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LovHealth: LovIoTech Healthcare IoT-Cloud Platform for Patient Care Based On Diagnosis System with Fuzzy Logic and Machine Learning Approach

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Abstract: Innovation in the health sector in the world is advancing, and there are increasingly more challenges that need to be addressed. The current problem is that most of the world's population is afflicted with diseases, such as heart disease, that go undiagnosed because of their subtle symptoms and the difficulty and cost of diagnostic techniques. Many struggle to access adequate medical treatment and expensive diagnostic testing. The only function of medical devices is to monitor health data, and no diagnostic procedure aids patients. As an application of system diagnosis in IoT, this research develops a diagnosis system, provides treatment information, and an appointment system in health data processing. This study uses machine learning and fuzzy logic approaches to offer convenience to patients in self-diagnosis processes monitored by doctors. To optimize the IoT product, a fuzzy logic experiment was tested to produce a diagnosis with three variable parameters: stress level, oxygen, and temperature. These three variables will diagnose disease symptoms experienced by users based on the measurement of four data sensors: heart rate, oxygen saturation, galvanic skin response, and body temperature. In the machine learning approach, the experiment conducted trials with several Decision Tree, KNN, SVM, Random Forest, and Logistic Regression models to forecast cardiovascular disease diagnosis. The Confusion Matrix results show that the approach with the highest value is Random Forest, with an Precision of 81.5%, Recall of 83.7%, F1-Score 82.5%, and Accuracy of 82.6%. This indicates that diagnosing heart disease can be more efficient using the Random Forest approach. With these two approaches, patients can be facilitated in carrying out the diagnosis process independently and remotely without the need to come to the hospital. Doctors can easily monitor and provide treatment with each patient's electronic health record platforms. This is expected to increase the level of optimal health services.

Keywords: IoT, Machine Learning, Diagnose System, Fuzzy Logic, Random Forest

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.

The Internet of Things (IoT) can effectively oversee healthcare using real-time monitoring and expedited retrieval of patient health information. A significant proportion, over 60 percent, of healthcare organizations on a global scale are actively engaged in implementing or investigating IoT solutions within the healthcare sector. The use of IoT-connected devices for health monitoring and diagnosis by patients and healthcare professionals is projected to expand significantly in the near future. IoT can solve specific problems experienced in healthcare so far [4]. 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 [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 [4]. Currently, numerous Health IoT devices mainly serve the purpose of monitoring and collecting data. This study presents a system diagnosis application within the context of the IoT. The research focuses on developing a diagnosis system encompassing treatment information and an appointment system for processing health data. This study employs machine learning and fuzzy logic methodologies to enhance patients' convenience during self-diagnosis procedures under the supervision of medical professionals. To improve the efficiency of the IoT product developed, a group of researchers conducted tests on various data sets to identify indicators of stress levels, patient heart rate levels, as well as signs of hypoxemia and hypothermia. In addition, this study assessed the accuracy of data modeling strategies in the context of identifying cardiac disease. The data evaluation models made use of algorithmic learning techniques, such as Decision Trees, Random Forest, K-Nearest Neighbors (KNN), Logistic Regression, and Support Vector Machines (SVM).

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]. 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 CO2 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 that have used machine learning and fuzzy logic to diagnose symptoms and predict cardiac disease.

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Table I. Summary of comparison model approaches and features

Work	Scope	Diagnose Algorithm	Machine Learning(ML) Models	IoT Sensors	Cloud Deploy
Kent et al. [5]	In the framework of research, evaluate the viability and the efficacy of the IoT health monitoring system.	-	-	-	-
Rasyid et al. [6]	• Health Monitoring • History of health check sessions	-	-	MySignals Liberium Sensors	MySignals Liberium Cloud Platform
Md. Milon Islam. [7]	Health Monitoring	-	-	Heartbeats Sensor, Temperature Sensor, CO & CO2 Sensor	ThingSpeak Platform
Prabal Verma [8]	• Health Monitoring • Alert System Generation • Cloud-Centric IoT Framework • User Diagnosis	ML Method	Decision Tree, Naïve Bayes, SVM, KNN, and Random Forest.	Body temperature, blood oxygen, blood pulse, ECG, Weight, the gastrointestinal tract, and EE are all diagnostic indicators.	Cloud Platform
Rahman [9]	Health & diagnosis systems	Fuzzy Logic	-	ECG Sensor	IBM Cloud, Blynk IoT Platform
Dini [10]	• Detection of hypoxemia symptoms. • Detection of oxygen and heart rate levels • Health Monitoring	Fuzzy Logic	-	Heartbeats Sensor, Oxygen Saturation Sensor	Firebase
Kuswoyo [11]	Health Monitoring	-	-	Heartbeats Sensor, Oxygen Saturation Sensor, Temperature Sensor	Blynk IoT Platform
Abdullah et al. [12]	• Health Monitoring • Heart disease prediction	ML Method	SVM, KNN, Random Forest, Naïve Bayes	ECG Sensor	ThingSpeak Platform
Godi [13]	• Health Monitoring & Controlling • Diagnose system • Detection of Diabetes level	-	SVM, Logistic Regression, KNN, Decision Tree	Blood pressure sensor, BMI Sensor, Skin Thickness Sensor, Glucose sensor	Cloud Platform
Ganesan [14]	• Heart disease Prediction • Diagnose system • Patient Records	ML Method	J48, Logistic Regression, SVM, Multilayer Perceptron	Dataset	Cloud Platform
Our Proposed	• Health Monitoring & Controlling (device, doctor and patient) • Detection of the patient's stress levels and heart rate levels. Detection of symptoms of hypoxemia and hypothermia. • Diagnose and provide treatment or care information through Electronic Health Records • Heart disease Prediction • Cloud-Centric IoT Framework	Fuzzy Logic & ML Method	SVM, Logistic Regression, KNN, Random Forest, Decision Tree	Heartbeats Sensor, Oxygen Saturation Sensor, Galvanic Skin Response, Temperature Sensor	**Self-built Platform** Cloud Hosting Server, Firebase, MongoDB

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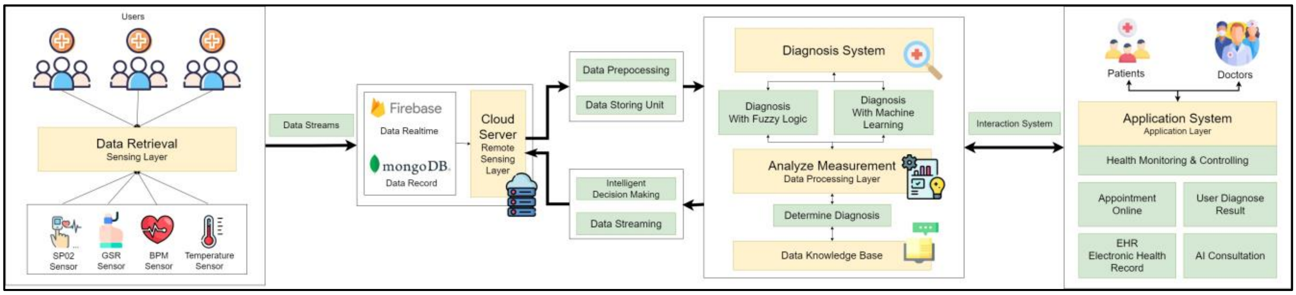

Figure 1. Framework conceptual for the LovHealth Diagnosis System.

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.

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 and 3 illustrate a detailed block diagram layout.

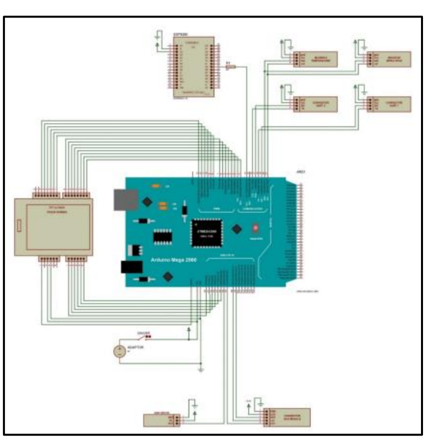

Figure 2. Diagram of Hardware System Components.

Figure 2 depicts the system's hardware block diagram. The sensor is responsible for data collecting, whereas the minicomputer/microcontroller is responsible for data processing and transmission to the next layer via communication protocols and interfaces.

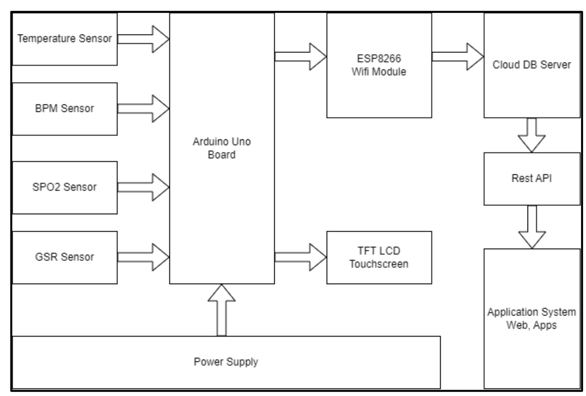

Figure 3. Hardware-design structure.

Figure 3 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 4. 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.

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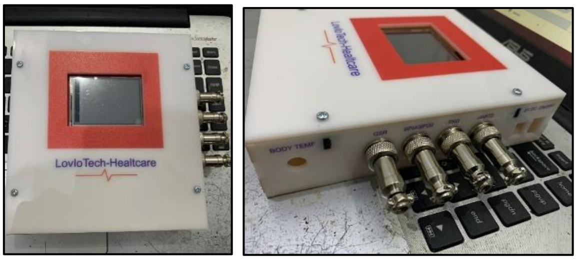

Figure 4. Healthcare IoT Platform

Figure 4 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.

$$F1Score = \frac{2 \times Recall \times Precision}{Recall+Precision} \tag{4}$$

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.

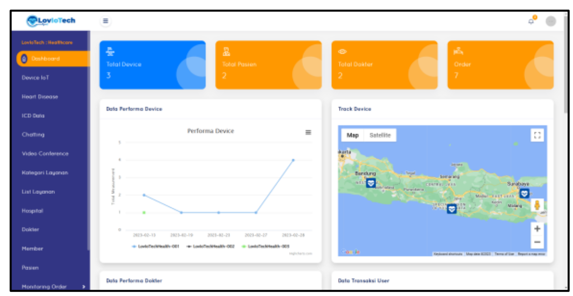

Figure 5. LovHealth website platform.

Figure 5 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.

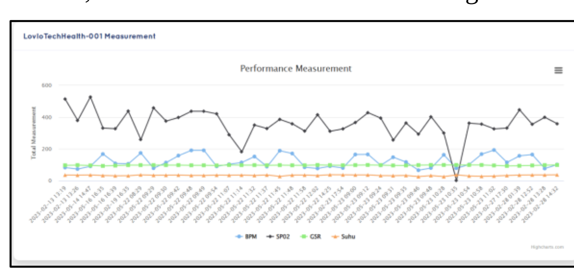

Figure 6. Health measurements monitoring

Figure 6 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.

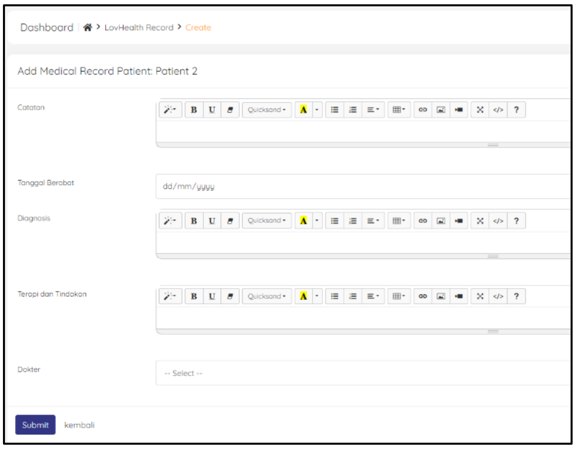

Figure 7. Electronic health records

Figure 7 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, drug data management platforms, patients, doctors, and health services.

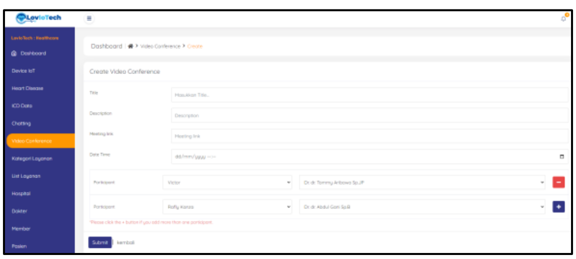

Figure 8. Telemedicine (chat & video conferencing)

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.

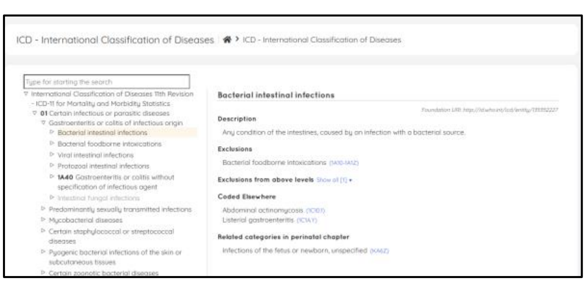

Figure 9. ICD-11 Systems.

Figure 9 shows the ICD-11 feature integrated with the LovHealth system. This ICD-11 system is information for integrating the symptom and disease classification system into the disease identification system in LovHealth. Doctors can also use this classification to diagnose patients.

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 10 depicts how security measures govern information transfer at various levels.

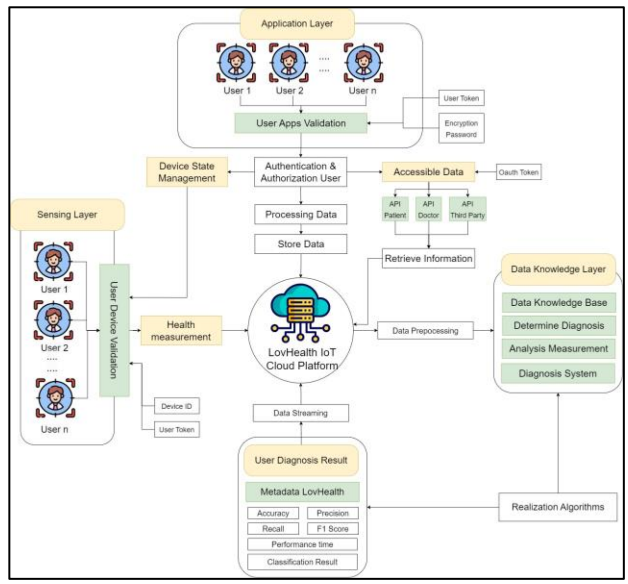

Figure 10. Flow diagram Cloud Centric IoT Diagnosis Systems.

Figure 10 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 11.

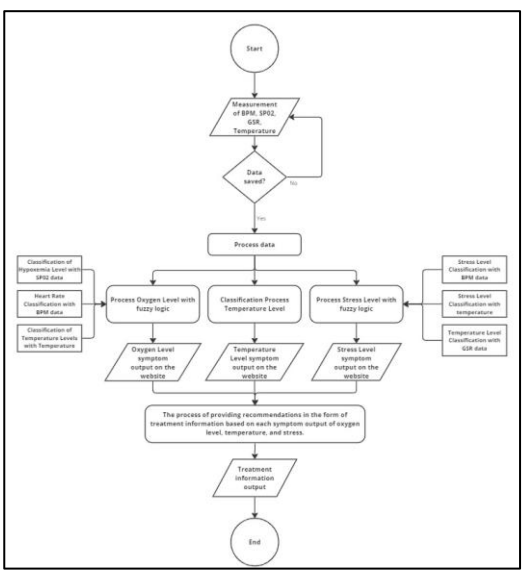

Figure 11. Flowchart of diagnosis systems

Figure 11 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

Users can use LovHealth products with touchscreen interactions to access their data measurements and the tools provided.

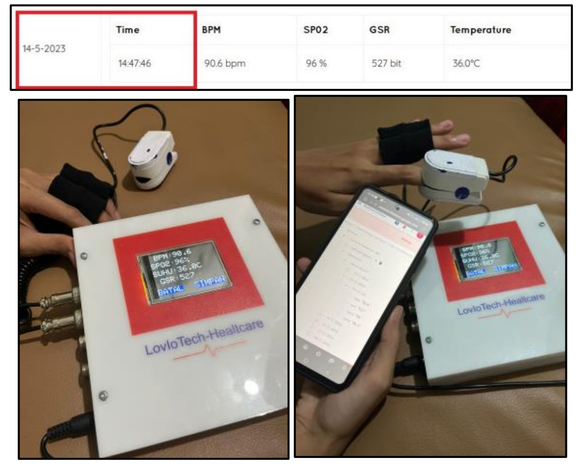

Figure 12. Data collection on the device used

Figure 12 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 13.

Figure 13. Measurement data collection

Figure 13 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 11, 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

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 shows the classification data based on the level of hypoxemia is presented in Table III. The sensor data utilized in this study is SP02, which assesses the patient's hypoxemia symptoms.

Table IV. Classification of heart rate levels

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

Table IV displays classification data based on heart rate levels. The sensor data used is BPM, measuring the data to determine how much the patient's heart rate is.

- 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

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

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	Moderate Hypoxemia
6	Moderate	Normal	Moderate Hypoxemia
7	Moderate	Bradycardia	Moderate Hypoxemia
8	Sever	Tachycardia	Severe Hypoxemia
9	Sever	Normal	Severe Hypoxemia
10	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. In BPM GSR data, temperature and the data are related to determine the stress level based on fuzzy logic. This stage acts as an output for the stress level with an if-and-then rule that is easy to understand, and 64 rules produce work.

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.

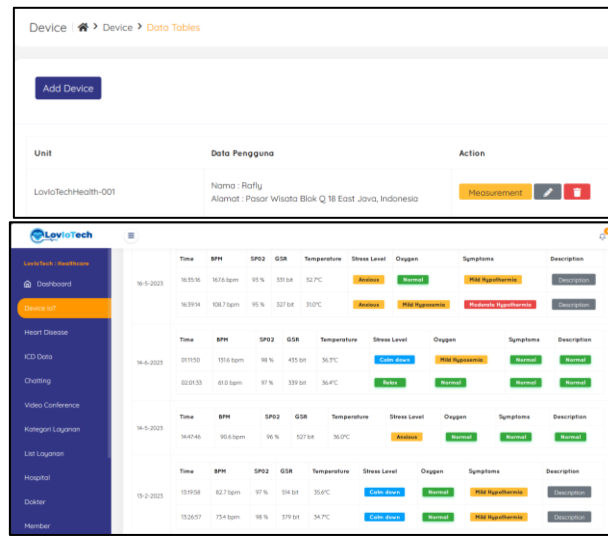

Figure 14. Device management and data measurement

Figure 14 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.

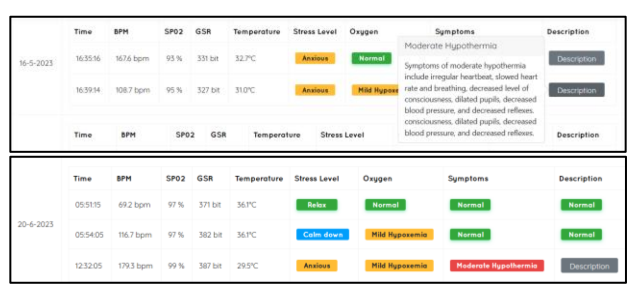

Figure 15. System diagnosis results and treatment information for patients

Figure 15 shows the diagnostic results based on the 3 classifications performed: BPM data as a measurement of heart rate, SP02 as a measurement of oxygen saturation, and GSR as a measurement of skin response and temperature. In addition, Figure 15 displays the results of the fuzzy logic model, namely oxygen, stress, and temperature levels. This is related to the color displayed; a detailed explanation can be seen in Figure 16.

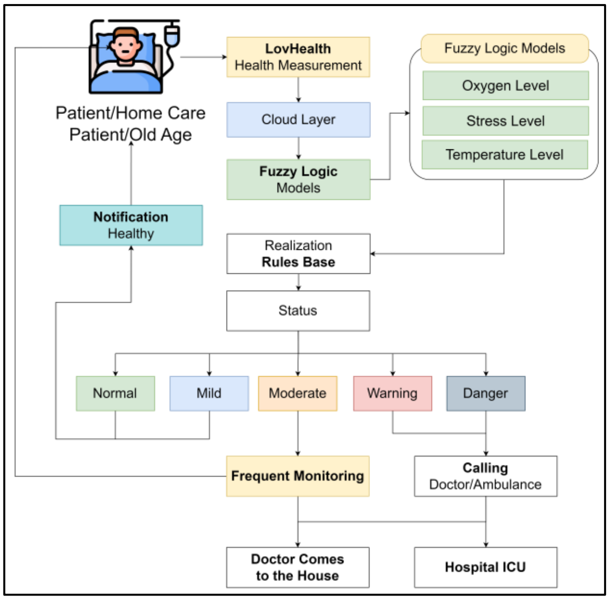

Figure 16. Interaction between fuzzy logic models and treatment systems.

Figure 16 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 15; several colors are displayed. In Figure 16, 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 bp	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 Tabel 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 11 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 [42]; the example is a display of the heart disease dataset.

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	condition
0	69	1	0	160	234	1	2	131	0	0.1	1	1	0	0
1	69	0	0	140	239	0	0	151	0	1.8	0	2	0	0
2	66	0	0	150	226	0	0	114	0	2.6	2	0	0	0
3	65	1	0	138	282	1	2	174	0	1.4	1	1	0	1
4	64	1	0	110	211	0	2	144	1	1.8	1	0	0	0
5	64	1	0	170	227	0	2	155	0	0.6	1	0	2	0
6	63	1	0	145	233	1	2	150	0	2.3	2	0	1	0
7	61	1	0	134	234	0	0	145	0	2.6	1	2	0	1
8	60	0	0	150	240	0	0	171	0	0.9	0	0	0	0
9	59	1	0	178	270	0	2	145	0	4.2	2	0	2	0

Figure 17. Heart disease dataset

Figure 17 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. According to the dataset, Table XI describes the variables table [42].

Table XI. 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 as follows: 0 corresponds to traditional angina, 1 to unusual angina, 2 to non-anginal pain, and 3 to benign pain in the chest.
treetops	the blood pressure at the stillness
chol	plasma cholesterol
fbs	The fasting glucose level is greater than 120 mg/dL. (0 is inaccurate and 1 is accurate)
restecg	The resting electrocardiographic findings can be categorized into three groups: normal (0), presence of ST-T wave abnormalities (1), and indication of possible or definitive hyper histories of the left ventricular olltest (2).
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 XI displays each variable description used to predict health diseases. The information results from Table XI are made into a system feature form that patients or doctors can fill in.

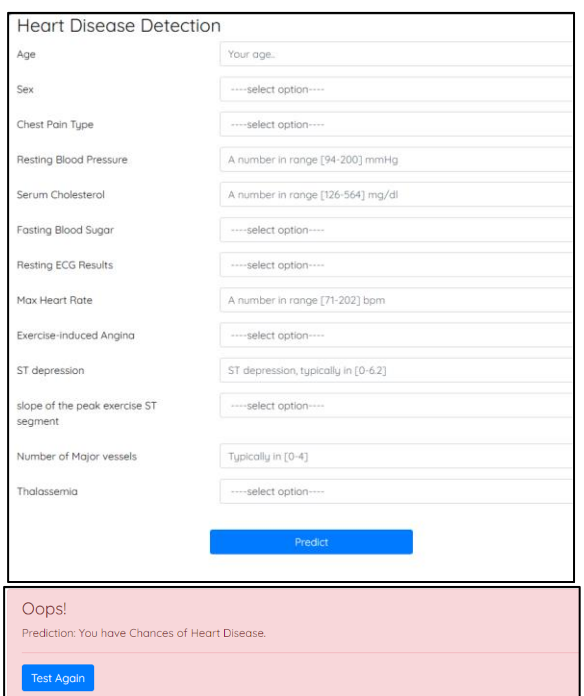

Figure 18. Health disease predictor

Figure 18 shows the health disease predictor simulation. Patients or doctor can use the form to determine if a patient has cardiac disease. The input data is in Table XI, namely 13 variables. After the input is successfully filled in, the system will automatically process and provide a notification as an alert whether the patient has heart disease. Based on some of these variables, testing is also carried out for distribution data based on datasets displayed as distplots to determine heart disease.

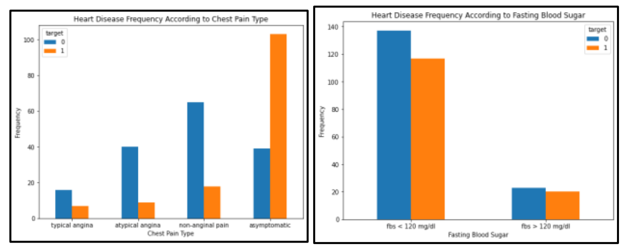

Figure 19. Chest pain type and fasting blood sugar distribution

Figure 19 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.

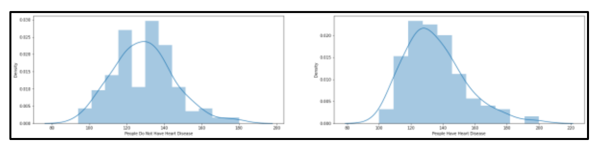

Figure 20. Blood pressure distribution

Figure 20 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.

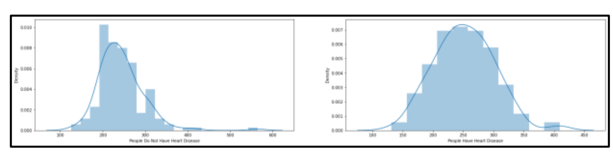

Figure 21. Cholesterol distribution

Figure 21 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.

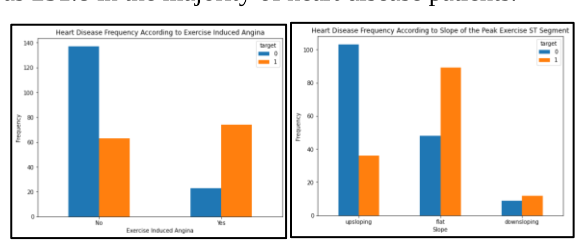

Figure 22. Exercise Induced Angina and slope distribution

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Table XII. 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%

Figure 22 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.

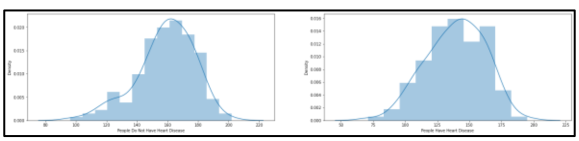

Figure 23. Maximum heart rate distribution

Figure 23 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.

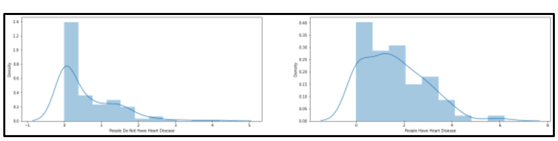

Figure 24. ST depression distribution

Figure 24 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.

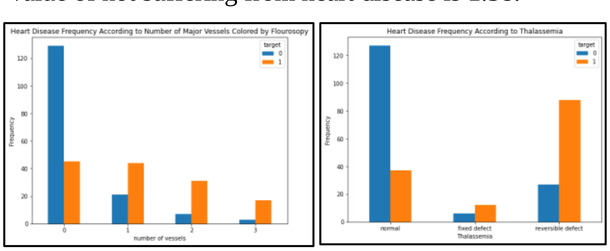

Figure 25. Fluoroscopy and thalassemia distribution

Figure 25 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. This was also done for the model evaluation process using several different approaches, according to Figure 26.

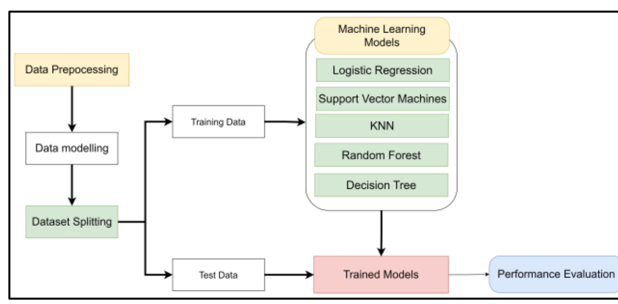

Figure 26. Model Processing

Figure 26 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 XII 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 development of IoT healthcare technology is increasing. The current challenge is that many medical devices only monitor and read data. Therefore, this research is about monitoring and controlling healthcare and focuses on the diagnosis system with several approaches. The approaches the model takes are fuzzy logic and machine learning. The fuzzy logic approach tested produced a diagnosis with three variable parameters: stress, oxygen, and temperature. These three variables will diagnose disease symptoms experienced by the user; of course, this is still limited because the sensors used are limited to SP02, BPM, GSR, and Temperature. In the machine learning approach, the experiment conducted trials with several KNN, Logistic Regression, Decision Tree, SVM, and Random Forest models to diagnose heart disease prediction. The Confusion Matrix findings indicate that the approach with the greatest value is Random Forest, with an Precision of 81.5%, Recall of 83.7%, F1-Score 82.5% and Accuracy of 82.6%. This indicates that diagnosing heart disease can be more efficient using the Random Forest approach.

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