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Disease Diagnosis Model for Smart Healthcare Systems Using Artificial Intelligence and the Internet of Things

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Abstract

The Internet of Things (IoT), cloud services, and artificial intelligence (AI) have all improved in recent years, converting traditional medical into smart healthcare. The application of important technologies such as AI and IoT to healthcare treatments could improve outcomes. The combination of IoT and AI in the medical industry opens up a world of possibilities. As a result, the current study suggests a new AI- and IoT-based disease detection paradigm for smart medical systems. The model includes phases such as preprocessing, data collection, parameterization, and categorization. IoT devices, such as wearables and detectors, allow for real-time data collecting, which AI systems then use to identify ailments. For illness detection, the suggested method employs a Crow Search Optimization algorithm-based Cascaded Long Short Term Memory (CSO-CLSTM) model. CSO is used to alter the CLSTM model's 'weights' and 'bias' variables to enhance the categorization of health data. This study also employs the isolation Forest (iForest) approach to reduce outliers. The CLSTM model's diagnostic outcomes are greatly improved when CSO is used. The CSO-LSTM model was put to the test using healthcare data. During the testing, the CSO-LSTM model identified diabetes and heart disease with the highest accuracies of 96.16 percent and 97.26 percent, etc. As a result, the suggested CSO-LSTM model can be used in smart health systems as a diagnostic tool.

Keywords: artificial intelligence, cloud computing, convergence, disease diagnosis. Internet of Things, smart healthcare,

I. INTRODUCTION

The Internet of Things (IoT) is the expansion of existing internet services. It refers to the web of physical items and stuff that exists in today's world. APIs, sensors, mobile phones, and actuators are all used in IoT to connect and share data via the internet. [1-3] It allows you to connect all of your devices to the internet, as well as other linked devices. Things will be identified automatically and will be able to speak with one another on their own.

Indeed, the IoT's power has a significant impact on different elements of daily life as well as the behavior of potential users. [4] The global IoT industry is predicted to hit $1 billion by 2017, according to the study report. It refers to a rapid expansion in the amount and variety of data available. [5-7] It can now accomplish activities that previously required human intelligence. Context-aware, Embedded, Personalized, and Anticipatory are all features of AI. In the future, IoT and AI will be critical in a variety of ways. [8-9] It primarily necessitates the implementation of industries, governments, scientists, engineers, and technicians in a variety of situations. When IoT and AI are merged in servers, the potential benefits and capabilities of both can be realized. [10] For example, AI can be used in conjunction with machine learning to analyze data and predict future actions such as equipment malfunction in the industry and marketing order substitutions. Additionally, AI can employ machine learning to enhance smart home performance. AI technologies with IoT can most likely be utilized to identify human behavior using sensors and Bluetooth signals, and then make the appropriate lighting and environment modifications.

The Internet of Things has been used to gather vast amounts of data, which is then processed by Artificial Intelligence systems. Fortunately, the Internet of Things (IoT) provides an interface for receiving data created by numerous means and incorporating it into AI systems. [11-12] There are a variety of uses, and the health sector has a lot of data. Medical equipment, fitness bands, and healthcare applications are all gathering and producing massive volumes of data in this industry. The AI and IoT techniques aid in disease prediction and maintenance recommendations. Hospitals and patients could gain from AI and IoT technologies when it comes to illness control and health protection.

In the healthcare sector, the IoT adds financial benefits and improves patient outcomes. There are unequaled benefits associated with the application of this technology in medicine, which could improve the efficiency and efficacy of therapy while also improving the patient's health. The advantages are as follows:

1. tracking and surveillance in real time
2. End-to-end communication
3. Data collection and analysis
4. Alerts and tracking
5. Medical help from afar

[13] I was able to explain the different IoT technologies. This paper, often known as the IoHT, describes a variety of IoT strategies for ambient supported living and healthcare (IoHT). This project highlighted technology advancements and analyzed the obstacles that must be overcome. It also looked at information sources for medical professionals, healthcare providers, and those who are interested in the Internet of Things. This research lacks a thorough understanding of core themes, structures, and IoT platforms.

[14] Described the smart health care network based on 5G. Healthcare is widely used and incorporates a variety of smart health care apps in the existing 4G network. It started with a 5G smart healthcare design and a variety of approaches like small cells, D2D connectivity, SDN, and edge computing. The categorization of 5G smart healthcare is then described. New criteria were developed, like wide throughput, ULL, and UHR. Finally, it defines physical network methods for IoT-based 5G smart healthcare, such as routing, traffic control, and timing.

It describes the framework for smart healthcare monitoring. The key problem in the current system was handling the millions of data provided by IoT. By handling the middle part between IoT devices and cloud computing, edge computing delivers the solution. This research proposes new Edge of Things services for secure operations and efficient health monitoring. It demonstrated how fully homomorphic encryption is used in the IoT architecture to protect data privacy. The suggested methodology looked at processing time, encrypted data speed, and data protection. The problem is that it does not explain modern homomorphic computing data mining approaches.

[15] IoT in huge healthcare data was described. The use of IoT in the medical field is the focus of this study. Based on data collecting, this work compiled a descriptive analysis. According to the poll, the importance of environmental preservation in the healthcare industry is 23.63 percent when it comes to developing the Internet of Things. It uses the FOG computing architecture to enable a variety of applications. FOG is the most advanced cloud computing platform for dealing with IoT platform challenges. With health-monitoring platforms, the Internet of Things enables new applications.

II. PROPOSED MODEL

2.1. A model for smart healthcare diagnosis

Figure 1 illustrates the entire working procedure. In terms of past wireless communications, the proposed approach is successful, and it uses less power while allowing users to move freely. Furthermore, this technique makes use of compact and light IoT devices that are user-friendly. Bracelets, smartphones, smartwatches, and other Internet-of-Things devices are just a few examples.

The implanted sensors are used to assess and distinguish between healthy and sick cardiac rhythms by performing sophisticated computations. Smart devices, like cell phones, are available to the subjects and can be carried in their pockets. In addition, for gathering data on the subject's heart parameters, implanted ECG and temperature monitoring are strongly advised. This information can be used to deduce the outcomes of their similar lifestyles.

Smartphones process received data via low-power Bluetooth connectivity and categorize it as either unhealthy or healthy. The Android system is capable of detecting diabetes and calculating an accurate heart rate. IoT devices collect client information and pre - process it before converting it to a format that other devices can understand. Data translation, format converters, and class labeling are some of the processes of pre-processing. Any outliers discovered in the patient data are subsequently removed using the iForest method. The CSO-CLSTM model is then used to categorize data into two categories: non-existence of sickness and existence of illness.

2.2. Outlier elimination based on iForest

It's ideal for data with a lot of dimensions and a lot of volumes. It is sensitive to isolation since the abnormalities are 'low and unexpected.' The records are pruned until separation is attained in the case of a data-based random tree. Outlier short and long data with recognised values are more likely to emerge from a random split. This is suggested that you split into the first division. iTrees make up the iForest (Isolation Tree). A binary tree is a name given to every iTree.

2.3. AI based IoT in healthcare

IoT considers the interconnection of numerous devices, monitors, and other services; it does not include direct communication, such as that provided by phones or computers. explains how to leverage IoT in smart healthcare in a variety of ways. It was once used to communicate between gadgets. However, in medical, m-health and e-health cannot still use smartphone sensors to communicate health-related data. Two additions are made in this study. To begin, it assesses the existing literature in conjunction with numerous elements to deploy IoT in the healthcare industry. Second, for patients' e-health, they presented the k-healthcare concept. The network layer, sensing layer, internet layer, and service layer are the four layers used in the suggested method. All of these layers worked together to create a new framework for obtaining a patient's health-related data via mobile devices.

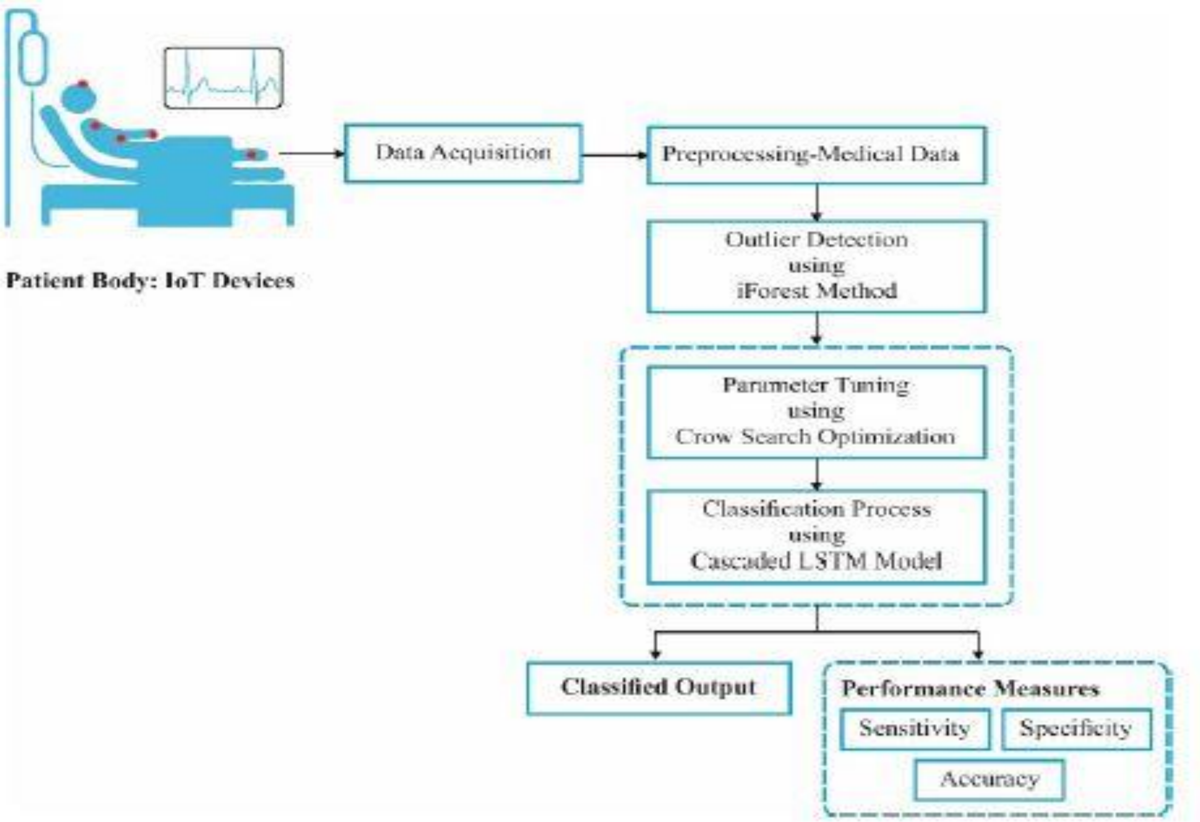

Fig. 1. *The CSO-CLSTM approach*

2.4. Model for disease diagnosis based on the CSO-LSTM model

After outliers have been removed from health records, the CSO-CLSTM model is utilised to categorise the data. RNNs are a sort of artificial neural network (ANN) that may be used to generate long-term architectural values in the form of time series. The addition of a time delay unit as well as a feedback connection, where data from the previous state is used in the next phase, is a key feature of RNNs. The input layer, also known as the sequence layer, receives data in the form of a vector of features with properties for each time step and the resulting vector for Z timesteps. A vector of zeros is assigned to the principal activation 0h0i.

$$a^{<Z>} = g\left(W_a \cdot \left[a^{<Z-1>}, x^{<Z>}\right] + b_a\right)$$
$$\hat{y}^{<Z>} = g\left(W_y \cdot a^{\langle z\rangle} + b_y\right)$$

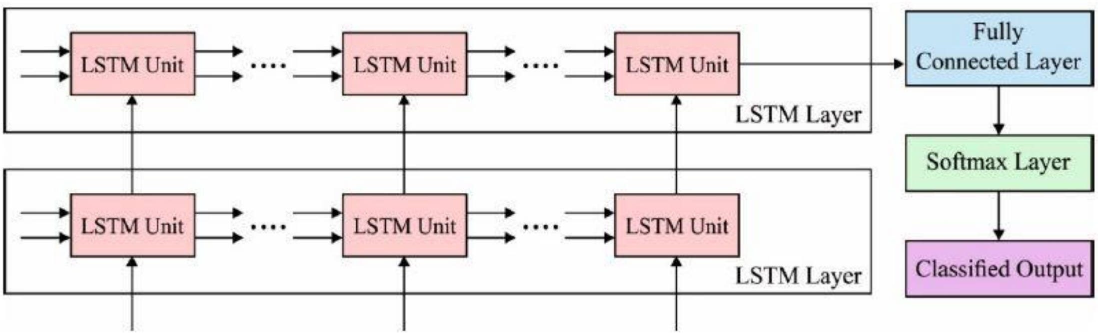

Fig. 2. *CLSTM Structure.*

2.5. The CSO algorithm optimizes the weights and biases of the parameters.

The CLSTM model's weights and bias variables are optimized using CSO in this study. In comparison to other bird species, crows are thought to be intelligent. A huge number of samples are used to estimate crow intelligence. In addition, once it leaves the nest, the bird keeps an eye on other birds and chases them to a secret food source. The crow then seeks a secure area to store the stolen food so that the actual bird is unaware of its presence. Figure 3 depicts CSO's _ow chart. Essentially, it employs a thief's knowledge to anticipate a thief's behaviors and choose a safe method of safeguarding its food.

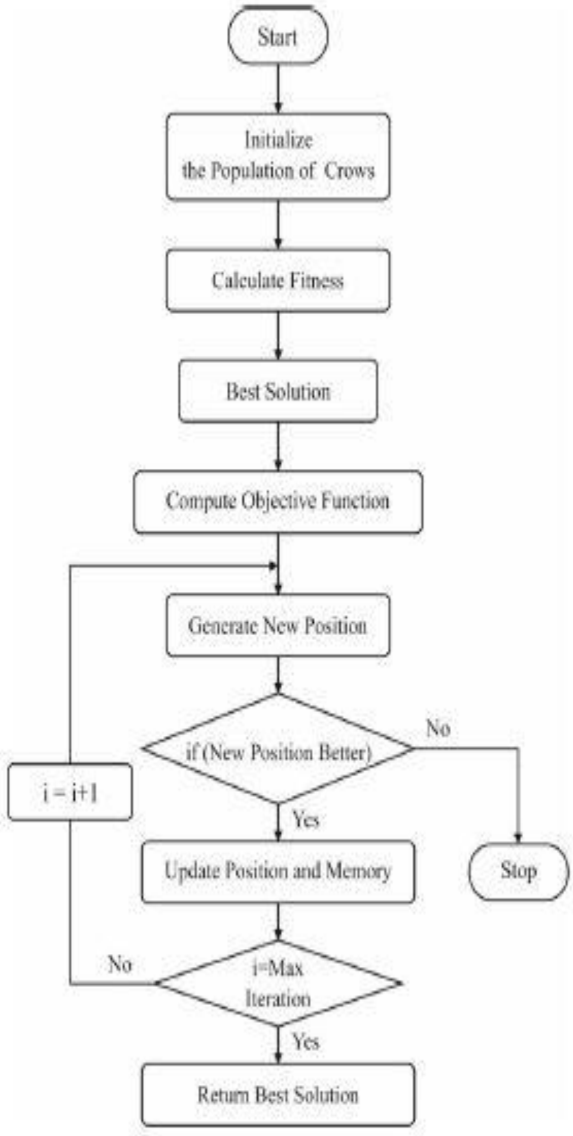

Fig 3. *CSO algorithm flowchart.*

III. VALIDATION THROUGH EXPERIMENTATION

This part authenticates the efficacy of the presented CSOCLSTM system in terms of specificity, accuracy, and sensitivity. Furthermore, the findings are validated using data from diabetes and heart disease cases of varied sizes. The given model was built with an MSI Z370 A-Pro motherboard, an i5-8600k processor, a GeForce 1050Ti 4GB graphics card, 16GB of RAM, and a 1TB HDD for file storage.

3.1. The outcome of a heart disease diagnosis

Table 1 illustrates the CSO-CLSTM model's classification result and relates it to current classifiers on a heart disease dataset using several measures. The SVM model performed poorly in terms of sensitivity when compared to other techniques. In addition, the NB-A model aimed for a somewhat high specificity than the SVM model. The offered CSO-CLSTM model, on the other hand, surpassed the others by reaching a higher sensitivity value. Under 10,000 occurrences, the recommended CSO-CLSTM methodology had a sensitivity of 98 percent, whereas the NB-A, J4, KNN, and SVM methods had sensitivity values of 94.23 percent, 90.23 percent, 85.23 percent, and 94.23 percent, respectively.

The SVM technique fared worse than conventional models, according to the results of the specificity analysis. Furthermore, in terms of specificity, the NB-A method outperformed SVM.

Table 1. *Effectiveness of existing and suggested methods of a heart illness data*

Sensitivity (%)					
Number of Instances	KNN	NB-A	SVM	J48	CSO-CLSTM
2000	92.60	87.90	83.20	93.30	94.80
4000	88.40	84.60	82.40	92.30	95.20
6000	93.20	86.40	83.90	93.60	96.30
8000	92.40	88.60	82.40	96.90	97.60
10000	93.60	89.10	84.20	96.00	98.00
Specificity (%)					
Number of Instances	KNN	NB-A	SVM	J48	CSO-CLSTM
2000	84.20	83.40	80.20	92.60	94.70
4000	86.10	83.60	82.10	91.20	96.80
6000	87.30	86.90	83.40	92.40	95.00
8000	88.30	82.10	78.40	88.60	91.20
10000	89.30	86.40	84.30	90.40	93.80

Accuracy (%)					
Number of Instances	KNN	NB-A	SVM	J48	CSO-CLSTM
2000	89.40	76.80	73.40	91.60	95.10
4000	91.30	78.60	77.70	92.40	95.90
6000	87.60	77.80	75.60	90.40	95.30
8000	86.40	80.10	78.40	93.20	97.10
10000	89.30	82.40	81.60	92.80	97.40

In comparison to other previous methodologies, the SVM framework fared poorly, according to the accuracy investigation. Furthermore, in terms of accuracy, the NB-A method outperformed SVM. Both the KNN and J48 techniques generated better and modest precision at the same time. As a result, by reaching the greatest accuracy value, the proposed CSO-CLSTM approach was able to achieve heavy categorization. Fig. 4 and Table 2 demonstrate the results of the CSO-CLSTM model's average classification evaluation on the relevant heart disease data.

Table 2. *effectiveness of existing and suggested CSO-CLSTM methods of a heart disease database*

Measures	KNN	NB-A	SVM	J48	CSO-CLSTM
Sensitivity	92.04	87.32	83.22	94.42	96.38
Specificity	87.04	84.48	81.68	91.04	94.30
Accuracy	88.80	79.14	77.34	92.08	96.16

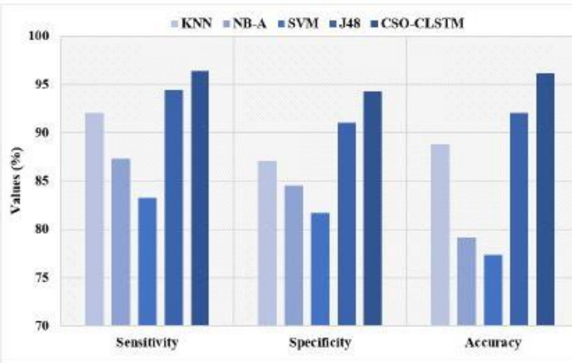

Fig. 4. *The average classifier analysis on the heart disease dataset yielded the following results.*

3.2. Findings from a diabetic dataset

Table 3 compares the CSO-CLSTM model's classification results on the diabetes disease database to current classifiers for key parameters. The CSO-CLSTM model, on the other hand, had a greater sensitivity value and performed better in terms of categorization. Under 2000 cases, the CSO-CLSTM model had the greater sensitivity of 97.34 percent, while the SVM, NB-A, FNCA, KNN, and J48 models had the lowest sensitivity of 93, 89.32, 84, 92, and 95.78 percent.

Table 3. *Effectiveness of present and suggested methods on a diabetes disease database.*

Sensitivity (%)						
Number of Instances	KNN	NB-A	SVM	J48	FNCA	CSO-CLSTM
2000	92.00	87.50	83.00	93.00	94.50	98.10
4000	88.00	86.00	82.50	92.00	93.50	97.50
6000	92.80	88.00	83.80	93.00	94.50	98.90
8000	93.50	88.00	83.00	97.00	98.00	99.40
10000	94.20	90.00	83.40	96.00	97.00	99.20
Specificity (%)						
Number of Instances	KNN	NB-A	SVM	J48	FNCA	CSO-CLSTM
2000	84.00	83.00	82.00	92.50	94.00	98.80
4000	90.00	83.00	83.00	91.00	94.20	97.50
6000	87.00	86.00	83.00	93.00	94.10	96.90
8000	87.50	85.00	80.00	88.00	90.00	94.20
10000	90.00	87.00	84.00	90.50	92.00	97.30
Accuracy (%)						
Number of Instances	KNN	NB-A	SVM	J48	FNCA	CSO-CLSTM
2000	89.00	77.00	74.00	92.00	93.00	95.70
4000	91.00	81.00	76.00	94.00	94.00	97.80
6000	87.00	76.00	75.00	90.00	91.00	96.10
8000	88.00	82.00	78.00	93.50	94.50	98.90
10000	90.00	83.00	80.00	92.50	94.00	97.80

Table 4 and Fig. 5 illustrate the mean grouping result of the CSO-CLSTM approach on the diabetes data. The CSO-CLSTM model appears to be beneficial in function, as it attained maximum accuracy values of 97.56 percent and 98.65 percent on diabetes and heart disease diagnoses, respectively, during the experiment, based on the above-mentioned tables and figures.

***Table 4** Mean efficiency analysis of proposed and existing CSO-CLSTM methods On a diabetes disease database,*

Measures	KNN	NB-A	SVM	J48	FNCA	CSO-CLSTM
Sensitivity	92.10	87.90	83.14	94.20	95.50	98.62
Specificity	87.70	84.80	82.40	91.00	92.86	96.94
Accuracy	89.00	79.80	76.60	92.40	93.30	97.26

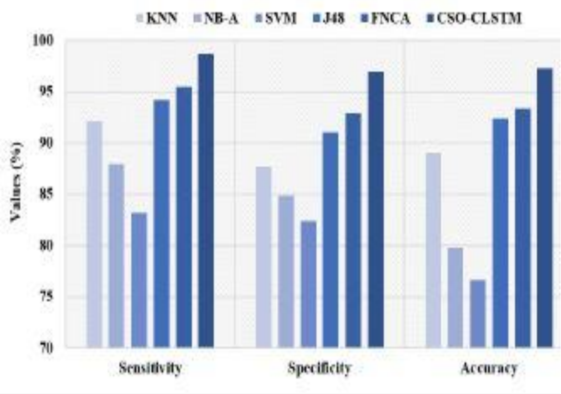

***Fig 5.** Analysis of the mean classifier outcomes on the Diabetes data.*

IV. CONCLUSION

Existing research has resulted in a disease detection model for a smart health service that is dependent on IoT and AI integration. Data collection, preprocessing, categorization, and variable adjustment are all stages in the model. Wearables and monitors are examples of IoT devices that collect data, which are subsequently used by AI techniques to diagnose diseases. After that, the iForest method is utilized to eliminate any outliers from the patient data. The CSO-LSTM system was put to the test using healthcare data. This demonstrates that the proposed paradigm is effective. Using feature selection strategies that reduce data dimensionality and processing complexity, efficiency can be enhanced in the future.

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