Advantages of Using Edge Machine Learning for Communication Networks and Grasp Analysis in Robotic Hand Network Based on Federated AVG & Machine Learning

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***Abstract*—Robotics provides multiple options for solving problems. Nowadays and in the future, this technology will play a vital role in daily life. Robotics not only help make things easier but also save time and money. These devices also come with challenges that need solving. Robotic hand grasp sensitivity is one of the problems in the robotics industry. Machine learning algorithms and artificial intelligence have several advantages and give clear results to solve this problem. These advantages can solve nonlinear problems well and predict contingencies at a high level. These advantages make machine learning algorithmics one of the best ways to solve problems. Nowadays, with growing internet of things technology most devices will be able to connect networks. Robotic arms also will work like IoT devices. With an internet connection, these devices will be able to send and receive data traffic. This ability will bring more challenges like data security, bandwidth usage, and latency. This study focuses on grasp precision on robotic hand networks with federated averaging which is an edge machine learning algorithm and shows the results and compares with the classical machine learning algorithms. In addition, it is aimed to discuss the performance of the federated averaging algorithm for network requirements and the advantages of this algorithm.**

Keywords—robotic rand grasp, machine learning, federated learning, internet of things, communication network.

I. Introduction

In recent years, robotics has become one of the most popular topics for engineers. Robots have a significant place because they are designed for different purposes in many fields like medicine [1, 2]. Robots are designed with various shapes to study extraterrestrial planets in space. Another research area is humanoid robotic arms and hands [3]. Such robots will have vital roles in human life in the future. Recently, humanoid robots combined with artificial intelligence are a subject of study [4, 5]. Many topologies have been developed to design and use these robots. These robots are widely used in the aerospace industry in factories. One of the primary purposes of robotic arms is to grasp an object. For this reason, robotic arms bring many advantages. One of them is to reduce the human factor. They increase productivity by minimizing human errors. In addition, they increase the production speed and efficiency by working without rest. These robotic arms have no specific shape or specific rules for development. The designs of robots differ according to their purpose. These robots can take the form of a five-fingered [3] hand, just like a human. On the other hand, these robots can have two, three [6], or more fingers. How these robots hold objects and grasp quality is an important factor. Researchers conduct many tests to observe this situation and experiment to develop the best architecture. One of the ways to improve the grasp quality of robotic hands is through machine learning (ML) techniques. ML is a technique that helps estimate future results and modeling based on experiences learned from pre-learned data [7]. ML techniques are mostly used for classification problems. They predict which class the data belongs to result of probabilistic calculation. Logistic regression, decision tree, k-nearest neighbors (KNN), gradient boosting machine (GBM), and light GBM are some of the algorithms that are used for classification. Additionally, to these algorithms, the neural network is one of the well-known techniques for classification. It was developed in the early 1940s regarding the biological neuron. It's simply the neuron's way of connecting other neurons and transmitting information to the nucleus. Synapses are points of connection of the dendrites to other neurons. A neural network works as a biological neuron. They receive information from the other neuron and perform the necessary mathematical operations. After that, they send them to the next neuron. Neural networks took some time to come into use because computers were not fast enough to solve these problems. With the development of microprocessor technology in the 21st century, neural network algorithms became popular and nonlinear problems [8] began to be solved with artificial intelligence. It is widely used in data science and mechatronics applications. Multilayer perceptron (MLP) is one of the neural network algorithms. MLP occurs in one or more hidden layers [9]. A single neuron is shown in Fig. 1.

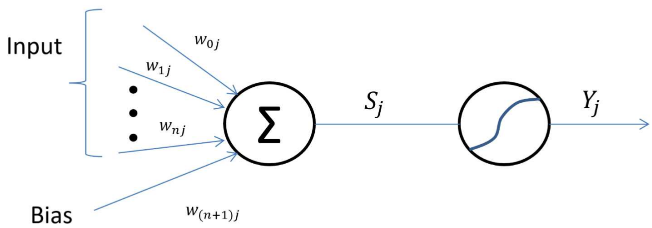

Fig. 1. Neuron block diagram representation.

Here w represent the weights. The inputs from the dataset are multiplied by weights and then all added together to get. This value is sent to the activation function. The activation function is the main factor for calculation. Activation functions provide a probabilistic value between 0 and 1 as a result. These are the possible results of which class it may belong to in classification problems. The sigmoid and relu functions are most used to solve problems. The outputs of the first layer are the inputs of the neurons of the second layer. The more neuron layers exist in the hidden layer, the deeper a structure is formed and represents a non-linear state [10]. These are called deep learning networks (DNN). As a result, the output of each neuron layer forms the input information of the next layer. The third and final part is the output layer. This layer receives values from the hidden layer and sends the output of the neural network algorithm after its calculations. Significant parameters in learning are weights and a bias value. When the algorithm starts the first iteration, weights and a bias are predetermined for all layers and neurons. In the first layer, weights and values are calculated and sent to other neurons. This process continues until the output value calculation. At the end of the first iteration, the expected output is compared with the system output. This process is called forward propagation [11]. The total error is calculated based on the output value compared to the expected value. These errors are returned to the network again. The weights of the neurons are updated by the algorithm to reduce the output error. The process follows for each neuron and its weight. This process then repeats itself until the error is minimal. At the end of the process, the network performs a learning process. It is called backpropagation [11].

II. Related Works

In recent research, authors of [12] have demonstrated a vision-based robotic grasp. The grasping model with different poses was examined using object detection, recognition, and deep learning. The VGG-16 model was used for region proposal generation (RPN) and object recognition and pose estimation. The results show that the system was sorted efficiently.

The researchers aim to estimate the grasp rectangle for the end-to-end intelligible object in RGB-D input [13]. A lightweight grasp detection model based on SqueezeNet is used for this purpose. The authors used the lightweight convolutional neural network (CNN) model for the dataset which provides real-time speed and high accuracy.

The researchers used the bag of word (BoW) method and support vector machine (SVM) to imitate a human hand and classify punches, cups, pens, and a real-time representation of holding objects in an office environment with this method [14]. In this experiment, objects were classified with 83% accuracy.

In the experiment [15], the researchers used the Cornell comprehension dataset as a benchmark and confirmed the use of both the curved bounding and axis-aligned boxes in the training. The results show that the rotational region CNN (R2CNN) algorithm has reached 96% accuracy.

The authors examined a two-stage grasp detection approach for grasp quality assessment with a lightweight CNN model [16]. Experimental results show that the method performs better in terms of accuracy and efficiency compared to existing grasping search methods. In addition, the training time has been significantly reduced.

In the study [17], the authors designed a remote-controlled fetch robot. It combines IoT technology and machine vision and deep learning techniques. The grasp detection process is to successfully identify the item through you only look once (YOLO) after selecting the item. After this step, a suitable grasp position can be found with its DNN.

With a general approach, these studies focus on the select the object and grasping them better and classifying them. They do not discuss the network requirement during this process. With the increasing number of devices in the future, these applications will request much more bandwidths less latency, and more data security. Especially, video or image data requires more space to work with it. In the next section, these problems will be explained in detail.

III. Problem Description

In recent years the concept is the internet of things (IoT) technology. IoT is a technology that is likely to form the basis of the future. In simple terms, IoT can be defined as a system that connects all devices in many different areas to the network. In this way, it is expected that several devices will be communicating so a huge amount of data flow occurs.[18]. Meaningful data will be obtained from this information. Combining this data with artificial intelligence can be seen as one of the biggest benefits of this technology. For instance, robotic arms can be converted into IoT devices to be a reference for this work. It can combine the data obtained from different devices with artificial intelligence and use it to increase the grasp quality of the devices. This whole system can be summarized simply as follows. Edge devices will collect data on its working principle and send it to artificial intelligence servers via the internet. These servers will collect the data and perform the learning process with an algorithm. Then using this algorithm our edge devices can be used more efficiently. In this context, the most widely used system today is cloud computing.

Cloud computing [19] is an option that offers easy applications and solutions. It is enough to have powerful servers to get better and faster responses to complex calculations, so most of the deep learning algorithms are cloud-based to use the power of centralized cloud computing. It is shown in Fig. 2. The advantages of cloud computing are that it provides low cost, easy backup and recovery, and virtually unlimited storage. On the other hand, cloud computing has some disadvantages [20].

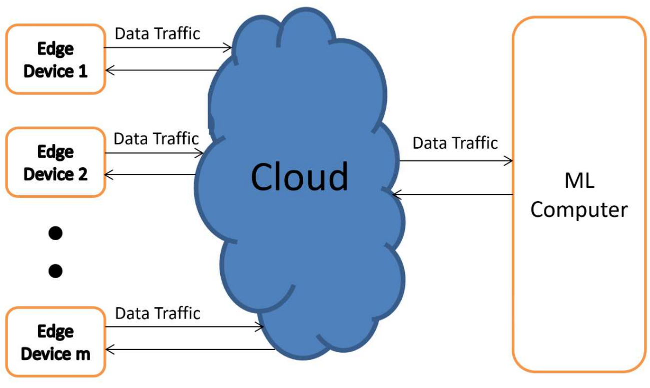

Fig. 2. Cloud computing.

A. Bandwith Usage

Sending all data to the cloud server will bring data traffic to the network between the edge device and the cloud server [21]. For future applications with IoT devices, they will connect to the internet and send their data to the cloud. It means that numerous devices will be connected to the network and data traffic will increase. This future will demand more and more bandwidth.

B. Latency

When we combine IoT devices and cloud services processing latency could be high [22]. To reach the cloud servers, much more IoT traffic will be transmitted over many routers and switches. It will bring operational latency due to the processing time of each device. In addition, the mathematical computation of a huge amount number of layers and neurons takes more and more time. Latency is unacceptable for critical networks. Although we define cloud computing as fast, this delay may not be enough in serious situations. For instance, autonomous cars have no latency tolerance.

C. Data Security

IoT deployers face pressing security challenges, including more vulnerabilities and security attacks. [23]. While classic cloud computing, all edge devices need to send their data to the cloud to train the neural network. It brings data security for confidential or important data. Many end users may not want to share their data and prefer to keep their data in their databases.

IV. Methodology

Recently, new solutions have been produced for artificial neural networks and ML. Edge machine learning, (Edge ML) is one of the decentralized learning solutions [24]. Edge neural networks do not have many layers and neurons as they are not as powerful as DNN. However, with the periodically shared network model, edge devices train each other without sharing their data. This technique is also used for IoT applications [25]. The process is called periodic pattern change [24]. There are several periodic pattern changes, these can be specified as federated averaging (federated AVG), federated stochastic variance reduced gradient (federated SVRG).

Edge devices do not share their data in the federated AVG algorithm, so it provides privacy [26]. They have a smaller neural network algorithm than cloud-based deep learning algorithms. It is concluded that the training dataset will increase, and the power of deep computation will be lost. One solution is edge devices using the global model. They have the same neural network model for all edge devices. For any k range, all these devices share their weights or gradients with the server [27]. The global model is the average of all local models. When the k^{th} sample arrives, all edge devices train their local models with the global model. In this way, all edge devices contribute to each other and achieve better results. Federated AVG weight update formula:

$$w_{k+1}^{i} = \begin{cases} w_k^i - \eta g'_k & k \bmod \tau = 0 \\ w_k^i - \eta g\left(w_k^i\right) & \end{cases} \tag{1}$$

Here w represents the weight matrix. i is edge device index. $g'_k = \frac{1}{m}\left[\sum_{i=0}^{m} g\left(w_k^i\right)\right]$ m mean gradient of edge devices. $g\left(w_k^i\right)$ i^{th} edge device gradient. η learning ratio [24].

The edge ML method will be used against these disadvantages. With Edge ML it is not to share all the data with the cloud and use cloud computing. Alternatively, all edge devices will have their neural network algorithm and use their data to train neural networks. As a result, the devices will not share their data with the cloud. It is shown in Fig. 3. In this way, the algorithm will ensure data security and reduce network usage for transferring all data. This will decrease the processing delays.

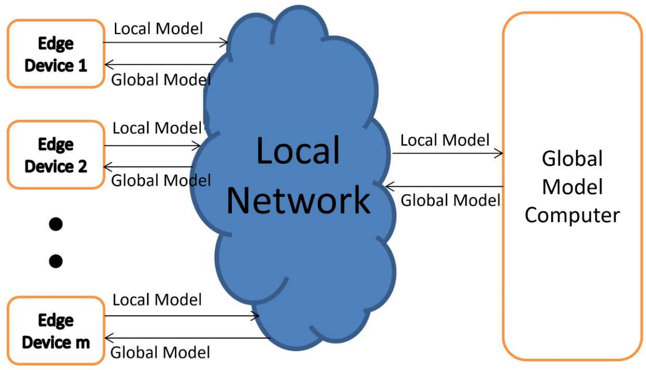

Fig. 3. Edge computing.

In this study, grasp quality results will be compared based on the federated AVG algorithm with KNN, BGM, Light GBM, logistic regression, decision tree and MLP. In addition, the benefits of the Edge ML communications network will be examined considering that it requires latency bandwidth usage and data security. Finally, the effect on learning different k values will be examined.

A. Material

The robotic hand which is used as a reference IoT device to solve network problems in the study has three fingers. It has three joints for each of the three fingers. Necessary information is needed to estimate grasp sensitivity concerning fingers and joints. The data set produced in the smart grasping sandbox provides a large data set for this purpose. This dataset is from Kaggle. In this dataset, F represents the finger, J represents the joints, "pos" stands for the position of the arm, "eff" stands for the torque information of this finger, and "vel" stands for the speed of the fingers. The robotic hand and the object are considered fixed and are shown in Fig. 4. By calculating the distance of the object to the robotic hand, it was decided whether the arm holds the object or not. This information is the input matrix used in the training of the algorithm.

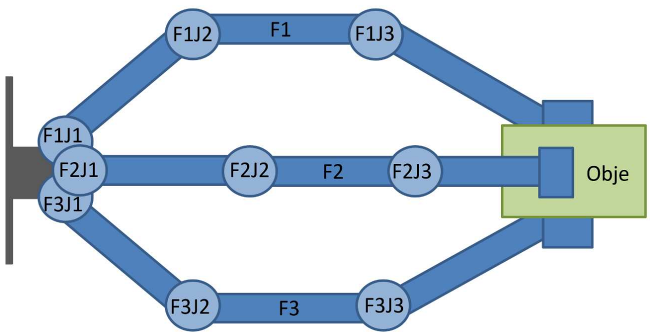

Fig. 4. Two-dimensional representaion of robotic hand.

B. Method

To solve the problem, an MLP algorithm based on the federated AVG algorithm has been developed for testing decentralized learning. In the data set, the grasp quality is accepted as "0" for failure and "1" for success. 80% of the data is reserved for training the algorithm and 20% for testing. It will be tested and compared with the different number of edge devices for training. The dataset reserved for training was divided for each edge device to train them separately. In addition, it was tested with four different values, three, five, seven, and ten, to see the effect of the k value. TensorFlow library is used to simulate the federated AVG algorithm. Three hidden layers are used in the neural network. To compare this algorithm with central learning, a similar MLP structure was used. Unlike the previous, this algorithm consists of 5 hidden layers.

V. Results

Simulation results show the best k values at which we can grasp an object given the different number of edge devices. The simulation results gave different accuracy results. These values are shown in Fig. 5. When the results for 5 edge devices were examined, the highest grasp rate was observed as 81.78%. It is observed that the k value is taken as 5. When the number of edge devices increases, it is expected to observe lower results as the data set is split for each edge device. Accordingly, the learning level was observed at 81% when 10 edge devices were used. The highest value 81.06% was obtained when k was 7 and 10. When the number of edge devices is increased to 15, the highest grasp rate is 80.91% in case k is 7. In addition, when the calculations are made as 20 edge devices, the highest grasp rate is 80.93%. This value was observed when k was 5. As a result, the highest learning results according to the number of devices were observed when k was 5 and 7. These values are the learned value of the latest global model.

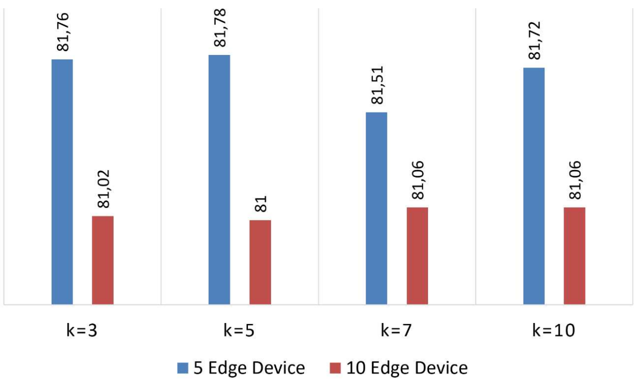

Fig. 5. Federated AVG results

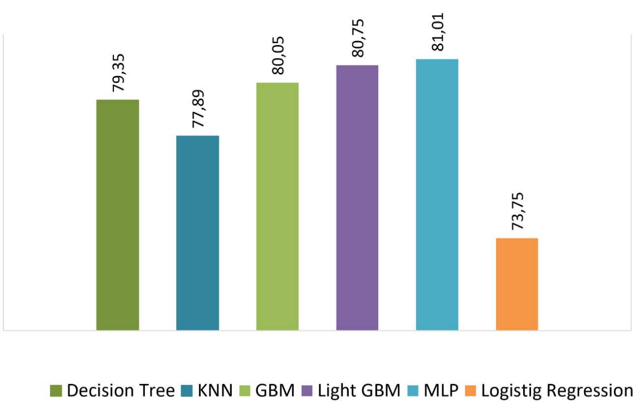

Fig. 6. Machine learning results

Fig. 6 shows the result of ML algorithms. The lowest value of 73,75% was obtained with logistic regression. The highest grasp prediction of 81.01% was obtained with the centralized MPL algorithm. When we compare these values with the rates with federated AVG algorithm 5 and 10 edge device situation gives better result than centralized MPL. In situations 5 and 10 edge devices, the values are slightly lower. The federated AVG algorithm gives better results than all the other ML algorithms. These results show that decentralized federated AVG algorithms can be used instead of centralized ML algorithms. Considering the benefits of the federated AVG algorithm, it will be more beneficial to use it.

VI. Conclusion And Future Works

In this study, the benefits of using edge ML for communication networks are explained. For this purpose, the robotic hand and its grasping methods are described for the first time with the edge ML structure as an IoT device. In addition, it is aimed to compare two different ML methods rather than to obtain the best grasp ratio. The method was the federated AVG algorithm that trains the data for each edge device and creates a global model through the model exchange. Results were compared with centralized ML. Obtained results are values open to improvement. Considering the advantages of Edge ML in the field of communication networks, these studies will be beneficial for any IoT device using ML in the future. When different types of neural network structures are combined with edge ML, better results can be obtained.

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