animals performed by author.

Conflicts of Interest

The authors are declared there are no conflicts of interest regarding the publication of this paper.

Funding Statement

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