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AI-BASED MODEL FOR DISEASE DIAGNOSTIC SYSTEMS IN THE HEALTHCARE SECTOR

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Abstract:

Because of recent developments in IoT, cloud computing, and AI, the traditional healthcare system has been replaced by a smart healthcare system. Improvements to healthcare may be made via the use of cutting-edge technology like the Internet of Things and artificial intelligence. Multiple possibilities exist for the healthcare industry as a result of the merging of IoT and AI. This study contributes to the literature by introducing a novel model for the diagnosis of diseases in a smart healthcare system that is based on the convergence of artificial intelligence and the internet of things. Focusing on AI and IoT convergence methods, this paper aims to create a model for the diagnosis of cardiovascular and metabolic disorders. The provided model consists of many steps, including data collection, pre-processing, classification, and fine-tuning of parameters. Bearables and sensors are examples of IoT devices that facilitate data collecting, and artificial intelligence approaches use this information to aid in the diagnosis of sickness. The suggested technique diagnoses diseases using a Cascaded Long Short-Term Memory (CSO-CLSTM) model based on the Crow Search Optimization algorithm. We use CSO to fine-tune the CLSTM model's 'weights' and 'bias' parameters so that we can better classify medical data. Also, the isolating Forest (Forest) approach is used to filter out anomalous data in this study. The diagnostic results of the CLSTM model may be greatly enhanced by using CSO. Utilizing medical records, the CSO-LSTM model's efficacy was verified. Maximum accuracy rates of 96.16% and 97.26% were achieved in the experimental diagnosis of heart disease and diabetes, respectively, using the given CSO-LSTM model. As a result, the suggested CSO-LSTM model may be used in advanced healthcare systems for the purpose of illness diagnostics.

Keywords: Alzheimer's, Parkinson's, Neuro, Heart disease, Artificial Intelligence, Classification.

1. INTRODUCTION

Over the last several years, the healthcare industry has been heavily investing in IT in order to create cutting-edge apps and improve the quality of diagnosis and treatment. Large quantities of data are produced primarily through cutting-edge scientific methods and theoretical frameworks. Then, cutting-edge healthcare apps are the results of IT research and development in recent years. It is also anticipated that complex healthcare systems have user-friendly interfaces that can perform several functions simultaneously. These adjustments are reflected in an expanded clinical model (from disease-based to patient-based care), revised formalisation development (from medical data to regional medical data), widened scope of clinical management (from general management to personal management), and a shift in emphasis from treatment to prevention (Shifting of concentration from disease treatment to preventive medical system).

As a result, the following alterations are focused on meeting people' fundamental needs in order to boost the efficiency of health care, which in turn improves health service knowledge and implies the future deployment of smart medicine. Doctors, patients, and institutions for medical research and clinical care are just few of the many players in the world of cutting-edge medical care. Disease prevention and monitoring, diagnosis and treatment, clinical management and decision making, health policy and research are just few of the many facets of medicine that need to be taken into account.

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Examples include the widely held belief that mobile internet, Cloud Computing (CC), big data, 5G systems, microelectronics, artificial intelligence (AI), and smart biotechnology mark inflection points in today's healthcare system. Modern healthcare at every level relies on these methods. Wearable or portable gadgets provide patients with the flexibility to apply health monitoring wherever and whenever it is necessary. They may get healthcare advice through remote assistance and manage their houses with remote amenities. Intelligent clinical decision support systems may be used to direct and improve diagnostic processes, as seen by clinicians.

This study introduces an innovative approach for the identification of diseases in smart healthcare systems based on the confluence of artificial intelligence and the internet of things. The purpose of this research is to create a disease diagnostic model for the detection of diabetes and cardiovascular disease via the convergence of AI and the Internet of Things. Data collection, pre-processing, classification, and fine-tuning are all parts of the described model. Internet of Things (IoT) gadgets like wearables and sensors collect the necessary data, and artificial intelligence (AI) methods use that data to provide a diagnosis of the ailment. The suggested AI and IoT convergence approach employ a Cascaded Long Short-Term Memory (CSO-CLSTM) model based on Crowd search Optimization algorithm for illness detection. In addition, the Forest (isolation) approach is used to filter out anomalous observations. CSO is used to fine-tune the CLSTM model's 'weights' and 'bias' parameters, both of which affect the diagnostic result. CSO is used since it aids in elevating the diagnostic result of the CLSTM technique. Using healthcare data, the CSO-LSTM model's efficacy was verified. The following is a synopsis of the article's contributions to the field of study.

Innovative disease detection paradigm for smart healthcare systems, based on the confluence of artificial intelligence and the internet of things.

• Advised the use of the CSO-CLSTM model in the detection of diabetes and cardiovascular disease

• Added a procedure based on the Forest approach to find outliers, which enhanced the classification results.

• Used the CSO algorithm to fine-tune the LSTM model's parameters.

CSO-LSTM model performance was verified using two standard datasets.

2. Related Work

As a result, programmers began to expect that most of the application's work would be done in the network's periphery (data compression, feature extraction well as classification). Existing classification models like RF, Naive Bayes (NB), k-Nearest Neighbours (kNN), and classification or regression trees were used to evaluate the findings. Additionally, the research utilised a small number of models developed by Azimuth et al. [16] to the task of categorising irregularities in ECG data. IBM designed the Monitor-Analyze-Plan-Execute Plus Knowledge (MAPE-K) mechanism as part of its Hierarchical Computing Architecture for Healthcare (High) to facilitate the distribution of workloads across the edge, fog, and cloud. An automated EEG pathology diagnosis approach using convolutional neural networks was published in [17]. Separate temporal and spatial details were recorded by 1D and 2D convolutions.

The suggested method is efficient relative to previous forms of wireless communication, and it requires little energy while providing a great deal of mobility for its users. In addition, user-friendly, compact, and lightweight IoT devices are used in this concept. Devices that connect to the internet include cell phones, wristbands, smartwatches, and other wearable tech. Through the use of the implanted sensors, complex calculations are performed to estimate and differentiate between normal and abnormal heart rates. Smart gadgets, such as cell phones, are implanted in the individuals and may be carried about in their pockets. In order to gather information on the subject's cardiovascular system, it is also advised that an embedded electrocardiogram (ECG) and temperature sensor be used. Consequences of their typical way of life might be deduced from this information as well. Information sent through Bluetooth's low power consumption is processed by smartphones and classified as healthy or harmful. Predictions of diabetes and cardiac efficiency may be made on the android platform. At first, IoT gadgets collect patient information and pre-process it into a more universal format. Data translation, format conversion, and labelling classes are only few of the steps that make up pre-processing. The patient data is then filtered using the Forest technique in order to remove any abnormal values. Then, we use a CSO-CLSTM model to determine whether or not the data indicate the presence of the illness.

The CSO-CLSTM model's classification results for the heart disease data set are compared to those of other classifiers using the same and new metrics [21]. If we look at how the SVM model performed relative to other approaches in terms of sensitivity, it is clear that it underperformed. The NB-A model further aimed to demonstrate somewhat enhanced sensitivity in comparison to the SVM. At the same time, the sensitivity values produced by the KNN and J48 models were comparably close and competitive. While other models may have achieved a better sensitivity, the proposed CSO-CLSTM model demonstrated superior classification performance. The CSO-CLSTM model, for instance, achieved a maximum sensitivity of 94.80% under 2000 instances, while the KNN model achieved a low sensitivity value of 92.60%, the NB-A model achieved a low sensitivity value of 87.90%, and the SVM and J48 models achieved low sensitivity values of 83.20% and 93.30% respectively. Under the same conditions, the suggested CSO-CLSTM approach achieved a greater sensitivity of 98% compared to the KNN, NB-A, SVM, and J48 techniques, which only achieved least sensitivity values of 93.60%, 89.10%, 84.20%, and 96% correspondingly. Based on the specificity analysis findings, it seems that the SVM method performed poorly in comparison to more conventional models. Furthermore, the NB-A scheme demonstrated superior specificity than SVM. The specificity values achieved by the KNN and J48 frameworks were comparable and commendable. Nonetheless, CSO-CLSTM is a brand-new system

3.SYSTEM IMPLEMENTATION

Alzheimer's disease detection

Data collection and pre-processing

In order to determine whether a dataset is suitable to be used as input data for a neural network once it has been made accessible in CSV format, it must be analysed in a variety of ways. Section 4.3 explains that a basic statistical investigation of each topic has been the starting point for this study. The CSV file was loaded into a data frame for analysis. The Pandas library was used to do this. Included in the fast examination of each variable is the determination of extreme values, minimums, and means. This little investigation has allowed us to see that the majority of the values for each variable fall roughly within the same range. The Mini-Mental State Examination (MMSE) ranges from 0–30, years of education from 0–36, and patient age from 18–109, making them the variables with the largest ranges of variation. We didn't see the initial necessity to standardise the results since the remaining values fall between 0 and 10.

Testing The outcomes of the system's last module will be exposed and explained in this chapter. For this reason, this section of the code will be in charge of the model's testing and assessment. It will try to meet requirements 3, 4, 11, and 12 by adhering to the rules laid forth in Section 4.5. The chapter will start off with a presentation of the model's accuracy and confusion assessment matrices. The resulting ROC curve plot will next be used to reveal his findings. Further, towards the conclusion of the chapter, the model's learning process will be analysed to determine whether or not over-fitting or under-fitting issues occurred. If you need a refresher on the results from the last lesson, including the accuracy and confusion matrix, have a look at Section 5.2. The model was developed, assembled, and trained at this stage, yielding a system capable of making predictions on fresh data in the future. However, its accuracy will be one of the first criteria to check before any new forecasts are made. The test dataset will be used to assess the efficacy of the model. It's crucial to stress that this set of data has never been viewed by the model before, since it was split at the very beginning of the code. The evaluation of the model using these test data inputs is shown in Figure 6.1, from which the accuracy metric performance may be derived. In this case, we get an accuracy rate of 82.61%, which measures how many predictions the model got right out of the total number of possible ones.

Parkinson's disease detection

The spiral and wave dataset

We thank Adriano de Oliveira Andrade and Joao Paulo Folado of the NIATS at Federal University of Uberlandia for their work in compiling the dataset we will be utilising today. The 204 photos that make up the dataset have already been divided into a training set and a testing set.

- Spiral: 102 images, 72 training, and 30 testing
- Wave: 102 images, 72 training, and 30 testing

There is a potential pitfall to using deep learning and Convolutional Neural Networks (CNNs) to create our Parkinson's detector. There is a dearth of training data to begin with, with just 72 photos available. We often resort to data augmentation when we find ourselves short on monitoring data, but this approach has its own set of problems when used here. Using data augmentation incorrectly might easily transform a healthy patient's painting into one that seems like it was done by someone with Parkinson's disease (or vice versa). In the same way that you wouldn't use a screwdriver to hammer in a nail, the key to successfully applying computer vision to a problem is to employ the appropriate instrument for the task at hand. If you know how to apply deep learning to a problem, it doesn't guarantee it's always the best decision.

Heart Disease Prediction

This study used a dataset obtained from the UCI Data Repository. 14 The data in the UCI Machine Learning Repository is open to the public without cost. Due to their smaller number of missing values and fewer outliers, the Cleveland and Hungarian datasets have been utilised by several studies. The data is prepared for training and testing with the proposed algorithm by being cleaned and pre-processed. The databases, domain theories, and data generators that make up UCI's Machine Learning Repository are put to use by the machine learning community in conducting empirical studies of machine learning algorithms. Our approach aims to improve the accuracy with which cardiac disease is detected in the early detection phase. In order to improve the reliability of the findings presented in this study, the UCI repository dataset is used. Decision trees and Naive Bay were used as categorisation methods for data mining.

3.1 ALGORITHMS

The Random Forest

Using a sample of data drawn at random from the training set, the Random Forest classifier constructs a forest of decision trees. In essence, it is a collection of decision trees (DT) drawn from a subset of the training set and uses the votes of those trees to make a final prediction.

GaussianNB

One subset of NB algorithms is the Gaussian Naive Bayes algorithm. It's put to use in cases when the feature values are continuous. All the characteristics are considered to have a normal, or gaussian, distribution.

LinearSVM

With their associated learning algorithms, supervised learning models such as Support Vector Machines (SVMs) analyse data for classification and regression purposes.

An SVM is a non-probabilistic binary linear classifier; given a set of training examples, each of which is labelled as belonging to one of two categories, the training process generates a model that labels new instances with one of the two categories.

Logistic Regression

When trying to forecast a binary class, statisticians often turn to logistic regression. This result or metric has just two possible values. When something is dichotomous, it only falls into two categories. It has potential applications in areas like as cancer diagnosis. It determines how likely something is to occur.

Linear regression with a categorical dependent variable is a specific instance of this technique. There is a reliance on the log of odds as the criterion for success. The logit function is used in Logistic Regression to make predictions about the likelihood of a binary event.

SAMPLE DATA

Healthy data

Parkinson's data

4.Results

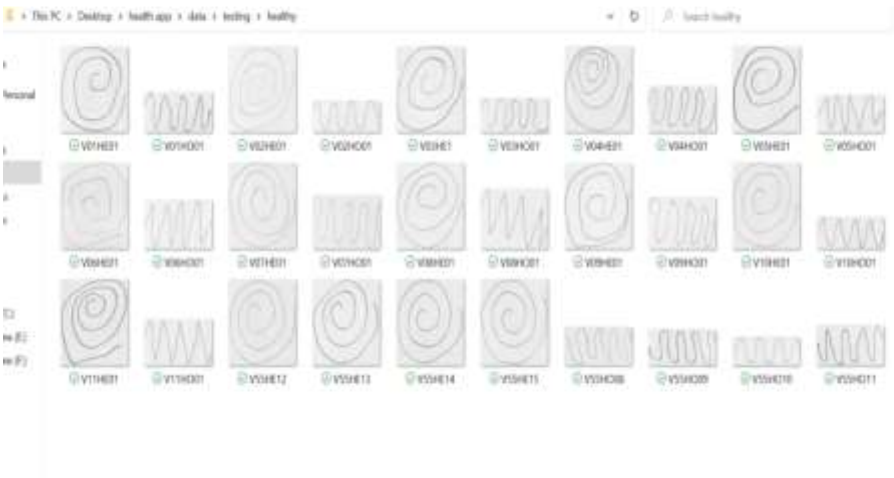


Fig File upload

Fig Alzheimer's disease detection

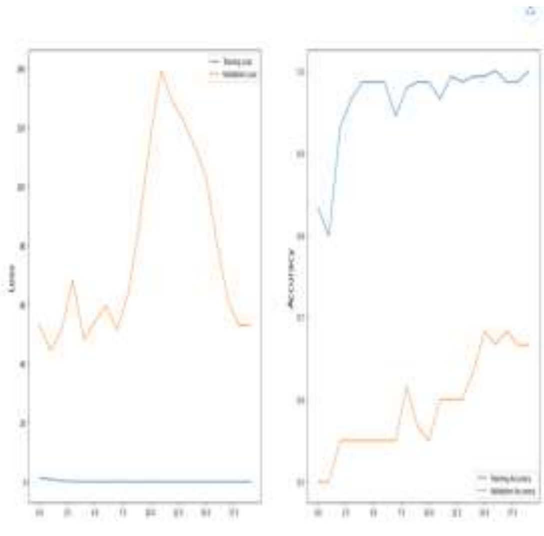
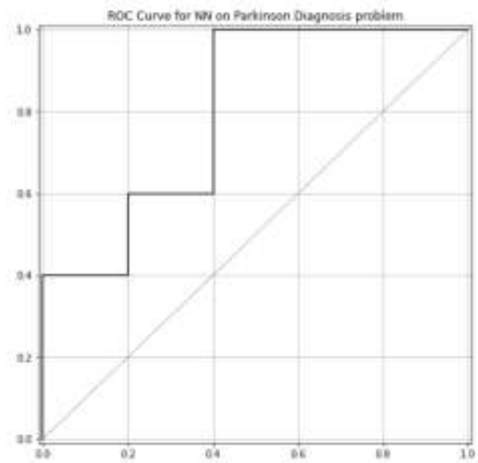
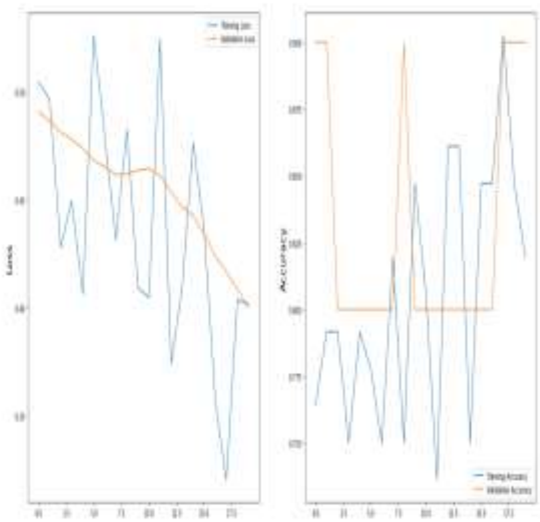


image-based analysis



neural network



recurrent neural network

ACCURACY RATE

Algorithms	Accuracy Rate
Neural network	93%
Recurrent neural network	89.5%
Image based analysis	81%

5. CONCLUSION

Recent studies have created a smart healthcare system disease diagnostic model based on the confluence of artificial intelligence and internet of things. Data collecting, pre-processing, classification, and parameter adjustment are all a part of the described model. Data collection is handled by Internet of Things (IoT) gadgets like wearables and sensors, and analysis is handled by artificial intelligence (AI) methods to diagnose diseases. The patient data is then run through the iForest outlier removal algorithm. Then, the CSO-CLSTM model is used to categorise the data according to the presence or absence of the illness. As an added bonus, the weights and bias parameters of the CLSTM model are optimised using CSO. CSO is used to enhance the diagnostic performance of the CLSTM model. Utilizing medical records, the CSO-LSTM model's efficacy was verified. In experiments, the CSO-LSTM model improved diagnostic accuracy for heart disease to 96.16 percent and for diabetes to 97.26 percent. The validity of the provided model is thus confirmed.

Feature selection methods that mitigate the "curse of dimensionality" and "computational complexity" might be used to boost performance as part of future plans. Hybrid meta heuristic algorithms may also be used to overcome the shortcomings of CSO algorithm, such as its limited search accuracy and strong propensity for entering local optima.

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