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Article

Deep Learning Enabled Intelligent Healthcare Management System in Smart Cities Environment

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Abstract: In recent times, cities are getting smart and can be managed effectively through diverse architectures and services. Smart cities have the ability to support smart medical systems that can infiltrate distinct events (i.e., smart hospitals, smart homes, and community health centres) and scenarios (e.g., rehabilitation, abnormal behavior monitoring, clinical decision-making, disease prevention and diagnosis postmarking surveillance and prescription recommendation). The integration of Artificial Intelligence (AI) with recent technologies, for instance medical screening gadgets, are significant enough to deliver maximum performance and improved management services to handle chronic diseases. With latest developments in digital data collection, AI techniques can be employed for clinical decision making process. On the other hand, Cardiovascular Disease (CVD) is one of the major illnesses that increase the mortality rate across the globe. Generally, wearables can be employed in healthcare systems that instigate the development of CVD detection and classification. With this motivation, the current study develops an Artificial Intelligence Enabled Decision Support System for CVD Disease Detection and Classification in e-healthcare environment, abbreviated as AIDSS-CDDC technique. The proposed AIDSS-CDDC model enables the Internet of Things (IoT) devices for healthcare data collection. Then, the collected data is saved in cloud server for examination. Followed by, training

and testing processes are executed to determine the patient's health condition. To accomplish this, the presented AIDSS-CDDC model employs data preprocessing and Improved Sine Cosine Optimization based Feature Selection (ISCO-FS) technique. In addition, Adam optimizer with Autoencoder Gated Recurrent Unit (AE-GRU) model is employed for detection and classification of CVD. The experimental results highlight that the proposed AIDSS-CDDC model is a promising performer compared to other existing models.

Keywords: Smart cities; e-healthcare; decision support system; cardiovascular disease; deep learning; feature selection

1 Introduction

Smart cities contribute towards the incorporation of conventional urban architectures with the support of Information Technology (IT), including Internet of Things (IoT) sensors. This phenomenon allows the cities to prosper economically and socially and provide sustainable and high-quality urban services [1,2]. For this purpose, smart cities need cooperation between private and public sectors to implement and deploy IT platforms that can collect and analyze vast quantities of data required for automated and intellectual processes. The significance of telemedicine and e-health is increasing among healthcare providers, patients, governments, citizens, and other shareholders [1]. Telemedicine has the ability to improve accessibility to services, decrease costs, and enhance self-management. Further, it can permit underserved populations earlier, to gain access to modern services without any hindrance. While the health system is developing, its technology and substructure too are increasing [2]. Since the significance of better health systems is projected amongst physicians, such healthcare models demands intellectual systems that can handle huge volumes of databases and offer improved medical treatments. The speedy advancements in the existing digitized healthcare data have brought innovative difficulties for scientific research society. Artificial Intelligence (AI), big data, and healthcare management have its own complications in terms of efficiency and social effects [3]. However, they play a progressive and vital role in guiding doctors across the facets of medicine. Healthcare organizations generally experience an issue i.e., to provide quality healthcare services at a fair cost. An inaccurate clinical prognosis and low quality medication might result in insufficient results. Healthcare organizations can employ Decision Support Systems (DSSs) as a mechanism for cost reduction [4].

In general, healthcare models involve a huge volume of patient reports, disease prognoses databases, source management, and so on. The prevalent expansion of IoT and its application in medicinal research enhanced the efficiency of distant health monitoring systems [5]. IoT is regarded as a compendium of several physical materials to detect the physical events without any interruptions [6]. By utilizing IoT technology, Cardiovascular Disease (CVD) monitoring system can collect and transfer the physical variables of a patient to a distant healthcare facility center on real-time basis. In human body, heart is one of the highly significant organs [7] while CVD specifically affects the heart's functioning. In clinical research, CVD diagnosis is a main and difficult problem to overcome. It can be diagnosed through observation of numerous indications such as cold sweats, chest pain, blood pressure, chest congestion, and shortness of breath [8].

In order to assist in prognosis and predict CVD, IoT sensor values are considered as input values. The prognosis of CVD has been often made by examining the patient's medical history, physical inspection records, and scrutiny of disturbed indications by a doctor [9]. However, the outcomes

attained from this prognosis methodology may not be precise in recognizing whether a patient has CVD or not. Furthermore, it becomes affluent and computationally tough for analysis using such huge volumes of data [10]. In this background, there exists a need to develop a non-invasive prognosis system on the basis of classifications of Machine Learning (ML) so as to resolve the above-discussed issues. An expert decision system, on the basis of ML classifiers and the implementation of fuzzy logic (FL), can successfully help in CVD prognosis. This in turn reduces the death ratio [11].

The execution of ML system can be raised, when balanced datasets are utilized for testing and training the system. Additionally, the analytical abilities of the model can be advanced through appropriate and relevant features extracted from the data. Thus, Feature Selection (FS) and data balancing are significant steps in the development of the proposed model [12]. In the studies published earlier, several prognosis methods has been suggested by numerous authors. However, such methods could not provide a well-defined prognosis for CVD. Conversely, an appropriate ML system is essential for decent outcomes. An ML technique can be segregated as good one when it produces good performance not only with the data provided during training time (or else an ML method can easily study the training data), but also with hidden data [13].

The current study develops Artificial Intelligence enabled Decision Support System for CVD disease detection and classification in smart city e-healthcare environment abbreviated as AIDSS-CDDC technique. The proposed AIDSS-CDDC model enables the IoT devices for collect healthcare data which is then saved in cloud server for examination purposes. In addition, the presented AIDSS-CDDC model employs data pre-processing and Improved Sine Cosine Optimization (ISCO) based Feature Selection (FS) named ISCO-FS technique. In addition, Adam optimizer with Autoencoder Gated Recurrent Unit (AE-GRU) model is employed for detection and classification of CVD. The proposed AIDSS-CDDC model was experimentally validated using benchmark dataset.

Rest of the paper is organized as follows. Section 2 offers the information on related work, Section 3 introduces the proposed model, Section 4 provides experimental validation, and Section 5 concludes the study.

2 Related Works

Li et al. [14] suggested an accurate and efficient system for prognosis of heart disease while the system depends upon ML approaches. The model could further suggested 'original rapid conditional mutual information FS method' to resolve the FS issue. FS methods are utilized for feature selection so as to increase the accuracy of classification and reduce the performance period of classification method. In literature [15], a difficult mission was achieved i.e., the selection of serious features from a huge data set with existing features and prognosis for heart disease. FS is one of the broadly-employed pre-processing levels in classification. An altered Differential Evolution (DE) methodology was utilized to perform FS for cardiac disease and optimization of particular features.

Zhang et al. [16] suggested an effective and Privacy Preserving Disease Prediction (PPDP) model. In PPDP, historical medical data of the patients was encoded and outsourced to cloud server so that it can use it for training the estimation systems through Single-Layer Perceptron learning technique in privacy preserving means. Kumar et al. [17] intended to provide an improved healthcare structure with the advantages of big data analytics. The massive medical data was managed efficiently in this study with the help of several analytical methods and in-depth insights were achieved from the data. The prevailing structures use methods like Artificial Neural Networks (ANN), Logistic Regression (LR), and fuzzy-related methods. In literature [18], HeartFog, an intelligent real-time decision support system was developed based on suitable scrutiny and IoT so as to achieve distant recognition of heart

disease and increase the accuracy of prognosis upon unsolved data. The presented work was assessed in relation to execution time, test accuracy, training accuracy, power consumption, arbitration time, and latency.

Haq et al. [19] recommended a prognosis system with the help of ML systems for diagnosis of diabetes mellitus. The presented methodology was tested on diabetes data sets i.e., a clinical dataset sourced from clinical history of the patients [20]. Internet of Medical Things (IoMT) outline was used for the prognosis of Cardiovascular Disease with the help of Adaptive Neuro-Fuzzy Inference System (ANFIS) while Modified Salp Swarm Optimization (MSSO) was suggested. The suggested MSSO-ANFIS advanced the searching ability by means of Levy Flight (LF) process.

3 The Proposed Model

In this study, a novel AIDSS-CDDC model has been developed for disease detection and classification of CVD in e-healthcare environment. The proposed AIDSS-CDDC model enables the IoT devices to collect healthcare data. Besides, CVD classification process encompasses a series of processes namely, data pre-processing, ISCO-FS based feature subset selection, AE-GRU classification, and Adam optimizer. Fig. 1 shows the overall block diagram of AIDSS-CDDC technique.

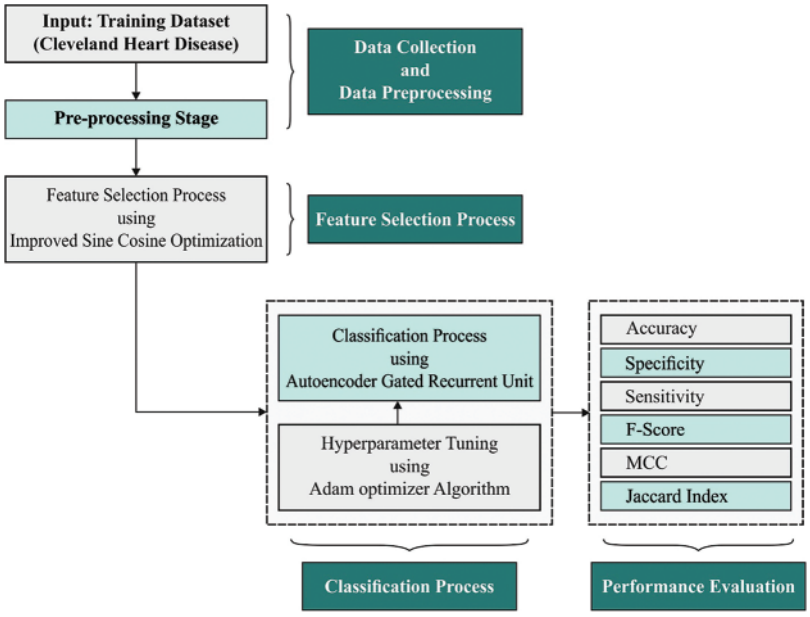

Figure 1: Block diagram of AIDSS-CDDC approach

3.1 Data Pre-processing

In current study, the data undergoes scaling process prior to moving onto ISCO-FS model. This is done so to ensure that every feature gets upgraded at a concurrent rate. Here, Min-Max scaler is applied to scale the dataset at an interval between 0 and 1 to assure rapid convergence for the gradient learning procedure of Deep Learning (DL) model. It can be defined as follows.

$$f_{scaled} = \frac{f - f_{min}}{f_{\max} - f_{min}} \tag{1}$$

where $f_{\min}$ and $f_{\max}$ denote the lower and higher bounds of the features respectively.

3.2 Design of ISCO-FS Technique

Once the input data is pre-processed, ISCO-FS technique is exploited to elect the feature subsets. Similar to other Swarm Intelligence (SI) techniques, a primary population is created arbitrarily in the provided solution space during the initial phase of Sine Cosine Optimization (SCO) algorithm. Next, the optimum solution is attained in the primary population. The following steps are repeated until the end criteria are attained. Primarily, the adaptive parameter $r1$ and arbitrary parameters containing 2, $r3$, and $r4$ [21] are upgraded as given below.

$$\begin{aligned} r_1 &= a - t * \frac{\mathrm{a}}{\mathrm{t}_{\max}} \\ r_2 &= 2 * \pi * rand() \\ r_3 &= 2 * rand() \\ r_4 &= rand() \end{aligned} \tag{2}$$

Here, a implies a value equivalent to 2 whereas t and t_{max}. stands for the existing iteration and maximal iteration correspondingly; $rand()$ is utilized in the production of arbitrary real number in an interval between 0 and 1. π refers to constant. Secondarily, the place of all the agents gets upgraded dependent upon Eq. (3) with i^{th} individual X_i being an instance.

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{T} + r_1 * \sin(r_2) * \left| r_3 * P_j^t - X_{i,j}^t \right| \\ X_{i,j}^{T} + r_1 * \cos(r_2) * \left| r_3 * P_j^t - X_{i,j}^t \right| \end{cases} \tag{3}$$

whereas $X_{i,j}^{t+1}$ and $X_{i,j}^{t}$ imply the j^{th} dimension of i^{th} agent at t^{th} iteration and $(t+1)^{th}$ iteration correspondingly; and P_j^T represents the j^{th} dimension of optimum solution at t^{th} iteration.

Eventually, the cross-border procedure is executed to guarantee that every agent exists in the potential area. In case of an agent being superior to the optimum solution, then the optimum solutions are upgraded by this agent. In order to avoid a decline due to local optima and define a further potential area, a search approach called Disperse Foraging Strategy (DFS) is projected based on disperse foraging performance of wolves at the time of food shortage. The original SCO algorithm inclines to decrease towards local optima if higher dimension and multi-dimension optimization problems are resolved. In order to tackle this issue, an enhanced technique termed ISCO is presented in this case to establish DFS as SCO algorithm. In the presented DFSCA, DFS process forces all the agents to achieve 'expanded searching space' so as to define further potential solutions. This approach not only utilizes them to jump out of local optima with superior chance, but also allows the definition of further potential solutions. This scenario is highly important to enhance the efficiency of optimization. The stages involved in the execution of ISCO algorithm are reprised from literature [22]:

Step 1: Initialize the appropriate parameters of ISCO algorithm such as the maximal fitness computation time is MaxFES, the existing fitness computation time *FES*, the population size N and the searching space dimension D. Then, go to Step 2;

Step 2: Arbitrarily initialize the population and estimate the primary population, attain the optimum solution P with optimum agents from the primary population, $FES = FES + N$, go to Step3;

Step 3: If the $FES >= Ma\chi FES$ go to Step4 or else repeat the subsequent sub-steps i.e., Step 3.1–3.3:

Step 3.1: Upgrade the place of agents in the population. Modify the place of all the agents in the boundary. Estimate the existing population. Upgrade the optimum solution P. $FES = FES + N$.

Step 3.2: Create the candidate place of searching agent by DFS. Modify the candidate's place in the boundary. When the candidate place is superior to the existing place of searching agents, replace the existing place of searching agents with candidate place; or else keep the present place of searching agent unaffected.

Step 3.3: Estimate the existing population. Upgrade the optimum solution P. $FES = FES + N$.

Step 4: Return the optimum solution, P.

The fitness function of ISCO-FS technique is derived to attain a proper tradeoff between the chosen feature count in every solution and classifier accuracy that is attained via elected features. The fitness function for evaluation solution is defined below.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \tag{4}$$

where $\gamma_R(D)$ signifies the classification error rate for AE-GRU model. $|R|$ is the cardinality of the chosen subset and $|C|$ denotes the total number of features in the dataset, α, and β denote the significance of classification quality and subset length respectively, $\in [1, 0]$ and $\beta = 1 - \alpha$.

3.3 CVD Classification Process

Next, Adam optimizer with AE-GRU model is employed for detection and classification of CVD. GRU is a particular case of Long Short Term Memory (LSTM) that is established for the reduction of long training time of LSTM [23]. GRU is far easier than LSTM as it contains only two gates such as reset and update gates that control the flow of data inside the unit. The alteration function amongst the neurons of GRU is provided as follows

$$r(n) = \sigma\left(w_r x(n) + u_r h(n-1) + b_r\right) \tag{5}$$

$$z(n) = \sigma\left(w_z x(n) + u_z h(n-1) + b_z\right) \tag{6}$$

$$\hat{h}(n) = \sigma\left(w_h x(n) + u_h\left(r(n) * h(n-1)\right) + b_h\right) \tag{7}$$

$$h(n) = (1 - z(n)) * h(n-1) + z(n) * \hat{h}(n) \tag{8}$$

whereas $r(n)$ refers to reset gate, $z(n)$ denotes the update gate, and w and u imply the parameter matrices from GRU. Besides, $h(n)$, $h(n)$, and b are the candidate output, output, and bias correspondingly. The activation function is demonstrated as σ. The presented AE-GRU method has the same features alike AE-LSTM method. AE is utilized to shrink the clinical information by determining the infrastructure of data and attaching the encoding data for GRU networks. The encoded clinical information and its equivalent historical solar PV power are provided to GRU network so as to make it fit and train the neurons that are capable of predicting the desired output. Fig. 2 depicts the

structure of AE-GRU technique. Especially, AE-GRU method is trained with a group of historically-encoded clinical information and its equivalent PV power i.e., encoding parameters and solar power. The prediction procedure, utilizing AE-GRU, is summarized herewith.

1. Historical clinical information is encoded with the help of encoding side of AE.
2. The encoded clinical information is split into training as well as testing sets. A small percentage of the trained data is conserved for validation.
3. All the testing, training, and validating datasets are efficient as to chunk or window which demonstrates the amount of historical preceding days (window size).
4. The presented method is trained and simultaneously validated with the help of windows of historically-encoded clinical information and equivalent power.
5. The presented method was verified on testing set which is nothing but the rearranged chunks of preceding instances.
6. At last, the presented AE-GRU method is a great ML approach used in the prediction of data for a provided chunk of preceding clinical information.

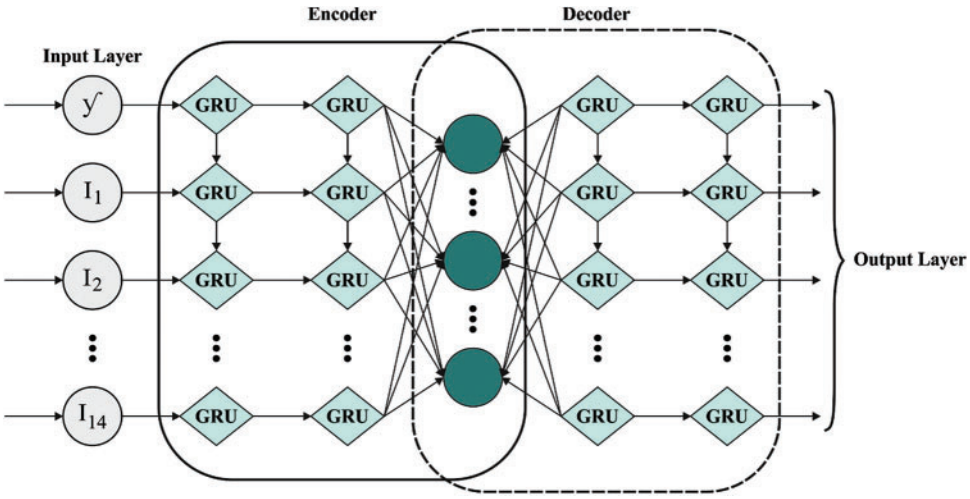

Figure 2: Structure of AE-GRU

In order to fine-tune the hyperparameters of AE-GRU technique, Adam optimizer is exploited. Adam model is a commonly applied technique that alters the learning rate adaptively for every parameter. It can be a group of distinct gradient optimization techniques. It exponentially decays the average of the past-squared gradient, i.e., Root Mean Square propagation (RMSprop) and Adadelta. Further, it takes the above-mentioned gradientssimilar to Momentum.

$$M_t = \beta_1 M_{t-1} + (1 - \beta_1)\, g_t, \tag{9}$$

$$G_t = \beta_2 G_{t-1} + (1 - \beta_2)\, g_t \odot g_t, \tag{10}$$

whereas β_1 and β_2 represent the decay rates that are defined as default values. M_t and G_t are defined to estimate the average of the past gradient (initial moment) and uncentered variations of earlier

gradients, correspondingly. As the decay rate results in few bias issues, it is vital to achieve bias-correction process.

$$\hat{M} = \frac{M_t}{1-\beta_1^t}, \quad \hat{G}_t = \frac{G_t}{1-\beta_2^t}. \tag{11}$$

Then, the updated value of Adam optimizer is resolved as follows.

$$\Delta\theta_t = -\frac{\alpha}{\sqrt{\hat{G}+\varepsilon}}\hat{M}_t. \tag{12}$$

The gradient part of $\triangle\theta_t$ is represented herewith.

$$g_t^{'} = \frac{1}{\sqrt{\hat{G}_t+\varepsilon}}\hat{M}_t, \tag{13}$$

$$\triangle\,\theta_t = -\alpha\left(\frac{1}{\sqrt{\hat{G}_t+\varepsilon}}\hat{M}_t\right) \tag{14}$$

$$= -\alpha g_t^{'}.$$

Here, it is confirmed that every function is based on the previous gradient of current parameter that has no relation with learning rate. So, Adam has an operational outcome via learning rate model.

4 Experimental Validation

In current section, the proposed AIDSS-CDDC model was experimentally validated using a benchmark dataset [24] that comprises of 303 samples with 14 features as depicted in Table 1. The proposed AIDSS-CDDC model has a total of 8 features. The proposed model was simulated using Python 3.4.5 tool.

Table 1: Dataset details

Descriptions	Values
Absence class	164
Presence class	139
Number of attributes	14
Total No. of samples	303

Fig. 3 depicts the correlation matrices generated by AIDSS-CDDC technique on test data with distinct attributes. The confusion matrices generated by the proposed AIDSS-CDDC model on test data under distinct Cross Validation (CV) are illustrated in Fig. 4. On CV-1, AIDSS-CDDC model categorized 162 samples under absence class and 135 samples under presence class. Afterward, on CV-3, the proposed AIDSS-CDDC methodology recognized 163 samples as absence class and 134 samples as presence class.

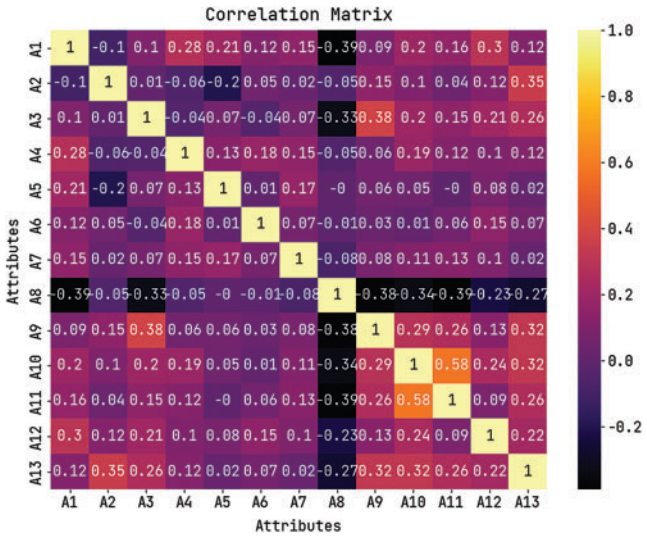

Figure 3: Correlation matrix of AIDSS-CDDC algorithm

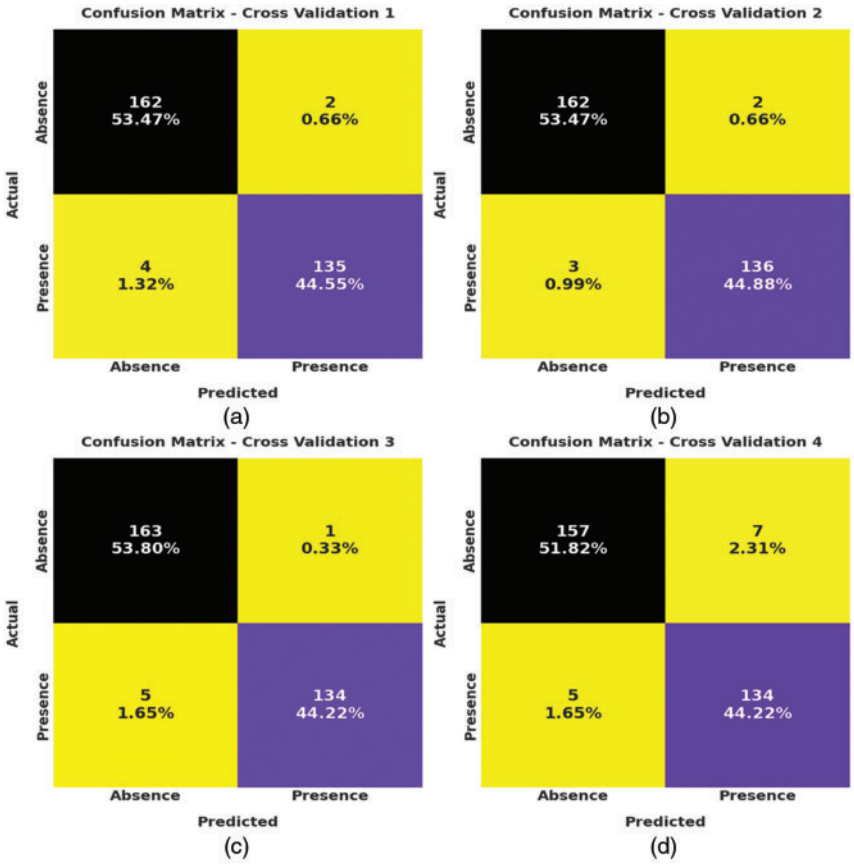

Figure 4: (Continued)

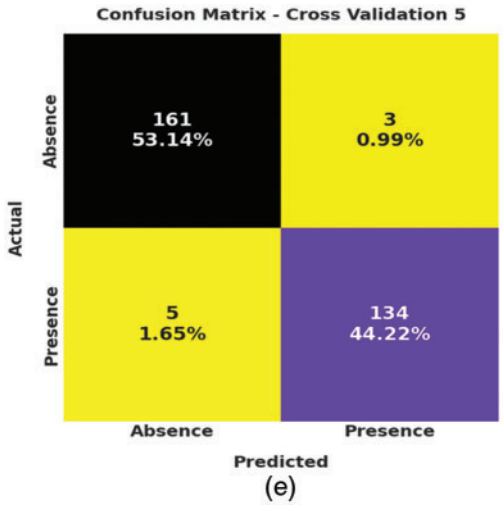

Figure 4: Confusion matrices of AIDSS-CDDC technique (a) CV-1, (b) CV-2, (c) CV-3, (d) CV-4, and (e) CV-5

Moreover, on CV-4, the proposed AIDSS-CDDC approach categorized 157 samples under absence class and 134 samples under presence class. At last, on CV-5, the proposed AIDSS-CDDC system recognized 161 samples as absence class and 134 samples as presence class.

Table 2 and Fig. 5 provide a detailed overview on the classification outcomes achieved by AIDSS-CDDC model under distinct Cross Validation (CV). The results imply that the proposed AIDSS-CDDC model gained effectual outcomes under every CV. For instance, on CV-1, AIDSS-CDDC model offered average $sens_y$, $spec_y$, $accu_y$, F_{score}, Mathew Correlation Coefficient (MCC), and $Jaccard_{index}$ values such as 97.95%, 97.95%, 98.02%, 98%, 96.02%, and 96.09% respectively.

Table 2: Results of the analysis of AIDSS-CDDC approach under different measures and CVs

Labels	Sensitivity	Specificity	Accuracy	F-score	MCC	Jaccard index
Cross validation-1						
Absence	98.78	97.12	98.02	98.18	96.02	96.43
Presence	97.12	98.78	98.02	97.83	96.02	95.74
Average	97.95	97.95	98.02	98.00	96.02	96.09
Cross validation-2						
Absence	98.78	97.84	98.35	98.48	96.68	97.01
Presence	97.84	98.78	98.35	98.19	96.68	96.45
Average	98.31	98.31	98.35	98.34	96.68	96.73
Cross validation-3						
Absence	99.39	96.40	98.02	98.19	96.04	96.45
Presence	96.40	99.39	98.02	97.81	96.04	95.71

(Continued)

Table 2: Continued

Labels	Sensitivity	Specificity	Accuracy	F-score	MCC	Jaccard index
Average	97.90	97.90	98.02	98.00	96.04	96.08
Cross validation-4						
Absence	95.73	96.40	96.04	96.32	92.04	92.90
Presence	96.40	95.73	96.04	95.71	92.04	91.78
Average	96.07	96.07	96.04	96.02	92.04	92.34
Cross validation-5						
Absence	98.17	96.40	97.36	97.58	94.69	95.27
Presence	96.40	98.17	97.36	97.10	94.69	94.37
Average	97.29	97.29	97.36	97.34	94.69	94.82

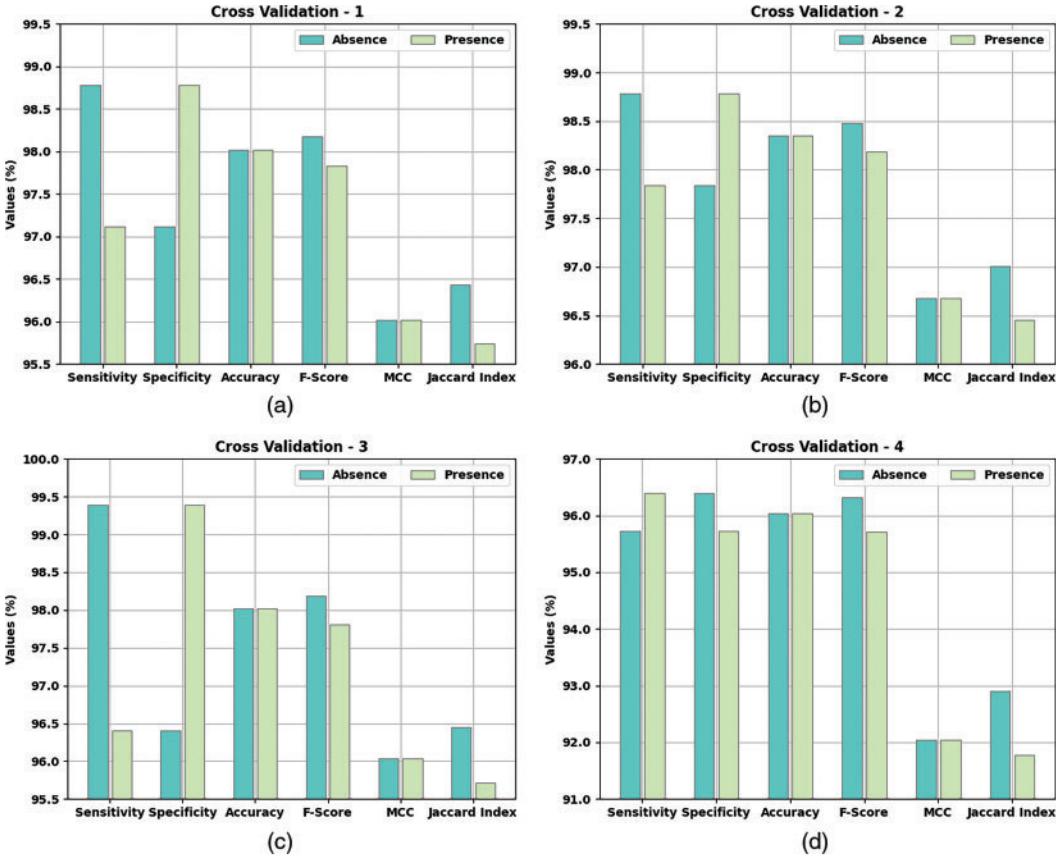

Figure 5: (Continued)

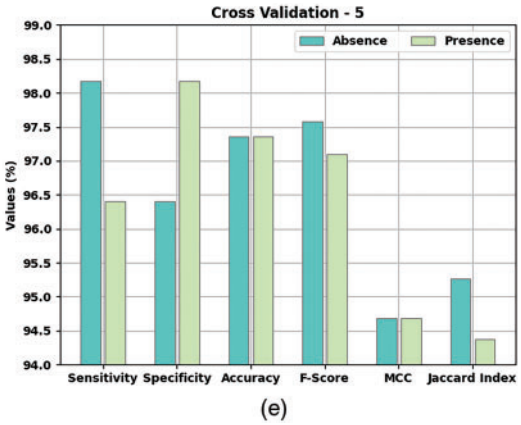

Figure 5: Results of the analysis of AIDSS-CDDC technique (a) CV-1, (b) CV-2, (c) CV-3, (d) CV-4, and (e) CV-5

Meanwhile, on CV-2, the proposed AIDSS-CDDC model achieved average $sens_y$, $spec_y$, $accu_y$, F_{score}, MCC, and $Jaccard_{index}$ values such as 98.31%, 98.31%, 98.35%, 98.34%, 96.68%, and 96.73% respectively. Also, on CV-2, the presented AIDSS-CDDC approach accomplished average $sens_y$, $spec_y$, $accu_y$, F_{score}, MCC, and $Jaccard_{index}$ values such as 96.07%, 96.07%, 96.04%, 96.02%, 92.04%, and 92.34% correspondingly. Then, on CV-5, the proposed AIDSS-CDDC algorithm attained average $sens_y$, $spec_y$, $accu_y$, F_{score}, MCC, and $Jaccard_{index}$ values such as 97.29%, 97.29%, 97.36%, 97.34%, 94.69%, and 94.82% correspondingly.

Both Training Accuracy (TA) and Validation Accuracy (VA) values, attained by the proposed AIDSS-CDDC algorithm on test dataset, are portrayed in Fig. 6. The experimental outcomes imply that the proposed AIDSS-CDDC system gained the maximum TA and VA values. To be specific, VA seemed to be higher than TA.

Figure 6: TA and VA analysis results of AIDSS-CDDC approach

Both Training Loss (TL) and Validation Loss (VL) values, achieved by the proposed AIDSS-CDDC model on test dataset, are shown in Fig. 7. The experimental outcomes infer that the proposed AIDSS-CDDC approach accomplished the least TL and VL values. To be specific, VL seemed to be lower than TL.

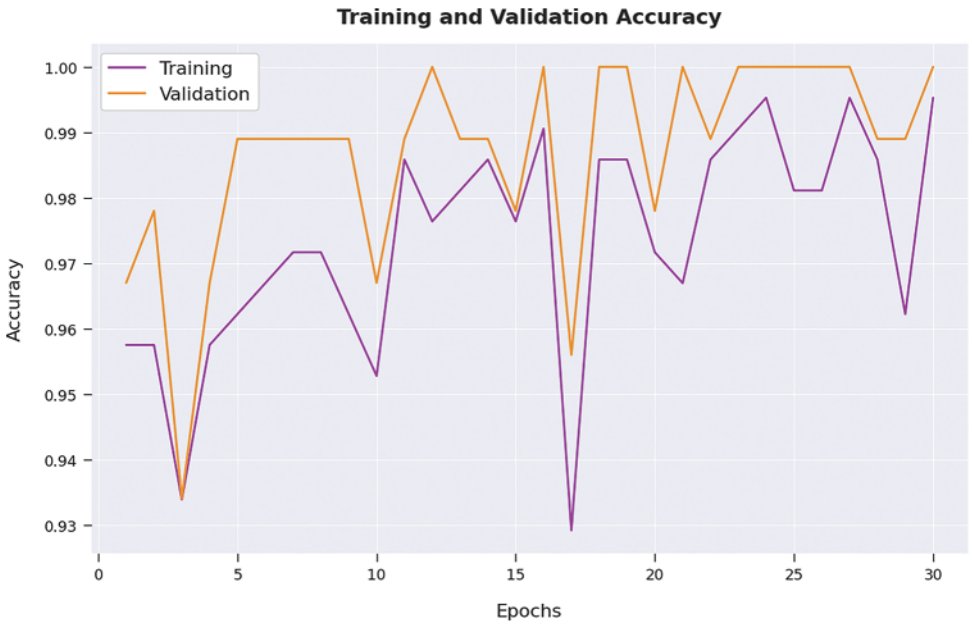

Figure 7: TL and VL analysis results of AIDSS-CDDC approach

Table 3 provides a comprehensive comparative CKD classification performance of the proposed AIDSS-CDDC model and other recent models such as Logistic Regression (LR), k-Nearest Neighbor (K-NN), Artificial Neural Network (ANN), Support Vector Machine with Radial Basis Function (SVM-RBF), SVM-Linear, Naive Bayes (NB), and Decision Tree (DT).

Table 3: Comparative analysis results of AIDSS-CDDC approach and other existing algorithms

Methods	Sensitivity	Specificity	Accuracy	F-score	MCC
AIDSS-CDDC	98.31	98.31	98.35	98.34	96.68
LR model	91.70	88.95	83.24	91.16	84.81
K-NN model	91.46	86.38	86.94	95.00	83.91
ANN model	91.90	87.59	85.62	91.13	90.25
SVM-RBF model	91.09	91.94	85.08	83.37	88.27
SVM-linear model	89.49	83.85	89.28	88.30	90.11
NB model	87.83	82.90	84.23	84.40	93.16
DT model	89.46	91.43	84.55	82.30	84.09

Fig. 8 shows the comparative $sens_y$ and $spec_y$ examination results achieved by the proposed AIDSS-CDDC model and other recent models. The figure implies that the proposed AIDSS-CDDC model gained improved performance over other techniques. With respect to $sens_y$, AIDSS-CDDC model achieved the highest $sens_y$ of 98.31%, whereas LR, K-NN, ANN, SVM-RBF, SVM-Linear, and NB models gained the least $sens_y$ values such as 91.70%, 91.46%, 91.90%, 91.09%, 89.49%, 87.83%, and 89.46% respectively. Also, in terms of $spec_y$, the proposed AIDSS-CDDC approach offered the maximum $spec_y$ of 98.31%, whereas LR, K-NN, ANN, SVM-RBF, SVM-Linear, and NB algorithms gained the least $spec_y$ values such as 88.95%, 86.38%, 87.59%, 91.94%, 83.85%, 82.90%, and 91.43% correspondingly.

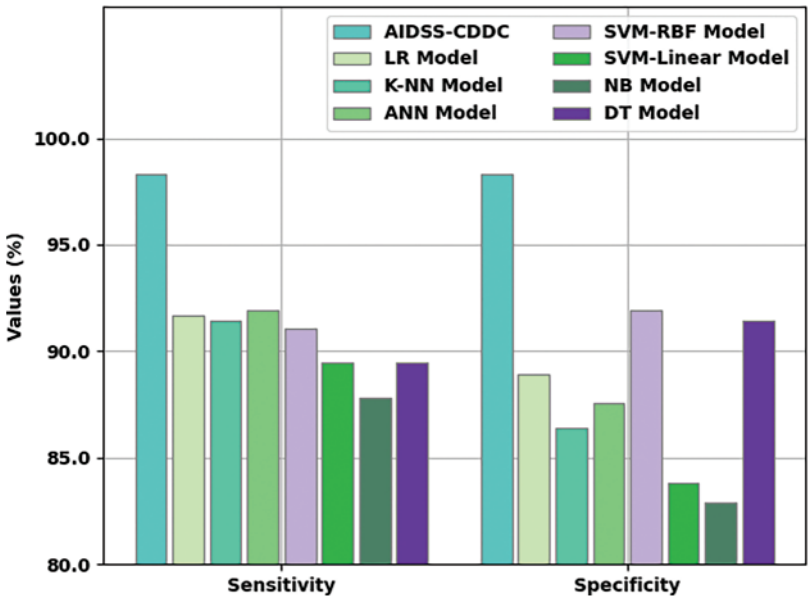

Figure 8: $Sens_y$ and $Spec_y$ analysis results of AIDSS-CDDC approach and other existing algorithms

Fig. 9 shows the comparative $accu_y$, F_{score}, and MCC analysis results attained by the proposed AIDSS-CDDC approach and other existing models. The figure implies that the proposed AIDSS-CDDC system gained improved performance over other techniques. With regard to $accu_y$, AIDSS-CDDC algorithm yielded the highest $accu_y$ of 98.35%, whereas LR, K-NN, ANN, SVM-RBF, SVM-Linear, and NB methodologies attained the least $accu_y$ values such as 83.24%, 86.94%, 85.62%, 85.08%, 89.28%, 84.23%, and 84.55% correspondingly. Moreover, in terms of F_{score}, the proposed AIDSS-CDDC technique attained the highest F_{score} of 98.34%, whereas LR, K-NN, ANN, SVM-RBF, SVM-Linear, and NB approaches attained the least F_{score} values such as 91.16%, 95%, 91.13%, 83.37%, 88.30%, 84.40%, and 82.30% correspondingly. Eventually, with respect to MCC, the proposed AIDSS-CDDC system accomplished the maximum MCC of 96.68%, whereas LR, K-NN, ANN, SVM-RBF, SVM-Linear, and NB models gained minimal MCC values such as 84.81%, 83.91%, 90.25%, 88.27%, 90.11%, 93.16%, and 84.09% correspondingly.

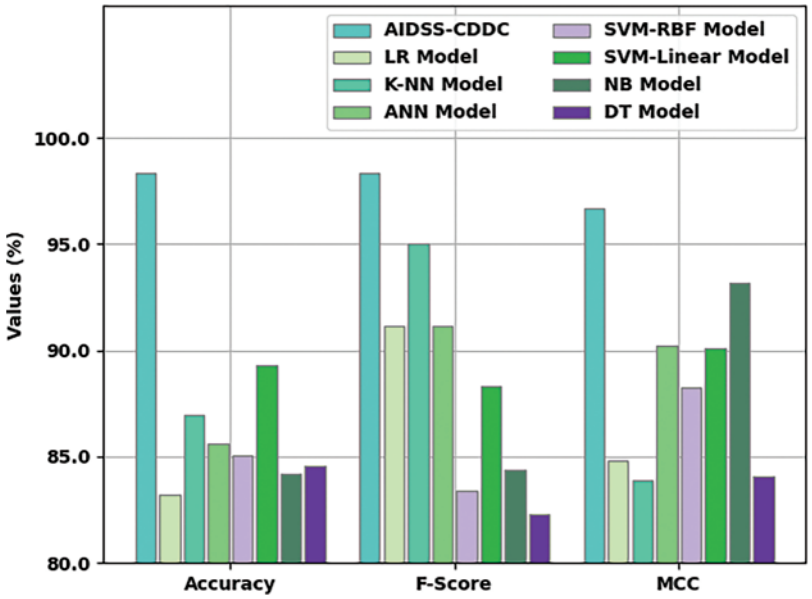

Figure 9: Comparative analysis results of AIDSS-CDDC approach and other existing algorithms

Finally, a detailed execution time analysis was conducted between the proposed the AIDSS-CDDC model and other recent models and the results are shown in Table 4 and Fig. 10. The results imply that SVM-linear model gained ineffectual outcomes with a maximum execution time of 16.860 s. At the same time, ANN and NB models shown slightly reduced execution times such as 9.620 and 9.150 s respectively. In addition, LR, KNN, SVM-RBF, and DT models produced moderately closer execution times such as 4.610, 4.770, 5.730, and 5.100 s respectively. However, the presented AIDSS-CDDC model accomplished the least and effectual execution time of 0.002 s. Therefore, the proposed AIDSS-CDDC model can be employed as an effectual tool for detection and classification of CVD.

Table 4: Execution time analysis results of AIDSS-CDDC technique and other existing methodologies

Methods	Execution time (sec)
AIDSS-CDDC	0.002
LR model	4.610
K-NN model	4.770
ANN model	9.620
SVM-RBF model	5.730
SVM-linear model	16.860
NB model	9.150
DT model	5.100

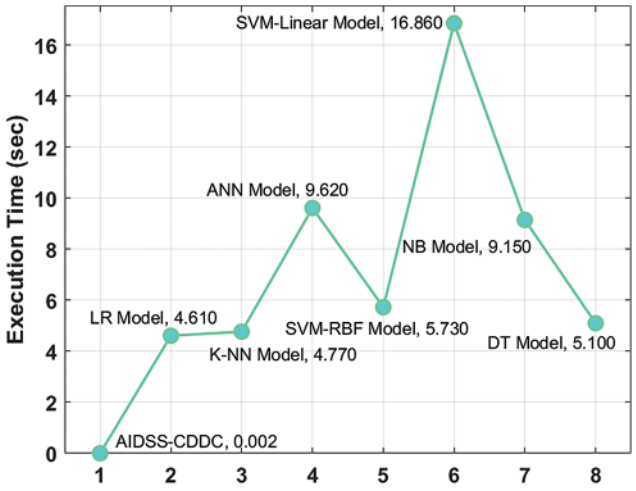

Figure 10: Execution time analysis results of AIDSS-CDDC technique and other existing methodologies

5 Conclusion

In current study, a novel AIDSS-CDDC model has been developed for CVD disease detection and classification in smart city environment. The proposed AIDSS-CDDC model enables the IoT devices to collect healthcare data which is then stored in cloud server for examination. Followed by, training and testing processes are executed to determine the patient's health condition. In addition, the presented AIDSS-CDDC model employs data pre-processing and ISCO-FS technique to elect the feature subsets. Moreover, Adam optimizer with AE-GRU model is also employed for detection and classification of CVD. The experimental results highlight that the proposed AIDSS-CDDC model is a promising performer over other models. Thus, the presented AIDSS-CDDC model can be exploited for effectual detection of CVD in e-healthcare environment. In future, ensemble voting-based DL models can be utilized to enhance the detection efficacy of AIDSS-CDDC model.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

[1] A. Kishor and W. Jeberson, "Diagnosis of heart disease using internet of things and machine learning algorithms," in *Proc. of Second Int. Conf. on Computing, Communications, and Cyber-Security*, Lecture Notes in Networks and Systems book series, Singapore, Springer, vol. 203, pp. 691–702, 2021.

[2] K. Shankar, E. Perumal, V. G. Díaz, P. Tiwari, D. Gupta *et al.,* "An optimal cascaded recurrent neural network for intelligent COVID-19 detection using chest X-ray images," *Applied Soft Computing*, vol. 113, no. Part A, pp. 1–13, 2021.
[3] R. Gopi, P. Muthusamy, P. Suresh, C. G. G. S. Kumar, I. V. Pustokhina *et al.,* "Optimal confidential mechanisms in smart city healthcare," *Computers, Materials & Continua*, vol. 70, no. 3, pp. 4883–4896, 2022.
[4] E. K. Hashi and M. S. U. Zaman, "Developing a hyperparameter tuning based machine learning approach of heart disease prediction," *Journal of Applied Science & Process Engineering*, vol. 7, no. 2, pp. 631–647, 2020.
[5] R. Beri, M. K. Dubey, A. Gehlot, R. Singh, M. A. Elnaby *et al.,* "A novel fog-computing-assisted architecture of E-healthcare system for pregnant women," *The Journal of Supercomputing*, vol. 78, no. 6, pp. 7591–7615, 2022.
[6] S. Nandy, M. Adhikari, V. Balasubramanian, V. G. Menon, X. Li *et al.,* "An intelligent heart disease prediction system based on swarm-artificial neural network," *Neural Computing and Applications*, 2021. https://doi.org/10.1007/s00521-021-06124-1.
[7] A. Al-Qarafi, F. Alrowais, S. Alotaibi, N. Nemri, F. N. Al-Wesabi *et al.,* "Optimal machine learning based privacy preserving blockchain assisted internet of things with smart cities environment," *Applied Sciences*, vol. 12, no. 12, pp. 5893, 2022.
[8] A. M. Hilal, B. S. Alfurhood, F. N. Al-Wesabi, M. A. Hamza, M. A. Duhayyim *et al.,* "Artificial intelligence based sentiment analysis for health crisis management in smart cities," *Computers, Materials & Continua*, vol. 71, no. 1, pp. 143–157, 2022.
[9] S. Pandu, A. Francis, P. Sekhar, P. Vijayarajan, A. A. Albraikan *et al.,* "Artificial intelligence based solar radiation predictive model using weather forecasts," *Computers, Materials & Continua*, vol. 71, no. 1, pp. 109–124, 2022.
[10] P. Kaur, R. Kumar and M. Kumar, "A healthcare monitoring system using random forest and internet of things (IoT)," *Multimedia Tools and Applications*, vol. 78, no. 14, pp. 19905–19916, 2019.
[11] T. Munirathinam, S. Ganapathy and A. Kannan, "Cloud and IoT based privacy preserved e-healthcare system using secured storage algorithm and deep learning," *Journal of Intelligent & Fuzzy Systems*, vol. 39, no. 3, pp. 3011–3023, 2020.
[12] I. M. E. Hasnony, O. M. Elzeki, A. Alshehri and H. Salem, "Multi-label active learning-based machine learning model for heart disease prediction," *Sensors*, vol. 22, no. 3, pp. 1184, 2022.
[13] A. Saboor, M. Usman, S. Ali, A. Samad, M. Abrar *et al.,* "A method for improving prediction of human heart disease using machine learning algorithms," *Mobile Information Systems*, vol. 2022, pp. 1–9, 2022.
[14] J. P. Li, A. U. Haq, S. U. Din, J. Khan, A. Khan *et al.,* "Heart disease identification method using machine learning classification in e-healthcare," *IEEE Access*, vol. 8, pp. 107562–107582, 2020.
[15] T. Vivekanandan and N. S. N. Iyengar, "Optimal feature selection using a modified differential evolution algorithm and its effectiveness for prediction of heart disease," *Computers in Biology and Medicine*, vol. 90, pp. 125–136, 2017.
[16] C. Zhang, L. Zhu, C. Xu and R. Lu, "PPDP: An efficient and privacy-preserving disease prediction scheme in cloud-based e-healthcare system," *Future Generation Computer Systems*, vol. 79, pp. 16–25, 2018.
[17] S. R. Kumar, N. Gayathri, S. Muthuramalingam, B. Balamurugan, C. Ramesh *et al.,* "Medical big data mining and processing in e-healthcare," in *Internet of Things in Biomedical Engineering*, pp. 323–339, 2019. https://doi.org/10.1016/B978-0-12-817356-5.00016-4.
[18] S. Tuli, N. Basumatary, S. S. Gill, M. Kahani, R. C. Arya *et al.,* "HealthFog: An ensemble deep learning based smart healthcare system for automatic diagnosis of heart diseases in integrated iot and fog computing environments," *Future Generation Computer Systems*, vol. 104, pp. 187–200, 2020.
[19] A. U. Haq, J. P. Li, J. Khan, M. H. Memon, S. Nazir *et al.,* "Intelligent machine learning approach for effective recognition of diabetes in e-healthcare using clinical data," *Sensors*, vol. 20, no. 9, pp. 2649, 2020.
[20] M. A. Khan and F. Algarni, "A healthcare monitoring system for the diagnosis of heart disease in the iomt cloud environment using msso-anfis," *IEEE Access*, vol. 8, pp. 122259–122269, 2020.

[21] L. Abualigah and A. Diabat, "Advances in sine cosine algorithm: A comprehensive survey," *Artificial Intelligence Review*, vol. 54, no. 4, pp. 2567–2608, 2021.
[22] J. Xia, D. Yang, H. Zhou, Y. Chen, H. Zhang *et al.,* "Evolving kernel extreme learning machine for medical diagnosis via a disperse foraging sine cosine algorithm," *Computers in Biology and Medicine*, vol. 141, pp. 105137, 2022.
[23] M. AlKandari and I. Ahmad, "Solar power generation forecasting using ensemble approach based on deep learning and statistical methods," *Applied Computing and Informatics*, 2020. https://doi.org/10.1016/j.aci.2019.11.002.
[24] Dataset: https://archive.ics.uci.edu/ml/datasets.php.