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AN AI–IOT INTEGRATED FRAMEWORK FOR DISEASE DIAGNOSIS IN SMART HEALTHCARE SYSTEMS

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ABSTRACT

This study introduces an AI–IoT integrated framework for smart healthcare diagnosis, focusing on diabetes and heart disease. The proposed model leverages IoT-enabled wearable devices for real-time data acquisition and employs advanced Artificial Intelligence techniques for accurate disease prediction. Data preprocessing is enhanced using the Isolation Forest (iForest) algorithm to eliminate outliers, while the Cascaded Long Short-Term Memory (CLSTM) model optimized with Crow Search Optimization (CSO) is utilized for classification. The integration of IoT devices with AI ensures efficient, low-power, and user-friendly healthcare monitoring. Experimental validation demonstrates the model's superior accuracy, sensitivity, and specificity compared to traditional approaches. The framework provides a scalable, reliable, and intelligent solution for early disease detection, thereby supporting preventive care in modern healthcare systems.

KEYWORDS: AI–IoT; Integrated Framework; Smart Healthcare Systems; Cascaded Long Short-Term Memory (CLSTM); Crow Search Optimization (CSO)

1 INTRODUCTION

In recent times, the healthcare (HC) sector has made great strides in harnessing information technology to produce modern apps and enhance diagnosis and treatment processes. Scientific ideas and complex procedures are the primary sources of the vast quantities of digital data. Sophisticated healthcare apps are the second progeny of modern information technology.

People also think that today's healthcare systems are multifunctional, complex, and user-friendly. These upgrades include a change in emphasis from illness treatment to preventive care, an extension of clinical management from top-down to bottom-up, and changes in informatization development from national to regional data (Abdellatif, et al 2019). Thus, in order to enhance HC efficiency, which then increases health service knowledge and suggests the future implementation of smart medicine, the following changes are focused on addressing people's essential demands.

Advanced medical services consist of many different people and organizations, including doctors, patients, hospitals, and research centers. Considerations such as medical research, health decision-making, clinical management, disease prevention and monitoring, treatment, and prognosis are crucial. Cloud computing, microelectronics, artificial intelligence (AI), big data, mobile internet and cloud computing, along with 5G systems and smart biotechnology are some of the characteristics that are widely cited as defining modern HC. These methods are utilized in every facet of contemporary HC. From the patient's point of view, they can monitor their health status with the help of portable or wearable equipment. They have access to therapeutic assistance through virtual help and remote home control through remote facilities. Experts in the medical field have found that smart clinical decision support systems greatly enhance and simplify the diagnosis procedure.

With the broad deployment of modern medical sensors and well-integrated hardware, a new concept called the Internet of Medical Things (IoMT) is being considered to create individualized healthcare. Redesigning healthcare delivery and increasing the number of connected medical devices are two ways it plans to increase future earnings (Wu, et al; 2016). Based on a user's mobile habits, device usage patterns, and data gathered from ingestible, portable, and integrated sensors, this data can be utilized to follow their behaviors. Modern methods grounded in Deep Learning (DL) or Machine Learning (ML) might be employed to ascertain their health condition after additional data is collected. According to Mshali et al. (2018), traditional cloud technology, built on structures for huge data analysis—achieves optimal performance, and scalability, along with support for non-safety and delay-grounded IoT domains. Critically sick patients with limited resources who require a high degree of efficiency along with accessibility in an emergency can be catastrophically affected by a disconnection from the primary network or a latency discrepancy. Building architectures that study the interplay of cloud, and fog, along with edge computing quickly is still challenging. The main objective of this technique is to do functional data processing, analysis, correlation, and inference using complete edge nodes along with low-level fog nodes. This is why deploying scalable healthcare domain services using the aforementioned methodologies yields challenging outcomes. This occurs when operations requiring smart processing mapping and resource management prevail over nodes, satisfying the essential needs of the IoMT paradigm (Mutlag, et al 2019).

Highly accurate medical diagnosis and treatment are now possible thanks to mixed reality apps, surgical tools, and AI models (Abdulkareem, et al., 2021). Clinical Decision Support Systems (CDSS) use AI to accomplish results like skin cancer, hepatitis, and lung tumor diagnoses. Beyond that, AI diagnosis has surpassed manual diagnosis concerning accuracy. When it comes to accuracy, ML-based models far outstrip human doctors, particularly imaging specialists and pathologists. Thus, IBM's Watson introduced a significant and iconic product inside CDSS. A potent cognitive process aids in the provision of the optimal remedy by doing thorough analyses of medical and literature details. The reliability of cancer and diabetes diagnoses has been severely compromised as a result (Kaur, & Jasuja, 2017). The CDSS program is highly efficient since it helps clinicians improve diagnostic processes, reduces the occurrence of unexploited and misdiagnosed cases, and ensures that users receive timely medical care that is suited for them. Smart diagnostics asserts that it can accurately evaluate the patient's present health status and the severity of their illness in order to adopt a personalized treatment plan (Meng, et al. 2021).

Per the confluence of AI and IoT, this study presents a new model for smart HC system disease diagnostics. By combining AI with IoT, researchers are creating a disease diagnostic model that can detect cardiovascular disease and diabetes. The provided model is the result of multiple steps, including data collecting, preprocessing, classification, and parameter tuning. In order to diagnose a disease, IoT devices like sensors and wearables gather data, which is subsequently processed using AI techniques. A Crow search Optimization–grounded CLSTM (CSO–CLSTM) model is utilized in the proposed AI–IoT convergence strategy for disease identification. The iForest method is utilised to eliminate the outliers in this research. The diagnostic result is improved by using CSO to adjust the CLSTM model's 'weights' along with 'bias' parameters. Because it boosts the CLSTM approach's diagnostic results, CSO is utilized here. The CSO-LSTM model's efficacy was validated by means of HC data.

The development of a system to detect physiological variables along with health indicators to evaluate serious instances and accidents has been the subject of extensive prior research. Mustlag et al. (2020) utilised Wireless Body Sensor Network (WBSN) to track users' vitals and movements at any time, even when they're far away. The study's central component is an internet-connected "edge node" that notifies loved ones through cell phone anytime critical events like the early prediction of falls, tachycardia, or bradycardia take place. Accordingly, Elouni et al. (2020) proposed a system to compute basic examination of electrocardiogram (ECG) data in order to remotely monitor patients' heart rates.

Uddin (2019) proposed a method to study human behavior using wearable sensors in conjunction with a local fog server and GPU acceleration to train a LSTM-Recurrent Neural Network (LSTM-RNN). Previous research by Ram et al. (2019) utilised supplementary sensors to monitor motion and probe the utilisation of SVM and RF classification methods for motion prediction. Analyzing physiological data inside portable sensors has lately become easier with the use of models that mimic edge ML techniques. Predicting the anomalies of physiological variables within the framework of edge stream computing is not without its challenges, though. This research put Hierarchical Temporal Memory (HTM) into a distributed setting. Inference was carried out using the model that was implemented right on edge nodes. On top of that, Dammak et al. (2020) suggested an edge-executed LSTM RNN approach for fall prediction. We defined the Multi Access Edge Computing method's performance and utilised EEG data as a case study. As a result, the developers fell into the trap of thinking that the application's primary demands (such as data compression, feature extraction, and classification) could be met by having these operations run on the edge. We compared the results' accuracy to that of other popular classification models, such as k-Nearest Neighbors (kNN), RF, and regression and classification trees. As an alternative, the research followed the methodology of Greco et al. (2020) utilised a small number of models to identify abnormalities in ECG signals. In order to distribute the workload among the "edge, fog, and cloud layers", "IBM" presented the "Hierarchical Computing Architecture for Healthcare (HiCH)" and its variation, the "Monitor-Analyze-Plan-Execute Plus Knowledge (MAPE-K)" mechanism. One model for automatic EEG disease diagnosis that was published in the literature by Muhammad et al. (2020) utilised convolutional neural networks (CNNs). It separated spatial and temporal data using 1D and 2D convolutions, respectively.

Research Gap

Despite advancements in AI and IoT for healthcare, existing models struggle with real-time data processing, outlier management, and diagnostic accuracy. There is a lack of optimized, scalable frameworks integrating IoT sensors with AI for reliable early disease detection.

Objectives

1. To design and develop an AI–IoT convergence-grounded disease diagnosis model utilised for smart HC systems.
2. To implement a CSO-CLSTM model optimized for accurate detection of diabetes along with heart disease.

Problem statement

The healthcare sector faces challenges in early diagnosis due to heterogeneous data, latency in cloud-based systems, and limited accuracy of existing models. Traditional methods often fail to manage real-time, high-dimensional medical data effectively. There is a need for an intelligent, scalable, and low-power diagnostic framework that integrates IoT devices with AI for precise disease detection and preventive healthcare.

2 PROPOSED METHODOLOGY FOR SMART HEALTHCARE DIAGNOSIS

Figure 1.1 shows the whole procedure. The proposed technology offers significant improvements over earlier wireless communications concerning efficiency, battery consumption, and the amount of freedom it grants users when they are outdoors. In addition, this method employs IoT devices that are compact, lightweight, and easy to use. The IoT encompasses many different types of devices, including smartphones, fitness trackers, smartwatches, and many more.

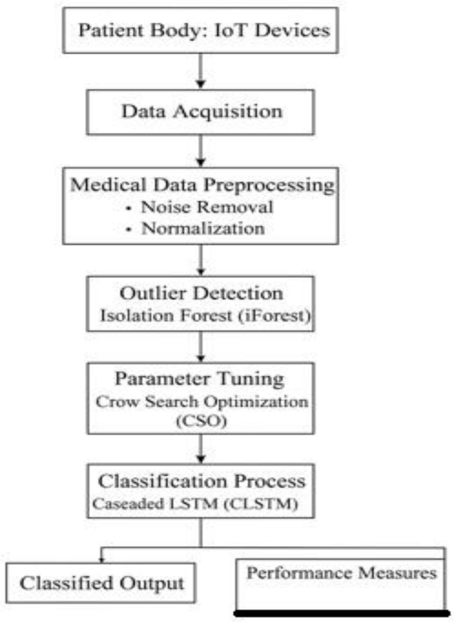

Figure 1. Proposed Method Flowchart

Using complex algorithms, the implanted sensors can evaluate and distinguish between normal along with abnormal heart rates. People taking part in the study have access to pocketable smart devices, such cellphones. It is strongly recommended to incorporate implanted electrocardiogram (ECG) and temp. sensors to collect additional data regarding the subject's cardiac parameters. From these statistics, we can also deduce the results of their common lifestyle. When data is acquired over low-power Bluetooth communication, a smartphone can evaluate if it is healthy or unhealthy. The efficiency of one's heart rate and blood sugar levels can be predicted by the Android platform. In order to ensure compatibility, IoT devices must first gather patient data. Data transformation, format conversion, and classification are the few processes that comprise pre-processing. Next, the iForest method is utilised to eliminate any extreme cases from the patient data. The next step is to use the CSO-CLSTM model to classify the data per the absence or presence of the illness.

iForest-Based Outlier Removal

To ensure data quality, the preprocessed medical dataset is refined using the iForest algorithm, a tree-grounded anomaly detection technique having linear time complexity along with high scalability. Given that medical abnormalities are sparse and diverse, they are prone to early isolation in randomly generated partitioning trees (iTrees). Each iTree recursively splits subsamples of data until single instances are isolated. During testing, the average path length of records across all iTrees is computed; samples with shorter average path lengths than a defined threshold are classified as outliers and removed.

Disease Diagnosis Model using CSO-CLSTM

After outlier removal, a hybrid CSO-CLSTM (Competitive Swarm Optimized Cascaded LSTM) model is employed for disease diagnosis. RNNs are adapted with LSTM units to overcome vanishing gradient issues and capture long-term temporal dependencies. The CLSTM framework consists of two cascaded networks:

1. The first LSTM network classifies sleep stages into four classes (W, and NI-REM, and N2, and N3; with N1 and REM merged).
2. The second network refines NI-REM into N1 and REM using PCA-reduced features.

Each network applies sequence-to-label learning through LSTM layers, followed by a fully connected (FC) layer and a Softmax classifier. The model minimizes cross-entropy loss to optimize weights and biases, ensuring robust classification accuracy for healthcare data.

Calibration of weights and biases with Cat Swarm Optimization technique

In this study, we utilised CSO to find the best values for the bias factors and weights in the CLSTM model. Everyone agrees that crows are among the cleverest birds out there. It has tremendous potential and a brain that is disproportionately large to its body. Per the brain-to-body hypothesis, which is paraphrased, the typical human body is considerably larger than the human brain. Crows' intelligence has been demonstrated in numerous instances. Crows are skilled toolmakers and have self-experience in mirror tests, according to a survey. Amazingly, crows can remember details about human faces, and they can even communicate with one another to warn one other of impending danger. Along with these qualities are the following: the use of already-established technology, the exchange of details, and the memorization of the location of the hidden food. After leaving the nest, it keeps an eye out for other birds and may even pursue them in an attempt to find the hidden food sources. After stealing food, the crow puts it wherever the actual bird can't find it. The CSO flow diagram is displayed in Figure 1.2. In its most basic form, it mimics a thief's actions in order to foresee their potential moves and select a foolproof method of food protection (Manimurugan, et al 2020).

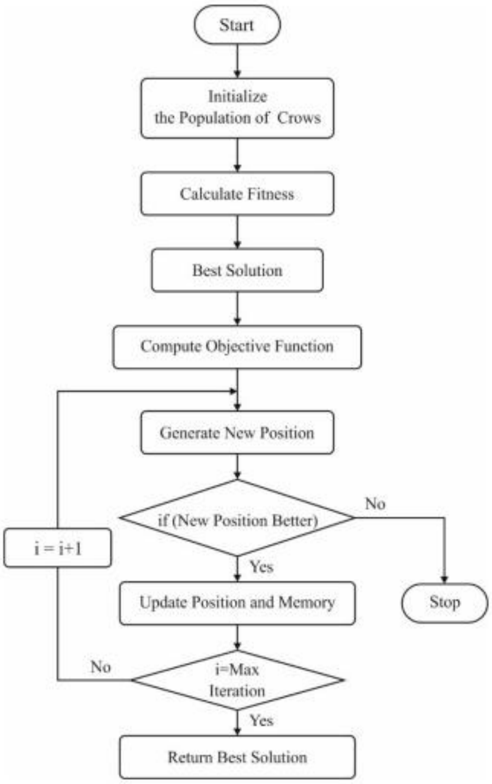

Figure 2. Algorithmic Flow of Cat Swarm Optimization

Afterwards, there are platforms consisting of N-dimensional crows. Here, u is the crow's position inside a Search Space (SS) at a certain instant, and C is the total crow count. This is gauged by the function that is listed below. The vector U with the iteration parameters set to

$V^{u,\text{ iter}}\ (p = 1,2,\ldots,C;\ \text{iter } = 1,2,\ldots,)\ \text{iter}_{\max}$

the maximum value of

$V^{u,iter} = \left[V_1^{u,iter}, V_2^{u,\text{iter}}, \ldots, V_c^{u,iter}\right]$ repeat the process with more iterations of each

A crow might serve as a useful memory aid while trying to find a hidden place. The new deduced position of crow u's secret spot is $s^{u,\text{ iter}}$ The crow u has gotten to a better spot in this instance. Assume that $s^{v,\text{ iter}}$. is the iteration when the crow v needs to be put up at a secret position. Now Crow u looks to follow Crow v to the secret spot. Two steps are taken in the order given below:

Crow v makes no submissions in 1st Incident concerning the crow u is after. Thus, crow v's secret hiding place is eventually revealed to crow u. The following step is to build the new crow u site in accordance with the given directions.

$$V^{u,\text{iter}+1} = V^{u,\text{iter}} + k_j \times fll^{\text{u,iter}} \times (S^{\text{v,iter}} - V^{u,\text{iter}})$$

where k_j is a uniformly distributed integer between 0 and 1, and u is the length of the crow's flight, represented by the variable $fll^{u,\text{ iter}}$ A lower value of fll indicates a more localized search, whilst a higher number indicates a more globalized search.

In 2nd Incident: Crow u is tracking it, and Crow v knows it. At long last, crow v foils crow u's thievery plot by pretending to be an alternate post of SS. Following is an illustration of events 1 and 2.

$$V^{\text{u,iter}+1} = \begin{cases} V^{\text{u,iter}} + k_j \times fll^{\text{u,iter}} \times (S^{v,\text{iter}} - V^{\text{u,iter}})k_j \\ \qquad \geq AWP^{v,\text{ iter}} \\ \text{a random location other wise} \end{cases}$$

In which case, $AWP^{v,\text{ iter}}$ infers the alertness of crow v at recapitulation.

3 RESULTS AND ANALYSIS

This section verifies that the provided CSOCLSTM model is accurate, specific, and sensitivity tested. Also, datasets pertaining to cardiovascular disease[1] and diabetes[2] with varying case counts are utilised to test the results. To execute the model, a computer system was utilized that has the following components: system specifications: MSI Z370 A-Pro motherboard, Intel Core i5-8600k processor, Nvidia GeForce 1050 Ti 4GB graphics card, and also 16 GB of RAM, along with a 1 TB hard drive.

Results on Heart Disease Diagnosis

Looking at the results through a sensitivity lens, it is apparent the SVM model underperformed other contemporary techniques. In addition, the NB-A model tried to show somewhat more sensitivity than SVM. Concurrently, the J48 and KNN models generated sensitivity values that were competitive and quite similar to one another. A greater sensitivity value was obtained using the provided CSO-CLSTM model, however, suggesting improved classification performance. For example, other models like KNN, and NB-A, and SVM, along with J48 attained low sensitivity values, whereas the CSO-CLSTM model had a max. sensitivity of less than 2000 instances. Out of all the approaches tested, the CSO-CLSTM approach outperformed KNN, and NB-A, and SVM, along with J48 concerning sensitivity under 10,000 occurrences.

[1] Heart Disease Data Set. [Online]. Available: https://archive. ics.uci.edu/ml/datasets/heart+disease"

[2] "Pima Indians Diabetes Database. [Online]. Available: https://www. kaggle.com/uciml/pima-indians-diabetes-database

A specificity analysis revealed the SVM approach underperformed more traditional models. In addition, the NB-A scheme showed far higher specificity than SVM. At the same moment, the J48 and KNN frameworks both reached levels of competitive specificity. In contrast, the newly-developed CSO-CLSTM technology attained the perfect specificity value and exhibited outstanding classification performance. For instance, when comparing all of the investigated technologies, the CSO-CLSTM scheme exhibited the best specificity (under 2000 instances), while KNN, and NB-A, and SVM, along with J48 had the worst. While the KNN, and NB-A, and SVM, along with J48 approaches attained low levels of specificity when tested with 10,000 occurrences, the CSO-CLSTM model earned the highest level of specificity.

Compared to the more traditional approaches, the SVM framework did not perform better in the accuracy analysis. The NB-A method also outperformed SVM concerning accuracy, which is rather encouraging. Methods that utilized both KNN and J48 simultaneously achieved somewhat better accuracy. The predicted CSO-CLSTM technique yielded the highest accuracy value, allowing for heavy categorization to be completed. The CSO-CLSTM model achieved the highest accuracy for instances less than 2000, while KNN, and NB-A, and SVM, along with J48 all achieved restricted accuracies. In comparison to the CSO-CLSTM method, the accuracy of the KNN, and NB-A, and SVM, along with J48 models was low when tested with 10,000 instances.

Table 1. Comparative Evaluation of Existing Approaches and the Proposed CSO-CLSTM Model on Heart Disease Dataset.

Measures	KNN	NB-A	SVM	J48	CSO-CLSTM
Sensitivity	90.04	85.32	85.22	93.42	97.38
Specificity	86.04	83.48	83.68	90.04	95.30
Accuracy	87.80	80.14	80.34	91.08	94.16

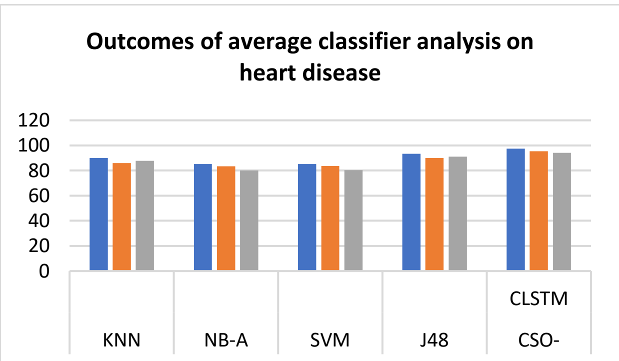

Figure 3. Outcomes of Average Performance Analysis of Classifiers for Heart Disease Data

Graph 1.3 and Table 1.1 display the results of the average classification analysis performed on the relevant cardiac disease dataset using the CSO-CLSTM model. With an average sensitivity - 97.38%, specificity - 95.30%, and accuracy - 94.16%, the CSO-CLSTM model obviously outperformed the other methods evaluated, as shown in the chart.

Results on Diabetes Dataset

A sensitivity study revealed that the SVM model lagged behind the other traditional methods concerning effectiveness. The sensitivity performance of SVM was not the only metric that the NB-A and KNN models sought to surpass. Furthermore, both the J48 and FNCA approaches demonstrated competitive sensitivity that was equivalent to one another. The offered CSO-CLSTM model, on the other hand, produced superior classification results and a great sensitivity value. For example, the sensitivity (under 2000 occurrences) of the CSO-CLSTM model was the highest of all the evaluated models, while that of the KNN, and NB-A, and SVM, and J48, along with FNCA models was the lowest. Under 10,000 instances, the CSO-CLSTM model achieved the highest sensitivity, while the KNN, and NB-A, and SVM, and J48, along with FNCA models achieved the smallest sensitivity.

Concerning specificity, the results showed that the SVM model did worse than other existing approaches. More specificity than SVM was also a goal of the NB-A and KNN models. On top of that, the J48 and FNCA models generated exclusive focus. However, the CSO-CLSTM model demonstrated here achieved high levels of specificity and performed admirably when it came to classification. Among the models tested with 2000 cases, the CSO-CLSTM model demonstrated the highest level of specificity, while the KNN, and NB-A, and SVM, and J48, along with FNCA methods did the worst. Thus, under 10,000 instances, the CSO-CLSTM model achieved very high specificity, whereas the KNN, and NB-A, and SVM, and J48, along with FNCA models achieved very low specificity.

The SVM model had poor accuracy results in comparison to other methods. Also, while SVM was somewhat accurate, NB-A and KNN models were far more so. Concurrently, the J48 and FNCA models both yielded fairly accurate findings. Nonetheless, the provided CSO-CLSTM model outperformed the others concerning classification performance and accuracy. For instance, among models tested, the CSO-CLSTM model outperformed all but one: KNN, and NB-A, and SVM, and J48, along with FNCA—all of which had accuracy below 2000 occurrences.

When 10,000 instances were present, the CSO-CLSTM model achieved very good accuracy, while the KNN, and NB-A, and SVM, and J48, along with FNCA models achieved extremely poor accuracy.
Table 1.2 and graph1.4 display the average classification results of the CSO-CLSTM approach on the applied diabetes illness dataset. Outperforming the comparison models significantly, the CSO-CLSTM technique attained an average sensitivity - 97.62%, specificity - 95.94%, and accuracy - 94.26%, as shown in the figure. The experimental findings demonstrate that the CSO-CLSTM model performs well; as illustrated in the tables and figures above, it achieved max. accuracy values of 94.26% for diabetes diagnoses and 94.16% for heart disease diagnoses.

Table 2. Comparative Evaluation of Existing Approaches and the Proposed CSO-CLSTM Model on Diabetes Disease Dataset.

Measures	KNN	NB-A	SVM	J48	FNCA	CSO-CLSTM
Sensitivity	92.10	87.90	83.14	94.20	95.50	97.62
Specificity	87.70	84.80	82.40	91.00	92.86	95.94
Accuracy	89.00	79.80	76.60	92.40	93.30	94.26

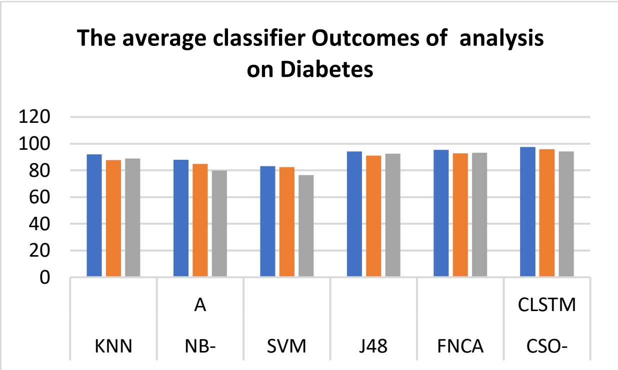

Figure 4. Outcomes of Average Performance Analysis of Classifiers for Diabetes Disease Data

4 CONCLUSION

Per the confluence of AI and the IoT, this study developed a model for smart healthcare system illness diagnostics that is both effective and efficient. Data collecting, preprocessing, classification, and parameter adjustment are the several phases that comprise the model that is being supplied. IoT devices, such as sensors and wearables, gather data – subsequently utilized by AI methods for illness diagnosis. After that, the iForest method is utilised to filter out any unusual patients from the database. The CSO-CLSTM model is then utilised to categorize the data based on whether the disease is present or not. Also, CSO is utilised to adjust the bias parameters and weights of the CLSTM model. Using CSO, the CLSTM model can produce better diagnostic outcomes. Healthcare data was utilised to validate the performance of the CSO-LSTM model. In terms of diabetes and heart disease diagnoses, the CSO-LSTM model reached a max. accuracy - 96.26% and 96.16%, respectively, throughout the experiment. The suggested paradigm has thus been shown to be effective. Potentially improving performance and being investigated for future scope are feature selection algorithms that reduce computing complexity and the curse of dimensionality. The CSO algorithm has a number of drawbacks, including poor search accuracy and an increased probability of reaching local optima; these can be remedied by using a hybrid metaheuristic algorithm.

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