Volume: 5, Issue: 6
Page: 197-208
2021

International Journal of
Science and Business
Journal homepage: ijsab.com/ijsb

IJSAB International

Deep Learning and Fog Computing: A Review

Shavan Askar, Zhala Jameel Hamad, Shahab Wahhab Kareem

Abstract

Fog computing (FC) is a new architecture that aims to reduce network pressures throughout the core network as well as the cloud computing (CC) by bringing resource-intensive functions like computation, analytics, connectivity, also storage, nearest to the clients. In their operations, FC systems can make use of intelligence features to reap the benefits of data that is readily accessible with computing resources to be able to resolve the problem of excessive energy use with power for Internet-of-Things (IoT) apps that require speed. It generates large volumes of data, prompting the creation of a growing number of FC apps and services. Furthermore, Deep Learning (DL), an important field, has made significant progress in a variety of research areas, including robotics, face recognition, neuromorphic computing, decision-making, computer graphics, and speech recognition. Several studies have been suggested to look at how to use DL to solve FC issues. DL has become more common these days to improve FC apps as well as provide fog services such as security, resource management, accuracy, delay, and energy reduction, cost, data processing, and traffic modeling. The current review paper will focus on how to provide an overview of DL functions throughout the FC sector. The DL implementation for FC has evolved into powerful clients with services at the highest level, allowing for deeper analytics and mission answers that are more intelligent.

IJSB
Literature review
Accepted 29 May 2021
Published 19 August 2021
DOI: 10.5281/zenodo.5222647

Keywords: *Internet of Things (IoT), cloud computing, fog computing.*

About Author (s)

Shavan Askar (Corresponding Author), Assistant Professor, CEO of Arcella Telecom, College of Engineering, Erbil Polytechnic University, Erbil, Iraq. Email: shavan.askar@epu.edu.iq

Zhala Jameel Hamad, Information System Engineering, Erbil Polytechnic University, Erbil, Iraq. Email: zhalla.mei20@epu.edu.iq

Shahab Wahhab Kareem, Lecturer, Erbil Polytechnic University, Erbil, Iraq.

1. Introduction

Throughout the next 5 years, it is projected that 50 billion IoT products will be produced, involving power and processor devices like wearables, driverless cars, drones, robots, artificial intelligence, and digital devices, the integrated solution of all "material" throughout the network poses a huge an issue (La et al., 2019) (Hamad and Askar, 2021). congestion produced through billions of IoT nodes due to the time-sensitive necessities of minimum delay and latency, energy consumption, context-aware, accessibility, and data privacy security (Hashem et al., 2015). To relieve the burden upon on cloud, a modern field of networking, transmission, processing, and facilities defined as FC, Edge Computing, and Mobile edge computing may be spread near to consumers with data sources at the edge of the network(Bonomi et al., 2012). Since the majority of certain processes are progressively evolving into complicated, heterogeneous, and dynamic structures, managing similar processes in fog nodes is difficult (Abdulkareem et al., 2019). Furthermore, to attract more users, fog node services should be enhanced in terms of diversity and performance (Sharma et al., 2017). DL was already successfully utilized in the FC model in some previous studies; as a result, FC will benefit from DL in a variety of ways (Li et al., 2018). FC is not required only to address cloud computing's limitations in evolving IoT applications but also to open up new opportunities to 5G and embedded Artificial Intelligence(AI) such as DL (Abeshu and Chilamkurti, 2018) (Kiss et al., 2018). When each Fog node tries to gather and evaluate any amounts of information that comes in through its own IoT devices, it will take a long time, then combining DL with each Fog node would improve Fog Analytics (Prabhu, 2019). Because of its flexibility and ability to self-learn, DL offers more reliable and faster processing (Tang et al., 2016). Therefore, this review paper demonstrates the necessity and importance of DL functions for FC, and how can it help and improves fog performance once implemented. The remainder of this paper is arranged as follows: The second section describes the Fog Computing. Deep Learning is explained in section three. Section four delves into the literature review. Then, the findings are presented and discussed throughout section five. Finally, section six brings the paper to a conclusion.

2. Fog Computing

FC is a cloud computing extension, often referred to as edge computing. FC is a term that places storage and computing capacities at the network's edge (Loja et al., 2019) (Hu et al., 2017) (Svorobej et al., 2019). It can allow new services and applications to be delivered, particularly for the future of the Internet (Yi et al., 2015b). 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. The growing number of smart apps assists the FC model significantly (Hassan and Fareed, 2018). Fog nodes are facilities with infrastructures that can provide support for services at the network's edge in FC. Devices with limited resources involve wireless networks, set-top boxes, switches, routers, base stations, and edge devices (Yi et al., 2015a).

Fog is described by the following characteristics:
Geographical distribution is significant. The services and applications targeted by the Fog, in comparison to the more centralized Cloud, require widely dispersed deployments (Askar et al., 2011; Al Majeed et al, 2014). For example, the Fog will actively participate in achieving great streaming to passing traffic through proxies with access points strategically placed along pathways and tracks.

Sensor Networks on a wide scale for environmental monitoring and the Smart Grid, Other fundamentally distributed systems that include necessitate computing and storage tools that are distributed.

Mobility assistance. Many Fog applications must communicate directly with mobile devices, so they must embrace mobility strategies like the LISP protocol, which decouples host identification with position identity and necessitates the use of a remotely accessing system.

The word "heterogeneity" does have a number of connotations. Fog nodes come in a range of shapes and sizes and can be found in a variety of settings.

As a consequence of the huge geo-distribution, there are a huge number of nodes. As demonstrated by the Smart Grid in particular, sensor networks in general.

The communication that occurs in important real-time fog apps that necessitate real-time instead of data aggregation (Bonomi et al., 2014) (Dastjerdi et al., 2016).

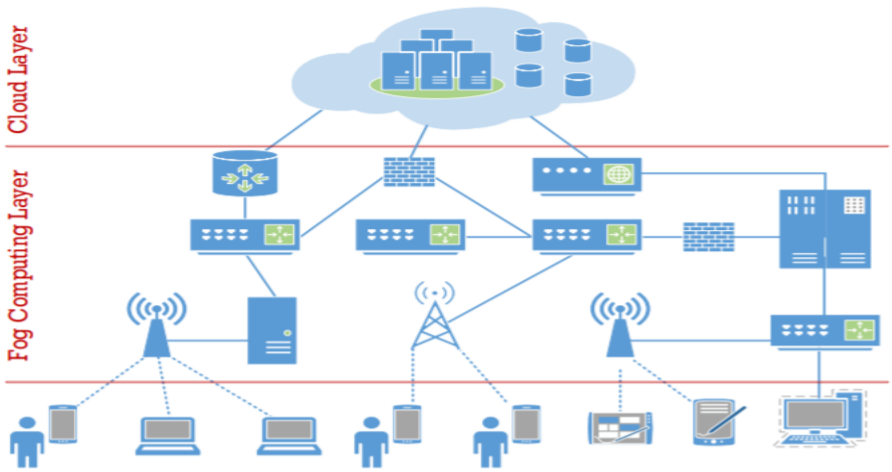

Figure 1. Fog Computing Architecture (Gedeon et al., 2018)

3. Deep Learning

DL is described in a number of ways, but the following are the central and main terms in relation to deep learning: Unsupervised machine learning, learning multiple layers, and artificial intelligence are all terms that refer to a broad range of machine learning methods that are strongly neural networks-related, pattern recognition, and so on (Kamilaris and Prenafeta-Boldú, 2018) (Litjens et al., 2017). This is similar to how the human brain processes data and creates patterns in order to make decisions (Kwon et al., 2019). It learns multi-level features in hierarchical architectures and representations using unsupervised with supervised techniques for pattern recognition and classification tasks. Recent advances in sensor networks and networking technologies have enabled the processing of large amounts of data (Zhang et al., 2018) (Mohammadi et al., 2018). Throughout the machine-learning world, DL is now one of the most popular research paths, with huge achievements in many areas(Yuan et al., 2020). DL has the ability to solve complex problems because that's the most general tool for modeling a problem (Pouyanfar et al., 2018). It can not only generate useful results in which other approaches fail, but it can also create very accurate models and shorten the time it takes to create a good concept in half. DL models, on the other hand, necessitate a lot of computing power to practice (Min et al., 2018).In today's IoT and fog networks, data analysis to identify meaningful trends and information is critical, and DL algorithms are at the root of all data analytics activities. Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Long Short-Term Memory Networks (LSTM), and Recurrent Neural Networks (RNN) are examples of traditional deep learning algorithms (Ahmed & Askar, 2021; Mohammed & Askar, 2021; Ali & Askar, 2021; Huang et al., 2017).

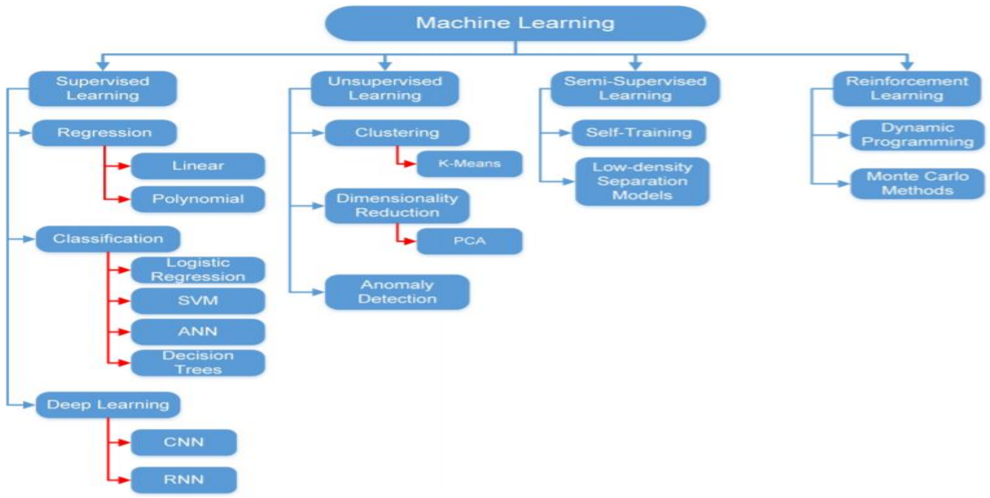

Figure 2. classification of machine learning algorithms (Moubayed et al., 2018)

4. Literature Review

Depending on the different papers that we read and mentioned below and also selected the results of some of them. We notice that DL has a great role and positive impact in the case of integration and applied with FC. In (Li et al., 2018) demonstrated that many sensors are used in factory output, resulting in a huge amount of data. The produce inspection, among the most famous examples, is a tool that is used to detect product flaws. They proposed a DL-based classification method to introduce a robust inspection system for greater accuracy, that can find possible faulty items. Given the possibility of multiple assembly lines in a single plant, one major issue throughout this situation how to handle such large volumes of data during real-time is the question. As a result, they developed the framework around the idea of FC. The machine gains the ability to deal with incredibly large data by transferring the processing load according to the cloud server to a fog node. There are two strong benefits to the system. The first is to adjust the CNN template to the FC, which increases its computing performance significantly. The other is to construct an inspection system that can display the defect form and severity at the same time. Experiments would show that the presented method is both reliable and effective. In (Teerapittayanon et al., 2017) implemented Distributed DNNs (DDNN) for distributed computing structures that included cloud, fog, and end devices. Although DNN can be inferred in the cloud, a DDNN can also be used to perform quick and localized deductions utilizing deep parts of the neural network at both the edge device and surface. A DDNN will grow exponentially in neural network scale-out and size in a geographical span when assisted by a scalable distributed computing structure. Data protection, sensor fusion system, and fault-tolerant are all improved with DDNNs because of their distributed design. They map DNN parts over to a distributed computing structure in order to implement a DDNN. Automatic sensor fusion with fault tolerance is built-in to the system as a result. As a test of the project, they demonstrate how well a DDNN should use sensor diversity to increase object recognition rate while lowering communication costs. It was utilized to monitor the multiple sensors on a local level across end devices, ensuring optimum reliability while cutting contact prices by more than a factor of 20.

In (Dey and Mukherjee, 2018) presented a series of approaches, findings, and conclusions that can aid in the development of Edge enhanced data analytics systems able to manage large amounts of data with minimal human interaction. In an Edge-Cloud set up, they showed that tools at hierarchical, middle levels of effective analytics across DL were required. Including a reference to current norms in the Edge Computing with Fog, the significance of having the ability to assign optimal resources at the edge of the network to efficient as well as cost-effective DL-based analytics applications was highlighted. DL is quick will become the power solution for conducting evaluative data due to its capability to minimize human interference in certain workflows. Cloud outages and fairly high latency are significant deterrents to delivering DL-based cloud services. The deployment and parallel processing characteristics of an Edge-based DL design based on off-the-shelf modules are discussed in detail, as well as their evaluation. Focused on experiments on CNN Deep, as well as techniques in order to provide optimal resource provisioning in restricted edge devices. In (Priyadarshini et al., 2018)presented Deep Fog, a fog-based DL model that gathers information from patients and estimates wellness stats that used a DNN model which should handle data that is multidimensional and heterogeneous. For experimental research, three significant anomalies in wellness were chosen: (a) hypertension attacks, (b)diabetes, (c) stress type classification. In conventional setups, the cloud backend collects healthcare data and conducts illness, diagnosis, and wellbeing prediction tracking and prediction. FC makes use of low-power multicore applications in a node seen between client and cloud layers. The cloud layer could move the diagnosis for health and wellness tracking to the fog layer. As a consequence of this paradigm, latency is decreased while throughput is increased. The findings proved that the proposed framework and design were effective in accurately monitoring these important health and fitness parameters. For their studies, they used common datasets and open-source software resources. In (Zhu et al., 2019) showed that to achieve efficient task computation, throughout the local fog, developed a weighted total optimization problem of overall project energy consumption and time. To address such concerns, a DL-based integrated transferring judgment and resource allocation (DLJODRA) method is being built to maximize offloading processes, the proportions of local CPU, delay, and external Processor profession at the same moment. The network performance is improved even further with optimum offloading decision-based holistic management consideration for network resources. When compared to benchmark approaches, the comprehensive simulation results show that the proposed DLJODRA could attain efficient offloading decisions with minimal computational resource requirements and achieve a substantial reduction of network costs (i.e., delays and power). In (Memon and Maheswaran, 2019)proposed the use of DL approaches to help with FC mobility management throughout the Internet of Vehicles. To gain insight into fog node interactions by observing vehicle interactions, they employ DL algorithms. On a test set, the method predicts the correct fog node at such a given place and time to 99.2 percent to enhance efficiency utilizing 3-layer feed-forward NN. They also built the dual RNN with LSTM cells that could learn the cost, or latency, of these customer inquiries. The system's success on a testing sample as well as experiments. display that it can predict exactly fog node handover positions as well as low-coverage areas for a vehicle. A fog node's performance at a specific location can also be forecasted using a cost prediction model that learns respectively geographical and temporal patterns in data. In (Homayoun et al., 2019) suggested system can be applied as a completely automated ransomware security mechanism on the fog layer (Abdulkahleq & Askar, 2021; Khalid & Askar, 2021). They presented the Deep (DRTHIS) in order to distinguish good ware from ransomware and to recognize families. DRTHIS uses the soft max algorithm to classify data and using two deep learning techniques: LSTM and CNN. Throughout the categorization of ransomware instances, it receives a 99.6 percent F-measure with a positive predictive value of 97.2 percent. Furthermore, according to the results of their tests, LSTM with eight units produces a more effective binary classifier than CNN for detecting ransomware.

In (Liang et al., 2019) proposed a novel for optimizing machining processes, a fog-enabled diagnosis system has been created. Among the system's features are (1) dynamic diagnosis – a CNN-based diagnosis system is used to identify possible faults in specialized machining processes. CNN's pre-processing techniques are required can improve the efficiency of the system by partitioning and de-noising-controlled signals in manufacturing work situations. (2) a novel diagnosis supported by fog system enhancement of the machining operation, to minimize data traffic and improve device efficiency, a gateway layer, a cloud server, as well as a fog layer is used. The design uses the qualified, upon this fog surface, CNN was deployed to process controlled signals received on the terminal layer throughout machining in order to successfully recognize abnormal situations. Energy and output quality increased by 29.25 percent and 16.50 percent, respectively, after the system was installed. This fog system achieved a 70.26 percent bandwidth compression, as well as a 47.02 percent reduction in data transmission time when compared to a cloud system. In (Priyadarshini and Barik, 2019) developed a DL-based method, to secure a Fog network against DDoS attacks. To manage the entire Fog network, they used SDN technology (Askar, 2017; Fizi & Askar, 2016; Askar, 2016; Keti & Askar, 2015; Qadir & Askar, 2021). The open flow-based SDN network is abused, as well as a DDoS defense framework is installed based on DL. Of all the deep DL models, the LSTM model is selected. Since LSTM operates very well data sets, and the packet data that are primarily used during DoS detection are obtained across time. The DL technique is trained using historical data and then evaluated using simulated and actual DDoS attack packets. The model has tested various parameters to come up with a selection of optimized output tuners. On the data collection for this study, the model has a precision of 98.88 percent. The Open Flow switch within SDN will prevent the incoming data packets from propagating to the cloud server if it detects them as suspicious malicious packets. In (Lyu et al., 2019) showed that to prevent bottlenecks in Cloud-based architectures, a Fog-embedded privacy-preserving DL (FPPDL) architecture is proposed. They create a two-level security system to protect privacy. Random projection is used to disturb the original data during data transmission between end nodes with Fog node in order to increase the degree of privacy security while also maintaining certain numerical characteristics of the original data. Computation is moved from the cloud Environment to Fog nodes close end nodes. The results of the experiments on benchmark image datasets in various settings show that the FPPDL achieves a level of accuracy comparable to the centralized SGD is a stochastic gradient descent framework that produces better results. Moreover, both computing and communication costs are shown to be high FPPDL significantly reduces this. Resulting in the desired tradeoff both quality and confidentiality. In (Priyabhashana and Jayasena, 2019) applied machine learning approaches to the IoT in a practical and efficient manner. With the assistance of technologies including Tensor Flow and Cloud Platform, as well as container technologies such as Docker. Without transferring all of the information to a data center, the analytics framework is introduced. Cloud-native architectures like Cloud Data lab and Cloud Machine Learning Engine are used to build and teach machine learning applications. DDN were used to further develop the data analytics process. This contribution will be important because it will concentrate on fog devices by pre-processing information before sending it over the Internet, as well as monitoring the fog station's output. This aide in the early identification of problems as well as the tracking for fog channel results to ensure efficient allocation of resources. In (Lin et al., 2020) proposed an FC-based Hybrid DL Framework (FC-HDLF) for detecting potential product defects. Since a single plant may have a large number of production lines, one of the most pressing concerns is this information are managed throughout live time. Since the load is distributed from the central servers to the fog nodes, the device can manage extremely large volumes of data. There are two clear benefits of this, the CNN model has been modified for FC, which significantly increases the accuracy of its calculations. Another is that a control model is created that can simultaneously represent the defect's type and degree. Calculation burdens would be transferred to the fog node, greatly decreasing the load upon on central server (Husain & Askar, 2021; Samann et al, 2021). The simulations demonstrate the method's robustness and efficiency, demonstrating that it can outperform other current research methods. In (Luong et al., 2020) developed an efficient auction for fog resource allocation in block chain networks using DL. They used neural networks to create assignment and payment mechanisms for the auction. The assignment system generates miners' assignment probabilities, while the payment system generates prices. and demonstrated how to build a loss function with neural networks as well as how to prepare DNN. The simulation results show that their plan outperforms the standard approach by a significant margin. As the number of miners grows, the proposal becomes scalable. In (Lee et al., 2020) proposed a solution aimed to satisfy the greatest number of applications needing DL service although reducing internet usage and cloud burden, by using the full available capacity of fog nodes. They proposed the DLEFN (DL Entrusted to Fog Nodes), which determines which layers of the DL algorithm should be executed on every fog node based on their computational power and bandwidth. In about the same experimental setting, the analyzed results were compared to existing methods and revealed substantial improvements in available bandwidth, power efficiency, the number of permitted DL apps, and cloud overhead. Individual decision-making regarding fog node resources had a substantial positive impact on efficiency, as demonstrated by significant improvements in performance. As a result, the proposed algorithm provided excellent aid for fog nodes with varying resource capacities as a response to existing issues. Finally, they may say confidently that the proposed DLEFN algorithm is an effective scheme for grafting DL into FC-based precision agricultural environments, allowing for efficient operation without service delays caused by network congestion. In (Siasi et al., 2020)presented a thorough investigation into DL through FC service function chain provisioning for network function virtualization. The set-up is built based on an innovative heterogeneous fog design, which is made up of lower and higher fog nodes with varying resource capacities. The LSTM network algorithm is used to predict the popular categories and volumes of incoming VNFs. As an alternative to traditional provisioning, this provides a dataset of prefetching and caching new requests. The scheme identifies and maps common network functions with high-capacity nodes, while uncommon network functions are predicted and mapped to low-capacity nodes. Predicting the next incoming feature and prefetching it on the node is the target. As a consequence, if a future requirement needs a certain feature, the node can cache it directly, saving resources, processing time, price, and energy. As a result, a greater amount of the request is fulfilled, and availability is increased. The DL network creates a loss model with a low failure rate and a high success rate. In (Li et al., 2020) designed an (SPDDL) method based on fog-cloud computing. To safeguard users' privacy, and an authentication system to prevent foreign attackers from impersonating users. Distributed Deep Learning (DDL) can have better results. Learning which focuses exclusively on swapping variables protects privacy. Nonetheless, when DDL is combined with fog and cloud, it is faced with two big security concerns.: 1) How to prevent external adversaries from manipulating consumers' identities; and 2) how to avoid sharing users' private information to a large range of many other participants were recruited during the teaching practice. Several techniques using different methods have been suggested to tackle them. However, those methods have security, performance, and accessibility flaws, and they can't guarantee the authenticity of participants' identities throughout the practice (Sulaiman & Askar, 2015; Fares & Askar, 2016). The proposed solution achieves a better balance of protection, performance, and functionality. In addition, The SPDDL will ensure that users' identities are unforgeable in the face of external threats. Extensive test results suggest that their SPDDL is both realistic and effective. In (Chen et al., 2020)provided a novel constructive and data-driven methodology to route optimization with the primary aim of guaranteeing Age of Information (AoI) trust. They detail a 3-month analysis of a multi-vehicle campuses shuttle system that is linked to cloud/fog servers through an industrial LTE network. In addition, empirical models of AoI to connected vehicles were developed, as well as the impact of major elements on AoI results was investigated and suggested a DL (DQN)-based method for determining the best driving route with the highest level of trust for each connected vehicle. The proposed method has the potential to dramatically lower driving costs while also increasing overall AoI efficiency, according to numerical results. In (NG and Selvakumar, 2020) proposed an IoT congestion intrusion detection system in an FC area utilizing the Vector Convolutional DL- (VCDL) method, the target was to solve the VCN's inability to scale due to its anomalous existence. The main fog node identified internal and external anomalies of IoT traffic using the learned VCDL model. The Bot-IoT dataset from UNSW was used to test the proposed anomaly detection system. The experiments showed that in a fog computing context, the established scheme aided a clustered detection system with a lower detection rate than a centralized approach. The results showed that the proposed solution outperformed state-of-the-art anomaly protection systems and standard DL models by a large margin. When compared to all of the features, the selected features obtained impressive accuracy and performance.

5. Result and Discussion

Depending on the different papers that we read and mentioned in part literature review and also selected the results of some 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.

Table1. display some experimental results of applied DL algorithms in FC.

Authors	Methodology	Objective	Significant Result
(Li et al., 2018)	CNN	to find the weaknesses in the products for the smart industry. In order to incorporate a more reliable and accurate inspection scheme.	presented method is both reliable and effective
(Teerapittayanon et al., 2017)	Distributed DNN	Automates sensor fusion and system fault tolerance by implementing distributed cloud offloading.	Most sensor data is processed locally on end devices through DDNN, which achieves high accuracy while reducing connectivity costs by a rate of over 20x.
(Dey and Mukherjee, 2018)	Deep CNN	Using Fog and Edge Computing Systems to Apply Deep Learning and Inferencing	DL is quick when it comes to its ability to minimize human interaction, data analytics is becoming increasingly popular.
(Priyadarshini et al., 2018)	DNN	Hypertension Attacks	latency is decreased while throughput is increased.
(Zhu et al., 2019)	DL-JODRA	The issue of overall project energy and time avoidance with a weighted total elimination consumption in the local fog	minimal computational resource requirements and achieve a substantial reduction of network costs
(Memon and Maheswaran, 2019)	LSTM RNN	to help with fog computing mobility management throughout the Internet of Vehicles	To 99.2 per precision, it determines the right fog node at a given location and time.
(Homayoun et al., 2019)	LSTM CNN	To distinguish good ware from ransomware and to recognize families	DRTHIS has a positive predictive value of 97.2 percent and an F-measure of 99.6%.
(Liang et al., 2019)	CNN	to process controlled signals received on the terminal layer	Energy and output quality increased by 29.25 percent and 16.50 percent

		throughout machining in order to successfully recognize abnormal situations.	and achieved a 70.26 percent decrease in bandwidth
(Priyadarshini and Barik, 2019)	LSTM	DDoS mitigation Using DL to build a fog area based intelligent system	prevent the incoming data packets from propagating to the cloud server if it detects them as suspicious malicious packets.
(Lyu et al., 2019)	(FPPDL)	to prevent bottlenecks in Cloud-based architectures, a Fog-embedded privacy-preserving DL (FPPDL) architecture is proposed	computing and communication costs are reduced and achieves a higher level of accuracy comparable to the centralized SGD
(Priyabhashana and Jayasena, 2019)	DNN	applied machine learning approaches to the IoT in a practical and efficient manner.	the early detection of issues and the monitoring of fog station results to ensure effective resource allocation.
(Lin et al., 2020)	CNN	for detecting potential product defects	a significant reduction in the load mostly on central server the simulations show how reliable and efficient the process is.,
(Luong et al., 2020)	DNN	development of a fog computing allocation of resources auction focused through deep learning	their plan outperforms the standard approach by a significant margin
(Lee et al., 2020)	DLEFN	effective scheme for grafting DL into FC-based precision agricultural environments	allowing for efficient operation without service delays caused by network congestion
(Siasi et al., 2020)	LSTM	deep learning for service function chain providing in FC for network function virtualization	a higher number of requests being fulfilled and increased availability.
(Li et al., 2020)	DDL	to safeguard users' privacy, and an authentication system to prevent foreign attackers from impersonating users.	the better trade-off between security, efficiency, and functionality.
(Chen et al., 2020)	DQN	to route optimization with the primary aim of guaranteeing Age of Information (AoI) trust	significantly reduce driving costs and increase average AoI efficiency
(NG and Selvakumar, 2020)	VCDL model	anomaly detection system for IoT traffic in a fog computing	obtained impressive accuracy and performance.

6. Conclusion

Despite the growing popularity of cloud computing, concerns such as inaccurate latency, user mobility, and location awareness remain unresolved due to the inherent problems of cloud computing. FC addresses these issues by offering elastic infrastructure and services to end clients at the network's edge, whereas CC focuses on distributing resources across the core network. FC systems can use intelligence features throughout their activities to take full advantage of the availability of data with networking devices to address the challenges of energy efficiency and delay in IoT applications. The DL framework for FC has evolved into a powerful end-user and elevated service that provides deep analytics and more intelligent responses to challenges. While FC intelligence is still in its early stages, it has enormous potential for practical application, as discussed in our studies, and it unquestionably merits further consideration. This review convincingly demonstrates that using DL algorithms or incorporating them into FC improves fog performance and 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.

References

ABDULKAREEM, K. H., MOHAMMED, M. A., GUNASEKARAN, S. S., AL-MHIQANI, M. N., MUTLAG, A. A., MOSTAFA, S. A., ALI, N. S. & IBRAHIM, D. A. J. I. A. 2019. A review of Fog computing and machine learning: Concepts, applications, challenges, and open issues. 7, 153123-153140.

Abdulkhaleq, I. S., Askar, S. (2021). Evaluating the Impact of Network Latency on the Safety of Blockchain Transactions. International Journal of Science and Business, 5(3), 71-82.

ABESHU, A. & CHILAMKURTI, N. 2018. Deep learning: The frontier for distributed attack detection in fog-to-things computing. IEEE Communications Magazine, 56, 169-175.

Ahmed, K. D., Askar, S. (2021). Deep Learning Models for Cyber Security in IoT Networks: A Review. International Journal of Science and Business, 5(3), 61-70

Al Majeed, S., Askar, S., Fleury, M. (2014). H.265 Codec over 4G Networks for Telemedicine System Application. UKSim-AMSS 16th International Conference on Computer Modelling and Simulation (UK), Cambridge (pp. 292-297), doi: 10.1109/UKSim.2014.59.

Ali, K., Askar, S. (2021). Security Issues and Vulnerabilities of IoT Devices. International Journal of Science and Business, 5(3), 101-115.

Askar S., Zervas, G., Hunter, D. K., & Simeonidou, D. (2011). Evaluation of Classified Cloning Scheme with self-similar traffic. 3rd Computer Science and Electronic Engineering Conference (CEEC), Colchester, 2011, pp. 23-28, doi: 10.1109/CEEC.2011.5995819.

Askar, S. (2016). Adaptive Load Balancing Scheme For Data Center Networks Using Software Defined Network. Journal of University of Zakho, Vol. 4(A), No.2, Pp 275-286,

Askar, S. (2017). SDN-Based Load Balancing Scheme for Fat-Tree Data Center Networks. Al-Nahrain Journal for Engineering Sciences (NJES), Vol.20, No.5, pp.1047-1056

Askar, S., Zervas, G., Hunter, D. K., & Simeonidou, D. (2011). Service differentiation for video applications over OBS networks. 16th European Conference on Networks and Optical Communications, Newcastle-Upon-Tyne, pp. 200-203.

Askar, S., Zervas, G., Hunter, D. K., & Simeonidou, D. (2011). A novel ingress node design for video streaming over optical burst switching networks. Optics Express, Vol. 19 (26), pp. 191-194

Askar, S., Zervas, G., Hunter, D. K., & Simeonidou, D. (2011). Adaptive Classified Cloning and Aggregation Technique for Delay and Loss sensitive Applications in OBS Networks. in Optical Fiber Communication Conference/National Fiber Optic Engineers Conference 2011, OSA Technical Digest (CD) (Optical Society of America, 2011), paper OThR4.

BONOMI, F., MILITO, R., NATARAJAN, P. & ZHU, J. 2014. Fog computing: A platform for internet of things and analytics. Big data and internet of things: A roadmap for smart environments. Springer.

BONOMI, F., MILITO, R., ZHU, J. & ADDEPALLI, S. Fog computing and its role in the internet of things. Proceedings of the first edition of the MCC workshop on Mobile cloud computing, 2012. 13-16.

CHEN, M., XIAO, Y., LI, Q. & CHEN, K.-C. Minimizing Age-of-Information for Fog Computing-supported Vehicular Networks with Deep Q-learning. ICC 2020-2020 IEEE International Conference on Communications (ICC), 2020. IEEE, 1-6.

DASTJERDI, A. V., GUPTA, H., CALHEIROS, R. N., GHOSH, S. K. & BUYYA, R. 2016. Fog computing: Principles, architectures, and applications. Internet of things. Elsevier.

DEY, S. & MUKHERJEE, A. Implementing deep learning and inferencing on fog and edge computing systems. 2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), 2018. IEEE, 818-823.

Fares, N., Askar, S. (2016). A Novel Semi-Symmetric Encryption Algorithm for Internet Applications. Journal of University of Duhok, Vol. 19, No. 1, pp. 1-9

Fizi, F., & Askar, S. (2016). A novel load balancing algorithm for software defined network based datacenters, International Conference on Broadband Communications for Next Generation Networks and Multimedia Applications (CoBCom), Graz, 2016, pp. 1-6, doi: 10.1109/COBCOM.2016.7593506.

GEDEON, J., HEUSCHKEL, J., WANG, L. & MÜHLHÄUSER, M. 2018. Fog computing: Current research and future challenges. 1. GI/ITG KuVS Fachgespräche Fog Computing, 1-4.

Hamad, Z., Askar, S. (2021). Machine Learning Powered IoT for Smart Applications. *International Journal of Science and Business, 5*(3), 92-100.

HASHEM, I. A. T., YAQOOB, I., ANUAR, N. B., MOKHTAR, S., GANI, A. & KHAN, S. U. 2015. The rise of "big data" on cloud computing: Review and open research issues. Information systems, 47, 98-115.

HASSAN, S. F. & FAREED, R. Video streaming processing using fog computing. 2018 International Conference on Advanced Science and Engineering (ICOASE), 2018. IEEE, 140-144.

HOMAYOUN, S., DEHGHANTANHA, A., AHMADZADEH, M., HASHEMI, S., KHAYAMI, R., CHOO, K.-K. R. & NEWTON, D. E. J. F. G. C. S. 2019. DRTHIS: Deep ransomware threat hunting and intelligence system at the fog layer. 90, 94-104.

HU, P., DHELIM, S., NING, H. & QIU, T. 2017. Survey on fog computing: architecture, key technologies, applications and open issues. Journal of network and computer applications, 98, 27-42.

HUANG, Y., MA, X., FAN, X., LIU, J. & GONG, W. When deep learning meets edge computing. 2017 IEEE 25th international conference on network protocols (ICNP), 2017. IEEE, 1-2.

Husain, B. H., Askar, S. (2021). Survey on Edge Computing Security. International Journal of Science and Business, 5(3), 52-60.

KAMILARIS, A. & PRENAFETA-BOLDÚ, F. X. 2018. Deep learning in agriculture: A survey. Computers and electronics in agriculture, 147, 70-90.

Keti, F., Askar, S. (2015). Emulation of Software Defined Networks Using Mininet in Different Simulation Environments. 6th International Conference on Intelligent Systems, Modelling and Simulation, Kuala Lumpur, 2015, pp. 205-210, doi: 10.1109/ISMS.2015.46.

Khalid, Z., Askar, S. (2021). Resistant Blockchain Cryptography to Quantum Computing Attacks. International Journal of Science and Business, 5(3), 116-125.

KISS, P., REALE, A., FERRARI, C. J. & ISTENES, Z. Deployment of IoT applications on 5G edge. 2018 IEEE International Conference on Future IoT Technologies (Future IoT), 2018. IEEE, 1-9.

KWON, D., KIM, H., KIM, J., SUH, S. C., KIM, I. & KIM, K. 2019. A survey of deep learning-based network anomaly detection. J Cluster Computing, 22, 949-961.

LA, Q. D., NGO, M. V., DINH, T. Q., QUEK, T. Q. & SHIN, H. 2019. Enabling intelligence in fog computing to achieve energy and latency reduction. Digital Communications and Networks, 5, 3-9.

LEE, K., SILVA, B. N. & HAN, K. 2020. Deep learning entrusted to fog nodes (DLEFN) based smart agriculture. Applied Sciences, 10, 1544.

LI, L., OTA, K. & DONG, M. 2018. Deep learning for smart industry: Efficient manufacture inspection system with fog computing. IEEE Transactions on Industrial Informatics, 14, 4665-4673.

LI, Y., LI, H., XU, G., XIANG, T., HUANG, X. & LU, R. 2020. Toward Secure and Privacy-Preserving Distributed Deep Learning in Fog-Cloud Computing. IEEE Internet of Things Journal, 7, 11460-11472.

LIANG, Y., LI, W., LU, X. & WANG, S. 2019. Fog computing and convolutional neural network enabled prognosis for machining process optimization. Journal of Manufacturing Systems, 52, 32-42.

LIN, S.-Y., DU, Y., KO, P.-C., WU, T.-J., HO, P.-T. & SIVAKUMAR, V. 2020. Fog Computing Based Hybrid Deep Learning Framework in effective inspection system for smart manufacturing. Computer Communications, 160, 636-642.

LITJENS, G., KOOI, T., BEJNORDI, B. E., SETIO, A. A. A., CIOMPI, F., GHAFOORIAN, M., VAN DER LAAK, J. A., VAN GINNEKEN, B. & SÁNCHEZ, C. I. 2017. A survey on deep learning in medical image analysis. Medical image analysis, 42, 60-88.

LOJA, N., RIVAS, W., HEREDIA, A. & BARROS, G. Performance analysis of a CNN counting application for fog and cloud computing. 2019 XLV Latin American Computing Conference (CLEI), 2019. IEEE, 01-07.

LUONG, N. C., JIAO, Y., WANG, P., NIYATO, D., KIM, D. I. & HAN, Z. 2020. A machine-learning-based auction for resource trading in fog computing. IEEE Communications Magazine, 58, 82-88.

LYU, L., BEZDEK, J. C., HE, X. & JIN, J. 2019. Fog-embedded deep learning for the internet of things. IEEE Transactions on Industrial Informatics, 15, 4206-4215.

MEMON, S. & MAHESWARAN, M. Using machine learning for handover optimization in vehicular fog computing. Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing, 2019. 182-190.

MIN, E., GUO, X., LIU, Q., ZHANG, G., CUI, J. & LONG, J. 2018. A survey of clustering with deep learning: From the perspective of network architecture. J IEEE Access, 6, 39501-39514.

MOHAMMADI, M., AL-FUQAHA, A., SOROUR, S. & GUIZANI, M. 2018. Deep learning for IoT big data and streaming analytics: A survey. IEEE Communications Surveys & Tutorials, 20, 2923-2960.

Mohammed, C. M., Askar, S. (2021). Machine Learning for IoT HealthCare Applications: A Review. International Journal of Science and Business, 5(3), 42-51.

MOUBAYED, A., INJADAT, M., NASSIF, A. B., LUTFIYYA, H. & SHAMI, A. 2018. E-learning: Challenges and research opportunities using machine learning & data analytics. IEEE Access, 6, 39117-39138.

NG, B. A. & SELVAKUMAR, S. 2020. Anomaly detection framework for Internet of things traffic using vector convolutional deep learning approach in fog environment. Future Generation Computer Systems, 113, 255-265.

POUYANFAR, S., SADIQ, S., YAN, Y., TIAN, H., TAO, Y., REYES, M. P., SHYU, M.-L., CHEN, S.-C. & IYENGAR, S. 2018. A survey on deep learning: Algorithms, techniques, and applications. J ACM Computing Surveys, 51, 1-36.

PRABHU, C. 2019. Fog Computing, Deep Learning and Big Data Analytics-Research Directions, Springer.

PRIYABHASHANA, H. & JAYASENA, K. Data Analytics with Deep Neural Networks in Fog Computing Using TensorFlow and Google Cloud Platform. 2019 14th Conference on Industrial and Information Systems (ICIIS), 2019. IEEE, 34-39.

PRIYADARSHINI, R. & BARIK, R. K. 2019. A deep learning based intelligent framework to mitigate DDoS attack in fog environment. Journal of King Saud University-Computer and Information Sciences.

PRIYADARSHINI, R., BARIK, R. K. & DUBEY, H. J. C. 2018. Deepfog: Fog computing-based deep neural architecture for prediction of stress types, diabetes and hypertension attacks. 6, 62.

Qadir, G. A., Askar, S. (2021). Software Defined Network Based VANET. International Journal of Science and Business, 5(3), 83-91.

Samann, Fady E. F., Zeebaree, S. RM, Askar, S. IoT Provisioning QoS based on Cloud and Fog Computing, Journal of Applied Science and Technology Trends, Vol. 2, No. 1, pp. 29-40.

SHARMA, P. K., CHEN, M.-Y. & PARK, J. H. 2017. A software defined fog node based distributed blockchain cloud architecture for IoT. Ieee Access, 6, 115-124.

SIASI, N., JASIM, M., ALDALBAHI, A. & GHANI, N. J. I. A. 2020. Deep Learning for Service Function Chain Provisioning in Fog Computing. 8, 167665-167683.

Sulaiman, S., Askar, S. (2015). Invetigation of the Impact of DDoS Attack on Network Efficiency of the University of Zakho. Journal University of Zakho, Vol. 3(A) , No.2, Pp 275-280.

SVOROBEJ, S., TAKAKO ENDO, P., BENDECHACHE, M., FILELIS-PAPADOPOULOS, C., GIANNOUTAKIS, K. M., GRAVVANIS, G. A., TZOVARAS, D., BYRNE, J. & LYNN, T. 2019. Simulating fog and edge computing scenarios: An overview and research challenges. Future Internet, 11, 55.

TANG, T. A., MHAMDI, L., MCLERNON, D., ZAIDI, S. A. R. & GHOGHO, M. Deep learning approach for network intrusion detection in software defined networking. 2016 international conference on wireless networks and mobile communications (WINCOM), 2016. IEEE, 258-263.

TEERAPITTAYANON, S., MCDANEL, B. & KUNG, H.-T. Distributed deep neural networks over the cloud, the edge and end devices. 2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS), 2017. IEEE, 328-339.

YI, S., HAO, Z., QIN, Z. & LI, Q. Fog computing: Platform and applications. 2015 Third IEEE workshop on hot topics in web systems and technologies (HotWeb), 2015a. IEEE, 73-78.

YI, S., LI, C. & LI, Q. A survey of fog computing: concepts, applications and issues. Proceedings of the 2015 workshop on mobile big data, 2015b. 37-42.

YUAN, Q., SHEN, H., LI, T., LI, Z., LI, S., JIANG, Y., XU, H., TAN, W., YANG, Q. & WANG, J. J. R. S. O. E. 2020. Deep learning in environmental remote sensing: Achievements and challenges. 241, 111716.

ZHANG, Q., YANG, L. T., CHEN, Z. & LI, P. 2018. A survey on deep learning for big data. Information Fusion, 42, 146-157.

ZHU, X., CHEN, S., CHEN, S. & YANG, G. Energy and delay co-aware computation offloading with deep learning in fog computing networks. 2019 IEEE 38th International Performance Computing and Communications Conference (IPCCC), 2019. IEEE, 1-6.

Cite this article:

Shavan Askar, Zhala Jameel Hamad, Shahab Wahhab Kareem (2021). Deep Learning and Fog Computing: A Review. *International Journal of Science and Business, 5*(6), 197-208. doi: https://doi.org/10.5281/zenodo.5222647

Retrieved from http://ijsab.com/wp-content/uploads/756.pdf

Published by