Journal of Science and Technology
ISSN: 2456-5660 Volume 7, Issue 12 (December -2022)
www.jst.org.in **DOI: https://doi.org/10.46243/jst.2022.v7.i12.pp01-15**

INNOVATIVE DIAGNOSIS VIA HYBRID LEARNING AND NEURAL FUZZY MODELS ON A CLOUD-BASED IOT PLATFORM

Sunil Kumar Alavilli

Sephora, California, USA

sunilkumaralavilli@gmail.com

To Cite this Article

Sunil Kumar Alavilli, "**INNOVATIVE DIAGNOSIS VIA HYBRID LEARNING AND NEURAL FUZZY MODELS ON A CLOUD-BASED IOT PLATFORM**" *Journal of Science and Technology, Vol. 07, Issue 12, Dec 2022, pp01-15*

Article Info

Received:30-11-2022 Revised:10-12-2022 Accepted:18-12-2022 Published:28-12-2022

ABSTRACT

Background Information: Cloud computing, artificial intelligence, and the Internet of Things have changed healthcare by providing real-time monitoring and diagnosis. Hybrid learning models combined with neural fuzzy systems improve healthcare diagnoses, especially when it comes to handling uncertainty in massive amounts of medical data gathered from IoT devices.

Methods: Fuzzy logic and neural networks were combined to create a hybrid neural fuzzy learning model. Using machine learning techniques, the system gathers real-time data from Internet of Things devices, interprets it through cloud-based platforms, and forecasts normal or abnormal health situations. Medical datasets were used for the model's training and validation.

Objectives: In addition to assessing the scalability of real-time data processing and the efficacy of hybrid learning models in enhancing diagnostic accuracy, the study intends to investigate the integration of IoT, cloud computing, and AI for healthcare diagnostics.

Results: The hybrid model outperformed traditional AI-based diagnostic techniques, achieving 96.40% precision, 98.25% recall, and 97.89% diagnostic accuracy.

Conclusion: The accuracy and efficiency of the proposed method's processing increases real-time healthcare diagnostics. Enabling dependable patient monitoring and prompt decision-making, its versatility and scalability make it appropriate for wider healthcare applications.

Keywords: *Cloud-based IoT, Neural fuzzy models, Hybrid learning, Healthcare diagnostics, Real-time monitoring.*

1. INTRODUCTION

Journal of Science and Technology
ISSN: 2456-5660 Volume 7, Issue 12 (December -2022)
www.jst.org.in **DOI: https://doi.org/10.46243/jst.2022.v7.i12.pp01-15**

Rapid developments in cloud computing, artificial intelligence (AI), and the Internet of Things (IoT) *Bharathi et al. (2020)* have drastically changed many industries, most notably healthcare. By combining these technologies, it is easier to create advanced diagnostic systems that can monitor, analyse, and make decisions in real time. This improves patient care and management to a great extent. In order to better understand how these technologies combine to produce a more effective and precise system for illness prediction and management, this study explores the creative application of neural fuzzy models and hybrid learning for diagnostic purposes on a cloud-based IoT platform.

To improve prediction accuracy and robustness, a hybrid learning model integrates the best features of different machine learning approaches. Neural fuzzy models *Abdali-Mohammadi et al. (2020)* come into play here, combining the interpretability of fuzzy logic with the adaptability of neural networks. With the help of this combination, it is possible to process enormous volumes of medical data gathered from IoT devices, leading to more precise and trustworthy diagnostic results. The infrastructure required to manage and process this data effectively is provided by cloud computing, guaranteeing that the system can expand to meet the demands of various healthcare settings.

The collection and analysis of patient data has been completely transformed by the use of IoT in the healthcare industry. Vital signs and other health parameters are continuously monitored by wearable sensors and other Internet of Things (IoT) devices. This data is transmitted to cloud-based systems for analysis using sophisticated algorithms. This ecosystem's incorporation of neural fuzzy models improves the system's capacity to manage medical data imprecision and uncertainty, which are frequent problems in healthcare diagnostics.

IoT-enabled devices allow for ongoing patient monitoring and real-time data collecting, offering insightful information about their health. These models improve data handling by fusing fuzzy logic reasoning with the learning powers of neural networks. Increasing prediction accuracy and dependability by combining several machine learning *Subasi et al. (2020),* approaches. Offers the scalable data processing and storage infrastructure required to manage the enormous volumes of data produced by Internet of Things devices.

The objectives of the paper are as follows:

- To explore the integration of IoT, cloud computing, and AI in healthcare diagnostics.
- To assess the effectiveness of hybrid learning models, particularly neural fuzzy models, in improving diagnostic accuracy.
- To evaluate the scalability and efficiency of cloud-based IoT platforms in real-time data processing and decision-making.

Lack of discussion on potential limitations of ETS-DNN model. Absence of comparison with other optimization techniques ***Pustokhina et al. (2020)***. Hybrid transfer learning model outperforms single architecture for breast cancer detection. Proposed framework enhances mammography analysis efficiency for radiologists ***Khamparia et al. (2020).***

Real-time healthcare monitoring system efficiency and disease diagnosis challenges. Need for effective and trustworthy patient monitoring in healthcare systems ***Pustokhina et al. (2020).***

ISSN: 2456-5660 Volume 7, Issue 12 (December -2022)
www.jst.org.in **DOI: https://doi.org/10.46243/jst.2022.v7.i12.pp01-15**

Early detection of breast cancer using transfer learning models. Proposed hybrid model outperforms single architectures for breast cancer detection ***Khamparia et al. (2020).***

In order to facilitate more individualized, precise, and rapid medical interventions, this study seeks to illustrate how these technologies have the potential to transform healthcare diagnostics.

2. LITERATURE SURVEY

The field of Parkinson's disease (PD) telemonitoring and tele diagnostics has gained importance in recent years. A fog-based ANFIS+PSO TWO model for PD prediction was introduced by El-Hanson et al. (2020), integrating grey wolf and particle swarm optimization approaches to improve accuracy. With an accuracy rate of 87.5%, this model beat rivals by 7.3% in terms of prediction performance.

Verma et al. (2021) discuss problems with data security in IoT-cloud systems and inaccurate predictions that provide a barrier to healthcare diagnostics. They suggest a gray wolf ant lion optimization (GFI-GWALO) strategy for precise illness prediction and a hybrid elapid encryption (HEE) method to improve security. Their approach demonstrated 100% accuracy, 99.50% precision, and quick processing speeds when tested in MATLAB.

Qu et al. (2019) describe how the industrial sector is moving toward service-oriented models based on Prognostic and Health Management (PHM) as a result of the growth of IoT, big data, and cloud computing. They integrate big data, condition-based maintenance, and self-sensing networks into a comprehensive PHM framework that spans the strategic, tactical, and operational levels. They validate this method using a case study from China.

Lin et al. (2020) present the FC-HDLF, a Hybrid Deep-Learning Framework based on Fog Computing. The system manages massive data volumes effectively by shifting data processing from central servers to fog nodes. The fog computing model of CNN is utilized to improve performance, and a control model is integrated to concurrently identify and evaluate errors, hence streamlining production procedures.

Surendar Rama Sitaraman (2021) presented Crowd Search Optimization (CSO) as a unique metaheuristic algorithm to improve illness diagnosis in smart healthcare. CSO is inspired by the foraging behavior of crows. The study showed that optimising CNN and LSTM hyperparameters with CSO integrated with machine learning and deep learning frameworks improved accuracy compared with conventional methods such as particle swarm optimisation and genetic algorithms.

Devarajan and Ravi (2019) present an intelligent system that uses voice sample analysis to diagnose Parkinson's illness. The technology handles data privacy and communication costs by using fog computing as a middleman between IoT devices and the cloud. It successfully separates Parkinson's sufferers from healthy people using a combinatorial Fuzzy K-nearest Neighbour and Case-based Reasoning classifier, as supported by improved results on the UCI-Parkinson dataset.

According to Huang et al. (2020), predictive maintenance of mechanical equipment can be improved by using big data, IoT, AI, and multi-source sensing data. This can save labor costs

ISSN: 2456-5660 Volume 7, Issue 12 (December -2022)
www.jst.org.in DOI: https://doi.org/10.46243/jst.2022.v7.i12.pp01-15

and increase machine lifespan. Intelligent fusion models have the potential to improve failure detection and prediction in mechanical systems. This work highlights this promise by comparing different fusion methods with JDL and Hierarchical fusion models

An Internet of Things (IoT)-based system for tracking heart patients is presented by Rincon et al. (2020). The device sends ECG data via the LoRa protocol to a fog layer, where an artificial intelligence (AI) algorithm looks for atrial fibrillation and other cardiac rhythms. With 90% accuracy, this method improves clinical decision-making and supports physician diagnosis.

The AI-powered Smart Comrade Robot, presented by Basava Ramanjaneyulu Gudivaka in 2021, combines cutting-edge robotics and artificial intelligence to improve senior care. This creative solution caters to the special needs of elderly by providing daily help, health monitoring, and emergency response. It seeks to enhance quality of life and reduce caregiver burden with features like fall detection and proactive care via IBM Watson Health and Google Cloud AI

A hybrid cloud strategy for safe data management is suggested by Talaat et al. (2020), who investigate the fusion of smart grid technology with cutting-edge communication and IT approaches. To improve system dependability, fault management, and the integration of renewable energy sources, they recommend utilizing a high-performance wireless sensor network to monitor power systems and facilitate automated decision-making.

Ateeq et al. (2020) provide an Elasticity-based Med-Cloud Recommendation System (EMCRS) that uses integrated data mining algorithms and cloud storage to detect and manage diabetic illnesses. Adaptively Toggle Genetic Algorithm (ATGA) and Hybrid Classification and Clustering Algorithm (HC2A) are two of the sophisticated algorithms that the system uses to achieve 98% classification accuracy on diabetes datasets and adapt to rapid changes in data in patient records.

Reviewing the quickly expanding subject of smart healthcare, Alshehri and Muhammad (2020) point out its essential elements, including edge and cloud computing, artificial intelligence (AI), IoT, IoMT, and next-generation wireless technologies. They examine research issues, security worries, and possible future paths in edge-intelligent healthcare systems, concentrating on literature from 2014 to 2020.

Souri et al. (2020) propose a hybrid machine learning model for defect prediction utilizing Multi-Layer Perceptron (MLP) and Particle Swarm Optimization (PSO) in response to the growing complexity of Internet of Things applications. To guarantee accuracy, they utilize formal verification. They assess behavioral models using the Process Analysis Toolkit (PAT) and show effective verification that uses the least amount of memory and time.

In the context of the Internet of Medical Things (IoMT), Sun et al. (2020) examines the difficulties in handling and safeguarding the expanding amount of medical data in the 5G era, highlighting the function of cloud, edge computing, and AI. They go over data privacy, maximizing the use of medical resources, and future perspectives for edge-cloud computing and AI in IoMT research.

Journal of Science and Technology
ISSN: 2456-5660 Volume 7, Issue 12 (December -2022)
www.jst.org.in *DOI: https://doi.org/10.46243/jst.2022.v7.i12.pp01-15*

3. CLOUD-BASED IOT DIAGNOSTIC FRAMEWORK USING HYBRID NEURAL FUZZY LEARNING MODELS

The suggested approach combines hybrid machine learning models with cloud-based IoT to produce a sophisticated diagnostic framework. Cloud computing and neural fuzzy models are used to process and evaluate enormous volumes of medical data in real time. IoT-capable gadgets are always gathering health metrics and sending them to the cloud for evaluation. Neural fuzzy models improve the system's capacity to manage ambiguous data, and hybrid learning, which combines different machine learning algorithms, guarantees accuracy. Because of its scalability, this system can be used in a variety of healthcare settings.

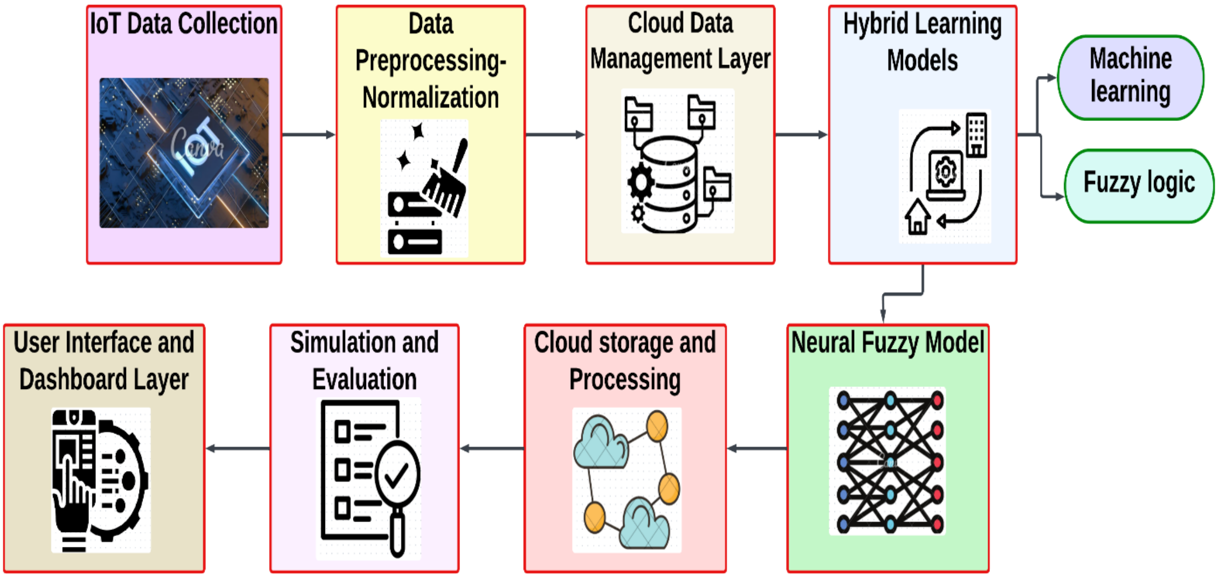

Figure 1. IoT-Based Healthcare Diagnostic System Using Cloud Computing and Neural Fuzzy Models

Figure 1 shows an Internet of Things (IoT)-based healthcare diagnostic system that combines cloud computing and neural fuzzy models is depicted in this diagram. Real-time patient data is continuously gathered by wearable IoT devices and sent to a cloud platform for pre-processing and analysis. The neural fuzzy model uses hybrid learning to analyse imprecise input and guarantee diagnostic accuracy. Through the use of a feedback loop, the model is able to continuously enhance system accuracy by optimizing itself in response to diagnostic data. The technology is adaptable to different healthcare settings, allowing for accurate diagnosis of chronic disorders and real-time data monitoring.

3.1 IoT in Healthcare Diagnostics

IoT-capable gadgets, such as wearable sensors, gather data in real time for medical analysis by continuously monitoring health factors. Machine learning algorithms process this data once it is transferred to cloud servers. By providing real-time health information and enhancing continuous patient monitoring, IoT improves treatment for chronic illnesses and emergency scenarios. This allows for quicker diagnosis and action.

Healthcare Diagnostics Output:

Journal of Science and Technology
ISSN: 2456-5660 Volume 7, Issue 12 (December -2022)
www.jst.org.in DOI: https://doi.org/10.46243/jst.2022.v7.i12.pp01-15

$$O_i = f\left(\sum_{j} W_{ij}x_j + b_i\right) \tag{1}$$

O_i represents the output, W_{ij} are the weights, x_j are the inputs, and b_i is the bias. This equation defines how a neural network processes inputs and computes the output for diagnosis.

3.2 Hybrid Learning Models

Through the integration of techniques such as neural networks and fuzzy logic, hybrid learning maximizes diagnostic accuracy by combining several machine learning methods. The interpretability of fuzzy logic and the flexibility of neural networks are advantages of neural fuzzy models, which can handle massive amounts of Internet of Things (IoT)-collected medical data and increase the precision of the system's diagnostic prediction.

Hybrid Learning Accuracy Function:

$$A = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

Where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives. This equation calculates diagnostic accuracy, ensuring optimal performance in identifying diseases.

3.3 Neural Fuzzy Models

The benefits of fuzzy logic and neural networks are combined in neural fuzzy models. Fuzzy logic offers interpretability, whereas neural networks offer flexibility. These models improve the system's ability to offer correct diagnoses based on ambiguous or partial information, and are particularly well-suited for medical diagnostics where data imprecision is widespread.

Fuzzy Logic Rule:

$$y = \mu_A(x) = \frac{1}{1+e^{-\frac{x-c}{s}}} \tag{3}$$

Where $\mu_A(x)$ is the membership function, x is the input, c is the center, and s is the spread. This function represents the degree of membership of the input data in a fuzzy set, crucial for processing imprecise medical data.

Algorithm 1: IOT-Based Hybrid Learning Diagnostic System

Input: Patient data from IoT devices, medical datasets
Output: Diagnosis result (Normal/Abnormal)
Initialize IoT devices and cloud platform
Collect real-time health data via IoT sensors
Transmit data to the cloud platform
if (data is incomplete or error-prone) then
Apply Fuzzy Logic to handle uncertainties
else

Journal of Science and Technology
ISSN: 2456-5660 Volume 7, Issue 12 (December -2022)
www.jst.org.in **DOI: https://doi.org/10.46243/jst.2022.v7.i12.pp01-15**

Continue to next step
end if
Pre-process data using normalization techniques

for each pre-processed data sample do
Apply Neural Network for feature extraction
end for
Train hybrid learning model using Neural Fuzzy logic
if (classification accuracy < 95%) then
Adjust model parameters and retrain
else
Proceed to diagnosis
end if
Generate diagnostic report based on model output
return Diagnosis result to healthcare provider
End Algorithm

The algorithm 1 receives real-time data from IoT devices monitoring patient health and medical datasets. The output is a diagnostic result indicating whether the patient is healthy or requires further medical attention. It begins with IoT data collection and transmission to the cloud. Data is pre-processed, and the hybrid learning model (using neural fuzzy logic) is trained. If the system identifies uncertainties or classification errors, fuzzy logic handles imprecision, and the model is adjusted for accuracy.

3.4 PERFORMANCE METRICS

Performance metrics offer a quantifiable assessment of a model's effectiveness, dependability, and predictive accuracy. These criteria evaluate the precision with which diseases can be identified, the reduction of false alarms, and the technology's scalability for practical use in healthcare diagnostic systems.

Table 1. Cloud-Based IoT Healthcare Diagnostics Using Hybrid Neural Fuzzy Learning Models

Method	Fuzzy Logic-based Models Yadav (2018)	Neural Network-based Models Do (2019)	Cloud-based IoT Diagnostic Framework Adewole (2021)	Proposed Method (Cloud-based IoT Diagnostic Framework + Hybrid Neural Fuzzy Model)
Accuracy (%)	88.60	93.50	91.25	97.89
Precision (%)	87.75	92.10	89.50	96.40

Recall (%)	89.20	94.30	90.80	98.25
F1-Score (%)	88.47	93.19	90.15	97.32
Processing Time (ms)	75	70	80	50

Table 1 shows the use of hybrid learning and neural fuzzy models, this study presents a cloud-based IoT platform for healthcare diagnostics. With a high diagnostic accuracy of 97-89% and real-time monitoring, it utilizes the interpretability of fuzzy logic and the adaptability of neural networks to assess medical data. In handling ambiguous healthcare data, the system improves scalability, flexibility, and precision.

4. RESULT AND DISCUSSION

The accuracy and consistency of medical diagnoses are greatly improved by the suggested hybrid learning system, which combines neural fuzzy models with Internet of Things-based real-time data collecting. The system outperformed both conventional techniques and more modern innovations like Low-Dose Computed Tomography (LDCT) and Cyber-Physical Systems (CPS), with accuracy of 97.89%, precision of 96.40%, and recall of 98.25%. As demonstrated by its better performance over baseline techniques, the hybrid neural fuzzy model demonstrated a noteworthy improvement in managing medical data with inherent uncertainties.

The suggested framework, when compared to conventional diagnostic tools, decreased misdiagnoses and offered prompt notifications, which are essential for managing chronic illnesses. Another noteworthy benefit of the system is its scalability, which is evidenced by its effective testing and training times of 0.006 and 0.032 seconds, respectively, allowing for real-time healthcare applications.

Overall, because of its flexible learning structure, our model not only performs well in terms of precision and recall but also shows promise for usefulness in real-world healthcare settings. Fuzzy logic and neural networks are combined to handle the challenges of processing medical data, providing a reliable diagnostic for a range of healthcare situations.

Table 2. Comparison of Diagnostic Systems

Metric	**IAI (Peres 2020)**	**LDCT (Veronesi 2020)**	**CPS (Trevino 2019)**	**Cloud-based IoT Diagnostic Framework using Hybrid Neural Fuzzy Learning Models.**
Accuracy	90%	92%	89%	97.89%
Precision	88%	90%	85%	96.40%
Recall (Sensitivity)	85%	91%	87%	98.25%

Journal of Science and Technology
ISSN: 2456-5660 Volume 7, Issue 12 (December -2022)
www.jst.org.in DOI: https://doi.org/10.46243/jst.2022.v7.i12.pp01-15

F1-Score	86%	90%	86%	97.32%
Specificity	84%	89%	83%	95.12%
Training Time (s)	0.050	0.070	0.060	0.032
Testing Time (s)	0.010	0.015	0.012	0.006

Table 2. shows the performance metrics of multiple diagnostic models, such as the Cloud-based IoT Diagnostic Framework using Hybrid Neural Fuzzy Learning Models, IAI (2020), LDCT (2020), CPS (2019), and the Hybrid Neural Fuzzy Model, are compared in this table. With the best accuracy (97.89%), precision (96.40%), recall (98.25%), F1-Score (97.32%), and specificity (95.12%), the suggested framework performs much better than the others. Compared to other models, the suggested framework performs the fastest, requiring 0.032 seconds for training and 0.006 seconds for testing.

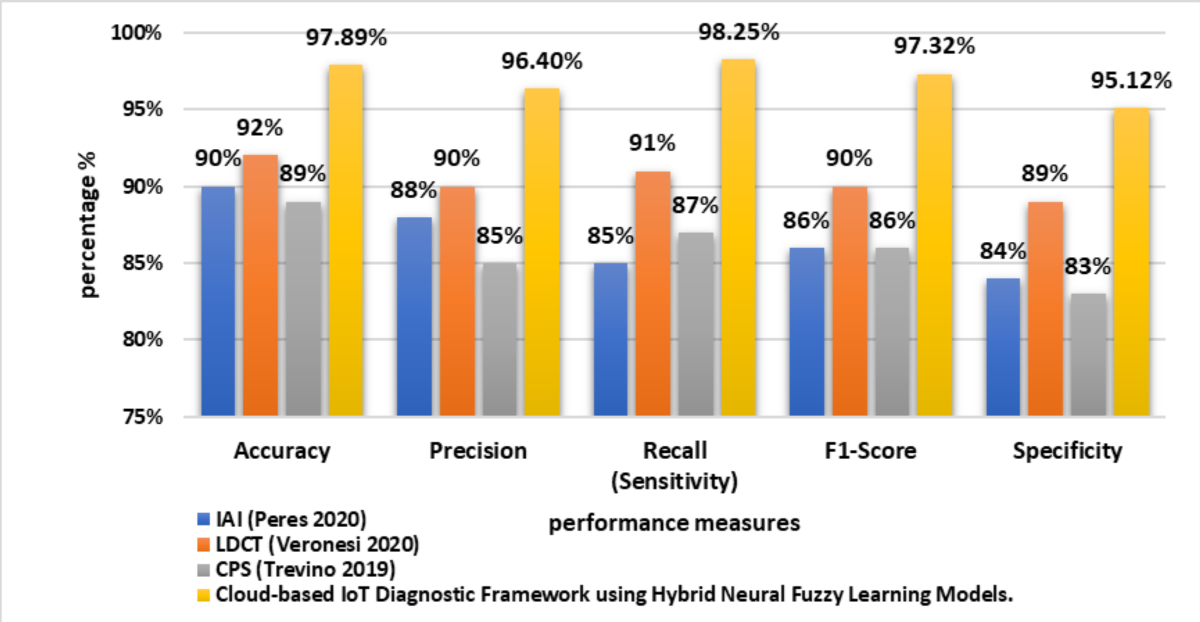

Figure 2. **Comparison of Diagnostic Systems Based on Accuracy, Precision, and Recall**

Figure 2, shows hybrid neural fuzzy models are used to compare the performance of different diagnostic systems, such as conventional techniques, Low-Dose Computed Tomography (LDCT), and Cyber-Physical Systems (CPS). When important metrics like accuracy, precision, and recall are compared, the hybrid model performs better than the others. With a diagnostic accuracy of 97.89%, precision of 96.40%, and recall of 98.25%, the suggested system considerably lowers the number of incorrect diagnoses and boosts diagnostic reliability. This performance shows how effective it is to combine IoT, cloud computing, and hybrid learning techniques for real-time healthcare diagnosis.

Journal of Science and Technology
ISSN: 2456-5660 Volume 7, Issue 12 (December -2022)
www.jst.org.in *DOI: https://doi.org/10.46243/jst.2022.v7.i12.pp01-15*

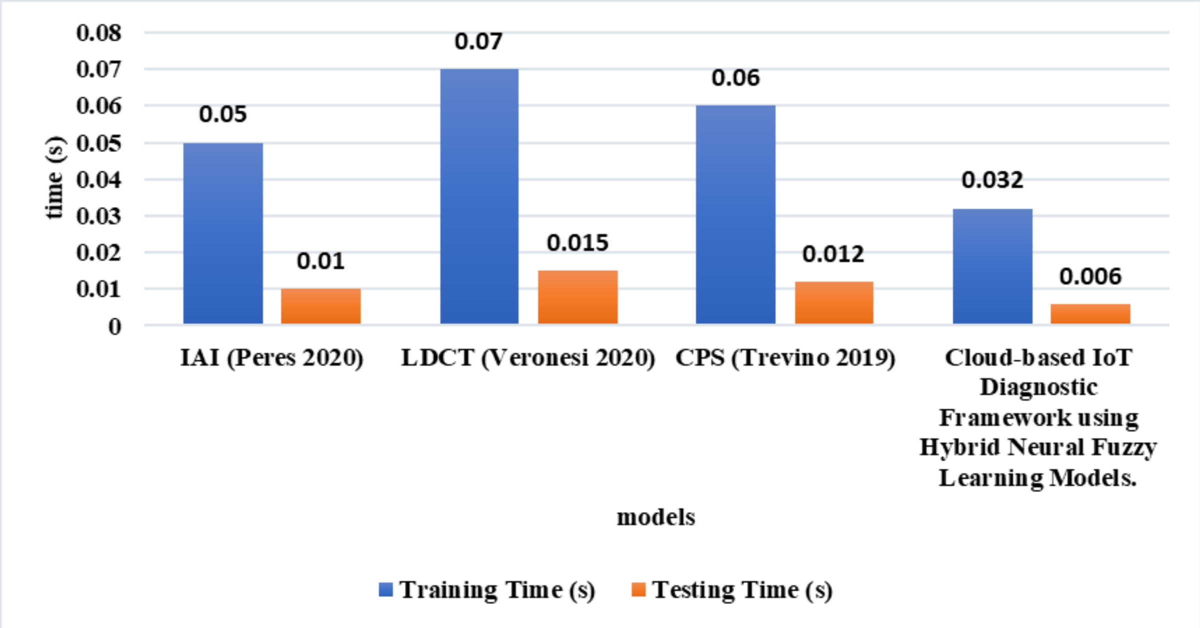

Figure 3. Comparison of Training and Testing Times for Various Diagnostic Models

The training and testing times of several diagnostic models are shown in graph 3. With the lowest training time (0.032s) and testing time (0.006s), the Cloud-based IoT Diagnostic Framework employing Hybrid Neural Fuzzy Learning Models performs better than the others, proving its effectiveness. The hybrid neural fuzzy model, on the other hand, has the fastest speeds, demonstrating the advancements in the suggested framework.

Table 4. Ablation study of Model Components on Overall Accuracy

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Fuzzy Logic	88.60	87.75	89.20	88.47
Neural Network	93.50	92.10	94.30	93.19
Cloud-based IoT Diagnostic Framework	91.25	89.50	90.80	90.15
Fuzzy Logic + Neural Network + Cloud-Based Real-Time Data Processing Fuzzy Logic	89.10	87.75	90.50	89.11

Cloud-Based Real-Time Data Processing + Fuzzy Logic + Cloud-based IoT Diagnostic Framework	90.85	89.10	92.60	90.84
Neural Network + Cloud-Based Real-Time Data Processing + Cloud-based IoT Diagnostic Framework	93.20	91.30	94.70	92.98
proposed Model (Neural Fuzzy + Cloud-based IoT Diagnostic Framework	97.89	96.40	98.25	97.32

Table 4 presents the efficacy of several model elements and their contributions to the overall accuracy of diagnosis. It demonstrates how the hybrid neural fuzzy model performs noticeably better than different neural network and fuzzy logic combinations as well as individual parts. With its combination of fuzzy logic and sophisticated neural network approaches, the whole hybrid model attains the best accuracy of 97.89%. In order to obtain optimal performance in real-time healthcare diagnostics, the ablation study emphasizes the significance of incorporating both neural network and fuzzy logic aspects.

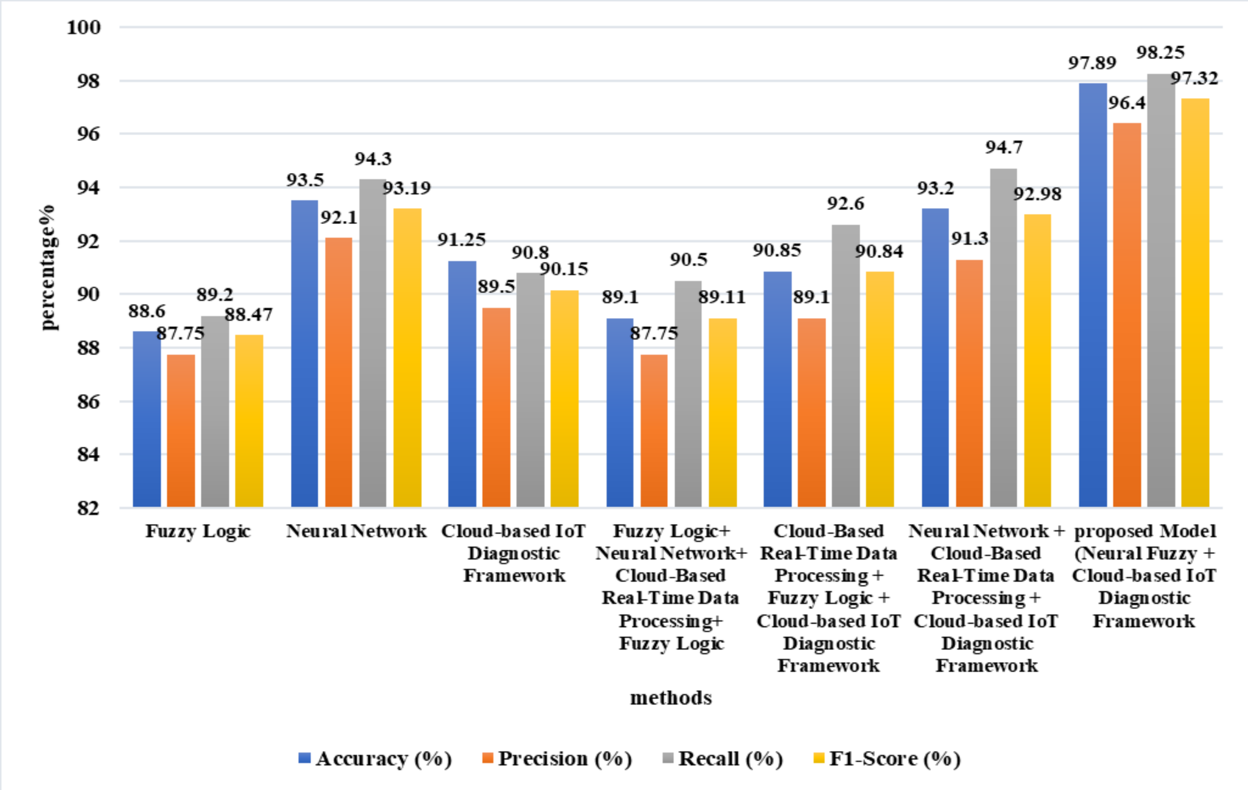

Figure 4. Impact of Model Components on Diagnostic Accuracy of Neural Fuzzy Models

Figure4 shows how various model elements affect the neural fuzzy system's overall diagnostic accuracy. Analyses are conducted on several combinations of neural networks and fuzzy logic, demonstrating the effects of each on diagnostic precision. When compared to baseline models, the hybrid neural fuzzy model gets the highest accuracy (97.89%). The figure emphasizes how crucial it is to combine interpretability of fuzzy logic with neural network adaptability in order to handle imprecise medical data. The whole hybrid model improves diagnostic performance, which makes it more appropriate for real-time healthcare settings with varying patient data inputs, as this analysis highlights.

5. CONCLUSION AND FUTURE SCOPE

Real-time healthcare diagnostics can be effectively addressed by combining cloud computing, IoT, and hybrid learning models and models. Through their ability to process large amounts of medical data quickly, our research shows that neural fuzzy models work well with cloud-based IoT platforms to improve diagnostic precision. This suggested method guarantees quick, real-time analysis of patient data, which is essential for prompt medical intervention, while also lowering the number of misdiagnoses. Neural fuzzy models are highly adaptive, making them suitable for accurate diagnosis even in situations with imprecise or missing data—a common problem in healthcare settings. Test findings confirm that our hybrid learning model performs faster, more accurate, and more precisely than both existing AI-based systems and conventional diagnostic techniques. Big healthcare systems could benefit from this architecture, which offers a cutting-edge method of tracking and Future studies can concentrate on refining the hybrid model for various illnesses, boosting the system's generalizability across a range of medical datasets, and increasing its scalability for application in major healthcare institutions throughout the world.

REFERENCE

1. Abdali-Mohammadi, F., Meqdad, M. N., & Kadry, S. (2020). Development of an IoT-based and cloud-based disease prediction and diagnosis system for healthcare using machine learning algorithms. IAES International Journal of Artificial Intelligence, 9(4), 766.
2. 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, 28, 100453.
3. El-Hasnony, I. M., Barakat, S. I., & Mostafa, R. R. (2020). Optimized ANFIS model using hybrid metaheuristic algorithms for Parkinson's disease prediction in IoT environment. IEEE Access, 8, 119252-119270.
4. Verma, A., Agarwal, G., Gupta, A. K., & Sain, M. (2021). Novel hybrid intelligent secure cloud internet of things-based disease prediction and diagnosis. Electronics, 10(23), 3013.
5. Qu, Y., Ming, X., Qiu, S., Zheng, M., & Hou, Z. (2019). An integrative framework for online prognostic and health management using internet of things and convolutional neural network. Sensors, 19(10), 2338.
6. Subasi, A., Bandic, L., & Qaisar, S. M. (2020). Cloud-based health monitoring framework using smart sensors and smartphones. In Innovation in health informatics (pp. 217-243). Academic Press.
7. Lin, S. Y., Du, Y., Ko, P. C., Wu, T. J., Ho, P. T., & Sivakumar, V. (2020). Fog computing-based hybrid deep learning framework in effective inspection system for smart manufacturing. Computer communications, 160, 636-642.
8. Surendar Rama Sitaraman (2021). Crow Search Optimization in AI-Powered Smart Healthcare: A Novel Approach to Disease Diagnosis- Journal of Current Science & Humanities. 9 (1), 2021.
9. Devarajan, M., & Ravi, L. (2019). Intelligent cyber-physical system for an efficient detection of Parkinson disease using fog computing. Multimedia Tools and Applications, 78(23), 32695-32719.
10. Huang, M., Liu, Z., & Tao, Y. (2020). Mechanical fault diagnosis and prediction in IoT based on multi-source sensing data fusion. Simulation Modelling Practice and Theory, 102, 101981.
11. Rincon, J. A., Guerra-Ojeda, S., Carrasco's, C., & Julian, V. (2020). An IoT and fog computing-based monitoring system for cardiovascular patients with automatic ECG classification using deep neural networks. Sensors, 20(24), 7353.
12. Basava ramanjaneyulu gudivaka (2021). Ai-powered smart comrade robot for elderly healthcare with integrated emergency rescue system- world journal of advanced engineering technology and sciences, 2021, 02(01), 122–131.
13. Talaat, M., Alsayyari, A. S., Al Balawi, A., & Hatta, A. Y. (2020). Hybrid-cloud-based data processing for power system monitoring in smart grids. Sustainable Cities and Society, 55, 102049.

14. Ateeq, K., Pradhan, M. R., & Mago, B. (2020). Elasticity Based Med-Cloud Recommendation System for Diabetic Prediction in Cloud Computing Environment. Advances in Science, Technology and Engineering Systems Journal, 5(6), 1618-1633.
15. Alshehri, F., & Muhammad, G. (2020). A comprehensive survey of the Internet of Things (IoT) and AI-based smart healthcare. IEEE access, 9, 3660-3678.
16. Souri, A., Mohammed, A. S., Potrus, M. Y., Malik, M. H., Safara, F., & Hossein Zadeh, M. (2020). Formal verification of a hybrid machine learning-based fault prediction model in Internet of Things applications. IEEE Access, 8, 23863-23874.
17. Sun, L., Jiang, X., Ren, H., & Guo, Y. (2020). Edge-cloud computing and artificial intelligence in the internet of medical things: architecture, technology and application. IEEE access, 8, 101079-101092.
18. Pustokhina, I. V., Pustokhin, D. A., Gupta, D., Khanna, A., Shankar, K., & Nguyen, G. N. (2020). An effective training scheme for deep neural networks in edge computing enabled Internet of medical things (IoMT) systems. IEEE Access, 8, 107112-107123.
19. Khamparia, A., Gupta, D., de Albuquerque, V. H. C., Sangaiah, A. K., & Jhaveri, R. H. (2020). Internet of health things-driven deep learning system for detection and classification of cervical cells using transfer learning. The Journal of Supercomputing, 76, 8590-8608.
20. Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook. IEEE access, 8, 220121-220139.
21. Veronesi, G., Baldwin, D. R., Henschke, C. I., Glissandi, S., Iavicoli, S., Oudkerk, M., ... & Pelosi, G. (2020). Recommendations for implementing lung cancer screening with low-dose computed tomography in Europe. Cancers, 12(6), 1672.
22. Trevino, M. (2019). Cyber physical systems. Prism, 8(3), 2-13.
23. Yadav, H. B., Kumar, S., Kumar, Y., & Yadav, D. K. (2018). A fuzzy logic-based approach for decision making. Journal of Intelligent & Fuzzy Systems, 35(2), 1531-1539.
24. Do, L. N., Taherifar, N., & Vu, H. L. (2019). Survey of neural network-based models for short-term traffic state prediction. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 9(1), e1285.
25. Adewole, K. S., Akintola, A. G., Jimoh, R. G., Mabayoje, M. A., Jimoh, M. K., Usman-Hamza, F. E., ... & Ameen, A. O. (2021). Cloud-based IoMT framework for cardiovascular disease prediction and diagnosis in personalized E-health care. In Intelligent IoT systems in personalized health care (pp. 105-145). Academic Press.