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Artificial intelligence and Internet of Things for sustainable healthcare system

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Abstract: Recent developments in the Internet of Things (IoT), cloud computing, and artificial intelligence (AI) have transformed traditional healthcare systems into intelligent healthcare. Medical services can be improved by incorporating key technologies such as IoT and AI. The fusion of IoT and AI opens up new possibilities for healthcare. From this perspective, the current article presents a new AI and IoT convergence-based disease diagnostic model for intelligent healthcare systems. The main purpose of this article is to use AI and IoT convergence technologies to create disease diagnostic models for heart disease and diabetes. The model presented has several phases, including data collection.

1 Introduction

In recent years, the healthcare sector has begun to use information technology to develop modern applications and improve diagnostic procedures and treatments. Advanced technology and scientific theory are the main entities that generate vast amounts of digital data. Advanced clinical applications are the idea of recently developed information technology. In addition, advanced health care is expected to be a simple and elegant multitasking application.

These changes are incorporated as clinical model extensions (from disease-based to patient-based care), informatization development changes (from medical data to regional medical data), clinical management extension (general management to personal management), and prevention and treatment modifications (shifting of focus from disease treatment to preventive medical system). As a result, the following changes focus on meeting the basic needs of individuals to improve their health literacy. This will improve your knowledge of healthcare services and suggest future uses of intelligent healthcare. Physicians, patients, clinical and research institutes, and other stakeholders embrace advanced medical services. Multiple aspects such as disease prevention and monitoring, prognosis and treatment, clinical management, health decision making, and medical research need to be considered. Mobile internet, cloud computing (CC), big data, 5G systems, microelectronics and artificial intelligence (AI), and smart biotechnology are considered modern healthcare milestones. These methodologies are used at all stages of advanced healthcare. Wearable or portable devices, from the perspective of patients, can be used to monitor their health condition as needed. They can seek clinical advice via virtual support and remotely control their homes via remote facilities. Smart clinical decision support systems, in the opinion of doctors, can be used to guide and improve diagnostic procedures. An extensive diffusion and deployment of effectively integrated hardware and modern medical sensors for one-of-a-kind healthcare has aimed to create a new concept known as the Internet of Medical Things (IoMT). It changes the healthcare process and the number of medical devices that use IoT in order to increase profits in the future.

The data collected using portable, ingestible, and integrated sensors, mobile patterns, and device usage patterns allow the researcher to track a user's habits. With additional data collection, it is possible to reveal their medical status using cutting-edge methods such as Machine Learning (ML) or Deep Learning (DL). Traditional cloud technology, which is based on structures for big data analysis, is used to provide optimal performance, scalability, and support for non- safety and delay-based IoT domains. However, if a patient is seriously ill with limited resources and requires a high level of efficiency and accessibility, disconnection from the main network or latency difference may have a dramatic negative effect and result in dreadful consequences in emergency situations.

The rapid development of structures that investigate the collaboration of cloud, fog, and edge computing is still a difficult process. This method's main goal is to use complete edge nodes and low-level fog nodes to manage functional tasks such as data processing, examination, correlation, and inference. As a result, the aforementioned approaches produce difficult outcomes by implementing scalable medical domain services.

This occurs because the smart mapping of processing and resource management operations outperforms the nodes in order to meet the fundamental needs of the IoMT model. Both diagnosis and disease treatment are highly robust when Artificial Intelligence (AI) models, surgical devices, and mixed reality applications are used. Specific outcomes from Clinical Decision Support System (CDSS) are obtained by using AI, such as the diagnosis of hepatitis, lung tumour, and skin cancer. Furthermore, the accuracy of AI diagnosis has surpassed that of manual diagnosis.ML-based models outperform well-trained physicians, particularly pathologists and imaging experts.

As a result, IBM's Watson released a remarkable and representative product in CDSS. This product has an effective cognitive mechanism and is used to provide the best solution by analysing medical and literature details in depth. As a result, healthcare professionals have seen a significant improvement in diagnosing diabetes and cancer. The use of CDSS is highly efficient, assisting physicians in improving diagnostic processes, reducing the incidence of unexploited diagnoses and misdiagnosis, and allowing users to receive timely and appropriate medical treatment. The patient's health status and disease are determined by smart diagnosis.

Current research presents new AI and IoT-based disease diagnostic models for intelligent healthcare systems. The goal is to use AI and IoT convergence technologies to create disease diagnostic models for diabetes and heart disease. The presented model contains several phases such as data acquisition, preprocessing, classification, and parameter adjustment. IoT devices such as wearables and sensors collect data and process it with AI technology to diagnose illness. For disease diagnosis, the proposed AI and IoT convergence methods use a crow search optimization algorithm-based cascade long short-term memory (CSO-CLSTM) model.

In addition, this study uses isolated forest (iForest) techniques to remove outliers. CSOs are used to adjust the Weight and Bias parameters of the CLSTM model to improve diagnostic results. In this case, the CSO is used to improve the diagnostic results of the CLSTM method.

The effectiveness of the CSO-LSTM model was validated using health data. This research article focuses on the following content on the design and development of new AI and IoT-based disease diagnostic models for smart healthcare systems: Proposal of CSO-CLSTM model for diagnosing diabetes and heart disease. Integration of outlier detection processes based on iForest tchnology to improve classification results. Use the CSO algorithm to perform parameter adjustments on the LSTM model. Verification of CSO-LSTM model performance against two benchmark datasets.

2 Research outcome

Several studies have been conducted in the past to develop a system that senses physiological variables and health indicators in order to assess severe cases and accidents. Mustlag et al. first used a Wireless Body Sensor Network (WBSN) to monitor the heart rate and movement of AI and IoT Enabled Disease Diagnosis Model for Smart Healthcare Systems users whenever they needed it, even from remote locations. In this study, an edge node is linked to the internet and sends a notification (via mobile phone) to family members whenever significant changes occur (early prediction of falls, tachycardia, or bradycardia). In line with this, Villarrubia et al. proposed a method to monitor patients' heart rates from home by computing fundamental electrocardiogram (ECG) information.

An emotion-aware connected healthcare model was developed in the literature using an efficient emotion detection module. In this study, a variety of IoT devices were used to capture speech and image signals from a patient in smart homes. Kaur and Jasuja investigated the use of the Bluemix cloud method to record physiological data and enable remote access by physicians. Simulation results are visualized and processed in relation to the IBM Watson IoT environment. Alwan and Rao conducted a case study of fever analysis using an integrated system that regularly monitors patient health data. Satija et al. We proposed real-time IoT-based ECG telemetry.

Researchers have announced the efficiency of the model based on various activities of this work. Static monitoring eliminates the need to use domain sensors to collect contextual data and run multimodal processes. Pham et al. then presented a model in which ecological sensors, Opti track cameras, and smartwatch-based sensors are used to collect video, image, and audio signals with specific wearables for physiological variable collection. In the literature, a novel smart healthcare model was proposed that included a pathology detection technique based on deep learning.

The pathogen can be identified from the patient's EEG signal. In this model, the smart EEG headset captures the EEG signal and sends it to the mobile edge computing server. The signal is preprocessed by the server before it is sent to the cloud server. Uddin studies various human activities using wearable sensors and Long Short-Term Memory-Recurrent Neural Networks (LSTM-RNNs) implemented on local GPU-accelerated fog servers. I proposed a solution. In a previous study, additional sensors were used to investigate the application of support vector machine (SVM) and random forest (RF) classifications for tracking and predicting movement. Several models recently developed to analyze the physiological data of wearable sensors simulate the analysis of the edge ML approach. However, there are problems predicting abnormalities in the physiological variables associated with edgestream computing structures. Hierarchical time memory (HTM) was widely implemented in this study. The model was built on edge nodes and used for inference. Queralta et al. also proposed a fall prediction solution based on the LSTM RNN method, which is executed at the edge level. The Multi Access Edge Computing method's performance was defined, along with a case study on Electroencephalography (EEG) data.

This resulted in a scenario in which the developers assumed that the major functions would be executed from the edge side to meet the needs of the application (data compression, feature extraction, and classification). The results were compared to existing classification models such as RF, Naive Bayes (NB), k-Nearest Neighbors (kNN), and classification or regression trees. Alternatively, the study used a few models to classify anomalies in ECG signals, as mentioned by Azimi et al.

IBM introduced the Hierarchical Computing Architecture for Healthcare (HiCH) and its variant, the Monitor-Analyze-Plan-Execute Plus Knowledge (MAPE-K) mechanism, to share the process among three layers called edge, fog, and cloud. A CNN-based automatic EEG pathology detection model was presented in the literature. It captured temporal and spatial information separately using 1D and 2D convolutions.

3 Proposed smart healthcare diagnostic model:

The proposed approach is effective in terms of previous wireless communications, consumes very little power and gives the user a high degree of freedom of movement in the outside world. In addition, this model uses a small and lightweight IoT device, which makes it easy to use. Examples include smartphones, bracelets, smartwatches and other IoT devices. Embedded sensors are used to perform complex calculations to estimate and distinguish between normal and abnormal heart rates. The subject has a smart device, such as a smartphone, that can be carried in your pocket. In addition, embedded ECG and temperature sensors are highly recommended to collect data on the subject's cardiac parameters.

The results of their shared lifestyle can also be derived from this data. When data is received via low-power Bluetooth communication, the smartphone processes the data and classifies it as a healthy or unhealthy AI and IoT-enabled disease diagnostic model for smart healthcare systems.

Diabetes and heart rate efficiency is predicted by the Android platform. First, the IoT device collects patient data and preprocesses it into a compatible format. Preprocessing consists of several phases, such as data conversion, format conversion, and class labeling. Then use the iForest technique to remove outliers from the patient data. The CSO-CLSTM model is then used to classify the data into the presence and absence of disease.

4 Outler removal processes using I Frost based technology

Preprocessed medical data passes through iForest, a tree-based outlier prediction technique with linear time complexity and maximum accuracy. It can process a huge amount of data at a high level.

The anomaly is "low and diverse" and therefore very vulnerable to quarantine. For database random trees, records are truncated until isolation occurs. Outliers for records of the same short length with identifiable values are more likely to result from random splits. In this case, it is advisable to split into the previous split. iForest consists of iTree (isolated tree). Each iTree is called a binary tree. The following are the steps related to the execution process.

i.) Few sample points from the training data were placed in the root node of a tree.

ii.) Attribute was selected and a cutting point 'p' generated using recent node data. Simultaneously, a cutting point was generated from the maximum and minimum values of certain parameters in recent node data.

iii.) From the cutting point, a hyperplane is emulated. While the data space of the most recent node was divided into two subspaces, the data that was less than 'p' in certain attributes were placed on the left child and the data that was greater than 'p' were placed on the right child of the current node.

iv.) Steps 2 and 3 were repeated until the child node had only one record.

When iTree is ready, iForest training is complete. The generated iForest is then used to estimate the test data. When testing datasets, traversal of all iTrees is taken into account to determine the height of each dataset. Then the average height of the records from each tree is determined. If the average height is below the applied threshold, the dataset is considered an outlier.

5 CSO Alogorithm based optimization of weight and basis

In this study, we use CSOs to optimize the weights and bias parameters of the CLSTM model. Crows are widely considered to be an intelligent species compared to other birds. The potential is high

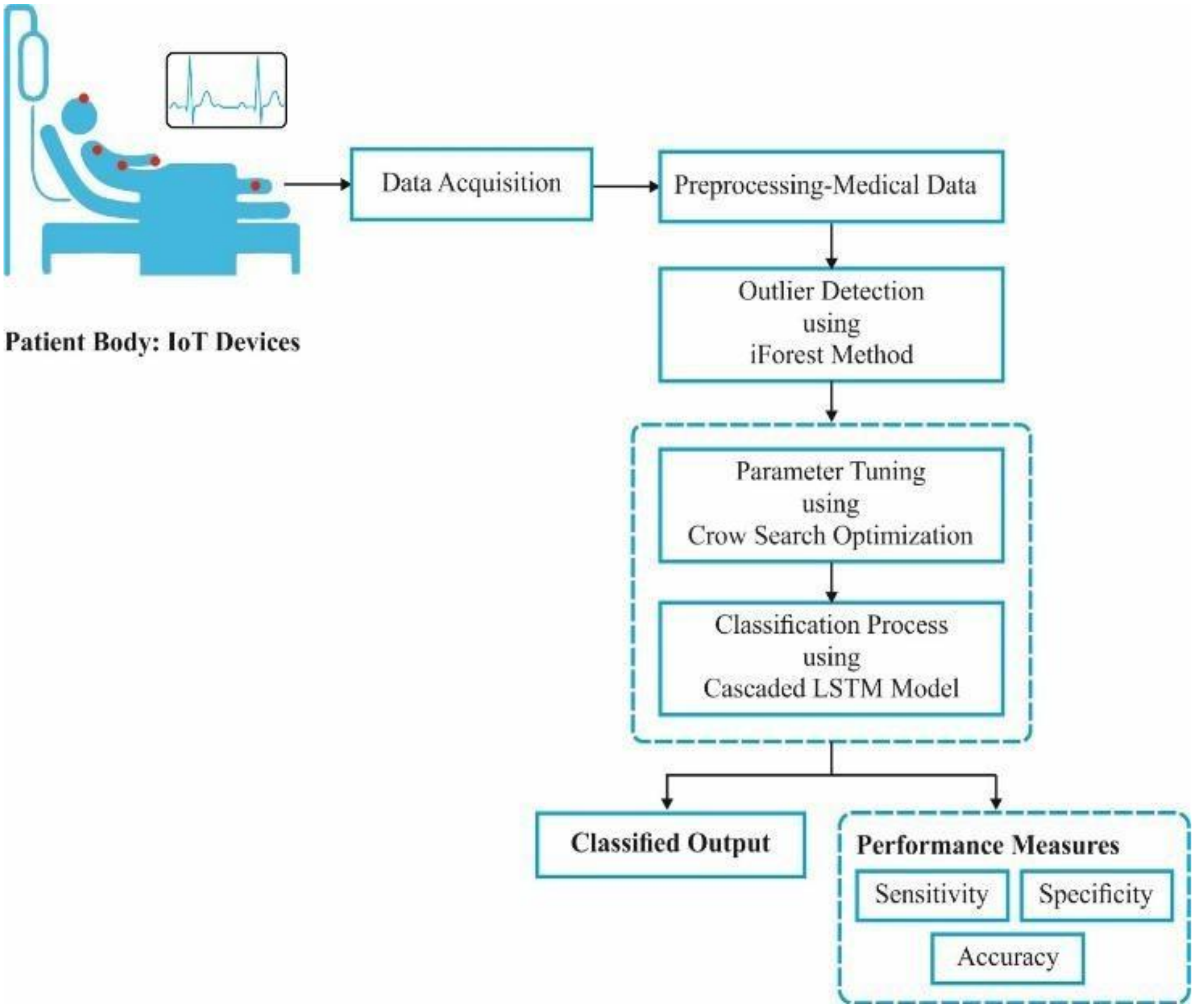

Fig. 1 Working of CSO-CLSTM method.

compared to the size of the body, and the brain is also large. According to the theory from the brain to the body, the human brain is slightly smaller. Crow intelligence is determined by a large number of samples.

Studies show that crows are self-aware in mirror tests and are good at creating tools. Crows can remember their faces and send warning signals to other crows when they are at risk.

We also use sophisticated tools to share details and remember the secret places of food. In addition, as birds leave their nests, they monitor other birds and chase them to find and grab secret places of food. The crow then finds a safe place to store the stolen food, preventing real birds from finding it. Figure 1 shows the CSO flow chart. Basically, it uses the thief's knowledge to predict the thief's behavior and choose safe ways to protect its food. A few crow standards are provided below.

- It is a member of the group
- It can recall the location of food stored in secret locations.
- It follows them one at a time to grab the food;
- It protects their food from being robbed.

Then there are N-dimensional platforms made up of massive crows, where C denotes the total number of crows and u denotes a crow's position in a Search Space at any given time (SS).

6 Design for Treatment and diagnosis

Following the removal of outliers from healthcare data, the CSO-CLSTM model is used to perform the classification process. RNNs are special standard Artificial Neural Networks (ANNs) that can be used to develop time series of long-term structural values. The inclusion of a time delay unit as well as a feedback connection, where data from previous states is applied in the next stage, is a fundamental theme of RNNs. The structure of RNNS

6.1 *Recording through Health Electronic Records (HER)*

Electronic health records are important in healthcare system because they help analyses data from the past to the present, which helps improve various types of treatments and drug usage to a disease. AI can be used to elucidate medical records and provide information to doctors. The algorithm has the ability to implement HER to determine the likelihood of illness based on past information and family history.

The AI algorithm uses a large amount of data, and during this process, the algorithm develops a set of rules that connect the observations to the final diagnosis. When new patient data is entered into AI, patients can be evaluated based on previous data to predict their condition or potential illness. Medical data such as patient

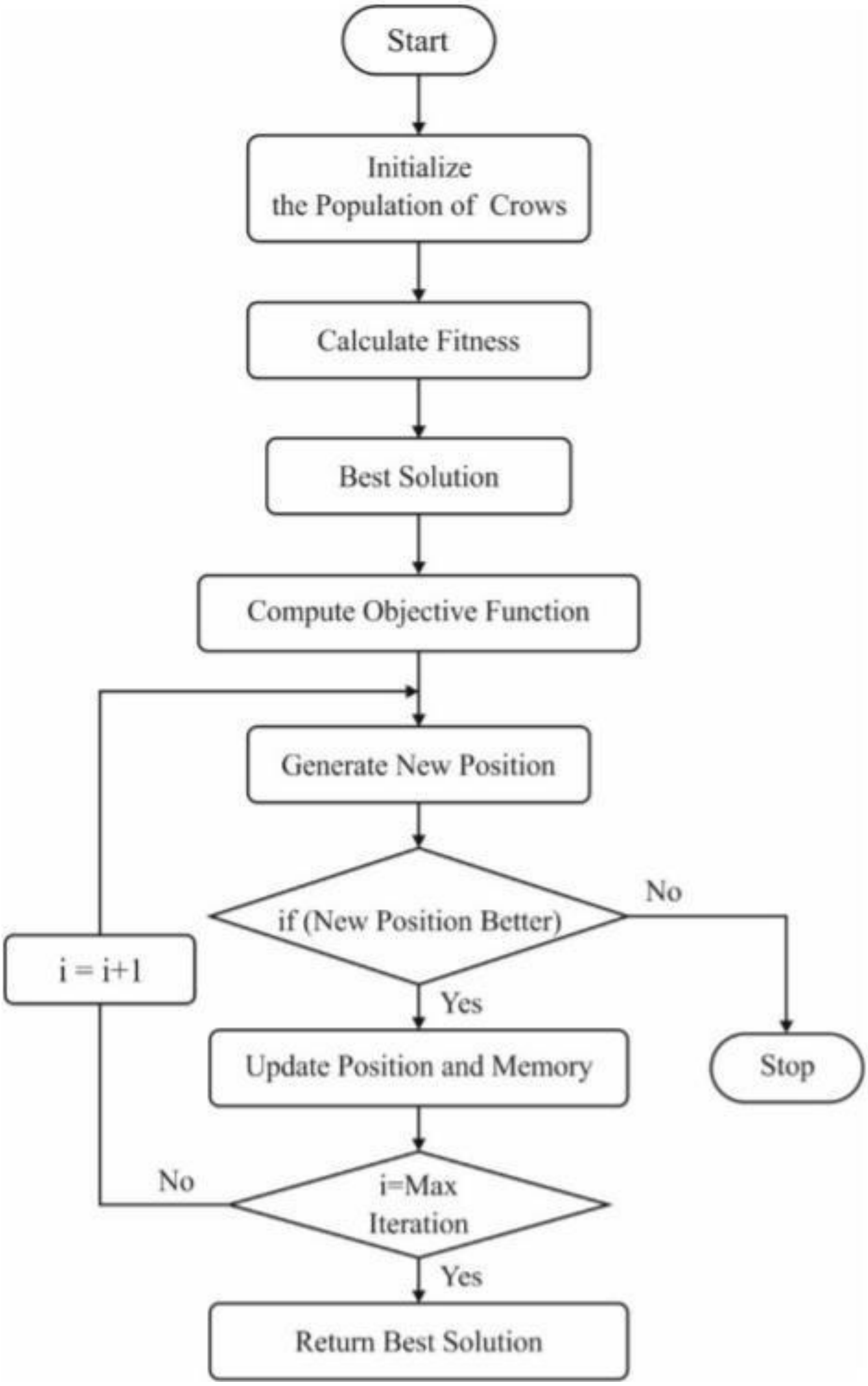

Fig. 2 Flowchart of CSO algorithm as adapted.

information, research results, and diagnostic information have been generated in large quantities every day for the past 10 years. Organizations can collaborate using analytical tools to gain the insights they need to treat patients efficiently and effectively.

7 Discovery of Drug and its Interactions

Drug interactions pose a risk to patients taking multiple medications at the same time, and the level of risk increases significantly with the number of medications taken.

Therefore, it is difficult to address all drug problems, including drug interactions and the resulting adverse effects. However, with the help of AI, the algorithm was able to collect data on drug interactions and from the medical literature. Drug discovery and development is a long process that takes years and costs about $ 7 billion. The time-consuming process of drug discovery is now being replaced by machine learning techniques. AI may not be fully useful at all stages of drug research, but it may be useful at some stages. B. Discovery of new compounds that may form suitable agents. In addition, AI can discover new applications for previously tested compounds.

7.1 Dermatology area

Healthcare dermatology relies heavily on imaging. Deep learning has greatly helped with image processing. There are three types of dermatological images: context images, micro images, and macro images. Deep learning has made great strides in each of these image types. Convolutional neural networks are 94% accurate in distinguishing between skin cancer and skin lesions.

7.2 Primary care and psychological condition

By replicating behavior, chatbots powered by AI technology are alleviating depression and anxiety. The latest AI technologies are being used to identify psychological conditions. Detection of autism spectrum disorder is possible through technology innovated right eye LLC determining autism experiment. Primary care is the major development in respect to AI. Various AI technologies have been proposed to give primary care to patients thus limiting the view of practitioner on AI to administrative and routine task.

The advances of healthcare system are due to the modern AI technology.AI imparts the ability to recognize disease from the medical images of MRI scans, CT scans, X rays and ultrasound. This implication of AI speeds up the diagnosis process and reduces the time limit from weeks or days to hours. Healthcare bots used help patients receive message in their mobiles and messaging apps. The healthcare bots also assist patients in managing their medications by providing information on the type of medication and dose to be taken. Skin cancer diagnosis is another area where deep learning is implicated.

AI techniques for recognising psychological conditions in children have been developed by a variety of medical technologies. In recent times, a technology innovator conducted an AI-powered autism experiment, which aids in the early detection of autism in children aged twelve to forty. A device that uses eye tracking to determine the health of the brain for children is used in this process.

Many diseases, such as cardiovascular disease, pulmonary disease, cancer, and psychiatric disorders, are influenced by environmental factors. Artificial intelligence (AI) is being used to mine data for environmental conditions in order to better understand disease mechanisms and improve care quality. Despite several advantages there are also some drawbacks with deep learning because patients do not cooperate to provide data, due to privacy concerns. Other fields of AI, such as vision, speech, and language, will have clean and structured data, whereas healthcar e data is ambiguous, noisy, and incomplete.

8 Conclusion

The current study outlined an effective AI and IoT convergence-based disease diagnosis model for smart healthcare systems.

The model presented includes several stages, including data acquisition, preprocessing, classification, and parameter tuning. IoT devices such as wearables and sensors collect data, which AI techniques use to diagnose diseases. The iForest technique is then used to remove any outliers in the patient data. Following that, the CSO-CLSTM model is used to classify the data and determine whether or not the disease exists. Furthermore, CSO is used to optimize the CLSTM model's weights and bias parameters.

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