

Integration of Fog-Cloud-IoT for Smart Health Care System using Machine Learning Algorithm for Monitoring of Patients

Ganesh D Gourshete¹, Dr. Susheel Kumar Tiwari², Dr. Prashant P Nitnaware³

^{1,2}Department of CS&E, Madhyanchal Professional University Ratibad, Bhopal, India

³Department of Information Technology, Pillai College of Engineering, New Panvel

¹goursheteganesh@gmail.com, ²sushiltiwari24@yahoo.co.in, ³pnitnaware@mes.ac.in

Abstract

The complexity of healthcare systems has posed a significant challenge globally, leading to an increase in morbidity and mortality rates, particularly among elderly patients. The risk of data processing errors rises with the multiple connections of edge devices in hospital environments. The quality of healthcare services has been greatly improved by the integration of technologies like the Internet of Things (IoT), which is facilitated by fog and cloud computing. By tackling the difficulties present in intricate healthcare systems, these developments increase the efficacy, dependability, and efficiency of healthcare delivery. This study explores the difficulties posed by cloud and fog computing in intelligent healthcare systems and suggests an ensemble-based learning strategy for edge device data segregation. The suggested approach maximizes the layered architecture of edge devices for real-time data processing by utilizing a stacking-based ensemble classifier. With an emphasis on enhancing Quality of Service (QoS), the algorithm's performance is assessed using the FogSim simulator, taking into account variables like energy usage and mobility in healthcare settings. The findings show that the suggested method improves system reliability and detection accuracy for intricate traffic nodes.

Keywords: Edge Computing, Layer Technology, Machine Learning, Ensemble Classifier, FogSim

1. INTRODUCTION

The impact of emerging communication technologies significantly enhances the services and utility of healthcare systems. Technologies like fog computing, cloud computing, and the Internet of Things (IoT) have set new benchmarks for real-time monitoring and management in healthcare[1]. These advancements enable continuous monitoring of patients, facilitating timely interventions and personalized care[2]. The integration of these technologies not only improves the quality of care but also enhances operational efficiency, allowing healthcare providers to make data-driven decisions swiftly. As a result, the adoption of these technologies is transforming the landscape of healthcare delivery, making it more responsive, efficient, and accessible. Fog computing, in particular, plays a crucial role in this transformation by acting as the backbone of edge computing[3]. While cloud computing provides centralized data storage and processing, By bringing these capabilities closer to the sensors and medical devices that generate the data, fog computing greatly lowers latency and makes it possible to process vital health data in real time. This is especially important for telemedicine, emergency response, and remote monitoring applications. Fog computing serves as a link between edge devices and the cloud, speeding up data processing and reducing the strain on cloud infrastructure, improving the dependability and effectiveness of healthcare services [4]. This synergy between fog computing and other emerging technologies is pivotal in advancing the capabilities of modern healthcare systems. Many IoT applications that don't need low latency or involve critical scenarios are a good fit for cloud-based solutions. However, conventional cloud-based methods can pose serious difficulties for applications involving patients with urgent medical needs, especially during emergencies [5]. Serious repercussions could result from any interruption in network connectivity or latency problems, possibly putting patients in critical conditions at risk. The limitations of cloud computing are made clear in these situations since data transmission delays or interruptions may jeopardise the standard of care and the promptness of medical interventions. For healthcare applications that are sensitive to latency, fog computing offers a better substitute. Fog computing addresses the inefficiencies frequently linked to cloud computing by processing, aggregating, and temporarily storing sensor-generated data closer to the source, minimising round-trip delays and network congestion [6]. This advantage is particularly crucial for e-health applications, such as remote ECG monitoring, where real-time data communication is essential for continuous patient monitoring and timely decision-making. To address issues of delay and security, a three-layer computing architecture—comprising Cloud, Fog, and

Edge layers—has been proposed for remote health monitoring[7]. This hierarchical arrangement, inspired by the concept of memory hierarchy in computer architecture, enhances performance by reducing access latency. In this architecture, the edge layer handles initial decisions using machine learning algorithms, prioritizing data transmission to alleviate congestion on NB-IoT base stations and minimize transmission delays. The fog layer further processes the data with more detailed medical analysis, while long-term computations and predictions are conducted at the cloud layer. Because fog devices have less processing and storage capacity than cloud data centres, fog computing still has drawbacks despite its advantages, especially when it comes to resource management for various IoHT tasks. Fog computing is still a viable option, though, for real-time medical applications where responsiveness and low latency are essential. There are many obstacles to overcome when integrating various platforms in data-intensive processes, especially when it comes to latency and fast data access. As the volume of data increases, the slow processing of this data can lead to higher rates of delay, which in turn exacerbates issues like security threats and inefficient resource utilization. These delays not only affect the overall performance of the system but also compromise the integrity and security of the data being processed. The integration of edge devices with fog computing infrastructures, which are designed to handle real-time data processing closer to the source, must therefore prioritize minimizing latency to ensure seamless and secure operations. Recent studies indicate that machine learning-based algorithms have been increasingly employed to predict traffic patterns and mitigate security risks in the integration and processing of edge node data. To address these challenges, this paper proposes an ensemble-based learning approach for data segregation on edge devices, which significantly enhances the performance of fog computing[8,9]. The proposed algorithm leverages the concept of stacking, where multiple models are combined to improve predictive accuracy and efficiency. By using stacking, latency is decreased and system performance is improved by speeding up the data transfer process from edge devices to fog servers. This method is a strong way to deal with the complexity of data-intensive environments because it not only streamlines the data processing workflow but also strengthens the security and dependability of the integrated platforms. Based on the reported survey finds gap of research and motivated for the proposing ensemble-based algorithm for the reduction of latency and improves processing of data speed on real-time mode.

1. Proposed novel algorithm based on stacking of ensemble classifier for layered architecture of edge devices for fast processing of real-time data.
2. Stacking ensemble play role as intermediate data cluster between edge devices and fog computing
3. Reduces rate of latency of edge networks
4. Test proposed algorithms on different parameters of communication

The remainder of this article is structured as follows: Section II reviews related work, Section III outlines the materials and methodology, Section IV presents the experimental analysis, and Section V concludes the study.

2. RELATED WORK

The emerging technology of various platforms provides reliable and efficient services for smart healthcare systems. However, the integration of these technologies faces challenges related to latency and data security. Despite several approaches, the issue of latency persists. Recently, several authors have proposed machine learning-based algorithms for fog computing in healthcare systems. In [1], the focus is on ML models for COVID-19 detection, emphasizing accuracy and efficiency. It includes the classification of severity levels and reducing decision time through AI, as well as the development of a cloud-based home hospitalization system using IoT, cloud computing, and fog computing. However, the study notes that limited patient data necessitates further collection and examines predictive features using diverse methods. In [2], a three-layer fog-computing architecture for healthcare-IoT is proposed, with a focus on real-time applications using continuous glucose monitoring as a case study. The paper presents mathematical models and resource models and highlights challenges in the existing IoT-cloud model, emphasizing the need for QoS improvement. In [3], a workload-aware dynamic resource allocation algorithm for IoHT applications in fog computing is discussed. The algorithm focuses on optimal resource allocation for delay-sensitive applications, with node sequencing and overhead-based dynamic scheduling implemented for optimized task execution. In [4], the Fog Learner framework for disease prediction in healthcare is

explored, examining the trade-off between accuracy and quality of service. A deep learning model for cardiac disease prediction is evaluated on the PureEdgeSim simulator, considering energy consumption and mobility in healthcare systems. In [5], remote monitoring for cost reduction and proper treatment is addressed, with mutual authentication frameworks proposed using fog computing in healthcare. The paper discusses security and privacy concerns in the current healthcare framework and proposes solutions for information irregularity and timely access. In [6], the focus is on emerging technologies (big data, IoT, AI, blockchain, cloud computing) for cost-cutting in healthcare. The importance of blockchain is analyzed, and challenges in IoT are addressed, with fog computing proposed for remote monitoring and latency reduction. In [7], fog computing is discussed as a solution to high latency in healthcare emergencies, with the concept of health fog for real-time heart disease analysis. The study evaluates FogBus for latency, bandwidth, accuracy, and power consumption efficiency and highlights cloud computing issues in data transmission. In [8], a YAC-based blockchain is proposed for efficient data computation in healthcare, with fog computing enhancing security in IoMT with blockchain. The paper shows improvements in security aspects compared to ledger-based blockchain designs. In [9], fog computing is reviewed as a low-latency infrastructure for healthcare, with a focus on stage-by-stage development of IoT solutions. Challenges in cloud computing for real-time applications are addressed by fog computing. In [10], the integration of IoT and fog computing for enhanced healthcare is discussed, along with security challenges in the healthcare industry. Mechanisms for data integrity, usability, auditing, and privacy are presented. In [11], performance issues of NB-IoT in healthcare are addressed, with a proposed architecture to reduce NB-IoT delay, execution time, and authentication time. The study uses a decision-tree method for medical data classification on the edge side. In [12], the investigation of options in the search space for a worldwide solution is explored, including a task planning technique for Cloud-IoHT optimization. A load-balancing strategy for improved performance is discussed, with the conclusion and future scope outlined. In [13], limitations facing IoT systems in healthcare are highlighted. In [14], the inspection of edge/fog and smart IoHT computing solutions for remote healthcare is discussed, with a focus on individualized care, injury prevention, and increased efficiency. Challenges in centralized access and cloud systems are also examined. In [15], a public blockchain framework using Ethereum for healthcare is proposed, with the implementation of blockchain to store training data instead of cloud storage. The paper discusses the use of smart contracts for setting and getting IPFS hash values. In [16], the emphasis is on emerging technologies for cost-cutting in smart cities and healthcare, with the integration of big data, IoT, AI, blockchain, and cloud computing. The role of blockchain in protecting private data is discussed, and fog computing is proposed for remote monitoring and reduced latency. In [17], an overview of computing offloading problems and the classification of algorithms and techniques is presented. A novel classification for optimization strategies for service placement in fog nodes is proposed, addressing challenges with device heterogeneity in fog computing. In [18], OffFog is proposed as an approach for guiding data offloading policies in fog computing. An experimental study shows the benefits of OffFog-recommended policies, with improvements in network latency and average execution time compared to the default strategy. In [19], the convergence of distributed applications, AI, and IoT to tackle latency challenges is discussed, with a conceptual reference architecture for merging IoT and AI technologies. The paper explores AI's potential in overcoming barriers in conventional IoT models. In [20], a fog-based approach for classifying IoT data based on criticality and privacy level is proposed, with a focus on enhancing IoT data privacy and response time. In [21], a module placement algorithm for fog cloud architecture is discussed, focusing on the effective use of network resources in a heterogeneous fog environment. Simulations are performed to validate the algorithm. In [22], a criticality and utility-aware remote health monitoring system is designed with the objective of maximizing utility based on profit and patient cost. The paper discusses the design of an FS-assisted remote health monitoring system. In [23], a dynamic congestion management brokering (DCMB) system is proposed for handling urgent requests from the fog layer and providing cloud providers with jobs. The DCMB system is used for cloud latency reduction in emergency response systems. In [24], the Energy-Efficient Internet of Medical Things to Fog Interoperability of Task Scheduling (EEIoMT) framework is proposed to address cloud latency issues in real-time healthcare applications. In [25], a three-module design for low-latency healthcare services using IoT, fog, and cloud modules is discussed, with the integration of a fog-managed data model with a

weighted fog priority job scheduling algorithm. In [26], architectural elements of 5G for efficient remote healthcare services are explored, with a scheme using IoT and fog computing to mitigate limitations. The system architecture blueprints for response-capable healthcare services are also discussed. In [27], verification of OFs OF0, AOF0, and MRHOF for RPL in a static environment is conducted, leading to the creation of a new RPL extension called AOF0 to overcome limitations. The paper investigates the convergence of fog computing with IoT applications. In [28], a review of fog computing and Internet of Everything (IoE) paradigms is presented, discussing optimization metrics in fog computing and IoE environments. The paper also discusses scheduling algorithms, lessons learned, and future research directions.

3. MATERIAL & METHODOLOGY

In order to improve the effectiveness and performance of IoT-based systems, this section introduces a layered framework that combines several computing platforms into a stacking ensemble classifier. The Internet of Things (IoT), cloud computing, fog computing, and edge computing make up the framework's four main layers. Fundamentally, edge computing, also known as front-end technology, creates a direct line of communication with users, allowing for real-time data processing at the point of data generation. The devices within this layer are interconnected through IoT, which serves as a communication bridge, utilizing sensors, actuators, and other sensory components to relay information across the network. By processing data closer to its source, this architecture reduces latency and enhances responsiveness in real time. At a higher level, cloud computing and fog computing are crucial for managing and processing data. While cloud computing functions at the top, managing central databases, processing user requests, and delivering data on demand, fog computing acts as an intermediary layer, handling data close to the edge. A stacking ensemble classifier must be incorporated into this framework in order to maximise information flow and improve system performance. By making informed decisions on data routing and processing, the classifier reduces traffic overload on edge devices and enhances communication throughput. This layered, integrated approach ensures a balanced distribution of computational tasks, improving overall system performance and reliability in IoT-based services. The processing of architecture present in figure (1).

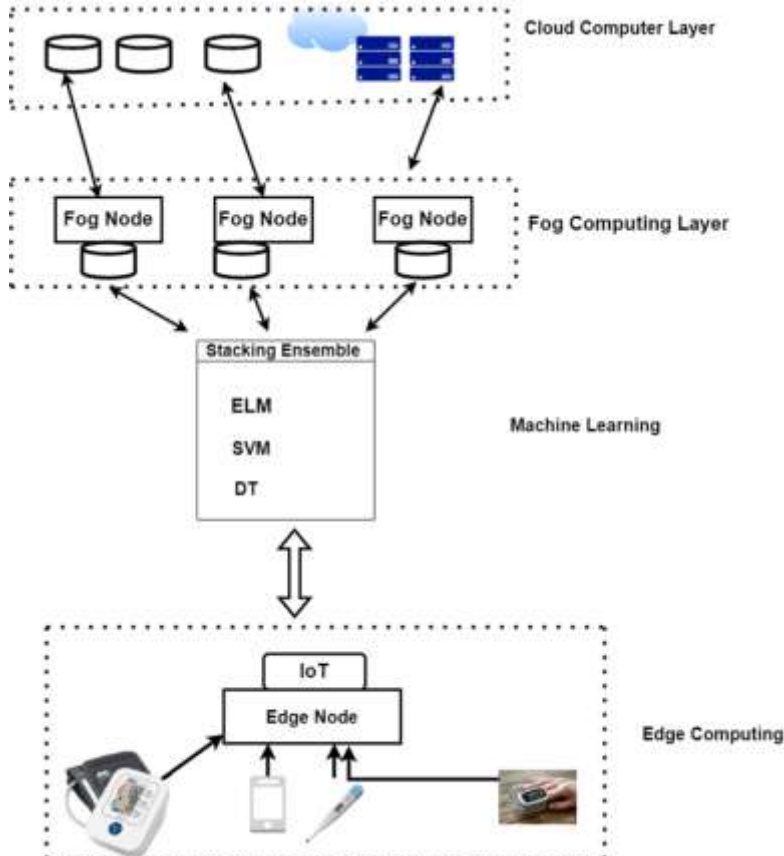


Figure 1. Layered Architecture of integrated Monitoring of Health-care Systems

The suggested integrated approach is very flexible and appropriate for a range of real-time services and applications in intelligent healthcare systems. Robot-assisted surgery, remote surgery, telehealth, telemedicine, telesurgery, e-healthcare, and the transfer of medical data like ECG, EEG, and EMG, as well as remote patient monitoring, can all benefit from its use. This method's capacity to improve patient confidentiality by securely moving historical data to the cloud and processing sensitive data locally is one of its main advantages. Communication latency, computational load, bandwidth usage, and energy consumption are all greatly decreased when fog nodes are installed at hospital locations. In contemporary healthcare systems, this localised implementation is expected to increase the efficacy and efficiency of real-time medical care.

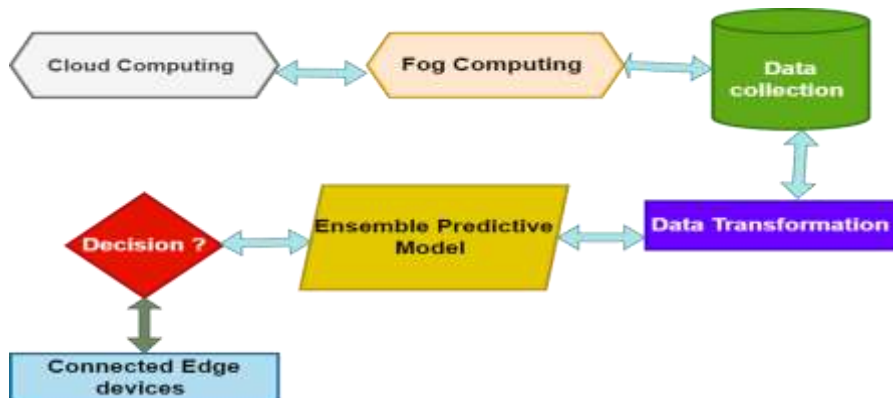


Figure 2. Interpolation of data based on machine learning

The suggested model, which integrates a three-tier architecture with an ensemble-based learning algorithm, is shown in Figure 2. This design's fog layer is made up of a number of elements, such as distributed ledgers and smart contracts that are written in a programming language. Decentralised apps (dApps) that enable distributed data processing seamlessly connect this layer to the healthcare IoT layer. Through a single-hop connection, patients and physicians can communicate directly with the fog layer, facilitating quicker and more effective access to medical care. This architecture's primary innovation is the way it integrates cloud computing and fog computing at the edge of healthcare IoT networks. This method guarantees IoT data authentication and device identification in addition to increasing the effectiveness of healthcare IoT communication. In contrast to traditional state-of-the-art techniques, this architecture successfully handles development limitations, real-world implementation difficulties, and quality of service (QoS) demands.

Particularly in real-time data transmission, ensemble classifiers are very successful methods for improving the precision and dependability of classification tasks [29,30,31,32]. Ensemble learning techniques like stacking, bagging, boosting, and hybrid approaches greatly enhance the performance of individual models by combining multiple classifiers. Out of all of these, stacking is a particularly successful tactic because it combines predictions from several base classifiers and uses a meta-classifier to improve the final judgement. This method produces a more reliable and accurate classification result by minimising the shortcomings of each base model while simultaneously leveraging its strengths. Real-time traffic data is categorised using a stacking-based ensemble classifier in the suggested smart healthcare system. Three classification algorithms are integrated into the model: Decision Tree (DT), Support Vector Machine (SVM), and Extreme Learning Machine (ELM). Every algorithm makes a distinct contribution to the group; ELM guarantees quick learning, SVM offers robust generalisation, and DT makes interpretation simple. The system efficiently manages the varied and dynamic nature of healthcare traffic data by integrating these classifiers, guaranteeing high classification accuracy and enhanced decision-making for crucial real-time applications. This method works especially well in situations where accurate and timely data classification is critical to patient care and system effectiveness. The ensemble classifier's stacking model is shown in Figure 3.

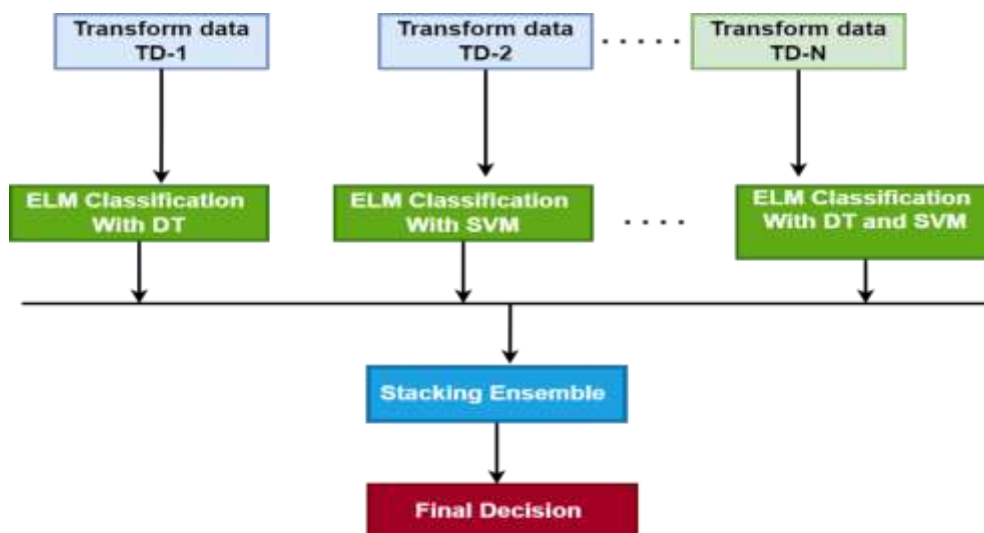


Figure 3. Stacking model of ensemble classifier of ELM, DT and SVM

Figure 3 illustrates the ensemble stacking model used in the decision-making system for real-time traffic within an integrated smart healthcare system. The model operates by segmenting the traffic data into various transformation segments, labeled as TD-1, TD-2, ..., TD-N. Each segment represents a distinct transformation of the traffic data, which is essential for the thorough processing required in real-time healthcare environments. This segmented data is then mapped according to the ensemble classifier's methodology, which systematically trains and tests the data across different classifiers. The ensemble approach ensures that each piece of traffic data is evaluated from multiple perspectives, enhancing the model's ability to accurately categorize and manage the data. Once the traffic data is mapped into different groups by the classifiers, the stacking process begins. This involves aggregating the outputs of these classifiers into a final stack, which is then used to make the ultimate decision regarding the real-time traffic data. The final decision represents a refined consensus that draws on the strengths of each classifier within the ensemble, ensuring that the traffic data is handled with optimal accuracy and efficiency. This process is crucial in a smart healthcare system where real-time data management can impact patient outcomes and system performance. The algorithm's detailed processing flow, as depicted in the figure, highlights the layered and systematic approach of the ensemble stacking model, making it a robust solution for managing complex and dynamic data traffic in healthcare environments.

S= stacking model of decision system
 E= ELM classifier
 SV = support vector machine
 DT = Decision Tree

The mapping of transform data as TD-1, TD-2,.....TD-N

$$M(x) = [t1, \dots, \dots, \dots, tn] \quad (1)$$

Here t1 and tn is mapped data of real-time traffic

Sampling of classifier data

$$S(x) = [Mi1, \dots, \dots, \dots, Mik] \quad (2)$$

M is mapped value of traffic data.

Training of stack classifier as

$$S_j = \begin{cases} 1, & \text{if } j = k \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Processing of test data

$$Test = \underset{\forall(x, |M1, \dots, \dots, MK|) \in Trf}{\operatorname{argmin}} \varepsilon b(K_{rT}(x), [M1, \dots, \dots, \dots, Mk]) \quad (4)$$

Where ϵb is error function for the base class feature voting measure as

$$\epsilon b = \sum_{k=1}^k |MK - K| \tag{5}$$

Now final stacking of classifier is

$$S = \frac{Kj}{\sum_{j=1}^{kc} Kc} \tag{6}$$

4. Experimental Analysis

To validate the performance of the integrated decision model within a fog computing environment, simulations were conducted using the FogSim simulator. FogSim is a Java-based simulation tool designed to replicate and analyse various computing environments, including cloud computing, fog computing, and edge devices. This simulator is particularly valuable for testing and validating complex models like the proposed decision system, as it provides a controlled environment where different scenarios and configurations can be evaluated. The use of FogSim allows researchers to simulate real-world conditions, ensuring that the model's performance is accurately assessed before actual deployment. One of the key features of FogSim is its extensibility, which allows for the integration of machine learning libraries. This capability is crucial for implementing and testing the ensemble algorithms that drive the decision-making process in the fog computing model. The FogSim master simulator serves as the primary platform where these machine learning algorithms are embedded and executed, enabling the simulation of various fog computing scenarios. By utilizing FogSim, researchers can efficiently experiment with different algorithmic approaches, fine-tune parameters, and optimize the model for real-time applications in smart healthcare systems. The results from these simulations provide valuable insights into the effectiveness of the integrated decision model, guiding further development and refinement[24,25,26,27,28].

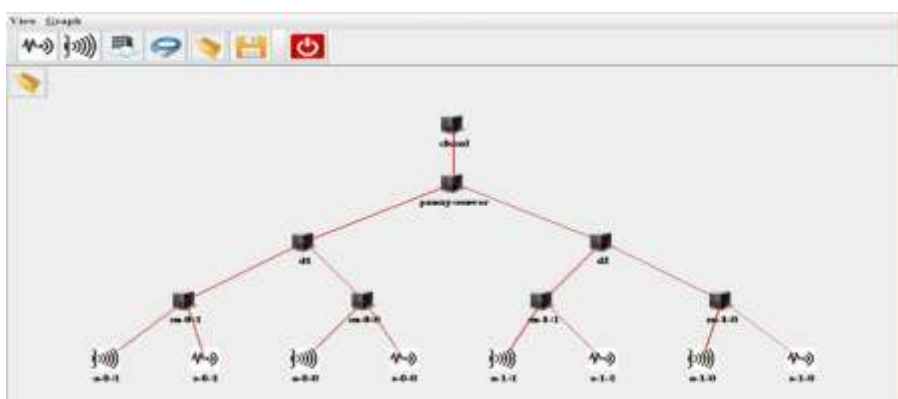


Figure 4 Simulation topology of integrated layer of smart health-care system

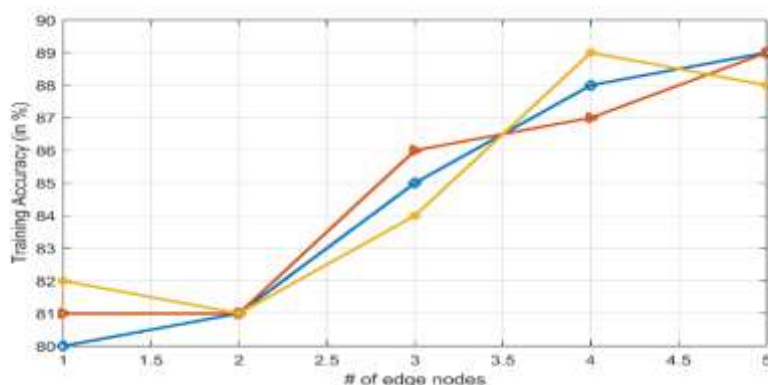


Figure 4. Variation in training accuracy with the number of edge nodes.

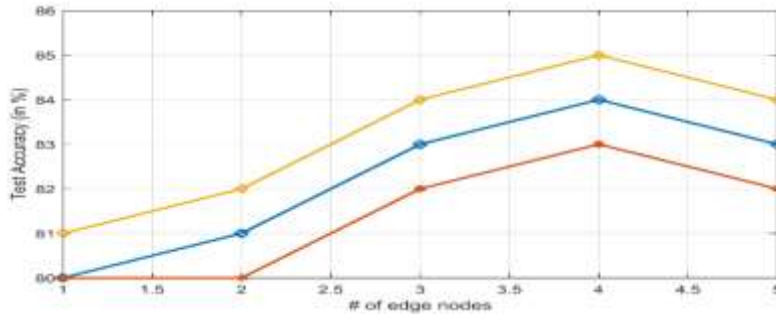


Figure 5. Variation in test accuracy with the number of edge nodes.

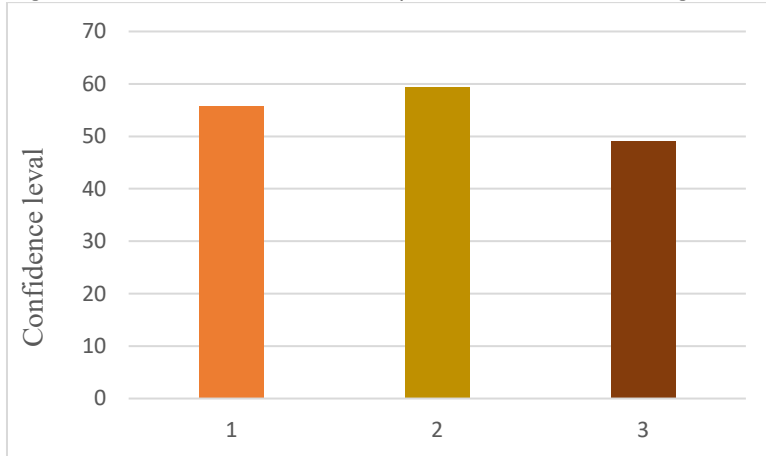


Figure 6. Confidence level of the model with different sample sets from the dataset.

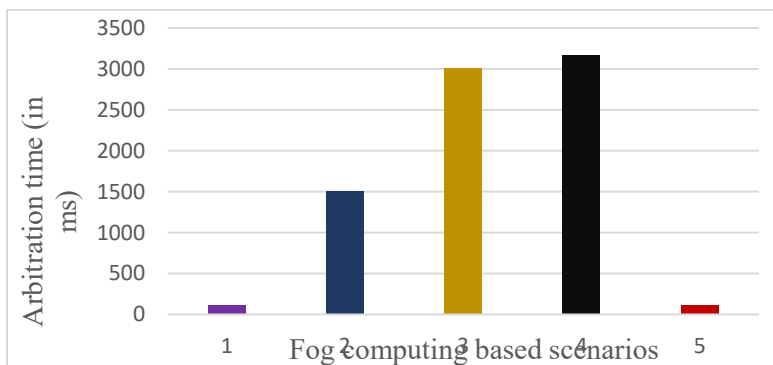


Figure 7. Arbitration time results (in milliseconds) across different fog computing scenarios.

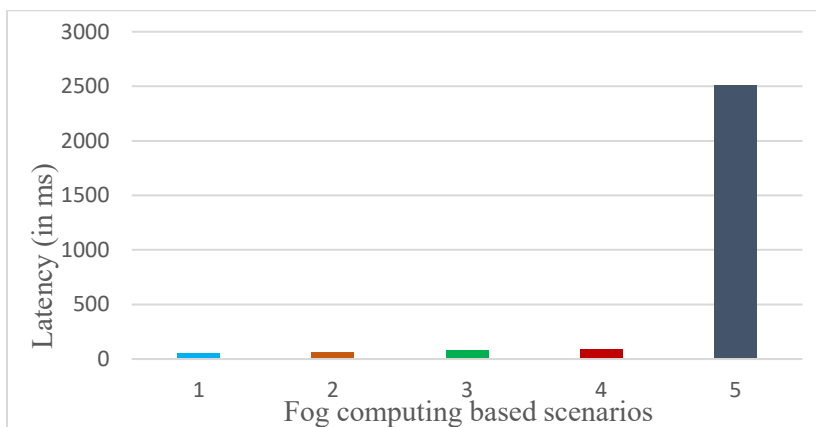


Figure 8. Latency results (in milliseconds) across different fog computing scenarios.

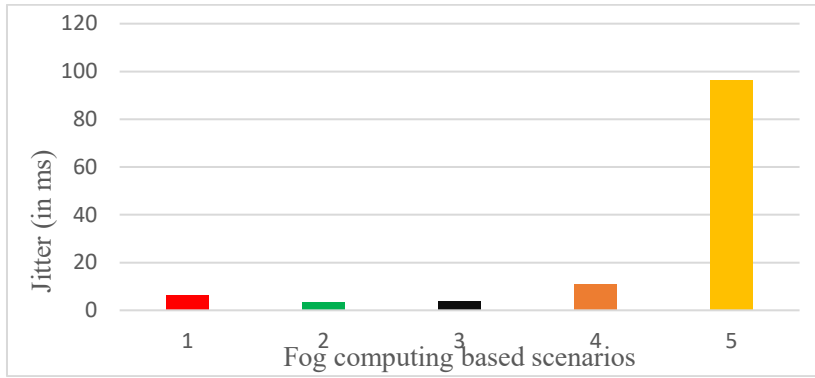


Figure 9. Jitter results (in milliseconds) across different fog computing scenarios

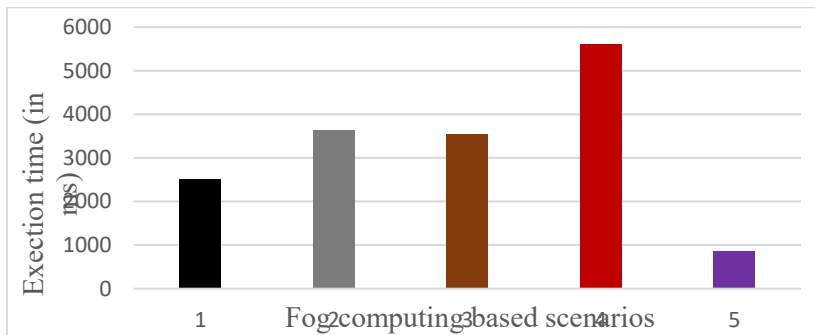


Figure 10. Execution time results (in milliseconds) across different fog computing scenarios.

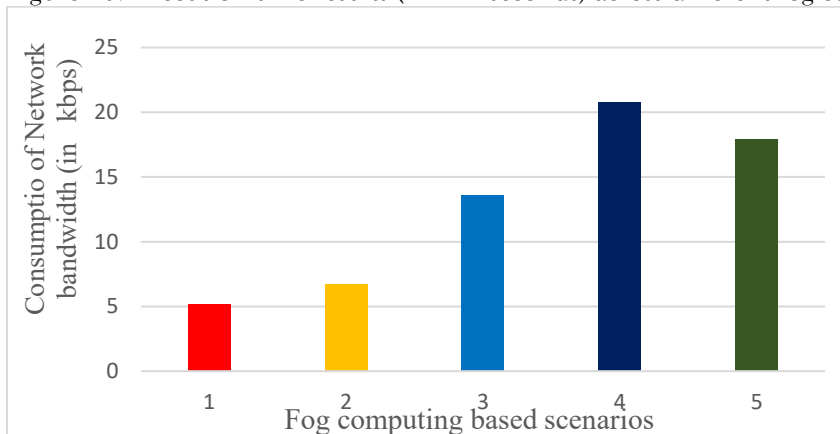


Figure 11. Network bandwidth consumption results (in kbps) across different fog computing scenarios.

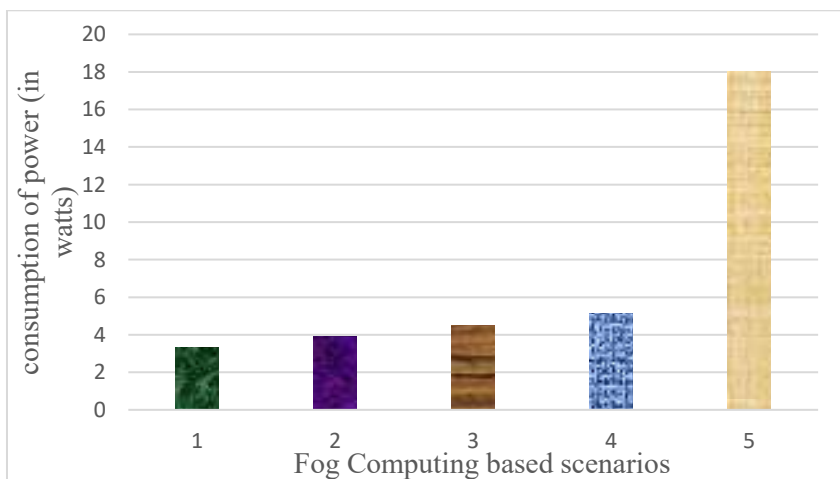


Figure 12. Power consumption results (in watts) across different fog computing scenarios.

5. CONCLUSION & FUTURE WORK

Improving the effectiveness of real-time traffic management in fog computing and edge devices is the aim of this paper. The suggested model efficiently speeds up data transfer and lowers latency. The latency, network usage, and energy consumption results show how important the suggested fog computing-based architecture is and how well it optimises performance metrics that are crucial for real-time applications. For complex traffic nodes, the suggested algorithm greatly increases detection accuracy while boosting dependability. Furthermore, when data is being transmitted between fog computing systems and healthcare IoT devices, the stacking algorithm reduces packet errors. The suggested algorithm routinely outperforms the current state-of-the-art methods in terms of performance metrics and overall efficiency, according to comparative analysis. By decreasing packet errors and improving the management of high-traffic nodes, it successfully tackles important issues like latency in healthcare IoT device identification. Additionally, the suggested method significantly affects fog computing and healthcare IoT, especially with regard to throughput and execution time. It guarantees that doctors and patients receive time-sensitive data with the least amount of service delay possible, frequently in a single hop-count. In healthcare settings, where prompt data transmission is essential, this degree of efficiency is essential. Additionally, the method improves security by using edge devices to protect sensitive data while preserving quick and dependable communication by processing healthcare data at the edge of IoT networks in a decentralised fashion. The information transfer process between the fog computing and offloading nodes, however, may present a number of difficulties. Future research will concentrate on addressing unpredictable variables by conducting experiments in real-world environments, even though the current study was carried out in a controlled laboratory simulation. This will guarantee the robustness and dependability of the suggested fog computing architecture in real-world applications and offer deeper insights into potential difficulties. We intend to expand on this research in the future by creating a mechanism for collaboration between fog computing nodes, which was not thoroughly investigated in this study. In particular, we want to enhance collaboration between east-west computing nodes by incorporating deep learning methods, which will increase the system's flexibility and effectiveness in real-time medical applications.

REFERENCES

- [1] Hameed Abdulkareem, Karrar, Ammar Awad Mutlag, Ahmed Musa Dinar, Jaroslav Frnda, Mazin Abed Mohammed, Fawzi Hasan Zayr, Abdullah Lakhan, Seifedine Kadry, Hasan Ali Khattak, and Jan Nedoma. "Smart healthcare system for severity prediction and critical tasks management of COVID-19 patients in IoT-fog computing environments." *Computational Intelligence and Neuroscience* 2022 (2022).
- [2] Chen, Apat, Hemant Kumar, Rashmikiran Nayak, Bibhudatta Sahoo, and Sagarika Mohanty. "Application Placement in Fog-Enabled Internet of Things (IoT) Healthcare System Using Body Sensor Networks." In *Handbook of Research on Mathematical Modeling for Smart Healthcare Systems*, pp. 383-408. IGI Global, 2022.
- [3] Khan, Salman, Ibrar Ali Shah, Nasser Tairan, Habib Shah, and Muhammad Faisal Nadeem. "Optimal Resource Allocation in Fog Computing for Healthcare Applications." *Computers, Materials & Continua* 71, no. 3 (2022).
- [4] Iftikhar, Sundas, Muhammed Golec, Deepraj Chowdhury, Sukhpal Singh Gill, and Steve Uhlig. "FogDLearner: A deep learning-based cardiac health diagnosis framework using fog computing." In *Proceedings of the 2022 Australasian Computer Science Week*, pp. 136-144. 2022.
- [5] Singh, Sunakshi, and Vijay Kumar Chaurasiya. "Mutual authentication framework using fog computing in healthcare." *Multimedia Tools and Applications* 81, no. 22 (2022): 31977-32003.
- [6] Kamruzzaman, M. M., Bingxin Yan, Md Nazirul Islam Sarker, Omar Alruwaili, Min Wu, and Ibrahim Alrashdi. "Blockchain and fog computing in IoT-driven healthcare services for smart cities." *Journal of Healthcare Engineering* 2022 (2022).
- [7] Mala, Deep, Abhineet Anand, Naresh Kumar Tiwari, and M. Arvindhan. "Fog computing & IoT based smart healthcare system for detecting heart related problem." In *AIP Conference Proceedings*, vol. 2451, no. 1. AIP Publishing, 2022.
- [8] Duhayyim, Mesfer Al, Fahd N. Al-Wesabi, Radwa Marzouk, Abdalla Ibrahim Abdalla Musa, Noha Negm, Anwer Mustafa Hilal, Manar Ahmed Hamza, and Mohammed Rizwanullah. "Integration of Fog Computing for Health Record Management Using Blockchain Technology." *Computers, Materials & Continua* 71, no. 2 (2022).
- [9] Premkumar, N., and R. Santhosh. "Challenges and Issues of E-Health Applications in Cloud and Fog Computing Environment." *Mobile Computing and Sustainable Informatics: Proceedings of ICMCSI 2021* (2022): 711-721.
- [10] Raj, Hritu, Mohit Kumar, Prashant Kumar, Amritpal Singh, and Om Prakash Verma. "Issues and challenges related to privacy and security in healthcare using iot, fog, and cloud computing." *Advanced Healthcare Systems: Empowering Physicians with IoT-Enabled Technologies* (2022): 21-32.
- [11] Daraghmi, Yousef-Awwad, Eman Yaser Daraghmi, Raed Daraghma, Hacène Fouchal, and Marwane Ayaida. "Edge-Fog-Cloud Computing Hierarchy for Improving Performance and Security of NB-IoT-Based Health Monitoring Systems." *Sensors* 22, no. 22 (2022): 8646.

- [12] Arivazhagan, N., Krishnan Somasundaram, D. Vijendra Babu, M. Gomathy Nayagam, R. M. Bommi, Gouse Baig Mohammad, Puranam Revanth Kumar et al. "Cloud-internet of health things (IOHT) task scheduling using hybrid moth flame optimization with deep neural network algorithm for E healthcare systems." *Scientific Programming 2022* (2022): 1-12.
- [13] Shanshoola, Abeer M., and Noor Alhuda F. Abbasa. "A Fog Computing Framework in IoT Healthcare Environment: Towards A New Method Based on Tasks Significance." *system 7*: 8.
- [14] Chu, Kuo Ming. "Understanding IoHT and Edge/Fog Computing Solutions for Smart In-Home Remote Healthcare." *Fog Computing Solutions for Smart In-Home Remote Healthcare* (2022).
- [15] Kodavali, Lakshmi Narayana, and Sathiyamurthy Kuppuswamy. "Adaptation of Blockchain using Ethereum and IPFS for Fog based E-Healthcare Activity Recognition System." *Trends in Sciences* 19, no. 14 (2022): 5072-5072.
- [16] Kamruzzaman, M. M., Bingxin Yan, Md Nazirul Islam Sarker, Omar Alruwaili, Min Wu, and Ibrahim Alrashdi. "Blockchain and fog computing in IoT-driven healthcare services for smart cities." *Journal of Healthcare Engineering 2022* (2022).
- [17] Gasmi, Kaouther, Selma Dilek, Suleyman Tosun, and Suat Ozdemir. "A survey on computation offloading and service placement in fog computing-based IoT." *The Journal of Supercomputing* 78, no. 2 (2022): 1983-2014.
- [18] Melo, Sávio, Felipe Oliveira, Cicero Silva, Paulo Lopes, and Gibeon Aquino. "OffFog: An approach to support the definition of offloading policies on fog computing." *Wireless Communications and Mobile Computing 2022* (2022): 1-15.
- [19] Firouzi, Farshad, Shiyi Jiang, Krishnendu Chakrabarty, Bahar Farahani, Mahmoud Daneshmand, Jaeseung Song, and Kunal Mankodiya. "Fusion of IoT, AI, edge-fog-cloud, and blockchain: Challenges, solutions, and a case study in healthcare and medicine." *IEEE Internet of Things Journal* 10, no. 5 (2022): 3686-3705.
- [20] Sarrab, Mohamed, and Fatma Alshohoumi. "Assisted fog computing approach for data privacy preservation in IoT-based healthcare." *Security and Privacy Preserving for IoT and 5G Networks: Techniques, Challenges, and New Directions* (2022): 191-201.
- [21] Hassan, Syed Rizwan, Ishtiaq Ahmad, Jamel Nebhen, Ateeq Ur Rehman, Muhammad Shafiq, and Jin-Ghoo Choi. "Design of Latency-Aware IoT Modules in Heterogeneous Fog-Cloud Computing Networks." *Computers, Materials & Continua* 70, no. 3 (2022).
- [22] Singh, Moirangthem Biken, Navneet Taunk, Naveen Kumar Mall, and Ajay Pratap. "Criticality and utility-aware fog computing system for remote health monitoring." *IEEE Transactions on Services Computing* (2022).
- [23] Al Masarweh, Mohammed, Tariq Alwada'n, and Waleed Afandi. "Fog computing, cloud computing and IoT environment: advanced broker management system." *Journal of Sensor and Actuator Networks* 11, no. 4 (2022): 84.
- [24] Alatoun, Kholoud, Khaled Matrouk, Mazin Abed Mohammed, Jan Nedoma, Radek Martinek, and Petr Zmij. "A novel low-latency and energy-efficient task scheduling framework for internet of medical things in an edge fog cloud system." *Sensors* 22, no. 14 (2022): 5327.
- [25] Benila, S. "Fog Managed Data Model for IoT based Healthcare Systems." *Journal of Internet Technology* 23, no. 2 (2022): 217-226.
- [26] Tselios, Christos, Ilias Politis, Dimitrios Amaxilatis, Orestis Akrivopoulos, Ioannis Chatzigiannakis, Spyros Panagiotakis, and Evangelos K. Markakis. "Melding Fog Computing and IoT for Deploying Secure, Response-Capable Healthcare Services in 5G and Beyond." *Sensors* 22, no. 9 (2022): 3375.
- [27] Kumar, Arun, Sharad Sharma, Nitin Goyal, Sachin Kumar Gupta, Saru Kumari, and Sachin Kumar. "Energy-efficient fog computing in Internet of Things based on Routing Protocol for Low-Power and Lossy Network with Contiki." *International Journal of Communication Systems* 35, no. 4 (2022): e5049.
- [28] Jamil, Bushra, Humaira Ijaz, Mohammad Shojafar, Kashif Munir, and Rajkumar Buyya. "Resource allocation and task scheduling in fog computing and internet of everything environments: A taxonomy, review, and future directions." *ACM Computing Surveys (CSUR)* 54, no. 11s (2022): 1-38.
- [29] Illy, Poulmanogo, Georges Kaddoum, Christian Miranda Moreira, Kuljeet Kaur, and Sahil Garg. "Securing fog-to-things environment using intrusion detection system based on ensemble learning." In *2019 IEEE wireless communications and networking conference (WCNC)*, pp. 1-7. IEEE, 2019.
- [30] Ramkumar, M. P., T. Daniya, P. Mano Paul, and S. Rajakumar. "Intrusion detection using optimized ensemble classification in fog computing paradigm." *Knowledge-Based Systems* 252 (2022): 109364.
- [31] Aouedi, Ons, Kandaraj Piamrat, and Benoît Parrein. "Ensemble-based deep learning model for network traffic classification." *IEEE Transactions on Network and Service Management* 19, no. 4 (2022): 4124-4135.
- [32] Kumar, Prabhat, Govind P. Gupta, and Rakesh Tripathi. "A distributed ensemble design based intrusion detection system using fog computing to protect the internet of things networks." *Journal of ambient intelligence and humanized Computing* 12, no. 10 (2021): 9555-9572.