ITC 2/52
Information Technology and Control
Vol. 52 / No. 2 / 2023
pp. 367-380
DOI 10.5755/j01.itc.52.2.32899

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Received 2022/12/02 | Accepted after revision 2023/02/13

HOW TO CITE: Karthikeyini, S., Vidhya, G., Vetriselvi, T., Deepa, K. (2023). Heart Disease Prognosis Using D-GRU with Logistic Chaos Honey Badger Optimization in IoMT Framework. *Information Technology and Control*, 52(2), 367-380. https://doi.org/10.5755/j01.itc.52.2.32899

Heart Disease Prognosis Using D-GRU with Logistic Chaos Honey Badger Optimization in IoMT Framework

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In recent years, heart disease has superseded several other contributory death factors. It is challenging to predict an individual's risk of acquiring heart disease since it requires both expert knowledge and real-world experience. Developing an effective method for the prognosis of heart disease using Internet of Medical Things (IoMT) technology in healthcare organizations by collecting sensor data from patients' bodies, utilizing robust expert systems, and incorporating vast healthcare data on cardiac disorders to alert physicians in critical situations is a challenging task. Several machine learning-based techniques for predicting and diagnosing cardiac disease have recently been demonstrated. However, these algorithms cannot effectively handle high-dimensional information due to the need for an intelligent framework incorporating multiple sources to predict cardiac illness. This work proposes a unique model for heart disease prediction based on deep learning, Deep Gated Recurrent Units (D-GRU), which combines with Stacked Auto Encoders. A novel optimization algorithm, the Logistic Chaos Honey Badger Algorithm, is proposed for optimal feature selection. Publicly available heart disease-related datasets collected from UCI Repository, Cleveland Database, are used for training the proposed D-GRU model. The trained model is further tested on the data gathered from the sensors in the IoMT framework. The performance of the proposed model is compared against several deep learning models and existing works in the literature. The proposed D-GRU model outperforms the other models taken for comparison and exhibits performance supremacy with an accuracy of 95.15% in predicting heart diseases.

KEYWORDS: Deep Learning, Internet of Medical Things, Gated Recurrent Units, Stacked Autoencoders, Honey Badger Algorithms.

1. Introduction

Heart disease is a severe condition affecting the heart's work and can have side effects like myocardial infarction and diminished endothelial function [33]. These issues lead to strokes and coronary heart attacks. According to a survey, heart disease affects approximately 720,000 people annually. Heart disease affects men and women, but men are more susceptible [25]. One out of every four people died in 2017 due to heart disease. 525,000 of the 735,000 people who suffer heart attacks experience their first attack. Cardiovascular problems can be identified using diagnostic procedures and wearable electronics [8]. First, integrating wearable electronics with Electronic Medical Records for cardiac surveillance systems is a significant challenge [17]. Second, it can be challenging to draw meaningful conclusions from data used to forecast heart disorders [32]. Therefore, an intelligent system that can automatically combine data from Electronic Medical Records and sensors is necessary. Wireless sensor networks are a breakthrough technology in public healthcare that enables sensors to be inserted into or placed on the body to gather and broadcast real-time patient health data, such as high blood pressure, respiratory oximetry, and breathing [22]. Sensors have recently contributed to the healthcare system's development across the globe. Detachable or adaptable electronics can be used for many functions, including motion detection, revitalization, wireless sensors, disease detection, etc., to increase human life's sanctity further. Among them, several sensing devices are worn by people or attached to their skin to capture sensory data and demonstrate remarkable results in identifying various bodily actions.

Applications for remote patient monitoring are typically supported by continuous information transfer for gesture recognition in conjunction with sensing devices [14]. Heart disorders impair the human heart's capacity to beat usually. It covers anatomical faults in the heart, rapid heartbeat or rhythms, and conditions affecting the blood vessels that supply blood to the heart. Electrocardiogram (ECG) sensors are frequently used by medical experts to quickly assess for signs of potential heart disease and abnormal ventricular pulse. According to the World Health Organization (WHO) [9], heart disease affects the lives of 20 million people yearly. Early recognition and management of heart disease are essential to preventing unanticipated fatality from a heart attack or sudden cardiac death.

Cardiovascular disease affects the body because it reduces blood flow and increases the risk of arterial disorders, particularly in elderly individuals and adults. To gather sensor data for assessing and forecasting heart illness, Internet of Medical Things (IoMT) technology has recently been implemented in healthcare systems [15]. Using a separate ECG, an IoMT solution leverages end-to-end heart condition detection. An electronic stethoscope can instantly examine patients' heart sounds and spot any issues. The advanced detection of potential health risks and the timing of pertinent activities, such as monitoring treatments and developing new evaluations, can be facilitated by applying emerging technology to cognitive systems and protective regulations. It comprises a challenging environment with various components for planning, health information systems management, disease detection and prevention, evaluation, and grading.

To optimize various algorithms for a particular task, deep learning is an artificial intelligence technique that uses several neural network layers and enormous amounts of data [28]. Deep learning has clinically good development potential, from exploration to forecast to decision-making. DL can spot trends of specific diseases in inpatient electronic medical information and alert practitioners of any irregularities [10, 27]. It is crucial to use a deep learning model for image analysis to predict heart disease because of several relevant risk factors, including Mellitus, hypertension, irregular respiratory oximetry, high blood cholesterol, and several others. Other limitations are that data obtained from these devices may be difficult to interpret for physicians, leading to misdiagnosis or inaccurate predictions. In mining statistics and neural networks, many methods were used to decrease the incidence of cardiac illness in humans [31, 7, 1]. The most effective method for predicting ailments like brain and cardiovascular diseases is generally regarded as neural networks. Artificial Neural Networks were used to obtain the data, effectively predicting heart disease. Neural network models include predicted values from various earlier methodologies and future probabilities.

This research focuses on developing Deep Gated Recurrent Units (D-GRU) by incorporating Gated Recurrent Units, a specialized version of RNN, and stacked autoencoders to classify heart diseases. Honey badger optimization algorithm, based on logistic chaos, is implemented to facilitate the feature selection. The Cleveland database employs a dataset from the UCI Machine learning repository to train the model. Further, the data collected from the IoMT framework is tested on the trained model.

The main contributions of this paper are as follows,

1 To develop a unique IoMT-enabled heart disease prognosis model D-GRU based on deep learning techniques such as Gated Recurrent Units and Stacked Auto encoders and apply it to data collected from the standard publicly accessible resources.
2 To propose an efficient feature selection algorithm, the Logistic Chaos Honey Badger algorithm for the IoMT enabled the heart disease prognosis model by maximizing the association between characteristics within the same class and minimizing the association between attributes within other courses.
3 To demonstrate the superiority of the suggested model over different optimization and deep learning-based architectures.

The remainder of the paper is organized as follows. Section 2 discusses the various existing works on heart disease prediction using Machine learning and neural network architectures. Section 3 describes the proposed methodology with a brief discussion of the IoMT framework, Honey Badger algorithm, Gated Recurrent Units, and Stacked Autoencoders. Section 4 briefs the results obtained on performing the experiments using the proposed model on the dataset collected from the UCI repository and the IoMT framework and compares it with existing models to show the performance supremacy of the proposed D-GRU model. Section 5 concludes the research.

2. Related Works

The various state-of-the-art works on heart disease prediction are discussed in this section. Machine learning and deep learning algorithms used for this problem are reviewed, and the limitations in the existing works are identified to decide on the problem formulation for the current work.

A fusion of the sparrow stacked system was proposed in the research detailed in [4]. Using the movie lens dataset, its competence and applicability are demonstrated. A sparrow is a little bird with a lot of memory and intelligence. Sparrows constantly switch between making their food and searching for it. Those in their immediate area observe the behavior of sparrows. One of the primary issues is the sustainability of techniques when applied to real-world datasets. Sustainability is a big difficulty for these datasets because the best Matching systems generate a sizable amount of dynamic data from user activities through comments and feedback. To forecast cardiac illness, this work offers a viability analysis and the creation of data mining and signal processing algorithms.

The presented architecture in [19] integrates Edge-Fog-Cloud computing for the precise and prompt transmission of outcomes. The hardware elements gather data from numerous individuals. Cardiovascular feature extraction from pulses [16] is done to get hidden patterns. Additional attributes feature extraction is also gathered. These features are captured and provided to the clinical diagnosis using an Efficient Multilevel Convolution Neural Network.

The hyperparameters are optimized via the galactic swarm optimization technique [3].

Every month, a staggering amount of patient-related data is produced. The information acquired can be utilized to spot potential faults in the system over time. Heart illness has been identified by applying unconventional data mining and machine learning methods [21]. Several deep learning algorithms using customized recurrent neural networks were developed in this study [23] to detect cardiac disease. Several feature extraction and selection techniques have been used to get essential qualities and gather data using specifically designed IoT configurations. The technology effectively and precisely offers cardiac risk scores in a runtime environment [5].

Using patient data on essential health parameters, the authors of [24] proposed many machine-learning approaches for heart disease prediction. The study demonstrated four categorization strategies [12] to build prediction models. Data cleaning and augmentation processes were used before the models were constructed. The models were evaluated based on accuracy as well as precision and recall, along with F1-score performance metrics. The Support Vector Machine model, out of the four classification techniques employed, achieved a 92.87% accuracy rate. The main objective of the proposed study is to use clinical records and diagnostic data to categorize data and forecast heart illness.

The authors in [13] suggested an intelligent healthcare system that uses feature segmentation and collective deep learning to forecast cardiac disease. They thoroughly studied recent methods used to monitor heart function and forecast cardiovascular illness. These systems use the Internet of Things and Bluetooth, including a GSM module and are embedded in a cloud-based server to send observed heart data to a physician. This research initially designed a cloud-based heart disease prediction system using machine learning techniques [6].

Research in [29, 30] uses generalized association pattern extraction to forecast cardiac disease based on the results of pertinent factors. To forecast cardiac illness, this work offers a feasibility assessment and the creation of information retrieval and processing algorithms. The recommended methodology follows the ideal clustering strategy by applying a specific improvement in spatial pattern and density-based segmentation [18]. In this case, the density-based segmentation is performed using K-means segmentation. The distance-based segmentation is performed using DBSCAN, which employs density-based segmentation of programs with noise in the spatial domain. In this research, an efficient system for predicting heart illness in the general population is developed using data from the UCI Repository and medical sensors.

Patients with stable coronary artery disease were considered for research in [26], which used patient data based on the records collected from wearable sensors. For recording daily activities, each participant received a Bluetooth Charge. All of the participants have completed the tests carried out using the Monitoring Data Systems. Two unique techniques were developed to classify the recorded scores using sensor data.

The following table, Table 1 presents the inferences and limitations in the existing works related to heart disease prediction.

After reviewing the relevant works using multiple classifiers and deep architectures, it was found that there were still several issues that needed to be addressed with an improved IoMT-enabled heart disease monitoring system.

Research Question 1: Are feature selection methods required in IoMT-supported heart disease prognosis systems?

Research Question 2: What are the optimal scientific uses of a heart disease prognosis system supported by the Internet of Medical Things?

Research Question 3: What deep architectures are best for achieving the highest accuracy rate for an Internet of Medical Things-enabled heart disease prognosis system?

In this work, a deep learning-based approach is used to propose a new IoMT-enabled heart disease prognosis model, D-GRU. To deal with the association restrictions, the D-GRU model employs the best feature selection strategy. For improving accuracy and reducing the computational time of the IoMT-enabled heart disease prediction method, a novel LCHBA optimization method is proposed. The proposed LCHBA approach is used to optimize the D-GRU model parameters

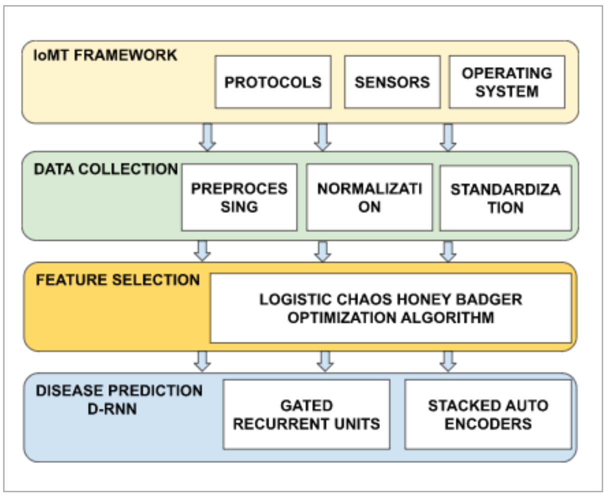
Table 1
Comparison of existing works

Reference	Method used	Inference	Limitation
[10]	Machine Learning	A clinical support system was developed to detect heart disease	The level of effectiveness of the disease cannot be identified using this system
[31]	Supervised Learning	Reduction in false predictions is achieved with high accuracy in predictions.	Requires only ensemble classification technique
[7]	Unsupervised Learning	Forms clusters to obtain precise predictions	Even minor changes in the input can create changes in the cluster
[4]	Machine Learning	Performs classification based on the investigations on the sensitivity of data	Incurs a huge amount of time to perform computations
[3]	Machine Learning	LASSO feature extraction techniques employed	Inconsistent data impacts the performance of the model to a larger extent
[23]	Deep Learning	Radial basis function with Optimization using Genetic Algorithm is used	Huge data considered leads to complexity in the training procedure
[24]	Deep Learning	Optimized Artificial Neural Networks are incorporated to analyze huge volumes of data	Computational complexity is the main drawback.
[6]	Data Analytics	Fuzzy logic-based data analysis is used for making appropriate predictions.	Missing data can lead to inconsistency in predictions.

3. Proposed Methodology

This section discusses the proposed methodology for heart disease prognosis by incorporating the Internet-of-Medical Things framework [34, 35], Logistic Chaos Honey badger optimization algorithm, Gated Recurrent Units, and Stacked Autoencoders. The architecture of the proposed model is presented in Figure 1. The IoMT framework collects real-time patient health data using the sensors implanted in the body. The training phase involves rigorously using the Cleveland database data to train the model to make it competent enough to make predictions. The testing phase involves the data collected from the IoMT framework to assess the performance of the trained model. The feature selection and disease classification phases are critical in this IoMT-enabled heart disease prognosis system. The optimal feature selection is implemented

Figure 1
Proposed architecture

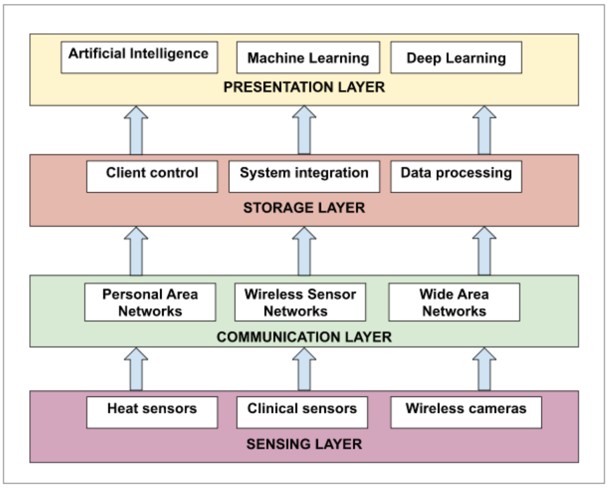


using the Honey Badger algorithm based on the Logistic Chaos method. Classification is performed by combining Gated Recurrent Units and Stacked Auto encoders to improve the prediction accuracy.

3.1. IoMT Framework

IoMT applications have been widely used recently due to the Internet's integration and occupancy into our environment. The IoMT framework is stacked in four layers: the Sensing layer, Communication layer, Storage layer, and Presentation layer, as shown in Figure 2.

Figure 2
IoMT framework



3.1.1. Sensing Layer

Data sources like intelligent devices, medical surveillance devices, and digital products incorporated with sensing devices like heat sensors, clinical sensors, connected device sensors, and wireless cameras make up the lowest layer of IoMT, known as the Sensing layer. With a robust distribution system that serves as a high-efficiency transfer medium, the sensing systems notice environmental changes, distinguish artifacts, positions, demographic changes, intensity, etc., and convert the data to digital format. These can also remember and save the information for later use.

3.1.2. Communication Layer

Wireless sensor networks (WSNs), can handle many sensors and are helpful for limited energy and bit rate connectivity. As previously noted, the sensors must be connected to the hub through networks that transmit and manage data remotely or globally. Long-distance or short-distance communication is possible over a variety of frequency bands. Personal area networks like ZigBee or Bluetooth and local area networks like Ethernet or Wi-Fi are generally the two different types of networks employed for communication. Wide Area Networks do not necessitate connectivity but utilize server-side applications.

3.1.3. Storage Layer

High volumes of original data must be processed to extract the pertinent information. This process requires tools that can operate quickly using insights, vulnerability scanning, modeling, and remote access. This layer provides client control, system integration, and data processing. Storage analysis will help cache massive amounts of information in randomly accessible memory types to speed up decision-making and decrease the time required for data search. The shared data may be kept on-site or centralized in a remote server. While being comprehensive, cloud-based technology is also adaptable and expandable. However, with centralized cloud storage, problems such as excessive data buildup, confidentiality, dependability, and latency in data retrieval due to the proximity between systems and information centers may increase.

3.1.4. Presentation Layer

The analysis of data and implementation of software services are the primary responsibilities of the presentation layer. Artificial Intelligence and Machine learning are used by the Presentation layer to understand Electronic Health data and to track subtle differences in the acquired data via everyday operational plots to make decisions regarding possible diagnoses and/or treatments.

The Honey Badger algorithm is a recently developed optimization algorithm under the meta-heuristic approach. Like any other optimization algorithm, this involves exploration and exploitation phases. Initially, a population of honey badgers is formed as denoted in (1),

$$HB_k = HB_l + v_1 \times (HB_u - HB_l)\,. \tag{1}$$

In the above Equation (1), HB_k represents the kth value of the honey badger with lower extremity value HB_l and upper extremity value HB_u along with a value rd_v chosen at random. The next step is to compute the redolent strength which depends on the force exhibited by the target and the distance between the honey badger and the target. The redolent strength is computed as in (2):

$$R_{strength} = v_2 \times \frac{Obs_{power}}{(4 \times \prod \times T^2)}. \quad (2)$$

In the above Equation (2), Obs_{power} represents the observation power which is denoted as in (3):

$$Obs_{power} = (HB_k - HB_{(k+1)})^2. \quad (3)$$

T in Equation (2) represents the distance between the target and the honey badger which is computed as in (4):

$$T = HB_{target} - HB_k. \quad (4)$$

Next, the badger forms a heart-shaped curve as part of the process to acquire the target and this movement is represented as in (5):

$$HB_{current} = HB_{target} + Search_{flag} \times G \times Obs_{power} \times HB_{target} + \\ + Search_{flag} \times v_3 \times Search_B \times T \times \left|\cos(2 \times \prod \times v_4) \times \\ \times [1 - \cos(2 \times \prod \times v_5)]\right| \quad (5)$$

$$Search_B = I \times \exp\left(\frac{-p}{pm}\right). \quad (6)$$

In (6), I denotes a constant value and not more than 1. p_m represents the maximum number of iterations taken in the quench to acquire the target by the badger. HB_{target} denotes the ptarget's positionfrom the badger. G stands for the capacity of the badger to obtain the target. The value of G is always greater than one. v_3,v_4,v_5 are the values chosen at random between the range starting from zero and ending up to 1. $Search_{flag}$ is an indicator which is utilized to modify the path of the search towards the target. The value of the $Search_{flag}$ will be equal to one if in case the random value v_6 is less than or equal to 0.5, else the value of the $Search_{flag}$ will be equal to the negative value of one.

Equation (7) denotes the quench by the badger to reach the target at the hive:

$$HB_{current} = HB_{target} + Search_{flag} \times v_7 \times Search_B \times T. \quad (7)$$

Nowadays, new scientific areas and research have begun to apply chaos theory. A probabilistic principle used in irrational behavior is called chaos theory. The system represents the entire cardiovascular disease prediction model. Non-linearity shows the differences between different risk variables connected to the diagnosis of heart disease. Dynamic denotes a system that evolves throughout a period. This work utilizes chaos theory to increase resolution and efficiency of prediction. These traits aid in preventing the population from going over the regional equilibrium bound. The mathematical representation of the logistic chaos theory is denoted as in (8):

$$fun(x) = \frac{Curve_{\max}}{1 + e^{-g(x - x_0)}}. \quad (8)$$

In Equation (8), the difference between x and x_0 indicates the center point of the logistic curve. $Curve_{max}$ represents the highest possible value of the curve. g denotes the rate at which the curve grows. This function fun(x) is used to track the increase in the optimization rate from the minimum rate to the maximum rate. In case of the time series information, the same function can be represented in differential form as in (9):

$$x_{i+1} = gx_i(1 - x_i). \quad (9)$$

The pseudocode of the proposed Logistic Chaos Honey badger algorithm (LCHBA) is shown in Algorithn 1.

Algorithm 1

Logistic Chaos Honey badger algorithm (LCHBA)

Step 1: Assign initial values for p_m,G,I

Step 2: Set the total number of possible outcomes as η

Step 3: Compute the fitness value of the badger with respect to HB_k as $HB_{fitness}$

Step 4: Similarly assign the fitness value for the target HB_{target} as $targe_{tfitness}$

Step 5: while

Step 6: Modify the value of the $Search_B$ using Equation (6)

Step 7: Compute the Redolent strength $R_{strength}$ using Equation (2)

Step 8: for k = 1 to D do

Step 9: if v < 0.5then

Step 10: Modify $HB_{current}$ using Equation (5)

Step 11: else

Step 12: Modify $HB_{current}$ using Equation (7)

Step 13: end if

Step 14: Determine current position of target and assign to $target_{current}$

Step 15: if $target_{current}$ <= $target_k$

Step 16: update $HB_k = HB_{current}$ and $target_k = target_{current}$

Step 17: end if

Step 18: if $target_{current}$ <= $target_{fitness}$ then

Step 19: update $HB_{target} = HB_{current}$ and $target_{fitness} = target_{current}$

Step 20: end if

Step 21: apply logistic chaos to $HB_{fitness}$ using Equation (8)

Step 22: modify the value of $target_{fitness}$ as per $HB_{fitness}$

Step 23: end for

Step 24: repeat until p is satisfied

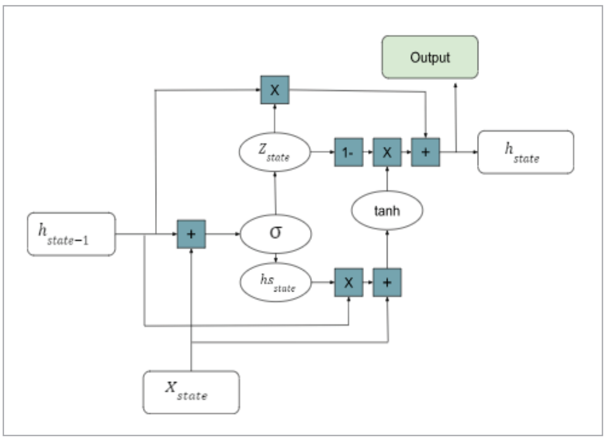
Step 25: return HB_{target}

3.3. Novel Gated Recurrent Units

Gated Recurrent units (GRU) are the extended versions of the Recurrent Neural Networks. The structure of a GRU model is shown in Figure 4. It can also be considered as a more simplified form of the Long-Short Term Memory (LSTM) Networks. This model requires less time for the training process and exhibits better performance. The working of GRU model is quite similar to the LSTM model with one difference that the hidden state in this model is a combination of the forget state and the input state. This combined state is represented as one update state. Moreover, in a GRU model the cell as well as hidden states are merged together, thus reducing the total number of states to half.

Figure 4

Structure of GRU model



The hidden state in any GRU model can be represented as in (10):

$$h_{state} = (1 - X_{state}) * h_{state-1} + X_{state} * hs_{state} . \tag{10}$$

Next, the update state is represented as in (11), which is necessary to make decision on how much the model is modified:

$$X_{state} = \sigma(B_x * h_{state-1,} Y_{state}) . \tag{11}$$

The state to be modified next to the update state is the reset state which is modified as denoted in (12):

$$Z_{state} = \sigma(B_z * h_{state-1}, Y_{state}) . \tag{12}$$

A new state for memory is produced by applying a tangent function to Equation (12) as represented in (13):

$$hs_{state} = \tanh(B * [Z_{state} * h_{state-1,}, Y_{state}]) . \tag{13}$$

3.4. Stacked Auto Encoder

An autoencoder in general can be described as a neural network which is unsupervised in nature with an encoder as well as a decoder. The main objective of the auto encoder is to learn the internal representations of the data in minor levels so that it can be used to make accurate predictions. The role of the encoder is to characterize the input data in a different way which is then transformed by the decoder to retrieve the original form as in (14):

$$I_f = A_f (W_t * i + E_b) . \tag{14}$$

In the above equation, A_f denotes the activation function, W_t denotes weight for i input and E_b represents the bias vector for the encoder.

$$N_f = O_f (UW_t * n + D_b) . \tag{15}$$

Here, O_f, UW_t, D_b denotes the activation function for the output layer, updated weights and bias for decoder.

The mathematical formulation of the activation function A_f and O_f are as in (16) and (17), respectively:

$$A_f = \frac{1}{1+e^{(-i)}}, \tag{16}$$

$$O_f = \frac{1}{1+e^{(-o)}}. \tag{17}$$

The error functions for I_f and N_f which are the original input data and encoded data is denoted in (18):

$$Err(f) = \frac{1}{D}\sum_{k=1}^{D} i_k + n_k^2. \tag{18}$$

Here, D denotes the total number of the samples considered as input.

Regularization is employed in the network to avoid the issue of overfitting and also manage the weights as represented in (19):

$$Re(f) = \frac{1}{2}\sum_{a}^{A}\sum_{b}^{B}\sum_{c}^{C}(W_{bc}{}^{(a)}). \tag{19}$$

Adam optimizer is used as the gradient descent and is denoted as in (20):

$$g_d = \delta_1 g_{d-1} + (1-\delta_1).\, n_d. \tag{20}$$

4. Results and Discussion

In this section, the performance of the proposed model D-GRU is evaluated by conducting experiments and compared against the existing models to demonstrate its performance superiority.

4.1. Dataset Used

As explained previously, a cutting-edge dataset from the UCI repository is used explicitly for experimental purposes. This part briefly overviews the dataset used in this study's practical work. Table 2 shows a list of the attributes utilized in the algorithm along with a brief description of each one and, where appropriate, a range of possible values. This set of attributes is a subset of a dataset created by medical professionals.

Table 2
List of Possible feature values

Feature number	Feature name	Possible values
F1	sex	0 and 1
F2	age	Between 29 to 77
F3	cp	1,2,3 and 4
F4	trestbps	Between 94 to 200
F5	chol	Between 126 to 465
F6	fbs	0 and 1
F7	restecg	0,1 and 2
F8	thalach	Between 71 to 188
F9	exang	0 and 1
F10	oldpeak	0, 1, 2, 3, 4, 5 and 6
F11	slope	1, 2 and 3
F12	ca	5
F13	thal	4
F14	num	1, 2, 3 and 4

Preprocessing is a set of procedures used to change the source of data. These steps entail missing information, changing the object's type, and taking different actions. During the preprocessing phase, the missing values function was located using the K-nearest neighbor (KNN) algorithm. Min-max normalization is one of the most widely applied methods for data normalization. Data transformation and normalization are aided by min-max normalization, which transforms the outcome of each quantitative feature into a goal value based on the most minor and most significant values. The scale for the data will be between 0 and 1.

4.2. Hardware Setup

The following setup as specified in Table 3 is made for the experimental setting on a personal computer to conduct this research and analyze the findings.

Table 3
Hardware setup

Component Name	Description
Processor	Intel Quad-Core i7 4th generation
Running speed	2.3 GHz
L1 Cache	32 KB
L2 Cache	256 KB
L3 Cache	4 MB
DDR3 RAM	16 gb
Hard drive	1 TB
Rotational speed	6 K RPM

4.3. Performance Metrics

The performance of the proposed model is evaluated based on the following criteria. The metrics are formulated based on the values of TP_{os}, TN_{eg}, FPos, FN_{eg}. The total number of individuals who are actually affected by heart disease and are classified accordingly is termed as TP_{os}. The total number of individuals who are not actually affected by heart disease and are classified as affected is termed as FP_{os}. The total number of individuals who are not actually affected by heart disease and are classified accordingly is termed as TN_{eg}. The total number of individuals who are actually affected by heart disease and are classified as not affected is termed as FN_{eg}.

$$Accuracy = \frac{TP_{OS} + TN_{eg}}{TP_{OS} + TN_{eg} + FP_{OS} + FN_{eg}} \times 100 \, . \tag{21}$$

$$\Pr ecision = \frac{TP_{OS}}{TP_{OS} + FP_{OS}} \times 100 \, . \tag{22}$$

$$\operatorname{Re} call = \frac{TP_{OS}}{TP_{OS} + FN_{eg}} \times 100 \, . \tag{23}$$

$$F1score = 2 * \frac{\Pr ecision + \operatorname{Re} call}{\Pr ecision * \operatorname{Re} call} \times 100 \, . \tag{24}$$

4.4 Performance of the Model in Multiple Iterations

The proposed D-GRU model is trained for different epochs, and the results are obtained for various performance metrics such as Accuracy, Precision, Recall, and F1 Score. The model's performance is computed on five different iterations, and the average value is taken as the results exhibited by the model. In the first iteration, the model produced 94.56%, 92.05%, 91.23%, and 92.55% as the metric values for Accuracy, Precision, Recall, and F1 Score, respectively. These values varied slightly for each of the iterations. Finally, the average of these values is taken as the performance metric values for the D-GRU model: accuracy as 95.15%, precision as 92.26%, recall as 91.48%, and F1 score as 92.21%.

4.5. Performance Comparison Against RNN and Proposed GRU+SAE

The performance of the proposed D-GRU which is a combination of Gated Recurrent Units and Stacked Auto encoders is compared against the Recurrent Neural Networks model. When RNN technique was applied to the heart disease dataset, it produced an accuracy of 88.25% which is lesser than the accuracy proposed by the GRU+SAE model which is 95.15% as shown in Figure 5. Similarly, the values of the other metrics are comparatively lower than the metric values produced by the proposed D-GRU model as shown in Table 4.

Figure 5
Performance analysis between RNN vs D-GRU

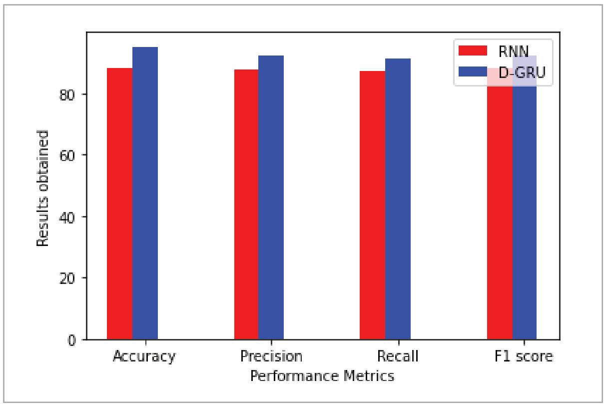


Table 4
Performance comparison between RNN vs D-GRU

Models	RNN	Proposed GRU+SAE
Accuracy (%)	88.25	95.15
Precision (%)	87.45	92.26
Recall (%)	87.05	91.48
F1 score (%)	88.1	92.21

4.6. Performance Comparison Against Existing DL Models

The proposed model is also compared against the Deep learning models combined with an optimization algorithm. The models considered for the performance analysis include Convolutional Neural Networks (CNN) with Particle Swarm Optimization (PSO), Long Short-Term Memory Networks (LSTM) with Harris Hawk Optimization, CNN and LSTM with Ant Colony Optimization (ACO), CNN+RNN with Honey Badger Algorithm. The proposed model D-GRU combines GRU and SAE with the Logistic Chaos Honey Badger Algorithm.

The Accuracy produced by the DL models is 87.56%,88.25%,89.25%, and 90.35% for CNN+PSO, LSTM+HHO, CNN+LSTM+ACO, and CNN+RNN+HBA, respectively. However, these accuracy values are lesser than the accuracy produced by the proposed GRU+SAE+LCHBA model for heart disease prediction. CNN+RNN+HBA model had better performance than the other DL models taken for comparison, which is behind the performance exhibited by the proposed model. Similarly, the DL models showed lower performance metric values for Precision, Recall and F1 score than the D-GRU model, as shown in Table 5.

Table 5

Performance comparison between the Proposed Model vs Deep Learning Models

Models	CNN	LSTM	CNN+ LSTM	CNN+ RNN	GRU+ SAE
Optimizer	PSO	HHO	ACO	HBA	LCHBA
Accuracy (%)	87.56	88.25	89.25	90.35	95.15
Precision (%)	86.54	87.35	88.75	89.45	92.26
Recall (%)	85.24	86.45	87.35	88.25	91.48
F1 score (%)	86.24	87.35	87.85	89.15	92.21

4.7. Performance Comparison Against Existing Works

The performance of the proposed model is analyzed against the existing works in the literature like RERF-ILM model [5], the Fuzzy-GBDT model [13] and the MSABA model [30]. The accuracy produced by these models is 91.24%, 92.35% and 93.45% for RERF-ILM, Fuzzy-GBDT and MSABA models, respectively. The MSABA model exhibited higher performance with 91.56% precision, 91.65% recall and 92.05% F1 score values. Although MSABA showed higher performance than the existing works under consideration, the proposed D-GRU outperformed MSABA in terms of all the metric values as shown in Table 6. The performance comparison between existing and proposed works can be observed from Figure 6.

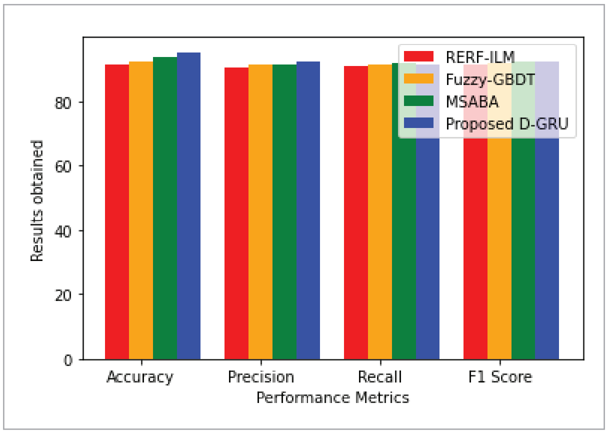
Table 6

Performance Comparison between Existing Works vs Proposed Work

Models	RERF-ILM [5]	Fuzzy-GBDT [13]	MSABA [30]	Proposed D-GRU
Accuracy (%)	91.24	92.35	93.45	95.15
Precision (%)	90.36	91.24	91.56	92.26
Recall (%)	91.1	91.35	91.65	91.48
F1 score (%)	91.16	91.85	92.05	92.21

Figure 6

Performance analysis between the Existing vs Proposed Works



It is evident from the performance analysis of the proposed model against the current works and DL models that the proposed model exhibits superior performance in predicting heart disease for the data collected from the UCI repository and the real-time data collected through sensors from the IoMT framework.

5. Conclusion

The proposed research was used to develop a unique IoMT-enabled heart disease prognosis system, D-GRU, which combines Gated Recurrent Units and Stacked Auto Encoders for classification purposes. The D-GRU model was trained with the publicly available dataset from the UCI repository, and further, it was tested on the data gathered from the IoMT framework. Logistic chaos Honey badger algorithm was used as the optimization algorithm to select the best features from the data. The performance analysis observed that the proposed model exhibits 95.15% accuracy, 92.26% precision, 91.48% recall, and 92.21% F1 score. These performance metric values are higher than those produced by deep learning models such as CNN+PSO, LSTM+HHO, CNN+LSTM+ACO, and CNN+RNN+HBA. Moreover, the performance of three existing works from the literature is analyzed in comparison with the proposed D-GRU model. The D-GRU model performs better in making accurate predictions on heart disease prognosis. The experimental results in this study show that the proposed D-GRU model transcends the other basic approaches in terms of accuracy and precision. It resolves the optimization problems and avoids the local search. It enhances search functionality, thus preventing optimization problems. It can incorporate a larger dataset and resolve the overfitting difficulties compared to conventional techniques. The future focus will be developing the ensemble techniques in conjunction with effective feature selection methods to further improve the IoMT-enabled health disease prognostic strategy.

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