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WHEN DEEP LEARNING MEETS FOG COMPUTING & IoT HEALTHCARE: A REVIEW

Abdulhafiz Sabo[1], Habib Shehu Jibrin[2], Muhammad Zia-Ul-Rahaman Abubakar[3], Jamilu UsmanWaziri[4]

Department of Mathematical Science, Bauchi State University Gadau, Nigeria [1]

Department of Computer Science, Federal Polytechnic Kaltingo Gombe, Nigeria[2]

Department of Mathematical Science, Bauchi State University Gadau, Nigeria [3]

Department of Mathematical Science Bauchi State University Gadau, Nigeria[4]

Abstract: Sensor–equipped smartphones and wearable device are transforming the way of health monitoring. Big data generated by sensor, sensitive application like health monitoring and surveillance system cannot be transferred to and processed by cloud. Moreover, faster processing is required by several internet of things (IOT) application, but current cloud capability will be unable to process such application. The emergence fog computing provide solution by bringing computing resources such as routers much closer to user, also reduce propagation latency for application that require real time response compared to cloud domain. Despite the benefit offered by FC, there are some limitations of fog computing model which focus from a limited perspective on either accuracy of result or response time both not both.

Deep learning algorithms, with their ability to process large scale datasets, have recently started gaining tremendous attentions in the fog computing literatures. However, no comprehensive literature review exists on the applications of deep learning approaches to solve complex problems in fog computing and IoT healthcare. To fill this gap, we conducted a comprehensive literature survey on when deep learning meet fog computing and IoT healthcare. The survey shows that when deep learning algorithms meet fog computing architectures in IoT healthcare are increasingly becoming an interesting research area for solving complex problems. We introduce a new taxonomy of deep learning techniques in fog computing and IoT healthcare. The synthesis and analysis of the articles as well as their limitation are presented. A lot of challenges were identified in the literature and new future research directions to solve the identified challenges are presented.

Keywords: Deep learning, fog computing, Internet of Things (IoT), Cloud computing

I. INTRODUCTION

Cloud computing provides centralized platform for storage and computation typically in data centres located far from users (Corchado & Prieta, 2016). The far distance from user devices to the cloud causes low communication latency, hence, affecting quality of service (QoS) and quality of experience (QoE) (Shi, Cao, Zhang, Li, & Xu, 2016; Varghese & Buyya, 2018). IoT is an infrastructure that uses sensors, actuators, and communication technologies to make communication feasible between the real and the digital world. With high influx of user devices especially in the IoT healthcare, huge amount of data is generated (Singh et al., 2018). This poses a challenge to the cloud data centre when dealing with requests that require real time and low latency responses (Sittón-Candanedo et.al.2019). In smart healthcare systems, latency and response time are very important factors. Reacting fast enough to diseases like heart attacks can save many lives; therefore, fog-based systems for health care can be introduced between sensor devices and the cloud layer to meet delay-sensitive health application needs. It provides cloud-like services at the edge of the network. It works as an intermediary computation layer, which provides scalability, low latency, low power consumption, seamless mobility, and many other advantages, e.g., as summarized in (Tariq et al., 2019). Despite the benefits offered by FC, there are still some challenges. (Ammar et al., 2019) explored the challenges of fog computing in healthcare applications and identified that latency and response time are the most important and difficult to optimize Quality of Service (QoS) parameters in real time fog environments and also handling privacy issues are among the challenges as various nodes interact with user devices (Vaquero, Rodero-merino, Vaquero, & Rodero-merino, 2014).

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Healthcare is one of the prominent application areas that require accurate, real-time results. Getting quicker results implies fast actions for critical heart patients. But faster delivery of results is not enough as with such delicate data we cannot compromise with the accuracy of the result. One way to obtain high accuracies is by using state-of-the-art analysis software typically those that employ deep learning and their variants trained on a large dataset. Deep Learning (DL) can be introduced running on Fog computing. Deep learning can learn features automatically from a dataset. Instead of using manually generated collection of rules to obtain features of data, deep learning possesses the ability to learn the essential features automatically at the training phase (Wani et al., 2020). Another advancement of deep learning has been to predict and classify healthcare data with extremely high accuracies (Oliver et al., 2018).

However, recent deep learning models for healthcare application are highly sophisticated and require large number of computational resources both for training and prediction (Xianlong et al., 2018). It also takes large amount of time to train these complex neural networks and analyse data using them. This has been a major challenge for healthcare and similar IoT applications where it is difficult to obtain results in real-time. To fill gap, as computation on the Edge has the great advantage of reducing response time, this gives a new direction of research of combining complex deep learning models with fog computing such that we obtain high accuracy results in real-time.

Therefore, this review paper demonstrates the necessity and importance of combining deep learning and Fog computing in IoT health. The rest of the paper is structured as follows: second 2 introduce deep learning and its various architectures. Fog Computing is explained in section 3. Section 4 delves into the literature review. Then, the findings are presented and discussed throughout section 5. Finally, section 6 brings the paper to a conclusion.

II. DEEP LEARNING

Deep learning is a branch of machine learning that has enticed attention in various domains because of its strength and accuracy in handling huge amount of data (Wani, Ahmad, Saduf, Asif, & Khan, 2020). In recent years, it has outperformed traditional methods in many areas like cyber security, natural language processing, bio-informatics, robotics, and medical information processing (Alzubaidi et al. 2021). Deep learning techniques are categorized into three: unsupervised, supervised, and semi-supervised (Amanullah et al. 2020).

Supervised learning algorithms uses fully labeled data for training of the model, while the unsupervised learning techniques learn by extracting beneficial information from given unlabelled data. The semi- supervised learning techniques use a combination of both labeled and unlabelled training dataset. Deep learning has gained popularity because of advancement in computing capability by the advent of graphics processing unit (GPU), reduced hardware cost, and improved network connectivity (Zhao et al., 2019).

In today's IoT and fog networks, data analysis to identify meaningful trends and information is critical, and deep learning algorithms are at the root of all data analytics activities. Deep learning works effectively with time dependent, noisy, sparse, and heterogeneous healthcare data. It is end to end learning and the ability to process complex and multi-modal data is very advantageous in healthcare sector (Riccardo et al. 2018).

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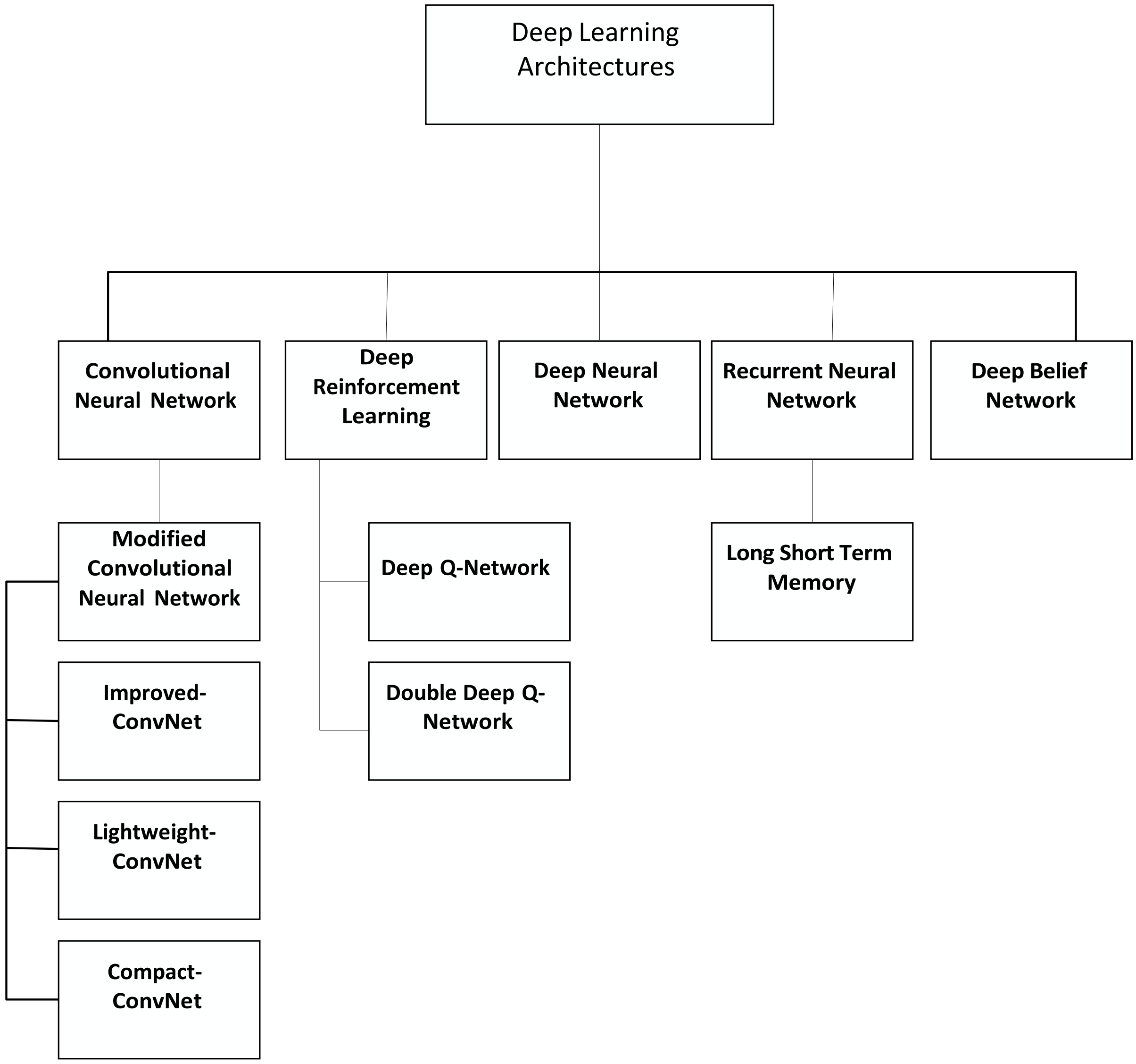

Figure 1: Taxonomy of Deep Learning Architectures

Many deep learning architectures exist in the literature. However, the scope of the study is the deep learning architectures used in solving problems in fog computing and IoT healthcare. The taxonomy is created based on the deep learning architectures that were found to be applied in solving problems in fog computing and IoT healthcare.

III. FOG COMPUTING

Fog computing (FC) takes advantage of computing resources such as the routers to bring computing much closer to the users (Baccarelli, et al., 2017). By bringing storage devices and servers close to the user, these capabilities can be realized. It's a decentralized computing system in which data is being processed and stored in the cloud between both the source and infrastructure. This decreases the overhead of data processing and, as a result, increases the rate of cloud computing by removing the need to manage and store vast volumes of data that aren't needed. Diverse goals perform via Fog computing such as efficiency improvement both in the context of resource utilization and energy consumption, data size-reduction that required to be transported to the cloud in multi purposes of data like data processing, analysis, and storage. (Mutlag et al. 2019) explored the challenges of Fog computing in healthcare applications and identified that latency and response time are the most important and difficult to optimize Quality of Service (QoS) parameters in real time fog environments. Improving security and handling privacy issues are among the challenges as various nodes interact with user devices (Vaquero, Rodero-merino, Vaquero, & Rodero-merino, 2014).

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The FC is applied in areas like smart grid, connected vehicles, smart cities, healthcare, etc. (Bonomi, Milito, Zhu, & Addepalli, 2012). Fog Computing uses devices such as gateways, small servers, routers, switches, etc. The fog severs are located at different places such as bus stations, shopping malls, road side, etc. and they have virtualization capability and can perform computation and storage of data (Luan et al., 2016). The fog computing architecture consists three different layers as presented in figure 2.

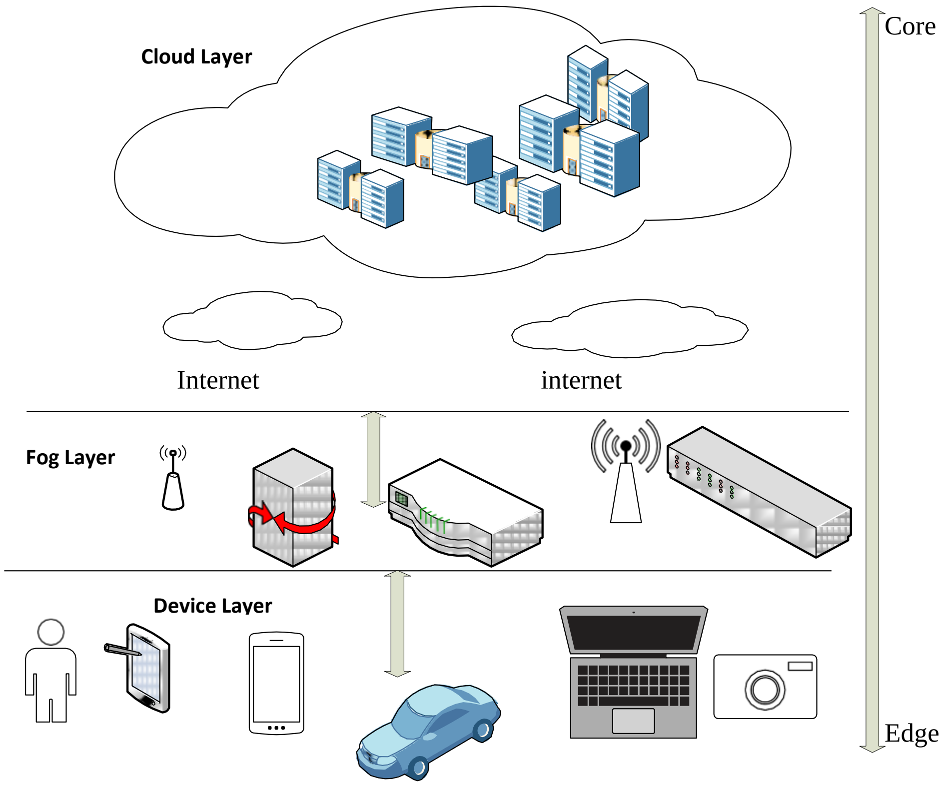

Figure 2: Fog Computing Architecture

Device layer is the closest layer to users and their environment. It contains different user/IoT devices such as sensors, cell phones, smart TVs, smart vehicles and so on. The IoT devices in this layer sense and transmit data to the higher layer for processing. *Fog layer* contains a number of broadly distributed fog nodes. The fog layer comes between the device and cloud. Fog nodes include devices like routers, switches, access points, gateways etc. those devices can perform computation, provide temporary storage or transmit received data to upper layer. It connects to the cloud and communicates when there is need for more complex computation or huge storage. *Cloud layer* contains multiple servers and storage devices with strong computing and storage capabilities. It supports computational intensive applications and provides permanent storage for huge amount of data (Hu, Dhelim, Ning, & Qiu, 2017).

IV. LITERATURE REVIEW

These sections provide an overview of published survey that we read and mentioned below and also selected the result and limitations of them in the healthcare and IoT field. We notice that deep learning has a great role and positive impact in the case of integration and applied with fog computing in IoT healthcare. For example (Chatzigiannakis et al. 2017) proposed an ECG-based Healthcare (ECGH) system to diagnose cardiac abnormalities using ECG but has low accuracy and high response time of detecting abnormal events because they are fetching data directly without using data analytics or other feature extraction techniques. Further, the data transmission to cloud server in case of large number of requests increases latency and consumes more energy consumption, which degrades the performance of the system. (Jiang et al. 2017) proposed a Low Cost Health Monitoring (LCHM) model to gather the health information of different heart patients. Moreover, sensor nodes monitor and analyses the Electro Cardio Graphy (ECG) in a real-time manner for processing of heart patients data efficiently, but LCHM has more response time which reduces the performance. Further, sensor nodes gather ECG, respiration rate, and body temperature and transmit to a smart gateway using wireless communication mode

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to take automatic decision quickly to help patient. Orange Pi One based small-scale test bed is used to test the performance of LCHM model in terms of execution time, but LCHM consumes more energy during collection and transmission of data. (Wang et al., 2017) proposed an IoT based healthcare management model called FogCepCare to integrate cloud layer with sensor layer to find out the health status of heart patients and reduces the execution time of job processing at runtime. FogCepCare uses the partitioning and clustering approach and a communication and parallel processing policy to optimize the execution time. The performance of FogCepCare is compared with existing model using simulated cloud environment and optimizes the execution time but this work lacks the evaluation of performance in terms of important QoS parameters such as power consumption, latency, accuracy etc. (Song et al. 2017) proposed a Graph-based Attention Model (GRAM) for healthcare representation learning that supplements electronic health records with hierarchical information inherent to medical ontologies. Further, the performance of GRAM is optimized in terms of training accuracy. GRAM uses predictive analysis to predict the chances of heart attack and compared the performance of GRAM with Recurrent Neural Network (RNN) using very small dataset and performs better than RNN in terms of training accuracy.

The performance of GRAM can be degraded in case of large datasets. (Ali and Ghazal 2017) proposed an IoT e-health service based an application using Software Defined Network (SDN), which collects data through smartphone in the form of voice control and finds the health status of patients. Further, an IoT e-health service finds the type of heart attack using mobile application based conceptual model but performance of the proposed application is not evaluated on cloud environments. (Nicholas et al. 2017) proposed a Smart Fog Gateway (SFG) model for end-to-end analytics in wearable IoT devices and demonstrated the role of the SFG in orchestrating the process of data conditioning, intelligent filtering, smart analytics, and selective transfer to the cloud for long-term storage and temporal variability monitoring. SFG model optimizes the performance in terms of execution time and energy consumption, but it does not consider latency as a performance parameter. (Mahmud et al. 2018) proposed a Fog-based IoT-Healthcare (FIH) solution structure and explore the integration of Cloud-Fog services in interoperable Healthcare solutions extended upon the traditional Cloud-based structure. Further, iFogSim simulator (Gupta et al., 2017) is used to test the performance of FIH solution in terms of power consumption and latency only. The performance of FIH solution can be evaluated in terms of execution time and accuracy. (Kaoru et al. 2018) proposed Fog based Efficient Manufacture Inspection (FEMI) system using deep learning for smart industry to process a large amount of data in an efficient manner. Further, FEMI system adapts the CNN model to the fog computing environment, which significantly improves its computing efficiency and optimizes the performance only in terms of testing accuracy. (Azimi et al. 2018) proposed Hierarchical Edge-based deep learning (HEDL) based healthcare IoT system to investigate the feasibility of deploying the Convolutional Neural Network (CNN) based classification model as an example of deep learning methods. Further, a case study of ECG classifications is used to test the performance of proposed system in terms of accuracy and execution time. (Minh et al. 2018) proposed a Cloud-based Smart Home Environment (CoSHE) to deliver home healthcare to provide humans contextual information and monitors the vital signs using robot assistant. Initially, CoSHE uses non-invasive wearable sensors to gather the audio, motion and physiological signals and delivers the contextual information in terms of the residents daily activity.

Further, the CoSHE allows healthcare professionals to explore behavioural changes and daily activities of a patient to monitor the health status periodically. Moreover, the case study of robotic assistance is presented to test the performance of CoSHE by utilizing Google APIs. However, CoSHE is general healthcare application to collect and process patient data at small scale without data analytics and they have not evaluated on real cloud environment to test its performance in terms of QoS parameters. (Sahoo et al. 2018) proposed a Service Level Agreement (SLA) based Healthcare Big Data Analytic (SLA-HBDA) architecture to perform the ranking of patients' data, which improves its processing speed. Further, an efficient data distribution technique is developed to allocate batch and streaming data using Spark platform to predict the health status of the patient. SLA-HBDA architecture improves the performance in terms of accuracy as compared to Naive-Bayes (NB) algorithm but it does not consider latency and other important QoS parameters. (Rabindra and Rojalina 2018) proposed a fog- based machine learning model for smart system big data analytics called Fog Learn for application of K-means clustering in Ganga River Basin Management and real-world feature data for detecting diabetes patients suffering from diabetes mellitus. (Tuan et al. 2018) proposed an IoT-based system for monitoring a person's Electrocardiogram (ECG) in real time. The architecture of the proposed system has three layers. The first layer consists of medical sensors, environmental sensors, and activity sensors. Medical sensors collect heart rate, respiration rate, body temperature, blood pressure, blood oxygen level, and ECG. The data is collected with a network of gateways. The data fusion and compression is done in Fog layer. The Cloud layer is used for storage and analyzing the status of a person's health. The solution is designed to address the issues of high latency and bandwidth usage. A small scale test was implemented, showing a 48.5% reduction in network delay under high network load. However, the minimum latency is poor when the network load is not high. (Mufti et al. 2018) proposed a Cloud-based heterogeneous Internet-of-Healthcare-Things communication framework.

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The framework is based on five layers: Perception layer, mist layer, Fog layer, Cloud layer and application layer. The goal of the work is to ensure high QoS, focusing on controlling end-to-end latency and packet drop rate using optimization of flow control and resource allocation. The evaluation was carried through a case study, which validates its suitability in the healthcare domain. However, it only focuses on data streaming and transmission rather than the processing and analysis of the data. Though Fog based healthcare systems have demonstrated their value in terms of response time and low latency, architectures of this type also increase the challenges in terms of privacy and security. Privacy and security concerns need to be carefully addressed to take full advantage of Fog based frameworks. (Abdulsalam et al. 2019) proposed an Autonomous-Monitoring-System (AMS) model is particularly used for the Internet of Medical Things (IoMT). This model is capable to provide functionality for medical care.

This research work is designed based on a reward mechanism that uses the Analytics Hierarchy-Process (AHP) for the proper dispersion of the flow of energy between the considered nodes in the model. Cloud computing enabled simulated framework has been used to simulate and test the presence of the autonomous monitoring system as far as energy use and the autonomous monitoring system are better in caparison to the FGCS strategy, but the timing of the correspondence between nodes reflects the high latency of patient solicitation preparation. (Rabiul et al. 2019) proposed a general Edge-of-Things Computation (EoTC) framework for healthcare service provisioning to optimize the cost of data processing. Further, a portfolio optimization solution is presented for the selection of Virtual Machines (VMs) and designed Alternating Direction Method of Multipliers (ADMM) based distributed provisioning technique for efficient processing of healthcare data. Further, experimental results demonstrate that EoTC framework performs better than greedy approach in terms of cost, but this framework lacks in performance evaluation in terms of QoS parameters. (Randa et al. 2019) proposed a Cloud-Fog Based Architecture (CFBA) for IoT based healthcare applications to monitor the health status of the patience. Further, a task scheduling and allocation mechanism is proposed for the processing of healthcare data by distributing the healthcare tasks in an efficient manner. The performance of CBFA is evaluated using iFogSim simulator (Buyya et al., 2017) in terms of only latency. (Devarajan et al. 2019) proposed an intelligent Fog-based system for monitoring and Control of mosquito- borne diseases, for the data collection, IoT and wearable sensors are used.

The data analysis, clustering and data sharing are done at the Fog layer. The data used for the analysis include physiological conditions, symptoms of the disease, contextual information, whether or not that region is at risk, and mosquito density in the region. The Cloud layer is used for social network analysis to prevent extensive spread of mosquito-borne diseases. A machine learning algorithm classifies the user as infected or uninfected and identifies the type of disease. This work demonstrated 95.5% classification accuracy but did not consider important parameters of a standard system such as latency, QoS needs and energy consumption. (Gulshan et al. 2019) worked on privacy preservation of medical records. At the Fog layer, they used a data aggregator that reduces the burden on the network. To ensure confidentiality and reliability of the records, Elliptic cryptography and Consensus algorithms were used. Their results suggested that using a data aggregator at Fog layer can minimize response time to some extent, and that Elliptic cryptography can preserve the privacy. (Malathi et al. 2019) proposed Fog-based energy-efficient healthcare system that monitors diabetic patients' nutritional intake and physical activity to manage blood glucose levels. For accurate prediction of blood glucose risk level they used J48Graft decision tree.

The evaluation was done by running a case study on smartphones. The results showed that in the case of continuous detection and judgment, its performance is better in the Fog than the Cloud. As it was a case study implemented using mobile phone, it does require larger scale experiments on larger scale in variety of scenarios. (Nipam et al. 2020) proposed an ensemble learning based heart disease prediction system. However, they have not considered the mobility of devices in their experiments, while these have an impact on the execution of tasks. (Munish et al. 2021) proposed An IoT and Fog based e-health framework. This framework determines the physical fitness of sedentary people. A wide variety of devices such as actuators, RFID tags, mobile phones, and smart sensors are used to sense data. The datasets of Health, Physical posture, Behavior and Environment were combined for the analysis. For the latency sensitivity of their system, the pre-processing was done on the Fog layer and the analysis in the Cloud. They used ANN and the experimental results showed 94.51% accuracy for the prediction of health abnormalities. Other performance criteria such as energy usage and network utilization were not evaluated in this study.

V. RESULT AND DISCUSSION

Depending on the different papers that we read and mentioned in the literature review, we also point out the results and limitations of them. We summarized them in the table below. The aim is to clarify and demonstrate the advantages and impacts of DL algorithms in FC and IoT healthcare.

Table1. The summary of literature review

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Reference	Proposed model	Objective	Result	Limitation
(Chatzigiannakis et al., 2017)	ECGH	To diagnose cardiac abnormalities	ECGH has high accuracy and high response time	It increases latency and consumes more energy
(Jiang et al., 2017)	LCHM	To gather the health information of different heart patients	Low execution time and high response time	LCHM consumes more energy
(Wang et al., 2017)	FogCepCare	Integration cloud layer with sensor layer to find out the health status of heart patients	The result showed FogCepCare has low execution time	The model lacks the evaluation of performance in terms of important QoS parameters such as power consumption, latency, accuracy
(Song et al. 2017)	GRAM	The use of predictive analysis to predict the chances of heart attack	GRAM has high training accuracy	The performance of GRAM can be degraded in case of large datasets
(Ali and Ghazal 2017)	IoT e-health service	To collects data through smartphone in the form of voice control and finds the health status of patients	IoT e-health service finds the type of heart attack	The performance of the proposed application is not evaluated on cloud environments
(Nicholas et al. 2017)	SGF	The process of data conditioning, intelligent filtering, smart analytics, and selective transfer to the cloud for long-term storage and temporal variability monitoring in SGF orchestrating.	The result showed that SGF has low, execution time and energy consumption is less	It does not consider latency as a performance parameter
(Tuli et al. 2018)	FIH	To explore the integration of Cloud-Fog services in interoperable Healthcare	FIH Performed well in terms of power consumption and latency only	FIH solution does not consider execution time and accuracy as a performance parameter
(Kaoru et al. 2018)	FEMI	The processing of large amount of data in an efficient manner using deep learning for smart industry	Significantly improves testing accuracy	lacks the evaluation of performance in terms of execution time, power consumption and latency
(Azimi et al. 2018)	HEDL	To investigate the feasibility of deploying the Convolutional Neural Network (CNN) based classification model as an example of deep learning methods	HEDL performed well in terms of accuracy and execution time	HEDL solution does not consider power consumption, latency, response time and jitter as a performance parameter
(Minh et al. 2018)	CoSHE	Monitoring of vital signs using robot assistant which provide humans contextual information	APIs Google are being utilized	Performance test in terms of QoS parameters have not evaluated on real cloud environment
(Sahoo et al. 2018)	SLA	Batch allocation and streaming of data using Spark platform to predict the health status of the patient	The result showed that SLA-HBD has high accuracy	latency and other important QoS parameters were not considered
(Rabindra and Rojalina 2018)	Foglearn	FogLearn for application of K-means clustering in Ganga River Basin Management and real-world feature data for detecting diabetes patients suffering from diabetes mellitus.	The result showed that Fog Learn performed well in detecting patients with mellitus diabetes	Fog Learn does not consider any performances evaluation
(Tuan et al. 2018)	Prototype	IoT-based system for monitoring a person's Electrocardiogram (ECG) in real time	The result showed that 48.5% reduction in network delay	Low latency when the network load is not high

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			under high network load	
(Mufti et al. 2018)	Not mentioned	Ensure high QoS, focusing on controlling end-to-end latency and packet drop rate using optimization of flow control and resource allocation.	Fog based healthcare systems performed well in terms of response time and low latency	Privacy and security concerns need to be carefully addressed
(Abdulsalam et al. 2019)	AMS	Providing functionality for medical care based on a reward mechanism that use AHP	Low energy consumption	High latency
(Rabiul et al. 2019)	EoTC	EoTC framework for healthcare service provisioning to optimize the cost of data processing	EoTC performed better in terms of cost	EoTC Framework lacks performance evaluation in terms of latency, accuracy, energy consumption execution time and jitter
(Randa et al. 2019)	CFBA	CFBA for IoT based healthcare applications to monitor the health status of the patience	The result showed that CFBA has low latency	Only latency is considered as performance evaluation
(Devarajan et al. 2019)	Not mentioned	intelligent Fog based system for monitoring and Control of mosquito-borne diseases	The result showed that95.5%classification accuracy	latency, QoS needs and energy consumption were not considered
(Gulshan et al. 2019)	Hyper ledger composer	Privacy preservation of medical records	Their results suggested that using a data aggregator at Fog layer can minimize response time to some extent.	Hyper ledger composer lacks performance evaluation in terms energy consumption, network usage and mobility
(Malathi et al. 2019)	NA	Fog-based energy-efficient healthcare system for monitoring diabetic patients' nutritional intake and physical activity to manage blood glucose levels	Fog-based energy-efficient healthcare system systems performed well in terms of power and execution time	Network usage and mobility were not considered
(Nipam et al. 2020)	FogBus	Ensemble learning based heart disease prediction system	FogBus performed well in terms of execution time, energy consumption and network usage	Fog Bus does not considered mobility of devices
(Munish et al. 2021)	Ubidots IoT platform	The framework determines the physical fitness of sedentary people	The result showed that Ubidots IoT platform has high accuracy and low execution time	Framework lacks performance evaluation in terms of energy usage and network utilization

VI. CONCLUSION

The paper proposes to conduct a survey dedicated to the application of deep learning algorithms in fog computing and IoT healthcare, including synthesis and analysis. The survey examines the performance of DL algorithms or incorporating them into FC and IoT healthcare improves efficiency while also providing end-users with services such as protection, management of resources, traffic predictions, latency, and energy reduction, as well as cost, data analysis, and reliability.

It is found that the applications of deep learning algorithms in fog computing and IoT healthcare is in an early stage but is growing. The synthesis and analysis of the literature regarding deep learning applications in fog computing and IoT healthcare are presented in the survey. The survey revealed new research directions from the perspective of deep learning and big data analytics for the future development of the research area.

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