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IoHT-enabled gliomas disease management using fog Computing computing for sustainable societies

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A R T I C L E I N F O

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A B S T R A C T

The proliferation of sensor-based applications in healthcare has given rise to Internet of Health Things (IoHT) that improves patient safety, staff morale, and operational efficiency. Edge-fog computing has seen significant development in recent years and supports the association of various intelligent things with sensors for establishing smooth data transfer. However, it becomes challenging for edge-fog computing to tackle diverse IoHT settings such as efficient disease management, emergency response management, etc. The key limitation of existing architectures is the restricted scalability and inability to meet the demands of hierarchical computing environments for IoHT. This is because latency-sensitive applications often require large quantities of data to be measured and transferred to the data centers, which causes delay and reduced output. This research proposes a novel edge-fog computing framework for the convergence of machine learning ensemble with edge-fog computing. The proposed architecture delivers healthcare as a fog system that handles data from different sources to manage the diseases effectively. The proposed framework is used for the real-life implementation and automatic detection of gliomas diseases. Glioma is a kind of tumor, which ensues in the spinal cord and a portion of the brain. Glioma instigates in the glial cells that surround the nerve cells. The proposed edge-fog framework efficiently manages the real-time data related to gliomas. This framework is configured for specific operating modes including diverse edge-fog scenarios, different user requirements, quality of service, precision, and predictive accuracy. The proposed framework is evaluated using real-time datasets from various sources and experimentally tested with reliable datasets that disclose the effectiveness of the proposed architecture. The performance of the proposed model is evaluated in terms of power consumption, latency, accuracy, and execution time, respectively.

1. Introduction

Glioma is a kind of tumor, which ensues in the part of brain. It instigates in the glial cells that surround the nerve cells (Jiang et al., 2021). Glioma is the prime tumor in the brain and 81.1% of central nervous system (CNS) malignancies are accounted for gliomas (Xu et al., 2020). As per the World Health Organization (WHO) cataloging, gliomas are classified into four different grades. Grade 1 and grade 2 are considered low-grade while grade 3 and grade 4 are considered high-grade (Louis et al., 2016). High-grade glioma is one of the most common brain tumor-occurring diseases. In the past 12 years, diminutive developments have been carried out in managing glioma (Cheng et al., 2019). To precisely and timely detect the gliomas require a strong technological set up to process the huge datasets available for the identification and detection of this disease. Currently, the advancement in technology enhances the healthcare systems. Particularly, artificial, intelligence, machine learning, deep learning, fog computing, and big data analytics are widely used. The deep learning-based proposals are introduced to

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cater for the COVID-19 detection in the context of timely prevention (Bhattacharya et al., 2021; Loey et al., 2021). This technology also plays an important role in the management of other diseases (Çapraz and Deniz, 2021).

Fog computing is a distributed computing framework that keeps the information, computation, processing, and applications somewhere between the cloud and the edges of the network (Gill et al., 2018). Paradigms of fog and edge computing have emerged as the moral backbone of modern technology and use the Internet to provide on-demand services (Rahmani et al., 2018). The IoHT presence has made it possible to interconnect and connect massive omnipresent things that have led to an unprecedented generation of large, heterogeneous data (Islam et al., 2015). Because most of the cloud data centers face numerous challenges such as security, electricity consumption, sustainability, and latency, fog computing has one of the most popular strategies to overcome these challenges. The robustness and ability of fog computing provide different response characteristics depending on target usage and technological developments (e.g., Edge, Fog, IoHT). By using the new technologies, we are facilitated with improved mobility, confidentiality, protection, low-latency bandwidth, and network capacity. Healthcare is one of the prominent sectors that demands precise and real-time results (Faust et al., 2018). Fog computing has been realized positively for real-time streaming. The resources are brought closer to the users and latency decreases and the safety measure is thus increased with the help of fog computing. High precision and accuracy are achieved using state-of-the-art analysis techniques that typically utilize machine learning and its variants.

The growth of deep learning is ranging from speech detection to NLP, and computer vision. Besides, ensemble learning is used to achieve the best of several classifications (Zhao et al., 2019). It provides a novel way to investigate multifarious ensemble profound models of learning in the edge paradigm for high precision results. Bagging classifier is one of the ensemble methods, where an estimator matches the basic classifier figures and then either votes or averages to add their predictions to the final prediction. These estimators support decreasing the variance in comparison with a single estimator by randomizing the process of the dataset. A step forward in DL is the forecast and grouping of health data with much higher precision (Maxwell et al., 2017). In general, it is difficult to detect disease problems, and people often do not even understand that they are in critical condition until they get into a very serious condition. Existing systems used on IoT-driven Fog connect preconfigured data processing devices to provide users with results within the deadline (Alshehri and Muhammad, 2021).

In current time, a growing tendency has been perceived in espousing ML to improve the applications of fog computing and offer fog-enabled facilities, like effective resource management, extenuating latency, security, and energy utilization. The exposure of ML in fog paradigm has yet to be examined in depth. In particular, fog computing is ideal for low-energy consumption, high security, fast data processing, more reliability, low latency, and therefore fog computing can be implemented in all applications that are prone to latency, such as medical services, and urgent or cyber-physical systems. Healthcare is a noticeable area of application that demands precise and simultaneous outcomes, and the Fog paradigm has been implemented in this field and is progressing positively. By using Fog computing, the resources are brought closer to the users that reduce the latency, and the safety measure is thus enhanced. In addition, Smart environmental technology and testimonials are very consistent with sustainability fog systems. In a smart city environment, Fog Computing plays a very important role/impact e.g. sensing bus data system that gathers data from the sensor's motion within buses. Another example is the tracking of objects, which tracks artifacts and individuals in crowds of sophisticated surveillance systems. In the fog environment, smart farm control systems, smart waste management systems, smart transport systems are all highly configurable and the most important is smart healthcare (Kirby and Finnerty, 2020). Such solutions are very robust and stable.

In this research, we suggest an automatic diagnosis of gliomas disease using a fog-based architecture built upon deep learning and IoHT infrastructure. The proposed architecture provides services of healthcare as a lightweight fog system and handles data from different IoHT devices effectively. The proposed model is automated in the context of disease prediction, but it performs the manual training (the training is operationalized and supervised by human). The major contributions are automatic multiple disease detection using the fog ensemble deep learning, and design of energy-efficient and low-cost wearable sensor device for collecting data. Moreover, demonstration and analysis of the proposed system in the context of accuracy, mobility, confidentiality, protection, low-latency bandwidth, and network capacity, are also discussed.

The rest of this paper is organized as follow. In Section 2, a fog-edge computing architecture for healthcare paradigm is discussed. The related work pertaining to our research is discussed in Section 3. In Section 4, our proposed methodology is elaborated followed by research and discussion in Section 5. The characteristics of our proposed methodology are briefly discussed in Section 6. Finally, the paper is concluded and future research directions are provided in Section 7.

2. Fog-edge computing architecture for healthcare

The fog architecture is discussed in this section. This architecture is based on the latest three-layered computer architecture: the cloud, fog, and edge, respectively. A core network to provide network services lies between the Cloud and the Fog (Alshehri and Muhammad, 2021). It can be seen that the Cloud is at the top and the edge is taken far from the Cloud. The Fog lies at the medium-level, closer to the edge as compared to the cloud. Every Fog node has a cloud connection. The Fog node is attached to each edge unit. We can see the connection between Fog nodes. All are two-way communications, i.e., Fog-Fog, Fog-Cloud, and Fog-Edge (Kirby and Finnerty, 2020). The ML techniques can be combined with the fog paradigm that improves the performances of the ML models. In this section, we discuss the individual components of our three-layered architecture.

- The Fog: It consists linked Fog node network. Each Fog Node is an ephemeral resource storage center and provides low latency, geo-distributed, location awareness, and immediate measurement. This involves transforming the network, collecting data, communications, processing, storage, uploading, and managing data compared to edge devices, Fog nodes have more computer memory and storage capacities that enable a large quantity of edge device data to be processed. From the other side, computation should be sent to the cloud through Fog nodes via different communication technologies accessible, for example, 3G/4G/5G mobile networks or WIFI, when the computational phase needs to be simpler and longer-lasting. Fog nodes are the meeting point from Cloud to Edge. Fog nodes are autonomous and for communication can be interconnected. The Fog nodes are used for the monitoring and supervision of operations and collective procedures. Fog nodes may work collaboratively through remote or regional communications. Fog computing has been implemented and progressing positively for real-time streaming. The resources are brought closer to the users and latency decreases and the safety measure is thus increased with the help of fog computing.
- The Edge: It comprises several physical devices allowing (vehicles, equipment, and mobile phones) to omnipresent identify sense, and interact. Every edge system has one Fog Node attached. The edge systems have a wide range of local data and sensors. The transfer of all information from terminal edge machines via a network to the cloud is costly and time-consuming. Therefore, you can process urgent information by linking them to Fog nodes, but you cannot move them directly from Edge devices to the cloud.
- ML Module: The ML module is integrated with the edge-fog architecture. It provides a model-building mechanism. The ML model

performances can be enhanced using fog-edge architecture.ML models building in the Fog nodes can improve the performance as the fog nodes have more computer memory and storage capacities that enable a large quantity of data to be processed. In addition, the Fog nodes are autonomous and for communication can be inter-connected. The ML models building using the Fog nodes can improve the monitoring and supervision of operations and collective procedures. Fog nodes may work collaboratively through remote or regional communications.

- The Cloud: The Cloud requires computers and storage devices with high performance for transmitting, archiving, and analyzing large data. The remote management center can store large information and perform complicated but as we know it not good for urgent activities as it has high latency. Via mobile and wired networking, information is transmitted to the Cloud. Maximum geographic exposure is given by the cloud. This provides data processing for the long-term demands of clients and an insightful data analysis as a repository.

3. Related work

There are numerous efforts to develop healthcare systems for mobile health surveillance using ML. FogCepCare was proposed to assimilate cloud for determining the status of cardiac patients (He et al., 2017). A customizable Low-power Wireless Personal Area Network (LoWPAN) was proposed for continuous safety surveillance (Gia et al., 2014). The system provides reliable network control of ECG, centrally and in real-time. A remote face expression monitoring system based on IoT was suggested for healthcare (Jiang et al., 2016). The sensor nodes of the devices are distributed using Wi-Fi via Electromyography (EMG). With the assistance of LabVIEW, bio-signals are interpreted and labeled in the cloud. A Low-Cost Health Monitoring (LCHM) system was proposed for gathering health data of patients with heart disease (Gia et al., 2017). Besides, the electrocardiogram (ECG) was monitored and analyzed in real-time for the care of cardiac patients' results. However, LCHM has higher reaction time to reduce its efficiency (Mello-Román et al., 2019).

SVM polynomial tests for accuracy, tolerance, and specialization are obtained above 90 percent by contrast (He et al., 2019). The decision tree is used to estimate diabetes mellitus and also uses random forests and neural networks; there are 14 features there. In this analysis, the models have been tested with 5-fold cross-validation. They have selected certain techniques to conduct objective testing to determine the universal applicability of the methods. There are 68994 stable persons and diabetic patients who have been randomly selected as a training set, respectively. They randomly collected five times the data due to the imbalance. And the effect is the five tests on average (Rajasekaran et al., 2019). In the scope of this review, the use of machine learning, data mining approach, and techniques in the area of diabetes research were regularly compiled and updated. Traditionally, ailments of mentioned diseases are tough to detect, and an actual doctor needs to monitor the patient to make sure the patient has the disease. This is hard to do because of the doctors' shortage.

The assessment of heart monitoring applications using fog computing was proposed (Akrivopoulos et al., 2017; Choi et al., 2017). The fog-enabled IoT, WIoT, and cloud systems are also proposed to overcome the challenges in healthcare applications (Constant et al., 2017; Azimi et al., 2018; Mahmud et al., 2018). FogLearn, scalable EHR, and HealthFog are also proposed for utilizing machine learning for healthcare (Barik et al., 2019; Rajkomar et al., 2018; Tuli et al., 2020). The goal is to enhance hepatitis diagnosis by exploring recognition approaches and gene expression patient parameters. This paper also addresses the estimation methods that can be integrated with the above models. This suggests ways to make Artificial Neural Networks, Machine Learning, and Bioinformatics algorithms more powerful and accurate. In the literature, there are many approaches to classify diseases. The bulk of approaches are however established using single learning techniques for specific disease. In this proposed method, we have analyzed the effectiveness of ensemble learning for gliomas-disease.

Glioma is a kind of tumor, which requires novel strategies to manage and monitor the gliomas classes (Kirby and Finnerty, 2020). The glioma instigates in the glial cells that surround the nerve cells and it is the common tumor that needs to be genomically profiled of low-grade gliomas (Mobark et al., 2020). A novel coronavirus, now known as COVID-19, was identified by the Chinese researcher with the conformation of human transmission. Since the appearance of the COVID-19, it has hastily blowout across the globe affecting various countries badly. Imperative attention is required for the gliomas patients during the COVID-19 pandemic (Mohile et al., 2020). The individual administration of glioma patients can be treated in an improved mechanis (Nabors, 2020). A Self-Organizing Map (SOM) method is utilized for clustering the ensembles of Neuro-Fuzzy Inference System for hepatitis prediction to perform non-linear iterative partial least squares (Nilashi et al., 2019). They also use decision trees in the experimental data collection to pick the most important characteristics. The prevalence of HBV (Hepatitis B Virus) serologic markers and HCV (Hepatitis C Virus) representative samples of published reports of physicians hospitalized with hepatocellular carcinoma (HCC) disease.

Gliomas are classified into four different grades by World Health Organization (WHO). Grade 1 and grade 2 are considered low-grade while grade 3 and grade 4 are considered high-grade. The healthcare application using ML techniques can manage Cirrhosis and HCC patients. Cirrhosis and HCC attributable fractions owing to these infections are measured at eleven WHO-based regions (Mello-Román et al., 2019). A particular data of patients who were previously diagnosed with dengue from the Paraguayan public health system is analyzed in 2016. With an average 96 percent reliability, 96 percent tolerance, and 97 percent precision, the ANN Multi-Layers perceptive obtained improved results for small variations in 30 different data set partitions. The ensemble process is utilized for multiple learning to gain better predictive performance than could be obtained from any of the constituent learning algorithms alone.

4. Proposed methodology

The proposed methodology suggests an automatic diagnosis of gliomas diseases using a fog-based architecture smart healthcare system built on deep learning and IoHT shown in Fig. 1. The proposed architecture provides services of healthcare as a lightweight fog system and handles data from different IoHT devices effectively. Mobile apps in several ways have made life easier. We now can link and share information with lots of phones. A device is a platform for IoT to make the technology even cooler. This partnership is already increasing with the emergence of more smartphones and the growth of more applications. Many IoT-enabled devices are used in the healthcare sector, such as IVs, vital sign sensors, cardiac monitoring systems, glucose meters, and infusion pumps, among others. All these products collect data using sensors. This information is sent to an application to generate a seamless workflow.

After collecting the data from different sensors, the application (app) will send the data to the fog device and cloud. In a fog device, the trained ML will predict the patient status. In the cloud, the data will pass through different ML algorithms to generate output. The app will only diagnose gliomas. Before sending data to the server, the user will select a particular disease. Cloud can manage the data of each patient transmitted by smartphone. Different models can be trained on different types of datasets. Depending on the disease, the best match model is trained on a particular dataset to define the status of a patient. The PCA could be utilized to decrease dimensions and reduce the number of variables, which restricts a vast number of variables to a small group while holding the majority of data in a large set. PCA is a computational tool that converts a range of associated variables (possibly) into (smaller) uncorrelated variables called primary components. The PCA

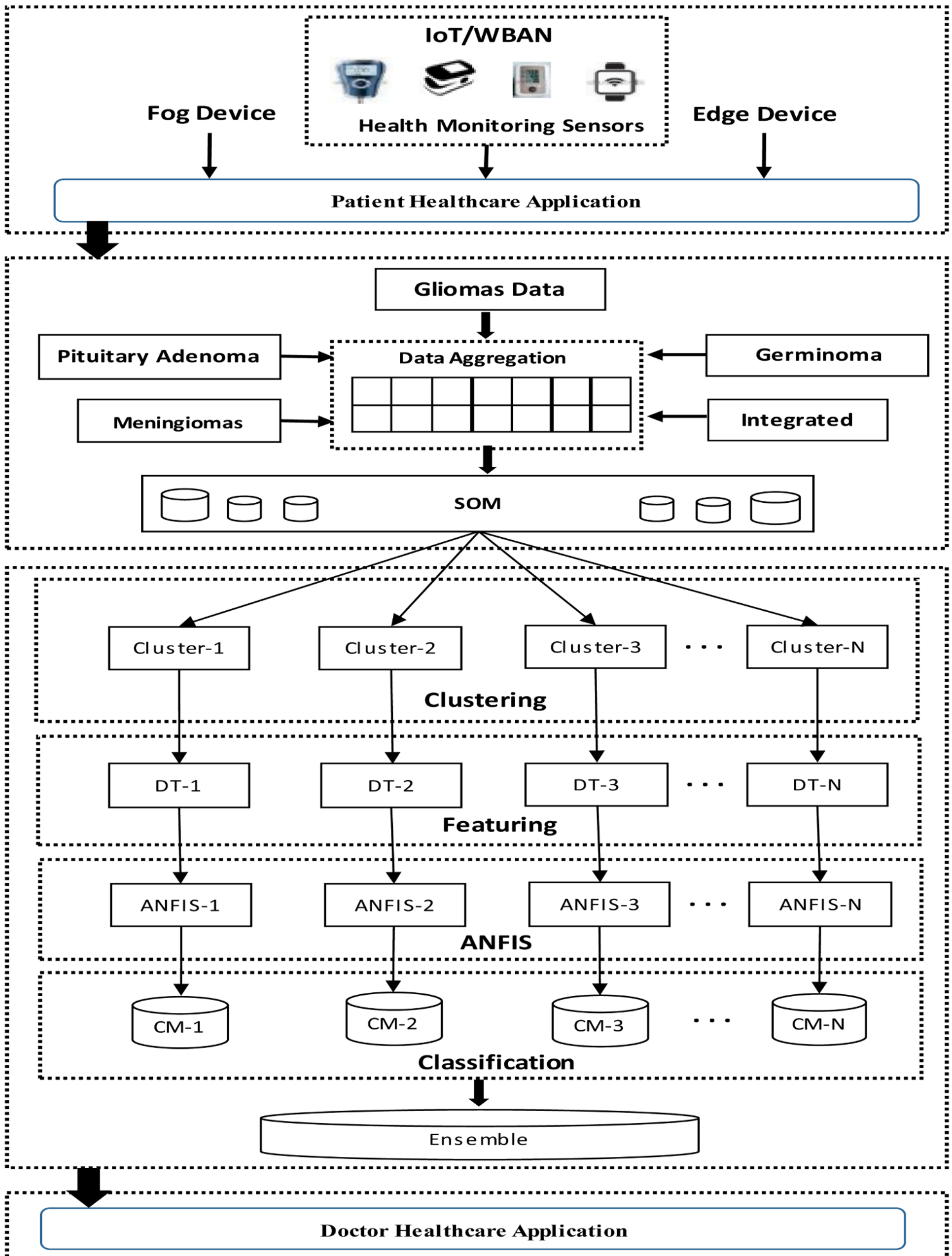

Fig. 1. Proposed Architecture.

used in many software areas is an effective dimensionality reduction engineering. It is used mainly for multivariate analysis as a statistical technique. It is also used to preserve the essential information from the data for the compression task. The decision tree (DT) can also be utilized to pick key features in the dataset. Similarly, the Random Forest, neural networks (NN), and logistic regression can be used to detect diseases. The cluster strategies such as the self-organizing map (SOM) and Expectation Maximum (EM) are built to reduce the data proportions.

We attempt to group information with SOM in the first phase. The clustering is used to serves the increase of readability of data for the classification task. For data dimensionality reduction to boost clustering efficiency, the non-linear Iterative Partial Least Squares (NIPALS) technique is used. In the next stage, decision trees are used in each cluster to choose the main characteristics of the dataset. During the last phase, we used adaptive neuro-fuzzy inference system (ANFIS) to diagnose a variety of medical data from various diseases. SOM's accurate use of NIPALS is expected to improve. We also use ensemble training by various types of membership functions in the ANFIS approach. NIPALS algorithm is a non-linear iterative PLS to locate its vectors, which can effectively manage missing values in data sets. This uses NIPALS to determine the most important components for the data. In the proposed framework, the cloud sends the processed data to the application installed at the doctor's device. The application shows the current status of patient-generated data from the cloud and also the detailed report of the patient. The report consists of weekly or monthly information of the patient in graphical form to show the complete image of the patient. A doctor can modify the auto-generated report to suggest improvements.

The classification model utilized is decision tree, SVM, Random Forest, K-nearest neighbor, and neural networks. A decision tree is a structure close to a flow chart, where every inner node is a test on an element. Every branch is the outcome and each branch node is a class tag. SVM is a well-known algorithm that is utilized for regression and classification problems. KNN stores all existing cases and classifies new cases based on a calculation of similarity. Random forests are an ensemble learning tool for selection, regression, classification, and other activities. It is utilized for creating a multitude of decision-making trees at training time and generating a category for prediction of an individual's tree. Neural networks are fuzzy computational structures influenced by neural biological networks that shape the brains of animals. These structures are "learned" to do tasks, generally without being configured using unique task guidelines, through considering cases.

5. Results and discussion

The device setup and hardware specifications are smartphones, Fog device- ESP32 performing at up to 600 DMIPS with ultra-low power (ULP) co-processor that has very low memory of 520KB SRAM, but it can be a high memory device (if required). The Azure cloud, i.e., a Microsoft-built cloud computing platform for the designing, reviewing, delivering and management of applications and services via data centers is utilized. The gateway is the tool to send data to the Fog device via an android executable application. These data are collected from different sensors of IoT. The smartphone acts as the mediator between the Body Sensor Network and the Fog nodes. The HTTP RESTful APIs are used for interaction. HTTP POST is used to download input data from the Smartphone and to download results from a fog device or the cloud. A pre-trained deep learning model and preprocessing code are included in both Fog device and Cloud. The proposed model is automated in the context of disease prediction, but it performs the traditional training.

5.1. Gliomas datasets

We utilized a dataset, which comprises the MRI pictures prepared in FLAIR-modality (27). It is taken from the archive of cancer pictures includes five columns that are ID, Age, Gender, and Diagnosis. The diagnosis includes oligodendroglioma (grade II, & grade III), glioblastoma, and astrocytoma (grades II & III). Another dataset has been utilized that is hauled out from MRI images that include four types of cancers with 1500 features and more than 700 records (28).

5.2. Data analysis

The data analysis is performed on the dataset that includes 4 different types of cancer. We have analyzed the dataset using the proposed improved architecture to detect the type of cancer. It has been observed that gliomas are most commonly detected cancer in the brain. Other types of cancers are also detected, e.g. Pituitary Adenoma, Germinoma, and Meningiomas. Fig. 2 depicts the number of gliomas and other types of cancers.

The Pituitary Adenoma is slow-growing and that is benign too. They do not blow out to the human's other parts. Though, as Pituitary Adenoma develops large could place compression on neighboring structures of the body (e.g., the eyes to the brain). The germinoma cell tumor is located in deep midline positions. Meningioma or meningeal tumor is also a slow-growing tumor. Signs rely on the position and occurrence of the tumor. The percentage of male and female patients suffering from gliomas is also depicted in Fig. 3.

Gliomas are classified further into 3 types. The diagnosis count of the different types of gliomas is depicted in Fig. 4. It is evident from the figure that the GBM-4 type is the having the highest number of detections. The number of counts concerning age is also depicted in Fig. 5. It is revealed that the most affected age in the context of gliomas is between 35-55. This is the evidence of the validity of the proposed idea.

5.3. Evaluation of proposed architecture

The proposed architecture evaluation results are highlighted in this section. Arbitration time is highlighted in Fig. 6 that shows the time of each scenario. As we can see the time of arbitration is nearly 400ms in the Master node because it is the node where requests arrive first. As moving forward, the arbitration time increases. There is no limit on the number of edges in the cluster. We highlighted only two edges as the performance is represented by two edges same as we improve the number of edges. The 2 edges are considered for simulation purpose.

The execution or processing time is shown in Fig. 7. Fig. 7 shows the execution time of each node. The cloud has a very low execution time it is just because of high computed systems. The fog node has a very high execution time because of low computing devices embedded there.

The latency of the proposed system is highlighted in Fig. 8. The latency of the first three cases is nearly equal because all communication is done only by single hope data transformation. The cloud has very high latency as compared to other nodes that are because of distance. As we know the cloud is far away to send and receive data via network. The cloud communication requires more time compared to the local edge.

The Jitter time is highlighted in Fig. 9. Jitter is the variation of round or response time for requests made by different patients. The jitter time of the cloud is very high as compared to other nodes.

5.4. Comparative analysis

Table 1 provides the comparative analysis. The symbol "✔", means the presence of the parameter in the proposal, the symbol "✖" means the absence of the parameter in the proposal, the symbol "S" is for single (single disease prediction), and the symbol "M" is for multi (multiple disease prediction). The selection criteria of the parameters utilized for the comparative analysis is based on the literature. We preferred only those criteria that are utilized in the existing proposals.

6. Characteristics of proposed model

6.1. Low latency

Locally, fog nodes obtain the data gathered by various devices and sensors and analyze the data in the local area network via network edge devices. It significantly reduces the flow of information across the network and offers fast centralized, endpoint-supported resources. It thus makes low latency and fulfills the necessity for real-time

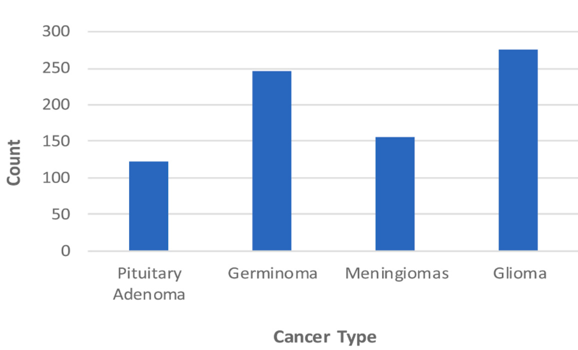

Fig. 2. Cancer Type Detection.

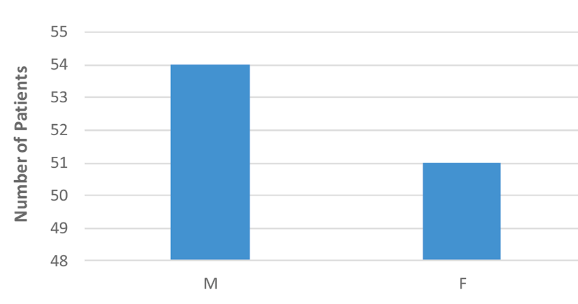

Fig. 3. Count based on Gender of Cancer Patients.

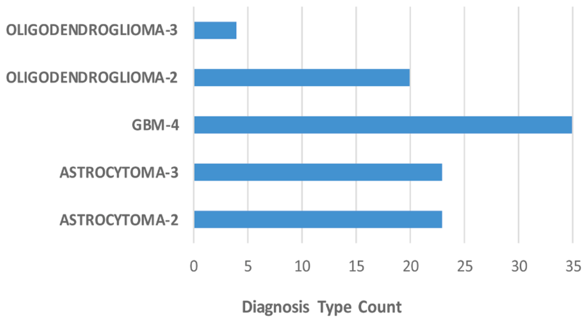

Fig. 4. Gliomas Class Detection.

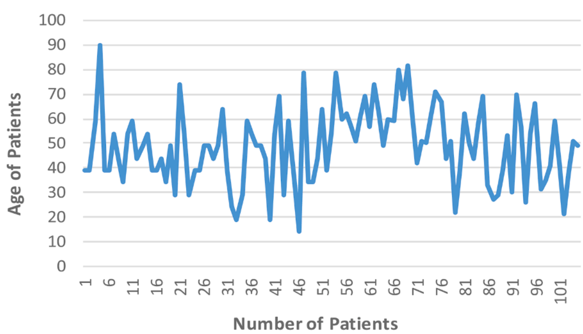

Fig. 5. Age of Gliomas Patients.

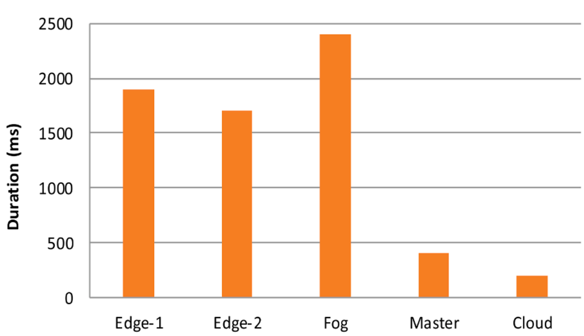

Fig. 6. Arbitration Time.

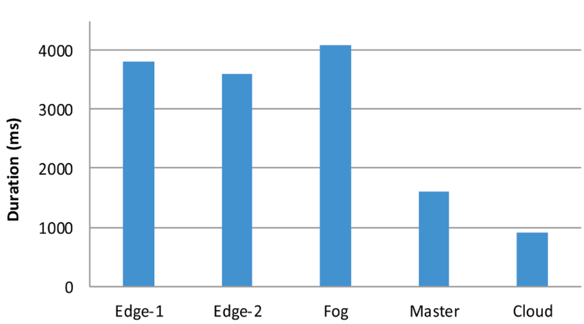

Fig. 7. Execution Time.

interactions, especially for applications that are sensitive to latency and time.

6.2. *Heterogeneity*

Fog nodes generally originated in diverse shapes and are installed in a variety of environments, for instance, physical nodes to virtual nodes.

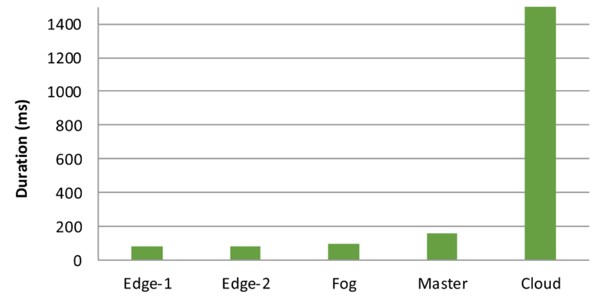

Fig. 8. Latency.

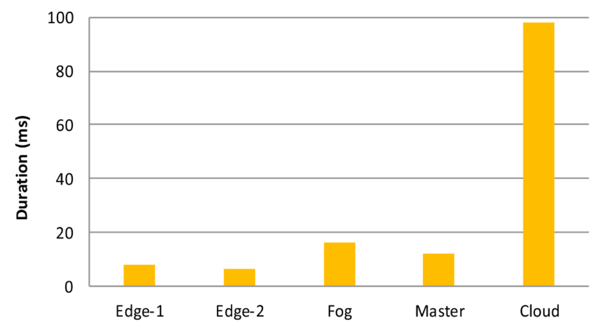

Fig. 9. Jitter Time.

Such computer architectures provide specific processing and memory capacities, run diverse types of OS, and load various software programs. Fog paradigm is a heavily virtualized system so that some virtual nodes can also be used as fog nodes. Therefore, the Fog nodes are heterogeneous. In contrast, fog computing's network infrastructure is heterogeneous, including high-speed networking and wireless systems (e.g. Ethernet, 3G, 4G, ZigBee, etc.) too that bind to the edge phones.

6.3. *Interoperability*

Fog nodes come from diverse vendors because of their heterogeneous existence and are typically deployed in different settings. The technology of fog has to be capable of working together and cooperate with different providers in terms of dealing with a wide set of services and to help these systems effortlessly.

6.4. *Low energy-consumption*

In fog computation, nodes of fog are globally distributed. Because of concentration, it won't generate much heat and doesn't need an additional7cooling7system. Therefore, short-range interaction mode and some appropriate mobile node energy management strategies naturally increasing the energy consumption for contact. This will result in a reduction in power consumption, energy savings, and cost reduction. Fog computing provides a greener paradigm for computing.

7. Conclusion

In this paper, an innovative strategy is proposed to cope effectively and accurately with health problems by insightful training. The proposed architecture delivers healthcare as a fog system that handles data from different sources to provide profound knowledge and is used for gliomas detection applications. Deep Learning models of classification are utilized in both preparation and prediction. This analysis facilitated complex networks of deep learning utilizing modern interaction and delivery methods such as assembly, which facilitated high accuracy with very small latencies. This was also confirmed by learning of different

Table 1
Analysis of Existing Work.

Proposal / Parameter	(Kirby and Finnerty, 2020)	(Nabors, 2020)	(Rajasekaran et al., 2019)	(Akrivopoulos et al., 2017)	(Choi et al., 2017)	(Constant et al., 2017)	(Azimi et al., 2018)	(Mahmud et al., 2018)	(Barik et al., 2019)	(Rajkomar et al., 2018)	(Tuli et al., 2020)	Proposed
Fog	✓	✓	✓	✗	✗	✓	✓	✓	✗	✗	✓	✓
IoHT	✗	✗	✓	✓	✗	✓	✓	✓	✗	✗	✓	✓
DL	✗	✗	✗	✗	✓	✗	✓	✗	✓	✓	✓	✓
Clustering	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
NIPALS	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Ensemble Learning	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓
Disease Prediction	S	S	S	S	S	S	S	S	S	S	S	M
Power Consume	✗	✗	✗	✓	✗	✓	✗	✓	✗	✗	✓	✓
Execution Time	✓	✓	✗	✗	✗	✓	✓	✗	✗	✗	✓	✓
Network Bandwidth	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓
Jitter	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓
Testing Accuracy	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓
Training Accuracy	✗	✗	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
ML Models	SVM KNN DT	NN LR DT SVC	LR DT NN	NN LR DT SVC	RF LR DT SVMKNN	DT SV CNN RF	RF DT SVM	DT SVC NN RF	DT SVM RF RL	SVM DT KNN	DNN	CNN DCNN Fog

classification systems in common databases of real-life data analytics for patients and by introducing a working system of real-time predictions. Accuracy has been one of the key considerations in developing methods for the diagnosis of diseases that require the best-predicted result in life. In this proposed method, we have analyzed the effectiveness of multi-disease ensemble learning techniques using several criteria for each dataset. Consequently, the ANFIS is used and SOM machine learning approaches as the un-supervised that used accurately the use of NIPALS. An ensemble training is also utilized by various types of membership functions in the ANFIS approach. Our system is validated using a real-world database derived from different sources. Non-incremental ANFIS was used in the cloud to learn classification models Therefore, the ANFIS approach does not promote gradual analysis and allows all training data to be recalculated while constructing prediction models.

Declaration of Competing Interest

The authors declare no conflict of interest exist for IoHT-enabled Gliomas Disease Management using Fog Computing for Sustainable Societies

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References

Jiang, T.ao, Nam, DoD.-Hy.un, Ram, Zv.i, Poon, Wa.i-sS.ang, Wang, Jigu.ang, Boldbaatar, Damdi.ndorj, Mao, Y.ing, et al. (2021). Clinical practice guidelines for the management of adult diffuse gliomas. *Cancer Letters, 499*, 60–72.

Xu, Shengc.hao, Tang, L.u, Li, Xiz.he, Fan, F.an, & Liu, Zh.ixiong (2020). Immunotherapy for glioma: Current management and future application. *Cancer Letters, 476*, 1–12.

Louis, D. N., Perry, A., Reifenberger, G., von Deimling, A., Figarella-Branger, D., Cavenee, W. K., … Ellison, D. W. (2016). The 2016 world Health organization classification of tumors of the central nervous system: A summary. *Acta Neuropathology, 131*, 803–820.

Cheng, Q., Huang, C., Cao, H., Lin, J., Gong, X., Li, J., … Huang, J. (2019). A novel prognostic signature of transcription factors for the prediction in patients with GBM. *Frontiers in Genetics, 10*, 906.

Bhattacharya, Sw.eta, Kumar Reddy Maddikunta, Pr.aveen, Pham, Quo.c-Vi.et, Reddy Gadekallu, Thip.pa, Lal Chowdhary, Ch.iranji, Alazab, Mam.oun, & Piran, M.d Jal.il (2021). Deep learning and medical image processing for coronavirus (COVID-19) pandemic: A survey. *Sustainable Cities and Society, 65*, Article 102589.

Loey, Mo.hamed, Manogaran, Gunase.karan, Hamed, Moha.med, Taha, N., Eldeen, No. ur, & Khalifa, M. (2021). Fighting against COVID-19: A novel deep learning model based on YOLO-v2 with ResNet-50 for medical face mask detection. *Sustainable Cities and Society, 65*, Article 102600.

Çapraz, Özka.n, & Deniz, Al.i (2021). Assessment of hospitalizations from asthma, chronic obstructive pulmonary disease and acute bronchitis in relation to air pollution in İstanbul, Turkey. *Sustainable Cities and Society*, Article 103040.

Gill, Sukhp.al Sin.gh, Arya, Raje.sh Ch.and, Wander, Gu.rpreet Si.ngh, & Buyya, Rajku. mar (2018). Fog-based smart healthcare as a big data and cloud service for heart patients using IoT. In *International Conference on Intelligent Data Communication Technologies and Internet of Things* (pp. 1376–1383). Springer.

Rahmani, Ami.r M., Gia, Tu.an Ng.uyen, Negash, Be.hailu, Anzanpour, Arm.an, Azimi, Im.an, Jiang, Min.gzhe, & Liljeberg, Pas.i (2018). Exploiting smart e-Health gateways at the edge of healthcare Internet-of-Things: A fog computing approach. *Future Generation Computer Systems, 78*, 641–658.

Islam, S. M. Ri.azul, Kwak, Daeh.an, Humaun Kabir, M. D., Hossain, Ma.hmud, & Kwak, Kyun.g-Su.p (2015). The internet of things for health care: A comprehensive survey. *IEEE Access, 3*, 678–708.

Faust, Ol.iver, Hagiwara, Y.uki, Hong, Ta.n Je.n, Shu Lih, O.h, & Rajendra Acharya, U. (2018). Deep learning for healthcare applications based on physiological signals: A review. *Computer Methods and Programs in Biomedicine, 161*, 1–13.

Zhao, Xia.nlong, Yang, Kex.in, Chen, Qim.ei, Peng, D.uo, Jiang, H.ao, Xu, Xia.nze, & Shuang, Xinz.huo (2019). Deep learning based mobile data offloading in mobile edge computing systems. *Future Generation Computer Systems, 99*, 346–355.

Maxwell, And.rew, Li, Run.zhi, Yang, Be.i, Weng, H.eng, Ou, Aih.ua, Hong, Huixia.o, … Zhang, Chaoy.ang (2017). Deep learning architectures for multi-label classification of intelligent health risk prediction. *BMC Bioinformatics, 18*(14), 121–131.

Alshehri, F., & Muhammad, G. (2021). A Comprehensive Survey of the Internet of Things (IoT) and AI-Based Smart Healthcare. *IEEE Access, 9*, 3660–3678.

Kirby, Alastair. J., & Finnerty, Ger.ald T. (2020). New strategies for managing adult gliomas. *Journal of Neurology*, 1–9.

Mobark, Nahl.a A., Alharbi, Mus.a, Alhabeeb, L.amees, AlMubarak, L.atifa, Alaljelaifv, Rash.a, AlSaeed, Mar.iam, Almutairi, A.mal, et al. (2020). Clinical management and genomic profiling of pediatric low-grade gliomas in Saudi Arabia. *PloS one, 15*(1), Article e0228356.
Mohile, Nim.ish A., Blakeley, Jais.hri O., Gatson, N.a To.sha N., Hottinger, A.ndreas F., Lassman, And.rew B., Ney, Doug.las E., Olar, Adria.na, et al. (2020). Urgent considerations for the neuro-oncologic treatment of patients with gliomas during the COVID-19 pandemic. *Neuro-oncology, 22*(7), 912–917.
Nabors, Lou.is Bu.rt (2020). Management of Gliomas: Individualized Treatment Options. *Journal of the National Comprehensive Cancer Network, 18*(7.5), 985–988.
Nilashi, Mehrba.khsh, Ahmadi, Ho.ssein, Shahmoradi, L.eila, Ibrahim, Oth.man, & Akbari, El.naz (2019). A predictive method for hepatitis disease diagnosis using ensembles of neuro-fuzzy technique. *Journal of Infection and Public Health, 12*(1), 13–20.
He, Sh.uqing, Cheng, B.o, Wang, Haife.ng, Huang, Yu.ze, & Chen, Jun.liang (2017). Proactive personalized services through fog-cloud computing in large-scale IoT-based healthcare application. *China Communications, 14*(11), 1–16.
Gia, T.uan Ngu.yen, Thanigaivelan, Nand.a Ku.mar, Rahmani, Am.ir-Moha.mmad, Westerlund, To.mi, Liljeberg, P.asi, & Tenhunen, Han.nu (2014). Customizing 6LoWPAN networks towards Internet-of-Things based ubiquitous healthcare systems. In *2014 NORCHIP* (pp. 1–6). IEEE.
Jiang, Min.gzhe, Nguyen Gia, Tua.n, Anzanpour, A.rman, Rahmani, A.mir-Moham.mad, Westerlund, To.mi, Salanterä, San.na, Liljeberg, Pa.si, & Tenhunen, Hann.u (2016). IoT-based remote facial expression monitoring system with sEMG signal. In *2016 IEEE sensors applications symposium (SAS)* (pp. 1–6). IEEE.
Gia, Tua.n Nguy.en, Jiang, Mingz.he, Sarker, Victo.r Ka.than, Rahmani, Am.ir M., Westerlund, Tom.i, Liljeberg, Pa.si, & Tenhunen, Han.nu (2017). Low-cost fog-assisted health-care IoT system with energy-efficient sensor nodes. In *2017 13th international wireless communications and mobile computing conference (IWCMC)* (pp. 1765–1770). IEEE.
Mello-Román, Jor.ge D., Mello-Román, Jul.io C., Gomez-Guerrero, Santia.go, & García-Torres, Mig.uel (2019). Predictive models for the medical diagnosis of dengue: a case study in Paraguay. *Computational and Mathematical Methods in Medicine, 2019*.
He, B.o, Shu, Kuan.g-I., & Zhang, He.ng (2019). Machine learning and data mining in diabetes diagnosis and treatment. In *, 490. IOP Conference Series: Materials Science and Engineering.* IOP Publishing, Article 042049.
Rajasekaran, Mani.kandan, Yassine, Abd.ulsalam, Shamim Hossain, M., Alhamid, Moham.med F., & Guizani, Mo.hsen (2019). Autonomous monitoring in healthcare environment: Reward-based energy charging mechanism for IoMT wireless sensing nodes. *Future Generation Computer Systems, 98*, 565–576.
https://www.cancerimagingarchive.net/.
https://www.kaggle.com/michaelchalamet/brain-cancer-data.
Akrivopoulos, Ores.tis, Amaxilatis, Dim.itrios, Antoniou, Athanas.ios, & Chatzigiannakis, Ioa.nnis (2017). Design and evaluation of a person-centric heart monitoring system over fog computing infrastructure. In *Proceedings of the First International Workshop on Human-centered Sensing, Networking, and Systems* (pp. 25–30).
Choi, Edw.ard, Bahadori, Moham.mad T.aha, Song, L.e, Stewart, Walt.er F., & Sun, Jim.eng (2017). GRAM: graph-based attention model for healthcare representation learning. In *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 787–795).
Constant, N., D. Borthakur, M. Abtahi, H. Dubey, and K. Mankodiya. "Fog-assisted wiot: A smart fog gateway for end-to-end analytics in wearable internet of things." *arXiv preprint arXiv:1701.08680* (2017).
Azimi, Ima.n, Takalo-Mattila, Ja.nne, Anzanpour, A.rman, Rahmani, Am.ir M., Soininen, Juh.a-Pek.ka, & Liljeberg, P.asi (2018). Empowering healthcare iot systems with hierarchical edge-based deep learning. In *Proceedings of the 2018 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies* (pp. 63–68).
Mahmud, Red.owan, Koch, Ferna.ndo Lu.iz, & Buyya, Rajku.mar (2018). Cloud-fog interoperability in IoT-enabled healthcare solutions. In *Proceedings of the 19th international conference on distributed computing and networking* (pp. 1–10).
Barik, Rabind.ra K., Priyadarshini, Ro.jalina, Dubey, Haris.hchandra, Kumar, Vin.ay, & Mankodiya, Ku.nal (2019). FogLearn: Leveraging fog-based machine learning for smart system big data analytics. *Geospatial Intelligence: Concepts, Methodologies, Tools, and Applications* (pp. 1225–1241). IGI global.
Rajkomar, Al.vin, Oren, Ey.al, Chen, K.ai, Dai, Andr.ew M., Hajaj, Niss.an, Hardt, Michael.a, Liu, Pet.er J., et al. (2018). Scalable and accurate deep learning with electronic health records. *NPJ Digital Medicine, 1*(1), 1–10.
Tuli, Shr.eshth, Basumatary, Nip.am, Gill, Sukh.pal Sin.gh, Kahani, Mo.hsen, Arya, Raje.sh Cha.nd, Wander, Gurp.reet Sin.gh, & Buyya, Ra.jkumar (2020). HealthFog: An ensemble deep learning based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in integrated IoT and fog computing environments. *Future Generation Computer Systems, 104*, 187–200.