International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 16, No.1 (Jul-24)

http://dx.doi.org/10.12785/ijcds/160115

Efficient Early Detection of Patient Diagnosis and Cardiovascular Disease using an IoT System with Machine Learning and Fuzzy Logic

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Received 6 Oct. 2023, Revised 31 Mar. 2024, Accepted 16 Apr. 2024, Published 1 Jul. 2024

Abstract: Rising healthcare challenges, particularly undiagnosed heart disease due to subtle symptoms and limited access to diagnostics, necessitate innovative solutions. This study introduces an innovative Internet of Things (IoT)-based system for early detection, leveraging the strengths of both fuzzy logic and machine learning. By analyzing patient-specific data such as heart rate, oxygen saturation, galvanic skin response, and body temperature, our system utilizes fuzzy logic to evaluate potential disease symptoms, enabling self-diagnosis under medical supervision. This personalized approach enables individuals to monitor their health and seek prompt medical attention as needed. Additionally, we train multiple machine learning algorithms (Decision Tree, KNN, SVM, Random Forest, Logistic Regression) on the well-established Cleveland heart disease dataset. Among these, Random Forest achieved the highest accuracy (82.6%), precision (81.5%), recall (83.7%), and F1-Score (82.5%), showcasing its effectiveness in predicting cardiovascular disease. This unique blend of fuzzy logic for personalized symptom assessment and machine learning for CVD prediction presents a new method for early diagnosis. While promising, further validation through large-scale clinical trials is essential. Ultimately, this system underscores the significance of integrating AI with medical expertise for optimal patient care, providing a potential pathway to improved health outcomes and enhanced accessibility to early detection of cardiovascular disease.

Keywords: IoT, early detection, machine learning, diagnose system, fuzzy logic

1. INTRODUCTION

Health can be defined as optimal physical, mental, and social well-being, enabling individuals to lead socially and economically fruitful lives. The health sector is an essential component of a nation's infrastructure. The health level of the population is one of the crucial benchmarks of the country's welfare. The government has made various efforts to improve public health, including providing or aiding health resources and facilities [1]. However, much of the world's population is afflicted with diseases, some of which, such as heart disease, go undiscovered due to subtle symptoms and the difficulty and expense of diagnostic procedures. Access to adequate healthcare and expensive diagnostic tests is challenging for many people, particularly those living in distant and rural locations, as well as persons with disabilities and the elderly, leaving them often ignorant of underlying health conditions [2]. Moreover, during this industrial revolution, the health and technology domains have a pretty strong interaction 5.0 era. One of the available technology platforms for health aids is the Internet of Things (IoT). The astounding finding of the Internet of Things is in health management and diagnosis, which enables tracking of health and environmental circumstances [3]. IoT can be used for sensor-based testing, remote analysis automation, and improved accessibility in the healthcare sector.

A diagnosis system for healthcare is a technology-driven solution that monitors, diagnoses, and manages health issues in real-time using connected devices, sensors, data analytics, and machine learning. From the standpoint of a healthcare professional, IoT is valuable for remotely optimizing the functioning of medical devices. Several studies on IoT healthcare research for patients have been undertaken [4], [5], [6], [7], [8]. Recently, the field of applied IoT in healthcare has attracted widespread attention from researchers to boost the potential performance of IoT in the healthcare industry by addressing the area's many issues. Despite several developments and research, an integrated system is still lacking to facilitate diagnosis and early detection [4]. About early detection, the disease case study in this research is Cardiovascular disease (CVD). CVD continues to be a major global health issue. Improved patient outcomes and a successful course of treatment depend on early detection.

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However current Health IoT devices mostly concentrate on gathering data, ignoring the ability to provide individualized insights and identify risks. By presenting an innovative, user-friendly IoT system that combines the benefits of fuzzy logic and machine learning for effective early CVD diagnosis, our research seeks to close this gap.

To close the essential gap in early CVD detection, this user-friendly IoT solution provides a special blend of precise forecasts and individualized evaluations. By analyzing specific patient data (heart rate, oxygen saturation, temperature, and galvanic skin response), fuzzy logic generates personalized symptom assessments that promote proactive patient involvement. Concurrently, gathered data is used by machine learning algorithms, especially the highly accurate Random Forest model, to predict the risks of CVD. This finally presents a promising answer in the fight against CVD by empowering patients with insightful health information and early risk warnings, as well as healthcare providers with data-driven insights to support prompt intervention and preventative actions. Large-scale clinical trials are required to validate the system's effectiveness. Future efforts will center on smoothly connecting the system with existing healthcare platforms to facilitate data interchange and patient management. In addition, this research will investigate the ethical and regulatory implications of using AI-driven diagnostic technologies in healthcare systems. This complete strategy, which combines accessible, user-friendly, and AI-powered early detection with tailored insights, lays the groundwork for a future in which individuals and healthcare professionals can collaborate to successfully address the burden of CVD.

2. LITERATURE STUDY

The discussion in this section focuses on several methods for diagnosis systems using the IoT, Fuzzy logic, and machine learning approaches. Some researchers have implemented IoT in the healthcare field [5], [6], [7], [8], [9]. Current Internet of Things (IoT)-based healthcare solutions often adopt a fragmented approach, focusing on specific capabilities without adequately addressing patient empowerment, customized diagnosis, and seamless integration with existing healthcare workflows. This study seeks to create an innovative IoT-based system by combining accurate CVD prediction through machine learning with personalized symptom assessment using fuzzy logic. Kent et al. [5] A suggested monitoring system, utilizing Wi-Fi connectivity, ZigBee, and RFID has been put forth with the aim of enhancing efficiency and minimizing superfluous tasks performed by medical personnel. Rasyid et al. [6] The development of an IoT framework for monitoring health problems was proposed. Utilizing a network of IoT health devices equipped with sensors and actuators enables the remote monitoring of patients from their homes. These devices collect health data from patients and transmit them to a cloud-based database. The system comprises MySignal sensor devices, including a pulse rate sensor, a temperature sensor, an oxygen level sensor, and an Arduino microcontroller responsible for transmitting health data to the patient. Islam et al. [7] Five sensors were utilized in this system to collect data from the hospital environment: a heart rate sensor, a body temperature sensor, a room temperature sensor, a CO sensor, and a CO_2 sensor. The percentage error of the devised scheme was within a specific limit (5%) for each situation. Verma et al. [8] The severity of the prospective diseases was predicted using a cloud-centric IoT-based m-health monitoring disease diagnosis system. The diagnosis scheme employs a variety of advanced classification algorithms, with the findings determined based on the sensitivity, specificity, f-measure, and accuracy. The experimental findings demonstrate that the proposed method outperforms the conventional disease prediction techniques.

Some studies have also used fuzzy logic [9], [10] and machine learning approaches to diagnose healthcare systems [11], [12], [13]. Rahman et al. [9] This study uses ECG data to focus on how intelligent systems and fuzzy logic can detect and classify significant cardiac arrhythmias in individuals, particularly those with COVID-19. The proposed methodology uses an IoT-based system to monitor and diagnose patients with arrhythmia continuously. Dini et al. [10] developed a computerized method to screen (predict) hypoxemia with a fuzzy value based on oxygen saturation concentration and respiration rate. According to research findings, the system detected hypoxemia with an accuracy of 80%, 60% sensibility, and 100% specificity. Based on the experimental results, this study may be helpful in screening for the detection (early prediction) of hypoxemia. Kuswoyo et al. [11] described the creation of OxyTemp, a personal health monitoring gadget based on IoT technology. OxyTemp combines a pulse oximeter, temperature sensor, and interpretation feature, making it small, informative, and easy to use.

Application of health diagnosis features and healthcare research in health diagnosis. Abdullah et al. [12] provided A medical facility that employs supervised learning algorithms to evaluate Electrocardiogram data; development of a safe IoT-based medicare system for monitoring that predicts cardiac ailments using Machine learning prediction algorithms. Godi et al. [13] describe an E-Health care monitoring system (EHMS) that uses the IoT wearable technology and algorithms for learning for online patient health tracking and check-ups. This study describes the EHMS architecture, the role of IoT wearable devices in data collection uses a machine learning algorithms for prediction and analysis. Ganesan et al. [14] discussed creating a Cloud and connected device paradigm for identifying diseases for monitoring, predicting, and diagnosing heart disease. This study employs a variety of classification algorithms, including multilayer perceptron, support vector machines, J48, and logistic regression. Table I provides a summary of the various IT HealthCare studies and comparison model approaches.

TABLE I. Summary of comparison model approaches and features

Feature	Our Research	Related Studies	Unique Value
Scope	Holistic approach: combines diagnosis, patient empowerment, remote monitoring.	Limited focus on specific functionalities (monitoring, prediction).	Offers a more complete solution for early CVD detection.
Data	Includes diverse real-world data from various sensors and sources.	Often use simulated data or small datasets.	Enhances generalizability and real-world effectiveness.
Integration	Seamless integration of Cloud Centric IoT with existing healthcare workflows.	Limited discussion on integration with existing infrastructure.	Addresses a crucial barrier to practical implementation.
Interpretability	Exploring mechanisms to explain AI model reasoning on early detection in system diagnosis.	Limited focus on interpretability, hindering trust.	Enhances transparency and trust for healthcare professionals.
Disease Scope	Potentially applicable to various chronic conditions.	Mostly focused on specific diseases like CVD.	Offers wider applicability and impact.
Personalized Assessment	Utilizes fuzzy logic for individualized risk assessment and early detection.	Some studies use fuzzy logic	Offers a more personalized approach to CVD detection.
Machine Learning	Integration Explores the synergistic integration of fuzzy logic and machine learning.	Often use both approaches individually.	Potential for improved accuracy and interpretability.
Ethical and Regulatory Considerations	Implement Cloud Centric IoT to address data privacy, security, and potential bias issues.	Limited discussion on ethical and regulatory concerns.	Demonstrates responsible development and implementation.
Cost-Effectiveness and Scalability	Evaluates feasibility and affordability for real-world healthcare settings.	Lack of focus on cost-effectiveness and scalability.	Enhances potential for wider adoption.

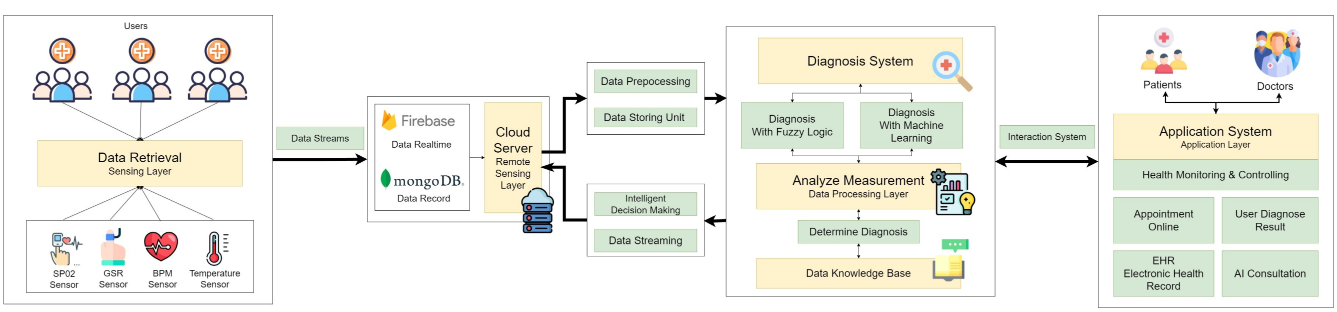

Figure 1. Framework conceptual for the LovHealth Diagnosis System

3. PROPOSED METHODOLOGY

Figure 1 depicts the proposed methodological approach. The IoT-based health monitoring system's conceptual framework was divided into four phases. In Phase 1, user health data are collected through medical equipment and sensors, known as the sensing layer, and transferred to the cloud subsystem through a gateway. In phase 2, referred to as the remote service layer, medical measurements are processed through the cloud server with two types of data: real-time and record data. The system diagnosis system employs this system in Phase 3 to make identifiable decisions about personal health. The interaction system produced by data processing in phase 3 in phase 4 is the application layer, which has numerous features, especially for User Diagnosing Results and health monitoring. The detailed explanation in Figure 1 will be explained in more detail at points A – D.

A. Sensing Layer

The Sensing Layer consists of several sensor nodes and actuators, where objects are generally located on the intranet network. This can be accomplished by connecting a sensor to a microcontroller. Figures 2 illustrate a detailed block diagram layout.

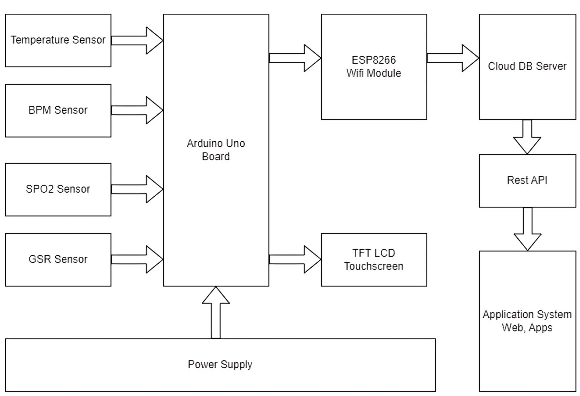

Figure 2. Diagram of Hardware System Components.

Figure 2 shows the hardware design; researchers have used several sensors in the sensing layer, including the SP02 (Oxygen Saturation), GSR (Galvanic Skin Response), BPM (Pulse Rate), and Temperature sensors. Each sensor was intended to collect health check data. In the system block diagram, researchers use four sensors as a reference for data collection, namely the MLX90614 temperature sensor, MAX 30100 BPM sensor, SP02 sensor, and GSR Grove sensor. Each sensor is connected to an Arduino Pro mega 2560 to accommodate project data in the health sector, and then on the communication layer side integrated with ESP 8266.

The block diagram shown in Figure 2 will be implemented into the LovHealth (LovIoTech HealthCare) tool, as shown in Figure 3. In the tool model, acrylic material was used as a hardware container. The socket used is a socket with the GX12 type as an intermediary for the connected sensor. A TFT LCD Touch Screen is used for user interaction on the display side. Users can operate the device through the touch screen.

Figure 3. Healthcare IoT Platform

Figure 3 shows that this tool is still in prototype form, accessing the sensor feature sharing and data capture features, which are still under development. The development also provides sensor plug slots if the LovHealth tool is to be expanded and if any other sensors are added.

B. Remote Service Layer

The remote service layer handles the connected sensor nodes that simultaneously interact with each other in a distributed database. Two types of data were retrieved and managed: real-time and recorded. The remote service layer uses a cloud server. Firebase, a Google database that displays data on IOT hardware in real-time and at the application layer, will be utilized to capture this type of real-time data. To accommodate distributed data from the data-sensing layer, the data record side of the MongoDB database manages it. In this layer, data distribution will be streamlined to each layer that requires data.

C. Data Processing Layer

The data-processing layer determines the characteristics of the system. This layer will carry out a selection process of stages: data streaming, data storing units, analysis measurement for determining decision-making on health diagnoses, and evaluation model. There are two main functions of a diagnosis system. First is a fuzzy logic for the diagnosis system by 4 sensor data according to the sensing layer. The second also includes the technology used, namely machine learning with a supervised learning approach: Support Vector Machine, Decision Tree, Random Forest, K-Nearest Neighbors, and Logistic Regression. This machine-learning approach is intended for data management in health diagnosis based on sensor data and datasets. The role of the supervised learning approach is to compare the evaluation model performance on diagnostic characteristics to determine the efficacy and precision of the employed algorithm method. In the model evaluation, the experiment also use the The Confusion Matrix is a widely used tool in machine learning to assess the effectiveness of a classification model.

- Fuzzy Logic
  Fuzzy logic is a kind of logic that addresses the

challenges posed by ambiguity and imprecision in the realms of decision-making and information processing. In contrast to classical (Boolean) logic, which operates on a binary system where propositions are considered either true or false, fuzzy logic allows for the representation of varying degrees of truth or membership within the range of 0 to 1. This characteristic makes it suitable for addressing situations where the boundaries between categories or states are indistinct. [15] [16] [17].

- K-Nearest Neighbors
  The K-nearest Neighbor (KNN) [18] [19] predicts the category of a new data point based on feature similarity. As a nonparametric method, KNN [20] makes no assumptions about the training data and thus does not derive any pattern or fit a curve. It maintains the training data and, when making predictions, employs KNN and majority voting to determine the class of a new observation. Fitriyadi et al. [21] utilized KNN to estimate the extent of COVID-19 diffusion, and [22] used KNN to predict the status of infected individuals.

- Logistic Regression
  The algorithm is a probability-based predictive analytic tool. Logistic Regression (LR) is the most basic version, and it predicts binary outcomes of either 0 or 1. It transfers the input data to these two values using a logistic function. LR is successful when data is linearly separable, but it might result in overfitting if the dataset contains more features than records [23] [24] [25].

- Support Vector Machine
  Support Vector Machine (SVM) represents separate classes in a multidimensional space using a hyperplane. Each coordinate on the plane represents a data point feature. The program use a search algorithm to identify an angle that efficiently separates the two classes, thereafter assigning the class label of a novel data point by determining its position relative to the hyperplane. It operates wonderfully with a greater number of features [26] [27] [28] [29].

- Decision Tree
  A Decision Tree is a decision structure in which the internal nodes are referred to as decision nodes since they are utilized to make choices. The output is represented by the leaf nodes. A decision was made for each branch of the tree depending on the factors discussed. The order of attributes used as a root node or decision node is determined by statistics that evaluate the significance of a particular attribute using measures such as entropy, information gain, and the Gini score [30] [31] [32] [33].

- Random Forest
  Random Forest (RF): An experimental method that uses a collection of decision trees to tackle complicated problems and improve model performance. Random Forest decision trees use numerous overlapping subsets of the training dataset and produce outputs based on majority voting on decision tree predictions. RF generally produces more precision as the number of trees increases [34] [35] [36] [37].

- Confusion Matrix
  The matrix of confusion serves as a commonly utilized tool in the field of machine learning and statistics for evaluating the effectiveness of a classification algorithm, with a focus on supervised learning. This is a summary illustrating a comparison between the predictions provided by a classification model and the actual valid values of the target variable. The matrix of confusion was a rectangular structure with two sides that served to express actual and predicted labels of classes [38] [39]. Confusion Matrix can be used to calculate accuracy, as in Table II.

TABLE II. Confusion matrix

		Actual	
		Positive (1)	Negative (0)
Predicted	Positive (1)	TP	FP
	Negative (0)	FN	TN

Table II shows the confusion matrix comprises four fundamental components. True Positives (TP) refer to occasions where the model accurately predicted a positive class. Instances in which the model accurately predicted the negative type are called true negatives (TN). False positives (FP) occur when the model erroneously denotes a positive class instead of a negative class. False negatives (FN) happen when the model incorrectly predicts the negative class instead of the positive class. The data contained within the confusion matrix can be utilized to calculate various performance indicators for classification models, including:

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{1}$$

The accuracy rate is calculated by dividing the sum of true positives and negatives by the total number of instances.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

The proportion of genuine positives to total positive cases. The evaluation assesses the model's accuracy in identifying and categorizing all optimistic scenarios.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

The proportion of genuine positive occurrences relative to the overall amount of optimistic predictions. The evaluation measures the model's capacity to identify cases incorrectly classified as positive.

$$F1Score = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (4)$$

The harmonic mean is utilized to achieve a compromise between precision and memory. The statistic in question is a well-balanced measure that considers both the occurrence of false positives and false negatives.

D. Application Layer

After the process at the knowledge layer, the data are sent to the application layer to provide diagnostic interaction to the target users, namely, patients and doctors/nurses. The data will be sent to the LovHealth website and its applications. On the application layer, LovHealth has a website platform.

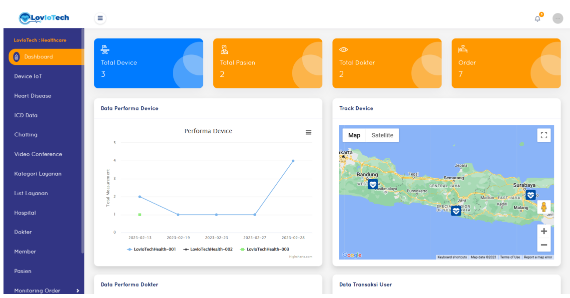

Figure 4. LovHealth website platform.

Figure 4 shows the view of the website created for the LovHealth Platform. This website is intended for admin and doctor users. This system aims to monitor the condition of IoT devices used by patients wherever they are. This is also to find out the performance of the devices when patients use them without needing to check directly. The implementation of the website functions as health agency data management for Electronic Health Records, IoT device management, patient monitoring, ICD-11 information, and health measurement monitoring.

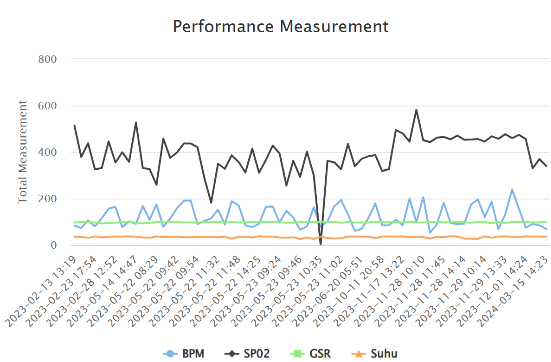

Figure 5. Health measurements monitoring

Figure 5 shows the health monitoring measurements on the system. This system aims to monitor patients by performing several health measurements. The system will convert it into a graph to watch usage data. The physiological data collected over a wearable device from February 13, 2023 to March 15, 2024. The y-axis represents the measurement value, while the x-axis shows the date and time. The data includes heart rate (BPM, blue line) in beats per minute, blood oxygen saturation (SPO2, black line) in percentage, body temperature (orange line) in degrees Celsius, and galvanic skin response (GSR, green line), an indicator of activity level or arousal.

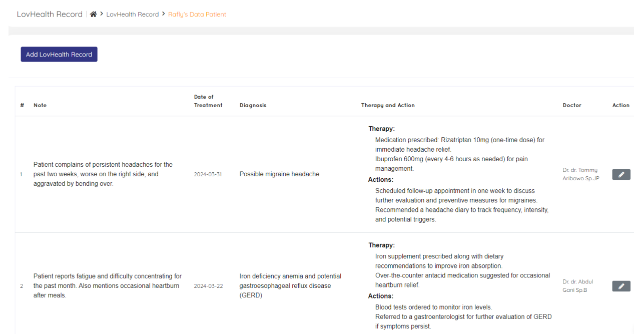

Figure 6. Electronic health record data list

Figure 6 displays the electronic health record feature. This feature is intended for doctors who control and monitor patients' health as a medium for health checks, scheduling appointments with patients, diagnosis and treatment, and health services. Electronic Health Records (EHRs) improve a doctor's workflow by providing rapid access to a patient's complete medical history, eliminating the need to trawl through paper documents. This not only saves doctors significant time during appointments, but also enables faster and more accurate recording and invoicing. Furthermore, EHRs enable secure communication among healthcare professionals involved in a patient's care, resulting in a more coordinated and efficient approach to treatment.

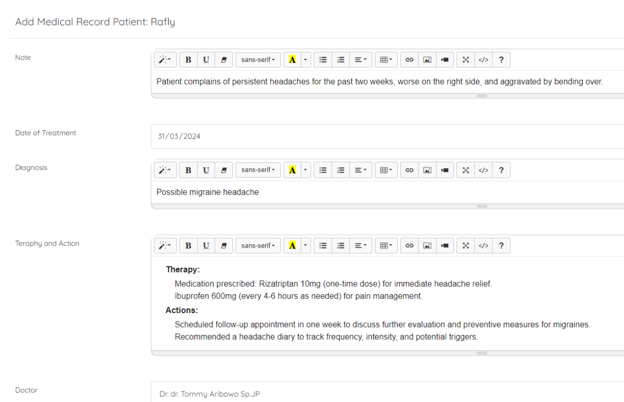

Figure 7. Electronic health records form

Figure 7 depicts the format of an electronic health record. The electronic health record (EHR) form serves as a computerized command center for doctors and nurses, facilitating patient care administration. It supports full data entry and tracking. Doctors can enter their observations and assessments into the notes section, and the date of each contact is automatically recorded. Doctors can record diagnoses based on medical history, examinations, and test findings, offering a complete picture of the patient's condition. This feature extends to the creation of a personalized treatment plan. The therapy section allows clinicians to detail drugs, surgeries, or therapies tailored to the patient's needs. The actions section takes a step further, providing instructions for patients and healthcare practitioners. Medication regimens, self-care advice, specialist referrals, and follow-up appointment reservations are all possibilities. The EHR form also clearly indicates the doctor who is accountable for the patient's care on that specific date.

Furthermore, the EHR system works seamlessly with other hospital service data. This lets doctors to access a patient's referral information, treatment history, and existing appointments all on the same platform. This complete picture promotes a more coordinated and efficient approach to care, guaranteeing a smooth flow of information between departments and, ultimately, improving the patient's healthcare experience.

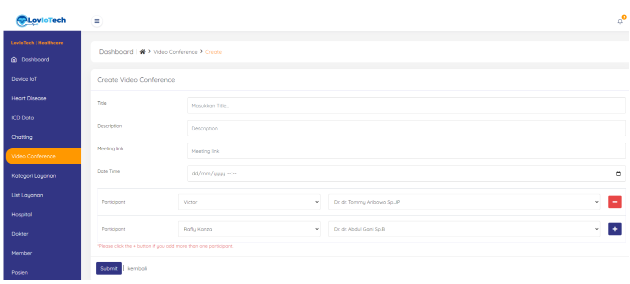

Figure 8. Telemedicine (chat & video conferencing)

Figure 8 displays the telemedicine feature. This system is an online consultation media for patients and doctors who have made an appointment. The system will create a schedule and adjust the users who have been selected to attend the consultation session.

E. Security Aspect

A cloud system and application data processing cannot be separated from the security system implemented [40]. The security implementation uses the cloud-centric concept, where the cloud is in the middle as an integration between IoT and applications. A cloud-centric IoT architecture [8] [41] is one in which the cloud plays a major and significant role in data processing, storage, and management. Devices are connected to the internet and interact with cloud-based services and platforms in a cloud-centric IoT system. Figure 9 depicts how security measures govern information transfer at various levels.

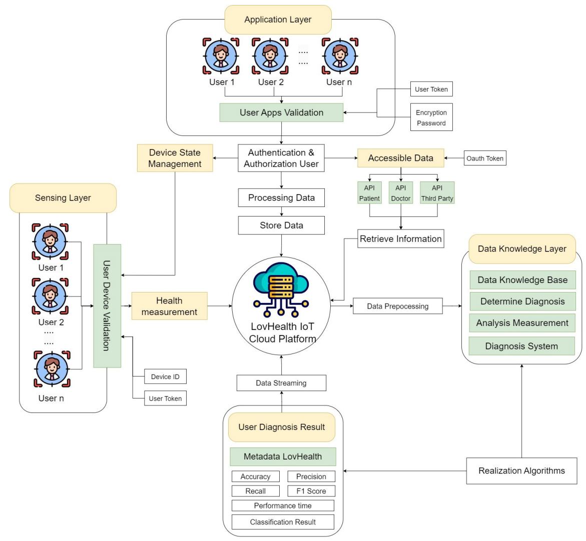

Figure 9. Flow diagram Cloud Centric IoT Diagnosis Systems.

Figure 9 presents the flow diagram illustrating the implementation of a Cloud-centric IoT diagnosis system. The system implements role-based access control techniques to safeguard the confidentiality and integrity of users' critical health information. The method employed in our study utilizes a Cloud-centric IoT technology framework encompassing two distinct user roles: Data Processing and Data Accessibility. The user is categorized as a data processor due to the storage of their medical data in our cloud-based IoT. Furthermore, it is sometimes necessary to disclose user personal data to medical professionals or individuals responsible for the care of the user. Utilizing the phrase "Assessed Partner" within the context of Application Programming Interfaces (APIs) serves the purpose of distinguishing individuals. API limitations are in place to ensure that only pertinent information is provided. The system employs three distinct categories of application programming interfaces (APIs) that have been delineated: (1) Physicians, (2) Parents/Caregivers, and (3) Third Parties. Physicians are consistently exposed to data about patients' Electronic Health Records. Moreover, by implementing an appropriate validation system, physicians can prescribe novel medications to patients using their Electronic Health Records.

The proposed system's security mechanism relies on a "private key" from a trusted third party (TTP) to encrypt the user's password. Moreover, the responsibility for executing the security procedure in the proposed system is with the TTP. After the completion of the authentication procedure, the authorization phase is contingent upon the specific responsibilities assigned to individual users. The data owner possesses the jurisdiction to restrict access to many partners and grant separate consent to them, referred to as Accessible Partners (APs). In addition, before storing the user's diagnosis result in the cloud storage repository, the system employs a key as an encryption method to safeguard the data.

4. EXPERIMENT RESULT

A. Diagnosis System with Fuzzy Logic

The health diagnosis system feature is intended for patients to self-diagnose based on measurement data from the device. These data can be used to diagnose the symptoms of the disease and provide treatment recommendations for the patient's health. The following is an overview of the system diagnosis flowchart in Figure 10.

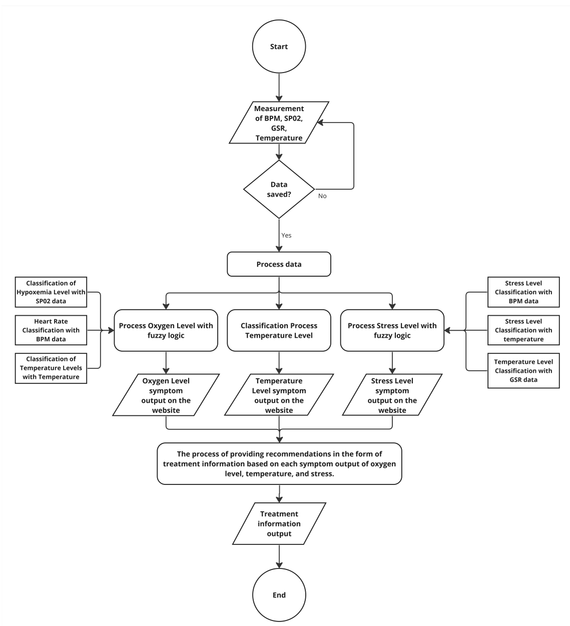

Figure 10. Flowchart of diagnosis systems with fuzzy logic

Figure 10 displays the flowchart on system diagnostics. Based on the system diagnosis flowchart design, there were several steps from the initial process to the end. Measuring data from the sensor to the database is processed to determine the classification based on oxygen, temperature, and stress levels. After obtaining these results through a fuzzy logic approach, it can determine the diagnosis results obtained based on the patient's measurements.

1) Data capture and measurement
   Health monitoring involves collecting and evaluating physiological data like blood oxygen saturation, body temperature, heart rate, and galvanic skin reaction. LovHealth uses various technologies to collect this data, including GSR sensors for sweat gland activity, electronic thermometers for temperature, and pulse oximeters for BPM and SpO2. However, individual variances, mobility, and sensor positioning can affect accuracy. LovHealth products make health monitoring more user-friendly by allowing touch-screen engagement.

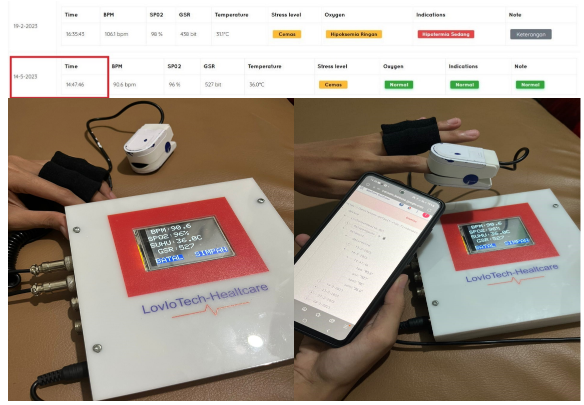

Figure 11. Data collection on the device used

Figure 11 is a test of the LovHealth device. Users can collect data based on temperature sensors, oxygen saturation, heart rate, and galvanic skin response. As many as 30 people have carried out this test to collect data. The product successfully takes measurements for data collection, for example, as shown in Figure 12.

```
{
  "device": {
    "LovIoTechHealth-001": {
      "datapengguna": {
        "alamat": "Pasar Wisata Blok Q 18 East Java, Indonesia",
        "lat": "-7.286030677499144",
        "lng": "112.78829980336478",
        "member": "63e14c025e191ffe56030172",
        "nama": "Rafly"
      },
      "dataunit": {
        "datarecord": {
          "13-2-2023": {
            "13:19:58": {
              "bpm": "82.7",
              "gsr": "514",
              "spo2": "97",
              "suhu": "35.6"
            },
            "13:26:57": {
              "bpm": "73.4",
              "gsr": "379",
              "spo2": "98",
              "suhu": "34.7"
            }
          },
          "14-5-2023": {
            "14:47:46": {
              "bpm": "90.6",
              "gsr": "527",
```


Figure 12. Measurement data collection

Figure 12 An illustration of JSON data is provided after data retrieval is accomplished correctly. The data from the gadget is categorized into two distinct types: user data and unit data. Users can perform several checks by referencing the time and date. The data will be collected and documented using four sensors: BPM, SP02, GSR, and Temperature.

2) Process data based on its classification
   By the Figure 10, the system will be classified into three parts, namely:
   - Oxygen Level
     To determine the oxygen level, it is necessary to classify hypoxemia and heart rate levels. The

following classification details were obtained.

TABLE III. Classification of hypoxemia levels [42]

No	Conditions	Hypoxemia Level
1	SP02 >= 95 and SP02 <= 100	Normal
2	SP02 >= 91 and SP02 <= 94	Mild
3	SP02 >= 86 and SP02 <= 90	Moderate
4	SP02 <= 85	Sever

Table III presents hypoxemia classification data using SP02 sensor data, aiming to understand hypoxemia mechanism and evaluate patients with hypoxemia symptoms. [42].

TABLE IV. Classification of heart rate levels [43]

No	Conditions	Heart Rate Level
1	BPM < 60	Bradycardia
2	BPM >= 60 and BPM <= 100	Normal
3	BPM > 100	Tachycardia

Table IV categorizes heart rate levels using BPM sensor data, categorizing bradycardia, normal, or tachycardia based on predefined criteria, simplifying understanding of heart rate's connection to health recommendations. [43].

- Stress Level
  In determining the stress level, it is necessary to classify it based on 3 data inputs: BPM, Temperature, and GSR. Here are the details of the classification carried out:

TABLE V. Stress level classification [44]

No	Sensor	Conditions	Stress Level
1	BPM	BPM >= 60 and BPM <= 70	Relaxed
	Temperature	Temperature >= 36 and Temperature <= 37	
	GSR	GSR > 300 and GSR <= 525	
2	BPM	BPM >= 70 dan BPM <= 90	Fatigue
	Temperature	Temperature >= 35 and Temperature <= 36	
	GSR	GSR >= 500 and GSR <= 600	
3	BPM	BPM >= 90 and BPM <= 100	Anxiety
	Temperature	Temperature >= 33 and Temperature <= 35	
	GSR	GSR > 600 and GSR <= 825	
4	BPM	BPM > 100	Stressed
	Temperature	Temperature < 33	
	GSR	GSR > 825	

- Temperature Level
  Temperature sensor data must be processed based on conditions to determine the temperature level. The following details the temperature classification carried out:

TABLE VI. Classification of temperature levels [45]

No	Conditions	Temperature Level
1	Temperature > 40	Hyperthermia
2	Temperature >= 37.5 and Temperature <= 40	Fever
3	Temperature >= 36 and Temperature <= 37.5	Normal
4	Temperature >= 32 and Temperature < 36	Mild Hypothermia
5	Temperature >= 28 and Temperature <= 32	Moderate Hypothermia
6	Temperature < 28	Severe Hypothermia

Table VI shows six levels of temperature classification: hyperthermia, fever, regular, mild hypermedia, moderate hyperemia, and severe hypothermia. The system will process the temperature data according to the condition and produce a temperature level classification according to the patient's temperature data.

3) Fuzzy logic process to determine symptom results
   In the fuzzy logic process, according to the design flowchart, there are two fuzzy logic processes, namely:
   - Oxygen level with fuzzy logic
     The oxygen level is determined from two condition variables: hypoxemia and heart rate levels. These two variables are made a rule based on fuzzy. The following stages of rule-based stress levels are shown in Table VII.

TABLE VII. Rule-based oxygen level

Rule	Hypoxemia	Heart Rate	Result
1	Normal	Bradycardia	Normal Hypoxemia
2	Normal	Normal	Normal Hypoxemia
3	Normal	Tachycardia	Mild Hypoxemia
4	Mild	Normal	Mild Hypoxemia
5	Mild	Bradycardia	Mild Hypoxemia
6	Mild	Tachycardia	Moderate Hypoxemia
7	Moderate	Normal	Moderate Hypoxemia
8	Moderate	Bradycardia	Moderate Hypoxemia
9	Sever	Tachycardia	Severe Hypoxemia
10	Sever	Normal	Severe Hypoxemia
11	Sever	Bradycardia	Severe Hypoxemia

Table VII shows the oxygen level is determined from two variable conditions, namely the level of hypoxemia and heart rate. These two variables are made a rule or rules based on fuzzy. This stage acts as an output for oxygen levels with an easy-to-understand if-and-then rule and ten output rules.

- Stress level with fuzzy logic
  Based on the stress level reference and some of the inputs obtained in Table V, a rule based

on fuzzy is created. The following are the rule-based stages of stress levels shown in Table VIII.

TABLE VIII. Rule-based stress level

Rule	GSR	BPM	Temperature	Result
1	Relaxed	Relaxed	Relaxed	Relaxed
2	Relaxed	Relaxed	Fatigue	Relaxed
3	Relaxed	Relaxed	Anxiety	Fatigue
4	Relaxed	Relaxed	Stressed	Anxiety
5	Relaxed	Fatigue	Relaxed	Relaxed
6	Relaxed	Fatigue	Fatigue	Fatigue
7	Relaxed	Fatigue	Anxiety	Fatigue
8	Relaxed	Fatigue	Stressed	Anxiety
9	Relaxed	Anxiety	Relaxed	Fatigue
10	Relaxed	Anxiety	Fatigue	Fatigue
11	Relaxed	Anxiety	Anxiety	Anxiety
12	Relaxed	Anxiety	Stressed	Anxiety
13	Relaxed	Stressed	Relaxed	Fatigue
14	Relaxed	Stressed	Fatigue	Fatigue
15	Relaxed	Stressed	Anxiety	Anxiety
16	Relaxed	Stressed	Stressed	Anxiety
17	Fatigue	Relaxed	Relaxed	Relaxed
18	Fatigue	Relaxed	Fatigue	Fatigue
19	Fatigue	Relaxed	Anxiety	Fatigue
20	Fatigue	Relaxed	Stressed	Fatigue
21	Fatigue	Fatigue	Relaxed	Fatigue
22	Fatigue	Fatigue	Fatigue	Fatigue
23	Fatigue	Fatigue	Anxiety	Fatigue
24	Fatigue	Fatigue	Stressed	Anxiety
25	Fatigue	Anxiety	Relaxed	Anxiety
26	Fatigue	Anxiety	Fatigue	Fatigue
27	Fatigue	Anxiety	Anxiety	Anxiety
28	Fatigue	Anxiety	Stressed	Anxiety
29	Fatigue	Stressed	Relaxed	Fatigue
30	Fatigue	Stressed	Fatigue	Anxiety
31	Fatigue	Stressed	Anxiety	Anxiety
32	Fatigue	Stressed	Stressed	Anxiety
33	Anxiety	Relaxed	Relaxed	Fatigue
34	Anxiety	Relaxed	Fatigue	Fatigue
35	Anxiety	Relaxed	Anxiety	Anxiety
36	Anxiety	Relaxed	Stressed	Anxiety
37	Anxiety	Fatigue	Relaxed	Fatigue
38	Anxiety	Fatigue	Fatigue	Fatigue
39	Anxiety	Fatigue	Anxiety	Anxiety
40	Anxiety	Fatigue	Stressed	Anxiety
41	Anxiety	Anxiety	Relaxed	Anxiety
42	Anxiety	Anxiety	Fatigue	Anxiety
43	Anxiety	Anxiety	Anxiety	Anxiety
44	Anxiety	Anxiety	Stressed	Anxiety
45	Anxiety	Stressed	Relaxed	Anxiety
46	Anxiety	Stressed	Fatigue	Anxiety
47	Anxiety	Stressed	Anxiety	Anxiety
48	Anxiety	Stressed	Stressed	Stressed
49	Stressed	Relaxed	Relaxed	Fatigue
50	Stressed	Relaxed	Fatigue	Fatigue
51	Stressed	Relaxed	Anxiety	Anxiety
52	Stressed	Relaxed	Stressed	Anxiety
53	Stressed	Fatigue	Relaxed	Fatigue
54	Stressed	Fatigue	Fatigue	Anxiety
55	Stressed	Fatigue	Anxiety	Anxiety
56	Stressed	Fatigue	Stressed	Anxiety
57	Stressed	Anxiety	Relaxed	Anxiety
58	Stressed	Anxiety	Fatigue	Anxiety
59	Stressed	Anxiety	Anxiety	Anxiety
60	Stressed	Anxiety	Stressed	Stressed
61	Stressed	Stressed	Relaxed	Anxiety
62	Stressed	Stressed	Fatigue	Anxiety
63	Stressed	Stressed	Anxiety	Stressed
64	Stressed	Stressed	Stressed	Stressed

Table VIII shows the rule-based stress level. The system uses fuzzy logic to determine stress levels by analyzing data from various sources: heart rate (BPM), skin conductance (GSR), and body temperature. Each data point has a range corresponding to different stress levels (Relaxed, Fatigue, Anxiety, Stressed). The system uses 64 easy-to-understand ”if-then” rules that combine these data points. Based on these rules, the system assigns stress levels by considering the interaction between these physiological factors, thus providing a more comprehensive picture of the patient’s stress state.

4) Diagnosis result and treatment information based on the symptoms obtained
After the experiment gets the results from oxygen and stress levels, the system will provide a treatment recommendation based on the symptoms of the disease obtained. By analyzing the oxygen and stress levels, the system can generate a preliminary diagnosis based on potential symptoms linked to those readings. It will then provide recommendations for treatment approaches tailored to the possible underlying condition. However, it’s important to remember that this information is for informational purposes only and shouldn’t replace a professional medical evaluation. Figure 13 is a website platform used by doctors, doctors can monitor patient conditions through the website based on their respective IoT devices.

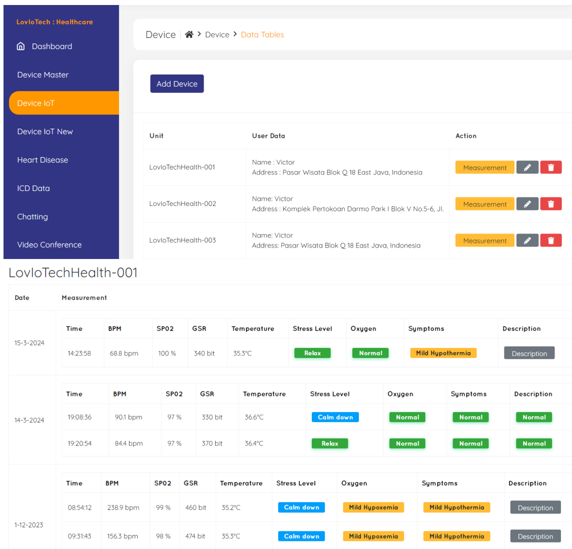

Figure 13. Device management and data measurement

Figure 13 shows the device management and measurement features. In device management, admins can add multiple devices to be integrated into the system. Admins can also monitor the location of devices used by patients. When the device clicks on the measurement, it will display the device data. Figure 13 shows the diagnostic results based on the 3 classifications performed: BPM data as a measurement of the patient's heart rate, SP02 as a measurement of oxygen saturation level in the blood, and GSR as a combined measurement of skin conductance (sweat production) and skin temperature, often used as an indicator of stress levels.

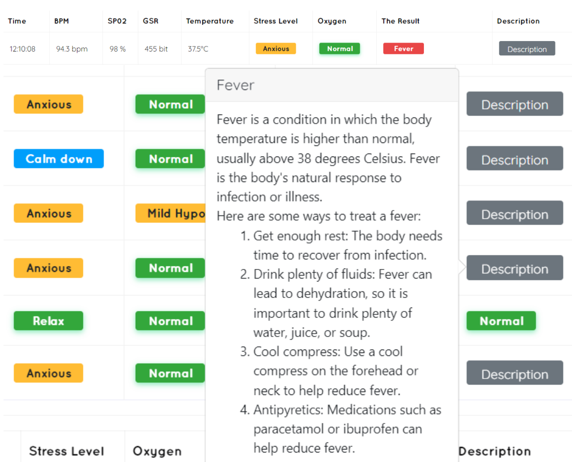

Figure 14. System diagnosis results and treatment information for patients

Figure 14 displays the results of the outputs derived from a fuzzy logic model, which considers the interplay between the three physiological measurements from the top section. The top panel displays three physiological parameters being monitored: oxygen levels, stress levels, and temperature levels. Fuzzy logic, a mathematical approach that deals with imprecision, investigates the interplay of various measurements to provide insights into a patient's health. In this case, the system identified a possible fever based on the input data. It shows a temporary diagnosis of "fever" along with information about what a fever is and how to manage it. It's vital to keep in mind that this information is most likely generic and should not be used to replace expert medical advice. While this approach provides a preliminary analysis, a doctor's evaluation is still necessary. The doctor would take the output of the fuzzy logic model into account, as well as the patient's medical history, symptoms, and physical examination. This comprehensive approach assures a correct diagnosis and the best course of treatment. This is related to the color displayed; a detailed explanation can be seen in Figure 15.

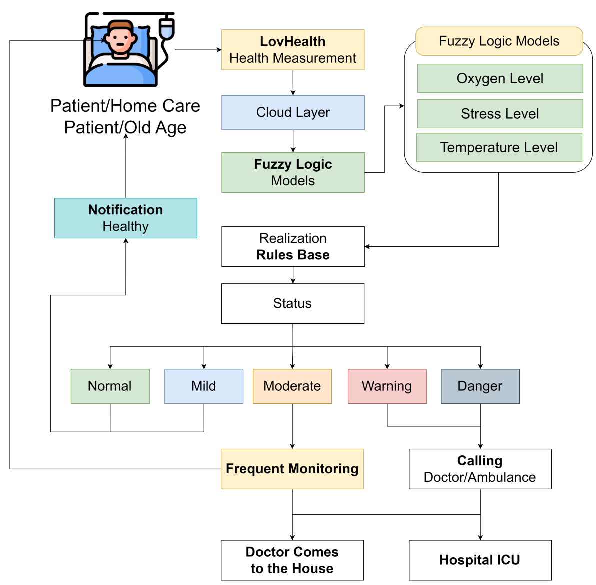

Figure 15. Interaction between fuzzy logic models and treatment systems.

Figure 15 shows the flow of fuzzy logic interaction with treatment systems. Fuzzy logic shows a rule realization process that displays the results of the output status based on the fuzzy logic model. The group says five different color states, as shown in Figure 14; several colors are displayed. In Figure 15, there are five color statuses: normal is green, mild is blue, moderate is orange, warning is red, and danger is black. Each color has a function, namely in normal and mild status, as green and blue will be connected to the notification function in the patient system. Moderate, warning, and danger statuses will be connected to the patient system. The system will automatically perform the alert process and call a doctor and ambulance to carry out the handling process. The experimental method uses the fuzzy logic model considering 4 sensors, which can be seen in Table IX for sample diagnoses. The test results were carried out in several samples, as in Table IX.

TABLE IX. Sample diagnoses

Trial	BPM	SP02	GSR	Temperature
1	69.2 bpm	97%	371 bit	36.1 °C
2	116.7 bpm	97%	382 bit	36.1 °C
3	179.3 bpm	99%	387 bit	29.5 °C
4	164.7 bpm	98 %	366 bit	36.2 °C
5	165.4 bpm	99 %	428 bit	36.4 °C
6	97.0 bpm	98 %	394 bit	32.0 °C
7	147.7 bpm	96 %	256 bit	31.4 °C
8	65.8 bpm	98 %	293 bit	25.6 °C

Table IX shows the form of the test data conducted and samples of the diagnosis on four measurements. The results of this test will become an experiment on diagnoses, as in Table X.

TABLE X. Experiment on diagnose

Trial	Stress Level	Oxygen Level	Diagnose Result on Symptoms
1	Relaxed	Normal	Normal
2	Fatigue	Mild Hypoxemia	Normal
3	Anxiety	Mild Hypoxemia	Moderate Hypothermia
4	Fatigue	Mild Hypoxemia	Normal
5	Fatigue	Mild Hypoxemia	Normal
6	Anxiety	Normal	Mild Hypothermia
7	Anxiety	Mild Hypoxemia	Moderate Hypothermia
8	Anxiety	Normal	Severe Hypothermia

Table X shows the classification results based on the rules in fuzzy logic. Figure 10 shows a flowchart for this experiment, which requires two variables, stress and oxygen levels, to diagnose disease symptoms. The diagnostic result becomes moderate hypoxemia by Table X with an Anxiety stress level and an oxygen level of mild hypoxemia. The data can be used to diagnose and provide treatment information.

B. Predictive Heart Disease Diagnosis System

In the health disease predictor feature, This simulation uses a machine learning model approach, namely Random Forest, Logistic Regression, SVM, and Decision Tree In order to forecast the probability of developing cardiovascular disease based on relevant data features. The dataset used is from the Cleveland database [46]; the example is a display of the heart disease dataset.

TABLE XI. Heart disease dataset

No	age	sex	cp	trestbps	chol	fbs	restecg	thalach
0	69	1	0	160	234	1	2	131
1	69	0	0	140	239	0	0	151
2	66	0	0	150	226	0	0	114
3	65	1	0	138	282	1	2	174
4	64	1	0	110	211	0	2	144
5	64	1	0	170	227	0	2	155
6	63	1	0	145	233	1	2	150
7	61	1	0	134	234	0	0	145
8	60	0	0	150	240	0	0	171
9	59	1	0	178	270	0	2	145

TABLE XII. Heart disease dataset

No	exang	oldpeak	slope	ca	thal	condition
0	0	0.1	11	0	0	0
1	0	1.8	2	0	0	0
2	0	2.6	20	0	0	0
3	0	1.4	11	0	1	1
4	1	1.8	10	0	0	0
5	0	0.6	10	2	0	0
6	0	2.3	20	1	0	0
7	0	2.6	1	2	0	1
8	0	0.9	0	0	0	0
9	0	4.2	2	0	2	0

Table XI and XII shows the example dataset usage comprised 297 data records, and 14 columns were used. 54 percent of the population has heart disease, while 46 percent of the population does not have heart disease. Based on this data, this dataset is already balanced, and there is no need for data balancing in the preprocessing step. This dataset compiles information about patients, such as their characteristics, test findings, and if they have cardiac disease. The objective is to find patterns that can predict cardiac disease in new individuals. For example, researchers may check for correlations between age, gender, and chest pain to determine whether certain combinations are more likely to signal cardiac disease. Similarly, they may examine blood pressure, cholesterol, and blood sugar levels to determine how frequently these indicators coincide with the condition. The table also includes findings from electrocardiograms, exercise tests, and thallium tests, which all provide information about heart function and possible blockages. By examining these variables together, researchers can uncover patterns that can be utilized to create tools for predicting heart disease. According to the dataset, Table XIII describes the variables table [46].

TABLE XIII. Variable Information

Variable Name	Description
age	The variable of interest is the individual's age, measured in years.
sex	The variable "sex" is coded as 0 for females and 1 for men.
cp	The classification of chest pain is based on its severity: 0 is traditional angina, 1 is unusual angina, 2 is non-anginal pain, and 3 is benign chest pain.
treetops	The blood pressure at the stillness
chol	Plasma cholestrol
fbs	The fasting glucose level is greater than 120 mg/dL. (0 is inaccurate and 1 is accurate)
restecg	Resting electrocardiographic findings can be categorized into three groups: normal, presence of ST-T wave abnormalities, and indication of possible or definitive left ventricular tetralogy hyper histories.
thalach	The most excellent cardiac pulse attained
exang	Using a binary variable, the presence of exercise-induced angina was determined, with 1 indicating its presence and 0 indicating its absence.
oldpeak	The occurrence of ST depression during activity in comparison to periods of rest.
slope	The variable indicating the gradient of the maximal exercise section ST is coded as follows: 1 for upsloping, 2 for flat, and 3 for downsloping.
ca	Fluorescence-colored number of major arteries (0-3)
thal	Thalassemia is a genetic disorder characterized by three distinct categories: normal (0), defect fixed (1), and defect reversible (2).
con	The value of 0 represents the absence of disease, whereas 1 indicates the presence of illness.

Table XIII displays each variable description used to predict heart diseases. The information results from Table XIII are made into a system feature form that patients or doctors can fill in. Each variable has a name and description to help patients or doctors fill out a system feature form. It includes patient demographics (age, sex), chest pain type, blood pressure, cholesterol, and blood sugar levels. Additionally, it gathers information on resting ECG results, exercise performance (maximum heart rate, presence of angina), and exercise test results related to ST segment changes, slope, and the number of affected blood vessels. Finally, it considers factors like thalassemia (a blood disorder) and the target vessel identified during a thallium stress test. By combining these details, the system can generate a more comprehensive picture of a patient's CVD risk. These variables provide the information needed by the system to analyze a patient's heart and predict potential diseases.

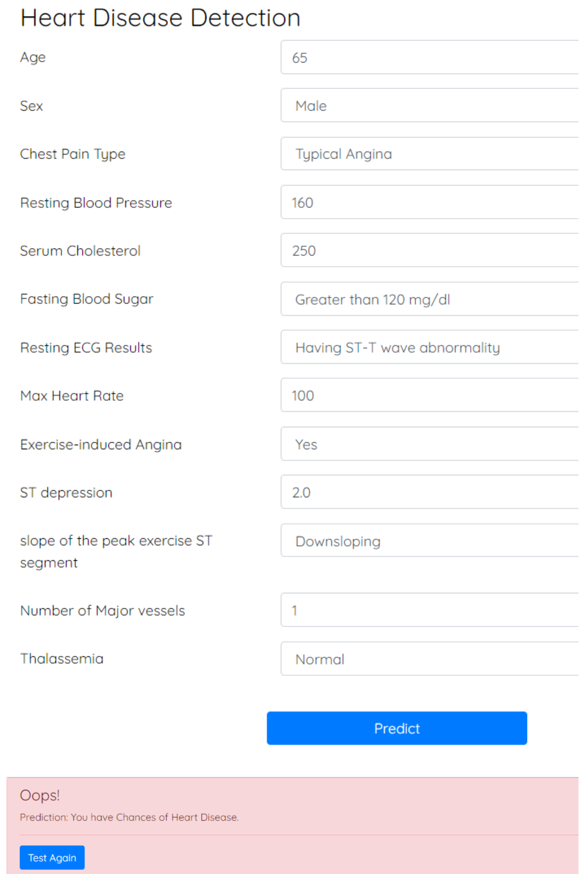

Figure 16. Health disease predictor

Figure 16 shows the health disease predictor simulation. Patients or doctors can use the form to determine if a patient has cardiac disease. The input data is in Table XIII, namely 13 variables. Factors like age, blood pressure, cholesterol, and ECG results are included. After filling out the form, the system evaluates the information and sends an alert indicating the possibility of heart disease. This simulation demonstrates how machine learning can be applied to heart disease detection. Machine learning algorithms can assess a patient's risk of heart disease by examining their medical history, which includes parameters such as age, gender, blood pressure, cholesterol, and findings from tests such as an ECG. These algorithms can also analyze medical images to identify symptoms of the illness and be integrated into wearable devices to monitor heart function and perhaps detect early warning signs. While not without limitations, machine learning can help doctors diagnose and treat cardiac problems. Based on some of these variables, testing is also carried out for distribution data based on datasets displayed as distplots to determine heart disease.

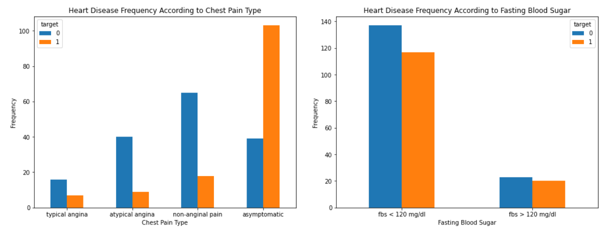

Figure 17. Chest pain type and fasting blood sugar distribution

Figure 17 shows the chest pain type and fasting blood sugar. In the chest pain type, most people with heart disease have asymptomatic chest pain. The fasting blood sugar, most people with heart disease have fbs value of less than 120 mg.

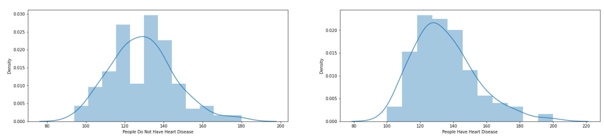

Figure 18. Blood pressure distribution

Figure 18 shows the blood pressure visualization that the max blood pressure is 200. Min blood pressure is 100, and average blood pressure is 134.6 for most people with heart disease.

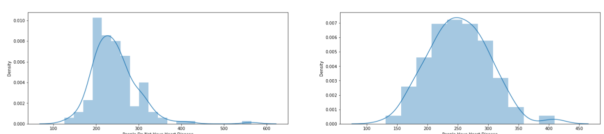

Figure 19. Cholesterol distribution

Figure 19 depicts a visualization of the maximum cholesterol level, known as 409. The lowest possible level of cholesterol was 131, and the median cholesterol level was 251.8 in the majority of heart disease patients.

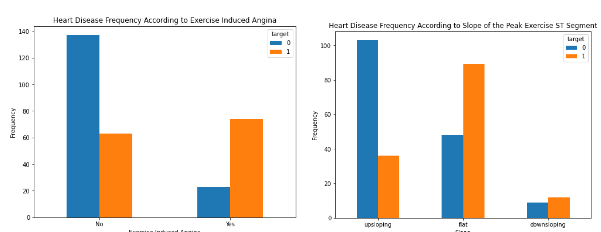

Figure 20. Exercise Induced Angina and slope distribution

Figure 20 shows the topic of discussion pertains to the distribution of angina and its relationship to slope. Exercise-induced angina is commonly observed in those at a higher risk of developing cardiovascular disease. Individuals with flat peak ST segments exhibit a higher propensity for heart illness, whereas those with upsloping peak ST segments display a reduced likelihood of developing heart disease.

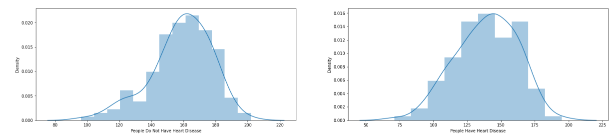

Figure 21. Maximum heart rate distribution

Figure 21 shows the heart rate visualization that the highest data of people with an increased heart rate of more than 150 are likelier to have heart disease.

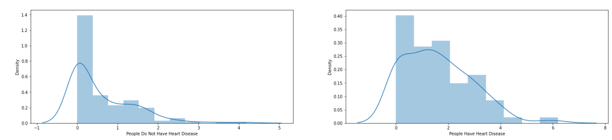

Figure 22. ST depression distribution

Figure 22 shows the ST depression visualization of the data of people with high heart rates. The minimum value is 0.0, the highest value is 6.2, and the average value of not suffering from heart disease is 1.58.

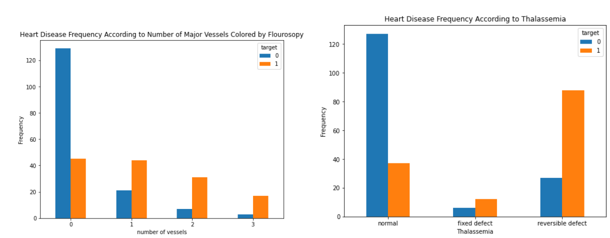

Figure 23. Fluoroscopy and thalassemia distribution

Figure 23 demonstrates the flouroscopy and distribution of thalassemia. Fluoroscopy typically does not color the major blood arteries of individuals without cardiovascular disease. Thalassemia-related heart disease is more prevalent in those with reversible abnormalities.

5. MODEL EVALUATION & DISCUSSION

Based on the diagnosis system for health disease predictors. The feature utilization of testing and training data is comprised of 25% testing data and 75% training data. A data split is frequently used in machine learning for heart disease prediction to guarantee that the model generalizes effectively to new data. 75% of the data is used as training data, and the model learns patterns and correlations between characteristics such as age, blood pressure, and the presence of heart disease. The remaining 25% serves as testing data, unseen by the model during training. This previously unseen data is then used to test the model's ability to reliably

TABLE XIV. Comparison table of confusion matrix to supervised learning models

Model	TP	FP	FN	TN	Accuracy	Precision	Recall	F1-Score
Logistic Regression	30	8	10	27	76%	78.9%	75%	76.9%
KNN	29	9	10	27	74.6%	76.3%	74.3%	75.2%
Support Vector Classifier	30	8	8	29	78.6%	78.9%	78.9%	78.9%
Random Forest	31	7	6	31	82.6%	81.5%	83.7%	82.5%
Decision Tree	25	13	8	29	72%	65.7%	75.7%	70.3%

forecast heart disease in new patients. This was also done for the model evaluation process using several different approaches, according to Figure 24.

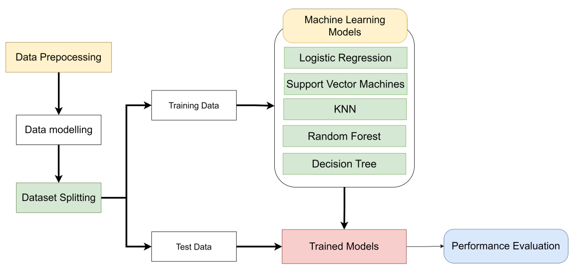

Figure 24. Model Processing

Figure 24 shows the processing model in question is utilized for model evaluation. The initial data processing stage involves the transformation and manipulation of data, which will afterward undergo data modeling using the dataset. The datasets will be partitioned into two subsets: the training and test data. Using training data as test data is a common practice in the model evaluation process within machine learning. The training data will be merged with the test data to form a trained model. The outcomes of the trained model will consist of the performance metric for each utilized modeling algorithm. The performance evaluation uses the confusion matrix methodology to ascertain the actual and expected values for the machine learning model methodology.

Table XIV shows the experiments using the confusion matrix, the accuracy of the predicted class values relative to the actual class values for each employed model was evaluated. Once the primary and projected values have been obtained, the subsequent stage involves the computation of precision, recall, f1-score, and accuracy metrics using five different machine learning model approaches from KNN, Logistic Regression, Decision Tree, SVM, and Random Forest. The highest accuracy value shows the Random Forest approach worth 82.6%. The purpose of comparing several methods is to determine the evaluation performance diagnosis system for heart disease predictors.

6. CONCLUSION

The current healthcare landscape faces a crucial gap in early detection of cardiovascular disease (CVD), mainly due to subtle symptoms and limited access to diagnostic tools. This study introduces an innovative IoT-based system that addresses this gap by merging the strengths of fuzzy logic and machine learning. By analyzing individual data such as heart rate and oxygen saturation, the system employs fuzzy logic to offer personalized symptom assessments, enabling individuals to monitor their health and seek timely intervention. Additionally, the system utilizes machine learning algorithms, with Random Forest showing high accuracy in CVD prediction. This unique combination provides a promising solution not just for early detection but also for enhanced accessibility and personalized care. While further validation is necessary, this research underscores the potential of AI in collaboration with medical expertise to transform CVD management, ultimately leading to improved health outcomes and decreased global burdens.

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