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PAPER

A Novel Approach to Improving Distributed Deep Neural Networks over Cloud Computing

Muhtada Zuhair Ali[1], **Karrar Shakir Muttair**[2](✉)

[1]Department of Computer Techniques Engineering, College of Technical Engineering, The Islamic University, Najaf, Iraq

[2]Nanotechnology and Advanced Materials Research Unit, Faculty of Engineering, University of Kufa, Najaf, Iraq

karraralnomani123@gmail.com

ABSTRACT

In recent years, deep distributed neural networks (DDNNs) and neural networks (NN) have excelled in an extensive list of applications. For example, deep convolutional neural networks (DCNNs) are constantly gaining new features in various tasks in computer vision. At the same time, the number of end devices, including Internet of Things (IoT) devices has increased prominently. These devices are attractive targets for machine learning applications because they are often directly connected to sensors. For example (cameras, microphones, and gyroscopes) that record large amounts of input data in a stream mode. This study presents the design of a DDNN with end devices, edges, and clouds that spans computer hierarchies. The idea presented is considered one of the new ideas because it depends on two layers to distinguish, namely the convolutional layer and the pooling layer. The main objective behind using these two layers in one proposal is to provide and obtain the best results. Finally, we discovered that the proposed technique produced the best results in terms of accuracy and cost, with the precision of the definition reaching 99 % and the cost being quite affordable at 25. As a result, we conclude that these results are far superior to those achieved by the researchers in their ideas provided in previous recent literature.

KEYWORDS

neural networks, DCNNs, IoT, convolutional layer, pooling layer, artificial intelligence, cloud computing, deep learning

1 INTRODUCTION

Since a year the 1950s, Artificial Intelligence (AI) small subset, frequently named Machine Learning (ML), has revolutionized some domains in recent decades. NN is a branch of ML because it was also where Deep Learning (DL) originated. Since its debut, it has caused ever-greater disruptions, demonstrating tremendous success in almost every one of its application domains. AI taxonomy is depicted in Figure 1 [1], [2].

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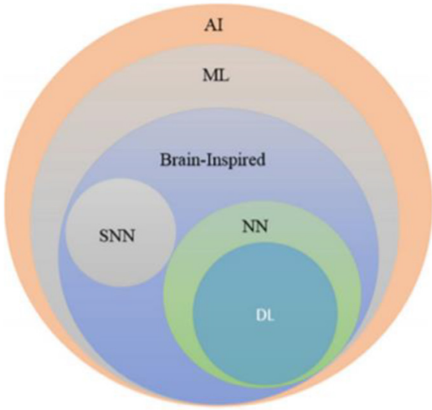

Fig. 1. Types of AI classifications

Since 2006, there has been a significant advancement in the ML class of DL, which uses either learning/hierarchical learning techniques or deep architectures [3], [4]. Learning is the procedure that includes estimating the parameters of a model so that the learned model (algorithm) can carry out a confident task. For instance, in an artificial neural network (ANN), parameters are matrices of weight [5], [6]. In contrast, DL contains specific relationships between layers of input and output that allow for the development of several non-linear information processing unit stages with hierarchical designs that are utilized for feature learning and the categorization of patterns [7], [8].

In addition, learning methods based on data representations are known as representation learning. Previous states of literature in which deep learning-based learning of representation includes features/concepts hierarchy, where concepts at a high level can be described from ones at a low level as well as the notions at low levels can be expressed from the ones at a high-level [9], [10]. In several papers, DL has been defined as a global approach to learning which can solve most of the issue types in various fields of application. On the other hand, DL is not task-specific [11], [12].

In particular, NNs and DNNs have seen significant success in several applications in recent years. For example, as shown in Figure 2 [13], [14], DCNNs achieve state-of-the-art continuous performance on many tasks in a computer's vision.

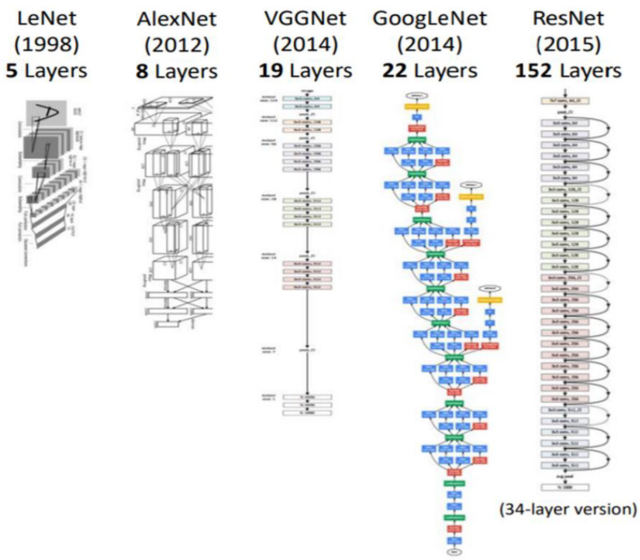

Fig. 2. Progression to the structures of deeper neural networks in the last years [13]

In the end, the number of such devices of IoT simultaneously has dramatically increased. Such gadgets are excellent targets for machine learning applications because they are typically connected directly to sensors (such as microphones, cameras, and gyroscopes) that capture an enormous variety of input data in streaming [15].

The rest of the sections are arranged as follows: Section 2 will define the problem of a NN. In section 3, we will present work that is relevant and close to the work proposed in this paper. Section 4 will introduce definitions of the basic concepts of DL for DDNNs. In section 5, we will present an evaluation and discussion of the findings presented in this paper. While section 6 will present conclusions and proposals for future works.

2 PROBLEM DEFINITION

The IoT vision is to turn traditional items into intelligent objects by utilizing advanced technologies ranging from embedded devices to communication technologies, internet protocols, data analytics, and numerous others. The influence of IoT on the potential economy is predicted to create several business possibilities while also boosting the economic growth of IoT-based services [16]. The IoT makes it achievable to establish services and applications in numerous fields, such as smart cities, industrial automation, environmental monitoring, and catastrophe warning. In the last few years, DL has become a technology of mainstream machine learning for the IoT [17].

Implementing DNNs to the devices could IoT, therefore, bring on applications generation capable of sensing and recognition tasks of performing complex for supporting the realm of the novel interaction among physical surroundings and humans. Despite embedded and mobile computing tasks' great variety in contexts of IoT, one can categorize them generally into two typical subtypes: classification and estimation tasks, depending on whether the results of prediction results are categorical/continuous, respectively. As a result, the question arises whether a generic neural network architecture exists that can successfully train the model structure necessary for classification and estimation tasks from sensor data. This design of a general deep learning neural network can overcome the drawbacks of today's technique, which are based on simplifications of analytical models/hand-crafted engineering features to employ in concept [18].

In recent years, DL has seen significant success, notably in computer vision; DNNs have improved their accuracy of the state-of-the-art in many types of visual identification tasks. Hence, also there are a lot of acts that have developed classical DNNs from augmentation of data, a function of loss, the structure of the network, an algorithm of optimization, the function of activation, neutral vector variables decorrelation of aspects [19].

3 RELATED WORK

The paper [20] presents the computing attack detection scheme of distributed deep-learning-driven fog-to-things using an accessible public dataset of NSL-KDD. The pre-trained stacked auto-encoder was used in feature engineering, whereas SoftMax was used for classification. For comparison, the model with shallow algorithms and metrics such as ROC curve, accuracy, and DR have been used for system assessment, and the accuracies over different nodes of workers are examined for a measure of scalability. An experiment shows that not only were deep models superior to traditional ML systems, but their distributed parallel learning optimization scalability and efficacy among fog nodes in increasing accuracy are superior. Writers conclude that detection systems of training attacks by utilizing the models of DL on the networks of distributed IoT supported by the cloud of fog nodes develop cyber-attack detection accuracy and efficiency by dividing up-dates of parameters, preventing local minima at every node.

The authors of the paper [21] present a new intrusion detection system (IDS) called hierarchical spatial-temporal features-based intrusion detection system (HAST-IDS) that first learns network traffic low-level spatial features using DCNNs and then learns high-level temporal features using long-term, short-term memory networks. The whole feature learning process is automated using deep neural networks; feature engineering procedures are not required. Effectively learned features of traffic automatically minimize FAR. Standard datasets of ISCX2012 and DARPA1998 are utilized for evaluating proposed system performance. The experimental results show that HAST-IDS surpasses the other published techniques in terms of accuracy, FAR, and percentage of identification, indicating that it is effective in both FAR reduction and feature learning.

In article [22], responsive neuro-stimulation (RNS and Neuropace) is used to deploy and develop both invasive and non-invasive approaches for epileptic brain assessment, monitoring, and regulation. Firstly, the framework of autonomic edge computing is presented to process the enormous data as a decision support system section for the candidacy of surgery. Secondly, the optimized model for the epileptogenic network estimation utilizing needed EEG and Rs-FMRI is provided independently. Thirdly, the extraction model of unsupervised feature is improved according to the structure of convolutional deep learning to distinguish periods of interictal epileptic discharge from periods of non-IED utilizing the signals of electro-graphic from electrocorticography (ECoG). The efficiency of the suggested approaches is validated by simulation and experimental results using specific patient data.

In the paper [23], writers have improved the optimal auction according to the DL for the allocation of edge resources in mobile networks of blockchain. They have specifically created neural network architecture based on solution analytics. They have modeled the training of data for neural networks by utilizing miners' valuations. According to data of training, they have trained neural networks with awaiting parameters for optimizing the ECSP expected, which negated revenue. As illustrated by simulation data, the suggested system may fast converge to the solution that ECSP income is significantly larger than that generated by the baseline method.

The study in [24] focuses solely on targeted/untargeted black box assaults using word/character-level disruptions and relates to the adversary attack on document categorization in the healthcare industry. People prefer black-box assaults to white-box ones because they feel more natural. They offer a protective mechanism to create a powerful CNN model and fend off these assaults. On the other hand, by employing the recommended defense mechanism during the same adversarial assaults, such a performance decrease can be prevented. Hence, it improves the CNN models stability for classifying clinical documents.

The authors in [25] present a seizure forecasting model that utilizes a two-layer LSTM with the swish learning algorithm. The suggested structure extracts features depending on the frequency and time domains and then applies the minimal distance method as a processing step. Using a Melbourne dataset, the suggested model receives the maximum AUC (Area Under Curve) value of 0.92 and the lowest FPR (False Positive Rate) value of 0.147.

While this paper aims to present the best methods to improve the accuracy of object recognition and the best methods to reduce the cost of communication between devices using intelligence. Therefore, the challenges of this paper can be summarized into four points and the following scenario:

1. To incorporate distributed end devices geographically is beyond the DNN literature scope generally. While the inputs from several sensors on diverse end devices are used, they must first be gathered for the categorization goal. Trained NN will be required to support this fusion of sensors.
2. For coordinated decision-making, it is necessary to jointly learn several models at the edge, end device, and cloud. The calculation previously performed on the end device model must apply to additional processing on the cloud/edge model.
3. The mechanism for quick and local inference at earlier points directly in neural networks (such as end devices) is not available in common DNN processing, which proceeds layer by layer from the input layer of the NN to the output layer of the NN.
4. Balance requires a compromise between model accuracy and the related model size at the distributed computing layer and transmitting cost to the layer above it. When supplying relevant features for classification in the cloud for another input, the solution should have good lower layers of NN layers that are reasonably on-end devices, and correct local categorization capable of handling multiple inputs.

4 DEFINITIONS OF BASIC CONCEPTS

4.1 Deep supervised learning

Supervised learning is a technique of learning which utilizes labeled data. In terms of supervised approaches to DL, the environment has inputs' set and corresponding $(x_t . \hat{y}_t) \sim \rho$. For instance, if for the input of x_t, smart factor $\hat{y}_t = f(x_t)$, the factor will receive the value of loss $\iota(y_t . \hat{y}_t)$. Then, the factor will modify the parameters of the network iteratively for desired outputs of better approximation. After the successful training, the factor can get proper solutions for the questions from an environment. There are various supervised learning approaches for DL, such as DNN, CNN, RNN, LSTM, and GRU. Such networks will be defined in detail in sections of respective [26].

Deep semi-supervised. Learning semi-supervised learning is learning which happens according to labeled datasets partially. In several cases, GAN and DRL are utilized as semi-supervised learning techniques.

Deep unsupervised. Unsupervised learning systems are capable of learning without the presence of data labels. In this instance, the factor discovers unknown structures/relationships in the incoming data by learning significant features/internal representation. Unsupervised learning techniques such as dimensionality reduction, generative, and clustering are often used. There are some DL family members which are good at non-linear and clustering reduction dimensionality, such as Restricted Boltzmann Machines, (RBM), Auto-Encoders as well as GAN which is developed recently. Furthermore, RANNs including RL and LSTM, are used for unsupervised learning in several applications [27].

Deep reinforcement. Deep Reinforcement Learning (DRL) is a technique of learning order to utilize in unknown environments as shown in Figure 3. DRL started in the year 2013 with Google Deep Mind. Since then, some advanced methods have been presented according to RL (Reinforcement Learning). There is an RL example: If environment inputs of samples: $x_t \sim \rho$, predict of factor: $= \hat{y}_t = f(x_t)$, agent receives cost: $c_t \sim P(c_t \mid x_t . \hat{y}_t)$, where P is the unknown likely distribution, environment requests a question from the factor, then gives the noisy score as a response. The strategy is frequently known as semi-supervised learning. According to this theory, several unsupervised and semi-supervised algorithms have been applied [7], [27].

We don't have a direct function of loss in RL, which makes learning more challenging compared to typical supervised techniques. The primary distinctions between supervised learning and RL are as follows: first, you do not have complete access to the function you are attempting to optimize; you must ask them via an interaction; and second, you are interacting with a state-based environment: the input is dependent on previous work. Depending on the space/scope of the challenge, one may determine which RL type is required to perform the task. If there are several parameters to optimize in a problem, DRL is the best method for performing optimization. If there are fewer parameters to optimize, the RL technique with no derivation is ideal. The cross-entropy approach, SPSA, and annealing are three examples of it [16], [22].

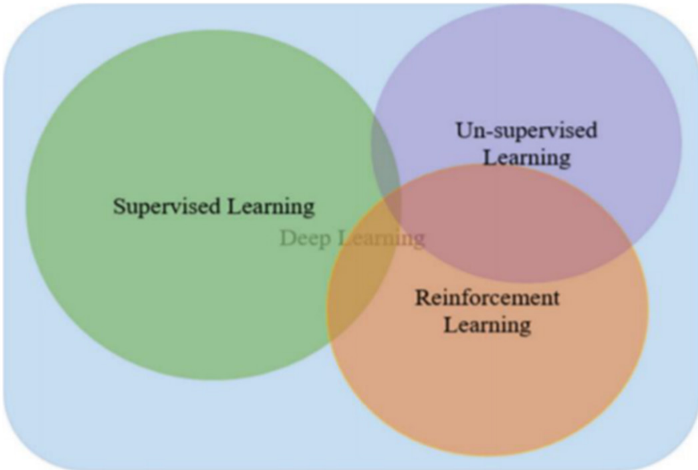

Fig. 3. DL approaches category

Main components of CNN. Today, CNN is regarded as the most widely used machine learning approach, especially in consideration of applications. Recently, CNNs have indicated the outcomes of state-of-the-art different applications of ML. ML system typical block diagram is indicated in Figure 4. In the ML system, CNN has powerful feature extraction and discrimination capabilities. This technology is primarily employed for feature extraction and classification. In the ML system, CNN has powerful feature extraction and discrimination capabilities. This technology is primarily employed for feature extraction and classification. In several ways, the pooling layer of the global average takes the place of the entirely linked layer. Additionally, additional regulatory units, including just as batch normalization and dropout, are introduced at different phases of learning to enhance CNN performance. To create unique architectures and get enhanced performance, CNN element layout is fundamental. The function of these components in CNN's design is briefly covered in this section [20].

Convolutional layer. The convolutional layer includes the convolutional kernels (each neuron works as a kernel) set. Such kernels are related to the image's small area called the domain of receptive. This acts by sharing an image into small blocks (fields of receptive) as well as convolving them with the certain weights' set (multiplying filter components with corresponding elements of the receptive domain). As seen in Eq. (1) [13], the convolution procedure may be described.

$$F_I^k = (I_{x,y} * K_I^k) \tag{1}$$

Where the image of input is presented by (x, y), $I_{x,y}$, indicates the locality of spatial also K_I^k shows *kth* layer *lth* convolutional kernel. Image division into the small blocks assists in locally extracting the correlated values of pixels. The feature's theme refers to the information it locally acquired. Features of various sets in an image are extracted by sliding the convolutional kernel on all the pictures with similar weight sets. In contrast to totally linked nets, the CNN parameter performs better because the convolution operation is a weight-sharing characteristic. Depending on the size and kind of filters used, the type of padding used, and the direction of the convolution, different types of convolution operations may later be categorized. Additionally, the convolution operation becomes the correlation operation if the kernel is symmetric.

Pooling layer. The feature patterns might appear in different places in a picture and influence the outcome of the convolution function. When features are retrieved, their precise placement becomes less significant if their proximity to other characteristics is preserved. A fascinating local procedure is down-sampling/pooling, such as convolution. This collects the same data in output and receptive field neighborhood more responses in the immediate area [15].

$$Z_I = f_P(F_{x,y}^I) \tag{2}$$

Eq. (2) indicates the operation of pooling that Z_I represents the feature map of 1th in it, $F_{x,y}^I$ indicates the feature map of lth input, while f_p explains pooling operation kind. The pooling procedure is used to extract the combination of characteristics that are resistant to minor translational and distortional changes. In addition to controlling network complexity, shrinking the size of the map of characteristics for the invariant set of features also helps to increase generalization by reducing over-fitting. CNN model uses several types of pooling formulation types, including average, max, L2, spatial pyramid pooling, overlapping, and others.

Cloud computing. Computing that is distributed portrays the other utilization of supplement as well as the display of conveyance for the administrations of IoT in web light also includes progressively versatile arrangement, as well as the assets of regularly, virtualized normally as the administration over an internet. If you own a desktop or laptop computer with internet access, you may download this program from any place in the globe. We can get to the application of cloud facilitated without any extra software/equipment; Hotmail, – Gmail, Yahoo [22].

5 EVALUATE AND DISCUSS THE RESULTS

5.1 Description of the dataset

We evaluate the proposed DDNN framework in a multi-camera multi-profile dataset. In the same broad region, this collection of photos taken simultaneously from six cameras placed at various positions is similar. To evaluate, we assume that each camera is connected to an end device, which can transfer the captured images via a wireless bandwidth limitation network to a physical endpoint connected to the cloud.

The annotation dataset includes an object-limiting box. Multiple limiting boxes may exist in a single picture, each corresponding to a separate item in the frame. For preparing the dataset, we extract an image for each limiting box and manually synchronize the same object among multiple devices where the object appears for the given frame. Examples of the extracted images are shown in Figure 4.

Fig. 4. Sample images of three objects (person, bus, car) from the multi-camera multi-profile dataset

The six devices (each with its camera) record the same object from different orientations are shown in Figure 5. The entire gray image indicates the absence of an object in the frame. Each row corresponds to a single sample, which is used for classification. We change each extracted sample to an image with x32 RGB 32 pixels. We utilize a blank picture and apply a –1 label to every device in which a certain object does not show; this indicates that that particular thing does not exist in the frame. The designations levels for automobiles, buses, and humans are 0, 1, and 2, respectively. The objects that exist in a frame (e.g., –1 label) are not used during training. We divided the dataset into 680 training samples and 171 test samples. Figure 5 shows the distribution of samples in each device.

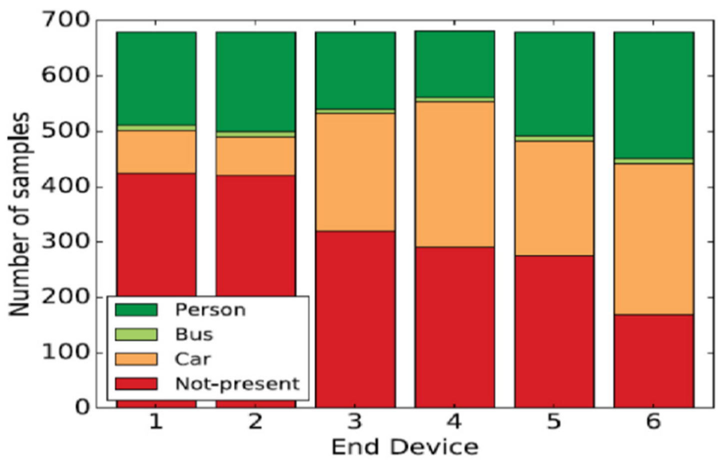

Fig. 5. Distribution of class samples for each end device in the multi-camera multi-profile dataset

5.2 Simulation environment

For implementing CNN, we used a Python environment. In Python, various exist in the field of DL. One of the libraries that we used is the TensorFlow library. TensorFlow: it is a low-level library. It is provided and supported by Google and has distributed processing capabilities. Due to its significance and significant influence on the growth of other well-known and useful Python libraries like Kera's and Lasagna, this library has been given the term "instructor". The primary use of this library's multidimensional arrays, which constitute its core, is for mathematical operations. It has high speed and is optimized using GPU, which is 140 times faster than the CPU. In other words, this library is the cornerstone of NN, and its importance is like the NumPy library in the scientific computing field. However, this library is rarely used directly in coding. It is usually used in higher-level libraries, except in cases where low-level changes and customizations are required.

5.3 DDNN inference communication cost

According to Eq. (3) [28], the end device's total communication cost with the cloud and the local aggregator is calculated.

$$c = 4 \times |c| + (1-\iota)\frac{f \times o}{8} \tag{3}$$

Where, *l* is samples' percentage locally exited, *C* is feasible labels set, *f* is the filters' number, and *o* is a single filter of output size for the last year of NN on an end-device. The constant 4 is equivalent to 4 bytes used to indicate the number of floating-point operations, while consistent 8 is equivalent to the bits used to express the byte's result.

The phases of the algorithm suggested in this study rely on two propositions. The first proposes one floating point for each level and communicates the likelihood of which sample is sent from an end device to a local aggregator and is part of the group. This stage occurs without regarding whether a selection is locally excited/at a further point of exit. The second term is communication among cloud and end devices that occurs (1 – *l*) time of fraction while there is a sample in the cloud rather than locally. The proposed method steps are stated in Figure 6.

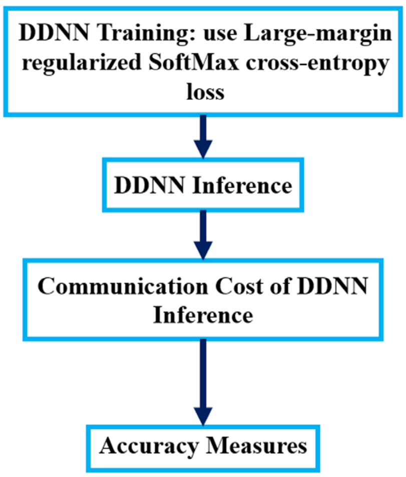

Fig. 6. Steps of the proposed method

5.4 The initialization of parameters

We employ binary NN blocks to accommodate the little memory of end devices. We use two types of blocks: a fully connected (FC) binary block and a binary convolution (ConvP) block. Each FC block consists of a layer fully connected to the m node for some m, batch normalization, and binary activation. Each of the ConvP blocks consists of a convolutional layer with filters for some *f*, a layer of pooling and batch normalization, and binary activation. The initial values of these layers are given in Table 1. All DDNNs in the experiments are trained using the following hyper-parameter settings with Adam: α from 0.001, β1 from 0.9, β2 from 0.999, and ϵ from $1 * e^{-8}$. We train each DDNN for 100 sessions.

Table 1. The initial values for parameters

Type of Layer	Parameters	Initial Values
Convolutional Layer	Core size	3×3
	Stride	1
	Padding	1
Pooling Layer	Core size	3×3
	Stride	2
	Padding	1
Hyper Parameter	α	0.001
	β1	0.9
	β2	0.999
	ϵ	$1 * e^{-8}$

5.5 Discuss the results

The results acquired from the suggested technique in this study in terms of accuracy and cost, as well as their comparison with the results achieved by other researchers in their prior recent publications, are displayed in Figure 7. We discovered that the suggested technique produces good results in terms of accuracy, which exceeds 99 %, while the cost value is 25, as shown in Figure 7. Therefore, we can see that these findings are far superior to those acquired by other researchers using the methods they provided in their research, as they received the best accuracy of 97 % and the lowest cost value of 62, as shown in Figure 7.

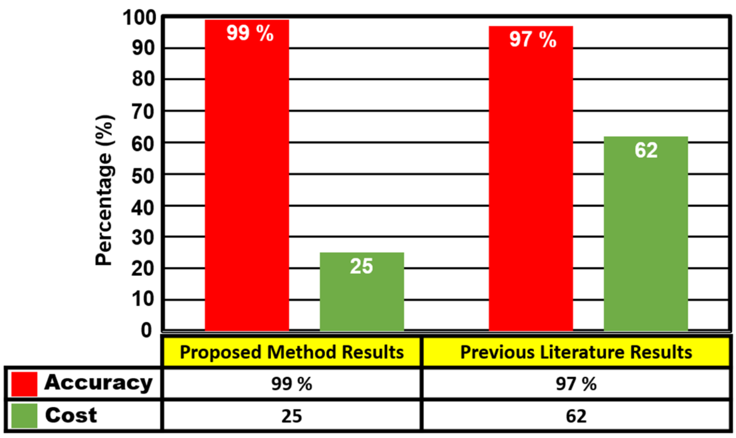

Fig. 7. A comparison between the results presented in this paper and the results obtained by other researchers in their previous recent research

Figure 8 shows the steps for increased accuracy during training sessions. At first, the accuracy is low, but the accuracy increases in each course.

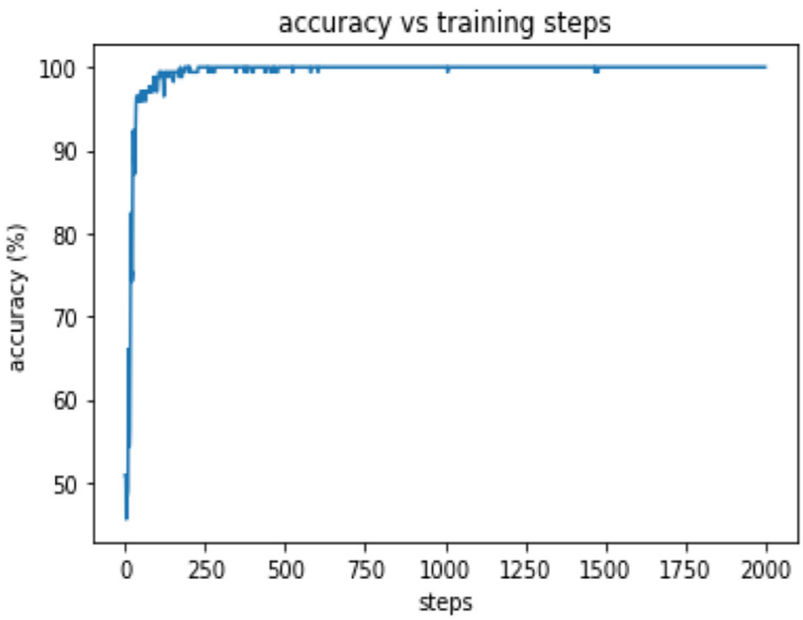

Fig. 8. The steps of increasing accuracy during training

6 CONCLUSION

Distributed hierarchical computing structures consisting of clouds, edges, and devices have inherent advantages like supporting central and local coordinated decisions and providing system scalability for intelligent tasks in large-scale IoT-based devices. In this study, the distributed strategy combines a smaller NN model (fewer parameters) on end devices with a bigger NN model (more parameters) on the cloud. A miniature model in an end device can quickly extract the initial feature and classify the model based on the existing reliability. Otherwise, the end device can move to the large NN model in the cloud, which performs more processing and final classification. This approach can be more accurate than a basic model in a device and has the benefit of reduced communication costs compared to the continuous uploading of NN to the cloud. In addition, since a summary based on the features extracted from the model of the end device is sent instead of raw sensor data, the system can provide more fantastic privacy protection. In future work, we will examine other types of integration schemes and hybrid accuracy schemes where end devices use layers of the binary neural network, and the cloud uses layers of the neural network with mixed accuracy or floating-point.

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9 AUTHORS

Muhtada Zuhair Ali works at The Islamic University in Najaf, Iraq. His research interests include Wireless Sensor Networks, Computer Communications Networks, Mobile Networks, and Antennas. (Email: muhtada.zuhair@iunajaf.edu.iq).

Karrar Shakir Muttair is a Lecturer at the Nanotechnology and Advanced Materials Research Unit, Faculty of Engineering, University of Kufa, Najaf, Iraq. His research interests are Computer Techniques Engineering, Computer Communications Networks, Multimedia Learning, Indoor Wireless Networks, Outdoor Wireless Networks, Wireless Sensor Networks, and Mobile Learning. He published several types of research in the Communications Engineering fields, Network Engineering, and Antennas. He has been awarded several awards and certificates of thanks and appreciation in his work field. (Email: karraral-nomani123@gmail.com, karraralnomani@gmail.com, karrars.alnomani@uokufa.edu.iq).