Original Article

Modified Cnn Based Heart Disease Detection Integrated With Iot

[1*]Chetna kwatra, [2]Bukya Mohan Babu, [3]M.Praveen, [4]Dr T.Sampath Kumar, [5]Ram Kumar Solanki [6]Dr A V R Mayuri

[1*]Department of Computer science &Engineering, Lovely Professional University
[2]Department of Computer science and engineering, University College of engineering, Osmania University
[3]Department of CSE(Data Science), CMR Technical Campus , JNTUH Hyderabad
[4]Dept of CS&AI, SR University , Telangana, India
[5]School of Computer Science & Engineering , Sandip University, Nashik , Maharshtra , India - 422213
[6]School of Computing Science and Engineering, VIT Bhopal University
[1*]chetna.27308@lpu.co.in, [2]mohanbabubukya@gmail.com, [3]praveen.matoori@gmail.com,
[4]t.sampathkumar@sru.edu.in, [5]hr.coet@gmail.com, [6]mayuri.avr@vitbhopal.ac.in
Corresponding Author: [1*]chetna.27308@lpu.co.in
DOI: 10.47750/pnr.2023.14.S02.120

Abstract

The Internet of Things (IoT) and Artificial Intelligence have joined forces to change the conventional healthcare system into an intelligent model (AI). The deployment of critical technologies like the Internet of Things and artificial intelligence (AI) can help to improve medical care. In healthcare, IoT and AI have a variety of uses. The primary goal of the research is to develop an AI and IoT-based model for detecting heart illness. The concept uses a modified imperialist algorithm to diagnose heart problems (MICA). One of the most effective and efficient classification methods for medical data is the Modified Deep Convolutional Neural Network (MDCNN).It's been established to work in various of hospitalized patients. As a result, in the diagnosis of heart disease, the proposed modified imperialist competitive algorithm for feature selection (MICA) model is used to pick features. The simulation findings show that this suggestion enhances classification accuracy in experimental study using a benchmark dataset.

Keywords: Internet of Thing (IOT), Artificial Intelligence (AI), Modified Deep Convolutional Neural Network (MDCNN) classifier, Modified imperialist competitive algorithm.

INTRODUCTION

The Internet of Things (IoT) has been widely used in so many applications that its significance in our daily lives is growing. IoT technology is also being developed in the healthcare monitoring system to provide patients with effective emergency services. It is also utilized as an E-health application for a number of purposes, including early detection of medical problems, emergency notification, and computer-assisted rehabilitation. Smartphones have become an essential part of people's daily lives, and they are now linked to sensors that monitor the subject's health.This sensor-based surveillance system gathers data from wards and diagnostic equipment, then analyses it for efficient and automated healthcare management. The Internet of Things (IoT) healthcare system facilitates improved resource management by allowing for more efficient monitoring and tracking. Patients' electronic health records (EHRs), Internet of Things (IoT) sensor devices, portable mobile devices, and social media data are all employed in the diagnosis of illnesses.To improve prediction and detection, this innovative system employs Artificial Intelligence (AI) approaches. Analytic models have been developed using a variety of techniques, including machine learning.These models learn and recognize illness trends and symptoms using data obtained from IoT. Artificial intelligence (AI) is changing our way of life, and there are two types of AI in medicine: virtual and physical.

The current work introduces a different illness detection methodology for smart healthcare based on AI and IoT convergence. The goal is to create a disease diagnosis model that detects heart disease using AI and IoT.For heart disease prediction and diagnostics, the proposed AI and IoT method employs a modified imperialist competitive algorithm. The proposed Modified Deep Convolutional Neural Network (MDCNN) classifier is one of the most effective and efficient classification methods for medical data classification. It's been shown to work in various of hospital environments.As a result, the proposed modified imperialist competitive algorithm (MICA) model can be used to develop a disease diagnosis tool for smart health care systems. The simulation findings show that this approach improves classification accuracy in experimental research using a benchmark dataset.

II LITRATURE SURVEY

Kishor A et al (2021) [1] A healthcare model is constructed using the classification algorithms DT, SVM, NB, AB, RF, ANN, and K-NN. These classifiers have been used to classify heart disease, diabetics, breast cancer, hepatitis, liver disease, dermatology, surgery data, thyroid, and cardiac datasets. The classifiers' accuracy, sensitivity, specificity, and AUC are all used to evaluate their performance. The created healthcare model achieves varying levels of disease accuracy, with RF classifier achieving 99.67 percent sensitivity and DT classifier achieving 72.26 percent sensitivity.The RF classifier has a maximum specificity of 97.81 %, whereas DT classifier has a minimum specificity of 66.42 %. [2] S Gopalan et al (2021) Between 2014 and 2019, an analysis of several classes based on historical survey reports and journal papers was conducted. With an emphasis on IoT security in healthcare, this study discusses a total of eighteen observations, taking into account both numerical and experimental assessments provided in the reviewed works. Security strategies and procedures for IoT in healthcare and related frameworks that employ AI-based approaches are also investigated. [3] S Sim and colleagues (2021) Using the suggested IoT/AI convergence virus disease control system in this paper, an integrated virus infection control model can be created. They may be able to apply the proposed model by detecting and monitoring infected persons prior to the spread of virus disease, as well as analyzing virus diseases in specific regions and countries and implementing a rapid containment mechanism in reaction to new virus outbreaks.

S Juyal et al (2021) [4] An 'Intelligent Skin Monitoring Device' was proposed, which would allow patients in rural areas to remotely check skin diseases. They suggested using IoT-enabled smart medical equipment to collect data from the patient. This data is stored in the cloud and used by the AI system to identify the disease kind.In the AI module, they used CNN, which is most suited to accurately evaluate biomedical images according to literature. We were able to attain a disease detection accuracy of 95% with this method. A preventive strategy is offered for an IoT-based skin monitoring system to solve the challenges faced by persons in remote areas who've already restricted or no access to skin care.[5] Ray P et al (2021) A revolutionary privacy-preserving system based on block chain technology and cluster transfer techniques that enables secure peer-to-peer data transmission via secured cluster nodes.BIoTHR is the preferred system for private blockchain-aided EHR management via IoT. The proposed scheme's backbone is made up of novel blockchain and swarm exchange infrastructures that enable secure and reliable data transfer as well as timely monitoring of data moved over IoT networks.The research project simulates a number of incompatible IoT-based medical sensor nodes, such as body temperature, heart rate, and oxygen saturation, i.e., SPO2, galvanic skin reaction, and blood glucose, in a blockchain assisted swarm exchange architecture.R. Bharathi et al (2020) [6] An excellent EEPSOC-ANN model for energy clustering and disease detection using IoT devices. The user subsystem, the cloud subsystem, and the alert subsystem are the three subsystems in the proposed paradigm. The data is collected from the user in the first user subsystem using IoT medical devices. Simultaneously, theEEPSOC method can be used to aggregate IoT devices then choose appropriate CHs. The detected data from IoT devices will then be sent to gateway devices by the CHs, which will eventually be sent to the cloud subsystem.

[7] L. Greco et al (2020) To construct smart healthcare systems capable of running near-Realtime applications, evaluating and executing Artificial Intelligence on the massive quantity of data produced by wearable sensor networks, a combination of Cloud and IoT architectures is extensively used. Abou-Nassar et al (2020) [8] The proposed model outperforms existing equivalent methodologies in terms of scalability, interoperability, availability, mutual authentication, trustworthiness, data integrity, authentication process, secrecy, and privacy. In the approach, we want to use artificial intelligence (AI) and deep learning techniques to improve our system. Based on data obtained from wearable sensors, these technologies will be employed in the early stages of training to discover patterns that suggest particular disorders.Chaudhary R et al (2020) [9] They provide a lightweight ciphering technique for IoT-based e-healthcare systems. Simple operations like swapping, XORing, dividing, and so forth are used in this technique. The implementation result shows that memory consumption is modest while performance is sufficient to build an efficient cypher. This method can be used to and tested in a wide range of limited devices. Elayan H et al (2021) [10]A digital twin paradigm for intelligent context-aware healthcare systems is proposed in this paper. It also demonstrates how a patient's digital twin can monitor real-time health status and find anomalies in body measures by using an ECG cardiac rhythm classifier model to diagnose and detect cardiac problems. In the defined use case, five different algorithms were examined for accuracy and performance. As a preliminary outcome, the suggested framework links the Virtual Dual to the healthcare sector to improve medical operations.

III PROPOSED METHOD

Heart disease risk can be reduced with early detection and treatment. We propose an AI and IoT-based platform for enhanced cardiac disease diagnostics in this study. Before and after the beginning of heart disease, the AI-IoT device captures patient data on their hearts. Patients' health parameters can be tracked remotely, in real time, and then recorded and communicated to a data center, such as the cloud, which dramatically improves the healthcare system's efficiently, accessibility, and cost efficiency. Based on a modified Imperialist competitive algorithm, a model for heart disease diagnostics has been developed (ICA). For medical data categorization, the Modified Deep Convolutional Neural Network (MDCNN) classifier is one of the most effective and efficient approaches.

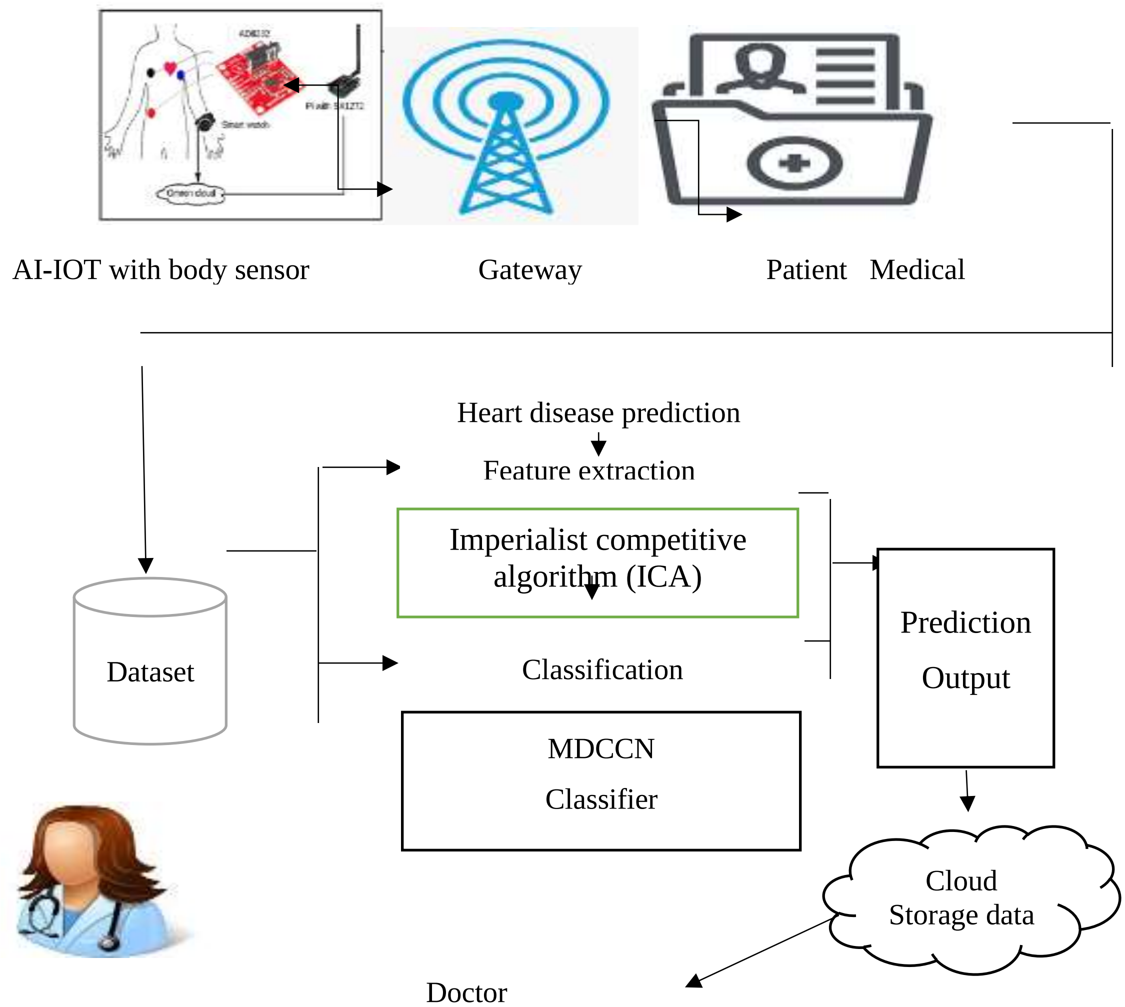


Fig 1: Proposed Architectur

A MDCNN is used in the suggested method to predict the patient's heart disease. The system is trained and tested for this purpose. The MDCNN classifier is used to train the system, which uses data from the UCI Dataset. The data's classified results make up the UCI dataset (normal and bad). If AI-based IoT sensor readings are analyzed instantly, it will take time to diagnose the sickness, and there is a chance of obtaining an inaccurate conclusion. As a result, the system is forced to work within its constraints.

3.1 MODIFIED IMPERIALIST COMPETITIVE ALGORITHM (MICA) MODEL

In the medical data innovation, artificial intelligence (AI) for producing medical software applications that use cognitive technology holds a lot of promise. To integrating artificial intelligence (AI) platforms for healthcare with your existing software and third-party applications, healthcare devices can collect a variety of patient data and get feedback from health practitioners, as well as the Internet of Things. Not only can healthcare improve a patient's health and provide assistance in life-threatening situations, but it may also increase the productivity of healthcare workers and streamline hospital procedures.

Sensors collect data from patients or doctors/nurses, the IoT device analyses the data using the Modified Imperialist Competitive Algorithm (MICA), and the data collected by the IoT device can then be used by physicians, medical doctors, but even machines to generate effective and educated judgments. The Modified Imperialist Competitive Algorithm (MICA) is used to select features in the diagnosis of heart disease. The number of attributes in this study is expected to remain constant, and the purpose is to identify the best features for improving heart disease detection accuracy.In the implemented tests, different datasets are assumed to have the same number of selectable features.

$$\text{country} = [\, P_1, P_2, \ldots \ldots .., P_N \text{ var }] \qquad (1)$$

It's typically represented as an Nvar dimensional array of variables to optimize. Each country's expense is inversely proportional to its strength. The cost function f is defined as follows:

$$\text{cost} = f\,(\text{country}) = f(P_1, P_2, \ldots \ldots .., P_N \text{ var }) \qquad (2)$$

The algorithm generates $N_{country}$ initial countries during the startup procedure. With the most powerful countries, N_{imp}, a set number of empires are built. The empires' surviving countries, N_{col}, become colonies.After a predetermined number of iterations, which indicates the maximum number of decades, the algorithm will come to a complete halt.

3.2MODIFIED DEEP CONVOLUTIONAL NEURAL NETWORK (MDCNN) CLASSIFIER

The MDCNN (Modified deep convolutional neural network) classifier to categories the features. MDCNN classifier receives each specified feature in this manner. The weights are attached to each input and given random values. The next hidden layer's hidden nodes' purpose is to add the combination of an input parameter and the linear function of all connected input layers.The backpropagation strategy for acquiring the outcome is improved by using random edge weights. This is how the optimization is done.After that, the activation technique is used, and the output of this layer is passed on to the next layer.

Equations (1) and (2) can be used to express the supplied feature values and their equivalent weights:

$$F_i = \{F_1, F_2, F_3 \ldots ..F_n \} \qquad (3)$$

$$W_i = \{W_1, W_2, W_3 \ldots ..W_n\} \qquad (4)$$

W_i signifies F_i i's weight value, which defines the n matching values of $W_1, W_2, W_3 \ldots ..W_n$.,, and F symbolizes the input value, $F_1, F_2, F_3 \ldots ..F_n$, which denotes n selected features.

$$A_{fi} = C_i(\sum_{i=1}^{n} (\, F_i W_i) \qquad (5)$$

The activation function $A_{fi}$is specified here, while C_i specifies the exponential of F_i. As a type of AF, this system employs a Gaussian function. Each layer of the MDCNN is submitted to the above equations. Finally, to calculate the output layer neurons' values, to determine the output values, add the values of all the input signals

$$R_i = B_i + \sum o_i W_j \qquad (6)$$

where $O_i$is the preceding output layer's layer value,The layer's hidden values are denoted by $B_i$and the output values of the preceding equation are denoted by R_i.

$$W_{ci} = \alpha\delta_i(F_i) \qquad (7)$$

W_{ci} represents for weight correction, momentum, and error diffusion over the network, while δ_i stands for the error.The proposed imperialist competitive algorithm (ICA) model is used to maximize the weight values.

IV. EXPERIMENTAL VALIDATION

The suggested MDCNN (modified deep convolutional neural network) model will be examined in this part for sensitivity, specificity, precision, recall, and accuracy. In addition, the results are verified using datasets with varying numbers of cases for heart disease and diabetes. The proposed method has been tested on a pc with 16 GB of RAM and a 1 TB hard disc for file storage.

MODELS	PRECISION	RECALL
DLNN	89.6	60.2
LR	90.1	74.2
MDCNN	**96.1**	**97.6**

Table 1: Performance analysis

As shown in table 1 and figure 2, the proposed MDCNN-based heart disease prediction and diagnosis system is compared to existing logistic regression (LR) and existing DLNN in terms of precision and recall.

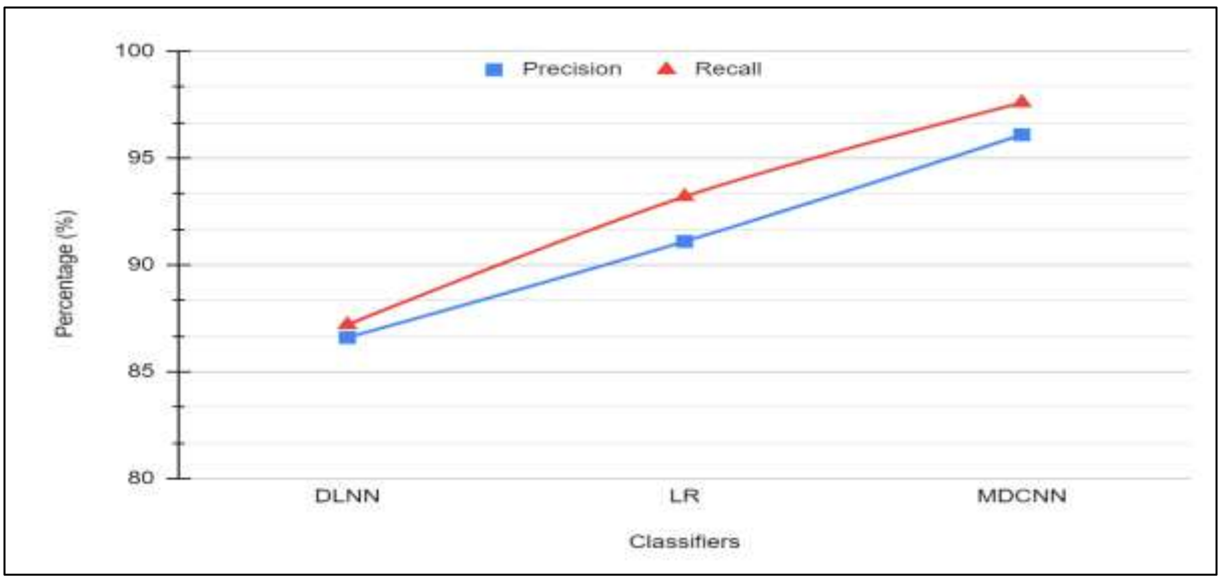


Figure 2: Performance analysis of various

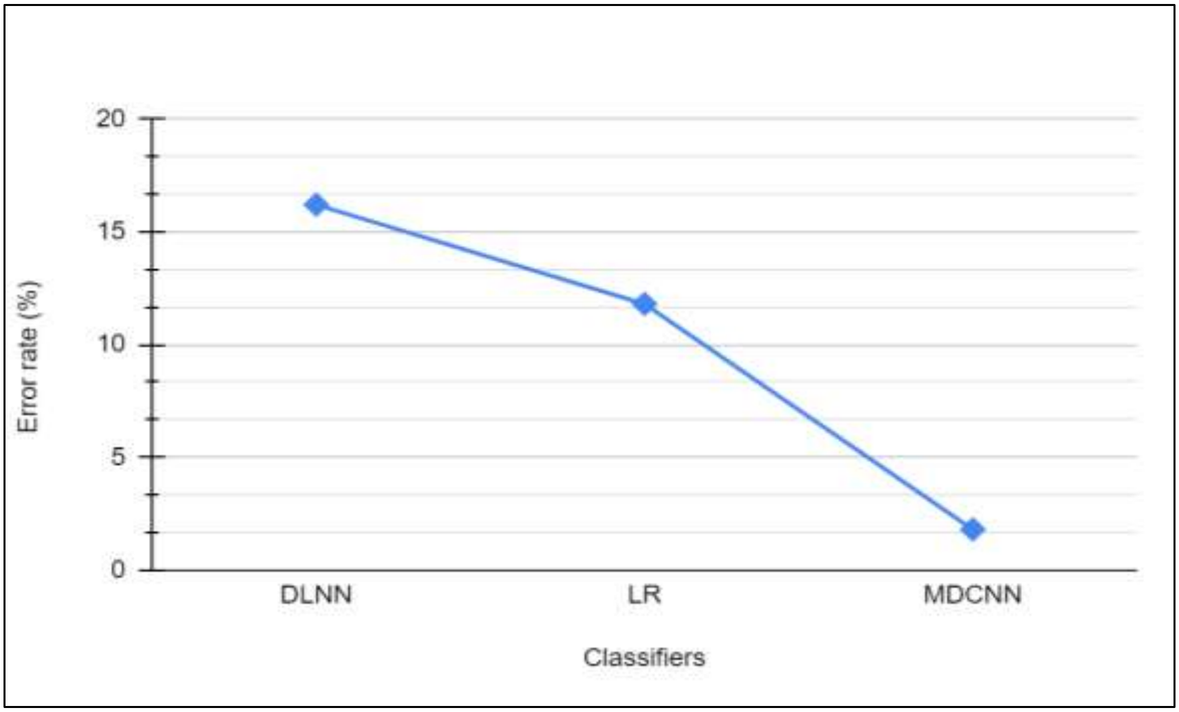
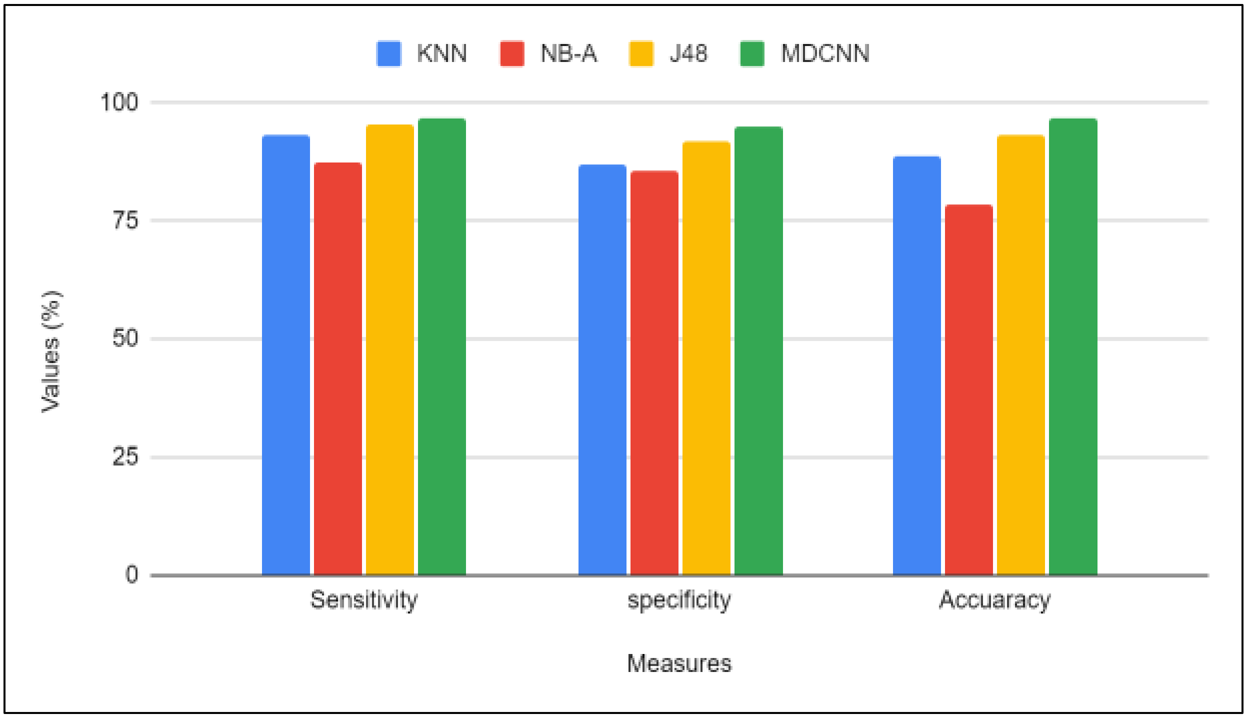


figure 3: The proposed and existing approaches' error rates were compared.

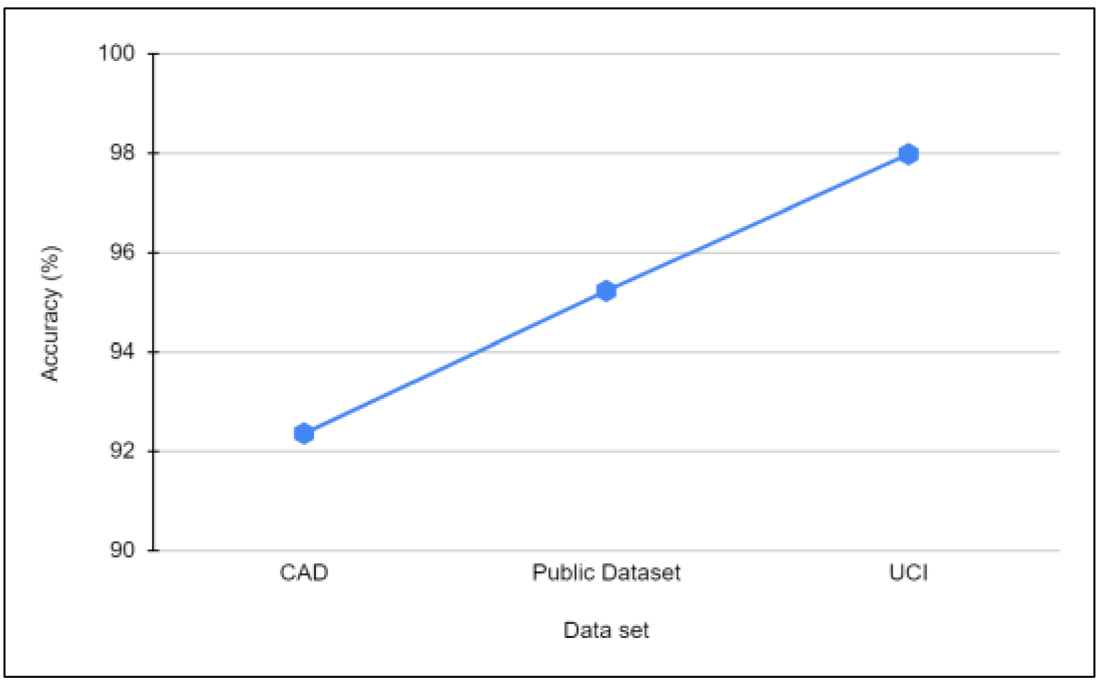
The Error Rate of Existing and Proposed Methods is shown in Figure 3. Table 2 compares the performance of various classification algorithms.

METRICS	**KNN**	**NB-A**	**J48**	**MDCNN**
Sensitivity	93.04	87.32	95.42	96.78
specificity	87.04	85.48	92.04	94.95
Accuracy	88.8	78.34	93.08	96.77

Figure 4 depicts the average classification analysis of the proposed MDCNN model on the relevant heart disease dataset. The MDCNN model outperformed alternative comparison techniques, as seen in the graph, with an average sensitivity of 96.78 %, specificity of 94.95 %, and accuracy of 96.77 %. The NB-A and KNN models exhibit moderate accuracy over Jv8.Simultaneously, the J48 and proposed MDCNN models produced similar but small accuracy. However, the provided proposed MDCNN model outperformed the competition in terms of classification performance and accuracy. The MDCNN model achieved a high level of accuracy, with a score of 97.77 %.



Figures 4: The average classifier results analysis on diagnosis dataset.



Figures 5:Compared the accuracy of our dataset to that of other datasets.

The UCI dataset achieves 97.98 accuracy for the maximum number of observations, as seen in Fig. 5. The accuracies of the other datasets, such as CD and the public health dataset, are lower, at 95.23 and 92.36, respectively. Similarly, if combined with other datasets, the UCI shows better performance.

V. CONCLUSION

A smart healthcare system requires an effective AI and IoT-based illness diagnosis model.The model goes through several steps, including data collection, classification, and feature optimization. Wearables and sensors are examples of IoT devices that collect data, which AI algorithms subsequently analyze to diagnose diseases. To classify the data and assess whether or not the disease is present, the proposed MDCNN model is used. The use of proposed MDCNN improves theModified Imperialist Competitive Algorithm (MICA) is used to select features in the diagnosis of heart diseasemodel's diagnostic result.The proposedDCNN model's performance was verified using healthcare data. During the study, the suggested Modified Imperialist Competitive Algorithm (MICA) model achieved a maximum accuracy of 96.16 percent and 97.26 percent on heart disease prediction and diagnosis, respectively.

REFERENCES

1. Kishor, A., & Chakraborty, C. (2021). Artificial Intelligence and Internet of Things Based Healthcare 4.0 Monitoring System. Wireless Personal Communications. doi:10.1007/s11277-021-08708-5
2. Gopalan, S. S., Raza, A., &Almobaideen, W. (2021). IoT Security in Healthcare using AI: A Survey. 2020 International Conference on Communications, Signal Processing, and Their Applications (ICCSPA). doi:10.1109/iccspa49915.2021.9385711.
3. Sim, S., & Cho, M. (2021). Convergence model of AI and IoT for virus disease control system. Personal and Ubiquitous Computing. doi:10.1007/s00779-021-01577-6.
4. Juyal, S., Sharma, S., & Shankar Shukla, A. (2021). Smart skin health monitoring using AI-enabled cloud-based IoT. Materials Today: Proceedings. doi: 10.1016/j.matpr.2021.01.074.
5. Ray, P. P., Chowhan, B., Kumar, N., &Almogren, A. (2021). BIoTHR: Electronic Health Record Servicing Scheme in IoT-Blockchain Ecosystem. IEEE Internet of Things Journal, 8(13), 10857–10872. doi:10.1109/jiot.2021.3050703
6. Bharathi, R., Abirami, T., Dhanasekaran, S., Gupta, D., Khanna, A., Elhoseny, M., & Shankar, K. (2020). Energy Efficient Clustering with Disease Diagnosis Model for IoT based Sustainable Healthcare Systems. Sustainable Computing: Informatics and Systems, 100453. doi: 10.1016/j.suscom.2020.100453.
7. Greco, L., Percannella, G., Ritrovato, P., Tortorella, F., & Vento, M. (2020). Trends in IoT based solutions for health care: moving AI to the Edge. Pattern Recognition Letters. doi: 10.1016/j.patrec.2020.05.016
8. Abou-Nassar, E. M., Iliyasu, A. M., El-Kafrawy, P. M., Song, O.-Y., Bashir, A. K., & El-Latif, A. A. A. (2020). DITrust Chain: Towards Blockchain-based Trust Models for Sustainable Healthcare IoT Systems. IEEE Access, 1–1. doi:10.1109/access.2020.2999468.
9. Chaudhary, R. R. K., & Chatterjee, K. (2020). An Efficient Lightweight Cryptographic Technique For IoT based E-healthcare System. 2020 7th International Conference on Signal Processing and Integrated Networks (SPIN). doi:10.1109/spin48934.2020.9071421.
10. Elayan, H., Aloqaily, M., & Guizani, M. (2021). Digital Twin for Intelligent Context-Aware IoT Healthcare Systems. IEEE Internet of Things Journal, 1–1. doi:10.1109/jiot.2021.3051158.