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RESEARCH ARTICLE

Enhanced LSTM for heart disease prediction in IoT-enabled smart healthcare systems

Olivia C. Gold*, **Jayasimman Lawrence**

Abstract

Cardiac patients require prompt and effective treatment to prevent heart attacks through accurate prediction of heart disease. The prognosis of heart disease is complex and requires advanced knowledge and expertise. Healthcare systems are increasingly integrated with the internet of things (IoT) to collect data from sensors for diagnosing and predicting diseases. Current methods employ machine learning (ML) for these tasks, but they often fall short in creating an intelligent framework due to difficulties in handling high-dimensional data. A groundbreaking health system leverages IoT and an optimized long short-term memory (LSTM) algorithm, enhanced by the red deer (RD) algorithm, to accurately diagnose cardiac issues. Continuous monitoring of blood pressure and electrocardiograms (ECG) is conducted through heart monitor devices and smartwatches linked to patients. The gathered data is combined using a feature fusion approach, integrating electronic medical records (EMR) and sensor data for the extraction process. The RD-LSTM model classifies cardiac conditions as either normal or abnormal, and its performance is benchmarked against other deep-learning (DL) models. The RD-LSTM model showed better improvement in prediction accuracy over previous models.

Keywords: Internet of things, Healthcare system, Deep learning, Prediction of heart disease, Red deer optimization.

Introduction

The wearable monitoring system has become increasingly important in a range of healthcare applications, leveraging the internet of things (IoT), a technology that has seen rapid development in recent years (Chopade, S.S. *et al*., 2023; Zou N. *et al*., 2020). IoT-based healthcare systems gather real-time data on various health parameters and update this information at regular intervals (Deepa S. *et al*., 2023). This process enables the prediction of diseases by analyzing the vast amounts of healthcare data produced by IoT devices (Poongodi T. *et al*., 2020). The IoT is recognized as a key future technology, drawing significant interest within the healthcare industry (Chen M. *et al*., 2018; N.V.L.M. Krishna Munagala *et al*., 2022).

Elderly individuals often prefer to stay at home while maintaining their health. Consequently, there is a growing emphasis on developing remote health monitoring systems (Alshamrani M., 2022). Researchers globally have developed advanced applications such as intelligent healthcare systems, mobile healthcare, and health-aware recommendations by incorporating the internet of things (IoT) into the healthcare field (Lakshmi G.J. *et al*., 2021; Sherif Tawfik Amin *et al*., 2024). People who need to monitor their heart rate, blood pressure, and glucose levels can use smart wearables. These wearable devices can continuously track health data and transmit it to smartphones (Mamdiwar S.D. *et al*., 2021; Muthu B. *et al*., 2020).

As a result, real-time and historical data can be accessed remotely (Besher K.M. *et al*., 2020). The health monitor captures key indicators such as ECG, temperature, blood pressure, heart rate, weight, and glucose level. Using IoT devices in personal healthcare can promote a healthy lifestyle at a low cost (Habibzadeh H. *et al*., 2019; Patil N. M. *et al*., 2023).

India has one of the highest rates of heart disease globally, with nearly 4.78 million people affected, according to a 2022 report (Verma M. *et al*., 2024). Even young children are experiencing cardiac issues, with primary risk factors including diabetes, obesity, and hypertension, which

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indicate a malfunction in the heart's electrical impulses (Khourdifi Y. *et al*., 2019).

Wearable sensors and medical screenings are used to detect heart disease in patients. Physicians face challenges in accurately diagnosing patients by extracting crucial risk indicators from electronic medical records (EMR) for quick predictions. The current detection method involves monitoring patients both internally and externally using wearable sensors (Al-Makhadmeh Z. *et al*., 2019, Phillips S. M. *et al*., 2018). The frequent medical tests generate large amounts of data, classified as unstructured. Corruption of sensor data, such as noise and missing values, can lead to inaccurate outcomes and reduced system performance. The primary challenge is monitoring heart patients using electronic records and wearable device data. Another challenge is extracting significant and relevant aspects from online data to predict diseases (Azimi I. *et al*., 2019). Thus, a fusion technique is necessary to develop an intelligent system for analyzing and identifying hidden signs of heart problems (G. Rajkumar *et al*., 2023; Nithya R *et al*., 2023).

This research introduces a smart healthcare system employing an optimized deep learning technique combined with feature fusion. Four distinct datasets are used for analysis, including data from EMRs and wearable sensors. The process involves extracting Framingham risk factors (FRF) from the data. Sensor data is integrated with feature fusion to create comprehensive healthcare data for cardiac disorders.

The rest of the research paper is organized as follows: Section 2 reviews the current methods, while section 3 details the proposed methodology. Section 4 covers the experimental evaluation of the proposed deep learning method in comparison to existing approaches. Finally, section 5 discusses the scientific contributions of this work and suggests directions for future development.

Related Works

This section discusses related research work carried out by various researchers. Gumaei *et al*. (A. Gumaei *et al*., 2019) employ machine learning for human activity recognition, specifically designing a multi-sensor hybrid deep learning model for identifying human activities. This model is tailored for elderly individuals to facilitate access to medical assistance through the use of multi-sensor data. Souri *et al*. (A. Souri *et al*., 2020) developed a health monitoring system for students utilizing machine learning models and data collected *via* the IoT. The physical conditions of children are assessed by monitoring their health and categorizing it using machine learning techniques. Ali *et al*. (F. Ali *et al*., 2020) predict heart disease by employing an information gain and feature fusion method within deep learning models. Their study identifies conditions leading to heart disease to develop suitable treatments for patients. Chui *et al*. reviewed previous research on heart disease prediction within intelligent medicine. Their paper summarizes various machine-learning approaches and discusses the challenges of using these techniques for disease management.

Muhammad Shafiq *et al*. (Muhammad Shafiq *et al*., 2023) stated that the World Health Organization (WHO) states that heart disease is the leading cause of death globally. A study across many hospitals developed a protocol for early, automated heart disease detection. The PASCAL dataset, created from digital stethoscope data, is widely used for research. The proposed research strategy involves three steps: Data collection *via* biosensors and IoT devices, uploading data to the cloud for analysis, and training models with existing medical records. Deep learning, particularly the deep CNN algorithm, is used to classify heart sounds, with the PASCAL dataset playing a crucial role. The deep CNN model has shown high accuracy.

Kamruzzaman (M. M. Kamruzzaman, 2020) developed an AI system designed to aid in early disease identification and emergency treatment within the medical field. This AI system can automatically analyze human body data and patient genetic information to provide clinical support to healthcare professionals *via* clinical reports. AI assists in decision-making due to significant advancements in healthcare data processing, enhancing the efficiency and accuracy of decision-making models. This improvement addresses shortages in medical resources, including equipment and staff, leading to cost savings.

Tuli *et al*. (S. Tuli *et al*., 2020) created an ensemble-based deep learning (DL) model integrated with fog computing for autonomous disease diagnosis in an intelligent healthcare system. Health fog provides a healthcare service within an IoT framework, enabling users to obtain cardiac patient data by submitting queries to the IoT-based fog model. While deep learning techniques that achieve high accuracy require substantial computational resources for both training and prediction, this model incorporates advanced deep learning networks with state-of-the-art computer models using new communication technologies and clustering-like models, resulting in improved accuracy and reduced latency.

E. Choi *et al*. (E. Choi *et al*., 2017) introduced the recurrent neural network (RNN) for early cardiac arrest detection. RNNs are well-suited for tracking events over a period of 20 to 18 months and handling timely events such as diagnostic and pharmaceutical procedures, as well as practical recommendations. The sample performance is measured using structured logistic regression, with the neural network approximating the K classifier that most closely matches the analysis. Advanced study models focused on utilizing temporal correlations to enhance predictive accuracy for heart failure will be presented over a 12 to 18-month period.

Tomov *et al*. (N S. Tomov *et al*., 2018) discovered that implementing a five-level deep neural network (DNN) structure can reduce algorithm risks and improve prediction accuracy. The optimization controls the architecture, as described by the authors, and effectively handles missing data and outliers automatically. The best structures were evaluated using k-fold cross-validation, and the Matthews correlation coefficient (MCC) was examined to assess performance.

Proposed Methodology

Heart disease is detected using a refined long short-term memory (LSTM) classification model that analyzes sensor data. During the training and testing phases, both normal and abnormal data are classified using information from the Lora cloud server. If the patient's results are abnormal, an alert is sent to the doctor for further treatment. Figure 1 illustrates the operational process of the intelligent healthcare-oriented deep learning (DL) framework, with additional tools acting as gateways to collect and transmit the acquired data. The system is trained to expedite disease detection, addressing the typically lengthy process involved. Directly testing sensor values can potentially lead to errors. Therefore, the devices maintain a constant connection with patients to continuously transmit sensor data. Testing begins once the training phase is completed. The forecast has two output classes: "regular," indicating the patient's condition is normal, and "abnormal," indicating the patient's condition is critical and requires care. Sensor values are classified based on the training outcomes to provide different effects when comparing system values. The steps of the training phase are outlined below.

Collection of Sensor Data

This section outlines how gathered sensor data is used in the prediction process within the research. Wearable sensors collect physiological data, while activity and medical sensors are employed for comprehensive data collection. Risk factors are identified by analyzing unstructured EMR data, which includes medical history records, laboratory findings, allergy prescriptions, and personal inquiries with comments for prediction purposes. The FRFs are extracted by analyzing the EMR, which contains information such as cholesterol levels, age, gender, body mass index, blood pressure, and

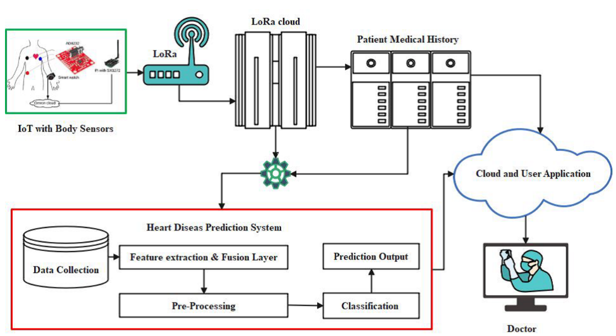

Figure 1: System architecture of smart healthcare based on optimized DL technique

heart rate. This data consists of complex variables with high dimensionality, resulting in a vast amount of EMRs. Therefore, a text mining method is required to effectively extract FRFs from the unstructured EMR data.

Layer for Extracting the Features and Fusion Process

This section discusses the process of extracting valuable information from unstructured data and converting it into a structured format. Initially, the extraction of FRFs is described. This is followed by a discussion on the feature fusion layer, which integrates sensor data with the FRF scheme to predict heart disease.

Extraction of FRF

Within the FRF extraction module, data is obtained from unstructured EMRs using two primary methods: rules-based engines and text-mining algorithms. Text mining involves three key processes. First, lemmatization and morphological algorithms are applied to the unstructured data to identify the lemma of each word. In the next stage, tokenization is used to extract small segments from the disorganized text and divide complex information. Finally, risk factors are identified using N-gram methods, which analyze two or three consecutive words in the risk factor data. Pictograms represent pairs of neighboring factor terms, while 3D graphs represent triplets of adjacent factor terms. Rules are established to capture the nuances and distinct characteristics of EMR data. By assigning unstructured EMRs to the FRF extraction module, risk factors related to heart disease are identified and retrieved.

Fusion of sensor data with FRFs

The fusion technique combines the retrieved FRFs with sensor data, enhancing the classification process by integrating diverse data sources to provide more valuable and relevant information. This research emphasizes both feature-level and data-level fusions. Sensor data is collected from patients' physiological activities, while FRFs are extracted, including the patient's medical history, age, gender, and other relevant factors for the fusion process. The combined data is stored in CSV files for convenient parsing and processing.

The system aims to determine the optimal set of attributes for accurate disease identification by utilizing pertinent and concise information from sensor data. However, missing values in sensor data and irrelevant information in derived features can increase feature dimensionality and reduce accuracy. Additionally, classification can lead to increased complexity and higher memory requirements. Therefore, data pre-processing is essential to enhance the quality of the extracted features before initiating the prediction process.

Data Pre-processing

After integrating the sensor data and EMR, the data must undergo a meticulous pre-processing procedure to ensure accurate diagnosis. This process involves three critical steps: redundancy elimination, separation, and missing attribute replacement.

Step 1: Redundancy elimination

The first step involves identifying and removing any redundant data. Redundant data refers to unnecessary or repetitive information that does not contribute to the diagnosis and can clutter the dataset, making it less efficient. By eliminating these redundant attributes, we reduce the overall volume of data, simplifying the analysis and improving the system's performance. This step requires a careful examination of the data to ensure that only the most relevant and essential information is retained.

Step 2: Separation

The second step is the separation of data based on specific criteria, such as the type of chest pain experienced by the patients. This classification is crucial as it allows for more targeted analysis and diagnosis. The types of chest pain are categorized into four groups:

- *Regular angina*

Characterized by predictable chest pain during physical exertion or stress.

- *Differential angina*

Refers to varying degrees of chest pain that might not always be predictable.

- *Non-angular pain*

Chest pain that is not related to angina, possibly due to other factors such as muscular or skeletal issues.

- *Asymptomatic pain*

Instances where the patient experiences no noticeable pain but may still have underlying heart conditions.

By separating the data into these categories, healthcare professionals can apply more specific diagnostic criteria and treatment plans suited to each type of chest pain.

Step 3: Missing attribute replacement

The final step addresses the issue of missing data within the dataset. Missing values can significantly affect the accuracy of the diagnosis. To handle this, each missing attribute is identified and replaced with an estimated value. This replacement process involves comparing the available attribute values of the patient with similar cases to estimate the most accurate substitute. For example, if a patient's blood pressure reading is missing, it might be estimated based on their previous readings or the readings of similar patients. This ensures that the dataset remains complete and reliable for analysis.

Additionally, any irrelevant or inappropriate attributes are removed to further streamline the data. This might include attributes that do not directly impact the diagnosis or are deemed extraneous.

Through these steps, the pre-processing procedure refines the dataset, ensuring that only high-quality, relevant data is used for the diagnosis. This enhances the overall accuracy and reliability of the intelligent healthcare system, allowing for more precise disease detection and treatment recommendations. By understanding the rationale behind each step—eliminating redundancy to streamline data, separating data for targeted analysis, and replacing missing values for completeness—healthcare professionals can better appreciate the intricacies involved in preparing data for advanced diagnostic processes.

Heart Disease Prediction using Optimized LSTM

Recurrent neural networks (RNNs) are an extension of the neural feedback network. In a standard RNN, the gradient tends to either vanish or grow exponentially during training. LSTM networks, on the other hand, are specifically designed to address these issues and are highly effective at problem-solving. LSTMs are efficiently implemented and consist of three gates (input gate, forget gate, and output gate) and a memory cell. The mathematical formulation of LSTM operations is described in equations (1-6). Figure 2 illustrates the typical structure of an LSTM network.

$$x = \begin{bmatrix} ht - 1 \\ xt \end{bmatrix} \tag{1}$$

$$f_t = \sigma(W_f.X) + b_f \tag{2}$$

$$i_t = \sigma(W_i.X) + b_i \tag{3}$$

$$o_t = (W_o.X) + b_o \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh\,(W_c.X + b_c) \tag{5}$$

$$h_t = o_t \odot \tanh\,(c_t) \tag{6}$$

The weighted matrices Wi, Wf, Wo ∈ R×2d and biases bi, bf, bo ∈ Rd are crucial components of the LSTM model. LSTM networks address the short-term memory limitations of standard RNNs by using integrated mechanisms called gates to regulate information flow. These gates determine which data should be retained or discarded at each step. The LSTM operates within an extended network that transmits relevant data to make predictions.

The key concept behind LSTM is the cell state and its multiple gates. The cell state acts as a conduit for information transmission. While processing sequences, valuable

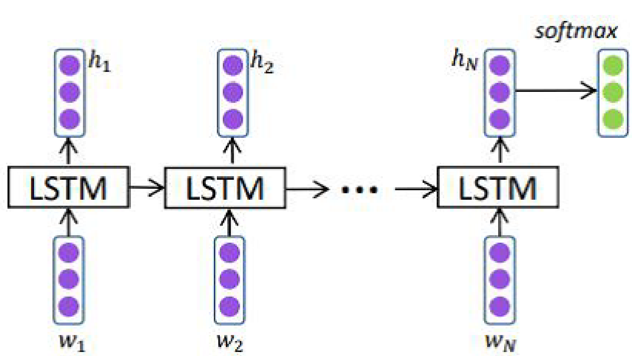

Figure 2: The architecture of a standard LSTM

information about the cell's status is maintained. Early information can lead to transient situations, reducing the impact of short-term memory. As the cell state progresses, data is added or removed through the gates. These gates enable the network to remember or forget information, thus uncovering significant insights.

The research optimizes the weighted matrices using the RD algorithm, which is detailed in the following section. This optimization enhances the performance and accuracy of the LSTM model by fine-tuning the weights to better capture the underlying patterns in the data.

Optimization using RD

The primary goal of any optimization technique is to find an optimal solution based on the problem variables. In the red deer algorithm (RDA) (Fathollahi-Fard, A.M. *et al*., 2020), the concept of 'red deer' is used to represent this layout. Here, RD corresponds to the variable X, and the prospective solution exists outside the feasible region, meaning it is unattainable for X. The dimensional optimization problem is intricate, and a red deer is represented as an array to navigate this complexity effectively.

The RDA works by mimicking the natural behavior and characteristics of red deer during the rutting season, where they compete and interact to find the best possible outcomes. Each 'red deer' in the algorithm represents a potential solution in the search space. These solutions are evaluated, and the best-performing ones are selected to guide the search process further. Through iterative processes, the RDA refines these solutions, aiming to reach an optimal or near-optimal solution for the given problem. This approach helps in efficiently handling the high-dimensional optimization challenges often encountered in complex systems like LSTM networks. Equation (7) defines this array.

$$Red\ Deer = [X1, X2, X3, \ldots XN_{var}] \tag{7}$$

Eq. (8) provides the validation of the function value for each RD:

$$Value = f(Red\ Deer) = f(X1, X2, X3, \ldots XN_{var}) \tag{8}$$

To implement the red deer algorithm (RDA) for optimizing the LSTM network, follow these steps to create the initial population and enhance the performance:

Initialize population (Npop)

Create an initial population of red deer, denoted as NpopNpop. This population includes both male and female red deer.

Pseudo-code: Initialize Population

```
Npop = 100  #Total population size
    #Number of male red deer, for example, 20% of the population
    Nmale = int (0.2 * Npop)
    Nhind = Npop - Nmale  #Number of female red deer
    population = initialize_population(Npop)
```

Determine Male and Female Red Deer

- Select the best-performing individuals from the population to be male red deer. The number of male red deer is NmaleNmale.
- The remaining individuals will be female red deer, with the number given by Nhind=Npop−Nmale.

Pseudo-code: Evaluate and select best male red deer

```
population = evaluate_population(population)
    male_red_deer = select_best_males(population, Nmale)
    female_red_deer = select_rest_as_females(population, Nmale)
```

Roaring Competition

Male red deer attempt to improve their status by "roaring." This step involves enhancing their solution's quality.

Male red deer, as effective options in this strategy, will try to outperform their peers through a competitive process.

Pseudo-code: Roaring competition

```
def roaring_competition(male_red_deer):
    for male in male_red_deer:
     neighbours = locate_neighbours(male, male_red_deer)
       best_neighbour = find_best_neighbour(neighbours)
       if best_neighbour.performance > male.performance:
           male.update_solution(best_neighbour.solution)
      return male_red_deer
```

Locate Neighbours

Identify the neighboring male red deer based on the proximity of their solutions in the search space.

Evaluate the objective performance of these neighboring solutions.

Pseudo-code: Locate neighbours and update solutions

```
def locate_neighbours(male, male_red_deer):
# Locate neighbouring male red deer based on solution proximity
  neighbours = []
  for neighbour in male_red_deer:
    if neighbour is not male:
      neighbours.append(neighbour)
  return neighbours
def find_best_neighbour(neighbours):
    best_neighbour = max(neighbours, key=lambda x: x.performance)
  return best_neighbour
```

Update Solutions

If a neighboring male red deer's objective performance surpasses that of the current male red deer, replace the current male red deer's solution with the superior neighboring solution.

Pseudo-code: Iterative optimization process

```
for iteration in range(max_iterations):
```

male_red_deer = roaring_competition(male_red_deer)
population = male_red_deer + female_red_deer
population = evaluate_population(population)

To enhance the state of guys, the following equation is proposed:

$$\text{malenew} = \begin{cases} maleold + a1 \times ((UB - LB) * a2) + LB), & if\ a3 \geq 0.5 \\ \text{maleold} - \text{a1} \times ((\text{UB} - \text{LB}) * \text{a2}) + \text{LB}), & \text{if a3} < 0.5 \end{cases} \quad (9)$$

The red deer algorithm (RDA) is used for optimizing LSTM networks by mimicking the natural behaviors of red deer. Initially, a population (Npop) is generated within defined upper (UB) and lower bounds (LB). This population is evaluated to identify the best-performing male red deer (Nmale), while the rest are categorized as female (Nhind). The top-performing males are further divided into commanders and stags, with commanders having a higher influence. During the roaring competition, each male generates new potential solutions by adjusting their current solutions within the bounds. If these new solutions show improved performance, they replace the old ones. This process iteratively refines the population through continuous evaluation and updating. The ultimate goal is to leverage the competitive and adaptive nature of red deer to enhance the accuracy and efficiency of LSTM network optimization by integrating sensor and EMR data, thus ensuring the most relevant and high-quality data is used for accurate disease prediction. Equation (10) is utilized to get the overall quantity of commander RD males:

$$N_{Com} = round\{\gamma . N_{male}\} \quad (10)$$

In the red deer algorithm (RDA), the top-performing male red deer are classified as commanders, denoted as N_{Com}. The parameter γ, which ranges from zero to one, represents the initial value of the algorithm model. The optimization process starts by generating a population (Npop) within predefined upper (UB) and lower bounds (LB). After evaluating the population to determine fitness levels, the best males are identified and further divided into commanders (NCom) and stags. During the roaring competition, each male creates new potential solutions by modifying their current solutions within the specified bounds. If these new solutions show better performance, they replace the previous ones. This iterative process continuously improves the population, using the competitive nature of red deer to enhance the optimization of the LSTM network. The \(\gamma\) parameter helps adjust the algorithm's convergence rate, balancing between exploration and exploitation for effective and efficient disease prediction. Equation (11) is utilized to determine the stag's number, denoted as $Nstag$.

$$N_{stag} = N_{male} - N_{Com} \quad (11)$$

Spontaneously, conflicts between commanders and stags will arise, leading to two potential solutions. Once the positions of these solutions are identified, the leaders and stags are guided towards convergence. This process generates two new solutions. The leader is then replaced with the best solutions, which are selected from the best of the four options: The two newly obtained solutions that surpass the leader and the original stag's solution. Two mathematical formulas are provided in Eq. (12-13) for the combat procedure.

$$New1 = (com + Stag)/2 + b_1 \times ((UB - LB) * b_2) + LB) \quad (12)$$

$$New2 = (com + Stag)/2 - b_1 \times ((UB - LB) * b_2) + LB) \quad (13)$$

During military operations in the red deer algorithm (RDA), two new solutions, New1 and New2, are generated. In this context, "Com" represents the commanders (leaders), and "stag" symbolizes the stags. The search space for potential solutions is defined by the upper bound (UB) and lower bound (LB), which set the maximum and minimum limits. The values B1 and B2 are generated using a uniform distribution function ranging from zero to one, reflecting the randomness of the battle process.

Among the four options–Com, stag, New1, and New2–only the best solutions are selected. This selection process illustrates the competitive nature of male red deer during conflicts, where proximity and interaction between leaders and stags are crucial. The formulas capture the essence of these interactions, as one participant emerges victorious while the other faces defeat. The superior solutions are those that outperform their counterparts, ensuring that the most optimal solutions are retained and further refined in subsequent iterations. Deer, like other species, engage in mating behavior. The mating process is typically determined by:

$$offs = (Com + Hind)/2 + (UB - LB) \times c \quad (14)$$

The symbols Com and $Hind$ represent commanders and hinds, respectively. Offs is a novel solution.

Two distinct procedures are employed to select the next generation in the red deer algorithm (RDA). Initially, we consider only the male red deer (RDs), who serve as both leaders and key contributors, representing the proportion of optimal solutions among all available options. The second technique focuses on the survivors for the next generation. This involves selecting all stags and offspring generated through a fitness value mating process, either by fitness matching or using the roulette wheel mechanism. Once the optimal solution quality is achieved after a specified number of iterations, the termination process is executed in the RD algorithm. This ensures that the most fit individuals are carried forward, continuously improving the solution quality.

Results and Discussion

The proposed IoT framework is a contemporary model that integrates existing hardware components, a microcontroller, and LoRA communication devices to transmit data to the cloud. The system securely maintains patient information, including age, gender, and identification number.

Description of Dataset

The system utilizes four databases: The University of California, Irvine (UCI) Hungarian cardiology database, sensor data (SD), Framingham (FG), and public health (PH), all of which are readily accessible online. The combined database consists of 76 features, but only 14 of these features were used in published studies. When creating the confusion matrix for prediction, four parameters are considered, as shown in Table 1. True positive is denoted as *HDp*, true negative as *HDn*, false positive as *NHDp*, and false negative as *NHDn*.

Simulation analysis involves the use of multiple parameters, with the following equation used to calculate accuracy (AC):

$$Accuracy\ (AC) = \frac{HDp + HDn}{HDp + HDn + NHDp + NHDn} \tag{15}$$

Here:

- *HDp* (True Positive) represents the instances correctly identified as having heart disease.
- *HDn* (True Negative) represents the instances correctly identified as not having heart disease.
- *NHDp* (False Positive) represents the instances incorrectly identified as having heart disease.
- *NHDn* (False Negative) represents the instances incorrectly identified as not having heart disease.

Precision/PPV

This identifies the chance of patients with real cardiac disease. PPV can be assessed using equation (16).

$$PPV = \frac{HDp}{HDp + NHDp} \tag{16}$$

NPV

Finding the patient with no risk factors of heart disease and is evaluated as shown in equation (17).

$$NPV = \frac{HDn}{HDn + NHDn} \tag{17}$$

Sensitivity/Recall

This measure is used to identify patients with risk factors for heart disease.

$$Sensitivity\ (SE) = \frac{HDp}{HDp + NHDn} \tag{18}$$

F1 score

This is the harmonic mean of precision and recall.

$$F_1 = 2.\frac{Precision.Recall}{Precision + Recall} \tag{19}$$

Proposed Performance Evaluation

The Framingham (FG) dataset contains the largest number of medical data records with 4000 entries, followed by the public health (PH) dataset with 1025 recordings, the sensor data (SD) dataset with 900 records, and the UCI dataset with 303 records. The proposed optimized LSTM model is initially tested for accuracy using these records, as depicted in Figure 3. The suggested model includes 16 characteristics from the UCI, FG, and SD datasets, while only 14 features are utilized from the PH dataset.

The proposed model achieved an accuracy of 98.20% on the FG dataset and 93.3% on the UCI dataset. This difference in accuracy is attributed to the distribution of data; typical entries in both the UCI and FG datasets contain 16 characteristics. The optimized LSTM attained an accuracy of 97.60% on the PH dataset and 96.30% on the SD dataset. Figure 4 shows the experimental evaluation of recurrent neural networks with LSTM and other deep learning approaches using different parameters on the FG dataset. The study focused exclusively on the FG dataset due to its larger number of records compared to the other three datasets, allowing for more robust testing of the proposed model using a substantial quantity of medical records.

The sentiment analysis results demonstrate that various models achieved the following accuracies: the recurrent model obtained 91.1%, the autoencoder reached 92.1%, the

Table 1: Confusion matrix (PPV: Positive Predictive Value; NPV: Negative Predictive Value)

Test results	*Truth*		*Total*
	Heart disease	*No heart disease*	
Positive	HD_p	NHD_p	$PPV=HD_p/(HD_p+NHD_p)$
Negative	HD_n	NHD_n	$NPV=NHD_n/(HD_n+NHD_n)$

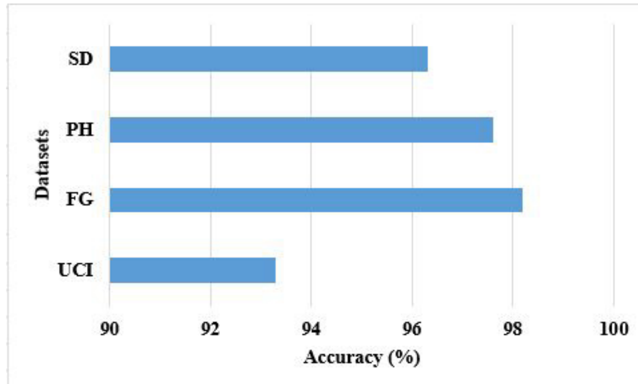

Figure 3: Graphical representation of proposed optimized LSTM on different datasets in terms of accuracy

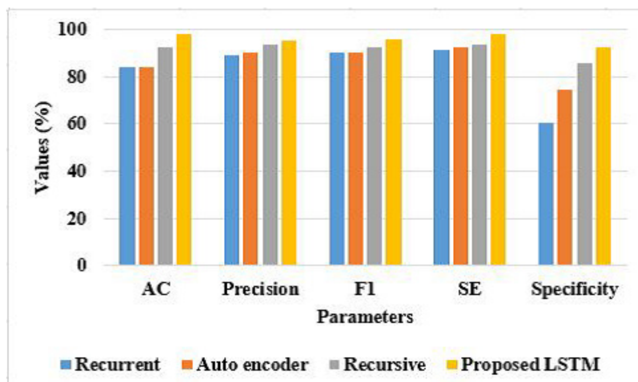

Figure 4: Graphical representation of proposed RD optimization with different DL classifiers on the FG dataset

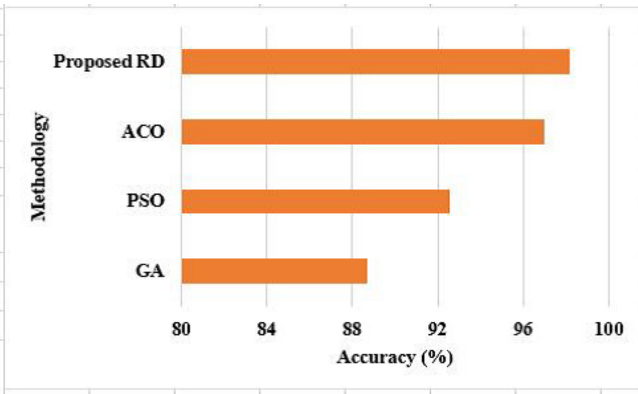

Figure 5: Graphical representation of proposed LSTM with different optimization techniques in terms of accuracy on the FG dataset

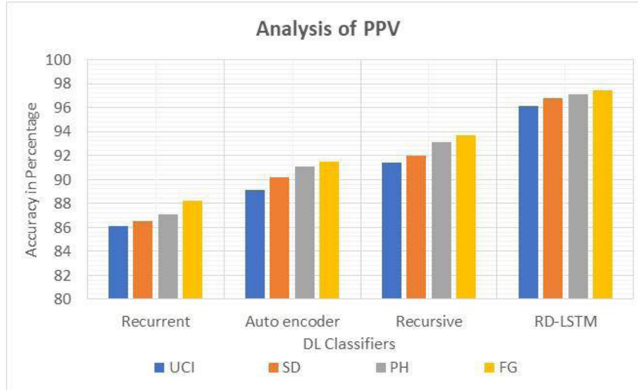

Figure 6: Analysis PPV

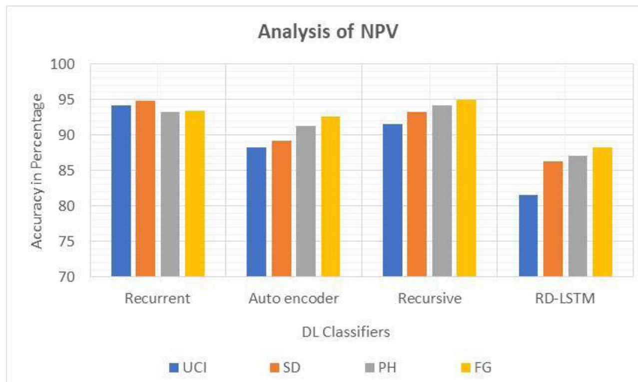

Figure 7: Analysis of NPV

recursive model achieved 93.3%, and the proposed LSTM model scored 97.8%. The recursive network's computation is slow due to issues like gradient vanishing and exploding. Autoencoders are particularly vulnerable to input errors and become more complex with the addition of extra layers. In contrast, LSTM is designed to address vanishing gradient issues without requiring extensive fine-tuning, and its weight optimization is achieved using the RD algorithm. Consequently, the LSTM with RD outperformed other current deep-learning classifiers. The recurrent model achieved 60.2% specificity and a 90.2% F1-score, while the proposed LSTM-RD model obtained 92.6% specificity and a 95.7% F1-score. The recursive model excelled in precision, achieving 93.4%. Overall, the proposed LSTM approach attained an accuracy of 95.1%.

The recurrent neural network and autoencoder each produced an accuracy of approximately 83%. In comparison, the recursive neural network achieved 92.4% accuracy, and the suggested LSTM model scored 98.2% accuracy on the FG dataset. Figure 5 illustrates the experimental evaluation of the suggested LSTM model using different optimization methods with respect to accuracy on the FG dataset.

Implementing different optimization approaches with the proposed LSTM results in varying levels of accuracy performance. The genetic algorithm (GA) obtained 88.7% accuracy, particle swarm optimization (PSO) achieved 92.59%, ant colony optimization (ACO) reached 97%, and the proposed red deer (RD) algorithm achieved the highest performance with 98.2% accuracy. GA's limited performance is attributed to its dependence on initial population selection and the fitness function. PSO tends to quickly converge to local optima in high-dimensional spaces, while ACO faces a stagnation phase due to a high rate of exploration and exploitation. The RD algorithm, on the other hand, effectively balances exploration and exploitation, leading to superior accuracy in optimizing the LSTM model. Figure 6 presents the experimental findings of different DL classifiers in the examination of positive predictive value (PPV).

The proposed LSTM model achieved nearly 98% PPV for the PH and FG datasets, significantly outperforming the recurrent model, which achieved around 88.50% PPV. The autoencoder model attained close to 92% PPV, while the recursive model achieved nearly 94% PPV. For the UCI and SD datasets, the suggested LSTM model reached a precision of almost 97%, whereas the recurrent model achieved 87% precision. The autoencoder and recursive approaches produced approximately 91 to 93% PPV on the UCI and SD datasets. This analysis indicates that the proposed LSTM model exhibits a high PPV, leading to enhanced prediction accuracy for heart disease. Figure 7 displays the evaluation of these classifiers on all datasets based on negative predictive value (NPV).

A low NPV indicates high categorization performance. The proposed LSTM model achieved NPV rates ranging from 83 to 86% on the UCI and SD datasets, while the recurrent model attained a 95% NPV rate on the same datasets. The autoencoder and recursive approaches achieved NPV rates ranging from 90 to 94% on the UCI and SD datasets. For the PH and FG datasets, the LSTM model achieved approximately 88.50% NPV, compared to the recurrent model's nearly 94%, the autoencoder model's approximately 92.50%, and the Recursive model's nearly 95% NPV. This analysis indicates that the NPV value is higher in the recurrent technique, which consequently reduces its prediction accuracy to 83.8% on the FG dataset.

Conclusion

The study develops an advanced healthcare model to predict heart disease using an optimized deep-learning approach. Initially, sensor data and EMR data are collected to gather fundamental medical details about the patient, followed by the extraction of FRF. The fusion procedure combines these extracted characteristics with the assembled data, and pre-processing steps are applied to eliminate missing values. The prediction process employs the LSTM method, with model optimization achieved through the RD algorithm, resulting in the proposed model being termed RD-LSTM. Experiments were conducted using four datasets: UCI, SD, PH, and FG. The simulation results demonstrated that the combined optimization (RD) and classifier (LSTM) strategies outperformed previous methods across various parameters. The RD-LSTM model achieved an accuracy of 98.2%, which shows that the proposed RD-LSTM produces higher accuracy than other methods. The LSTM model requires additional memory for training on the heart disease dataset, and implementing dropout is challenging with this technique. To address this issue, enhancing the LSTM model or utilizing a different deep-learning technique with the same datasets for heart disease identification is recommended.

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References

A. Gumaei, M. M. Hassan, A. Alelaiwi *et al*. (2019). A hybrid deep learning model for human activity recognition using multimodal body sensing data. IEEE Access, 7: 99152– 99160.

A. Souri, M. Y. Gh Afour, A. M. Ahmed *et al*. (2020). A new machine learning-based healthcare monitoring model for student's condition diagnosis in the Internet of things environment. Soft Computing, 24(22): 17111–17121.

Al-Makhadmeh, Z. and Tolba, A. (2019). Utilizing IoT wearable medical devices for heart disease prediction Using higher-order Boltzmann model: A classification approach. Measurement, 147: 106815.

Alshamrani, M. (2022). IoT and artificial intelligence implementations for remote healthcare monitoring Systems: A survey. Journal of King Saud University-Computer and Information Sciences, 34(8): 4687-4701

Azimi, I., Pahikkala, T., Rahmani, A.M., Niela-Vilén, H., Axelin, A. and Liljeberg, P., (2019). Missing data Resilient decision-making for healthcare IoT through personalization: A case study on maternal health. Future Generation Computer Systems, 96: 297-308.

Besher, K.M., Subah, Z. and Ali, M.Z. (2020). IoT Sensor Initiated Healthcare Data Security. IEEE Sensors Journal, 21(10): 11977-11982.

Chen, M., Li, W., Hao, Y., Qian, Y. and Humar, I. (2018). Edge cognitive computing-based smart healthcare System. Elsevier Future Generation Computer Systems, 86: 403-411.

Chopade, S.S., Gupta, H.P. & Dutta, T. (2023). Survey on Sensors and Smart Devices for IoT Enabled Intelligent Healthcare System. Springer Wireless Personal Communications, 131: 1957–1995.

E. Choi, A. Schuetz, W. F. Stewart, and J. Sun. (2017). Using recurrent neural network models for early detection of heart failure onset. Journal of the American Medical Informatics Association, 24(2): 361–370.

F. Ali, S. El-Sappagh, S. M. R. Islam *et al*. (2020). A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. Information Fusion, 63: 208–222.

Fathollahi-Fard, A.M., Hajiaghaei-Keshteli, M. and Tavakkoli-Moghaddam, R. (2020). Red deer algorithm (RDA): a new nature-inspired meta-heuristic. Soft Computing, 24(19), 14637-14665.

G. Rajkumar, T. Gayathri Devi, A. Srinivasan. (2023). Heart disease prediction using IoT based framework and improved deep learning approach: Medical application. Medical Engineering & Physics, 111:103937.

Habibzadeh, H., Dinesh, K., Shishvan, O.R., Boggio-Dandry, A., Sharma, G. and Soyata, T. (2019). A Survey of Healthcare Internet of Things (HIoT): A clinical perspective. IEEE Internet of Things Journal, 7(1): 53-71.

Khourdifi, Y. and Bahaj, M. (2019). Heart disease prediction and classification using machine learning Algorithms optimized by particle swarm optimization and ant colony optimization. International Journal of Intelligent Engineering and Systems, 12(1): 242-252.

Lakshmi, G.J., Ghonge, M. and Obaid, A.J. (2021). Cloud-based IoT Smart Healthcare System for Remote Patient Monitoring. EAI Endorsed Transactions on Pervasive Health and Technology, 7(28): e4.

M. M. Kamruzzaman. (2020). Architecture of smart health care system using artificial intelligence. International Conference on Multimedia & Expo Workshops (ICMEW), IEEE, London, UK: 1–6.

Mamdiwar, S.D., Shakruwala, Z., Chadha, U., Srinivasan, K. and Chang, C.Y. (2021). Recent advances in IoT-assisted wearable sensor systems for healthcare monitoring. Biosensors, 11(10): 372: 1-37.

Muhammad Shafiq, Changqing Du, Nasir Jamal, Junaid Hussain Abro, Tahir Kamal, Salman Afsar, and Md. Solaiman Mia. (2023). Smart E-Health System for Heart Disease Detection Using Artificial Intelligence and Internet of Things Integrated Next-Generation Sensor Networks. Journal of Sensors, Hindawi, 2023, 1-7.

Muthu, B., Sivaparthipan, C.B., Manogaran, G., Sundarasekar, R., Kadry, S., Shanthini, A. and Dasel, A. (2020). IOT-based wearable sensor for disease prediction and symptom analysis in the healthcare sector. Elsevier Peer-to-peer networking and applications, 13(6): 2123-2134.

N. S. Tomov and S. Tomov, "On deep neural networks for detecting heart disease," 2018: 1-10. arXiv:1808.07168. [Online]. Available: https://arxiv.org/pdf/1808.07168

N.V.L.M. Krishna Munagala, Lakshmi Rajeswara Rao Langoju, A.

Daisy Rani, D.V. Rama Koti Reddy. (2022). A smart IoT-enabled heart disease monitoring system using meta-heuristic-based Fuzzy-LSTM model. Biocybernetics and Biomedical Engineering, 42(4): 1183-1204.

Phillips, S.M., Cadmus-Bertram, L., Rosenberg, D., Buman, M.P. and Lynch, B.M. (2018). Wearable Technology and physical activity in chronic disease: opportunities and challenges. American Journal of Preventive Medicine, 54(1):144-150.

Poongodi, T., Krishnamurthi, R., Indrakumari, R., Suresh, P., Balusamy, B. (2020). Wearable Devices and IoT. A Handbook of Internet of Things in Biomedical and Cyber Physical System. Intelligent Systems Reference Library, Springer, 165: 245–273.

S. Tuli, N. Basumatary, S. S. Gill, M. Kahani, R. C. Arya, G. S. Wander, and R. Buyya. (2020). HealthFog: An ensemble deep learning based smart healthcare system for automatic diagnosis of heart diseases in integrated IoT and fog computing environments. Elsevier Future Generation Computational System, 104:187–200.

Sherif Tawfik Amin, Suresh Limkar, Mohammed Eltahir Abdelhag, Yagoub Abbker Adam, Mohammed Hassan Osman AbdAlraheem. (2024). Smart IoT-enabled Healthcare Systems: Real-time Anomaly Detection and Decision Support using Deep Learning Models. Journal of Electrical Systems, 20(1s): 318 -328.

Verma, M., Singh, J., Kumari, S. (2024). Enhancing Heart Disease Prediction with Ensemble Deep Learning and Feature Fusion in a Smart Healthcare Monitoring System. Advanced Computing and Intelligent Technologies. Lecture Notes in Networks and Systems, 958, Springer, Singapore. https://doi.org/10.1007/978-981-97-1961-7_34

Zou, N., Liang, S. and He, D. (2020). Issues and challenges of user and data interaction in healthcare-related IoT: a systematic review. Library Hi Tech, 38: 769–782.

Deepa S, Sripriya T, Radhika M, Jeneetha J. J. (2023). Experimental evaluation of artificial intelligence assisted heart disease prediction using deep learning principle. The Scientific Temper, 14(04): 1277–1282.

Patil, N. M., Krishna, P. M., Deena, G., Harini, C., Gnanamurthy, R., & Srinivas, R. V. (2023). Exploring real-time patient monitoring and data analytics with IoT-based smart healthcare monitoring. The Scientific Temper, 14(04): 1196–1201.

Nithya R, Shruthi Deivigarajan, Sindhuja Santhakumar, & Sneha Balakrishnan. (2023). Challenges encountered by health care professionals in monitoring adverse events due to medical devices: A review. The Scientific Temper, 14(02): 479–483.