ENABLED AND DIAGNOSIS TECHNOLOGIES WITH SMART HEALTHCARE MONITORING SYSTEMS USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

Internet of Things (IoT), cloud computing, and Artificial Intelligence (AI) technological advances have converted the traditional healthcare system into smart healthcare. Medical services can be enhanced by embracing important technology like IoT and AI. The healthcare sector has a variety of opportunities because of the confluence of IoT and AI. For a smart healthcare system, the current research study introduces a new AI and IoT convergence-based illness detection paradigm. Designing a disease diagnosis model for diabetes and heart disease utilizing AI and IoT convergence techniques is the main objective of this study. The many stages of the provided model include data collection, preprocessing, classification, and parameter adjustment. Data collection is made possible by IoT devices like wearables and sensors, and AI methods use that data in disease identification For disease detection, the suggested method makes use of the Cascaded Long Short Term Memory (CSO-CLSTM) model, which is based on the Crow Search Optimization algorithm. CSO is used to fine-tune the CLSTM model's "weights" and "bias" parameters in order to better classify medical data. In addition, the isolation Forest (iForest) technique is used in this study to weed out outliers. The CLSTM model's diagnostic results are significantly improved by the application of CSO. Utilizing healthcare data, the CSO-LSTM model's performance was verified. The reported CSO-LSTM model achieved maximum accuracies of 96.16% and 97.26% in diagnosing heart disease and diabetes, respectively, throughout the experiments. As a result, the suggested CSO-LSTM model can be used by intelligent healthcare systems as a suitable illness diagnosis tool.

1. INTRODUCTION

In recent years, the healthcare industry began utilizing information technology to create cutting-edge apps and improve the diagnostic and therapeutic procedures. The main forces behind the production of enormous amounts of digital data are cutting-edge methods and scientific theory. The offspring of information technology that have been developed in recent times are advanced clinical applications. Furthermore, programmes for advanced healthcare are expected to be straightforward, beautiful, and multitasking. Extensions to the clinical model (from disease-based to patient-based care), changes to the development of information technology (from medical data to regional medical data), modifications to clinical management (from general to personal management), and changes to prevention and treatment (shifting of focus from disease treatment to preventive medical system) are all included in these modifications [1]. As a result, the changes that follow are focused on meeting people's basic needs in order to improve the quality of healthcare, which in turn implies the deployment of smart medicine in the future. Many parties are involved in providing advanced medical services, including physicians, patients, and clinical and research facilities. Consideration should be given to a variety of factors, including illness prevention strategies, disease observation, prognosis, treatment options, clinical care, health decision-making, and medical studies. For instance, it is believed that smart biotechnology, mobile internet, Cloud Computing (CC), big data, 5G systems, microelectronics, and Artificial Intelligence (AI) would be the foundations of modern healthcare. Every level of modern healthcare uses these approaches. From the perspective of the patient, wearable or portable gadgets can be used to check their health whenever necessary. They can use virtual assistance to look for clinical direction and remote facilities to operate their residences. According to experts, sophisticated clinical decision support systems can be used to direct and improve diagnostic operations.

A new idea known as the "Internet of Medical Things" has been developed through the widespread dissemination and deployment of efficiently integrated hardware and contemporary medical sensors for specialised healthcare (IoMT). In order to increase profits in the future, it adjusts the healthcare system and the variety of IoT-enabled medical devices [2]. The researcher can follow a user's behaviours using the data collected with the aid of portable, ingestible, and integrated sensors, mobile patterns, and gadget usage patterns. By using cutting-edge techniques such as Machine Learning (ML) or Deep Learning (DL)-based techniques, it is possible to expose their medical status with more data collection. In order to give the best performance,

scalability, and support for non-safety as well as delay-based IoT domains, traditional cloud technology, which depends on structures for large data analysis, is employed. However, in emergency situations where there are little resources available and a patient requires a high level of efficiency and accessibility, the loss of connection to the main network or a significant change in latency may have disastrous effects. It is still difficult to construct structures quickly enough to study how cloud, fog, and edge computing interact. The major objective of this strategy is to manage functional activities related to data processing, inspection, correlation, and inference by applying complete edge nodes and low-level fog nodes. Thus, by creating scalable medical domain services, the aforementioned methodologies result in difficult outcomes. This happens as a result of the nodes being defeated by the processing and resource management operations' smart mapping in order to fulfil the core requirements of the IoMT paradigm [3].

Both illness diagnosis and treatment are quite reliable when using Artificial Intelligence (AI) models, surgical tools, and mixed reality applications [4], [5]. Clinical Decision Support System (CDSS) results including the diagnosis of hepatitis, lung tumours, and skin cancer are achieved by employing AI. Furthermore, AI diagnosis has become more accurate than manual diagnosis. Additionally, ML-based models are more accurate than skilled medical professionals, notably pathologists and imaging specialists. Therefore, IBM's Watson launched a noteworthy and exemplary CDSS product. With the aid of a thorough study of the relevant medical and literary information, this product's effective cognitive process helps to provide the optimal solution. Healthcare practitioners have noticed a significant change in how they diagnose diabetes and cancer as a result. The usage of CDSS is extremely effective and aids doctors in improving diagnostic procedures, reducing the likelihood of missed diagnoses and misdiagnoses, and enabling patients to obtain prompt and appropriate medical care. The patient's health status and disease severity can be precisely determined via smart diagnosis in order to implement a customised treatment plan.

A new illness detection model based on the convergence of AI and IoT is presented in the current research work for smart health-care systems. The goal is to create a disease diagnosis model for diabetes and heart disease using the convergence of AI and IoT. The many stages of the provided model include data collection, preprocessing, classification, and parameter adjustment. The data collection procedure is carried out by IoT devices like wearables and sensors, and AI approaches then process this data to diagnose the illness. The Crow search Optimization algorithm-based Cascaded Long Short-Term Memory (CSO-CLSTM) model is used in the suggested AI and IoT convergence method for disease detection. Additionally, this study uses the isolation Forest (iForest) technique to weed out outliers. The "weights" and "bias" parameters of the CLSTM model are tuned using CSO in order to enhance the diagnostic result. Here, CSO is used since it enhances the CLSTM method's diagnostic results. Using healthcare data, the CSO-LSTM model's efficacy was verified. Here is a summary of the research article's contributions.

- Designing and development of a novel AI and IoT convergence-based disease diagnosis model for smart healthcare system
- Proposed a CSO-CLSTM model for diagnosing diabetes and heart disease
- Incorporated iForest technique-based outlier detection process to improve the classification results
- Performed parameter tuning of LSTM model using CSO algorithm
- Validated the performance of CSO-LSTM model on two benchmark datasets.

2. RELATED WORK

Mazin Abed Mohammed, Ammar Awad Mutlag, and Mohd Khanapi Abd Ghani, 2020. Numerous sensors and equipment are used in healthcare applications, producing enormous volumes of data that are the focus of crucial tasks. Fog computing implementation is a method that may be used to manage them at the network's edge. However, Fog Nodes experience a lake of resources, which can reduce the amount of time required for the end result or analysis. Only a few jobs were capable of being completed by fog nodes. Choosing which jobs will be handled locally by fog nodes is a difficult decision. Such jobs should be carefully chosen by each node based on the available contextual data, such as task priority, resource load, and resource availability. In this study, we propose a Multi-Agent Fog Computing model for managing crucial tasks in healthcare. The primary purpose of theBy allocating jobs according to their priority, load on the network, and availability of network resources, a multi-agent system is mapping between three decision tables to maximise scheduling the crucial tasks. The first stage is to determine whether a crucial work can be completed locally; if not, the second step entails carefully choosing the best neighbouring Fog Node to allocate it to. The task is then routed to the Cloud with the highest latency if no Fog Node can complete it over the network. Using the iFogSim simulator and UTeM clinic data, we comprehensively test the suggested

strategy, confirming its applicability and optimality at the network's edge.

Shamim Hossain and M. Ghulam Muhammad, 2012. In a variety of industries, including the healthcare industry, distributed systems can be created quickly, accurately, and seamlessly with the help of contemporary deep learning models and new communication technologies. In this article, we propose a framework for smart healthcare that includes a deep learning-based pathology detection system. Signals from a subject's electroencephalogram can be used to identify pathology. A mobile edge computing server receives EEG signals from a smart EEG headset, which is used in the framework. The signals are preprocessed by the server before being sent to a cloud server. The cloud server uses deep learning to carry out the bulk of the processing and determine if the subject has pathology or not. Customers and participants in the framework are linked through a cloud server-based authentication manager. Results of experiments on a database that is accessible to the general public attest to the suitability of the suggested architecture.

Ghulam Muhammad, Neeraj Kumar, and M. Shamim Hossain, 2020. This paper suggests a remote disease detection system based on electroencephalograms (EEG). A deep convolutional network with 1D and 2D convolutions is what the system employs. Using a fusion network, features from many convolutional layers are combined. The sorts of networks explored include an autoencoder and a multilayer perceptron (MLP) with a range of hidden layers. A publicly accessible EEG signal database with two classes—normal and abnormal—is used in experiments. The experimental results show that the suggested system, when using the convolutional network, achieves higher than 89% accuracy.by the MLP with two hidden layers. The proposed system is also evaluated in a cloud-based framework, and its performance is found to be comparable with the performance obtained using only a local server.

3. METHODOLOGIES

Data Set:

A data set is a collection of data. In the case of tabular data, a data set corresponds to one or more database tables, where every column of a table represents a particular variable, and each row corresponds to a given record of the data set in question.

Pre-Processing:

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model.

When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way.

Splitting:

Data splitting is the act of partitioning available data into two portions, usually for cross-validatory purposes. one portion of the data is used to develop a predictive model. and the other to evaluate the model's performance.

- Training Data: Used for train the model or given as input to the to the learning model
- Testing Data: Used for test the model or given as input to the model for prediction.

Apply Algorithm:

In this we are using support vector machine algorithm to predict accuracy. It is a non-probabilistic supervised machine learning approaches used for classification and regression. It assigns a new data member to one of two possible classes. It defines a hyper plane that separates n-dimensional data into two classes.

Visualization:

Visualization is a technique that uses an array of static and interactive visuals within a specific context to help people understand and make sense of large amounts of data. The data is often displayed in a story format that visualizes patterns, trends and correlations that may otherwise go unnoticed.

Accuracy:

Accuracy is defined as the percentage of correct predictions for the test data. It can be calculated easily by dividing the number of correct predictions by the number of total predictions.

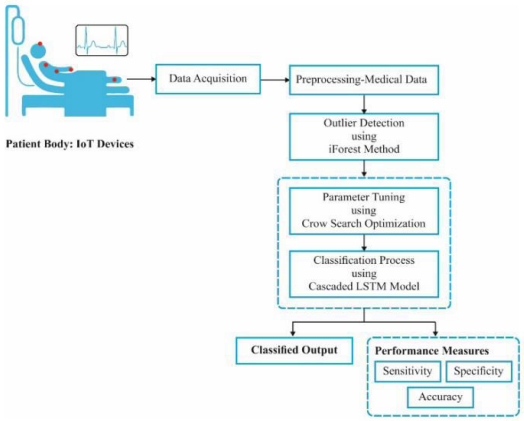

FIGURE 1. Working process of CSO-CLSTM method.

This led to a situation where the developers pretended that the main operations would be carried out on the edge and would fulfil the requirements of the application (data compression, feature extraction well as classification). The results' accuracy was compared to that of pre-existing classification models including regression or classification trees, RF, Naive Bayes (NB), and k-Nearest Neighbors (kNN). As an alternative, the study employed a few algorithms by Azimi et al. [16] to categorize irregularities in ECG signals. IBM designed the Monitor-Analyze-Plan-Execute Plus Knowledge (MAPE-K) mechanism, a variation of the Hierarchical Computing Architecture for Healthcare (HiCH), to distribute the process among the three layers of edge, fog, and cloud. A CNN-based automatic EEG pathology diagnosis model was introduced in the literature [17]. To separately capture temporal and spatial information, it used 1D and 2D convolutions.

4. PROPOSED MODULES AND ALGORITHM PROPOSED SMART HEALTHCARE DIAGNOSIS MODEL

The suggested method has a high degree of freedom of movement for users and is efficient in terms of previous wireless communications. Additionally, this strategy makes use of user-friendly, lightweight, and small IoT devices. Smartwatches, wristbands, and cellphones are a few examples of IoT gadgets.

The implanted sensors are used to carry out complex calculations to calculate and separate normal from abnormal heart rates. Smart devices like cellphones that can be carried around in pockets are installed in the subjects. To gather information on the subject's heart characteristics, implanted ECG and temperature sensors are also highly advised. The outcomes of their typical lifestyle can also be inferred from this data. Smartphones evaluate data received via low-power Bluetooth connectivity and classify it as either healthy or unhealthy. The Android operating system conducts accurate heart rate and diabetes prediction. IoT devices initially collect patient data and preprocess it to convert it into a format that is compatible. A few stages make up pre-processing, including data transformation, format conversions, and class labelling. Then, the iForest approach is used to remove any outliers that are present in the patient data. The CSO-CLSTM model is then used to categorize the data into instances of the disease occurring and instances in which it did not. Smartphones evaluate the data after it is received via low-power Bluetooth connectivity and classify it as either healthy or unhealthy. The Android operating system conducts accurate heart rate and diabetes prediction. IoT devices initially collect patient data and preprocess it to convert it into a format that is compatible. A few stages make up pre-processing, including data transformation, format conversions, and class labelling. Then, the iForest approach is used to remove any outliers that are present in the patient data. The CSO-CLSTM model is then used to categorize the data into instances of the disease occurring and instances in which it did not.

A. iFOREST-BASED OUTLIER REMOVAL PROCESS

iForest, a tree-based outlier prediction approach with linear time complexity and maximum precision, receives the preprocessed medical data. It can be used for extremely large and high-dimensional data sets. Because the anomalies are "mild and diversified," isolation is quite likely. Records in a data-based random tree are clipped before isolation is done. Outlier short length similar records with discernible values frequently result from random division. It is advised to separate sooner in this situation [18]. ITrees make up the iForest (Isolation Tree). A binary tree is a term used to describe every iTree. The following list of steps describes the execution procedure.

i. Select few sample points called subsamples from training data and place them in root node of a tree.

ii. Point the attribute and produce a cutting point ‘p’ from recent node data. At the same time, cutting point is produced from maximum as well as minimum values of certain parameter in recent node data.

iii. A hyperplane is emulated from cutting point. While the data space of recent node is classified into two subspaces namely, data which is minimum than ‘p’ in certain attribute and is placed on left child and the data which is maximum than ‘p’ and is placed on right child of the present node.

iv. Follow steps 2 and 3, till the child node reaches a single record.

Training in the iForest is finished once the iTrees have been completed. Then the created iForest is used to estimate the testing data. A traversal of all iTrees is taken into account while testing records, and the height of each record is calculated. The average height of a record from each tree is then calculated after that. A record is considered an outlier if the average height is below the imposed threshold.

B. DISEASE DIAGNOSIS MODEL USING CSO-LSTM MODEL:

After the removal of outliers in healthcare data, CSO-CLSTM model is applied to perform classification process. RNNs are special standard Artificial Neural Networks (ANNs) using which time series of long-range structural values can be developed. A

fundamental theme of RNNs is the inclusion of time delay unit as well as feedback connection, where the data from former state is applied in upcoming stage. The structure of RNN is comprised of input layer, otherwise called as sequence layer, which applies input as a series of Vectors {x<1>,..,x<z>,..,x<Z>} with features for every time step; Here, network proceeds with a series of hidden activations {a<1>,..,a<z>,…,a<Z>}as well as the resultant vector {Oy<1>,…,Oy<z>,..,Oy<Z>} for Z timesteps. A primary activation 0h0i is allocated as a vector of zeros. Then, both activation as well as final prediction at time z is illustrated as given herewith.

$$a^{<z>} = g\left(W_a \cdot \left[a^{<z-1>}, x^{<z>}\right] + b_a\right) \quad (1)$$

$$\hat{y}^{<z>} = g\left(W_y \cdot a^{\langle z\rangle} + b_y\right) \quad (2)$$

Here, the vector available in square brackets are referred to as a vector combination of activation from existing timestep as well as input from recent timestep, Wa and Wy denote activation as well as output weight matrices correspondingly. Here, ba and by imply activation and output bias terms. Additionally, operator g signifies a generic activation function. RNN feature is a neuron of hidden layer which activates the existing time step for computing an activation of recent time step. Thus, for RNN, the detection of final outcome at recent time step y^<z> is computed with data from input xfizfi. However, using the data from x<z> to x<z−1>, activation a<z> is done at former time step. It is named as unidirectional RNN since it applies data from old sequence inputs to evaluate the prediction at specific time step. Eqs. (1) and (2) imply forward propagation of RNN. During backward propagation, weights and bias are upgraded with the help of optimization method [19]. Hence, it is called Backpropagation Through Time (BPTT). One of the major complexities in training RNN is its diminishing gradient issues. Further, its partial derivatives are smaller in deep layers for maximum time steps. The network parameters, in this case, cannot be changed in consecutive iterations while the learning process gets terminated. The above-mentioned issues are resolved when RNN unit is replaced with gated cell unit named LSTM unit.

LSTM unit shows a modification in remarkable RNN to capture long-term dependencies and it enables to report the problem of diminishing gradient. Therefore, LSTM memory cell is composed of five modules namely, memory cell $c^{<z>}$, candidate value $\tilde{C}^{<z>}$ to replace the memory cell at every timestep and three other gates such as update gate T_u, forget gate T_f and output gate T_0. Memory cell is applied to record specific values for prolonged time during training process. Assume three gates are derived from 0 and 1. Both weight matrix as well as bias term might get upgraded during training process. Finally, forget gate enables the selection of type of data which is thrown away and is represented as shown below.

$$\Gamma_f = \sigma\left(W_f \cdot \left[a^{<z-1>}, x^{<z>}\right] + b_f\right) \quad (3)$$

Here, the update gate decides whether to replace the memory cell with candidate value which is defined herewith.

$$\Gamma_u = \sigma\left(W_u \cdot \left[a^{<z-1>}, x^{<z>}\right] + b_u\right) \quad (4)$$

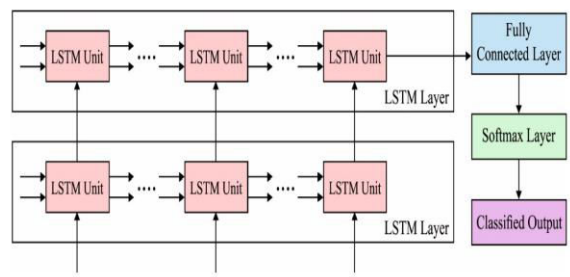

FIGURE 2. The Structure of CLSTM.

Consequently, output gate is a section in which activation at recent time step is produced and demonstrated as follows.

$$\Gamma_0 = \sigma\left(W_0 \cdot \left[a^{<z-1>}, x^{<z>}\right] + b_0\right) \quad (5)$$

In former function, implies the sigmoid function. Hence, the function which is used for monitoring the nature of LSTM unit is depicted as follows:

$$\tilde{C}^{<z>} = \tanh\left(W_c \cdot \left[a^{<z-1>}, x^{<z>}\right] + b_c\right) \quad (6)$$

$$\tilde{C}^{<t>} = \Gamma_u * \tilde{C}^{<z>} + \Gamma_f * \tilde{C}^{<z-1>} (7) \quad (7)$$

$$a^{<z>} = \Gamma_0 * \tanh\left(C^{<z>}\right) \quad (8)$$

where Wc and bc stand for the respective cell weight matrix and bias term. Hadamard product is implied by the function, and hyperbolic tangent function is denoted by tanh. The CLSTM model's structure is depicted in Figure 2.

This method uses a cascade of two RNNs with LSTM units. The core network performs 4-class (W, NI-REM, N2, and N3) classification using input features obtained from the mRMR model (N1 and REM epochs are combined within a single class). The alternative network utilises the PCA-estimated input characteristics. The epochs are then divided into two classes by the RNN and NI-REM epochs (namely, Nl and REM). As a result, RNNs are presented in a model that is similar to this one, where the input layer

is a sequence layer with 30-time steps and the LSTM layers are used, alternatively, or else the characteristics from the input signals are learned. The output size of the preceding layers is then converted into the number of sleep stages for the inspection process using the Fully Connected (FC) layer. The potential of the target class is analysed by the SoftMax layer. One of the main advantages of using the SoftMax activation function is that it can quickly generate the output probability range. The mathematical expression is displayed here.Alternatively, input signal properties are learned. The output size of the preceding layers is then converted into the number of sleep stages for the inspection process using the Fully Connected (FC) layer. The potential of the target class is analysed by the SoftMax layer. One of the main advantages of using the SoftMax activation function is that it can quickly generate the output probability range. The mathematical expression is displayed here.

$$\hat{y}_j^{(i)} = \frac{e^{z_j^{(i)}}}{\sum_{j=1}^{c} e^{z_j^{(i)}}} \tag{9}$$

The superscript i defines a generic training sample, sub-script j implies a generic neuron of ⌟C layer, z defines the final value of FC layer and C means the count of target classes. Hence, cost function is reduced in network training model, where the function of weights, W and bias term b, represent the average of cross entropy functions for C:

$$J(W, b) = -\frac{1}{M} \sum_{i=1}^{M} \sum_{j=1}^{C} y_j^{(i)} \cdot \log\left(\hat{y}_j^{(i)}\right) \tag{10}$$

Here, M defines the count of training sample, y signifies true label and Oy depicts the measure evaluated by the system. The measure of C is allocated as 4 for initial RNN and 2 for secondary RNN. The major difference between these two networks is that the first structure is a single LSTM layer with sequence-to-label manner, whereas secondary RNN has two LSTM layers. The first layer is composed of sequence to- sequence structure while the second one has sequence-to label manner.

C. PARAMETER OPTIMIZATION OF WEIGHTS AND BIASES USING CSO ALGORITHM

In this study, CSO is used to improve the weights and bias parameters of the CLSTM model. Crows are often regarded as a more intellectual species than other birds. It has huge brain size compared to body size and high potentials. According to the brain-to-body idea, humans have a somewhat smaller brain. The vast majority of samples are used to determine the crow's IQ. Crows have been found to have self-experience in mirror tests and to be skilled tool makers, according to a survey. Crows are able to recall faces, and in the event of danger, they can alert other crows. Additionally, it uses technologically advanced instruments to communicate information and memorise hidden food locations. Once the bird exits the nest, it also keeps an eye on other birds and chases them around to find hidden food sources. Crow then locates a secure location to hide the stolen food, keeping the original bird from discovering it. The CSO flowchart is shown in Figure 3. In essence, it chooses a safe method to defend its food and uses information of thieves to predict thieves' actions [20]. Few standards of crows are given herewith.

- It resides in group
- It is capable of remembering the location of food stored in secret places.
- It follows one by one to grab the food.
- It protects their food from being robbed.

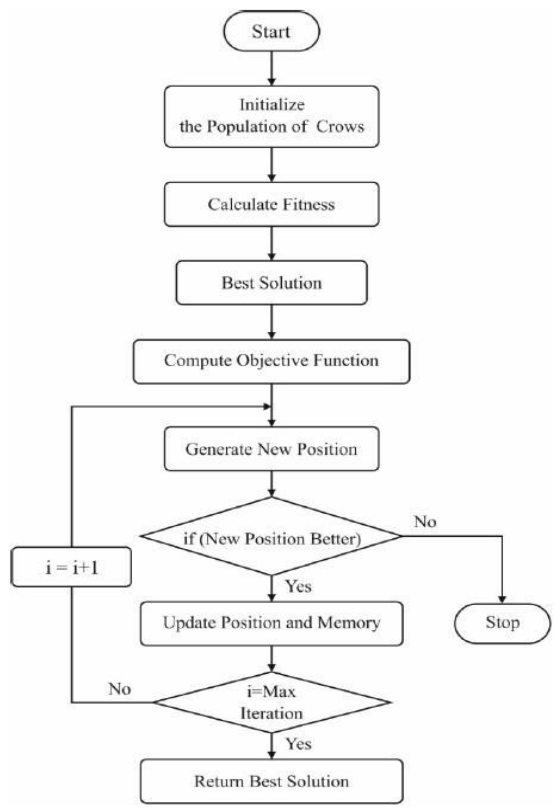

FIGURE 3. Flowchart of CSO algorithm.

Followed by, there are N-dimensional platforms which are composed of massive crows, where C denotes the overall count of crows and u defines the position of a crow at time in a Search Space (SS). This has been evaluated in the function given below.

$$V^{u,\text{iter}}\ (p = 1, 2, \ldots, C;\ \text{iter} = 1, 2, \ldots,)\ \text{iter}_{max} \quad (11)$$

where $V^{u,\text{iter}} = \left[V_1^{u,\text{iter}}, V_2^{u,\text{iter}}, \ldots, V_c^{u,\text{iter}}\right]$ and iter_{max} resemble the iterations with higher count. A crow is applicable to remember the place of secret location. At this point, the location of secret place of crow u is implied as $s^{u,\ \text{iter}}$. It is a better location which the crow u has accomplished. Assume the iteration in which the crow v requires to be placed in secret location, $s^{v,\ \text{iter.}}$ At this point, crow u plans to chase crow v to the secret place. Here, two processes are carried out as given herewith.

Event 1: Crow v has no suggestions about which crow u is chasing. Thus, in the outcome, crow u reaches the secret position of crow, v. Then, the new location of crow u is developed as given herewith.

$$V^{u,\text{iter}+1} = V^{u,\text{iter}} + k_j \times fll^{u,\text{iter}} \times \left(S^{v,\text{iter}} - V^{u,\text{iter}}\right) \quad (12)$$

where, k_j implies a random value with uniform distribution between 0 and 1, and $fll^{u;\text{iter}}$ refers to the fight length of crow, u. The lower value of fll tends to have local search whereas higher values result in global search.

Event 2: Crow v understands that crow u is tracking it. Finally, the theft is prevented and crow v deceives crow u by changing its actual position to alternate position of SS.

Therefore, events 1 and 2 are illustrated as follows

$$V^{u,\text{iter}+1} = \begin{cases} V^{u,\text{iter}} + k_j \times fll^{u,\text{iter}} \times \left(S^{v,\text{iter}} - V^{u,\text{iter}}\right) k_j \\ \quad \geq AWP^{v,iter} \\ a\ random\ location\ other\ \text{wise} \end{cases} \quad (13)$$

where $AWP^{v;\text{iter}}$ implies the awareness of crow v at iteration.

5. RESULT

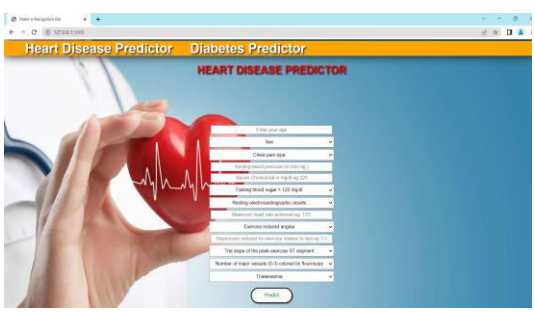

Fig 4. Home Page

Fig 5. Data Page

Fig 6. Sample Data Page

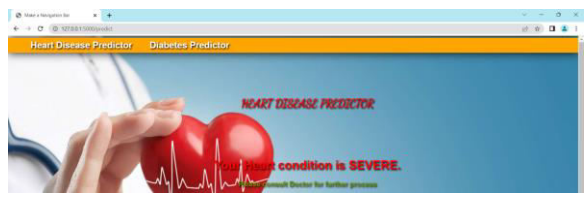

Fig 7. Results Page

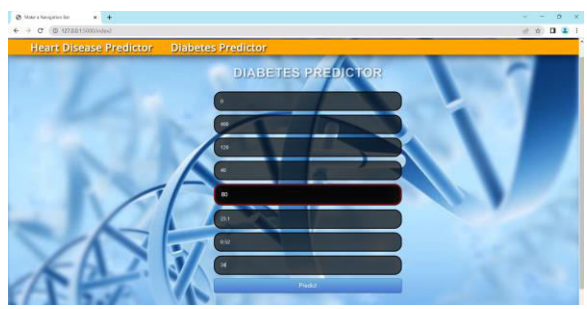

Fig 8. Output Page

6. CONCLUSION AND FUTURE ENHANCEMENT

The current research work has developed an efficient AI and IoT convergence-based disease diagnosis model for smart healthcare system. The presented model encompasses different stages namely data acquisition, preprocessing, classification, and parameter tuning. IoT devices such as wearables and sensors collect the data while AI techniques utilize the data to perform disease diagnosis. Then, iForest technique is executed to get rid of outliers that exist in the patient data. Followed by, the CSO-CLSTM model is employed to classify the data whether the

disease exists or not. In addition, CSO is applied to optimize the weights and bias parameters of the CLSTM model. The utilization of CSO assists in the improvement of diagnostic outcome of CLSTM model. The performance of CSO-LSTM model was validated using healthcare data. During the experimentation, the CSO-LSTM model accomplished a maximum accuracy of 96.16% and 97.26% on heart disease and diabetes diagnoses respectively. This establishes the effectiveness of the presented model. As a part of future scope, the performance can be improved using feature selection techniques which reduce the curse of dimensionality and computational complexity. In addition, the limitations of CSO algorithm such as slow search precision and high possibility of getting into local optima can be resolved with the help of hybrid metaheuristic algorithms.

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