Journal of Information Systems Engineering and Management
2025, 10(16s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Advanced Health Care Monitoring in IoMT Systems through Integrated CNN and LSTM

S. Gokuldev[1], Mrs Xma R Pote[2], Dr T. Veeramani[3], , Sarojini Yarramsetti[4], Dr. Mahaveerakannan R5, Mr. M. J. D. Ebinezer[6]

[1]*Professor, Department of Computer Science and Engineering, Sree Sakthi Engineering College, Coimbatore, Tamilnadu, India*
[2]*Assistant Professor, Dept of Electrical Engg, Yeshwantrao Chavan College of Engineering, Nagpur Maharashtra*
[3]*Department of Artificial intelligence and Data Science, Panimalar Engineering College, Bangalore Trunk Road, Varadharajapuram, Poonamallee, Chennai – 600 123.*
[4]*Professor, Department of Computer Science and Business Systems, Nehru Institute of Engineering and Technology, Coimbatore*
[5]*Professor, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India.*
[6]*Assistant Professor, Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India.*
[1]gokuldevs@gmail.com, [2] potexma@gmail.com, [3]drtveeramanicse@gmail.com, [4]mahaveerakannanr.sse@saveetha.com, [5]nietdrsarojiniyarramsetti@nehrucolleges.com, [6]ebinezer.mjd@gmail.com

ARTICLE INFO

Received: 01 Dec 2024

Revised: 25 Jan 2025

Accepted: 08 Feb 2025

ABSTRACT

Introduction: The developments in Internet of Medical Things (IoMT), communications technologies, and wearable sensors have made it possible for humans to live wiser lives, all thanks to pervasive computing. This has led to better healthcare services. The IoMT has the ability to completely transform the healthcare system. Caretakers, medical professionals, patients, and wearable sensors linked to software and ICT make up IoMT. Notable among the many growing industries with enormous demand is healthcare.

Objectives: This study uses the Chaotic Satin Bowerbird Optimization Algorithm (CSBOA) for feature selection in conjunction with Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to create an optimal heart disease diagnosis system. Improving classification performance while lowering computational complexity is the aim.

Methods: The incorporation of cognitive behaviour into IoT technology has also attracted the attention of several researchers. Combining CNN and LSTM networks with a Chaotic Satin Bowerbird Optimisation Algorithm (CSBOA) for feature selection is the proposed hybrid classical for heart disease detection in this study. To improve computing performance and decrease dimensionality, the CSBOA isolates the most important attributes.

Results: Convolutional neural network–long short-term memory (CNN–LSTM) construction enables strong classification by capturing data patterns in both space besides time. The suggested model outperformed previous approaches using the UCI heart disease dataset, achieving superior presentation indicators such as high recall, accuracy, precision, besides F1-score.

Conclusions: By using CSBOA, feature selection was further optimised, achieving a happy medium between precision and computational burden. Offering a dependable and efficient tool for heart disease detection, this hybrid technique shows great promise for real-world healthcare applications.

Keywords: Internet of Medical Things; Chaotic Satin Bowerbird Optimization Algorithm; Long Short-Term Memory; Heart Disease Detection.

INTRODUCTION

A network of networked computing devices, machines, items, people, or animals that can move data within the network autonomously is known as IoT [1]. Included in this category are the monitoring and regulating schemes that make smart homes possible, such as HVAC systems, thermostats, and the IoT. Besides transportation and healthcare, IoT has applications in industrial automation, energy response to both natural and man-made catastrophes, and other fields as well [2]. Several IoT uses throughout industries. IoT technology aids in persuading the top traffic authority to implement a data congestion monitoring scheme with a sharp area structure. In their presentation of the IoT for environmental condition monitoring, the authors from [3–4] used disappointment numbers, sullying control, and alert triggers in times of crisis.

According to the current situation, the most demanding fields of study are the Internet of Things (IoT) applications in healthcare [5]. An increasingly important role for the Internet of Medical Things (IoMT) is to recover the reliability, accuracy, and speed of healthcare IT [6]. Seeing a doctor for any minor issue is extremely dangerous in light of the present pandemic crisis. Therefore, to may simply keep tabs on health records with IoMT devices, letting us to take initial safeguards independently [7].

A web of interconnected, internet-enabled medical equipment is what makes up an IoMT framework consists of multiple stages [8]. The first step is to gather medical data from the patient's body through the use of smart sensors combined with smart implanted or wearable devices that are linked by a wireless sensor network (WSN) or a body sensor network (BSN) [9]. The following part, which handles the analysis and prediction, will then get this data via the internet. Appropriate data interpretation performances based on AI can be used for analysis after receiving the medical data [10]. Assistive artificial intelligence (AI) apps for smartphones make it easier to contact medical professionals or other services in the event of an emergency. People can take steps to protect themselves from less dangerous situations.

With the help of artificial intelligence (AI), a computer or robot can be programmed to mimic human intelligence and carry out formerly human-only jobs [11]. A machine can also monitor health parameters utilising the implanted or wearable sensors on the body of the person under observation within a healthcare system with procedures [12]. AI can improve the user experience while managing and preventing diseases in real-time. The patient's highly private medical records are handled by SHS. This makes the provision of critical security measures in SHS based on IoMT an extremely important undertaking [13]. Performing web-based security device, identifying network intrusions and intermediate security threats within IoMT systems, etc. are all ways in which AI can help with IoMT security. Artificial intelligence (AI) can automatically warn several parties in an emergency, allowing them to take immediate action and maybe save a life [14]. As a result, physicians may quickly handle patient records and offer after-hours medical care with the help of AI. An further use case for blockchain technology is enhancing the safety of an IoMT network [15]. Data integrity and security are ensured by this distributed database, which stores information digitally in a decentralised and safe manner. Therefore, it establishes credibility independently of any intermediaries. One potential application of blockchain technology in IoMT is the enhancement of server security for electronic health records (EHRs) such as MedRec, which can be utilised for the management of access controls and permissions related to patient data [16].

Given the foregoing, it is clear that LSTM and CNN are equally capable of producing respectable outcomes when it comes to short-term load forecasting [17]. Hence, it is reasonable to assume that combining CNN with LSTM will further decrease the forecasting error. Current methods could not work all the time because of sudden shifts in demand, according to recent studies. Hence, additional study is necessary to address the present difficulties and shortcomings of the current methods.

This study suggests a novel hybrid model that integrates Convolutional Neural Networks (CNN) besides LSTM networks Satin Bowerbird Optimization Algorithm (CSBOA). The CSBOA enhances the model's efficiency by selecting the most relevant features, while the CNN-LSTM architecture leverages the complementary strengths of CNN for spatial pattern recognition and LSTM for temporal sequence modeling. Building a reliable, effective, and precise system for noticing cardiac disease is the objective. The main goal of the research project is stated below:

- To analyse numerous IoMT constructions used in AI- healthcare scheme
- To effectively capture spatial and temporal patterns in heart disease data, a hybrid model combining CNN and LSTM networks should be developed. - To optimise feature selection, reduce dimensionality, and enhance model performance, the Chaotic Satin Bowerbird Optimisation Algorithm (CSBOA) should be implemented.
- To evaluate the model using the UCI dataset with score, ensuring robust and reliable performance.

- To compare the proposed model with existing state-of-the-art approaches, demonstrating its superiority in accuracy, computational efficiency, and real-world applicability.

The goal is to investigate whether the hybrid classical can be used in clinical settings, which could lead to better early detection besides treatment of disease.

Here is how the remainder of paper is structured: Section 2 mentions the related works; Section 3 provides the proposed procedure; Section 4 discuss the result investigation and finally, the conclusion is made at Section 5.

RELATED WORKS

An intelligent, automated edge computing situation for healthcare in illness detection has been developed by Lakshmanaprakash et al., [18] using an IoMT-enabled model of a Deep Optimised Network. With this goal in mind, to have employed a feature selection method known as Coot Optimised Feature Selection to extract useful information from preprocessed medical data and boost the classifier's performance during training besides testing. Moreover, to present a new method based on deep learning called Attention Network (CRAN). It can efficiently identify and categorise a variety of diseases pertaining to genetic disorders, chronic diseases, or heart-related disorders, all while preserving low time intricacy. In this regard, the CRAN model's hyper-parameters are optimised for classification learning by use of the Cray Fish Optimisation method. Extensive tests on the well-known open-source medical datasets prove that the suggested DON model works. As a dependable option for effective health monitoring, the results show that the model's outputs classify diseases with high accuracy. It is reasonable to assume that healthcare delivery systems would be much improved by combining IoMT with cutting-edge computational methods, given these results. Better patient outcomes are guaranteed by the DON model's streamlined healthcare operations, which are made possible by efficient monitoring and high precision in disease detection.

The conjugate applications of learning techniques with cloud-based C-IoT model systems have been presented by Qi [19]. Health and clinical data are provisionally protected by this paradigm, which is a lightweight encryption block model. By utilising the patient's medical history in the database, this prediction model aids in the identification of health conditions and the subsequent administration of appropriate treatment. The diagnosis is derived from the patient's database, which includes pre-historical information. This intelligent C-IoT system in the cloud uses Artificial Neural Network (ANN) algorithms to provide findings with an accuracy of about 91%. A smart health issue diagnostic model based on C-IoT is a step forward in society 5.0's modernisation. With the use ANN algorithms—whose superiority is based on data intensity with previous patient data—and lightweight encryption algorithms, the suggested IoT-based secure health monitoring scheme enhances health care operations by attaining a extraordinary accuracy of 91%.

Ghayvat et al., [20] has developed patterns for ADLs, behavioural patterns, and anomaly classification by combining sensor data from the IoMT with innovative multimodel data analytics. An innovative approach to data analytics, AiCareLiving makes use of numerous models. AI-enabled AicareLiving is an IoMT solution. The study begins by describing activity data using an individual's behaviours inside a certain area in order to figure out if there's an anomaly. After that, it checks the data for any discrepancies with the activity profile, which depicts the person's predicted behaviour and daily activities. Carers, affiliated healthcare professionals, care municipalities would all have access to this wellness data thanks to the IoMT and the Secured Exchange Protocol. When it comes to anomaly identification and forecasting, the AiCareLiving framework strives for the lowest possible false positive rate, and its high accuracy is very near to the 95% confidence level.

Continuous heart rate monitoring, electrocardiograms (ECGs), and blood pressure readings are only a few examples of the physiological data collected by Baseer et al., [21] using the IoMT. In order to handle and understand the complicated data acquired using IoMT, the Artificial Intelligence (AI) algorithms tabNet and catBoost are essential. For feature selection and extraction, to use TabNet, a popular tool due to its efficiency with tabular data. However, by managing categorical characteristics and reducing overfitting, CatBoost—a robust gradient boosting algorithm—adds to the model's predictive accuracy. When these state-of-the-art methods are combined, the results are more accurate and easier to understand, leading to a better grasp of the elements that impact the predictions. The training process of the model makes use of a big dataset that contains a risk variables, and medical histories. The flexibility of the model to various demographic and clinical situations is enhanced through the fine-tuning of this broad dataset, which opens the door to individualised risk assessments for cardiovascular disease. Quick forecasts using streaming

IoMT data are also possible with the help of the suggested model's instant processing capabilities. Last but not least, by integrating the benefits of IoMT with state-of-the-art computer vision techniques, Heart Disease Prediction Classical signifies a sea change in predictive healthcare. This integrated approach is envisioned by the research as a game-changing tool for healthcare when implemented. The model's goal is to offer accurate and rapid risk assessments of cardiovascular disease by integrating data collecting capabilities of IoMT with TabNet's and catBoost's predictive capabilities. With any luck, this ground-breaking method will pave the way for more targeted and efficient preventative care in the future, which will benefit patients' cardiovascular health.

In this paper, Yadav et al. [22] introduce a Deep Neural Network (DNN) architecture based on IoMT that is used in an IoMT system that is helped by computing at the edge. In order to make decisions based on data, the proposed IoMT-AAL seeks to expedite data collection besides processing. The patient is identified using the IoMT-AAL model, which communicates with the IoMT sensors and sends the data obtained to the edge computing system. After then, a plethora of empirical investigations are carried out, and the results are scrutinised from many perspectives. From what to can see, the IoMT-AAL uses DNN to make accurate predictions about the healthcare framework in terms of metrics like security, specificity, improvement, tracking, and physical activity. Results from the simulations proved that the IoMT-AAL model was superior to the alternatives.

PROPOSED METHODOLOGY

The likelihood of emerging heart disease can be reduced with prompt identification and management. In this study, to offer a framework for better cardiac disease prediction that is based on IoMT. Before and after heart disease develops, the IoMT gadget records data on the patient's heart. Improved efficiency, accessibility, and effectiveness in healthcare can be achieved through continuous, monitoring of patient health parameters, which can subsequently be recorded and communicated to a data centre, such the cloud.

The data generated from the sensors is sent to the hospital administration so they can determine the patient's cardiac state. It is possible to learn about a patient's cardiac health through testing and training. Prior to classification, the data values are trained using the UCI data repository. If the patient's cardiac status is normal or abnormal, it will be shown by the final categorisation results. The physician will proceed with the appropriate course of action in light of these findings. Figure 1 shows the suggested framework's architecture. In all, there are five parts to the framework: IoMT, the network and cloud infrastructure, the gathering of datasets, and the prediction system. The key components' functions are presented in the self-explanatory sub-component.

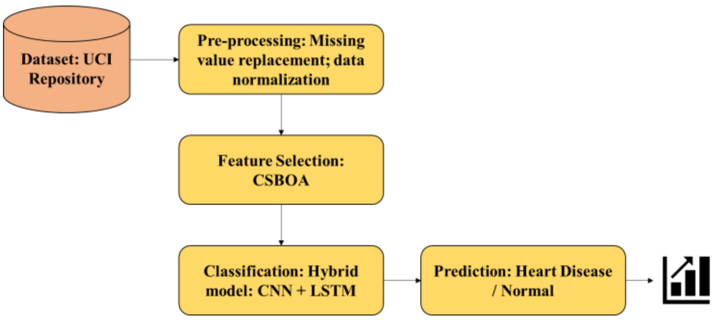

Figure 1. Projected healthcare monitoring scheme for diagnosis of heart diseases.

3.1. Heart Disease Prediction System

The patient's cardiac status is tracked and recognised when the necessary patient data has been collected. In order to regulate the status, the suggested IoMT framework for disease prediction runs tests and training. Values from the UCI data repository are utilised to train the system [23]. Prior to feature selection and classification, the dataset's data values go through pre-processing. Following training, the findings are compared and used to classify the patient's sensor data. What follows is an explanation of each step in the training process.

3.2. Preprocessing

Preprocessing involves removing noise or replacing missing data when data values are obtained from the UCI dataset. Detecting patterns linked to cardiac disease becomes much easier with noiseless data [24]. Because it examines the correlation between the dataset's values, the median student zed residual procedure is used to remove undesired or noisy data. By reducing background noise, cardiac illness can be more accurately detected.

a: Replacing Missing Values

Looking over the dataset and finding the median for values is the first step. Sorting the data in ascending order yields the median value, which is then used to compute the middle value. The median value is used to replace missing or irrelevant values [25].

b: Data Normalization

After missing values are removed, the data should be standardised within the range of 0 to 1. This will make it easier to evaluate patterns of cardiac disease. As a means of standardisation, the residual studentized method is applied once the standard deviation has been computed. Multiple data distributions and regression analysis are used to normalise the data for the purpose of heart disease forecast. To normalise data, to can see the regression equation in (1).

$$P = \beta_0 + \beta_i Q + \in_i, \ for \ i = 1,2, \dots . n \tag{1}$$

This model is satisfied by all possible combinations of random data trials. The data regression model is given by equation (2).

$$P_i = \beta_0 + \beta_i Q + \in_i^* \tag{2}$$

The variables ∈_i^* represent the data samples in equation (2) that have the same variance and error. The numbers that are designated as β_0 and β_0 respectively, represent the least squares. The residual value, denoted by, is calculated using Equations (1) and (2). Using the deviation, to can get the sample data and average values. The following is an approximation of the average value in equation (3):

$$\mu = \frac{\sum_{i=1}^{n} Q_i}{N} \tag{3}$$

where N characterises the frequency of data besides Q_i is the input statistics. The formula for data standardisation is given in equations (4) besides (5):

$$n_r = \frac{\in_i^*}{\dot{\sigma_\iota}} \tag{4}$$

$$n_r = \frac{Q_i - \mu_i^*}{\dot{\sigma_\iota}} \tag{5}$$

Where, $\in_i^*$ - residual charge, $\dot{\sigma_\iota}$- variance

3.3. Feature selection using Modified Optimizer

To optimise meta-learners, this study employs a novel metaheuristic optimisation algorithm—the Chaotic Satin Bowerbird Optimisation Algorithm (CSBOA) [26]—as a feature selection tool. The following provides a more detailed overview of the algorithm's optimisation process.

A) Chaotic satin bowerbird optimization algorithm (CSBOA)

A satin bowerbird's nest is a work of art, crafted with precious stones decided in a bow form. Female birds are more likely to visit nests that male birds make that are aesthetically pleasing. When female birds watch other birds build nests and compare them, they can select the best one. Motivated by observations of Satin Bowerbird's actions, the metaheuristic optimisation method known as SBOA was developed.

Phase one of this approach includes causal the birds' arbitrarily populace vectors. Here is how SBOA defines the initial population:

$$L_c = (l_1, l_2, \dots . , l_k) \tag{6}$$

here, the cth solution of the procedure is indicated by L_c. The other solutions are distinct by $(l_1, l_2, \dots, l_k)$. To help female birds choose the best men, the fitness probability function specifies the likelihood that male birds will be attracted to them. The female the male after he is defined. The subsequent equation characterises this procedure:

$$Prob_i = \frac{fit_i}{\sum_{n=1}^{NC} fit_n} \quad (7)$$

$$fit_i = \begin{cases} \frac{1}{1+f(y_i)}, & f(y_i) \geq 0 \\ 1 + |f(y_i)|, & f(y_i) < 0 \end{cases} \quad (8)$$

Here, the cost function charge for the site i is distinct by $f(y_i)$.

Nobility; this process is carried out by the most competent members of this algorithm. The type of bows used by male birds have a significant impact on the preferences and tendencies of the birds. Typically, females seek for construct nests that are both more functional and aesthetically experience is directly related to attractiveness for men. Throughout the SBOA, the most advantageous nest is considered elite at the end of each era. The selected elite keep track of where the other nests are.

In each iteration of the algorithm, the positions are renewed according to the formula provided below.

$$L_{cj}^{recent} = L_{cj}^{old} + \lambda_j \left(\frac{l_{ij}+l_{elite,j}}{2}\right) - l_{cj}^{old} \quad (9)$$

Where, l_{elite} marks the spot where the powerful live. With li being the current iteration's chosen solution and i being the result of the roulette wheel method, l_cj denotes the jth component of l_cm. The allure of a specific satin is defined by the equation below.

$$\gamma_j = \frac{\theta}{1+\tau_i} \quad (10)$$

Here, τ_i signifies the solution's maximum stage size and denotes the probability that is attained using Eq. (7).

As a result of natural selection, the strongest and more experienced male birds are able to mate with the most beautiful females. This can lead to violent behaviour, such as attacking besides destroying nests. To can describe this task by examining the probability of l_{cj}; therefore, a normal assumed with variance of σ^2 besides mean charge of l_{cj}^{old}.

$$L_{cj}^{recent} \sim P(l_{cj}^{old}, \sigma^2) \quad (11)$$

$$P(l_{cj}^{old}, \sigma^2) = l_{cj}^{old} + (\sigma \times P(0,1)) \quad (12)$$

In this case, α denotes the area width proportion, and the corresponding formula is provided below:

$$a = x \times (Var_{max} - Var_{min}) \quad (13)$$

Here, the proportion of the variance of bonds has been signified by x, besides Var_{min} and Var_{max} show the boundaries at the bottom and the top. Finding besides integrating inhabitants creates the final populace. The algorithm terminates when the last supplies are met.

While the SBOA method consistently produces good results for optimisation issues, it does have a few drawbacks that are based on chaotic theory. Its poor convergence rate is one of these drawbacks because it leads to solutions that aren't up to par. Two methods are proposed to address this issue. One of them is fixing the convergence problem using the pseudo-opposite learning method. Every member of the population is compared to their inverse in this procedure. The procedure is carried out by dimensional search space inside the interval [λ, κ]. Here is the formula that defines this process:

$$\tilde{y}_i = \lambda_i + k_i - y_i \quad (14)$$

$$i = 1,2, \dots, D$$

The calculation of the quasi-opposite number in the opposite learning technique is as follows:

$$\hat{y}_i = rand(\frac{\lambda_i + k_i}{2}, \tilde{y}_i) \quad (15)$$

A more appropriate population has been produced through the use of this method. Chaotic theory, which may provide a way out of the convergence trap, should be our next port of call. According to this hypothesis, the core system is complicated and not linear. It is defined by the quasi-random part of the equation, which is also the basis for several approaches. With the support of Querandí's principles, the concept of quasi-opposite has been developed with each new generation. The second technique for enhancement, the Bernoulli shift map, is definite as follows:

$$\hat{y}_n^{q+1} = \begin{cases} \frac{\hat{y}_n^q}{1-\lambda} & 0 < \hat{y}_n^q \leq 1-\lambda \\ \frac{\hat{y}_n^q - (1-\lambda)}{\lambda} & 1-\lambda < \hat{y}_n^q \leq 1 \end{cases} \quad (16)$$

Here, λ equals 0.4.

3.4. Classification using Hybrid Model

The approaching sub-section will describe the model with the hybrid model, which is utilised to diagnose the disease in this work.

3.4.1. LSTM Architecture

LSTM networks are a subset of RNNs that can keep historical data in their memory unit. Predicting time series data with it is a breeze. Cells, input gates, output gates, and forget gates are the four main building blocks of a lnetwork. Every cell transmits data at its own random pace. The gates monitor the cellular input and output flows. Using an LSTM network can help reduce the issues of gradient vanishing and exploding that are encountered with RNN. The following is the process for computing the node outputs of an LSTM network:

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (17)$$

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \quad (18)$$

$$\hat{C}_t = \tanh\,(W_c.[h_{t-1}.x_t] + b_c) \quad (19)$$

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \quad (20)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_0) \quad (21)$$

$$h_t = o_t * \tanh\,(c_t) \quad (22)$$

where input variable at time t is signified by x_t. Further, W_i, W_f, W_c, W_o are known as weight input gates; f_t, O_t besides C_t stands for the forget gate, the output gate, and the cell output in that order. To calculate the hidden state outputs at structure, the sigmoid activation function is given by σ and allocated. In addition,, b_i, b_c, b_f and b_0 refer to the biased values of dissimilar gates.

3.4.2. CNN Architecture

In order to detect cardiac problems, a specific sort of neural network known as a CNN has recently been employed. This network shows great promise and can manage lengthy time series data sets. By combining two functions using a convolutional process, it creates a third function. This calculation can be expressed in the following way:

$$s = (x * w) \quad (23)$$

where x represents the input function and w denotes the weighting function. A two-dimensional representation of feature map, the output of convolution procedure, is shown below.

$$s = (I * K)(i, j) = \sum_m \sum_n I(m, n)K(1 - m, j - n) \quad (24)$$

Three layers make up a CNN: the convolutional layer, the pooling layer, and the dense layer. In addition, there are three steps to a convolutional layer. The initial step involves performing a convolution operation using linear activation. After converting the activation function from the first stage into a linear function, the second stage, known as the detector stage, finds it. This is followed in the third stage by the pooling operation. The network's training time is reduced by using a pooling function to decrease the dimensionality of the data. Additionally, it is essential for downsampling the acquired feature map while maintaining the original depth. In most cases, the pooling layer's maximum pooling operation will take the highest values returned by the convolution layer besides apply them to the maximum pooling window. The parameter of convolutional layers is different from this. On the other hand, when necessary, other pooling operations like minimum pooling and average pooling are typically employed.

To summarise, in order to extract features, the pooling layer receives values from the convolutional layer. The output data must be flattened and sent to the dense layer once the pooling stage is complete. A one-dimensional output sequence is the final product. One way this model extended the network's learning process was by using the back propagation mechanism.

3.4.3. Hybrid CNN-LSTM network

To present LSTM and CNN, two methods that can produce very accurate predictions. Specifically, it plans to use a hybrid neural network architecture to accurately predict diseases by extracting and facilitating a number of hidden information from load sequences. Modules for feature fusion, memory, and convolution neural networks make up a CNN-LSTM hybrid network. To top it all off, the CNN unit is employed to record the data pattern's local trend. Additionally, it reduced the samples to a single vector, which the LSTM layer uses as an input for a single time step. In most cases, the LSTM module's purpose is to figure out how the dataset is interdependent over the long run. After a full link through dense layers, the final forecast is generated.

3.4.4. Building forecasting model

An encoder-decoder CNN-LSTM classical, which primarily handles one-dimensional data in pattern, must be implemented. The suggested model's CNN block is defined by two convolutional layers, with the kernel filter used for convolution. The input sequences are projected onto the feature windows by the first convolution layer. The features acquired from the first layer are amplified by operating the second convolution layer. Each convolutional layer in the suggested model has 64 feature mappings and a three-time step kernel filter. In obtain the values following two convolutions layers, a maximum pooling layer is typically utilised. In fact, its primary function is to streamline the input features. By combining one-fourth of the data with the initial sequence, the suggested model's maximum pooling operation can be executed. After this procedure is complete, the results are compressed into a lengthy vector. This vector is then sent into the LSTM unit's decoding process, which is shadowed by a dense layer. The output is provided by this layer.

3.4.5. Training the proposed model

Keras, a Python- network library, is used to construct the CNN-LSTM architecture that is being proposed. To ensure the model is applicable in a variety of contexts and to improve its performance, it must next be tested using new, unknown data sets. The following hyper limits are used to train the network in the proposed architecture.

- One dimensional convolution type
- There are 64 filters with a kernel size of 3.
- The activation for CNN, LSTM,
- Dense layer is the Rectified linear unit (RELU).
- Optimisation: Adam

The LSTM model has 200 hidden layers. - There are 20 epochs of training. - The batch size is 16.In order to ensure that the suggested model does not suffer from over-fitting, to use the hyper parameters described above and choose low bias and low variance.

RESULTS

Research for the proposed model was conducted using Python's deep learning toolbox and Google Colab. To utilised an NVIDIA Quadro P4000 graphics card with 8 GB of RAM for teaching and testing purposes. By dividing the benchmark datasets into a training set besides a test set, to were able to employ a 10-fold cross-validation procedure to assess the suggested models. Several hyper-parameters need to be set in order for the suggested architecture to be employed throughout the prediction process. In order to get the most out of the architecture, this is necessary. Epochs, learning rate, dropout, and batch size are these hyper-parameters.

4.1. Validation analysis of proposed prototypical with existing procedures

Using a variety of criteria for varying training to testing ratios, Figures 2–4 compare the suggested model to current approaches.

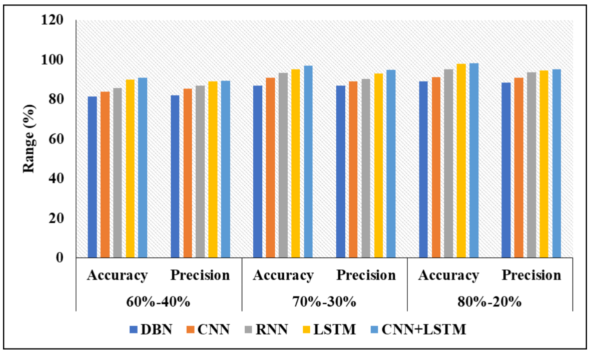

Figure 2: Comparative Investigation of proposed classical with existing techniques

The comparison table evaluates the accuracy and precision of various models across three dataset splits: 60%-40%, 70%-30%, and 80%-20%. The Deep Belief Network (DBN) achieves moderate performance, with accuracy increasing from 81.333% (60%-40%) to 88.976% (80%-20%), and precision from 81.993% to 88.321%. The CNN demonstrates notable improvement, accuracy of 91.188% besides precision of 90.996% in the 80%-20% split. The RNN outperforms the previous models with reaching 95.039% and 93.479%, respectively, in the 80%-20% split. The LSTM further improves, with accuracy peaking at 97.979% and precision at 94.391%. Finally, the CNN+LSTM hybrid model achieves best results, with an accuracy of 98.127% and precision of 95.109% in the 80%-20% split, demonstrating its superior ability to capture sequential and spatial features.

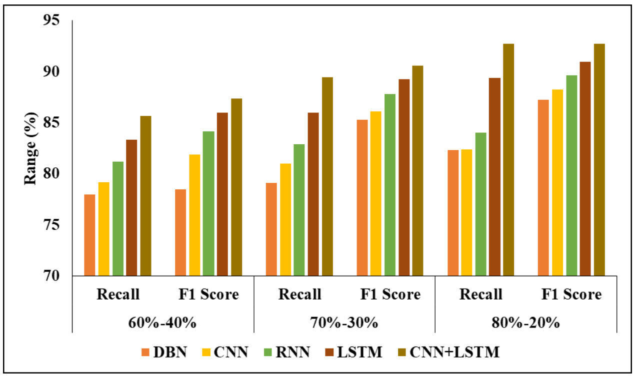

Figure 3: Study of projected hybrid model

The analysis of recall and F1 scores for different models across dataset splits (60%-40%, 70%-30%, and 80%-20%) shows progressive improvement in performance. The DBN achieves modest recall and F1 scores, increasing from 77.991% and 78.489% (60%-40%) to 82.333% and 87.221% (80%-20%). The CNN performs slightly better, with its highest recall and F1 scores reaching 82.375% and 88.220% (80%-20%). The RNN shows a stronger performance, achieving recall and F1 scores of 83.998% and 89.644% (80%-20%). The LSTM outperforms standalone models, peaking at 89.373% recall and 90.982% F1 score in the 80%-20% split. Finally, the CNN+LSTM hybrid model achieves the best results, with recall and F1 scores reaching 92.717% and 92.718% (80%-20%), demonstrating its superior capability in leveraging sequential and spatial data for classification tasks.

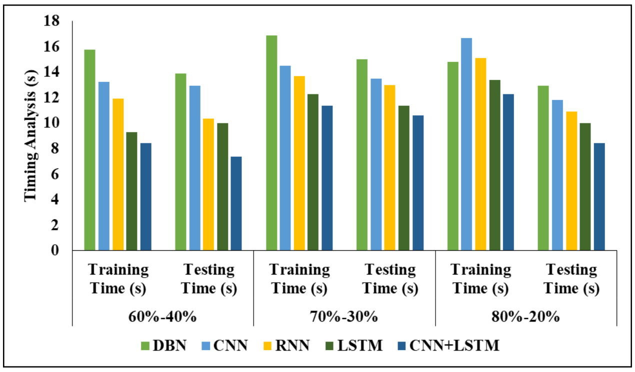

Figure 4: Timing Analysis

The analysis of training and testing times for various models across dataset splits (60%-40%, 70%-30%, and 80%-20%) highlights notable differences in computational efficiency. The DBN exhibits longer training and testing times, with the highest at 16.88s (training) and 14.98s (testing) in the 70%-30% split, decreasing slightly in the 80%-20% split. The CNN offers moderate computational times, with a peak training time of 16.64s (80%-20%) and a testing time of 13.46s (70%-30%). The RNN demonstrates better efficiency, with its training and testing times increasing marginally as the dataset split becomes more granular, peaking at 15.10s (training) and 12.98s (testing) for 80%-20%. The LSTM shows superior efficiency, with training times starting at 9.30s (60%-40%) and testing times consistently below 12s. The CNN+LSTM hybrid model is the most computationally efficient, with the shortest training and testing times across all splits, reaching a minimum of 8.45s (training) and 7.35s (testing) in the 60%-40% split, emphasizing its computational advantage in handling larger dataset proportions.

CONCLUSION

In this paper, to have outlined the factors that should be account when designing protocols for an IoMT network-based smart healthcare scheme. These factors include the patient's normal range of motion, the health monitoring device's range, the IoMT heterogeneous situation, service quality, besides security. Through the use of the UCI dataset, this research introduces a new hybrid model for cardiac illness diagnosis that combines CNNs with LSTM networks and feature selection based on the Chaotic Satin Bowerbird Optimisation Algorithm (CSBOA). Problems with high-dimensional data, redundant features, and the requirement for precise, real-time predictions in healthcare applications are all handled by the suggested approach. By streamlining the process and using the CSBOA as a guide, to may improve the model's performance by lowering computational complexity and making it easier to understand and work with. Combining CNN's with LSTM's ability in capturing temporal relationships, the CNN-LSTM architecture allows for accurate and robust categorisation. When tested against current approaches, the experimental consequences demonstration that the hybrid model outdoes them in terms of presentation measures score. The model is able to attain a good trade-off among computational efficiency and excellent detection accuracy since CSBOA is used to guarantee appropriate feature selection. Lastly, the suggested hybrid method provides an effective means of detecting cardiac disease, providing a potential answer for practical healthcare uses where accurate and rapid diagnosis is of the utmost importance. To recover the model's transparency and trustworthiness, future work might look into adding more datasets, testing in real-time in clinical settings, and using explainable AI methodologies. A thorough evaluation and potential upgrade are necessary to ensure the system's security, especially in light of the delicate nature of medical data.

REFRENCES

[1] Rajkumar, G., Devi, T. G., & Srinivasan, A. (2023). Heart disease prediction using IoT based framework and improved deep learning approach: medical application. Medical Engineering & Physics, 111, 103937.
[2] Bani Hani, S. H., & Ahmad, M. M. (2023). Machine-learning algorithms for ischemic heart disease prediction: a systematic review. Current cardiology reviews, 19(1), 87-99.
[3] Mall, S. (2024, May). Heart Attack Prediction using Machine Learning Techniques. In 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 1778-1783). IEEE.

[4] Khan, A., Qureshi, M., Daniyal, M., & Tawiah, K. (2023). A novel study on machine learning algorithm-based cardiovascular disease prediction. Health & Social Care in the Community, 2023(1), 1406060.

[5] Mall, S., & Singh, J. (2023, March). Heart diagnosis using deep neural network. In 2023 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE) (pp. 7-12). IEEE.

[6] Gangadhar, M. S., Sai, K. V. S., Kumar, S. H. S., Kumar, K. A., Kavitha, M., & Aravinth, S. S. (2023, February). Machine learning and deep learning techniques on accurate risk prediction of coronary heart disease. In 2023 7th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 227-232). IEEE.

[7] Hassan, D., Hussein, H. I., & Hassan, M. M. (2023). Heart disease prediction based on pre-trained deep neural networks combined with principal component analysis. Biomedical signal processing and control, 79, 104019.

[8] García-Ordás, M. T., Bayón-Gutiérrez, M., Benavides, C., Aveleira-Mata, J., & Benítez-Andrades, J. A. (2023). Heart disease risk prediction using deep learning techniques with feature augmentation. Multimedia Tools and Applications, 82(20), 31759-31773.

[9] Bhanurangarao, M., & Mahaveerakannan, R. (2024, October). Enhancing Hybrid Object Identification for Instantaneous Healthcare through Lorentz Force. In 2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 1365-1368). IEEE.

[10]Sarra, R. R., Dinar, A. M., & Mohammed, M. A. (2023). Enhanced accuracy for heart disease prediction using artificial neural network. Indonesian Journal of Electrical Engineering and Computer Science, 29(1), 375-383.

[11] Miah, J., Ca, D. M., Sayed, M. A., Lipu, E. R., Mahmud, F., & Arafat, S. Y. (2023, November). Improving Cardiovascular Disease Prediction Through Comparative Analysis of Machine Learning Models: A Case Study on Myocardial Infarction. In 2023 15th International Conference on Innovations in Information Technology (IIT) (pp. 49-54). IEEE.

[12]Ahmed, R., Bibi, M., & Syed, S. (2023). Improving heart disease prediction accuracy using a hybrid machine learning approach: a comparative study of SVM and KNN algorithms. International Journal of Computations, Information and Manufacturing (IJCIM), 3(1), 49-54.

[13]Baswaraju, S., Thirumalraj, A., & Manjunatha, B. Unlocking the Potential of Deep Learning in Knee Bone Cancer Diagnosis Using MSCSA-Net Segmentation and MLGC-LTNet Classification. In Sustainable Development Using Private AI (pp. 190-213). CRC Press.

[14]Chandrasekhar, N., & Peddakrishna, S. (2023). Enhancing heart disease prediction accuracy through machine learning techniques and optimization. Processes, 11(4), 1210.

[15]Kumar, D. V. S., Chaurasia, R., Misra, A., Misra, P. K., & Khang, A. (2023). Heart disease and liver disease prediction using machine learning. In Data-centric AI solutions and emerging technologies in the healthcare ecosystem (pp. 205-214). CRC Press.

[16]Arumugam, K., Naved, M., Shinde, P. P., Leiva-Chauca, O., Huaman-Osorio, A., & Gonzales-Yanac, T. (2023). Multiple disease prediction using Machine learning algorithms. Materials Today: Proceedings, 80, 3682-3685.

[17] Subramani, S., Varshney, N., Anand, M. V., Soudagar, M. E. M., Al-Keridis, L. A., Upadhyay, T. K., ... & Rohini, K. (2023). Cardiovascular diseases prediction by machine learning incorporation with deep learning. Frontiers in medicine, 10, 1150933.

[18]Lakshmanaprakash, S., Abirami, A., Madanachitran, R., Mekala, R., & Vaishali, V. H. (2025). DON: Deep Optimized Network model based on Coot and Convoluted Recurrent learning algorithms for healthcare monitoring in IoMT systems. Measurement, 242, 116226.

[19]Qi, K. (2025). Advancing hospital healthcare: achieving IoT-based secure health monitoring through multilayer machine learning. Journal of Big Data, 12(1), 1.

[20] Ghayvat, H., Awais, M., Geddam, R., Tiwari, P., & Löwe, W. (2024). Revolutionizing healthcare: IoMT-enabled digital enhancement via multimodal ADL data fusion. Information Fusion, 102518.

[21]Baseer, K. K., Sivakumar, K., Veeraiah, D., Chhabra, G., Lakineni, P. K., Pasha, M. J., ... & Harikrishnan, G. (2024). Healthcare diagnostics with an adaptive deep learning model integrated with the Internet of medical Things (IoMT) for predicting heart disease. Biomedical Signal Processing and Control, 92, 105988.

[22] Yadav, R., Pradeepa, P., Srinivasan, S., Rajora, C. S., & Rajalakshmi, R. (2024). A novel healthcare framework for ambient assisted living using the internet of medical things (IOMT) and deep neural network. Measurement: Sensors, 33, 101111.

[23] Shrestha, D. (2024). Advanced Machine Learning Techniques for Predicting Heart Disease: A Comparative Analysis Using the Cleveland Heart Disease Dataset. Applied Medical Informatics, 46(3).

[24] Mahaveerakannan, R., Rajakumar, B., Sharma, R. R., & Pushpa, S. (2024, September). Optimized Feature Selection and Transfer Learning for Accurate Fundus Image Classification in Glaucoma Detection. In 2024 3rd International Conference for Advancement in Technology (ICONAT) (pp. 1-6). IEEE.

[25] Baswaraju, S., Maheswari, V. U., Chennam, K. K., Thirumalraj, A., Kantipudi, M. P., & Aluvalu, R. (2023). Future food production prediction using AROA based hybrid deep learning model in agri-sector. Human-Centric Intelligent Systems, 3(4), 521-536.

[26] Chaturvedi, A., Pathak, N., Sharma, N., & Mahaveerakannan, R. (2024, February). Deep Learning in the Context of Artificial Intelligence: Advancements and Applications. In International Conference On Innovative Computing And Communication (pp. 23-44). Singapore: Springer Nature Singapore.