Deep Learning Architectures in Emerging Cloud Computing Architectures: Recent Development, Challenges and Next Research Trend

Fatsuma Jauro[1,3], Haruna Chiroma[2,*], Abdulsalam Y. Gital[3], Mubarak Almutairi[4], Shafi'i M. Abdulhamid[5], Jemal H. Abawajy[6]

[1]Department of Computer Science, Ahmadu Bello University, Zaria, Nigeria
[2]Future Technology Research Centre, National Yunlin University of Science and Technology, Douliu, Taiwan
[3]Department of Mathematical Sciences, Abubakar Tafawa Balewa University, Bauchi, Nigeria
[4]Department of Computer Science and Engineering, University of Hafr Albatin, Saudi Arabia
[5]Department of Cyber Security and Information Technology, Community College Qatar, Doha, Qatar
[6]Deakin University, Australia

[*]**Corresponding author**: Haruna Chiroma, Future Technology Research Centre, National Yunlin University of Science and Technology, Douliu, Taiwan; Email: freedonchi@yahoo.com; chiromaharun@fectgombe.edu.ng.

Abstract: The challenges of the conventional cloud computing paradigms motivated the emergence of the next generation cloud computing architectures. The emerging cloud computing architectures generate voluminous amount of data that are beyond the capability of the shallow intelligent algorithms to process. Deep learning algorithms, with their ability to process large-scale datasets, have recently started gaining tremendous attentions in the emerging cloud computing literatures. However, no comprehensive literature review exists on the applications of deep learning approaches to solve complex problems in emerging cloud computing architectures. To fill this gap, we conducted a comprehensive literature survey on deep learning in emerging cloud computing architectures. The survey shows that deep learning algorithms in emerging cloud computing architectures are increasingly becoming an interesting research area for solving complex problems. We introduce a new taxonomy of deep learning techniques for emerging cloud computing architectures and provide deep insights into the current state-of-the-art active research works on deep learning to solve complex problems in emerging cloud computing architectures. 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. We believed that this article can serve as a reference guide to new researchers and an update for expert researchers to explore and develop more deep learning applications in the emerging cloud computing architectures.

Keywords: Convolutional Neural Network**;** Deep Learning**;** Deep Reinforcement Learning; Edge Computing; Fog Computing; Emerging Cloud Computing; Serverless Computing.

1. Introduction

Over a period of years, cloud computing has provided good solutions to the growing demands for data storage and processing on a pay-per-use model. It benefits users by reducing management effort, providing convenience, elasticity and so on. The cloud heavily relies on data centers (Zhou, et al, 2018), which are connected to each other forming data center networks (DCNs) (Dolui & Datta, 2017). These data centers are usually located at a far distance from the users and user devices relying on cloud services is increasing at a faster rate. It was projected that billions of internet of things (IoT) devices would be in existence by the year 2020 (Idex, 2018). 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). In addition, information on user location, local network conditions and users' mobility behaviour cannot be accessed directly (Roman, Lopez, & Mambo, 2018). Similarly, the high number of requests sent to the DCNs result in high duty cycle leading to release of harmful gases in the environment (Dolui & Datta, 2017).

Next generation cloud computing architectures have emerged to provide solutions to the aforementioned problems by allowing data or part of the data to be processed at a layer closer to the user devices instead of the cloud data center. The emerging cloud computing architectures include software defined computing, edge computing, fog computing, serverless computing and volunteer computing (Varghese & Buyya, 2018). The next generation cloud computing architectures are associated with challenges such as resource allocation, security, privacy (Luo, et al., 2018), energy consumption (Shojafar, et al. 2019), reliability, sustainability, etc. The emerging cloud computing architectures come with consequences in terms of data generation. The emerging paradigms generate voluminous amount of data referred to as the big data. The data being generated has the possibility of not having the opportunity to be analyzed to uncover new information. The data that has not been subjected to analytics is referred to as the dark data. The decentralization of the cloud architectures provided the opportunity for the generated data to be analyzed close to the source of the data before it can be transferred for storage purposes. As an example, the edge node can be used to process images or video before the data can be transferred to be stored (Varghese & Buyya, 2018). Data make sense after analytics.

Algorithms are known to be applied in solving data analytics problems such as prediction, clustering, classification and association rule mining in real world. However, shallow algorithms lack the capacity to handle large volume of data because the performance of the shallow algorithms diminishes as the volume of the data increases. However, deep learning algorithms' performance increases as the volume of the data increases. The studies that applied deep learning in big data analytics are presented in (Chiroma, Abdullahi, et al., 2019; Chiroma et al., 2018). The 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). As a result of that, deep learning algorithms have been applied in recent times to solve various problems in the emerging cloud computing architectures such as object detection, anomaly detection, cyber security, fruit classification, street cleanliness, person re-identification, food recognition, smart vehicles and so on. Also The applications deep learning in emerging cloud computing paradigms is attracting unprecedented attention from the research community.

Despite the attention that the application of deep learning in emerging cloud computing architectures is attracting from the research community, there is a lack of comprehensive systematic survey of the literature on the applications of deep learning in emerging cloud computing architecture. In this regard, we formulate the following research question for the purpose of this work:

> What are the literature that adopted deep learning architectures to solve machine learning problems in emerging cloud computing architectures?

To answer the main research question, the following sub-research questions are formulated:

i. What researches have been conducted using deep learning to solve problem in different emerging cloud computing architectures?
ii. In what domains have deep learning been applied to solve problems in emerging cloud computing architectures?
iii. What are the sources of data for emerging cloud computing architectures?
iv. To what extent has deep learning been applied in emerging cloud computing architectures?
v. What other challenges are yet to be explored by researchers in the research area?

This paper presents an extensive systematic literature survey on the applications of deep learning in emerging cloud computing architectures. The review is in four perspectives: First, technical perspective of the deep learning algorithms and emerging cloud computing architectures. Secondly, concise summary of deep learning adoption in emerging cloud computing architectures. Thirdly, creation of taxonomy on emerging cloud computing paradigm, deep learning algorithms and the domain of applications. Fourth, the synthesis and analysis of the literature. This comprehensive systematic review is intended to provide a doorway for novice researchers and to serve as update to experts for developing new solutions/applications in emerging cloud computing architectures.

The list of the contributions of the survey article are summarized as follows:

- The major deep learning algorithms applied to solve complex problems in emerging cloud computing architecture in different projects are summarized. From the technical perspective, the basic operations and general adoption of the deep learning algorithms are categorized to create taxonomy of the deep learning algorithms into convolutional neural network, deep belief network, deep reinforcement learning, recurrent neural network and deep neural network.
- A dedicated comprehensive review of literature that apply deep learning algorithm to solve problem in serverless computing, volunteering computing, edge computing, fog computing and mobile edge computing is presented. To be specific, the application of convolutional neural network in fog computing, edge computing, and volunteer computing. Application of deep reinforcement learning in mobile edge computing, fog computing and edge computing. Application of deep neural network in serverless computing, fog computing and mobile edge computing. Application of long short term memory in edge computing, fog computing and lastly, the application of deep belief network in mobile edge computing. The survey article is organized based on the adoption of the deep learning algorithm in a particular emerging cloud computing architecture. A new taxonomy based on the deep learning and emerging cloud computing architectures is created to show the visual of the article organization.
- A taxonomy on the adoption of the deep learning algorithm in emerging cloud computing from different domain is created based on cybersecurity, energy, transportation, resource management, insects, vehicle, object detection, waste management, smart industry, content sharing, agriculture, sentiment analysis and health.
- The survey extended (Varghese & Buyya, 2018) by creating taxonomy of the emerging cloud computing architecture based on volunteer computing, serverless computing, edge computing, mobile edge computing, software defined computing and fog computing including their technologies.

- The trend of publications up to 2019, popularity of deep learning variants in emerging cloud computing architecture and sources of data are outlined.
- Open research issues relating to the adoption of deep learning in emerging cloud computing are identified and discussed. New perspective of solving the identified challenges are outlined to provide theoretical guide for practical implementation.

The rest of the paper is structured as follows: Section 2 presents the systematic literature survey methodology. Section 3 introduces deep learning and its various architectures. Section 4 discusses the background and the taxonomy of the emerging cloud computing architectures. Section 5 presents a summary on the adoption of deep learning in emerging cloud computing architectures. Section 6 contains taxonomy on different domains of applications extracted from different projects. Section 7 presents the datasets used in different projects. Section 8 points out the different platforms and system configuration used for implementation. Section 9 provides the analysis and general overview of the research area. Section 10 uncovers the challenges and prospective research directions before conclusions is presented in Section 11.

2. Methodology

The main aim of this section is to ensure that the procedure for systematic literature review is followed to reduce the level of bias and ensure the review covers the subject matter sufficiently. In this section, the procedure used for reviewing literature on the applications of deep learning in emerging cloud computing architectures is discussed. Search keywords, search technique, data sources, databases, inclusion and exclusion criteria are explained. The systematic literature review used the procedure provided in (Weidt, F., & Silva, 2016) for systematic literature review in computer science. The work in (Thilakaratne, Falkner, & Atapattu, 2019) is also used as a guide to conduct our systematic literature review.

2.1 Keywords

Having defined the review goal, keywords were carefully selected in order to obtain relevant articles. At the initial phase, several keywords were formulated and later narrowed down based on the research objectives. The keywords used for extracting the articles are as follows: "deep learning, edge computing", "deep learning, fog computing", "deep learning, volunteer computing", "deep learning, severless computing", "deep learning, software defined computing", "convolutional neural network in edge computing", "deep reinforcement learning, edge computing", "deep belief network, fog computing", "convolutional neural network, serverless computing", "deep learning and software defined computing", " deep neural network in volunteering computing", *etc*. the keywords were used for searching the relevant academic databases to retrieve articles.

2.2 Searching the articles

At the search period, articles found to correspond with the keywords were scanned through to extract more relevant papers from their citations. The first search was conducted from 15th to 29th August, 2019. The second search period was between September 23rd to October 5th, 2019. The final search was conducted in November/December, 2019.

2.3 Academic databases

The literatures were retrieved based on the formulated keywords as shown in the preceding section. The study targeted articles from reputable peer review journals, edited books and conference proceedings indexed in different academic databases. The academic databases used to extract articles are listed in Table 1. The searches were first conducted without specifying any period, later it was refined to a range from 2015. This is because at the initial search, relevant articles were observed to be mostly published from 2017 to date.

Table 1: Academic databases used and their links

Academic Database	Web Link
ISI Web of Science	https://apps.webofknowledge.com/
Scopus	https://www.scopus.com/
IEE Xplore	http://ieeexplore.ieee.org/
ScienceDirect	http://www.sciencedirect.com/
SpringerLink	http://www.link.springer.com/
ACM Digital Library	http://dl.acm.org/
DBLP	http://dblp.uni-trier.de/
Wiley Online Library	http://onlinelibrary.wiley.com/

2.4 Article Inclusion/Exclusion Criteria

To extract only the relevant articles for review, certain inclusion and exclusion criteria was setup. The papers were either included among the relevant articles or excluded as irrelevant for the review by studying their titles, abstracts, conclusions and the complete content. The inclusion and exclusion criteria is presented in Table 2.

Table 2: Inclusion and exclusion criteria

Inclusion	Exclusion
The review focuses on only emerging cloud computing architecture	Articles on traditional cloud computing were not considered
Articles with the application of deep learning in emerging cloud computing architecture were considered	Articles with shallow algorithm in emerging cloud computing architecture were excluded
Articles published in reputable peer review journals, conference proceedings, and edited books were considered	articles published as part of text books, abstracts, editorials and keynotes speeches were excluded
Only articles written in English language were considered for the review	Articles written in other languages were not considered for review

2.5 Eligibility

To determine the eligibility of the selected articles, we applied the set of the criteria on the articles obtained from the academic databases. At initial search, a total of 1,904,348 papers were obtained from the whole academic databases. After removing duplicates and elimination based on titles, 1,064,134 articles were eliminated. At the second stage, abstract and conclusion were considered where a total of 840163 articles were rejected. Finally, at the full content stage, only 34 papers succeeded and hence were used for the review. Figure 1 shows the article selection process.

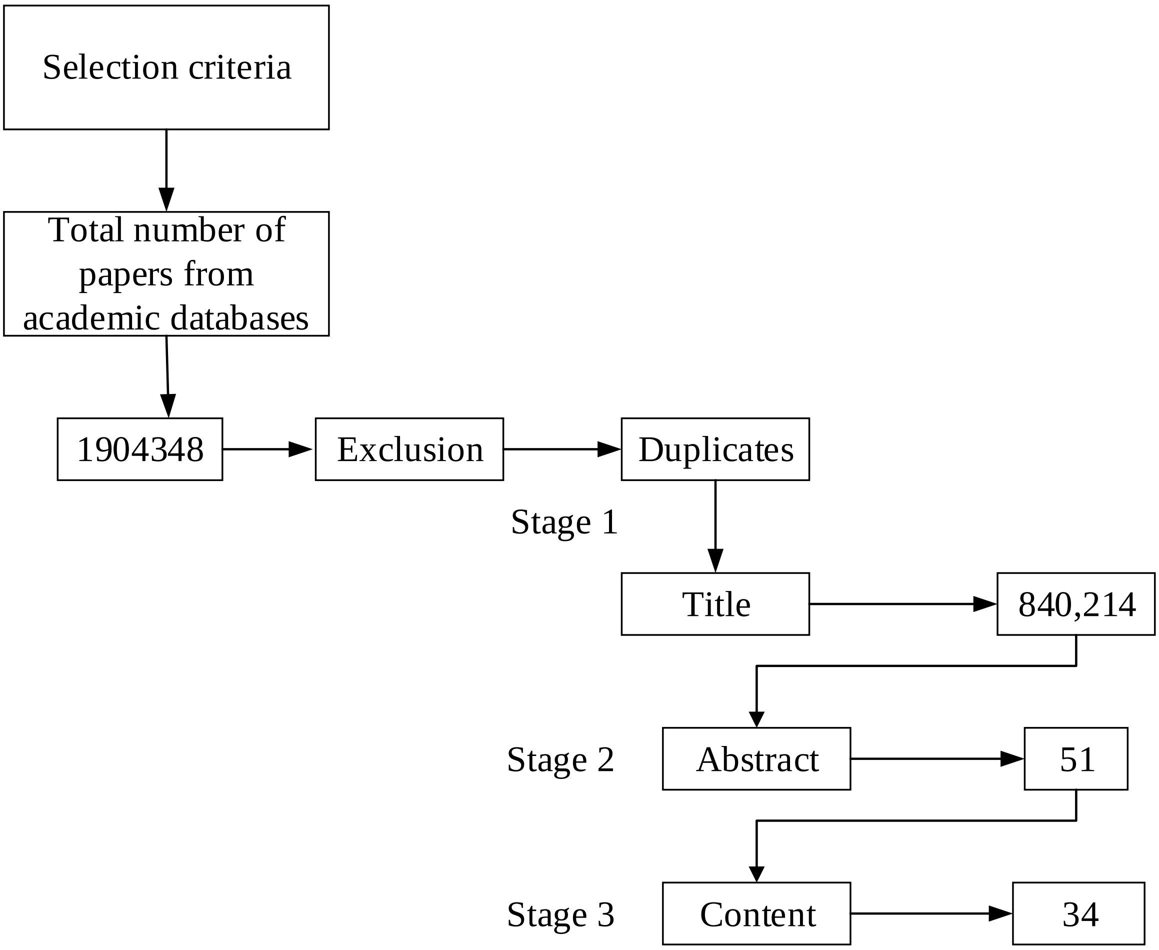

Figure 1: Articles exclusion processes

2.6 Extraction

The data was purposely extracted to obtain empirical studies that reported the application of deep learning in emerging cloud computing architectures. At the same time, redundant and duplicate articles were all eliminated. The data extracted was presented in a form of table and sent to two different reviewers for assessment alongside the study objectives. Again, more reviewers were given the data for review. Results from the different reviewers were later compared and no disparity was observed on the independent reviewer's comments.

3. Deep learning

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). Proliferation of training data and the current research progress in machine learning and information processing are also contributing factors to prominence of deep learning (Ahmad, Farman, & Jan, 2019). Unlike in traditional machine learning where domain expert is needed to assist in feature extraction, 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). Deep learning uses a number (tens to even hundreds) of consecutive layers with each layer giving more significant representation of input data (Wani et al., 2020). It has been applied in challenging fields of machine learning like image classification, voice recognition, handwriting transcription, natural language processing, self-driving cars and many more. Figure 2 presents the taxonomy of the deep learning architecture.

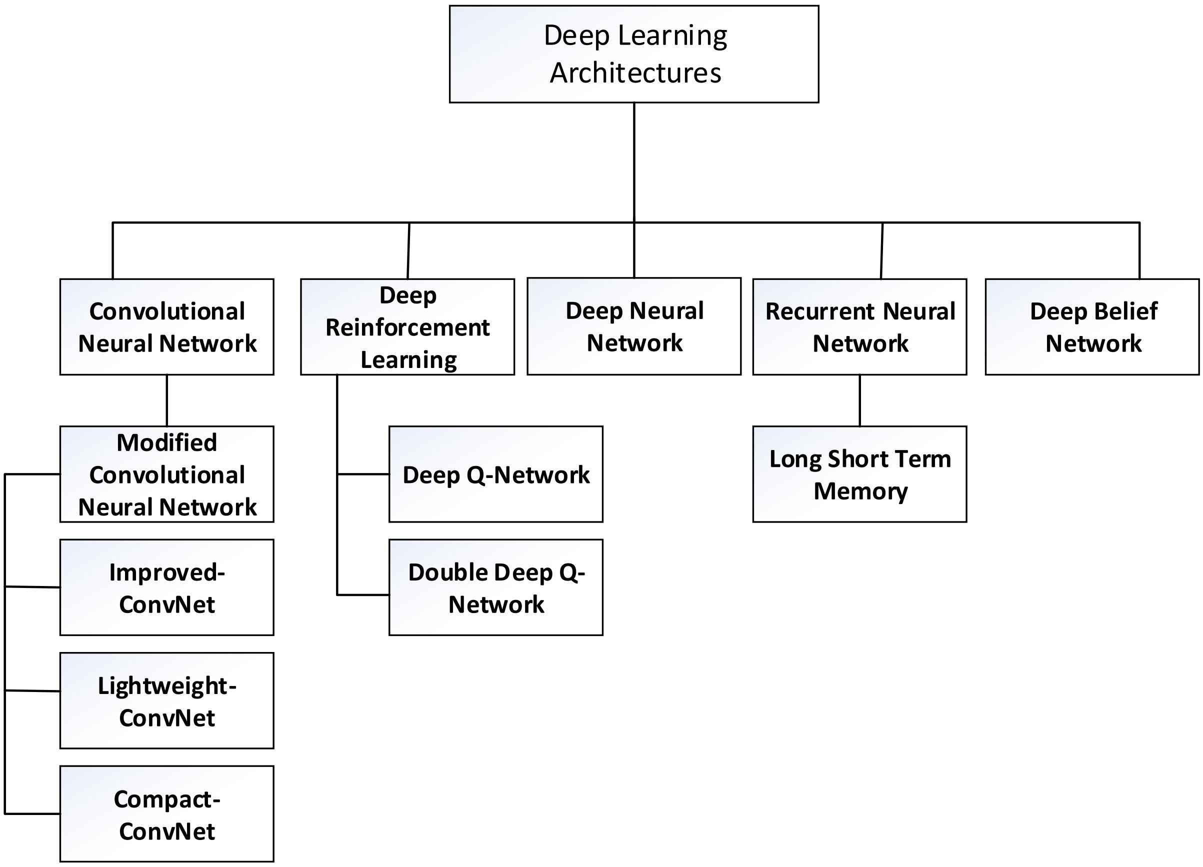

Figure 2: Taxonomy of Deep Learning Architectures

Many deep learning architectures exist in the literature. However, the scope of the study is the deep learning architectures used in solving problems in emerging cloud computing architectures. The taxonomy is created based on the deep learning architectures that were found to be applied in solving problems in emerging cloud computing architectures. The discussion on the different deep learning architectures are provided as follows:

3.1 Convolutional Neural Network

Convolutional neural network (ConvNet)(Lecun & Bengio, 1997) is a deep learning algorithm that was developed for visual data processing such as images and videos. Its strength was discovered to handle not only visual images but also many types of data with text and audio data. It performs well when applied in image processing especially in image classification, detection, recognition, segmentation, restoration and enhancement (Ahmad et al., 2019). The ConvNet uses mathematical operation named convolution. It is a type of operation performed on two functions written as $(f\ *\ g)$ $where\ f\ and\ g$ are the functions. The convolution output for a given domain *n* is expressed as (Wani et al., 2020):

$$(f * g)(n) = \sum_{m} f(m)g(n-m)$$

n is replaced by *t* when dealing with time-domain functions. The convolution equation can also be represented as:

$$(f * g)(n) = \sum_{m} f(n-m)g(m)$$

Convolution can also be applied to multi-dimensional functions. For instance, given a two dimensional image as input denoted as Z, the 2D filter with size $m \times n$ denoted as K, 2D feature map denoted as X, the convolution operation can be expressed as;

$$X(i,j) = (Z * K)(i,j) \sum_{m} \sum_{n} Z(m,n)K(i-m,j-n)$$

The operation is commutative and therefore can be written as:

$$X(i,j) = (Z * K)(i,j) \sum_{m} \sum_{n} Z(i-m,j-n)K(m,n)$$

The commutative property holds as a result of flipping the Kernel relative to the input. Without flipping the kernel, the convolution operation will be just as cross-correlation operation shown as:

$$X(i,j) = (Z * K)(i,j) \sum_{m} \sum_{n} Z(i+m,j+n)K(m,n)$$

The ConvNet has different types of layers performing varying tasks: convolution layer, activation function layer, pooling layer, fully connected layer and dropout layer.

The convolution layer is the main building block for ConvNet. It uses convolution operation denoted as *. The layer majorly identifies features in the local region of a given image that are recurrent in the dataset and maps their occurrence to feature map. It is normally stacked with activation function layer. For every filter in a layer, a feature map is obtained by repeatedly applying the filter over sub-regions of the whole image. The Convolution layer passes its output to activation function layer which in turn produces activation map as output using an activation function. Different activation functions exist. The most prominent is the Rectified Linear Unit (ReLU). Training is faster with ReLU. It is mathematically expressed as:

$$f(x) = \max(0,x)$$

The Pooling layer decreases the size of the input. It receives feature maps from convolution layer and summarizes it by discarding unessential data while keeping discovered features. Feature extraction is done at the convolutional and pooling layers. The Fully connected layer is employed when there is need for classification. Each neuron from preceding layer has connection with every other neuron in the succeeding layer and each is significant in the classification decision.

Finally, the last fully connected layer passes its output to a classifier, which in turn produces the class scores. The ConvNet performed better than almost all the prevalent methods in visual tasks. Different types of CovNet models have been proposed since its inception (Wani et al., 2020). The ConvNet architecture is presented in Figure 3.

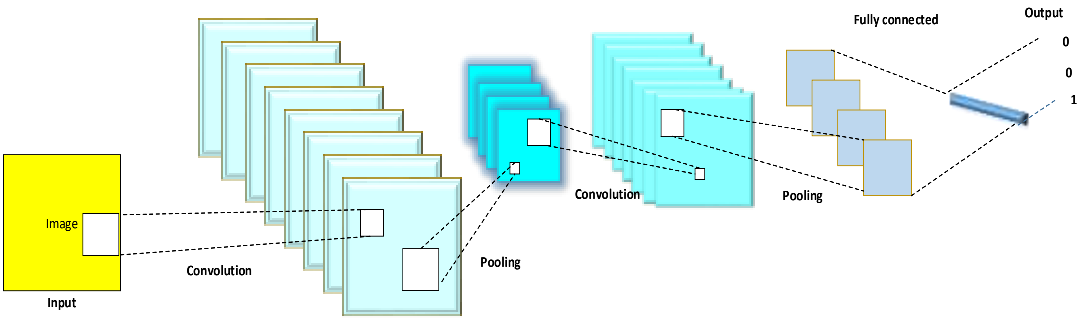

Figure 3: Convolutional Neural Network architecture

Deep ConvNet (D-ConvNet) can also be applied in regression task for mapping of input distance matrix to output distance matrix, pooling or dense layers are not involved in this case (S. P. Nguyen, Li, Xu, & Shang, 2017)

3.2 Deep Reinforcement Learning

Deep reinforcement learning (DRL) (Mnih et al., 2015) is a semi supervised learning algorithm where unlabelled data is given as input for the algorithm to learn feature representation of the data. Learnt features are then used in supervised learning task (Wani et al., 2020). In DRL, no guiding dataset is required; an agent learns to accomplish a task by means of trial and error. The DRL uses exploration and exploitation to take decision. In exploitation, action is taken based on recent best policy. Exploration deals with taking action purposely to gain additional training data. The challenges in DRL include: trade-off has to be made between exploitation and exploration, evaluating and comparing policies is challenging (Goodfellow, Bengio, & Courville, 2016). It has been applied in factory control, autonomous helicopter, webpage indexing, etc. (Wani et al., 2020).

Generally, in reinforcement learning (RL), an agent starts at a certain initial state in a given environment $s_o \in S$ by collecting some initial observation $w_o \in \Omega$. For every time step t, an action is taken by the agent $a_t \in A$.(François-lavet, Henderson, Islam, Bellemare, & Pineau, 2018). Figure 4 shows a pictorial representation of the RL operations.

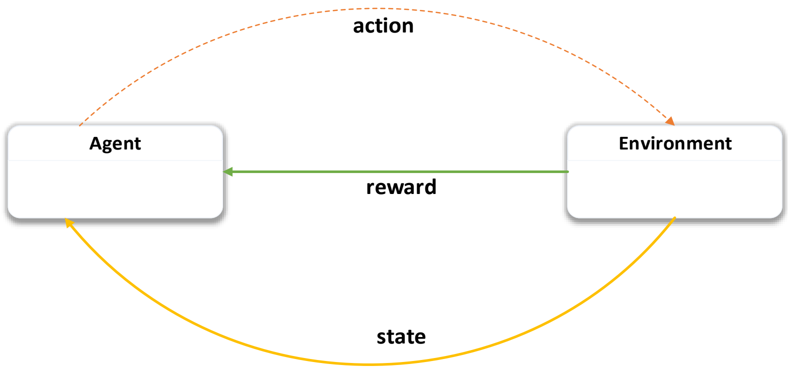

Figure 4: Reinforcement learning process between agent and its environment

The Q-learning (QL) is a prominent RL algorithm and is known for its simplicity and easy implementation. The Q-learning method is used in DRL. Q-learning has a Q-table that is updated by agents according to some rules. At an initial stage, the Q-table contains zeros and the agent doesn't have prior knowledge of the environment. When initial values are placed on the table, policies are outlined to guide the agent in selecting the right actions and preventing unwanted actions (Mämmelä, 2018). The major aim of Q-learning is to achieve maximum total reward known as Q-value. This can be expressed as:

$$Q(s,a) = \gamma(s,a) + \gamma \max_{a} Q(s',a)$$

Where $Q(s,a)$ is the Q-value obtained by performing action a at state s, $\gamma(s,a)$ is the immediate reward gained, $\max_{a} Q(s',a)$ is the largest Q-value attainable from next state s', γ is a discount factor controlling future contribution of rewards. It can be observed that $Q(s',a)$ will depend on $Q(s'',a)$ making γ coefficient squared. Therefore, all Q-values are dependent upon Q-values of future states expressed as:

$$Q(s,a) \rightarrow \gamma Q(s',a) + \gamma^2 Q(s'',a) \dots \dots \dots \gamma^n Q(s''^{\dots n},a)$$

Since the equation is recursive, initial assumptions can be made for all Q-values so that it converges to the optimum policy which can be expressed as:

$$Q(S_t,A_t) \leftarrow Q(S_t,A_t) + \propto \left[R_{t+1} + \gamma \max_{a} Q(S_{t+1},a) - Q(S_t,A_t)\right]$$

Where $\propto$ denotes the learning, R_{t+1} is the immediate reward.

Dealing with problems that involve high number of actions leads to generating complex Q-tables with millions of cells. The tables consume large amount of memory. Also, exploring all the states to generate Q-table is time consuming (Choudhary, 2019). Deep Q-learning adopts the use of neural network such that states serve as input while the Q-values of all probable actions are produced as output (Choudhary, 2019). Such algorithms are referred to as Deep Q-networks (DQN). The DQN is a DRL algorithm that combines QL with a flexible neural network (Wani et al., 2020).

3.3 Recurrent Neural Network

Recurrent Neural Network (RNN) (Elman, 1990) is a strong algorithm that is good in dealing with problems involving sequential input for example speech, video and text. When given an input sequence, RNN processes the elements sequentially and implicitly conserving information regarding prior elements of the sequence in a vector space (Lecun, Bengio, & Hinton, 2015). This implies that RNN harness the recent and past input to produce output for the newly received data. When given $(x_1, x_{2,} \dots, x_r)$ as input sequence of vectors, RNN generates sequence of hidden states as $(h_1, h_{2,} \dots, h_r)$ usually computed at a given time step *t* and expressed as:

$$h_t = \varphi W_h h_{t-1} + W_2 x_t$$

Where W_h signifies the recurrent weight matrix, W_x defines input-to-hidden weight matrix, and φ an activation function.

Bidirectional RNN uses information from both past and future time frames (Schuster & Paliwal, 1997). This can be expressed as:

$$\overrightarrow{h_t} = \varphi(\overrightarrow{W_h}\ \overrightarrow{h_{t-1}} + \overrightarrow{W_{xX_t}})$$

$$\overleftarrow{h_t} = \varphi\left(\overleftarrow{W_h}\ \overleftarrow{h_{t+1}} + \overleftarrow{W_{xX_t}}\right)$$

$$h_t = \left[\overrightarrow{h_t} \colon \overleftarrow{h_t}\right]$$

Where $[a\colon b]$ is the concatenation of *a* and *b*. Deep RNN can be obtained by stacking the RNNs and using *h* as input to other RNN (Laurent, Pereyra, Brakel, Zhang, & Bengio, 2016)

$$h_t^l = \varphi(W_h h_{t-1}^l + W_x h_t^{l-1})$$

The deepness of RNN could be as far as the span of the input sequence (Deng, 2014). RNN can excellently predict next character or next word in a series. The RNNs mostly use sigmoid function as φ (activation function). But the algorithm is very difficult to train due an inherent problem known as "Vanishing gradient" (where back-propagated gradients vanish after multiple steps) (Deng, 2014). Architecture of the deep RNN is shown in Figure 5.

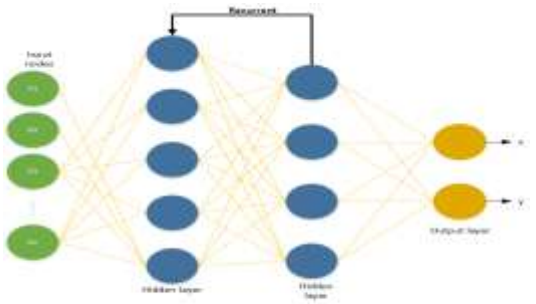

Figure 5: Deep RNN Architecture

3.3.1 Long Short Term Memory

The long short term memory (LSTM) is a variant of RNN developed to provide solution to vanishing gradient problem associated with the RNN (Laurent et al., 2016). The LSTM has three layers; input layer, recurrent hidden layer, and output layer (Ma, Tao, Wang, Yu, & Wang, 2015). The architecture of LSTM consists of memory blocks where a memory block is formed by memory cells sharing common input gate and output gate which control the flow of error and weight conflicts in the memory cell (Hochreiter & Schmidhuber, 1997). A memory cell consists of a self-connected constant error carrousel (CEC), the CEC activation functions indicates the state of a cell. With the aid of the CEC, multiplicative gates (input and output gates) learn to open and close constant flow of error hence solving the issue of vanishing gradient (Ma et al., 2015). Forget gate was incorporated in memory block to prevent limitless growth of internal cell values especially when dealing with incessant time series data that has been segmented earlier (Ma et al., 2015). This allows the memory block to automatically reset when the information flow gets outdated and CEC weight is substituted with the forget gate activation.

Given an input sequence $x = (x_1, x_{2,} \dots, x_r)$ and an output sequence $y = (y_1, y_{2,} \dots, y_r)$, LSTM iteratively performs computation expressed as: $t = 1\ to\ T$ (Sak, Senior, & Beaufays, 2014):

$$i_t = \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i)$$

$$f_t = \sigma(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{cm}m_{t-1} + b_c)$$

$$o_t = \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o)$$

$$m_t = o_t \odot h(c_t)$$

$$y_t = \varphi(W_{ym}m_t + b_y)$$

With $\odot$ representing the scalar product of two vectors, and *W*s represent weight matrices, *b* represents bias vector, σ denotes sigmoid function, φ denotes the network output activation function, *i, f, o,* and *c* respectively denote input gate, forget gate, output gate and cell activation vector and m signifies the cell size. The LSTM has been successfully employed in different domains such as robotics, transportation, handwriting recognition, human action recognition, speech recognition, image translation, etc (Ahmad et al., 2019; Ma et al., 2015).

3.4 Deep Neural Network

Deep Neural Network (DNN) (Ciresan, Meier, Masci, & Schmidhuber, 2012) is a deep architecture mostly employed for solving regression and classification problems (Rav et al., 2017). It is in form of a hierarchy of layers with each layer containing some neurons. Succeeding layers progressively learn complex patterns from input received from preceding layers (Ahmad et al., 2019). The architecture of the DNN is shown in Figure 6. The DNNs are less complex structures due to the use of feed-forward networks with multiple layers. They perform well in handling non-sequential data.

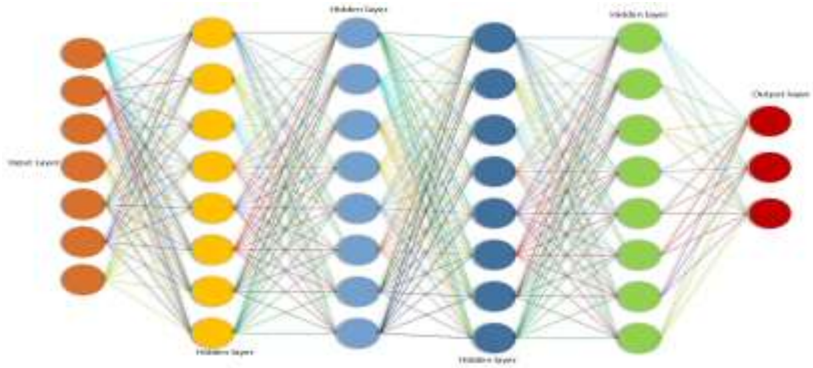

Figure 6: Architecture of the deep neural network

DNNs are trained with supervised and unsupervised learning techniques. The supervised learning methods utilize labeled data for training of the DNNs and error minimizing weights are learnt to accurately predict classification/regression target while the unsupervised learning methods do not need any labelled data to be trained and are mostly used in feature extraction, clustering, and or dimensionality reduction (Rav et al., 2017). Applications sometimes use the unsupervised learning in training the DNN to obtain most significant features at initial stage before applying the supervised learning for classification using those extracted features.

In image classification for example, the DNN receives image as input, it generates vector scores for every class of objects, the class having the highest score is the most likely class of the image. Training is essential in DNN to obtain weights that maximize the score of the correct class and minimize scores of the incorrect class and the gap between the correct scores and the scores computed by the DNN is referred to as loss function (Sze, Chen, Yang, & Emer, 2017). In the training, weights are normally updated by gradient descent optimization process. To generally reduce the loss function, the weight vary iteratively by the following process (Sze et al., 2017):

$$W_{ij}^{t+1} = W_{ij}^{t} - \alpha(\partial L/\partial W_{ij})$$

Where W_{ij} denotes the weights, α signifies the learning rate.

A major weakness of DNN is its need for large dataset and powerful computing resources for iterative update of weights. Due to this, it is preferable to train the DNN at the cloud while inferencing can be done at the edge devices. Its application areas include healthcare, games, robotics, autonomous vehicles, etc.

3.5 Deep Belief Network

Deep Belief Network (DBN) (Hinton & Salakhutdinov, 2006) is a generative neural network with multiple layers. Each layer having visible units as its input and hidden units as its output. The layers but not the units are connected to each other i.e, the visible units are fully connected with the hidden units but no interconnection exists among visible units or between hidden units (Wani et al., 2020). Upper layers have indirect and symmetric connections amongst them, while lower layers have direct and top-down connection with the upper layers (Mach & Becvar, 2017). Usually, the connections between the two leading layers is undirected and a directed connection exist for all other layers with the flow pointing towards the layer that is nearest to the input (Goodfellow et al., 2016). DBNs are trained in an unsupervised way which gives it the strength to avoid overfitting and underfitting challenges (Wani et al., 2020). DBN generates a probability distribution expressed as (Goodfellow et al., 2016):

$$P(h^{(l)}, h^{(l-1)}) \propto exp(b^{(l)T} + b^{(l-1)T}h^{(l-1)} + h^{(l-1)T}W^{(l)}h^{(l)})$$

$$P\left(h_i^{(k)} = 1 \,\middle|\, h^{(k+1)}\right) = \sigma\left(b_i^{(k)} + W_{l,i}^{(k+1)T}h^{(k+1)}\right) \forall i, \forall k \in 1, \ldots, l-2$$

$$P\left(v_i = 1 \,\middle|\, h^{(1)}\right) = \sigma\left(b_i^{(0)} + W_{l,i}^{(1)T}h^{(1)}\right) \forall i$$

where l is the number of hidden layers, $W^{(1)}, \ldots, W^{(l)}$ are the weight matrices with $l + 1$ bias vectors as $b^{(0)}, \ldots, b^{(l)}$ where $b^{(0)}$ produces the bias for visible layer.

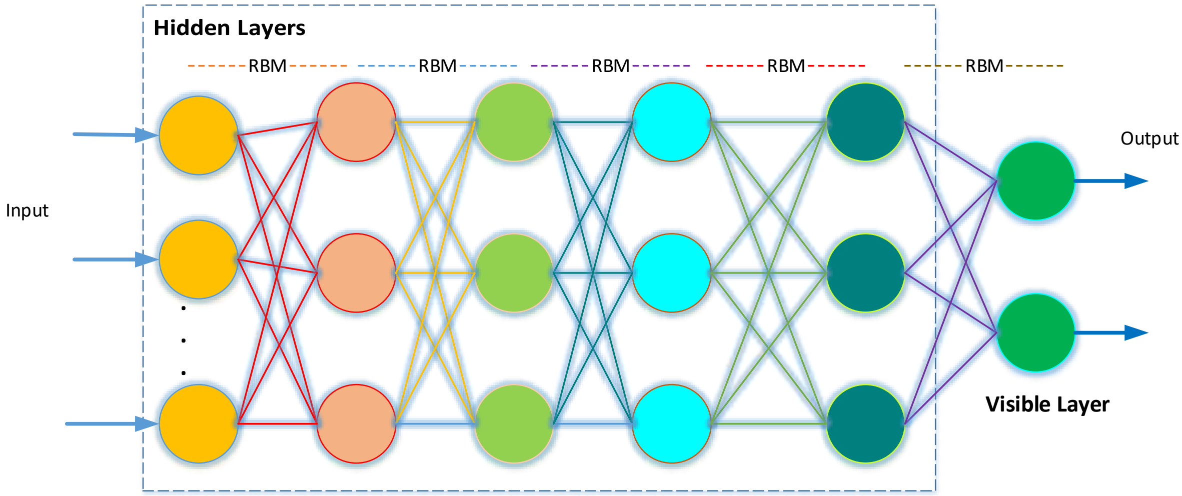

Figure 7: The architecture of Deep Belief Network

Each layer of DBN is defined by a restricted Boltzmann machine (RBM). This implies the DBN if formed by a group of RBMs as depicted in Figure 7. The first layer of RBM can be trained with a given training data set as visible input. The output of the first layer serves as hidden unit to it and is sent to the next RBM to serve as visible unit for training. The process continues until the required RBMs are exhausted. The application of DBN has been seen in different domains, image processing is one of the example (Wani et al., 2020).

3.6 Comparing strength and limitations of the deep learning algorithms

The deep learning algorithms discussed in the preceding sections 2.1 to 2.5, each has its strengths, limitations and suitable application area. It is well known that no intelligent algorithm without a limitation despite the fact that those intelligent algorithms are powerful and effective in solving real world problems. In Table 3, the summary of the major strength, limitation and suitability of each deep learning algorithm discussed are presented.

Table 3: Summary of deep learning algorithms strength, limitations and suitability

Deep Learning Algorithm	**Suitability**	**Strength**	**Limitation**

Convolutional Neural Network	Image	Requires less neuron connections	Sometimes require many layers to extract hierarchy of features
Deep Reinforcement Learning	Decision making	Labelled data is not required	Tradeoff between exploitation and exploration Policy evaluation and comparison is challenging
Recurrent Neural Network	Speech/Video	Memorizes sequential events Models time dependencies	Vanishing and exploding gradient Extremely difficult to train
Long Short Term Memory	Time series	Good for data with long time interval Memory cells are secured by gates	Only handles short term dependencies High memory and bandwidth requirement
Deep Neural network	Regression	Dimension reduction	Learning process is sometimes slow It is computational intensive
Deep Belief Network	variety	Labelled data is not required for training Avoids overfitting and underfitting Adopts layer by layer greedy learning approach for initializing network	Initialization and sampling process renders training to be computationally expensive

4. The Emerging Cloud Computing Paradigm: Concept, Architecture and Taxonomy

The idea of emerging cloud computing was developed to provide solutions to the challenges of the traditional cloud computing. It tries to bring computation much closer to the users by adding a layer between the cloud and the users. The aim is to improve QoS and QoE (Varghese & Buyya, 2018). Processing of data generated by user devices is done at the edge of the network in place of being transferred to the far away cloud data centre. This reduces bandwidth and amount of energy consumed (Ai, Peng, & Zhang, 2018). The emerging cloud computing architectures as already outlined in the introduction section are discussed in this section.

4.1 Taxonomy of Emerging Cloud Computing Architectures

Figure 8 presents a taxonomy of the emerging cloud computing architectures. It has five different architectures: Fog computing, edge computing, serverless computing, volunteer computing, and software defined computing. The devices and technology involved in each architecture are discussed.

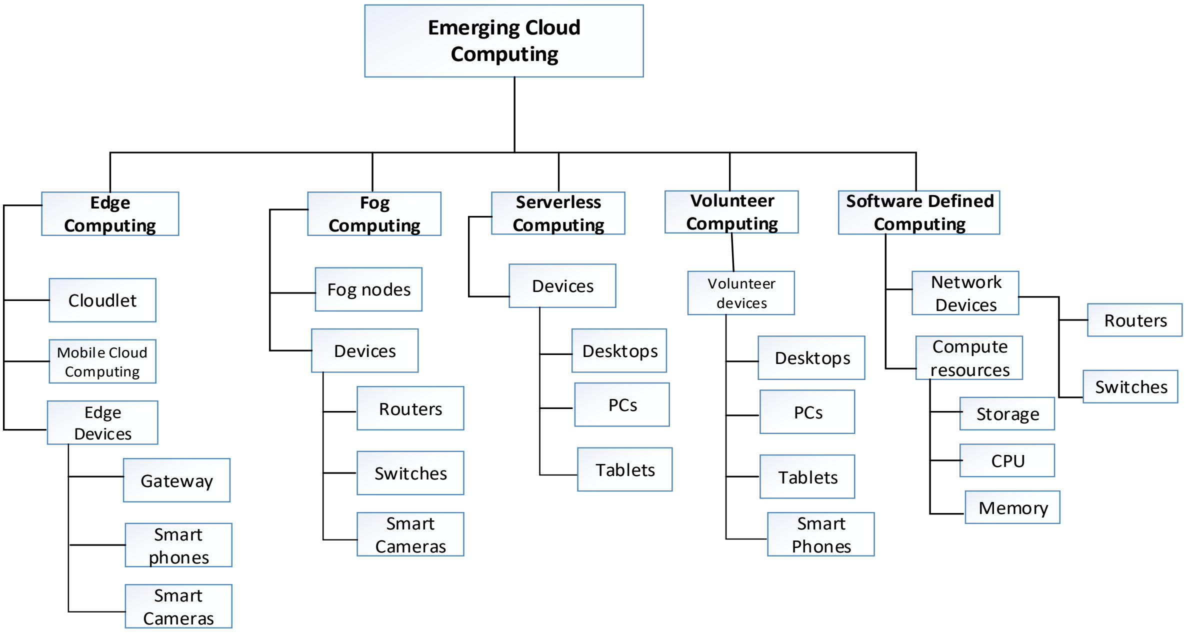

Figure 8: Emerging Cloud Computing Taxonomy

Different architectures have been proposed for the emerging cloud computing. The trending architectures of the emerging cloud computing are discussed as follows:

4.1.1 Edge Computing

Traditional cloud computing provides centralized platform for storage and computation typically in data centres located far from users(Prieta & Corchado, 2016) as already discussed. With high influx of user devices especially in the IoT, huge amount of data is generated. Cisco global cloud index projected by the year 2019 data produced will be around 500zettabytes (Idex, 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). The idea of edge computing came up as a way of boosting the capabilities of the traditional cloud computing (Calheiros, Ranjan, Beloglazov, & Rose, 2011). Instead of processing data on the cloud, edge computing enables data pre-processing at the device edge before sending it to the cloud(Shi et al., 2016). Edge computing is located much closer to the IoT devices. As a result, offers lower latency than the traditional cloud computing. Also, service availability has higher guarantee in edge computing (Yousefpour et al., 2019). Mobile Edge computing (MEC) provides cloud-computing services to mobile users through Radio Access Networks within the vicinity of the users (Chen, Jiao, Li, & Fu, 2015.; Patel et al., 2014). Application areas of MEC include health monitoring, connected vehicles, video analytics and so on. Despite being able to generate real time responses with low latency, MEC has limited storage and high power consumption (Mach & Becvar, 2017). Edge computing uses devices such as gateways are located very close to user devices (Yousefpour et al., 2019).

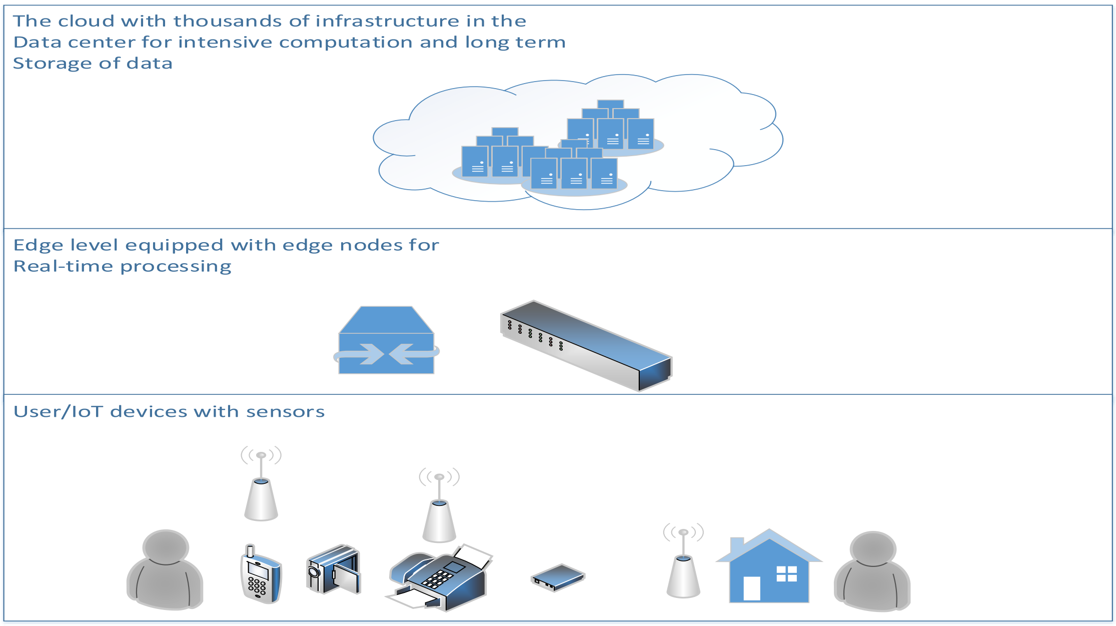

Figure 9: Edge Computing Architecture

Figure 9 presents the architecture of edge computing. Input data generated by IoT devices needing fast response are processed very close to the devices. While those with intensive computation and long term storage are sent to the cloud. Edge computing has some challenges associated with the edge devices: limited energy and resources, heterogeneity, privacy, security, mobility, etc (Baktir, Ozgovde, & Ersoy, 2017).

4.1.2 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). With the high increase of user devices including PCs, cell phones, wearable devices and so on, various requests expecting real time response are posed to the cloud. The FC brings computational services closer to the users. It was argued that FC is devoted to serve mobile users by addressing the issue of location awareness. Benefits of FC as stated in (Gupta, Dastjerdi, Ghosh, & Buyya, 2016) show that it reduces network traffic by providing an environment for filtering and processing data on the edge devices, also reduces propagation latency for applications that require real time response. Once network traffic is reduced, congestion and latency are both decreased. The goals of FC include: latency, efficiency both in the context of resource utilization and energy consumption. Despite the benefits offered by FC, there are still some challenges. Improving security and handling privacy issues are among the challenges as various nodes interact with user devices (Vaquero, Rodero-merino, Vaquero, & Rodero-merino, 2014). Resource management is another challenge due to different tasks associated with it such as resource discovery, resource allocation and maintaining group of distributed resources (Yi, Hao, Qin, & Li, 2015). Some of the fog nodes are resource constrained and mostly rely on battery power (Yi et al., 2015). 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 10.

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).

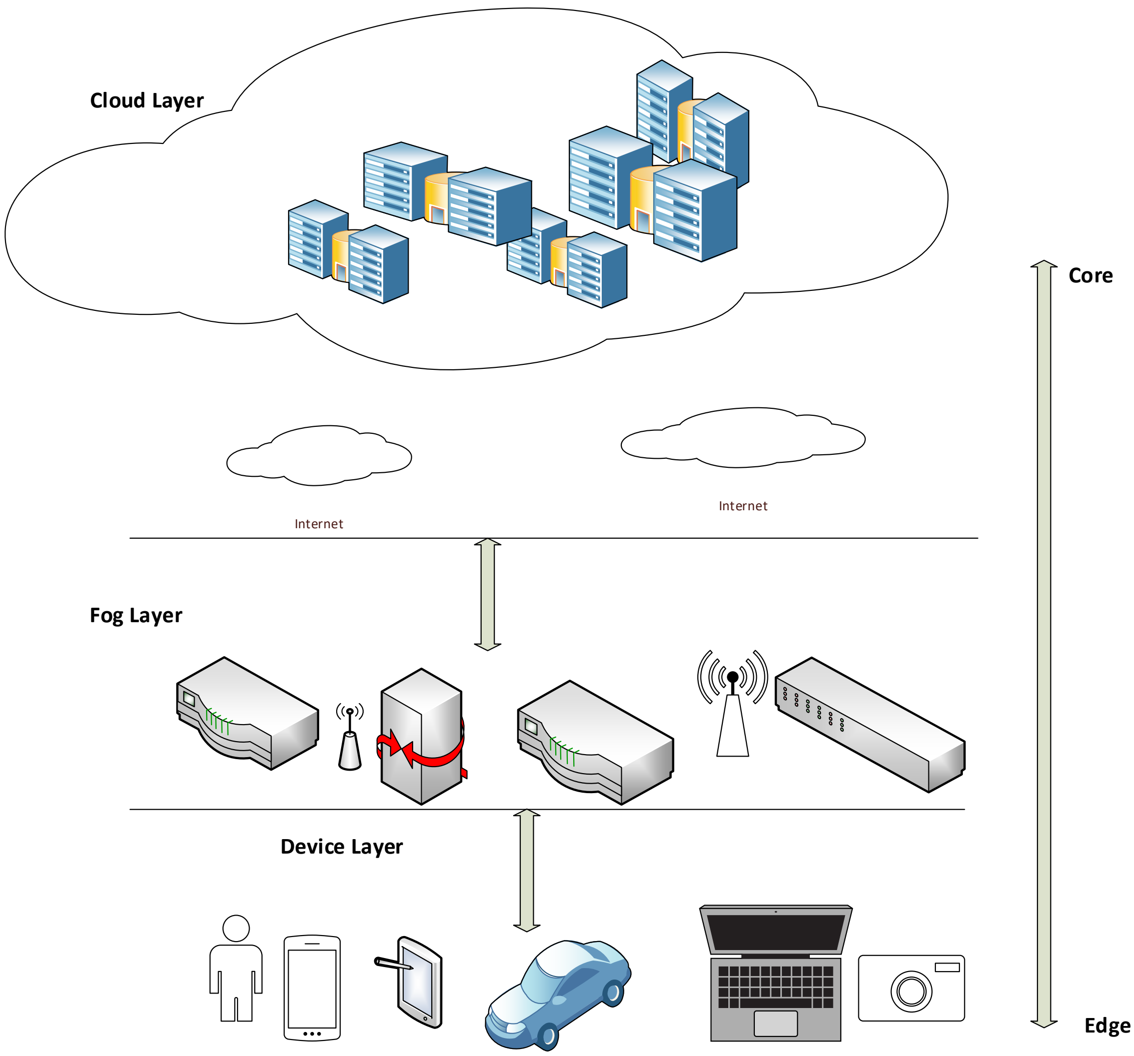

Figure 10: Fog Computing Architecture

Other cloud computing paradigms: Cloudlets - Cloudlets are mini data centres that are very close (a hop) to mobile devices. Cloudlets provide decentralized computing resources with high proximity to the resource-poor mobile devices. They are located in-between the mobile devices and the conventional cloud. The cloudlet architecture is composed of a collection of multi-core systems having high speed internal connectivity and high speed wireless local area network (Satyanarayanan, Bahl, Caceres, & Davies, 2009). Cloudlets are often called "smaller clouds"(Baktir et al., 2017). Cloudlets could be used by service providers wanting to bring services very close to mobile devices. It offers moderate computing resource with minimal latency and power consumption (Yousefpour et al., 2019). Tasks demanding high computation with low response time can be migrated to cloudlet instead of the traditional cloud data centre. Achieving this will enhance processing speed for mobile devices. Cloudlet provides mobile devices with the capability to handle new technological services related to natural language processing, augmented reality, speech recognition and machine learning (Baktir et al., 2017). Cloudlet has the capability of caching data within its internal storage making it readily available when the need arises (Shaukat, Ahmed, Anwar, & Xia, 2016). Loss of data in cloudlets is not disastrous because they only possess cache copies which are stored at other places (Satyanarayanan et al., 2009). Privacy and security are among the major challenges of cloudlet deployment.

Mobile Cloud Computing (MCC): MCC combines three important fields: mobile computing, cloud computing, and wireless sensors (Raei & Yazdani, 2017). According to (Khan, Othman, Madani, & Khan, 2014), MCC integrates mobile devices with cloud computing technologies in order to increase the computational capability, memory and storage capacity, energy, and context awareness of the mobile devices. MCC is made up of three major components: mobile device, access technology and cloud service (Shaukat et al., 2016). Mobile devices, smart phones for example have high demand for computing resources and the advancement in their technology is too slow especially in terms of battery duration and computing devices. Computation offloading allows compute-intensive tasks to be moved to the cloud from mobile devices. Smart phones need computation offloading techniques that are optimised to handle context awareness, heterogeneity, bandwidth, energy consumption etc. in mobile cloud environment (Khan et al., 2014). Improving user experience based on processing time, battery life, bandwidth, communication and so on is a major goal of MCC. Privacy is one of the issues preventing the high acceptance of MCC. This is because users store data concerning health, salary, pictures and so on in the cloud and cannot risk the leakage of such vital information. Security is another challenge in MCC which needs to be seriously taken into consideration during development and deployment of the models (Khan et al., 2014). MCC can be useful in Games, file search, image processing, complex mathematical computations, application downloads and many more (Khan et al., 2014).

4.1.3 Volunteer Computing

Volunteer computing (VC) takes advantage of computing resources donated through the internet around the globe to form distributed computing platform (Costa, Silva, & Dahlin, 2008). It provides a cheaper alternative to traditional cloud computing. Volunteered resources can be used to solve computing intensive scientific problems in subjects like physics and astronomy. The VC uses a crowd funded strategy whereby users donate spare resources from their computers/devices to form ad hoc cloud (Varghese & Buyya, 2018). Social cloud computing is a form of VC in which members of a particular social network share heterogeneous computation resources forming ad hoc cloud. Berkeley open infrastructure of network computing is reported to be the most prevalent platform for VC with millions of donated resources used by many projects around the world (Tessema Mindaye Mengistu & Che, 2019). The donated resources are mostly but not limited to idle desktops, laptops, routers, smart phones and smart TVs.

Traditional cloud with centralized data centers are cheaper because users are relieved from the burden of hardware maintenance while service providers gain profit. On the other hand, there are risks of single point failure, high energy consumption and emission of gases that affect the environment, high cost of setting up data center and its maintenance (Tessema Mindaye Mengistu & Che, 2019). The VC is a cloud set up from donated spare resources. Unlike conventional cloud, VC does not require upfront startup cost, energy consumption and maintenance cost are not needed (Tessema M Mengistu, Albuali, Alahmadi, & Che, 2019). Cooling devices are not needed therefore volunteer cloud serves as a remedy to the carbon emission that affects the environment (Tessema Mindaye Mengistu & Che, 2019).

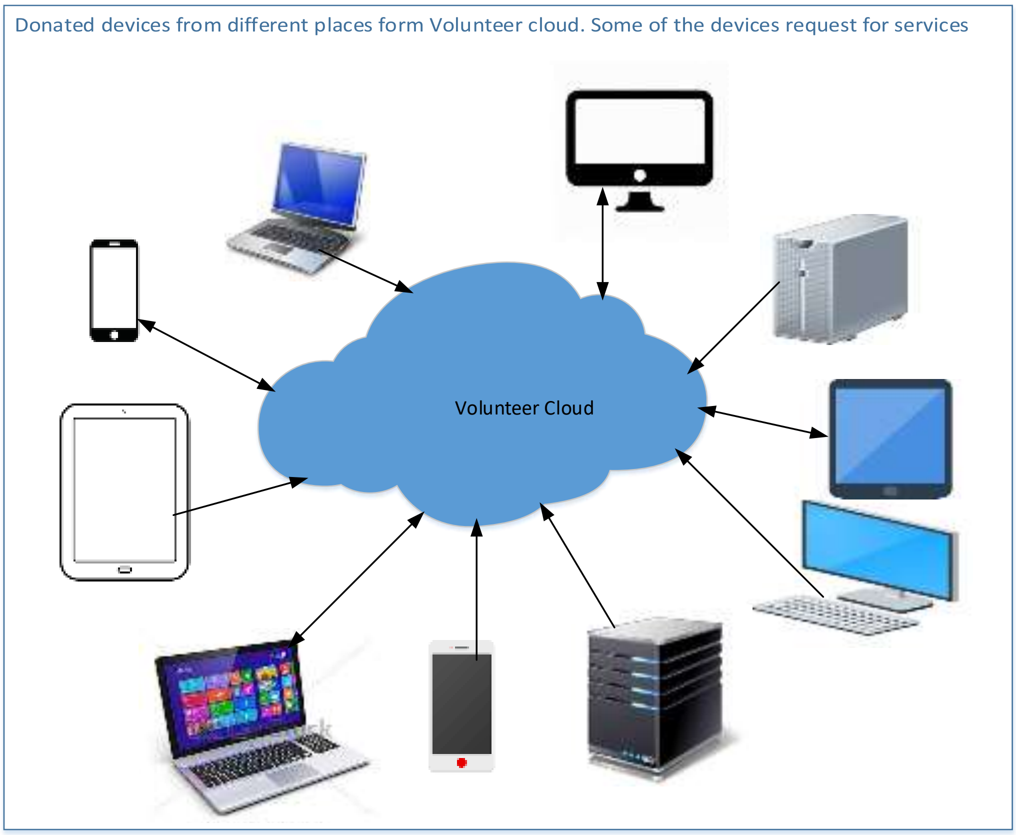

Figure 11: Volunteer Computing Architecture

One of the challenges preventing VC from achieving its full potential is heterogeneity in hardware and software which makes optimum task distribution difficult (Tessema Mindaye Mengistu & Che, 2019). Also, privacy and security issues are major concerns in VC (Varghese & Buyya, 2018). The VC can be classified as mobile cloud, edge cloud, desktop cloud, volunteer storage cloud, P2P cloud and social cloud (Tessema Mindaye Mengistu & Che, 2019). Figure 11 depicts VC with different types of devices donated from around the globe to form volunteer cloud. The volunteered devices may also send service request to the cloud.

4.1.4 Serverless Computing

In serverless Computing (SC), severs will no longer be rented by users as in the traditional cloud computing. This is a new architecture available to platform as a service (Buyya et al., 2018). Developers would not have to be concerned with challenges associated with resource allocation, scalability and application placement on virtual machines. The SC is seen as a doorway to achieving event-driven idea where functions are executed by events that trigger them (Mcgrath & Brenner, 2017). It allows huge applications to be broken into chunks of functions allowing modules to be executed independently when the need arises (Varghese & Buyya, 2018). The SC services are provided based on computing runtime where application logic is executed without persistent data storage. Platforms providing such services include AWS Lambda, Microsoft Azure Functions, IBM OpenWhisk, Google Cloud Functions(Aditya et al., 2019; Varghese & Buyya, 2018). The SC is seen as a cost saving application because cost is only incurred when an application is being executed. Security is still a great challenge in SC.

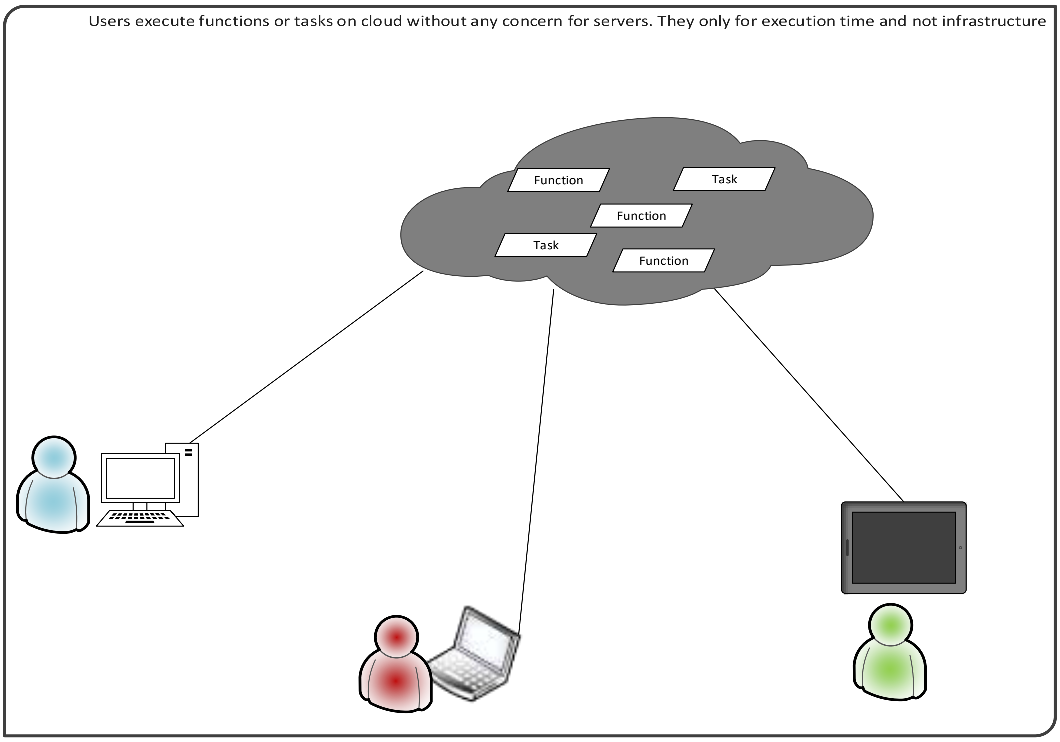

Figure 11: The architecture of a serverless computing

The advantages of SC as pointed in (Aditya et al., 2019): it eliminates the need for managing server resources allowing developers to concentrate more on application logic, provides efficient use of resources by allocating resources only when a request is received and retrieves resource after processing the request, minimizes cost as users are billed only for the resources used during execution of their applications, it has built-in scalability that allows deployed applications to be scaled up to process new requests and to be scaled down after processing the request. A major disadvantage of SC is the start-up latency for executing each request (Aditya et al., 2019). Figure 11 depicts the typical architecture of the SC where users execute tasks on the cloud without renting any server.

4.1.5 Software Defined Computing

In conventional networking, each device in a network is entirely secluded from other devices. Despite being able to interact with other devices, each device has its control plane isolated to itself in such a way that its functionality cannot be tempered with (Thames & Schaefer, 2016). The Software Defined Networking (SDN) provides a platform for central management of the control plane using software in such a way that it can be applicable to various devices (Al-mansoori, et al., 2020, Thames & Schaefer, 2016). This allows network devices to have a universal hardware that is not restricted to certain vendor software. The SDN has emerged as a result of the availability of multiple networking elements (Cao, Panwar, Kodialam, & Lakshman, 2017).

In SDN, the control plane and the data plane are disjointed making the control plane centralized while the data panel remains distributed. With centralized control plane, decision making becomes much faster (Jararweh et al., 2016). It also allows modification of the control panel features on many devices to suit any design objective (Thames & Schaefer, 2016). SDN is cheap, easy to manage, flexible and adaptive (Thames & Schaefer, 2016). Control plane allows programming instead of strictly configuring hardware. Different SDN controller platforms are in existence: Floodlight, NOX, OpenDaylight, Ryu, and Open Network Operating System (ONOS)(Son & Buyya, 2018). Among the issues preventing wide acceptance of SDN are; hardware support, availability of friendly programming tools, QoS, and security (Jararweh et al., 2016).

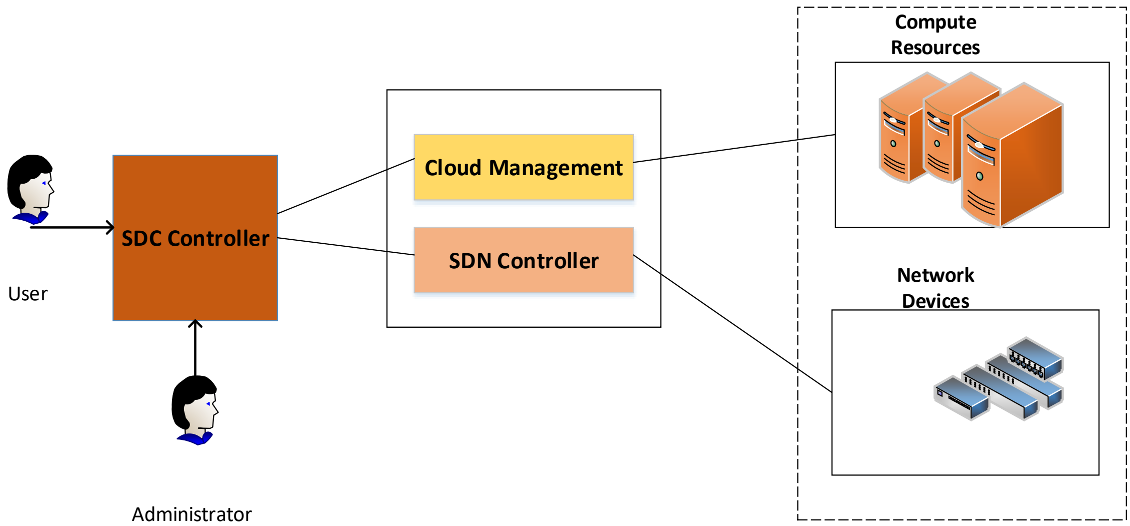

Figure 12: Software Define Computing Architecture

The SDN is essential in Software Defined Cloud Computing (SDCC) because it enables efficient processing of user requests based on the defined service level agreement (SLA) and within a specified time (Abbasi et al., 2019). The SDCC provide a means to easily process and dynamically configure devices and links via SDN controllers. This simplify both configuration and management of cloud resources making it easy for network administrators to change network settings in order to accommodate requests from subscribers (Abbasi et al., 2019). According to (Varghese & Buyya, 2018) applying the concept of SDN to data center resources (compute storage and network resources) is term as Software defined computing (SDC). This will relieve the difficulty of infrastructure configuration and management. Son & Buyya (2018) proposed SDC as a platform for integrated management of computing and networking resources by cloud provider. Figure 12 depicts the SDC architecture. Computing resources in servers such as the CPU and others are controlled by the cloud management, network devices are managed by SDN controller. SDC controller integrates the management of resources and SDN controller.

5. Deep Learning Algorithms in Emerging Cloud Computing Architectures

Question: What researches have been conducted using deep learning to solve problem in different emerging cloud computing architectures?

In this section, we present different projects where researchers applied deep learning algorithms to solve problem in emerging cloud computing architecture. Figure 13 is the taxonomy of the application of deep learning in emerging cloud computing architectures. The taxonomy indicates the deep learning algorithm in the relevant emerging cloud computing architecture.

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Figure 13: Taxonomy of the application deep learning in emerging cloud computing architecture

5.1 Convolutional Neural Network

Many projects applied ConvNet in the emerging cloud computing architecture to solve different categories of problems. The summary of the applications of ConvNet in emerging cloud computing is presented in Table 4. The discussion of the applications of ConvNet in different emerging cloud architectures are presented as follows:

5.1.1 Convolutional Neural Network in Edge Computing

The applications of ConvNet in edge computing architecture to solve problems is presented in this section, for example, (Li-pang Huang, Hong, Luo, Mahajan, & Chen, 2018) proposed a ConvNet for classification of mosquitoes in edge computing platform. A prototype device named smart mosquito zapper was developed to detect, film mosquitoes and pre-process videos serving as the edge device before sending automatically to data centre. A single server is employed at the data centre for the classification. The ConvNet is employed at the data centre to identify the mosquito type. The results indicated that the ConvNet has high accuracy in mosquito classification. Limitations of the work is that only two types of mosquitoes (culex and aedes) were considered in the project. Therefore, other type of mosquito can escape the system. C. Liu et al.(2017) proposed a ConvNet for food recognition supported by edge computing infrastructure. Smart phone cameras were used for visual sensing and image capturing. Images were first pre-processed and segmented at the edge device (smart phone). To setup the environment, a smart phone running android 6.0.1 was used as edge device, a sever equipped with centOS 7.0 was used at the cloud. A two-way communication between the edge device and the server was implemented using Apache http client on the smart phone and Django RESTful web server on the cloud sever. The ConvNet is adopted at the cloud for identification and classification of food images. The ConvNet proved to have better performance when compared with integrated computer vision algorithms with manually generated features running only at the mobile device (C-System) and deep learning algorithms at the cloud without pre-processing at mobile device (D-System). However, the response time is still low. Azimi et al. (2018) proposed a ConvNet for hierarchical edge-based health monitoring. The ConvNet is mainly for diagnosing heart diseases. A sensor node with WiFi module that connects to a local WiFi is programmed to read files and upload POST request to edge device which is an Ubuntu linux maching having Apache web server, python interpreter and PHP. The ConvNet was used to detect and classify different abnormalities from electrocardiogram signals. The classification result is subsequently used to make decision. The ConvNet performance was compared with traditional cloud based IoT system and was found to have better performance. The processing speed of the algorithm depends highly on the processing power of the edge device.

Hossain et al. (2018) proposed an edge computing based ConvNet for date fruit classification. Multiple devices with cameras were used for capturing images at the device layer. Radio access networks communication technology was used to send data to data centres. MEC server was used to form edge cloud. The ConvNet pre-processes images of dates and classifies them into four categories (sukkary, ajwa, mabroom, sagai). The ConvNet performance was compared with Artificial Neural Network (ANN) based single fruit classifier (ANNFC) and support vector machine (SVM) based single fruit classifier (SVMFC). The results proved that the proposed ConvNet outperforms the compared ANNFC and SVMFC. Video transfer latency over the network was high. Yan et al. (2019) proposed a ConvNet based system for privacy protection in edge computing environment. The architecture allows various IoT devices to send learning task to different edge servers through API depending on the proximity of the devices to the edge servers. The approach consists of private dense training and private compressive training steps for privacy protection based on dense model and compressive model respectively. The private compressive training is based on compressive ConvNet model attached to edge servers and is basically used for image recognition. Compressive model is formed by compressing the dense model. The algorithm proved to perform better when compared with no privacy constraint (NPC) approach. However, the algorithm uses many layers for feature extraction. Sankar et al., (2019) proposed a ConvNet for movie review sentiment analysis. The algorithm uses edge computing approach to perform sentiment analysis on android phones. The environment used by the researchers consists of a desktop with intel xeon, Debian 9.0 for training of the model. The pre-trained model is then deployed on an android smart phone for text classification. The proposed system uses text matrix as a look up table in place of image pixels to extract features for training of the ConvNet. The ConvNet was used to categorize movie reviews as positive or negative. Evaluation results proved that the proposed algorithm has high accuracy. The study is limited to English language reviews.

5.1.2 Modified Convolutional Neural Network in Edge Computing

The studies that modified the architecture of the ConvNet to improve its effectiveness and applied to solve problems in edge computing are presented in this section. For instance, (Pang, Qiao, Song, Zhao, & Zheng, 2019) proposed an improved ConvNet (I-ConvNet) for person re-identification in edge computing. The ConvNet was combined with batch normalization, padding layer, residual model layer, and Neighbourhood difference layer to improve its performance in terms of feature extraction and detection accuracy. The ConvNet pre-processes and computes the relation between images. Evaluation results proved that the I-ConvNet is better than the compared Keep It Simple and Straightforward Metric (KISSME), Kernel Local Fisher Discriminant classifier (KLFDA), Single-image and Cross-image Representations (SIRCIR), JoinRe-id, Gussian of Gussian (GOG), Quadruplet, Comparative Attention Network (CAN-AlexNet), Domain Guided Dropout (DGD), eSDC, Filter Pairing Neural Network (FPNN), CAN-VGG-16, Singular Vector Decomposition (SVDNet), Quardruplet+Marg algorithms. However, reduction of energy consumption remained an issue. Nikouei et al. (2018) proposed a light-weight ConvNet (L-ConvNet) for real time human detection in edge computing. A Raspberry PI 3 serves as the edge device where L-ConvNet resides. Depth wise separable convolution was introduced into the ConvNet to mitigate computational complexity of the traditional ConvNet. Single shot multi-box detector (SSD) was incorporated into the ConvNet for faster and more reliable human object detection. The L-ConvNet was used at the edge device for fast and accurate object detection. Experiment results proved that the L-ConvNet performs better than the SSD, GoogleNet Harr-Cascade and Histogram of Oriented Gradients + SVM (HOG + SVM), VGG, SqeezeNet, MobileNet. Yet, resources efficiency remains unresolved. B. Yang et al. (2018) proposed compact ConvNet (CConvNet) for real time passenger counting in edge computing environment. Videos of passengers' entry are recorded by a camera and the counting is done using an NVIDIA TX2 device. Unlike the classical ConvNet that has multiple columns, CConvNet has a single ConvNet column with six convolution and three deconvolution layers. The CConvNet maps crowd images to the density maps for the passenger counting. The proposed CConvNet proved to be more accurate than the contextual pyramid ConvNet (CPConvNet), cascaded multi-task learning (Cascade-MTL), switching ConvNet, multi-column ConvNet (MConvNet), fully connected convolutional crowd counting (FCCC) and cross-scene counting. However, the algorithm has no ability to recall its recent computation.

5.1.3 Convolutional Neural Network in Mobile Edge Computing

The studies that used ConvNet in MEC are presented in this sub-section. For example, (P. Zhang, Zhao, Gao, Li, & Lu, 2019) proposed faster region-ConvNet (FR-ConvNet) to assess street cleanliness based on MEC. A total of 100 streets were selected and 100 edge servers were placed in each of the street. Each server processes 80 images. Regional proposal network was employed to suggest regions that are likely to have objects. The ConvNet is used to identify, categorize and count the number of street garbage. The result shows that FR-ConvNet performed better than the traditional cloud server. However, the model does not consider cleanliness on rainy days, only common garbage data were used. Filtering pre-processing is done manually which could affect the real time transmission. Blanco-filgueira et al.(2019) proposed a ConvNet for real time tracking of multiple object in MEC. The platform is set up to use a 3S Lipo battery powered NVIDIA jetson TX2 which is controlled remotely by a tablet through WiFi. The algorithm is based on generic object tracking using regression networks (GOTURN) ConvNet tracker and hardware-oriented pixel-based adaptive segmenter (PBAS) object detector. The ConvNet was used for multiple object tracking to distinguish objects and predict the next position of each tracked object. The ConvNet was found to be fast in tracking multiple objects at low cost and low power consumption. However, the effectiveness of the proposed deep learning approach is not compared with another approach, so it is difficult to measure the algorithm performance.

5.1.4 Convolutional Neural Network in Fog Computing

It is found that ConvNet has being applied in FC, therefore, this sub-section is dedicated for the studies that applied ConvNet in FC. L. Li et al.(2018) proposed a ConvNet for product inspection in smart industries with FC. Cameras and sensors equipped with wired network adapters are placed at different positions of the production line to capture images of the products. The captured images are sent to a number of fog nodes for analysis of low level features and probable output of quick results or upload of the ConvNet values to a cloud server for more accurate processing. The ConvNet is used in the fog environment to detect possible defects in the products. Experimental results proved that the proposed ConvNet outperforms the compared contour detection and pixel based algorithms. However, the study is limited to a single product. Tuli et al.(2019) proposed ConvNet for real-time object detection in fog and cloud environment. The system has the capability of performing parallel processing by distributing task across fog nodes and cloud virtual machines. The setup uses Samsung S7 running android 9.0 as gateway device, a Dell XPS 13 used in fog environment for scheduling and task distribution, Dell latitude 5490 running windows 10 was used as fog server for performing computation, Microsoft Azure B1s machine running windows server 2016 was used as cloud sever. The ConvNet was employed to detect objects' locations and categorize the objects into different classes. The ConvNet shows better performance than the traditional cloud. However, the algorithm requires large dataset to perform well. Wang et al.(2019) proposed a ConvNet for salient object detection in FC environment. Pre-training of ConvNet was performed on the cloud servers before distributing to fog servers. In the environment, a server with 4 NVIDIA Telsa P100 GPU was used for training, Telsa K80 was used for testing and another K80 with less memory used as the fog device. At the testing stage, ConvNet extracts background information and submits the salient contents to the cloud for final processing. The ConvNet predicts the saliency map from the given image. The proposed algorithm outperformed the Vanilla-Generative Adversarial Network (Vanilla-GAN), Gradient Penalty Wasserstein Generative Adversarial Network (WGAN-GP), and Cycle Generative Adversarial Network (Cycle GAN), Minimum Spanning Tree (MST), Discriminative Regional Feature Integration (DRFI), Deep Contrast Learning (DCL+) and Weakly Supervised Saliency (WSS). However, the algorithm requires large dataset to perform well.

5.1.5 Convolutional Neural Network in Volunteer Computing

The application of ConvNet in VC is presented, it is the emerging cloud architecture with the less number of ConvNet applications, only one is found to be applied. Kijsipongse et al. (2018) proposed hybridized GPU cluster and VC for training of ConvNet. The platform is capable of extending GPU cluster into VC to leverage computing capability from donated resources. This reduces cost of setting up GPU cluster and provides vast resources for complex computation. The environment is set up with a 2-node cluster, a PBS-to-BOINIC gateway, and the VC consists of a set of 8 nodes with 3 desktop machines, 4 notebooks and 1 standalone GPU server. The model was tested by training ConvNet in image classification. The platform was found to be cheaper and faster. The volunteer nodes lack direct communication link for easy replication of files.

Table 4: Summary of the convolutional neural network applications in emerging cloud computing architecture

Reference	Deep learning structure	Algorithm(s) compared with	Results	Limitation
(P. Zhang et al., 2019)	ConvNet	Traditional cloud server	ConvNet has better detection accuracy and processing speed than traditional cloud server	Model is only used on sunny days, uncommon street garbage not considered
(Li-pang Huang et al., 2018)	ConvNet	Not compared	The results showed that ConvNet has high accuracy	The work is limited to two types of mosquitoes
(C. Liu et al., 2017)	ConvNet	C-System and D-System	ConvNet performed better than the C-System and D-System	Low response time
(Pang et al., 2019)	I-ConvNet	KISSME,FPNN, KLFDA, SIRCIR, GOG, Quadruplet, CAN-	The I-ConvNet outperformed the compared	Does not minimize energy consumption

		AlexNet, CAN-VGG1-, 6, DGD, eSDC, FPNN, Quardruplet+Marg, SVDNet and Spindle	algorithms with the exception of spindle	
(Nikouei et al., 2018)	L-ConvNet	SSD GoogleNet Harr-Cascade and HOG + SVM, VGG, SqueezeNet, MobileNet	The L-ConvNet perform better than GoogleNet HOG + SVM, VGG, SqueezeNet, MobileNet	Resource efficiency remain an issue
(L. Li et al., 2018)	ConvNet	Contour and pixel base algorithm	The ConvNet outperformed contour and pixel based algorithms	The algorithm was only tested with a single type of product
(Azimi et al., 2018)	ConvNet	Traditional cloud	ConvNet performed better than the traditional cloud	The speed highly depends on performance of the edge device
(Hossain et al., 2018)	ConvNet	ANNFC and SVMFC	ConvNet outperformed ANNFC and SVMFC	Video transfer latency is high
(Tuli, Basumatary, & Buyya, 2019)	ConvNet	Traditional Cloud	ConvNet outperformed the Traditional cloud	The algorithm requires large dataset to perform well
(Blanco-filgueira et al., 2019)	ConvNet	Not compared	ConvNet Performed well in terms of latency, cost, and power consumption	The effectiveness of the proposed deep learning approach is difficult to measure due to lack of comparison
(Yan et al., 2019)	ConvNet	NPC	ConvNet performed better than the NPC	Many layers are used in feature extraction
(Kijsipongse et al., 2018)	ConvNet	Not compared	ConvNet Performed well	Lack direct communication link to volunteer nodes
(B. Yang et al., 2018)	CConvNet	CPConvNet, Cascade-MTL, Switching ConvNet, MConvNet and Cross-scene Counting, FCCC	CConvNet outperformed Cascade-MTL, Switching ConvNet, MConvNet, Cross-scene Counting, FCCC	The CConvNet cannot recall its recent computation
(Sankar et al., 2019)	ConvNet	Not compared	ConvNet is efficient in sentiment classification	Only reviews in English language were considered
(Wang et al., 2019)	ConvNet	VanillaGAN, CycleGAN and WGAN-GPS, MST,	ConvNet outperformed VanillaGAN,	The algorithm requires large dataset to perform well.

	DRFI, DCL+, SRM,HDFP, WSS	CycleGAN, WGAN-GPS, MST, DRFI, DCL+, WSS

5.2 Deep Reinforcement Learning

The DRL has been used in diverse cloud computing architectures to solve various problems. In this section, we present different works involving DRL and summary of the projects is presented in Table 5.

5.2.1 Deep reinforcement learning in mobile edge computing

The DRL is found to be adopted in MEC for solving real world problems in the emerging cloud computing architecture. For example, (Zhang & Zheng, 2019) proposed DQN for migration of task in autonomous vehicles. The simulation environment set up has four by four grid area with 16 locations, each location has eNB and a MEC server for offloading tasks. The DQN takes decision on offloading tasks whenever user equipment changes state. The aim was to tackle issue of service stability of the MEC applications for equipment that move from one network region to the other. For every good decision, a reward is attached. Simulation results showed that DQN has higher number of rewards than the compared approaches: dynamic programming (DP) and No migration algorithm (where tasks offloading in not involved). However, no data security measure attached to the task migration process. T. Yang et al. (2018) proposed a DQN for real-time resource allocation in MEC. The simulation environment set up is simply a 2-user scenario with a MEC node having 3-core CPU. The DQN serves as an intelligent agent that surveys the best and real time resource allocation policy at the edge device. It takes the current state as input and explores the best strategy through interaction with the environment by trial and errors. The DQN is applied to decide the best resource allocation strategy. The experiment results showed that the DQN algorithm is better than the equal allocation algorithm (EAA) and random allocation algorithm (RAA). Only 2-user scenario was used to test the algorithm, therefore, its performance with many users cannot be ascertained.

Huang et al. (2019) proposed a DQN for offloading of tasks and allocation of bandwidth in MEC. The simulation platform consists of an edge server and 5 mobile users with each user having 4 tasks. Users offload computation tasks to the server through wireless connection. The DQN was used to select the best decision for task offloading and the optimum resource allocation for each user. Results showed that the DQN achieves better performance than the local processing only scheme, edge processing only scheme, greedy scheme, and MUMTO algorithm. However, local optimum solution is obtained instead of global optimum as learning rate increases. K. Zhang et al. (2019) proposed a DQL for optimal task offloading in MEC-based vehicular network. Simulation platform has been set up by using 3 different roads with 1 base station and 5 roadside units (RSUs) on each of the chosen roads. the base station and each of the RSUs were equipped with MEC server via wired connection. The algorithm is capable of offloading tasks to servers. It has a redundant algorithm for enhancing reliability of task offloading that may occur due to data transmission failure in vehicular network. Q-learning is used for selecting the optimal MEC server and the best task offloading strategy in vehicular networks. The DQL is found to outperformed greedy algorithm in terms of reliability and optimum utility. However, with high traffic density, redundant transmission worsens communication interference which affects reliability of the offloading.

5.2.1 Deep reinforcement learning in fog computing

The researches that applied DRL in FC are presented in this sub-section. For example, (Ning et al., 2019) proposed a Double DQN (DDQN) for minimizing of energy consumption in internet of vehicles and fog computing. In their environment set up, a district was selected and considered to have a single cloudlet server and 5 RSUs all equipped with MEC servers. Vehicles whether moving or parked are considered as fog nodes where RSUs can upload tasks. The DQN was employed to make task offloading decision such that power consumption is minimised. The algorithm was evaluated alongside traditional Q-Learning algorithm, MEC-enabled Energy-Efficient Scheduling (MEES) which is a heuristic algorithm, and cloudlet processing. The experiment result prove that the proposed DDQN performs better than the compared MEES and Cloudlet. Nevertheless, energy consumption increases when offloading tasks above 80MB (the set computation capacity of vehicles). H. Li et al. (2019) proposed a DQN based scheduling approach for mobile crowd sensing in fog computing. The environment uses intel core i7 workstation computer and a scheduler placed in an NVIDIA intel core i7 server to make decision on scheduling strategy. The DNN was incorporated in the DRL to learn representation of the data and generate a Q-network to get the optimal scheduling decision. ConvNet was also employed in the scheduling problem to accept number of tasks starting at a given time and generate a single valid action. The performance of the DRL outperformed the first in, first out (FIFO), reward first greedy (RFG) method, Online scheduling algorithm (OSA), and deep resource management (DRM). Though, evaluation of policies is challenging.

5.2.2 Deep reinforcement learning in edge computing

The applications of the DRL in edge computing are discussed in this section. The study by (Qi et al., 2019) proposed a DQN based Knowledge driven service offloading decision algorithm for internet of vehicles. In the environment set up, different service scenarios with multiple number of tasks and 3 types of edge nodes were created for training the model. Also, 2 base station, edge nodes, 2 access point edge nodes and 6 vehicular nodes were placed in the vehicular environment. The DQN is used to make best offloading decision at the edge. When making decision, the algorithm takes into consideration the resource requirement, access network, mobility of user, and dependencies of future tasks. Simulation results proved the proposed algorithm to have fast convergence and outperformed greedy offloading decision algorithm. However, evaluation of future rewards becomes complex as number of service task increases. W. Li et al. (2019) proposed a double DQN (DDQN) for optimizing edge caching in device to device (D2D) content sharing. The D2D content sharing reduces network traffic and improves QoS for mobile users. Four base stations were adopted for the simulation where large number of users communicate with the base station through cellular link. The DDQN replaces the Q-table with neural networks to enable solving of complex reinforcement learning tasks. The DDQN was used in training the DRL models. Experiment results showed that DDQN is more efficient than the least recently used (LRU), FIFO, and least frequently used (LFU). But hit rate decreases with increase in number of content. Q. Zhang et al. (2018) proposed double DQL (DDQL) energy efficient task scheduling in edge computing environment. Instead of using SIGMOID as activation function as used by a typical DQL, DDQL uses rectifiable linear unit (ReLu) as activation function. The DDQL periodically schedules tasks for edge nodes. It also produces Q-values for dynamic frequency voltage scaling (DFVS) and generates target Q-values for parameter training. The DDQL performed better than the DQL in terms of energy conservation. However, trade-off between exploration and exploitation was a challenge.

Table 5: Summary of deep reinforcement learning in emerging cloud computing architectures

Reference	**Deep learning structure**	**Algorithm compared**	**Results**	**Limitations**
(Zhang & Zheng, 2019)	DQN	DP and NMA	The DQN outperformed DP and NMA	Data security technique during task migration not employed
(T. Yang et al., 2018)	DQN	EAA and RAA	DQN outperformed EAA and RAA	Only 2-user scenario was considered for testing
(Huang et al., 2019)	DQN	Local processing scheme, edge processing scheme, greedy scheme, and MUMTO algorithm	DQN performed better than the compared algorithms	Increase in learning rate generates local optimum
(Ning et al., 2019)	DDQN	Q-Learning, MEES, cloudlet	The DDQN outperformed Q-Learning, MEES and cloudlet	Energy consumption increases when task offloading is above 80MB
(Qi et al., 2019)	DQN	Greedy offloading decision	The DQN outperformed greedy algorithm	Evaluation of future rewards becomes complex with increase in number of tasks
(K. Zhang et al., 2019)	DQL	Greedy algorithm	DQL performed better than Greedy algorithm	High traffic density affects offloading reliability
(Q. Zhang et al., 2018)	DDQL	DQL	DDQL outperformed DQL	There is trade off challenge between exploration and exploitation
(H. Li et al., 2019)	DQN	OSA, DRM, FIFO and RFG	DRL performed better than the compared algorithms	Evaluation of policies is difficult
(W. Li et al., 2019)	DDQN	RLU, FIFO and LFU	The DDQN is more effective than the compared algorithms	Increase in number of content decreases hit rate

5.3 Deep Neural Network

In this section, we present different DNN proposed by different researchers in solving problems in emerging cloud computing architectures. Table 6 present the summary of the DNN application.

5.3.1 Deep neural network in fog computing

The applications of the DNN in FC is presented in this section. The work of (Diro & Chilamkurti, 2017) proposed a DNN for distributed and parallel attack detection in IoT based on FC. In the environment set up, the deep learning model is deployed on a single node in case of centralized system and on numerous nodes for the case of distributed attack detection. The number of network training machines were varied to compare the performance of distribution and parallelism. The deep learning model is used in detecting possible attacks on distributed fog nodes. The performance of the proposed algorithm was compared with the shallow learning softmax algorithm. The experiment result shows that the DNN is more effective in detecting attacks than the compared softmax algorithm. However, the algorithm's learning process is slow. Tuli et al. (2019) proposed an ensemble deep learning system for health monitoring in FC environment. A Samsung galaxy S7 with android 9.0 was used as gateway device for the environment along with Dell XPS 13 and Raspberry pi 3B+ as master node (which receives input from gateway device) and worker node (which performs the given task). Microsoft Azure B1 machine running windows server 2016 deployed as the cloud server to perform computation when fog nodes are overloaded. A collection of DNN classifiers was used as the ensemble model for preprocessing of data and prediction of heart disease in real time. The system was tested using single node, ensemble, and cloud data center prediction. The ensemble DNN was found to have higher accuracy in predicting heart disease. However, the system only receives file based input which are not directly from the sensor.

5.3.2 Deep neural network in mobile edge computing

Only a single project is found to apply DNN in MEC. The project of (Hussain, Du, Zhang, & Imran, 2019) proposed a MEC-based DNN for anomaly detection in mobile cellular networks. The system distributes core network's computation across MEC servers located at base stations to reduce workload for the core network. Every MEC server observes users' activities and employs L-layered feed forward DNN. The DNN was used to detect anomalies (outage and abrupt traffic upsurge) in mobile cellular networks by leveraging user call detail record. DNN shows better performance than the Mini-Batch GD (MBGD), Batch GD (BGD), and momentum. The project is limited to a single timestamp (10 minutes).

5.3.3 Deep neural network in serverless computing

The DNN is used to solve problem in serverless computing, (Ishakian, Muthusamy, & Slominski, 2018) examined the suitability of training deep learning models for prediction tasks in serverless computing environment. The MXNet deep learning framework and AWS Lambda environment were used for the experiment. Apache JMeter was used to send http requests to the Lambda function. Experiment results proved serverless environment is suitable for training of deep learning for prediction tasks. However, delay was experienced at the start which could skew the latency distribution leading to service level agreement violation.

Table 6: Summary of deep neural network in emerging cloud computing architecture

Reference	Deep learning structure	Algorithm compared	Results	Limitation
(Diro & Chilamkurti, 2017)	DNN	DNN-Softmax	DNN is more effective in attack detection than the compared DNN-Softmax	Algorithm has slow learning process

(Hussain et al., 2019)	DNN	MBGD, BGD and Momentum	DNN outperformed the compared algorithms.	limited to a single timestamp
(Tuli et al., 2019)	DNN	Single node and cloud data center	DNN proved to be accurate in prediction than the compared methods	Does not receive input directly from sensors
(Ishakian et al., 2018)	DNN		DNN tasks can be suitably run in severless platform	Delay at cold start might skew latency and affect SLA

5.4 Recurrent Neural Network – Long short term memory

Table 7 present the summary of the applications of LSTM in emerging cloud computing architecture. The application of LSTM in solving different emerging cloud computing problems has been found in many researches and discussed as follows:

5.4.1 Long short term memory in edge computing

The work of (Jian, Chen, Ping, & Zhang, 2019) proposed edge computing based scheduling algorithm using LSTM and improved chaotic bat swarm optimization (LSTM-ICBS). The platform uses multiple number of edge servers arranged in hierarchy receiving scheduling tasks from edge devices via a wireless connection. Tasks are moved to the cloud when capacity of the edge devices is exceeded. The improved chaotic bat swarm optimization (ICBS) is used to generate data from large number of tasks. The LSTM is applied for scheduling prediction. The LSTM-ICBS result outperformed genetic algorithm (GA), bat algorithm (BA), and quantum-behaved particle swarm optimization (QPSO). However, prediction was observed to be inaccurate for tasks with very small length. Fan et al. (2019) proposed RNN for prediction in edge computing environment. Multiple IoT sensors continuous to produce data from various IoT devices running time series applications concurrently. Attached edge devices receive and process the time series data before sending it to upper layer for further processing. The RNN extracts features from raw data and performs real time monitoring and time series prediction. Particularly, LSTM encoder-decoder networks were employed to predict future time series. Experiment results proved that RNN outperforms the compared baseline methods: LSTM, Vector Autoregression VAR autoregressive integrated moving average (ARIMA), Seq2Seq, attention RNN. However, there is challenge of vanishing gradient for RNN and RNN requires much bandwidth.

Similarly, (Jianguo Chen, Li, Deng, Li, & Yu, 2019) proposed deep learning algorithm in edge computing for distributed intelligent video surveillance. The environment consists of a 2-level edge nodes with 200 monitoring terminals placed at the meeting points of 30 streets, 35 edge servers and a cloud server. Connection between monitoring terminals and the edge nodes is achieved via a high speed Gigabit network. The study employs ConvNet and LSTM on every edge node to conduct varying analysis concurrently. In traffic monitoring, ConvNet was applied to extract features of vehicles from videos and make classification. The LSTM is used for traffic flow prediction. Dynamic data migration technique was also integrated in the algorithm to maximize load balancing. Experiment proved LSTM and ConvNet to be efficient in performing surveillance. However, the algorithm consumes large memory and bandwidth. G. Liu et al. (2019) proposed an LSTM for channel prediction in connected vehicles in edge computing platform. The LSTM learns from past channel information and uses the knowledge to predict future channel information. Channel prediction is important to achieve high reliability and low latency in vehicle to vehicle (V2V) communication. The LSTM performance was compared with ARIMA and support vector regression (SVR). It was found that the LSTM performs better than the compared algorithms. However, the algorithm only handles short term dependencies.

5.4.2 Long short term memory in fog computing

The applications of the LSTM in FC is presented in this sub-section, for example, (Priyadarshini & Barik, 2019) proposed a LSTM based distributed denial of service attack detection algorithm in fog environment. Their platform consists of a Cent OS7 cloud server with the fog layer having few virtual machines with an Apache server SDN. Multiple attacker and legitimate virtual machines running windows and Linux OS form the application layer. The LSTM was employed because it is powerful in managing time dependent and sequential data. The LSTM is employed in fog server to detect and forward valid packets to the cloud server. Suspicious packets are prevented from reaching the cloud which protects the entire fog environment from malicious attack. Comparison with Stacked Auto Encoder Detection (SAED) and LSTM-1 proved the proposed LSTM is superior. However, large memory is consumed by the LSTM.

Table 7: Summary of recurrent neural network applications in emerging cloud architecture

Reference	Deep learning structure	Algorithm compared	Results	Limitations
(Priyadarshini & Barik, 2019)	LSTM	SAED and LSTM-1	The LSTM is better than the SAED and LSTM	Not memory efficient
(Fan et al., 2019)	RNN	LSTM, VAR, Seq2Seq, ARIMA, Attention RNN	The RNN outperform the compared algorithms	Requires much bandwidth
(Jian et al., 2019)	LSTM-ICBS	GA, BA, QPSO	The LSTM-ICBS outperformed the compared algorithms	Low accuracy is observed for tasks with very small length
(Jianguo Chen et al., 2019)	LSTM	Not compared	The LSTM is efficient in video surveillance	high memory and bandwidth requirement
(G. Liu et al., 2019)	LSTM	ARIMA and SVR	LSTM outperformed the ARIMA and SVR	Limited to handling short term dependencies

5.5 Deep Belief Network algorithms

This section presents the application of DBN in MEC. Table 8 present the summary of the study. The work of (Y. Chen, Zhang, Maharjan, Alam, & Wu, 2019) proposed a DBN for securing MEC environment in cyber physical transportation systems. The platform allows large number of MEC devices to communicate via a wireless communication mode The system learns attack features to detect eavesdropping and jamming attacks. The DBN learns attack features without resorting to manual labelling of the data required for the process of training.

The DBN algorithm was found to have the best performance compared with Support Vector Machine (SVM), Softmax Regression (SR), Decision Tree (DT), and Random Forest (RF). However, it is still weak in managing streaming data.

Table 8: Summary of the study on DBN in MEC

Reference	Deep learning structure	Algorithm compared	Results	Limitations
(Y. Chen et al., 2019)	DBN	SVM, SR, DT and RF	DBN outperformed the compared algorithms	Weak in managing streaming data

5.6 The summary of adopting deep learning algorithms in emerging cloud computing architectures

The summary of adopted deep learning algorithms in emerging cloud computing architectures discussed in section 5.1 – 5.5 is presented in Table 9. Table 9 has two columns, the first column is the emerging cloud computing architectures and the second column is the deep learning algorithm column with five sub-columns each representing the type of deep learning algorithm found to be applied in a particular emerging cloud computing architecture. Each cell in Table 9 has the references that applied a particular deep learning architecture in the emerging cloud computing architectures. Table 9 clearly indicated the references showing a particular deep learning algorithm applications and those emerging cloud computing architectures that received less or no applications of deep learning algorithm. The cells showing nil, means that the corresponding deep learning architecture has not being applied in the corresponding emerging cloud computing architecture. This summary can clearly reveal to researchers where exploration or more extensive studies on the application of deep learning in emerging cloud computing architecture is required. As indicated, VC and SC received less attention in terms of the application of deep learning algorithms to solve problem in the two emerging cloud architectures, it is clearly indicated by the last two rows. The last column shows that the DBN received less attention in the emerging cloud computing architectures.

Table 9: Summary of references with respect to the deep learning and emerging cloud computing architectures

Emerging Cloud Architecture	Deep Learning Algorithm				
	Convolutional Neural Network	Deep Reinforcement Learning	Deep Neural Network	Recurrent Neural Network	Deep Belief Network
Edge Computing	(Li-pang Huang et al., 2018), (C. Liu et al., 2017), (Azimi et al., 2018), (Hossain et al., 2018), (Yan et al., 2019), (Pang et al., 2019), (Nikouei et al., 2018), (B. Yang et al., 2018), (Sankar et al., 2019)	(C. Zhang & Zheng, 2019), (Qi et al., 2019), (Q. Zhang et al., 2018), (W. Li et al., 2019)	Nil	(Fan et al., 2019), (Jian et al., 2019), (Jianguo Chen et al., 2019), (G. Liu et al., 2019)	Nil

Mobile Edge Computing	(P. Zhang et al., 2019), (Blanco-filgueira et al., 2019)	(T. Yang et al., 2018), (Liang Huang et al., 2019), (Ning et al., 2019), (K. Zhang et al., 2019)	(Hussain et al., 2019)	Nil	(Y. Chen et al., 2019)
Fog Computing	(L. Li et al., 2018), (Tuli, Basumatary, & Buyya, 2019), (Wang et al., 2019)	(H. Li et al., 2019)	(Tuli, Basumatary, Gill, et al., 2019) (Diro & Chilamkurti, 2017)	(Priyadarshini & Barik, 2019)	Nil
Volunteer Computing	(Kijsipongse et al., 2018)	Nil	Nil	Nil	Nil
Serverless Computing	Nil	Nil	(Ishakian et al., 2018)	Nil	Nil

6. The domain of deep learning applications in the emerging cloud domain of applications

Question: In what domains have deep learning been applied to solve problems in emerging cloud computing architectures?

The application of deep learning in emerging cloud computing has been found in different domains from agriculture, health, resource management, transportation, waste management, sentiment analysis, object detection, cyber security, etc. Figure 14 shows a taxonomy of the different application domains and subdomains, for example in the domain of agriculture, the application of deep learning algorithms was found in food and fruit sub-domains. In health domain, research was found to apply deep learning for prediction of heart disease. In cybersecurity, different researchers worked on anomaly detection, eaves dropping and jamming, privacy, parallel attack detection, distributed denial of service and surveillance. In transportation domain, researchers have focused on traffic flow prediction, traffic flow monitoring, passenger counting, etc. As research goes on in the field, many more domains and subdomains will be explored. This have shown that an integration of deep learning with emerging cloud computing paradigms has high significance in technological advancement.

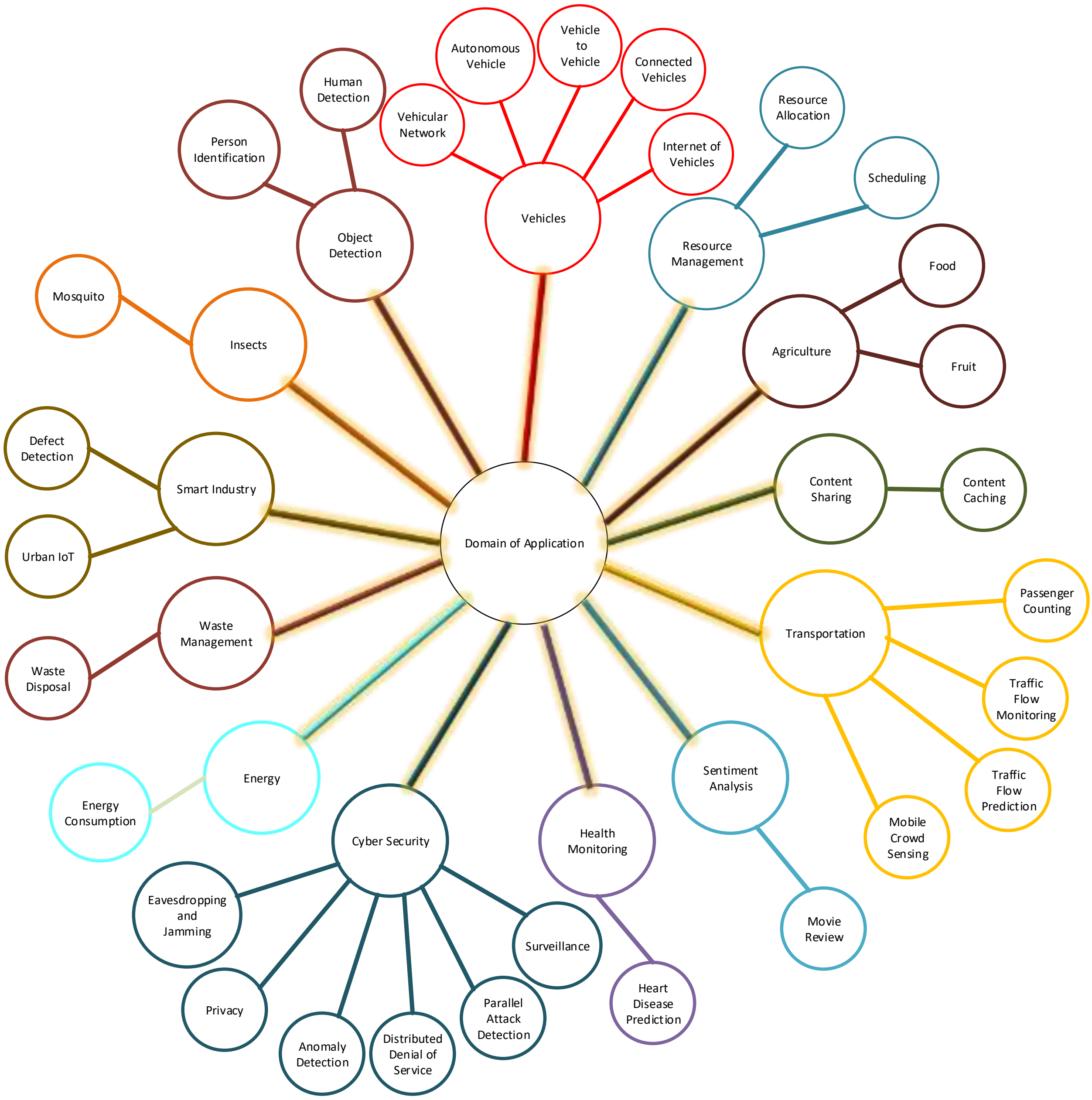

Figure 14: The taxonomy of the domains of deep learning applications in emerging cloud architecture

7. Emerging cloud computing architecture datasets

Question: What are the sources of data for emerging cloud computing architectures?

The purpose of this section is to provide sources of datasets collected for deep learning in emerging cloud computing architecture. This can help researchers especially new researchers with the sources of dataset to start a research in this area. For the expert researchers, more sources will be revealed for a novel application. Table 10 presents summary of the datasets used by different researchers. The sources of the datasets are presented. The study has shown that some of the datasets are real datasets collected by the researchers for the purpose of the research for example, (Zhang et al., 2019) used real street images collected at different locations. Other researchers used benchmark dataset for example, (C. Liu et al., 2017) used the existing UEC dataset provided by the DeepFoodCam project. For the datasets that are freely available online or accessible online, the links are provided for easy access. Only projects that revealed source of dataset are presented in Table 10. Projects that didn’t revealed source of dataset are not included.

Table 10: Summary of dataset from different projects that apply deep learning in emerging cloud computing architecture

Reference	**Source**	**Data collection**
(Zhang et al., 2019)	https://pan.baidu.com/s/1aVQ8lLA4AmRBF1Sga_etWg	Real street image data set
(Huang et al., 2018)	Prof. Kun-Ta Chuang [online: https://cv_ktchuang.cannerapp. com/	Wild mosquitoes using SMZ
(C. Liu et al., 2017)	UEC-256/UEC-100 and Food-101	Food images
(Pang et al., 2019)	CUHK03 (http://www.ee.cuhk.edu.hk/~xgwang/CUHK_identification.htm) and Market-1501 http://www.diaochapai.com/survey/a61751ca-4210-4df1-a5bb-1e7a71b5262b	People’s images captured by different surveillance cameras
(Nikouei et al., 2018)	ImageNet (http://image-net.org) and VOC07 (http://host.robots.ox.ac.uk/pascal/VOC/voc2007/)- footage from an online open source videos	Surveillance videos
(T. Yang et al., 2018)	Not specified	MEC node
(L. Li et al., 2018)	Not specified	Manually captured images
(Diro & Chilamkurti, 2017)	NSL-KDD data set http://nsl.cs.unb.ca/KDD/NSL-KDD.html	Intrusion detection data
(Ning et al., 2019)	Real world traces of taxies collected in April 2015	Traces of taxies
(Tuli, Basumatary, Gill, et al., 2019)	Cleveland database http://archive.ics.uci.edu/ml	Heart patients data
(Azimi et al., 2018)	MIT Arrhythmia database https://www.physionet.org/physiobank/database/mitdb/	ECG recordings
(Hossain et al., 2018)	Images from google search engine	Date fruit images
(Priyadarshini & Barik, 2019)	CTU-13 Botnet and ISCX 2012 IDS	Features of attacks
(Tuli, Basumatary, & Buyya, 2019)	https://pjreddie.com/projects/pascal-voc-dataset-mirror/ http://cocodataset.org/#home	Images
(Blanco-filgueira et al., 2019)	dETRUSC video dataset https://citius:usc:es/ investigacion/datasets/detrusc	videos
(Yan et al., 2019)	MNIST https://storage.googleapis.com/cvdf-datasets/mnist/ CIFAR-10 http://www.cs.toronto.edu/~kriz/cifar.html]	Handwritten digits and images

(K. Zhang et al., 2019)	1.4 billion of above 14000 traces of taxis by GPS http://www.pkbigdata.com/common/zhzgbCmptDataDetails.html	Traces of taxis
(Q. Zhang et al., 2018)	MiBench task set hTp://www.eecs.umich.edu/mibench/	Tasks
(Hussain et al., 2019)	CDR dataset generated at LTE-A CN https://dandelion.eu/datagems/SpazioDati/telecomsms-call-internet-mi/description/	Subscriber activity record
(Fan et al., 2019)	Building Occupancy Data https://eif-wiki.feit.uts.edu.au/ National Electricity Market Data http://www.aemo.com.au/ Traffic Volume Data. http://www.rms.nsw.gov.au/	Urban sensory data
(B. Yang et al., 2018)	WorldExpo'10 dataset http://www.ee.cuhk.edu.hk/∼xgwang/expo.html ShanghaiTech dataset https://github.com/desenzhou/ShanghaiTechDataset Bus dataset	Images and Videos
(H. Li et al., 2019)	CRAWDAD https://crawdad.org/mit/reality/20050701	Activities of mobile devices
(Jianguo Chen et al., 2019)	7-days traffic monitoring videos collected from different terminals	Traffic videos
(W. Li et al., 2019)	Xender mobile App	1month Xender's trace
(Sankar et al., 2019)	Internet Movie Database (IMDB) http://ai.stanford.edu/~amaas/data/sentiment/	Internet Movie

8. Deep learning framework and libraries as well as system configurations

Different project used different deep learning frameworks, libraries and system configuration for implementing deep learning in emerging cloud computing architectures. The system configuration from different projects is presented in Table 11. Only the projects that provide system configuration are presented in Table 11 to show the different type of the hardware used to serve as benchmark to researchers in similar study in the future.

Table 11: summary of system configuration for implementing the application of deep learning in emerging cloud computing

Reference	System configuration
(Zhang et al., 2019)	Intel Core i5-7500 CPU 16G RAM, Ubuntu16.04. NVIDIA GeForce GTX 1050ti GPU and 4GB memory
(Huang et al., 2018)	Raspberry pi, CPU Intel i7-8700k ,GPU NVDIA GTX 1080Ti
(C. Liu et al., 2017)	Quad-core 2.5 GHz Krait 400 and an Adreno 330 GPU. 64 GB of internal storage,3 GB of RAM. For back-end, GPU SuperMicron server 4027GR-TR with two Intel Xeon processor E5-2600, 512GB RAM and 4 NVIDIA Tesla K40 GPU.
(Pang et al., 2019)	NVIDIA GTX1080Ti GPUs
(Nikouei et al., 2018)	Raspberry PI 3 Model B with ARMv7 1.2 GHz processor and 1 GB of RAM

(T. Yang et al., 2018)	3-core-CPU
(Liang Huang et al., 2019)	CPU rate at 10 x10^9 cycle/s.
(Tuli, Basumatary, Gill, et al., 2019)	Dell XPS 13, Intel(R) Core(TM) i5-7200 2.50GHZ, 8.00 GB DDR4 RAM, Raspberry Pi 3B+, ARM Cortex-A53 quad-core SoC CPU 1.4 GHz, 1GB LPDDR2 SDRAM 1vCPU, 1GB RAM, 2GB SSD
(Tuli, Basumatary, & Buyya, 2019)	DELL XPS13 Inte® Core™ i5-7200 2.50GHz, 8.00 GB DDR4 RAM, Dell 5490, Intel® Core™ i7-8650U 1.9GHz, 16.00 GB DDR4 RAM, 1vCPU, 1GB RAM, 2GB SSD
(Blanco-filgueira et al., 2019)	NVIDIA Jetson TX2
(K. Zhang et al., 2019)	On RSUs taken randomly at range100-200 units. 20MHz and q_v @10MHz.
(Kijsipongse et al., 2018)	2-node cluster grid computer each with 1 CPU core, 8G memory, and NVIDIA GPU. 8 volunteer nodes with 3 desktops, 4 notebooks, 1 GPU server.
(Hussain et al., 2019)	PC- i7-7700T CPU, 16GB RAM
(B. Yang et al., 2018)	Desktop with NVIDIA 1080, Caffe with cudnn 10.0
(H. Li et al., 2019)	Workstation computer with Intel Core™ i7, 16GB memory, 128GB SSD, 2TB hard disk. Server with Intel Core™ i7 7700 @ 4.2GHz, 32GB, 256GB SSD, 3TB HDD and NVIDIA Geforce GTX 1080
(Jian et al., 2019)	Intel Core i5-7500 CPU, 8GB memory
(Jianguo Chen et al., 2019)	Intel Core i5-6400 quad-core CPU, 6GB DRAM, 32GB main memory. EX six-core CPU, 64GB main memory, 8GB DRAM
(Sankar et al., 2019)	Server with Intel Xeon E5-2630, 2.60GHz CPU, 10GB RAM, Nvidia GeForce GTX 1050Ti, 789 cores GPU, Smart phone with 3 GB memory, Octa-Core 2.0GHz, 64-bit Qualcomm Snapdragon 625 processor, Adreno 506 GPU
(Wang et al., 2019)	Server with 4 NVIDIA Telsa P100 GPU Telsa K80 GPU, 12G memory

From the perspective of the deep learning framework and library, most researchers used Caffe, Keras, and TensorFlow as shown in Figure 15. In some cases, implementation frameworks have not been stated in the project. Therefore, we didn't include those projects in analysing the deep learning frameworks and library. The main platforms used are briefly explained as follows (Hatcher & Yu, 2018; G. Nguyen et al., 2020): ***TensorFlow:*** Developed by google as an open source framework to support large scale distributed training and inferencing. It performs computation using data flow graphs. Graph nodes represent operations while the graph edges represent the multidimensional data arrays. It interfaces with Pyhton, Go, C++ and Java. ***Caffe:*** C++ and CUDA framework developed by Berkeley Artificial Intelligence and Berkeley Vision and Learning Centre to support image classification. It has a data layer that accepts input and other layers that perform processing. It interfaces with python and MATLAB. It's a suitable framework for classification with ConvNet.

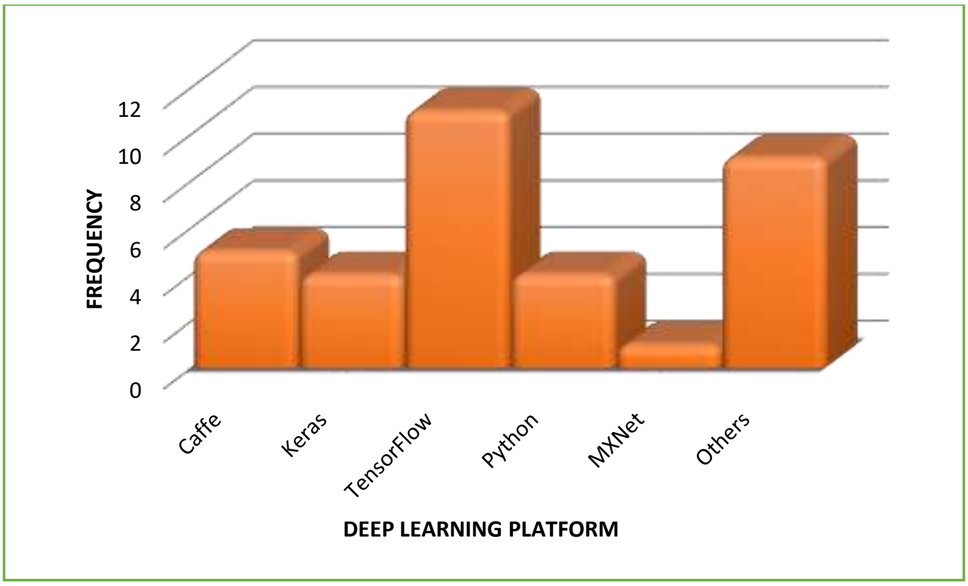

Figure 15: Frequency of deep learning platforms extracted from different projects

Keras: A python wrapper with user-friendly and extensible interface to support easy experimentation on deep learning models. It functions on CPUs and GPUs, it has high support for ConvNet and RNN. An analysis of the deep learning frameworks and libraries is presented in Figure 15.

9. Discussion and analysis of the research area

Question: To what extent has deep learning been applied in emerging cloud computing architectures?

The survey has indicated that the new generation ANN that is deep learning begins to penetrate the emerging cloud computing architecture for data analytics. The deep learning was found to solve clustering, classification and prediction problems in emerging cloud computing architecture. The deep learning achieved successful results from different projects. The analysis capture the trend of publication, frequency of deep learning algorithms deployment, and the emerging cloud computing architectures.

From the review conducted, we can say that research in this area began only early 2017 with little attention. The field started gaining attention in 2017 with rise in 2018 and much increase in 2019. The publication trend as depicted on Figure 16 shows that the least number of articles was recorded in 2017. The publication rises through 2018 to 2019, with 2019 recording the highest number of publications. With this, it can be concluded that the synergy between the research domain is still at its infant stage and it is gaining high interest from the research community.

Figure 16: Trend of publications on the applications of deep learning in emerging cloud computing architecture

From the perspective of the emerging cloud computing architectures, most researchers have given attention to the application of deep learning in edge computing, FC and MEC. The least explored areas include VC and the SC while SDC remain unexploited. Figure 17 presents the trend of deep learning applications in emerging cloud computing architecture. The highly explored area is edge computing gaining 47%, followed by FC with 24%, then MEC having 23%. VC and SC are the least with just 3% each. So far, no article has been found on the application of deep learning in SDC. Though, is not surprising because it is a new concept but it is expected in the future to have deep learning application.

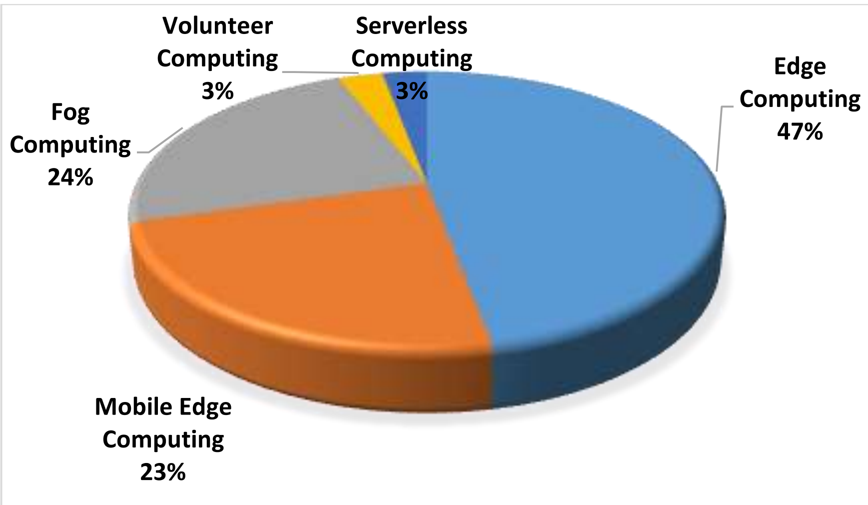

Figure 17: Trend in Emerging Cloud

Looking at the deep learning trend shown in Figure 18, ConvNet is the most applied deep learning algorithm in emerging cloud computing as at the time of conducting this literature survey, possibly because most of the works are on image/video classification.

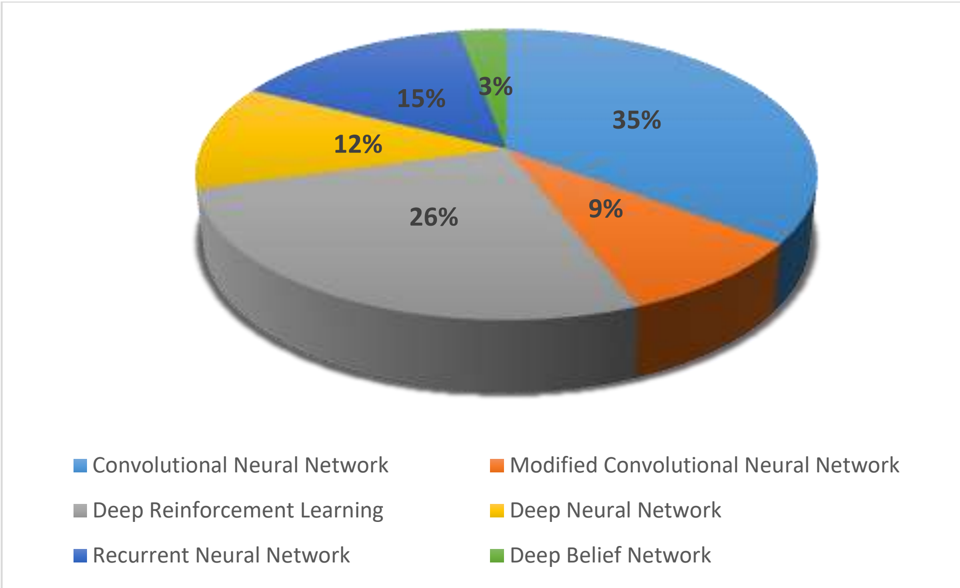

Figure 18: The percentage of applying deep learning algorithm in emerging cloud computing architecture

The ConvNet is well known to be suitable for image/video processing. The DRL is the second most applied algorithm in emerging cloud computing architecture followed by RNN, DNN, modified version of the ConvNet, and lastly DBN as the least applied deep learning algorithm in emerging cloud computing architecture.

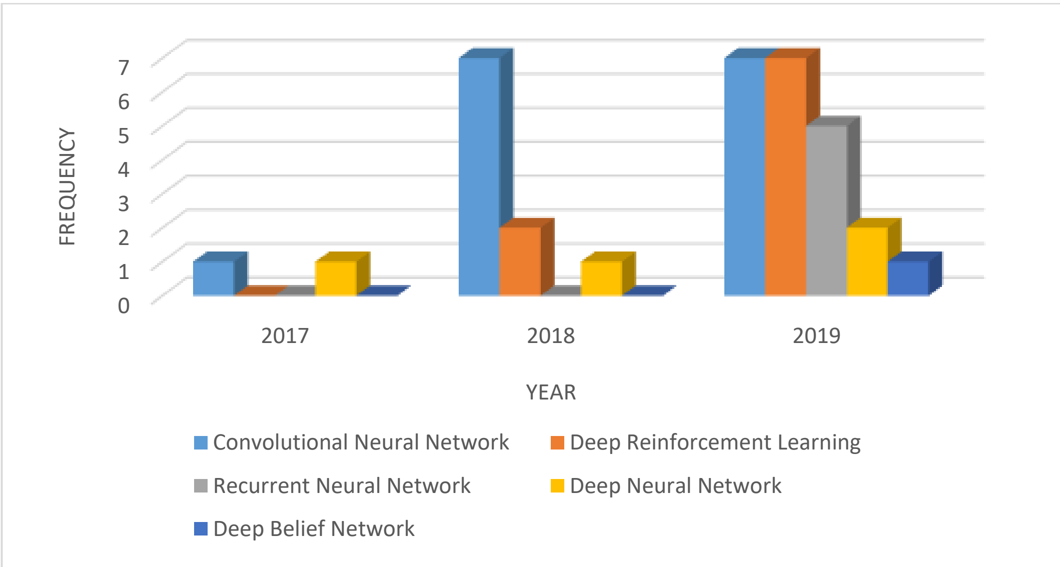

Figure 19: The frequency of deep learning algorithm in emerging cloud architecture per year

Figure 19 shows the visualization of the deep learning algorithm applications in emerging cloud computing architecture per year. In 2017, 2018 and 2019 it shows that the ConvNet has been active more than any other deep learning architecture except in 2017 where the number of applications of ConvNet in emerging cloud computing architecture is the same with other architectures. The DBN, DRL, and RNN were not utilised in 2017. In 2018, RNN and DBN were not utilized. However, DRL got the same number of applications with ConvNet in 2019. As the interest continues to grow, DBN and RNN started gaining attention in 2019 and may likely continue into the future in view of the fact that they have a lot of potential for applications in the emerging cloud computing architecture.

10. Challenges and new perspective for future research direction

Question: What challenges are yet to be explored by researchers in the research area?

The adoption of deep learning in emerging cloud computing architectures has brought a lot of benefits. Given the attention attracted by the extensiveness of the research area, there are unresolved challenges. The challenges are discussed and future research directions with new perspective are outlined to facilitate future development of the research area:

10.1 Multi-objective optimization problem in the emerging cloud computing architectures

When executing deep learning models on edge devices, trade-offs need to be made between latency, accuracy and battery life (Jiasi Chen & Ran, 2019). Some applications focused on accuracy leading to high latency and low battery life. Others focused on latency at the stake of accuracy. In both cases, QoE is negatively affected. Device users would prefer to have high accuracy at low latency and maximized battery lifespan. This leads to multi-objective optimization problem. Research by (Jian et al., 2019) have shown that meta-heuristic algorithms can be incorporated with deep learning to achieve multiple objectives. Therefore, we suggest researchers to propose a novel deep learning models that can solve the multi-objective optimization problems in emerging cloud computing architectures.

10.2 Advance deep learning: Transfer learning and multi-task learning

Deep learning requires large dataset for effective performance. In a situation where the available dataset is not large enough, applications may not benefit from deep learning. It has been uncovered from the survey that the application of transfer learning and multi-task learning for deep learning in emerging cloud computing architectures remained unexploited. The transfer learning for deep learning model developed for solving problem in emerging cloud computing architecture can be re-used for another task within the emerging cloud computing architecture especially in a situation where there is no sufficient data in the second task. With multitask learning for deep learning, multiple task can be done in the emerging cloud computing architecture, the concept of multitasking learning has the ability to drastically reduce the amount of data required for modelling the deep learning algorithms. In the domain where there is no voluminous data, the concept of transfer learning and multi-tasking for deep learning can be applied to reduce the issue of lack of large data size. Therefore, we suggest researchers to apply the concept of transfer learning and multi-tasking learning in emerging cloud computing architectures. In addition, the deep learning needs to be modified in such a way that applications can leverage on deep learning regardless of the data size.

10.3 Hybrid and ensemble deep learning algorithm

As shown in Table 9 and Figures 18 – 19, the adoption of hybrid deep learning algorithm in emerging cloud computing architectures received less attention from the research community.

However, it is known that hybrid deep learning algorithms typically outperform individual deep learning algorithm because the limitations of both deep learning algorithms can be eliminated through the hybridization by capitalizing on the strengths of the constituent deep learning algorithms. In addition, ensemble deep learning algorithms remain unexploited in the emerging cloud computing architecture. It can be interesting to adopt the hybrid and ensemble deep learning algorithms to solve complex problems in emerging cloud computing architectures. We suggest researchers to explore the concept of hybrid and ensemble deep learning algorithms in emerging cloud computing architectures.

10.4 Optimization of deep learning algorithm through nature inspired meta-heuristic algorithm

The survey revealed that the deep learning algorithms mainly applied in the emerging cloud computing architectures relied on manual hyperparameter settings of the deep learning algorithms. The manual hyperparameetr settings is cumbersome, time consuming and lacks standard systematic process to arrive at the optimal hyperparameter values. Global optimization algorithms: cuckoo search algorithm, firefly, artificial bee colony, immune system, etc. should be considered in the future to optimize the hyperparameters of the deep learning algorithms for application in emerging cloud computing architectures. This is in view of the fact that evidence in (Chiroma, Ya'u, et al., 2019) proves that the deep learning algorithms optimized via global optimization algorithm outperform the conventional deep learning algorithms with hyperparameters optimised using manual approach.

10.5 Software defined computing remain unexploited with deep learning algorithms

The deep learning algorithms have not been explored in the SDC architecture as shown in the survey. This can be seen clearly in Table 9 and Figure 17. It will be interesting to adopt deep learning algorithms in SDC environment to solve machine learning problems such as the classification, clustering and prediction for efficient resource management, scheduling, security and reliability. We suggest the research community to propose novel applications of deep learning in the SDC.

10.6 Marketplace in the emerging cloud computing architectures is complex

Competition in the cloud computing marketplace prompt the consideration of CPUs, storage and communication for billing a customer. Therefore, pricing will depend on the number of virtual CPUs and the memory allocated to the virtual CPU. As a result of that, the emerging distributed cloud computing architecture require complex marketplace and it remains as an open research issue (Varghese & Buyya, 2018). We suggest the development of deep learning based context aware recommender system that takes complexity of the distributed cloud computing architectures marketplace into consideration.

10.7 Energy Consumption as a result of frequent running of deep learning models

The edge devices are powered by batteries. The numerous computations performed by such devices lead to high energy consumption which in turn result in low battery lifespan. Deep learning algorithms when executed frequently could lead to high energy consumption on the devices. Cloud data center could also experience high energy consumption when deep learning algorithms are executed on the servers. Although hardware manufacturers are now focusing on producing low energy consuming devices. It is essential to device techniques that will minimize energy consumption by reducing the need for frequent execution of deep learning models. A theoretical study on reducing energy consumption while running computational algorithms on big data is provided in (Chiroma, Abdullahi, et al., 2019).

10.8 Latency issue

Most of the reviewed works focus on reducing latency. However, the issue of latency has not been solved to the maximum especially when deep learning applications are executed on resource constrained IoT devices. This can have a grave impact especially in the field of connected vehicles and health monitoring where little delay could cost lives. Researchers should focus on the improvement of deep learning computational time to make it suitable for application in resource constrained devices where convergence speed matters a lot.

10.9 Difficulty in selecting suitable deep learning algorithm

Different deep learning algorithms with their variants are in existence. Researchers/developers find it difficult to decide on the best deep learning algorithm to adopt in emerging cloud computing architectures for solving problem. This is because there is no defined deep learning model-hardware mapping. The developers are more interested in the computing capability of the servers and edge devices (Jiasi Chen & Ran, 2019). This could be a serious issue especially when deploying deep learning in volunteer computing in view of the fact that there is high heterogeneity as devices are donated by many volunteers. Since deep learning is becoming prominent in emerging cloud computing architectures, there is need for an insight on performance of various deep learning models on heterogeneous hardware. This can ease the selection of the most suitable deep learning algorithm for a specific problem in emerging cloud computing architectures.

10.10 More extensive research on deep learning in emerging cloud computing architectures is required

As this is an infant research area currently receiving attention from the research community. More extensive research on the adoption of deep learning is needed to fully understand the concept of the emerging cloud computing architecture for further development of the domain. Many deep learning algorithms remain unexploited in some of the emerging cloud computing architectures as shown in Table 9. In Table 9, nil is indicating a clear research gap requiring novel deep learning applications. Therefore, we suggest researchers to explore the research gap as identified in Table 9. There is the need for more synergy between the cloud computing research community and machine learning research community for development of the research area.

10.11 Lack of interpretation and transparency

Typically, deep learning lacks interpretation and transparency, the imaging feature that determine the output is not known (Belfiore et al., 2020). The deep learning architectures applied in the emerging cloud computing architectures lacks interpretability and transparency. The researchers that applied the deep learning in emerging cloud computing architectures ignore to make efforts in making the deep learning interpretable and transparent in it is application in emerging cloud computing architectures. Tan, Sim, & Gales (2015) reported that the deep learning architecture comprised of generic multiple number of layers that are nonlinear which makes the deep learning architecture to be powerful and flexible. Typically, the deep learning architecture model complex mapping function by means of learning from data. Therefore, the deep learning architectures are considered as “black box” and lacks interpretation which makes the deep learning model difficult to be modified at the post-training level. We suggest for researchers working in this domain to adopt explainable artificial intelligence in emerging cloud computing architecture to mitigate the issue of deep learning lack of interpretation and transparency.

10.12 Privacy and security issues

Data is the heart of deep learning operations, without data, deep learning algorithm becomes impotent. The running of deep learning algorithm in emerging cloud computing architecture to solve machine learning problems highly requires data. The data been generated from the emerging cloud computing architectures e.g. edge computing may contain information that could compromised the privacy and security of the users especially as the data is delivered to third party. In machine learning, data need to be delivered to third party for it is processing and analytics based on deep learning algorithm. J. Zhang et al. (2018) pointed out that as data is release to third party, the ownership and control become separated. Therefore, it can lead to data loss, privacy leakage, injection of information, data tempering, illegal operations e.g. publishing, dissemination & replication. The confidentiality, integrity and other security issues cannot be guaranteed. The data can have user data, location and personal identities information which are exclusively the privacy of the user. As such, both privacy and security of the users cannot be guaranteed. The best approach to ensure the security and privacy of data generated from the emerging cloud computing architecture for data analytics releases to third party for solving machine learning problems remain an open research problem. We suggest researchers to propose a new machine learning framework that can give users confidence in preserving their security and privacy and protect the data from misused by third party.

10.13 Sensitivity to parameter settings

The deep learning architectures are highly sensitive to hyper-parameter settings. Deep learning requires settings of a lot of hyper-parameters. For example, ConvNet requires the setting of the but not limited to the following hyper-parameters: number convolutional layers, kernel size, pooling size, activation function in each of the convolution layer, number of kernels, number of dense layers, number of neurons in each of the dense layer, weight regularization, dropout, batch size, learning rule and learning rate. The performance of the deep learning architecture is determined by the hyper-parameter settings. The emerging cloud computing architecture typically generate large scale data size, therefore, running the deep learning architecture on the data that increases on daily bases can increase the complexity of the deep learning model which can make the hyper-parameters settings difficult to be achieved. As argued in (Feurer & Hutter, 2019) that increasing the size of data, makes the optimization of the hyper-parameters difficult as the data increases because the complexity of the model increases. The best approach to realize optimum parameter settings for the deep learning architecture remains an open research problem. We suggest researchers to device new approaches that can make deep learning a hyper-parameter free algorithm.

11. Conclusions

An in-depth literature survey on the adoption of deep learning in emerging cloud computing architectures have been conducted. The concept of five major architectures including edge computing, FC, VC, SDC, and serverless computing have been discussed. Different deep learning algorithms were found to have been applied to solve various problems in emerging cloud computing architectures. The deep learning algorithm that generate a lot of interest as shown from the reviewed works is ConvNet, followed by DRL particularly DQN. The most explored emerging cloud computing architecture is the edge computing followed by FC. The least explored architectures are VC and serverless computing while SDC is yet to witness any adoption of deep learning to solve problem. From the trend of publication, we believe that the adoption of deep learning in emerging cloud computing is gaining very high interest and is expected to continue because of the growing trend and new opportunities for future research. Unresolved research challenges and new perspective for future research directions have been discussed to provide direction for solving the identified challenges. This review can help new researchers in the field as an initial reading material and benchmark for proposing a novel deep learning approach to solve problem in emerging cloud computing architecture by expert researchers.

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Curriculum Vitae of the Authors

Jemal H. Abbawajy

jemal.abawajy@deakin.edu.au

Jemal H. Abawajy is a Full Professor with the School of Information Technology, Faculty of Science, Engineering, and Built Environment, Deakin University, Australia. He is currently the Director of the Parallel and Distributing Computing Laboratory. He is a Senior Member of the IEEE Technical Committee on Scalable Computing, the IEEE Technical Committee on Dependable Computing and Fault Tolerance, and the IEEE Communication Society. His leadership is extensive, spanning industrial, academic, and professional areas. He has served on the Academic Board, Faculty Board, the IEEE Technical Committee on Scalable Computing Performance Track Coordinator, Research Integrity Advisory Group, Research Committee, Teaching and Learning Committee, and Expert of International Standing Grant and External Ph.D. Thesis Assessor. He has delivered over 50 keynote addresses, invited seminars, and media briefings and has been actively involved in the organization of over 200 national and international conferences in various capacity, including Chair, General Co-Chair, Vice-Chair, Best Paper Award Chair, Publication Chair, Session Chair, and Program Committee. He has also served on the editorial-board of numerous international journals and currently serving as an Associate Editor of the IEEE TRANSACTIONS ON CLOUD COMPUTING, International Journal of Big Data Intelligence, and International Journal of Parallel, Emergent and Distributed Systems. Prof. Abawajy has also guest edited many special issues. He is actively involved in funded research supervising large number of Ph.D. students, postdoctoral, research assistants, and visiting scholars in the area of cloud computing, big data, network and system security, decision support system, and e-healthcare. He is the author/co-author of five books, more than 300 papers in conferences, book chapters, and journals, such as the IEEE TRANSACTIONS ON COMPUTERS and the IEEE TRANSACTIONS ON FUZZY SYSTEMS. He also edited 10 conference volumes. Contact: jemal.abawajy@deakin.edu.au & bduuree@gmail.com.

Personal URL: https://www.deakin.edu.au/about-deakin/people/jemal-abawajy

List of publications

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DBLP: https://dblp.org/pers/hd/a/Abawajy:Jemal_H= with over 100 Journals, 7 Editorials, and over 100 conference proceedings.

Scopus: Over 320 documents: https://www.scopus.com/results/authorNamesList.uri?sort=count-f&src=al&sid=d97d65f502f88bc1b6d00181e6edb86f&sot=al&sdt=al&sl=43&s=AUTHLASTNAME%28Abbawajy%29+AND+AUTHFIRST%28Jemal%29&st1=Abbawajy&st2=Jemal&orcidId=&selectionPageSearch=anl&reselectAuthor=false&activeFlag=true&showDocument=false&resultsPerPage=20&offset=1&jtp=false&currentPage=1&previousSelectionCount=0&tooManySelections=false&previousResultCount=0&authSubject=LFSC&authSubject=HLSC&authSubject=PHSC&authSubject=SOSC&exactAuthorSearch=false&showFullList=false&authorPreferredName=&origin=searchauthorfreelookup&affiliationId=&txGid=7b8f8507c547c35ac8cf8b70fb5d36c8

Haruna Chiroma

Haruna Chiroma received B.Tech., M.Sc., and Ph.D. in computer science from Abubakar Tafawa Balewa University, Bayero University Kano and University of Malaya, respectively. He is an a*ssociate editor* – IEEE Access, Q1, Impact Factor 4.09, USA – (ISI WoS/Scopus Indexed), a*ssociate Editor* – Telecommunication, Computing, Electronic and Control Journal (TELKOMNIKA), Indonesia – (Scopus Indexed), Editorial board member – Recent advances in Computer Science and Communications, (Scopus Indexed). *Editor - Edited Book* "*Advances on Computational Intelligence in Energy- The Applications of Nature-Inspired & Metaheuristic Algorithms in Energy*" (Scopus indexed) by *Springer Berlin Heidelberg*. His research interest includes: machine learning with emphasis on deep learning, nature inspired algorithms and their applications in internet of vehicles, self-driving vehicles, big data analytics, emerging cloud computing architecture, fake news and IoT. Also, as a teacher he has a special interest in technology enhanced learning. He has published over 100 academic articles relevant to his research interest in different venues including ISI WoS/Scopus indexed journals with impact factor including but not limited to Supercomputing (*Springer*), Applied Soft Computing (*Elsevier*), PLoS ONE, International Journal of Information Management (*Elsevier*), Applied Energy (*Elsevier*), Neural Computing and Applications (*Springer*) and IEEE Access. He is an invited reviewer for 18 ISI WoS indexed journals such as Applied Soft Computing (*Elsevier*), PLoS ONE, Applied Energy (*Elsevier*), Knowledge-Based System (*Elsevier*), Journal of the Operational Research Society (*Springer*), International Journal of Bio-inspired Computation (*Inderscience*), Neural Computing and Applications (*Springer*), etc. He has been a technical programme committee member for more than 20 international conferences, workshops and symposium. He was invited by QS world universities ranking in 2017, 2018 & 2019 to evaluate research strength of universities in computer science. Presently, chiroma is supervising 7 M.Sc. students and 2 Ph.Ds., He graduated 3 M.Sc. students. Chiroma is a visiting senior lecturer at Abubakar Tafawa Balewa University, Bauchi, Nigeria, Senior research associate at the University of Johannesburg, South Africa and a senior lecturer at the Federal College of Education (Technical), Gombe, Nigeria. Contacts: chiromaharun@fcetgombe.edu.ng; freedonchi@yahoo.com; freedonchi@gmail.com; +2347065393385; Skype: haruna.chiroma. URL: orcid.org/0000-0003-3446-4316.

List of selected publications

EDITORIAL

Associate Editor – IEEE Access, Q1, Impact Factor 4.09 – (ISI WoS/Scopus Indexed)
URL: http://ieeeaccess.ieee.org/editorial-leadership-and-staff/associate-editors/
2018 - date

Associate Editor – Telecommunication, Computing, Electronic and Control Journal TELKOMNIKA – (**Scopus Indexed**)
URL: http://www.journal.uad.ac.id/index.php/TELKOMNIKA/about/editorialTeam
2017 – date

Editorial Board Member – Recent advances in Computer Science and communications – (**Scopus Indexed**)
URL: https://benthamscience.com/journals/recent-patents-on-computer-science/editorial-board/
2019 – date

Editor - *Edited Book "Advances on Computational Intelligence in Energy- The Applications of Nature-Inspired & Metaheuristic Algorithms in Energy" (**Scopus indexed**) by Springer Berlin Heidelberg.*
URL: http://www.springer.com/us/book/9783319698885

Editor - Edited Book "Machine learning and data mining for emerging trend in cyber dynamic" *(**to be submitted to Web of Science and Scopus for indexing)** by Springer Berlin Heidelberg*. Ongoing project

RECENT SELECTED PUBLICATIONS

International Journals

ISI Web of Science Indexed Journals with Impact Factor

Chiroma, H., Herawan, T., Fister Jr, I., Fister, I., Abdulkareem, S., Shuib, L., ... & Abubakar, A. (2017). Bio-inspired computation: Recent development on the modifications of the cuckoo search algorithm. *Applied Soft Computing*, *61*, 149-173., (*ISI/SCOPUS Cited Publication*), **Impact factor = 3.541, USA, Q1.**

Chiroma, H., Gital, A. Y. U., Rana, N., Shafi'i, M. A., Muhammad, A. N., Umar, A. Y., & Abubakar, A. I. (2019). Nature Inspired Meta-heuristic Algorithms for Deep Learning: Recent Progress and Novel Perspective. In *Science and Information Conference* (pp. 59-70). Springer, Cham. (*ISI/SCOPUS Cited Publication*).

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Al-garadi, M. A., Hussain, M. R., Khan, N., Murtaza, G., Nweke, H. F., Ali, I., **Chiroma, H.** ... & Gani, A. (2019). Predicting Cyberbullying on Social Media in the Big Data Era Using Machine Learning Algorithms: Review of Literature and Open Challenges. *IEEE Access*. (*ISI/SCOPUS Cited Publication*), Impact Factor = 4.09, Q1.

Ibrahim, T. M., Alarood, A. A., **Chiroma, H.**, Al-garadi, M. A., Rana, N., Muhammad, A. N., ... & Gabralla, L. A. (2019). Recent Advances in Mobile Touch Screen Security Authentication Methods: A Systematic Literature Review. *Computers & Security*. (*ISI/SCOPUS Cited Publication*), Impact Factor = 3.06, Q1.

IAT Hashem, NB Anuar, M Marjani, E Ahmed, **H Chiroma**, A Firdaus, et al. (2018). MapReduce scheduling algorithms: a review. The Journal of Supercomputing, 1-31. doi.org/10.1007/s11227-018-2719-5. (*ISI/SCOPUS Cited Publication*), Impact Factor = 1.532, Q2.

Chiroma, H., Abdullahi, U. A., AlArood, A. A., Gabralla, L. A., Rana, N., Shuib, L., ... & Herawan, T. (2018). Progress on Artificial Neural Networks for Big Data Analytics: A Survey. *IEEE Access*. **DOI:** 10.1109/ACCESS.2018.2880694. (*ISI/SCOPUS Cited Publication*), Impact factor = 3.55, Q1.

Chiroma, H., Khan, A., Abubakar, A., Saadi Y., Hamza FM, Shuib L, Gital, AY., Herawan, T. (2016). A New Approach for Forecasting OPEC Petroleum Consumption

Based on Neural Network Train by using Flower Pollination Algorithm. *Applied Soft Computing,48:50-58*, (*ISI/SCOPUS Cited Publication*), **Impact factor = 2.81, USA, Q1**

Mukhtar Fatihu Hamza, Hwa Jen Yap, Imtiaz Ahmed Choudhury, **Haruna Chiroma**, Tufan Kumbasar (2017). A survey on advancement of hybrid type 2 fuzzy sliding mode control. *Neural Computing and Applications, Accepted for publication* (*ISI/SCOPUS Cited Publication*) **Impact factor = 2.505, USA, Q1.**

Danjuma, S., Herawan, T., Ismail, M. A., **Chiroma, H.**, Abubakar, A. I., & Zeki, A. M. (2017). A review on soft set-based parameter reduction and decision making. *IEEE Access*, *5*, 4671-4689. (*ISI/SCOPUS Cited Publication*), **Impact factor = 1.27, USA, Q2**

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Latiff, M. S. A., **Chiroma, H.,** Osho, O., Abdul-Salaam, G., Bakar, A. A., & Herawan, T. (2017). A Review on Mobile SMS Spam Filtering Techniques. *IEEE Access*. (*ISI/SCOPUS Cited Publication*), **Impact factor = 1.27, USA, Q2**

Chiroma, H., Shuib, N. L. M., Abubakar, A., Zeki, A., Gital, A., Herawan, T., & Abawajy, J. (2017). Advances in Teaching and Learning on Facebook in Higher Institutions. *IEEE Access*. (*ISI/SCOPUS Cited Publication*), **Impact factor = 1.27, USA, Q2**

Hashem, IAT., Chang, V., Anuar, NB, Adewole, K., Yaqoob, I., Gani, A., Ahmed, E., **Chiroma, H.** (2016). The Role of Big Data in Smart city. *International Journal of Information Management.* 36(5): 748-758 (*ISI/SCOPUS Cited Publication*), **Impact Factor = 1.5, England, Q1**

Zeki, A., Abubakar, A., & **Chiroma, H.** (2016). An intermediate significant bit (ISB) watermarking technique using neural networks. *SpringerPlus*, *5*(1), 1-25. (*ISI/SCOPUS Cited Publication*), **Impact Factor = 0.9, Germany, Q2**

Nawi, N. M., Rehman, M. Z., Khan, A., Kiyani, A., **Chiroma, H.,** & Herawan, T. (2016). Hybrid Bat and Levenberg-Marquardt Algorithms for Artificial Neural Networks Learning. *Journal of Information Science and Engineering*, *32*(5), 1301-1324. (*ISI/SCOPUS Cited Publication*), **Impact Factor = 0.41, Taiwan, Q4**

Chiroma H, Abdul-kereem S, Shukri AMN, Abubakar AI, Safa NS, Shuib L, Chiroma, H., Abdul-kareem, S., Shukri Mohd Noor, A., Abubakar, A. I., Sohrabi Safa, N., Shuib, L., Hamza, M.F ., Gital Y. & Herawan, T. (2016). A Review on Artificial Intelligence Methodologies for the Forecasting of Crude Oil Price. *Intelligent Automation & Soft Computing*, 1-14. (*ISI/SCOPUS Cited Publication*), **Impact Factor = 0.21, USA, Q4**

Saadi, Y., Yanto, I. T., Herawan, T., Balakrishnan, V., **Chiroma, H**., & Risnumawan, A. (2016). Ringed Seal Search for Global Optimization via a Sensitive Search Model. *PLoS One*, *11*(1). (ISI/SCOPUS Cited Publication), **Impact Factor = 3.53, USA, Q1**

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Abubakar, A. I., Khan, A., Nawi, N. M., Rehman, M. Z., Wah, T. Y., **Chiroma, H.**, & Herawan, T. (2016). Studying the Effect of Training Levenberg Marquardt Neural Network by Using Hybrid Meta-Heuristic Algorithms. *Journal of Computational and Theoretical Nanoscience*, *13*(1), 450-460. (*ISI/SCOPUS Cited Publication*), **Impact Factor = 1.34, USA, Q2**

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Chiroma, H., Abdul-kereem, A., Khan, A., Nawi, NM., Shuib L, Gital, AY., Rahman , MZ., Herawan, T. (2015). Global Warming: Predicting OPEC Carbon Dioxide Emissions from Petroleum Consumption using Neural Network and Hybrid Cuckoo Search Algorithm. *PloS one*, *10*(8), e0136140. (*ISI/SCOPUS Cited Publication*), **Impact Factor = 3.53, USA, Q1**

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Chiroma, H., Abdul-kareem, S., Ibrahim, U., Ahmad, I.G., Garba, A., Abubakar, A., Herawan, T. (2015). Malaria severity classification through Jordan–Elman neural network based on features extracted from Thick blood smear. *Neural Network World*, 5(15):565-584. (*ISI/SCOPUS Cited Publication*), **Impact Factor = 0.41, Czech Republic, Q4**

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Herawan, T., **Chiroma, H.**, Vitasari, P., Abdullah, Z., Ismail, M. A., & Othman, M. K. (2015) Mining critical least association rules from students suffering study anxiety datasets. *Quality & Quantity*, 1-21. (*ISI/SCOPUS Cited Publication*), **Impact Factor = 0.76, Netherlands, Q3**

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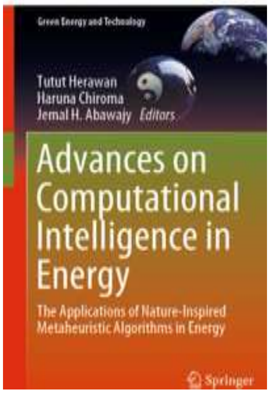	**Springer**	https://link.springer.com/book/10.1007/978-3-319-69889-2	Herawan, T., **Chiroma, H.**, & Abawajy, J. H. (Eds.). (2019). Advances on Computational Intelligence in Energy: The Applications of Nature-Inspired Metaheuristic Algorithms in Energy. Springer.

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Technical Programme Committee Member: 2019 International Workshop on IoT Big Data and Blockchain (IoTBB'2019) in conjunction with 2019 IEEE International Conference on Big Data, December 9-12, 2019, Los Angeles, USA. Proceedings to be published by *IEEE.*

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Technical Programme Committee Member: The Second International Conference on Soft Computing and Data Mining SCDM-2016, August 18-20, 2016, in Bandung, West Java, Indonesia**.** *Proceedings to be published by Springer* (http://fsktm2.uthm.edu.my/scdm2016/upload/)

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Technical Programme Committee Member: Second International Conference on Mechanical and Control Engineering (ICMCE 2016) (http://icmce2016.weebly.com/) 18-19 March, Bandung, Indonesia. All accepted papers to be published in special issue journal

Technical Programme Committee Member: 2015 Recent Advances in Informatics, Electrical and Electronics Engineering International Conference RAIEIC – 2015, Medan, Indonesia, 8th – 10th December, 2015. Papers to be published in *Jurnal Technologi – SCOPUS cited*

Technical Programme Committee Member: 2015 International conference on machine Learning and Signal processing MALSIP – 2015, Melaka, Malaysia, 15 – 17 December, 2015.

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REVIEWER TO THE UNDER LISTED JOURNALS

1. Soft Computing - *Springer* [Q1, ISI/Scopus indexed, Impact factor = 2.36, USA]
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3. Journal of Healthcare Engineering – *Hindawi* [Q4, ISI/Scopus indexed, Impact factor = 0.965, England]
4. International Journal of Bio-Inspired Computation – *Inderscience* [Q2, ISI/Scopus indexed, Impact factor = 1.538, England]
5. Knowledge Based System – *Elsevier* [**Q1,** ISI/Scopus indexed, Impact factor = 4.529, Netherland].
6. Journal of the Operational Research Society – *Springer* [ISI/Scopus indexed, Impact factor = 1.225, England].
7. Scientia Iranica - *Scientia Iranica* [ISI/Scopus indexed, Impact factor = 1.02, Iran].
8. Technological Forecasting & Social change – *Elsevier* [ISI/Scopus indexed, Impact factor = 2.678, USA].
9. International Journal of Electronics and Communications – *Elsevier* [ISI/Scopus indexed, Impact factor = 0.73, Germany].
10. Energy and building – *Elsevier* [**Q1,** ISI/Scopus indexed, Impact factor = 2.973, Switzerland].
11. Applied Soft Computing – *Elsevier* [**Q1,** ISI/Scopus indexed, Impact factor = 2.81, USA].
12. Neural Computing and Applications – *Springer* [**Q2**, ISI/Scopus indexed, Impact factor = 1.567, USA].
13. KSII Transactions on Internet and Information Systems - *Korean Society for Internet Information* [ISI/Scopus indexed, Impact factor = 0.56, South Korea].
14. Applied Energy – *Elsevier* [**Q1**, ISI indexed, Impact factor = 5.61, England].
15. PLoS ONE – *PloS ONE* [**Q1**, ISI/Scopus indexed, Impact factor = 3.23, USA]
16. Malaysia Journal of Computer Science [**Q4**, ISI/Scopus indexed, Impact factor = 0.405, Malaysia].
17. MethodX – *Elsevier* [Scopus indexed, Denmark]
18. Data in Brief – *Elsevier* [Scopus indexed, USA]
19. Evolutionary Intelligence – *Springer* [Scopus indexed, Italy]

20. International Journal of Pervasive Computing and Communications – *Emerald* [Scopus indexed, Austria].
21. Research Square
22. Journal of Computational Methods in Sciences and Engineering – IOS Press [Scopus indexed, Greece].
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Shafi'i M. Abdulhamid

shafii.abdulhamid@futminna.edu.ng

Shafi'i Muhammad ABDULHAMID received his PhD in Computer Science from Universiti Teknologi Malaysia (UTM), MSc in Computer Science from Bayero University Kano (BUK), Nigeria and a Bachelor of Technology in Mathematics/Computer Science from the Federal University of Technology Minna, Nigeria. His current research interests are in Cyber Security, Cloud computing, Soft Computing and BigData. He has published many academic papers in reputable International journals, conference proceedings and book chapters. He has been appointed as an Editorial board member for UPI JCSIT and IJTRD. He has also been appointed as a reviewer of several ISI and Scopus indexed International journals such as JNCA Elsevier, ASOC Elsevier, EIJ Elsevier, JKSU-CIS Elsevier, NCAA Springer, BJST Springer, IJNS, IJST, IJCT, JITE:Research, JITE:IIP, JAIT, IJAER and JCEIT SciTechnol. He is a member of IEEE, International Association of Computer Science and Information Technology (IACSIT), Computer Professionals Registration Council of Nigeria (CPN), International Association of Engineers (IAENG), The Internet Society (ISOC), Cyber Security Experts Association of Nigeria (CSEAN) and Nigerian Computer Society (NCS). Presently he is a lecturer at the Department of Cyber Security Science, Federal University of Technology Minna, Nigeria.

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Jimoh, Y., **Shafi, A**., Haruna, C., Haruna, C., & Mohammed, A. (2019). Security challenges in fog-computing environment: a systematic appraisal of current developments. J Reliab Intell Environ.

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INTERNATIONAL REVIEWER

TYPE OF SERVICE	ORGANISATION/JOURNAL
Editorial board member	The UPI YPTK Journal of Computer Science and Information Technology (*JCSIT*).
Reviewer	Journal of Network and Computer Applications (JNCA), Elsevier. (ISI/Scopus Indexed)

Reviewer	Egyptian Informatics Journal (EIJ), Elsevier. (Scopus Indexed)
Reviewer	International Journal of Network Security (IJNS). (Scopus Indexed)
Reviewer	Indian Journal of Science and Technology.(ISI Master List/Scopus Indexed).
Reviewer	Journal of King Saud University - Computer and Information Sciences, Elsevier. (ISI/Scopus Indexed)
Reviewer	Neural Computing and Applications (NCAA), Springer. (ISI/Scopus Indexed)
Reviewer	Journal of Information Technology Education: Research. (Scopus Indexed).
Reviewer	Journal of Information Technology Education: Innovations in Practice (*JITE:IIP*). (Scopus Indexed).
Reviewer	International Journal Of Computers & Technology
Reviewer	Merit Research Journal of Education and Review (MRJER)
Reviewer	International Journal of Grid and Utility Computing (IJGUC), InderScience Publishers. (Scopus Indexed)
Reviewer	Journal of Educational Research and reviews (JERR), ScienceWeb Publishing.
Reviewer	International Journal of Computer Network and Information Security(IJCNIS). (Scopus Indexed).
Reviewer	IEEE, 3rd International Conference on Machine Learning and Computing (ICMLC 2011).
Reviewer	Journal of Engineering and Computer Innovation (JECI)
Reviewer	International Journal of Education and Development using Information and Communication Technology (IJEDICT)
Reviewer	International Journal of Trend in Research and Development (IJTRD)
Reviewer	*Journal of Advances in Information Technology. (JAIT).*
Reviewer	*Journal of* Computer Engineering & Information Technology
Reviewer	The 2nd International Conference on Fuzzy Systems and Data Mining (FSDM 2016)
Reviewer	The 6th International Conference on Electronics, Communications and Networks (CECNet 2016)
Reviewer	Journal of Scientific Research and Reports (JSRR)

Reviewer	African Journal of Political Science and International Relations (AJPSIR)
Reviewer	International Conference on Information and Communication Technology and Its Applications (ICTA) 2016, F.U.T. Minna, Nigeria.

Abdulsalam Ya'u Gital

Abdulsalam Y. Gital received B.Tech, M.Sc., and Ph.D in computer science from Abubakar Tafawa Balewa University and Universiti Teknologi Malaysia. He is currently an associate professor (reader) at Mathematics department of Abubakar Tafawa Balewa University Bauchi. He graduated 1 Ph.D student and 9 M.Sc students. He is a member of different professional bodies and has published over 50 articles. Contacts: ygabdulsalam@atbu.edu.ng; asgital@gmail.com; +2348033936492.

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AWARD AND HONOURS

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Certificate of Excellent Award 2018, by National Association Of Mathematical Sciences Student ATBU Chapter.
Excellent Award, 2018 by National Association Of Mathematical Sciences Student ATBU Chapter.

Mubarak Almutairi

almutairi@uhb.edu.sa

Mubarak S. Almutairi is currently the Dean of College of Computer Sceince & Engineering, University of Hafr Albatin (UHB). He received the B.Sc. degree in systems engineering from King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia, in 1997, the MSc. degree in industrial and systems engineering from the University of Florida, Gainesville, Florida, USA, in 2003, and the Ph.D. degree in systems design engineering from the University of Waterloo, Waterloo, Canada, in 2007.

From 1997 to 2000, he was an industrial engineer with the Saudi Arabia Oil Company (Aramco). He is currently an assistant professor in the computer science and engineering department at the University of Hafr Albatin, Hafr Albatin, Saudi Arabia. His research interests include decision analysis, expert systems, risk assessment, information security, fuzzy logic, deep learning and mobile government application.

Dr. Almutairi is a recipient of three research grants in the field of ITC. He has edited two books and published 19 journal, conference papers and book chapters. He served as a member of the KFUPM board 2011-2015 and serving as a member of the UOHB board 2015-present. He is a member of IEEE (USA), senior member IIE (USA), ASNT (USA), ASEE (USA), and SCE (Saudi Arabia). He is also the recipient of the distinguished teaching award of the University of Waterloo for the year 2007.

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Fatsuma Jauro

Fatsuma Jauro is a lecturer at computer science department, Ahmadu Bello University Zaria, Nigeria. She received B.Tech and M.Sc degree in computer science from Abubakar Tafawa Balewa University, Bauchi Nigeria and Ahmadu Bello University Zaria Respectively. She is currently a Ph.D computer science student at Abubakar Tafawa Balewa University Bauchi. Her research interests include deep learning, edge computing and data mining.

List of Publications

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