applied sciences

MDPI

Article

An Optimized Neuro_Fuzzy Based Regression Trees for Disease Prediction Framework

Ankit Verma [1], Gaurav Agarwal [1], Amit Kumar Gupta [2] and Mangal Sain [3,*]

[1] Department of Computer Science & Engineering, Invertis University, Bareilly 243123, India
[2] Department of Computer Applications, KIET Group of Institutions, Delhi-NCR, Ghaziabad 201206, India
[3] Division of Computer and Information Engineering, Dongseo University, Busan 47011, Korea
* Correspondence: mangalsain1@gmail.com

Abstract: Nowadays, all the applications have been moved to the intelligent world for easy usage and advancements. Hence, the sensed data have been utilized in the smart medical field to analyze the disease based on the symptom and to suggest controlling the disease severity rate. However, predicting the disease severity range based on the sensed disease symptom is more complicated because of the complex and vast data. So, the present work has introduced a novel Generalized approximate Reasoning base Intelligence Control (GARIC) with Ant Lion Optimization (ALO) algorithm to forecast the disease type and measure the severity range. Here, the presence of the Ant lion fitness has afforded the finest disease classification and severity analysis results. Finally, the parameters were measured and compared with other conventional models and have recorded the finest disease prediction score and severity range. This verified the success rate of the designed model in estimating the disease severity range. In addition, the presented system helps to notify the people of medical advice by message, email, or other application.

Keywords: Ant Lion Optimization; disease prediction scheme; emergency measures; generalize approximation; Internet of Things (IoT); intelligence control; neuro-fuzzy; reasoning base; sensor

Citation: Verma, A.; Agarwal, G.; Gupta, A.K.; Sain, M. An Optimized Neuro_Fuzzy Based Regression Trees for Disease Prediction Framework. *Appl. Sci.* **2022**, *12*, 8487. https://doi.org/10.3390/app12178487

Academic Editor: Yu-Dong Zhang

Received: 15 June 2022
Accepted: 19 August 2022
Published: 25 August 2022

1. Introduction

By developing medication facilities, the contemporary healthcare system has significantly extended human life expectancy [1]. Moreover, the brain is an essential organ that regulates the neural function of the body. Hence, it is made up of 100 billion nerve cells [1]. Furthermore, if nerve cells are destroyed, it can cause different health issues and abnormalities in the human brain. These injured cells have detrimental effects on the brain's tissues. Such a condition raises the incidence of normal brain tumors [2]. Moreover, metastatic and primary brain tumors are dual distinct types. Astrocytoma start within the brain, including the blood arteries, nerves, and glands, while metastases brain tumors form in other regions of the body [3], such as the lungs or breasts, and then spread to the brain. Tumours are either cancerous or benign. Thus, the malignant tumors develop rapidly in the organism and are aggressive. Glioblastoma is by far the most frequent malignant brain tumor [4]. In innocuous neurological disorders, the comparatively slow-growing cells are also noncancerous. Such tumors do not metastasize to other areas of skin. If it is carefully removed after the operation, it will not return to the organism [5]. If gliomas are detected in their earliest stages, patients have a greater chance of survival [6]. Both these foremost brain tumors involve pituitary tumors that are typically benign and situated close anterior pituitary; neurotransmitter release tumors, [7] which can be either noncancerous; or central nervous malignancies, that are malignant. Moreover, it often occurs between the ages of 40 and 70 and is typically benign; and gliomas are severe and situated in the outer layer of the brain [8].

Utilizing a variety of techniques, many diseases and health problems are examined [9]. Similarly, brain computerized tomography scans are utilized to detect the development of the modeling [10,11]. Moreover, computed-tomography (CT) is indeed an alternative tool for tumor identification, but it also gives additional information about particular brain images [12]. This research presents a unique model that utilizes an extensive dataset and analyses the suggested model for wellness based on several characteristics [13]. Implementing pre-treatment techniques, such as data normalization and feature extraction, has enhanced the reliability of the proposed model [14]. Therefore, these automatic systems help reduce time and improve productivity [15]. The system applies to clinical facilities, health treatment, and the maintenance of patient health records [16,17]. Figure 1 depicts the design of the current system [18].

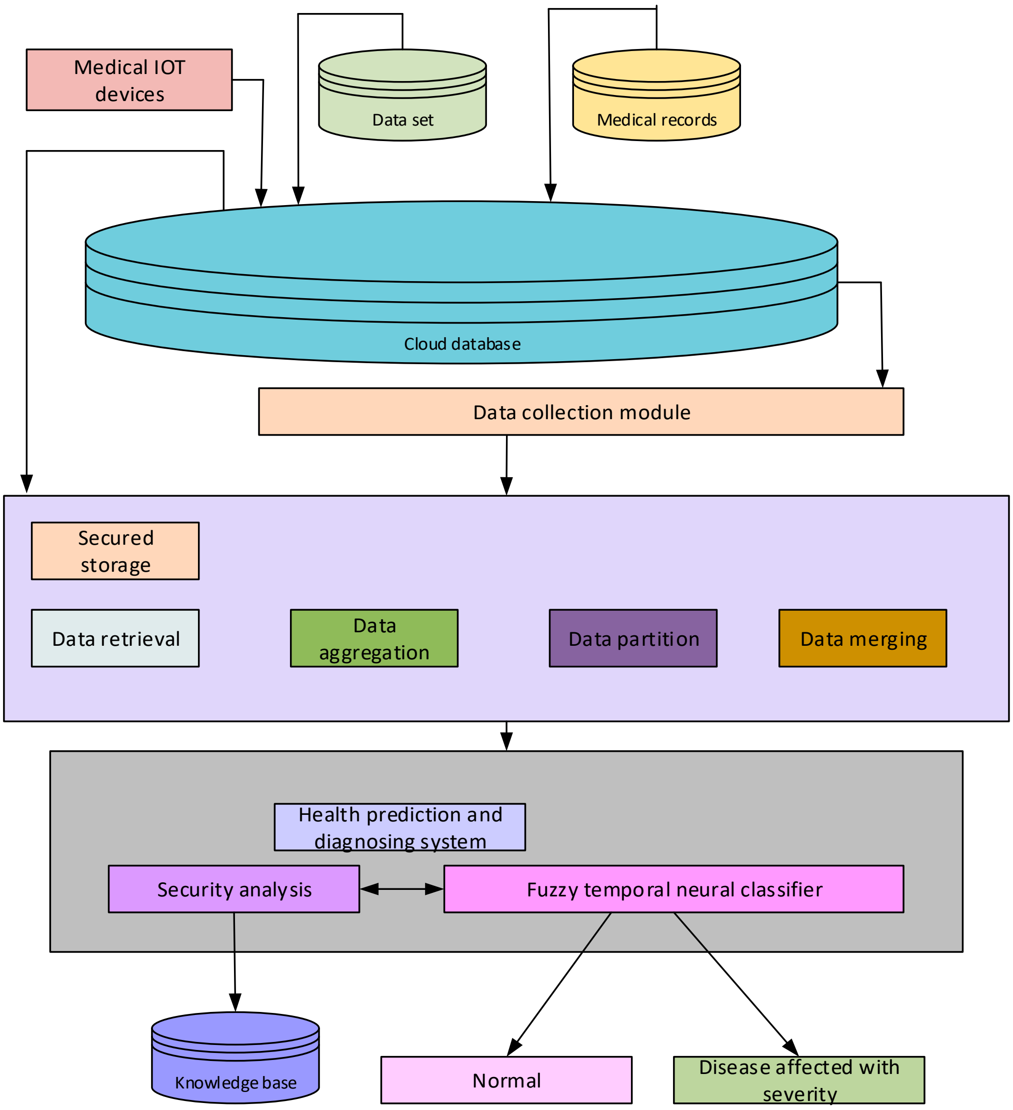


Figure 1. System architecture.

An intermediate computing paradigm is required to make an immediate medical judgment rather than processing all data in the cloud [19]. Furthermore, an IoT application, particularly for healthcare services, requires mobility [20], low latency [21], and location awareness support [22]. A robust healthcare system should remain functional when a patient transfers from one location to another and network availability is minimal or non-existent. As a result, intermediate fog computing arises as a way to extend the cloud computing environment to the edge devices of end users. By gathering and aggregating all data from IoT devices and transmitting it as a single packet to the data center, bandwidth can be conserved by placing a fog node at the network's edge [23]. In this technique, by using IoT, many data are collected. The dataset includes patient name, gender, sex, sugar value, cholesterol value, and pressure value gathered.

2. Related Work

Various authors and researchers have highlighted the same study shown in the research article. Some of the significant contributions are discussed here in the section below:

An illness could be a pathological condition during which the part of the body or organ and therefore the system might not work correctly. Mostly, it is due to some infection, hereditary or genetic disorders. Heart disease, also called artery disease, is caused by the artery and veins becoming slim. Coronary failure is mainly due to blood flow circulation to the guts. Several techniques are projected to predict guts illness; however, their design and calculation are incredibly advanced. K. Maes et al. [24] presented the various pre-processing strategies for neural network-based mostly heart condition prediction to beat this drawback. PCA, in collaboration with LDA, defines pre-processing techniques, which are used to reduce the spatial property of the dataset, resulting in a classification accuracy of 94.53% for the detection of cardiac problems.

In recent times, the primary issue the cloud-based system faces is merging data before cutover and data migration. To overcome this issue, the cloud-based structure must be integrated with the IoT. Thus, P. Verma et al. [25] proposed a new technique named FETCH, combining deep learning and cloud-based IoT. This system helps in analyzing the healthcare of humans. This framework uses a fog bus which illustrates the system's latency, execution time, bandwidth, and accuracy. Moreover, this technique monitors the heart rate and other body functions. However, no prevention or control technique is discussed.

Artificial intelligence (AI)-based solutions are gaining significant traction in the development of medical diagnostic systems. Many researchers use different decoding methods; however, they're troublesome to handle and sophisticated evaluation. To achieve this, N. Gupta et al. [26] planned state-of-the-art AI techniques in heart condition designation, and therefore, AL techniques, such as ANN, algorithmic rules, and mostly symbolic-based systems, are preponderantly applied within the assignment for heart condition prediction.

Recently, a massive volume of health data has been developed due to recent breakthroughs in information and communication technologies (ICT) and online assistance services. The analysis of disease prediction networks (DPSS) has attracted several academics worldwide thanks to advances in machine learning methodologies. For this purpose, O. Baser et al. [27] developed a hybrid reasoning-based privacy-aware malady prediction network for diagnosing problems. Although DPSS facilitates good aid services, information security and privacy are still crucial complex problems to be self-addressed.

T1DM is a kind of diabetes that occurs when the body's immune system assaults and kills insulin-producing cells in the exocrine gland. To keep T1DM patients alive, an insulin pump or daily injections are essential for internal secretion supplied by Associate in Nursing. WHO should also carefully synchronize internal secretion dosages with uptake and physical activity day and night. Despite rigorous monitoring, they are at risk of dangerously high and low blood glucose levels (BGL), which can lead to catastrophic repercussions and life-threatening hypoglycaemic episodes. F. L. Guillen and T. Ghazi et al. [28] modeled prognosis management for type 1 diabetic rats using a neural network-based model.

The following summarizes one of our research's most important contributions.

- Incorporate a sensor into the human body.
- Using the Internet of Things, collect real-time medical information about a patient.
- Using GARIC architecture, process and classify information gathered about the patient.
- To use data mining techniques such as regression trees and optimize utilizing ALO to evaluate and forecast any disease or disorder in its early stages.
- Receive notifications through SMS, email, etc.
- To give healthcare solutions based on the Internet of Things at any time and location.

3. System Model and Problem Statement

The paper has shown the proposed model where the sensor is used to detect and predict diseases in human beings. According to the blood circulation, our body organs like the heart, brain, lungs, etc., are working correctly. If the blood circulation is improper, the body stops working, leading to death. Pre-processing, the diagnosis unit, and feature extraction are the three primary roles of heart disease diagnosis. In, pre-processing phase, the entire dataset was filtered to remove the noise parameters present in the dataset. The pre-processing unit removes the noisy signal and recovers the noiseless signals. In MATLAB for pre-processing the medical data, filters are used in pre-processing phase. The pre-processed data enters into the feature extraction module, where the features useful for classification are extracted. The signal is examined in both the frequency domain and temporal domains. Second, feature extraction is performed by extracting features using the optimality criterion. Next, the diagnosis unit ensuing a reduced set of theories functional to establish the decision rule. The pre-processing steps are acquisition of the dataset and importation of all the required libraries, followed by importation of the dataset, identification and handling the missing values (Handle Noisy data), encoding the categorical data, splitting the dataset, and finally feature scaling. Then, the decision rule is diagnosis, and prediction of disease is performed in a critical way, as shown in Figure 2.

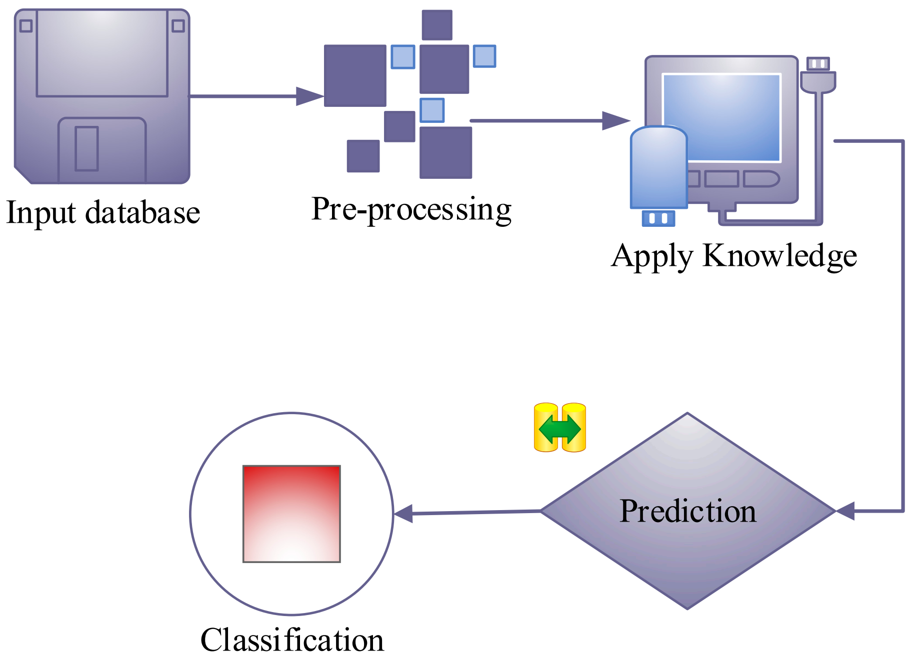


Figure 2. Fundamentals of detection and prediction of diseases.

4. Proposed Methodology

Because of changing cultures and circumstances, it is increasingly difficult to survive in a world with good health conditions today. In the paper, the authors have introduced neural fuzzy-based machine learning methods. To forecast the disease early, approximation reasoning basis intelligence control is combined with regression algorithms. To calculate the severity, we develop the Ant Lion Optimization algorithm. Moreover, there are insufficient hospital facilities in rural areas to help the poor and others. For that purpose, we have to inject the sensor into the human body, and the sensor function is linked with IoT (Internet of Things), e.g., a mobile app or any other. Moreover, it's connected to hospitals or service providers. Thus, if people are infected with diseases, they will be notified via SMS, emails, and other means. After that, they will be given medicines and medical advice, as shown in Figure 3.

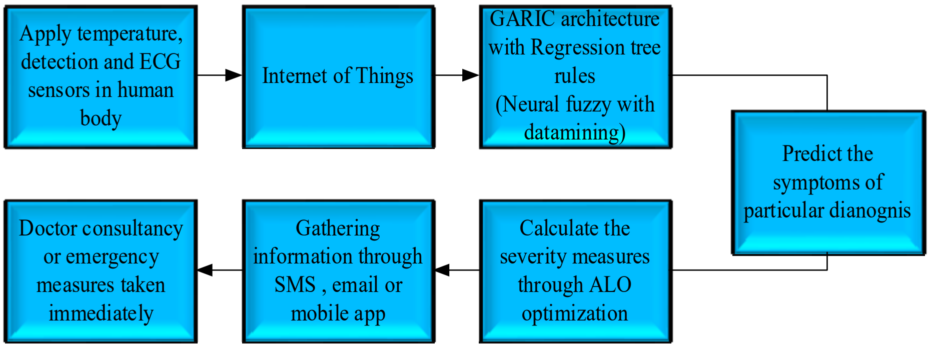


Figure 3. Proposed methodology.

4.1. Apply Sensors in the Human Body

A sensor implanted in the human body detects and predicts disease. These days, various people in many conditions suffer from diseases due to the severity of infections. Here the sensors are used to diagnose the diseases in medical sensors. Medical sensors are sense into different classes based on their risk profile. So, the risk profile is predicted with the lowest or highest potential risk. Medical sensors are different types; their temperature probes are employed to live the body's temperature, force sensors are utilized to kidney dialysis machines, and the flow of air sensors is engaged to a heart pump, laparoscopy, delivery systems, etc ... Pressure sensors are used to pressure watching, diagnosing, infusion, etc. The implantable pacemaker may be an actual time-embedded sensor system; it is accustomed the heart muscle to continue effective heart rhythm. A measuring system is utilized to the full hemoglobin tally within the blood. A gluon meter measures the glucose concentration, and an electroencephalogram (ECG) sensor is used to measure the heart's electrical activity. A heart rate sensor is utilized to the amount of heart contraction per minute. An EEG device is employed to live the electrical activity of the brain, an EMG device is utilized to proceedings electrical activity shaped by skeletal muscles, while a respiration rate sensor counts how many periods the chest rises in small.

Internet of Things

The net of things (IoT) obtains real-time medical information concerning patients. IoT refers to instruments, connected sensors connecting something, anytime, anywhere, anyone, and any service. The IoT network is employed within security, good health, disaster services, good cities, healthcare, trade, and business management. Here, we tend to use IoT networks for healthcare. The sensing element is connected with IoT, e.g., a mobile app or other, which is also connected to a service provider or hospitals, as shown in Figure 4.

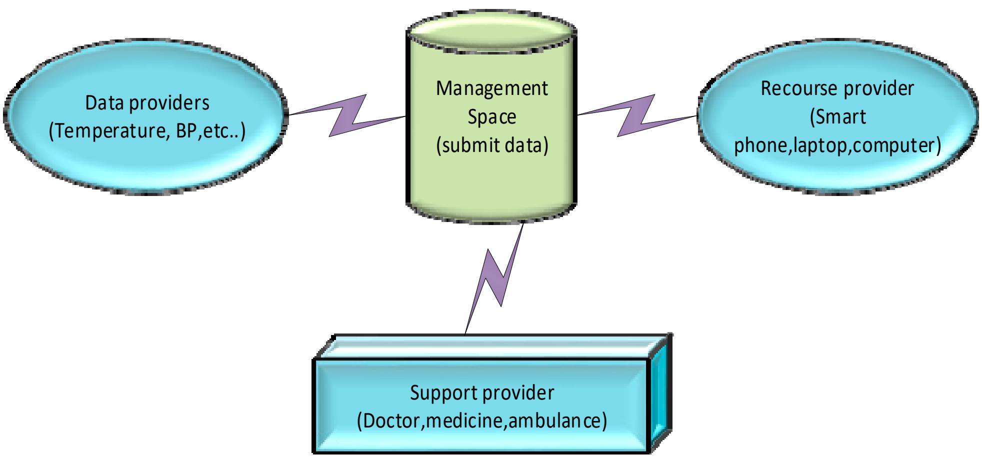


Figure 4. Health care solution using IoT.

IoT is referred to as multiple gears of a primarily based network for care and indicates the medication atmosphere. The PC grid, by its heterogeneous nature, gathers an infinite amount of detector information and imperative signs, such whereas body heat, respiration speed, and blood pressure, making an IoT topology. The application layer is used to exchange messages and provides admission for worldwide info regarding various services. Cloud server for storing and processing data, as well as sending SMS or email to the observer based on the data from the sensing device in the cloud. Each piece of data is transferred to the cloud, and if the value changes, an alarm message is sent to the doctor and carer. Here, the bio signals from the patients, e.g., temperature, sugar value, cholesterol value, heartbeat rate, and pressure values, are attained from IoT. These sensed data from IoT are stored in cloud storage.

4.2. GARIC Architecture with Regression Rule

GARLIC architecture is used to process and classify information acquired about the patient. One type of GARIC architecture is the action selection network (ASN). For fuzzy inference, ASN is considered a state vector that turns into an instructive action. ASN is made up of five layers of nodes, each of which represents a single stage of the fuzzy interference approach. On the other hand, the estimated weighted add of inputs is likely to be different. The input layer is the first one. The input variable for the ASN real-valued is information set, as far as we can tell. The second layer consists of a node for each variable in layer one and a single potential price. Figure 5 shows the input and output values. Equation gives the operation. (1) and (2). Nomenclature tabulates the notations and definitions.

$$\mu_{dw}, T_{VL}, T_{VR}(z) \tag{1}$$

$$\mu(z) = \frac{1}{1 + \left|\frac{z-e}{t}\right|^{c}} \tag{2}$$

where μ represents weighted variables and T represents the triangular functions.

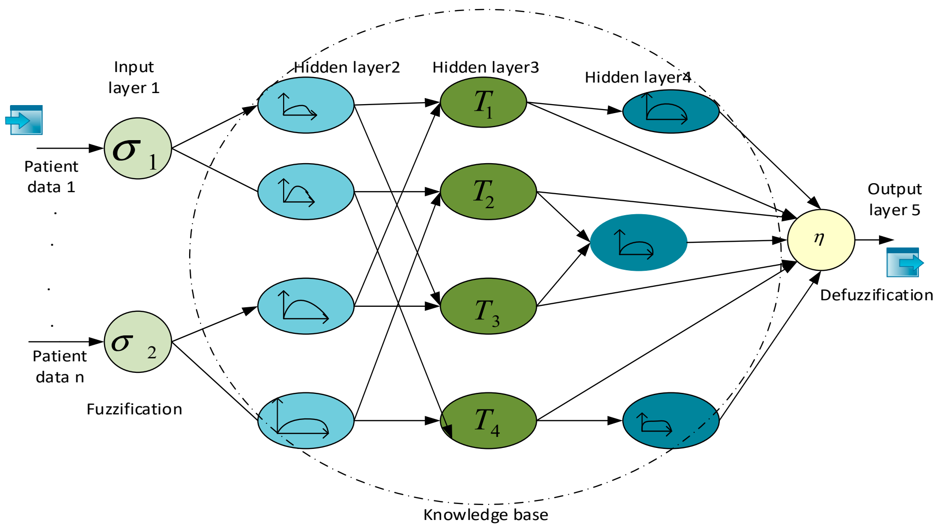


Figure 5. Action selection network with its activation function.

Where $T = T_{VL}$ or $T = T_{VR}$, $z < e$ or $y \geq e$, and d is denoted control curvature. Moreover, the triangular formation is shown in Equation (3).

$$\mu_{w,t_L,t_R}(x) = \begin{cases} 1 - |z-e|/t_R, z \in [e, e+t_R] \\ 1 - |z-e|\,/t_{L,}|y \in [e-t_L, d] \\ 0, otherwise \end{cases} \tag{3}$$

The third hidden layer represented the linguistics value of the productivity factors. Hence, softmin is applied to the following continuous, exposed in Equation (4), and the hub executes the least operation. (4) A softmin operation that is differentiable is

$$Q_{R3} = \omega_\tau = \frac{\sum_j \mu_j e^{-l\mu_j}}{\sum_j e^{-l\mu_j}} \tag{4}$$

The softmin operation denotes the degree of contest linking fuzzy labels. The softmin process hardness is accomplished by parameter. Denoted the minimum operators. The fourth layer is represented to a consequential label. It is used for transformation, as shown in Equation (8). The actual consequential label-supported input comes from all the degree of match between fuzzy labels is indicated by the softmin process. The harshness of the softmin operation is controlled by a parameter. The minimum operators are indicated. The fourth layer is denoted with a significant label. It is presented in Equation and is used for transformation (8). All rules contribute to the real, meaningful, label-supported input. Is there a node that computes the equivalent output as per the rule? In Equation (5), this mapping is revealed.

$$\mu^{-1}{}_{cv,T_{WM},T_{WS}}(\omega_\tau) \tag{5}$$

which is eliminated, as exposed in Equation (6)

$$Q_{w4} = \left(ex + \frac{1}{2}(T_{xt} - T_{xn})\right)\left(\sum_\tau \omega_\tau\right) - \left(-\frac{1}{2}(T_{xt} - T_{xn})\right)\left(\sum_\tau \omega^2{}_\tau\right) \tag{6}$$

The output action for the fifth layer is adequate; there are various nodes. In a (7), fuzzy control rules are based on each node and output node.

$$H = \frac{\sum_\tau \omega_\tau \mu^{-1}(\omega_\tau)}{\sum_\tau \omega_\tau} \tag{7}$$

$$H = \frac{\sum_x Q_{x4}}{\sum_t Q_{t3}} \tag{8}$$

The estimation derivative $\frac{\partial x}{\partial r}$ uses a learning rule to change the parameter values of gradient descent, as shown in Equation (9)

$$\Delta r = 100X\frac{\partial x}{\partial r} = 100X\frac{\partial x}{\partial H}\frac{\partial H}{\partial r} \tag{9}$$

As a result, the chain follows five levels of ASN learning rules. The resulting and precursor labels con (S_k) and ant (S_k) are followed by the rule. The resulting label is exposed in Equations (10)–(15).

$$H = \frac{\sum \omega_\tau b_\tau}{\sum \omega_\tau} \tag{10}$$

$$b_w(\omega_\tau) = ex + \frac{1}{2}(T_{xt} - T_{xn})(1 - \omega_\tau) \tag{11}$$

$$\frac{\partial H}{\partial px} = \frac{1}{\sum_\tau \omega_\tau} \sum_{w=cont(S)} \omega_k \frac{\partial bx}{\partial rx} \tag{12}$$

$$\frac{\partial bx}{\partial ex} = 1 \tag{13}$$

$$\frac{\partial bx}{\partial T_{xt}} = \frac{1}{2}(1 - \omega_\tau) \tag{14}$$

$$\frac{\partial bx}{\partial T_{xn}} = \frac{1}{2}(1 - \omega_\tau) \tag{15}$$

$$\frac{\partial x}{\partial rx} = \frac{\partial x}{\partial H}\frac{\partial H}{\partial rx} \tag{16}$$

where $\frac{\partial H}{\partial rx}$ derivatives consequent labels.

4.2.1. Diseases Prediction Using Regression Tree Rule

Gary's design technique is a natural evolution. We may utilize a GARIC format with neuro-fuzzy to better look at the problem. The GARLIC approach extracts one attribute from a vast number of features. Optimized weights and biases were used to establish the back proliferation net to take the input parameters. As a result, a GARIC Neuro-Fuzzy System was created, with GARIC design being utilized to optimize the Neuro-Fuzzy System's initial weights and biases, predicting any disease or ailment at the early stage utilizing the info mining approach regression.

4.2.2. Predict The Symptoms of Particular Diagnosis

Using the data mining approach, regression forecasts the symptoms of the preliminary stage of cardiac disease. Because it affects the cholesterol levels in the blood arteries, heart disease is one of the most dangerous illnesses. The regular blood pressure reading is 120/80 mm of mercury. The blood pressure reading is lower than it should be, indicating a problem with the heart's appropriate functioning. If the blood pressure value is higher than optimal values, that is no risk. The first stage of blood pressure is hypotension. That value is higher than an optimal value, which means medication stabilizes the high pressure. The second stage is hypertension, which means your blood pressure is significantly higher than it should be, and you should start taking the medication immediately. You should also have regular exams. Finally, if the patient's blood pressure is more than 180 mm Hg (systolic), they should be sent to the hospital immediately. The cholesterol level is divided into two categories when the blood sugar level is less than 100 mg/dL after not eating for at least eight hours; moreover, when the blood sugar level is less than 140 mg/dL two hours after ingestion. Low density (bad cholesterol) and high density (good cholesterol) are the two types (good cholesterol). Low-density cholesterol levels are less than 200 mg/dL, whereas high-density cholesterol levels are greater than 240 mg/dL. A cholesterol level of 200–239 is considered borderline. Low-density cholesterol tends to accumulate on the inside of blood vessels.

4.3. Ant Lion Optimizer

Ant Lion Optimization (ALO) is a nature inspired meta-heuristic algorithm developed for optimization problems. It is based on the hunting behavior of antlion. It digs a hole in form of cone shape using its jaws and then it hides itself in the bottom region of the cone. When an ant traps inside the cone, it starts to throw sand towards the trap in order to bury the prey. Moreover, it has numerous advantages, such as it is easy to implement, scalable, flexible, and demonstrates a great balance between exploration and exploitation. Here, the ALO approach is applied to measure the severity of the disease. ALO has five essential steps on hunts: random continues about ants, constructing traps, etc. The random selection of test cases is described in Equation (17).

The ALO algorithm presents the mathematical models, which, in general, follow the algorithms shown in Equation (17)

$$\mathrm{S}\ (\mathrm{t})\ = \begin{cases} 1rand > 0.5 \\ 0sand \leq 0.5 \end{cases} \tag{17}$$

A maximum number over a generation is m. S (t) is a stochastic feature, then rand is a wide variety generated, including equal allocation among the end of [0, 1]. The location concerning ants stays stored between the following matrixes shown within Equation (18)

$$N_{ANT} = \begin{bmatrix} B_{1,1} & B_{1,2} & . & B_{1,d} \\ B_{2,1} & B_{2,2} & . & B_2,d \\ . & . & . & . \\ B_{n,1} & B_{n,2} & . & B_{n,d} \end{bmatrix} \tag{18}$$

where N_{ant} is the saving the position concerning every ant, B the value regarding the ith variable about stability kth. M is the number regarding ants or range on the variable is d.

The equivalent objective value is selected as every ant lion is calculated or stored among the similar form shown in Equation (19)

$$N_{oA} = \begin{bmatrix} g[B_{1,1} & B_{1,2} & . & B_{1,d}] \\ g[B_{2,1} & B_{2,2} & . & B_{2,}d] \\ . & . & . & . \\ g[B_{n,1} & B_{n,2} & . & B_{n,d}] \end{bmatrix} \tag{19}$$

where N_{OA} is the saving the position concerning each ant? $B_{j,k}$ is the value regarding the durability *ith* variable on longevity *kth*. M is the number concerning ants, the range on the variable is d, then g is the objective function. The central equation is shown in Equation (20). The flow of the proposed model is illustrated in the form of pseudo code in Algorithm 1.

$$N_{oAL} = \begin{bmatrix} g[BM_{1,1} & BM_{1,2} & . & BM_{1,d}] \\ g[BM_{2,1} & BM_{2,2} & . & BM_{2,}d] \\ . & . & . & . \\ g[BM_{n,1} & BM_{n,2} & . & BM_{n,d}] \end{bmatrix} \tag{20}$$

Algorithm 1: GARLIC-ALO

```
Start()
{
Input
 sense input data → dataset
Fuzzy function ()
{
 remove → noise (data)
//removing unwanted noise from the bio-signal
}
Feature exaction ()
{
 extract → feature (data)
//exacting the feature of data
}
ALO_fitness ()
{
 calculate(fitness) → classify (diseases)
Heartbeat rate ()
{
        60–100 beats/min     //normal heart beat range
        >60–100 beats/min    //high heart beat range
        <60–100 beats/min    //low heart beat range
}
Respiratory rate()
{
        12–18 breaths/min, Normal;
        <12–18 breaths/min High;
        >12–18 breaths/min Low
}
Diastolic blood pressure()
{
        60–90 mmHg, Normal;
        >60–90 mmHg, High;
        <60–90 mmHg, Low.
}
```

Algorithm 1: *Cont.*

```
Systolic blood pressure()
{
        90–120 mmHg, Normal(0);
        >90–120 mmHg, High(2);
        <90–120 mmHg, Low(−1)
}
LDL cholesterol ()
{
        100–129 mg/dL, Normal(0);
        >129 mg/dL, High(1)
}
HDL cholesterol
{
        41–59 mg/dL, Normal(0);
        >59 mg/dL, High(0)
}
Total cholesterol
{
        200 mg/dL, Normal(0);
        >200 mg/dL, High(1)
}
Body temperature
{
        97–99F, normal(0);
        >99F, High(1)
}
}
Output
{
Heart-disease(0);
Diabetic(1);
High-Cholesterol(2);
Kidney-failure(3);
Hypertension(4)
}
}
End
```

Initially, the sensed medical dataset was collected from the standard site kaggle [29] and imported into the system. It contains more than 10 sensed patient samples with the labels 0 and 1. The foremost step in prediction process is pre-processing the dataset. In this phase, the noise data present in the sensed dataset is removed using filters like median, Gaussian, etc. Then, the filtered dataset enters into the feature analysis module. In this module, the disease features (features necessary for classification) are extracted. In feature analysis phase, the attributes like HDL cholesterol, body temperature, e.g., respiratory rate, systolic and diastolic blood pressure, etc., are extracted from the dataset. These extracted features are then trained using the proposed approach to classify the diseases. In the designed model, the normal, high, and low level of the features are set in three states, where the normal rate of the body features is indicated as "0", the high level is denoted as "1", and low level is indicated as "−1". The proposed model is a hybrid technique which is the combination of advanced neuro-fuzzy with an ALO algorithm. This model has five different layers, i.e., the input and output fuzzification layer and three hidden layers. Subsequently, the filtered input data is given to n number of patients in the GARLIC-ALO input layer. Moreover, features, such as respiratory rate, HDL cholesterol, age, heartbeat rate, gender, body temperature, systolic and diastolic blood pressure, LDL, and total cholesterol of the patient, are considered as the input data. These features are trained to the input layer, and the fuzzification output layer is given to the second layer. The predicted result calculates the variation between the actual output and error rate.

5. Result and Discussion

The approaches we offer are implemented in MATLAB version 2018 on a Windows 7 environment. Math Works designed a numerical and limiting indoctrination language. We use the data mining learning approach in this research and do tests with the dataset. GARLIC using regression rules provides the maximum accuracy, according to our findings. Therefore, it increases the performance of cardiac illnesses prognosis. Assess the categorization method's accuracy, specificity, and sensitivity. Because the sensitivity and specificity are both high, the accuracy is as well. When illnesses are present, sensitivity is used to forecast the positive. This is also known as the true positive rate (TPR). When the illness is not present, specificity is used to forecast the negative. It is also called true negative rate (TNR). Figure 6 displays the execution results: Intelligent heart disease perdition.

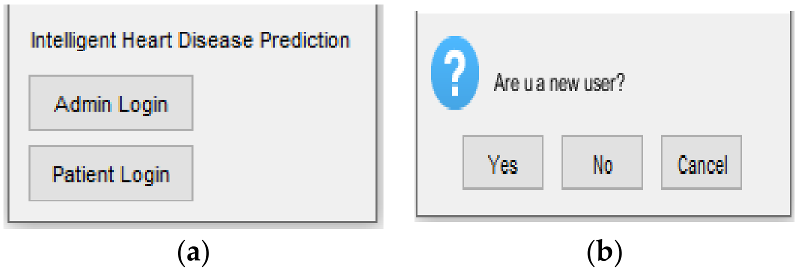


Figure 6. Execution result: (**a**) Intelligent heart disease prediction (**b**) Creating and managing users.

Figures 7 and 8 show the execution results: patients not shown in Figure 8a; registration completed shown in Figure 8b; patient login shown in Figure 8c. Neural network training state shown in Figure 9. Iteration vs. best score obtained so far for predicting the severity using Ant Lion Optimization shown in Figure 10. Figure 11 shows the result: Menu button Figure 11a and Sugar check-up shown in Figure 11b. Final report for patient shown in Figure 12. Sensitivity vs. specification for predicting the disease using GARIC with regression rules is shown in Figure 13.

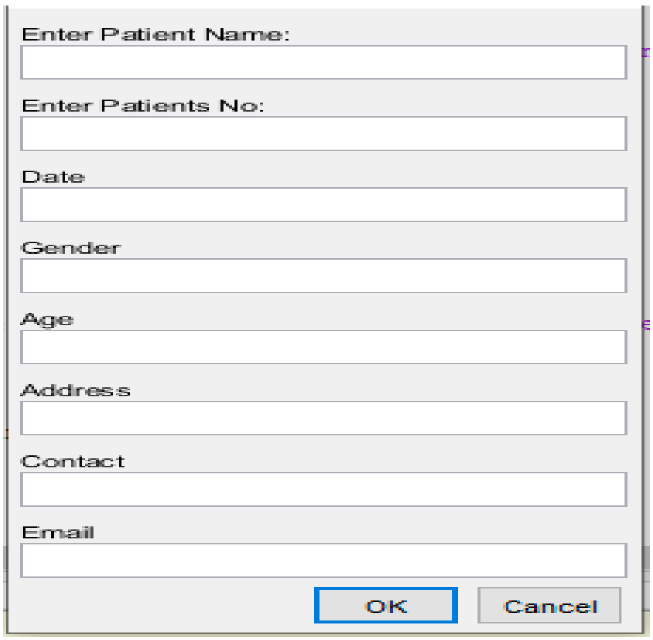


Figure 7. Registration details.

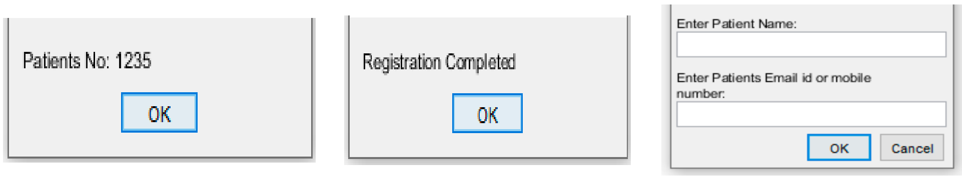


Figure 8. Execution results: (**a**) Patient no (**b**) Registration completed (**c**) Patient login.

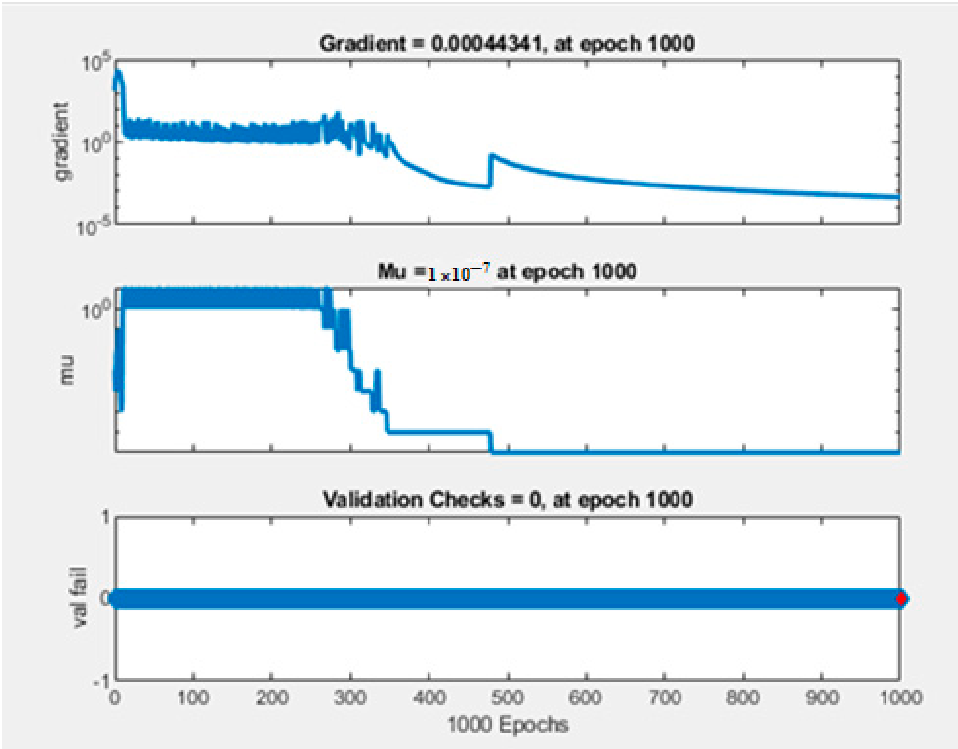


Figure 9. Neural network training state.

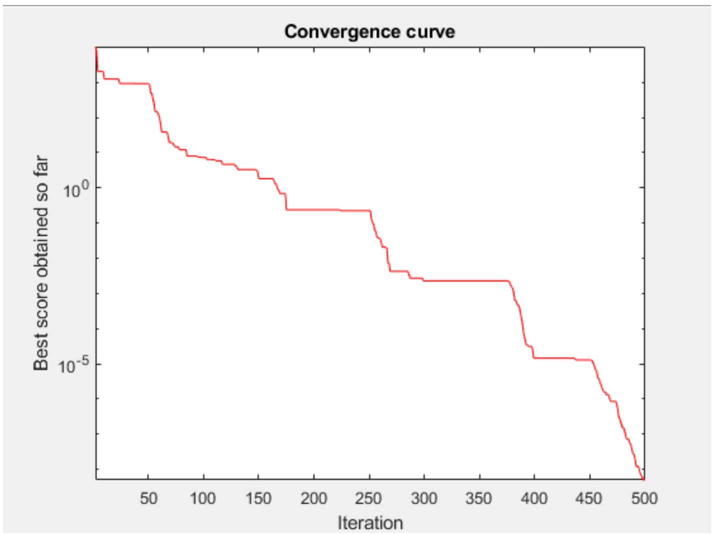
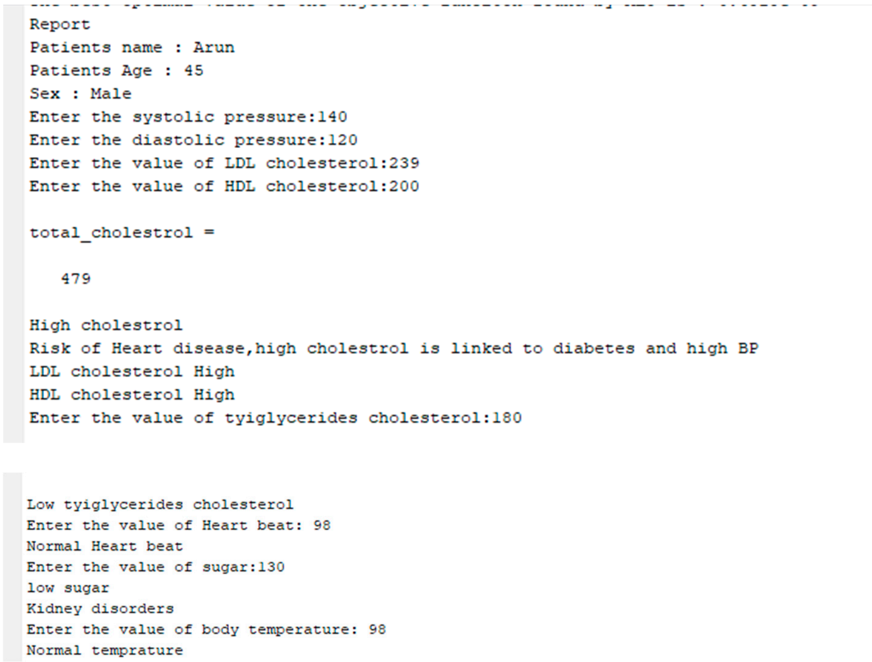


Figure 10. Iteration vs. best score obtained so far for predicting the severity using Ant Lion Optimization algorithm.

(**a**) (**b**)

Figure 11. Result: (**a**) Menu Button (**b**) Sugar Check Up.



```
Report
Patients name : Arun
Patients Age : 45
Sex : Male
Enter the systolic pressure:140
Enter the diastolic pressure:120
Enter the value of LDL cholesterol:239
Enter the value of HDL cholesterol:200

total_cholestrol =

   479

High cholestrol
Risk of Heart disease,high cholestrol is linked to diabetes and high BP
LDL cholesterol High
HDL cholesterol High
Enter the value of tyiglycerides cholesterol:180

Low tyiglycerides cholesterol
Enter the value of Heart beat: 98
Normal Heart beat
Enter the value of sugar:130
low sugar
Kidney disorders
Enter the value of body temperature: 98
Normal temprature
```

Figure 12. Final report for patient.

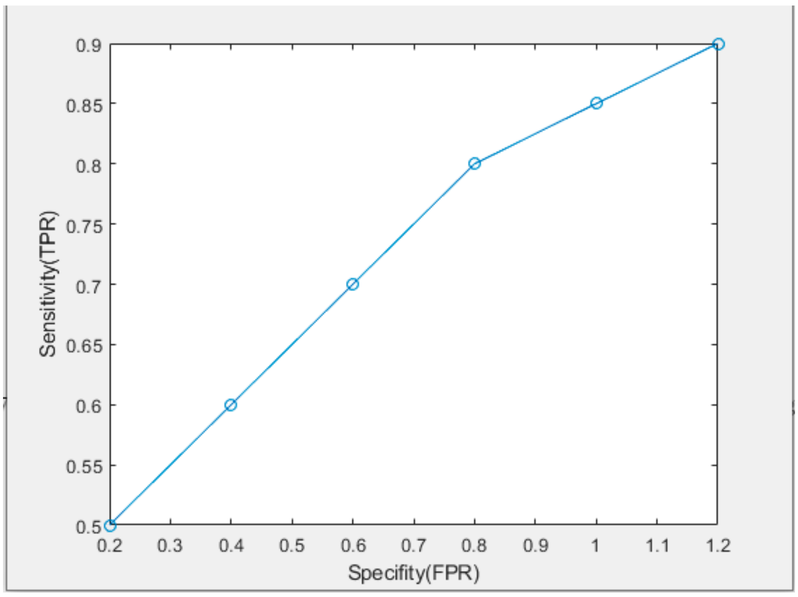


Figure 13. Sensitivity vs. specification for predicting the disease using Generalize approximate Reasoning base Intelligence Control (GARIC) with regression rules.

Performance

The performance is discussed on behalf of the confusion matrix and its components. Comparison of sensitivity (false positive rate) and specificity (true positive rate) with Hs-CT I (high sensitivity cardiac troponin I and Hybrid-DT) is shown in Figure 14. A comparison of accuracy with existing techniques. Also, some exiting models are Hybrid DT [30], Hs-CT [30], Fuzzy K neighbor (FKNN) [31], multimodal data based recurrent convolution (MD_RCNN) [15], and Ant Lion Optimizer (ALO), is shown in Figure 15. Comparison with existing techniques shown in Figure 16.

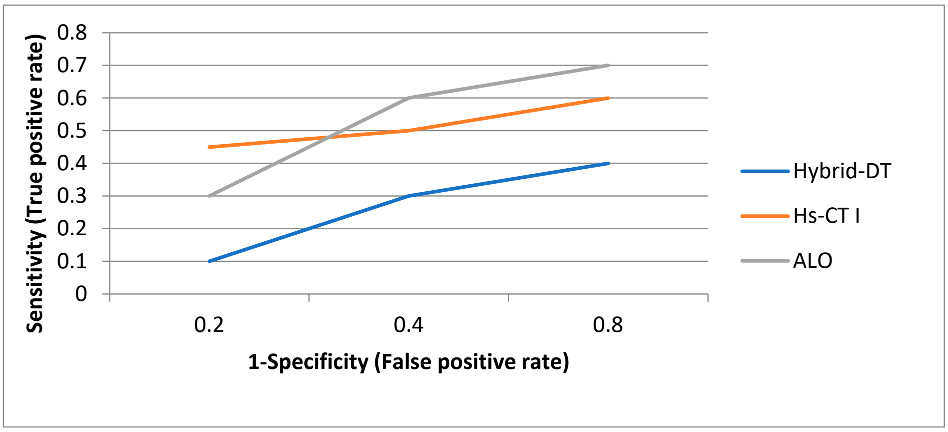


Figure 14. Comparison of Sensitivity-Specificity.

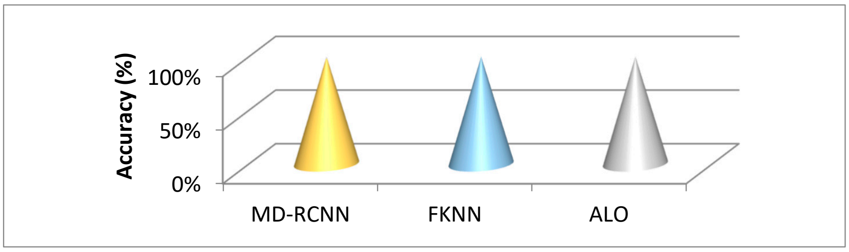


Figure 15. Comparison of Accuracy with existing techniques.

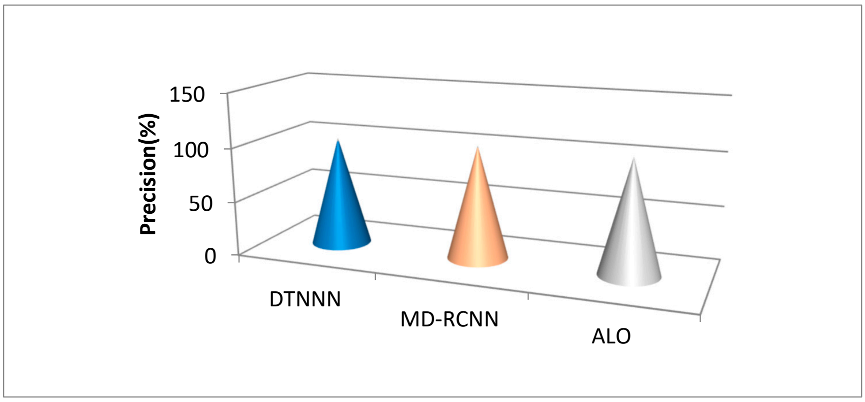


Figure 16. Comparison of Precision with existing techniques.

Figure 6 displays the execution result of the system: (a) Intelligent heart disease prediction and (b) Creating and managing users. Figure 6a shows the Intelligent heart disease prediction. An intelligent heart disease prediction system, the system asks for login details like whether the user is an admin or patient. Figure 6b shows the creation and management of users. In this menu, the system asks whether the user is a new user or not. In the case of a new user, then the user can select yes, or else, the user can choose no.

After the login process, the system asks for registration details if the user is new. Figure 7 illustrates the registration details of the system. In the registration process, the system asks the user to enter a patient name, patient number, date, gender, age, address, contact, and email. After entering all this information, the user can click ok to register.

Figure 8 shows the execution result of the system: (a) Patient no, (b) Registration completed, (c) Patient login. After the registration process, the system displays the patient no as shown in Figure 8a. Figure 8b depicts the status of the registration process as completed. After completing registration, the system asks for a login. Figure 8c displays the patient login. In inpatient login, the system asks the user to enter the patient's name, email address, or mobile number. After entering the details, the user can click on OK to continue the process.

Initially, the validation checks, Mu, and the gradient are used to acknowledge the changes in the system. In this system, to terminate the learning function, the validation checks are used, 'Mu' denotes the control parameter, and the gradient refers to the tangent of the slope. The system learning speed is 0.09, 1000 epochs are the maximum number of training allowed in the system, and 0.001 is the minimum convergence error occurred in the activity. Figure 9 displays the neural network training state. It is observed that, at the 1000 epoch, the gradient value is 0.00044341, Mu is 1×10^{-7}, and the validation check is zero.

Figure 10 displays the result of iteration vs. best score obtained so far for predicting the severity using Ant Lion Optimization algorithm. Here, for different iterations, the best score is calculated. The result obtained is nothing but the convergence curve. In this system, the convergence error is less than 0.001. By increasing the number of iterations from 50 to 500, the convergence curve of the system is estimated.

This system helps the user to check their body conditions from home. Figure 11 displays the results (a) menu button (b) sugar check-up. Figure 11a displays the menu button. The user can select either the check-up option or visit the doctor in the menu section. Figure 11b shows the sugar check-up. On clicking the check-up option, the user can check the sugar level. In the sugar check-up option, the user asks to choose fasting, just ate, or 2 h after eating.

Figure 12 describes the final report of the patient. In this report, the health status of the patient will be reported. The patient's name, age, and sex will be displayed. Then, the system asks to enter the systolic and diastolic pressure of the patient. If the diastolic and systolic pressure is high, it shows hypertension. After this, the system asks for cholesterol value (i.e., to enter the value of LDL cholesterol, triglycerides, and HDL cholesterol). If the value of both LDL and HDL cholesterol is high, the total cholesterol will increase. The patient has a high risk of heart disease. Then, the system asks for the value of the heartbeat. If the heartbeat rate is within normal range, it displays a normal heartbeat. Then, the system asks the user to enter the sugar value. If the value exceeds the normal range, the patient has diabetes. Finally, the system asks to enter the body temperature. The patient's temperature is within the normal range and displays the average temperature.

When illnesses are present, sensitivity is a classifier's chance of predicting the positive. This is also known as the actual positive rate, and the formula for calculating it is presented in Equation (21). Figure 13 displays the sensitivity vs. specification for predicting the disease using generalized approximate reasoning base intelligence control (GARIC) with regression rules.

$$sensitivity = \frac{T\ddot{P}}{T\ddot{P} + F\ddot{N}} \tag{21}$$

When the specificity is high, the classifier has a reasonable probability of predicting the disease. The disease does not emerge in our bodies when the specificity is low. The true negative rate is another name, and it may be determined using Equation (22).

$$specificity = \frac{\ddot{T}N}{\ddot{T}N + \ddot{F}P} \tag{22}$$

Figure 14 compares sensitivity–specificity with Hs-CT I and Hybrid-DT. Table 1 illustrates the analysis of the false positive rate of different techniques.

Table 1. Analysis of False positive rate of different techniques.

False Positive Rate	Hybrid-DT [29]	Hs-CT I [29]	ALO
0.2	0.1	0.45	0.3
0.4	0.3	0.5	0.6
0.8	0.4	0.6	0.7

One of the most important metrics used to evaluate a classifier's performance is accuracy. It's calculated as a percentage of correctly identified samples, and the formula is presented in Equation (23). Figure 15 compares accuracy with existing techniques. Table 2 illustrates the accuracy and precision analysis.

$$Accuracy = \frac{\ddot{T}P + T\ddot{N}}{\ddot{T}P + \ddot{T}N + \ddot{F}P + F\ddot{N}} \tag{23}$$

Table 2. Accuracy and precision analysis.

Technique	Accuracy (%)	Precision (%)
MD-RCNN	89.4	96.24
FKNN	85.43	98.56
ALO	86.0	99.34

When a test is positive, the positive predicted value is the chance of a classifier sending illnesses. It is also known as precision and is displayed in Equation (24). Figure 16 shows the comparison of precision with existing techniques.

$$PPV = \frac{T\ddot{N}}{T\ddot{P} + F\ddot{P}} \tag{24}$$

When the test is negative, the negative predictive value represents the chance of the illness being sent by the classifier.

To validate the performance of the designed model, a few more methods are also considered. The techniques include PCA, FETCH, ANN, DPSS, Epistemological Framework (EF) [32], and Epistemological and Bibliometric Analysis (EBA) [32]. Moreover, the accuracy and precision comparison is described in Figure 17.

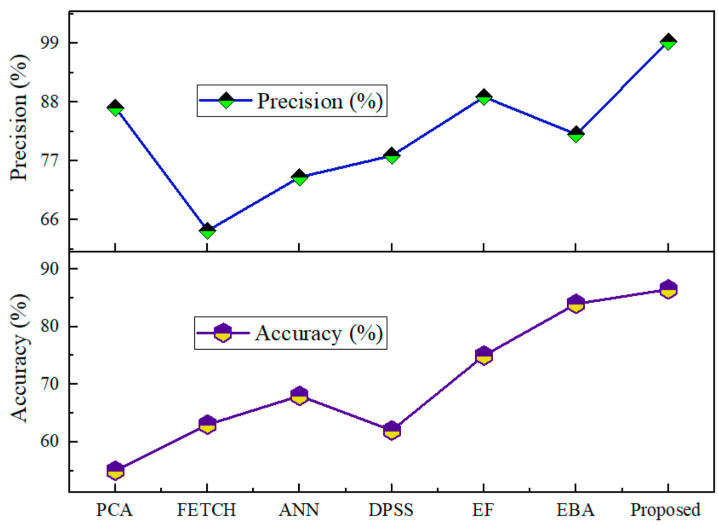


Figure 17. Comparison of Accuracy and precision of existing with the proposed method.

6. Conclusions

A novel optimized fuzzy based prediction framework was developed in this article to predict the heart diseases. This method is a hybrid incorporating the Generalized approximate Reasoning base Intelligence Control (GARIC) and Ant Lion Optimization (ALO) approach. This neuro-fuzzy based approach helps in identifying the heart diseases accurately based on the sensed disease symptom data. Moreover, the integration of fuzzy logic in the proposed model predicts the disease type and measures its severity level. In addition, the incorporation of ant lion fitness function improves the prediction rate. The designed model was evaluated with IoT-based medical dataset containing sensed disease features was considered. The presented was implemented in MATLAB system and the results are estimated as accuracy, precision, and specificity.

Using our proposed methodology, we obtained a prediction rate of 97% and an accuracy of 99.86%. The Internet of Things (IoT) links service providers and hospitals. As a result, if people are preoccupied with certain diseases, they will make a decision. Moreover, a comparative analysis was performed to verify that the designed model attained better results than other existing approaches. In addition, the improvement score was estimated for the presented approach. The comparative analysis shows that in the proposed model, the accuracy is improved by 7.25%, and the precision value is enhanced by 6.05%. Thus, the system accurately classifies the disease type and determines the severity rate. However, the designed model is not applicable for any other applications. Moreover, the resource usage and time consumption are high in the proposed method. So, in future, designing a multimodal deep learning with optimized features will provide the finest results. Hence, the resource usage and time consumption can be minimized.

Author Contributions: Conceptualization, A.V. and G.A.; methodology, A.V.; software, A.K.G.; validation, A.V., G.A. and A.K.G.; formal analysis, A.V.; investigation, G.A.; resources, A.K.G.; data curation, A.V.; writing—original draft preparation, A.V.; writing—review and editing, M.S.; visualization, A.K.G.; supervision, G.A.; project administration, M.S.; funding acquisition, M.S. All authors have read and agreed to the published version of the manuscript.

Funding: This This work was supported by Dongseo University, "Dongseo Cluster Project" Research Fund of 2022 (DSU-20220006).

Institutional Review Board Statement: Not Applicable.

Informed Consent Statement: Not Applicable.

Data Availability Statement: Not Applicable.

Conflicts of Interest: The author declares that there is no conflict of interest regarding the publication of this paper.

Nomenclature

Notation	**Definition**
$\frac{\partial x}{\partial r}$	Estimation derivative
D	Control the curvature
T	Hidden layer
L	Minimum operators
Δr	change in parameter values of gradient
$\frac{\partial H}{\partial rx}$	derivatives consequent labels
$S\ (t)$	stochastic feature
N_{ant}	saving the position concerning every ant
M	Number regarding ant
B	value regarding the *ith* variable about stability *kth*
N_{OA}	saving the position concerning each ant
$B_{j,k}$	value regarding the durability *ith* variable on longevity *kth*
D	range on the variable

G	objective function
$T\ddot{N}$	True negative
$T\ddot{P}$	True positive
$F\ddot{P}$	False positive
$F\ddot{N}$	False-negative
NPV	negative predictive value
PPV	positive predictive value

References

1. Shahidul, I.M.; Islam, M.T.; Almutairi, A.F.; Beng, G.K.; Misran, N.; Amin, N. Monitoring of the human body signal through the Internet of Things (IoT) based LoRa wireless network system. *Appl. Sci.* **2019**, *9*, 1884. [CrossRef]
2. Selvaraj, S.; Sundaravaradhan, S. Challenges and opportunities in IoT healthcare systems: A systematic review. *Appl. Sci.* **2019**, *2*, 1–8. [CrossRef]
3. Naik, S.; Sudarshan, E. Smart healthcare monitoring system using Raspberry Pi on IoT platform. *J. Eng. Appl. Sci.* **2019**, *14*, 872–876.
4. Karthick, R.A.; Manoj, P.; Selvaprasanth, P. Internet of things based high security border surveillance strategy. *Asian J. Appl. Sci. Technol.* **2019**, *3*, 94–100.
5. Yang, Y.; Nan, F.; Yang, P.; Meng, Q.; Xie, Y.; Zhang, D.; Muhammad, K. GAN-based semi-supervised learning approach for clinical decision support in health-IoT platform. *IEEE Access* **2019**, *7*, 8048–8057. [CrossRef]
6. Sony, P.; Sureshkumar, N. *Concept-Based Electronic Health Record Retrieval System in Healthcare IoT. Cognitive Informatics and Soft Computing*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 175–188.
7. Hao, Y.; Usama, M.; Yang, J.; Hossain, M.S.; Ghoneim, A. Recurrent convolutional neural network based multimodal disease risk prediction. *Futur. Gener. Comput. Syst.* **2018**, *92*, 76–83. [CrossRef]
8. DeMartini, J.; Fenton, J.J.; Epstein, R.; Duberstein, P.; Cipri, C.; Tancredi, D.; Xing, G.; Kaesberg, P.; Kravitz, R.L. Patients' Hopes for Advanced Cancer Treatment. *J. Pain Symptom Manag.* **2018**, *57*, 57–63. [CrossRef]
9. Chou, F.-I.; Huang, T.-H.; Yang, P.-Y.; Lin, C.-H.; Lin, T.-C.; Ho, W.-H.; Chou, J.-H. Controllability of Fractional-Order Particle Swarm Optimizer and Its Application in the Classification of Heart Disease. *Appl. Sci.* **2021**, *11*, 11517. [CrossRef]
10. Reddy, K.V.; Elamvazuthi, I.; Aziz, A.A.; Paramasivam, S.; Chua, H.N.; Pranavanand, S. Heart disease risk prediction using machine learning classifiers with attribute evaluators. *Appl. Sci.* **2021**, *11*, 8352. [CrossRef]
11. Chen, J.-J.; Su, T.Y.; Chen, W.S.; Chang, Y.H.; Lu, H.H.S. Convolutional neural network in the evaluation of myocardial ischemia from czt spect myocardial perfusion imaging: Comparison to automated quantification. *Appl. Sci.* **2021**, *11*, 514. [CrossRef]
12. Melgarejo-Meseguer, F.-M.; Gimeno-Blanes, F.-J.; Salar-Alcaraz, M.-E.; Gimeno-Blanes, J.-R.; Martínez-Sánchez, J.; García-Alberola, A.; Rojo-Álvarez, J.L. Electrocardiographic Fragmented Activity (II): A Machine Learning Approach to Detection. *Appl. Sci.* **2019**, *9*, 3565. [CrossRef]
13. Mastoi, Q.-U.; Wah, T.Y.; Raj, R.G. Reservoir Computing Based Echo State Networks for Ventricular Heart Beat Classification. *Appl. Sci.* **2019**, *9*, 702. [CrossRef]
14. Talal, M.; Zaidan, A.A.; Zaidan, B.B.; Albahri, A.S.; Alamoodi, A.H.; Albahri, O.S.; Alsalem, M.A.; Lim, C.K.; Tan, K.L.; Shir, W.L.; et al. Smart Home-based IoT for Real-time and Secure Remote Health Monitoring of Triage and Priority System using Body Sensors: Multi-driven Systematic Review. *J. Med. Syst.* **2019**, *43*, 42. [CrossRef]
15. Malathi, D.; Logesh, R.; Subramaniyaswamy, V.; Vijayakumar, V.; Sangaiah, A.K. Hybrid reasoning-based privacy-aware disease prediction support system. *Comput. Electr. Eng.* **2019**, *73*, 114–127.
16. El Zouka, H.A.; Hosni, M.M. Secure IoT Communications for Smart Healthcare Monitoring System. *Internet Things* **2019**, *13*, 100036. [CrossRef]
17. Carvalho, J.V.; Rocha, Á.; van de Wetering, R.; Abreu, A. A Maturity model for hospital information systems. *J. Bus. Res.* **2019**, *94*, 388–399. [CrossRef]
18. Pace, P.; Aloi, G.; Gravina, R.; Caliciuri, G.; Fortino, G.; Liotta, A. An Edge-Based Architecture to Support Efficient Applications for Healthcare Industry 4.0. *IEEE Trans. Ind. Inform.* **2018**, *15*, 481–489. [CrossRef]
19. Kaur, M.J. A Comprehensive Survey on Architecture for Big Data Processing in Mobile Edge Computing Environments. *Edge Comput.* **2019**, 33–49. [CrossRef]
20. Avola, D.; Cinque, L.; Foresti, G.L.; Marini, M.R. An interactive and low-cost full body rehabilitation framework based on 3D immersive serious games. *J. Biomed. Inform.* **2018**, *89*, 81–100. [CrossRef]
21. Dautov, R.; Distefano, S.; Buyya, R. Hierarchical data fusion for Smart Healthcare. *J. Big Data* **2019**, *6*, 19. [CrossRef]
22. Al-Tudjman, F. *Security in IoT-Enabled Spaces*; CRC Press: Boca Raton, FL, USA, 2019.
23. Yousefpour, A.; Fung, C.; Nguyen, T.; Kadiyala, K.; Jalali, F.; Niakanlahiji, A.; Kong, J.; Jue, J.P. All one needs to know about fog computing and related edge computing paradigms: A complete survey. *J. Syst. Archit.* **2019**, *98*, 289–330. [CrossRef]
24. Maes, K.; van Meerbeeck, L.; Reynders, E.; Lombaert, G. Validation of vibration-based structural health monitoring on retrofitted railway bridge KW51. *Mech. Syst. Signal Process.* **2021**, *165*, 108380. [CrossRef]
25. Saeed, U.; Shah, S.Y.; Ahmad, J.; Imran, M.A.; Abbasi, Q.H. Machine learning empowered COVID-19 patient monitoring using non-contact sensing: An extensive review. *J. Pharm. Anal.* **2022**, *12*, 193–204. [CrossRef]

26. Gupta, N.; Gupta, S.K.; Pathak, R.K.; Jain, V.; Rashidi, P.; Suri, J.S. Human activity recognition in artificial intelligence framework: A narrative review. *Artif. Intell. Rev.* **2022**, *55*, 4755–4808. [CrossRef]
27. Baser, O.; Yavuz, M.; Ugurlu, K.; Onat, F.; Demirel, B.U. Automatic detection of the spike-and-wave discharges in absence epilepsy for humans and rats using deep learning. *Biomed. Signal Process. Control* **2022**, *76*, 103726. [CrossRef]
28. Levrat-Guillen, F.; Ghazi, T. Cost-Effectiveness of Intermittently Scanned Continuous Glucose Monitoring Versus Advanced Hybrid Closed-Loop Systems in Type 1 Diabetes: Comment on Jendle et al. *Diabetes Ther.* **2022**, *13*, 1121–1123. [CrossRef]
29. Available online: https://www.kaggle.com/code/infernop/iot-temperature-readings-data-health-checkup (accessed on 14 June 2022).
30. Hamaya, R.; Yonetsu, T.; Kanaji, Y.; Usui, E.; Hoshino, M.; Hada, M.; Yoshinori, K.; Tadashi, M.; Tetsumin, L.; Tsunekazu, K. Interrelationship in the prognostic efficacy of regional coronary flow reserve, fractional flow reserve, high-sensitivity cardiac troponin-I and NT-proBNP in patients with stable coronary artery disease. *Heart Vessel.* **2019**, *34*, 410–418. [CrossRef]
31. Radanliev, P.; De Roure, D.; Ani, U.; Carvalho, G. The ethics of shared COVID-19 risks: An epistemological framework for ethical health technology assessment of risk in vaccine supply chain infrastructures. *Health Technol.* **2021**, *11*, 1083–1091. [CrossRef] [PubMed]
32. Radanliev, P.; De Roure, D. Epistemological and Bibliometric Analysis of Ethics and Shared Responsibility—Health Policy and IoT Systems. *Sustainability* **2021**, *13*, 8355. [CrossRef]