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Optimization of Federated Learning Communication Costs through the Implementation of Cheetah Optimization Algorithm

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Abstract

Recently, Federated Learning (FL) has promptly gained aggregate interest owing to its emphasis on the data privacy of the user. As a privacy-preserving distributed learning algorithm, FL enables multiple parties to construct machine learning (ML) algorithms without exposing sensitive information. The distributed computation of FL may lead to drawn-out learning and constrained communication processes, which necessitate client-server communication cost optimization. The two hyperparameters that have a considerable effect on the FL performance are the number of local training passes and the ratio of chosen clients. Owing to training preference across different applications, it is challenging for the FL practitioner to manually choose these hyperparameters. Even though FL has resolved the problem of collaboration without compromising privacy, it has a transmission overhead because of repetitive model updating during training. Various researchers have introduced transmission-effective FL techniques for addressing these issues, but sufficient solutions are still lacking in cases where parties are in charge of data features. Therefore, this study develops an Optimization of Federated Learning Communication Costs through the Implementation of the Cheetah Optimization Algorithm (OFLCC-COA) technique. The OFLCC-COA technique is mainly applied for effectually optimizing the communication process in the FL to minimize the data transmission cost with the guarantee of enhanced model accuracy. The OFLCC-COA technique enhances the robust performance in unsteady network environment via the transmission of score values instead of large weights. Besides, the OFLCC-COA technique improves the communication efficiency of the network by transforming the form of data that clients send to servers. The performance analysis of the OFLCC-COA model occurs utilizing different performance measures. The simulation outcomes indicated that the OFLCC-COA model obtains superior performances over other methods in terms of distinct metrics

Keywords: Federated Learning; Cheetah Optimization Algorithm; Communication Cost; Machine Learning; Elman Neural Network

1. Introduction

Today, many organizations search for update and enhance business methods, so machine learning (ML) has been presented as a great device for handling modernization [1]. It has helped in the improvement of commercial scalability and the development processes for businesses all around the world by removing significant visions from raw information to rapidly resolve difficult and data-rich business issues [2]. Also, in the field of healthcare, ML has been used for electronic health records (EHR) which produce illegal visions that range from enhancing patient danger score methods to forecasting disease start and restructuring hospital processes [3]. In addition, ML also prepared an important input to the agriculture area by helping agriculturalists decrease agriculture damages by delivering rich suggestions and insights into harvests. No application area will profit from employing the ML model for decision support [4]. While the organizations' advantage of utilizing ML models on their data, employing details from other related organizations for a similar reason could outcome in major developments to the current organization procedures [5]. Identifying the prominence of association, a major prominence was positioned on combining data from manifold organizations to plan superior ML techniques for enhancing consumer service and achievement.

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Presently, data sharing between organizations is vital owing to fears of confidentiality, upholding viable benefits, and/or other limitations [6]. While a major study was associated with distributed learning, to execute tasks on data dispersed across manifold servers, it mainly concentrates on declining the time needed to execute challenges by parallelizing computational power [7]. Then, federated learning (FL) concentrates on data neighbourhood and it is a promising model that permits a system of independent organizations that surface the similar ML challenge to collaboratively absorb a global method that provides superior analytical behaviour for all members without the necessity to share data of sensitive [8]. Distributed ML is extremely difficult method to run and estimate owing to platform needs and is less scalable. The above produced by synchronization actions is predictable because few nodes function very slowly when compared to other nodes [9]. The quicker nodes wait for the slow nodes to finish their tasks in order to match the jobs. So, the acceptance of conventional ML and distributed ML processes increases the confidentiality of consumers, along with calculating methods, and unfavorable scalability issues [10]. FL resolves the important drawbacks of previous models. The foremost benefit of FL is the availability of data from across the world while maintaining consumer privacy, which can be beneficial to training the strong techniques in numerous businesses. To take this benefit, we want to crack the tasks involved and construct few robust model structural designs to provide modified outcomes to the consumers. Communication cost is the biggest challenges in FL owing to the numerous edge devices involved.

This study develops an Optimization of Federated Learning Communication Costs through the Implementation of the Cheetah Optimization Algorithm (OFLCC-COA) technique. The OFLCC-COA technique is mainly applied for effectually optimizing the communication process in the FL to minimize the data transmission cost with the guarantee of enhanced model accuracy. The OFLCC-COA technique enhances the robust performance in unsteady network environment via the transmission of score values instead of large weights. Besides, the OFLCC-COA technique improves the communication efficiency of the network by transforming the form of data that users send to servers. The performance analysis of the OFLCC-COA model occurs utilizing different performance measures.

2. Literature Review

In [11], an intelligent optimizer-based FL (IOFL) structure has been presented. In this technique, the server explorations for perfect parameters by employing intellectual optimizer model. The users employ local information to authorize the delivered method by the server and yield the authenticated outcomes. The server computes the fitness function depending upon the weighted mean of the obtained authenticated outcomes that guide the intellectual optimizer model to hunt for novel perfect parameters. Nguyen et al. [12] developed an effectual FL method based on the Federated Averaging (FedFog) technique. Next, FedFog is employed in wireless fog-cloud methods by examining a new network-aware FL optimizer issue. Then, an iterative technique is presented in order to get an exact dimension of the system performance. A flexible consumer aggregation plan is also projected that monitors rapid customers to get a definite stage of accuracy. Elfaki et al. [13] propose a Quantum with Meta-heuristics Algorithm based Minimization of Communication Cost in the FL (QMAMCC-FL) model. This method is intended for a federated hybrid CNN with a GRU (HCNN-GRU) method with a quantum Aquila optimizer (QAO) model. The proposed method updates the overall technique through weighted collections of the learned method that is generally employed in FL.

In [14], the FedAvg technique enhanced an adaptive communication frequency AFedAvg method is projected. The gradient sparse process decreases the amount of parameters for a distinct transmission, whereas the transmission delay process permits training to unite quicker and get lesser damages. The amount of sparse parameters was employed in order to pick the communication frequency of subsequent rounds. Chen et al. [15] presented a novel customer scheduling plan by reprocessing stale local perfect parameters. A Lagrange multiplier technique is initially utilized by decoupling variables, with transmission indicators, bandwidth, and power to extend positive data exchange over systems. Next, a linear-search-based influence and bandwidth distribution model has been presented. In [16], a decomposition-based multi-objective optimizer algorithm (MOEAD) technique is offered. A scalable code technique is employed for coding that increases the efficacy of evolutionary neural networks. In contrast, the non-dominated sorting genetic algorithm II (NSGA II) is applied to enhance the issue below the similar states and confirm the efficiency of both systems as per the gained solution of Pareto.

Gupta and Alam [17] present an original technique for FL containing the Chimp Optimizer Algorithm (ChOA). The use of FL is intended to increase the model's efficiency. The projected model's main goal is to enhance the precision of the model forecasts by uniting FL and Chimp Optimizer called FLECO. In [18], the trade-off among learning rapidity and price in a 3-layer FL-enabled IIoT method is examined. Mainly, a weight learning efficacy function has been aimed by taking trade-off. The technique also targets extending the weight learning value in an FL training round by equally enhancing the edge association and distributions of computational volume, resource block, and spread of the power of the IIoT device.

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3. The Proposed Method

In this work, we developed an OFLCC-COA technique. The OFLCC-COA technique is mainly applied for effectually optimizing the communication process in the FL to minimize the data transmission cost with the guarantee of enhanced model accuracy. Fig. 1 depicts the complete procedure of the OFLCC-COA model.

A. Federated Learning

Konecný et al. proposed FL algorithm for distributed datasets. It is used to train the model through the distributed dataset over different devices while retaining data leakage [19]. FL is beneficial in that it reduces communication costs and enhances privacy. The ANN model could learn without personal information or data breaches through FL. Furthermore, transmitting information from various devices to a vital server raises storage cost and network traffic. FL greatly declines the communication overhead by only exchanging the weight attained from the model training.

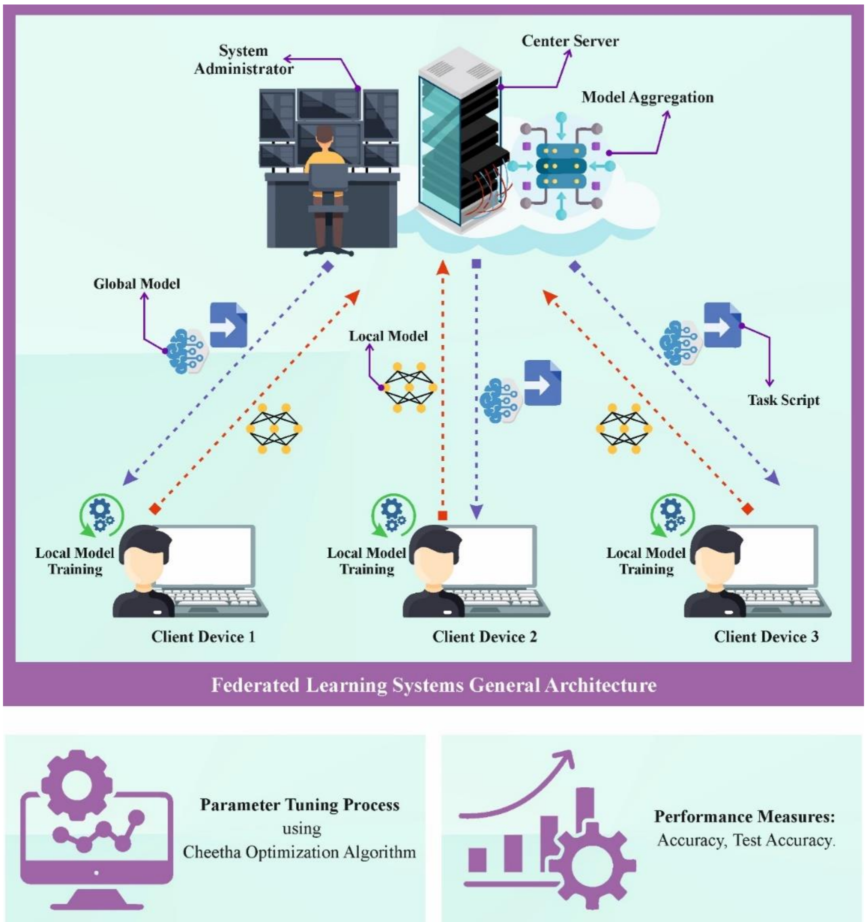

Figure 1. Overall process of OFLCC-COA technique

- The server is used to send the learning algorithm to all the users.
- The received model is trained on user information.
- Every client transfers its trained model to the server.
- The server procedures the models and aggregates them to updated method.
- The server transfers the updated model to the client and repeats steps 1 to 5.

B. Algorithmic Design of COA

The cheetah (Acinonyxjubatus) is known as the speediest land animal and positions as the main feline type, residing in vital areas of Africa and Iran [20]. It is possible to place prey when a cheetah watches or searches its current environment. After spotting its prey, the cheetah might sit in one place and watch till it considers and takes an attack. In the attack stage, there are dual stages such as capturing and rushing. The cheetah may conclude

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hunting for many causes, with the capability to catch prey rapidly, power limits, etc. The COA's overall base is the intellectual use of dissimilar hunting models during hunting sessions.

- Searching strategy

Cheetahs search for victims by employing single or dual techniques: either forcefully watching the area while standing or sitting to watch the surroundings. If there are many prey and foraging at the time of navigating the grasslands, the scanning method is highly suitable. But, if the victim is single and lively, it is better to select an active method that takes more energy than the scanning technique. The sequence of search plans is selected by the cheetah during the hunting period, it focuses on prey conditions and cheetahs' health and area coverage. Exactly, the cheetah's conditions generate a populace, and every prey is a stain of a result variable that is identical to the finest choice. Therefore, employing a random size of step and the existing location of every cheetah in this strategy is an initial point, the mathematical expression is given below:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + r_{i,j}^{-1} \cdot \alpha_{i,j}^{t} \tag{1}$$

In Eq. (1), $X_{i,j}^{t}$ indicates the current place of cheetah i $(i = 1,2,n)$ in j^{th} group $(j = 1,2,\dots,3D)$, D represents the problem size. $X_{i,j}^{t+1}i$ indicates the positions of i^{th} cheetah in plan j. n designates the size of the population, T and t are the highest, and the current hunting period. $r_{i,j}^{-1}$ and $\alpha_{i,j}^{t}$ is the randomly generated quantity and step distance for i^{th} cheetah in j^{th} cluster.

- Waiting and Sitting strategy

The victim may become noticeable to the cheetah's vision when it is in search mode. In this strategy, every movement makes the cheetah that they have the probable to aware of the prey or his life and origin the victim to escape. The cheetah will choose to trap to obtain adequate close to words the prey to relieve this concern (by resting on the ground or waiting among the greeneries). As an outcome, the cheetah waits till the prey acquires nearer while upholding their position. The below mentioned is the expression to pretend these behaviors:

$$X_{i,j}^{t+1} = X_{i,j}^{t} \tag{2}$$

In Eq. (2), $X_{i,j}^{t+1}$ and $X_{i,j}^{t}$ are the improved and existing locations of i^{th} cheetah in j^{th} plan, correspondingly. Simultaneously, this model requires the CO technique to withdraw from altering every cheetah in every group in order to upsurge hunting efficacy (discover superior outcomes). This will aid the technique to evade initial convergence.

- Attacking strategy

A cheetah tracks the victim at the highest velocity when it has the main intention to attack. Finally, the prey will be alert of the cheetah's attack and jerks to draw back. The cheetah quickly hunts the victim to capture and tracks the victim's place and adapts its path, therefore it blocks the victim's route at an assured point. The prey needs to escape and alter its position speedily to stay alive since the cheetahs have just gone a small break from full rapidity. During this stage, the cheetah arrests the prey by shifting rapidly and guiding. Every cheetah in the cluster searches for the capability to adjust their locations depending upon the leader position or nearer to the cheetah and prey position. Just, all cheetahs' attack tactics are mathematically defined as follows:

$$X_{i,j}^{t+1} = X_{B,j}^{t} + r_{i,j} \cdot \beta_{i,j}^{t} \tag{3}$$

In Eq. (3), $X_{B,j}^{t}$ signifies the existing location in $the\, j^{th}$ group. $\beta_{i,j}^{t}$, and $r_{i,j}$ are the interaction and turning coefficients linked to the i^{th} cheetah in the j^{th} cluster. Dependent on the hunting behavior of cheetahs, the developed COA integrates the following conventions and plans:

- Individual representation

In the COA, every row in the populace signifies that a cheetah is in dissimilar conditions. Every column matches an exact plan of cheetahs about the victim, demonstrating the finest result for decision variables. Cheetahs imitate the performance of chasing their victim (the finest value). To recognize the optimum solution, the cheetah should effectively arrest the victim in every plan. A cheetah's behavior has been measured over its fitness in all strategies with greater behavior representing a larger possibility of effective hunting.

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- Diverse reactions

The real cheetahs show dissimilar responses throughout group hunting, the COA permits every cheetah to be in several conditions in every plan. The energy level of the Cheetah is measured individually by the victim, and the technique presents randomly generated parameters to stop early convergence at the time of wide evolutional procedures. These randomly generated variables perform as a source of energy for the cheetahs throughout the hunting procedure.

- Random behavior

During attacking and searching plans, the behavior of cheetahs is supposed to be fully random, certifying assortment in the hunt. But then, during the capturing and rushing stages, the prey varies way rudely. Randomized parameters perfect these actions, and fluctuating step distances and contact factors with arbitrary variables donate to an effectual optimizer procedure.

- Adaptive strategy

The superior among attacking and searching plans is randomized, but the search becomes highly possible as a cheetah's energy drops. Early steps are devoted to search, whereas attack is chosen for a greater value of time (t) in order to attain a superior solution. The range of tactics is inclined by randomly produced factors and energy thoughts such as the cheetah’s performance in the wild.

- Scanning and sitting-and-waiting

In the COA, sitting-and-waiting and scanning tactics are measured equally, demonstrating that a cheetah (searching agent) rests motionless throughout the hunting time.

- Leader adaptation

Once the main cheetah constantly flops in hunting, an arbitrarily nominated cheetah’s location has been altered to the latter effective hunting location (the prey position). This technique preserves the prey place between a tiny populations and supports the search stage.

- Energy limitations and home range

In the COA, every group of cheetahs has a period constraint for hunting owing to energy restraints. Once the cluster fails during a hunting time, then they license the present victim and return to their initial location. The leader’s location was also upgraded. This plan aids to stop from getting immovable in local optimal solutions.

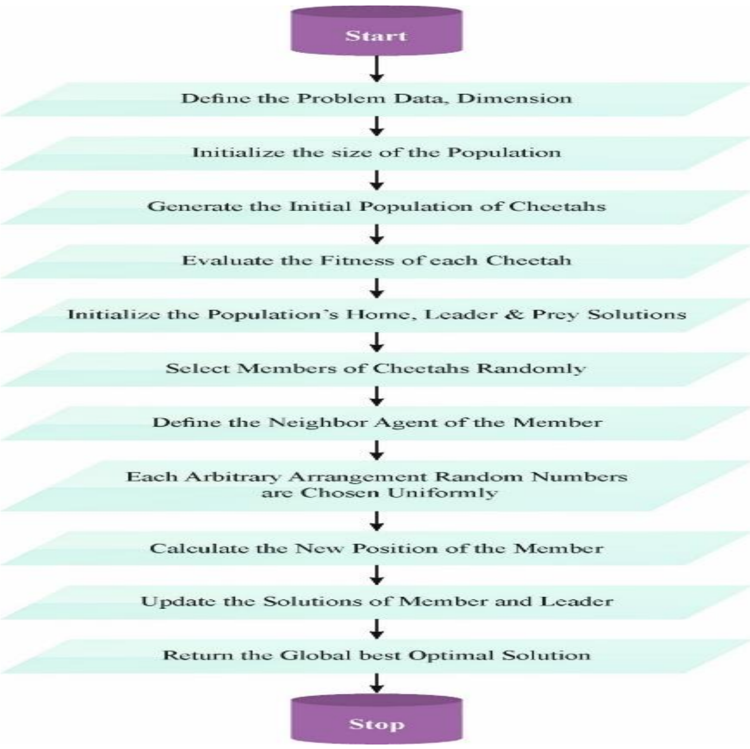

Figure 2. Flowchart of COA

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- Iterative evolution

In every iteration of COA, a population subset dynamically contributes to the evolution procedure. The expectations and plans draw motivation from the performance of cheetahs during hunting time, targeting to generate an effectual optimizer model that imitates their energy consideration, arbitrariness, and adaptability in the hunt for optimum solutions. Fig. 2 illustrates the flowchart of COA.

C. COA-based FL Communication Cost Optimization

Most of the preceding studies concentrate on communication among customers and global optimizers to enhance the performance of FL. However, there was no effective technique to uphold strength to data transmission failure in the uneven network atmosphere of FL [21]. We concentrate on enhancing the FL performance by varying the procedure of data utilized in communication among clients and servers in an upgrade method based on the OFLCC-COA approach. A common technique to enhance the ENN accuracy is to extend the layer of the method. This is known as a DNN. The amount of weight parameter needs training upsurges as all layers become deep. In the global FL, when the technique proficient on the customer is led to the server, then the communication of network price upsurges significantly. So, we offer the OFLCC-COA, which directs the finest score (like loss or accuracy) to the server by using COA features to convey the proficient method, regardless of dimension.

Next, the OFLCC-COA model obtains the method weight only for the customer that delivered the finest score, therefore the technique weights do not want to be conveyed from every customer. The finest score utilizes the lower loss value resultant after training the customer.

Elman Neural Networks (ENN) is one of the kinds of recurrent neural networks (RNN) structure that includes dual network layers. This network contains a unique design where extra feedback influences occur from the hidden layer (HL) yield to the input layer. The value produced by the HL neurons was kept by contextual unit beforehand they were served back into the HL. Remarkably, this feedback device does not prolong the value of the output layer. The context units function aids in moderating the previous output values impact from the HL, improving ENN memory depth but compromising its determination. The formulation given below defines the alteration in HL neurons:

$$S_i(t) = g\left(\sum_{k=1}^{K} V_{ik}\, S_k(t-1) + \sum_{j=1}^{J} W_{ij} I_j\,(t-1)\right) \tag{4}$$

Whereas, Sk(t) and Ij(t) represent the output and input, respectively. Vik and Wij denote their equivalent weight. g indicates a sigmoid squash function. The ENN is an effectual device to control issues that need consideration of preceding data or memory state, so donating its usage in an extensive collection of applications.

4. Result Analysis and Discussion

To inspect the performance of the OFLCC-COA system, an extensive of experimentations were executed to calculate the accuracy and convergence rate and investigate in unbalanced network environments. Primarily, CIFAR10 and MNIST datasets have been employed for the accuracy benchmark and studied the data distribution cost among users and servers. Afterward, the accuracy of the OFLCC-COA technique was examined in various network environments. Table 1 and Fig. 3 portray comparative $accu_y$ outcomes of the OFLCC-COA method on the CIFAR10 dataset [13].

Table 1: $Accu_y$ outcome of the OFLCC-COA method with recent techniques at CIFAR10 database

Accuracy (%); CIFAR10 Dataset						
No. of Epochs	OFLCC-COA	QMAMCC-FL	ACO-FED	GWO-FED	CSO-FED	Traditional Federated Learning
10	57.20	51.46	12.74	19.74	19.74	25.71
20	71.13	65.68	25.06	39.85	35.35	57.10
30	86.17	80.65	39.45	54.04	50.53	75.37
40	86.36	81.69	54.64	62.23	62.44	78.06
50	86.47	80.67	62.85	66.79	66.96	78.89

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60	86.88	81.51	64.50	70.07	72.70	79.28
70	85.69	80.25	63.87	71.48	72.72	79.70
80	86.14	81.49	64.69	71.71	74.14	79.09
90	88.49	82.93	64.74	71.07	75.60	79.49
100	89.70	84.79	64.93	71.69	76.82	78.88

These accomplished values specified that the OFLCC-COA technique gets effectual performance over several epochs. Based on 10 epochs, the OFLCC-COA technique offers a higher $accu_y$ of 57.20% while the QMAMCC-FL, ACO-FED, GWO-FED, CSO-FED, and TFL techniques obtain lessened $accu_y$ values of 51.46%, 12.74%, 19.74%, 19.74%, and 25.71%, correspondingly. Also, based on 50 epochs, the OFLCC-COA method provides a boosted $accu_y$ of 86.47% whereas the QMAMCC-FL, ACO-FED, GWO-FED, CSO-FED, and TFL techniques accomplish minimized $accu_y$ values of 80.67%, 62.85%, 66.79%, 66.96%, and 78.89%. Meanwhile, based on 100 epochs, the OFLCC-COA system achieves a higher $accu_y$ of 89.70% however, the QMAMCC-FL, ACO-FED, GWO-FED, CSO-FED, and TFL methods get diminished $accu_y$ values of 84.79%, 64.93%, 71.69%, 76.82%, and 78.88%, respectively.

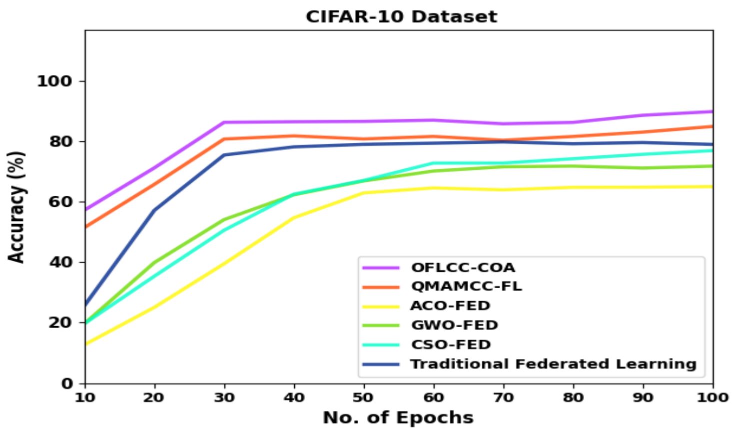

Figure 3. $Accu_y$ Outcome of the OFLCC-COA technique at CIFAR10 dataset

The efficiency of the OFLCC-COA method at the CIFAR10 dataset is clearly denoted in Fig. 4 in the procedure of training $accu_y$(TRAAC) and validation $accu_y$(VALAC) curves. This outcome displays a valuable analysis of the behavior of the OFLCC-COA algorithm over varying epochs, representative its learning and generalized capabilities. Mostly, the outcome assumes a constant development in the TRAAC and VALAC with progress in epochs. It confirms the adaptive aspects of the OFLCC-COA methodology in the pattern recognition process under both data. The higher trends in VALAC outline the capability of the OFLCC-COA algorithm to adapt to the TRA data and also to deal exact classification of unseen data, presenting strong generalized capabilities.

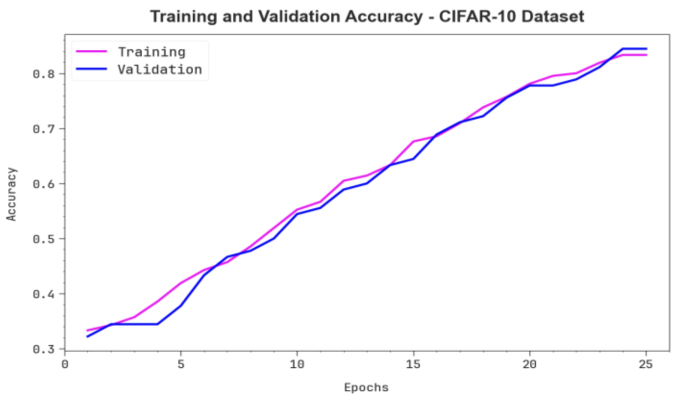

Figure 4. $Accu_y$ curve of the OFLCC-COA system on the CIFAR10 dataset

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Fig. 5 represents a comprehensive outcome of the training loss (TRALS) and validation loss (VALLS) curves of the OFLCC-COA system at the CIFAR10 dataset over various epochs. The progressive decreases in TRALS emphasized the OFLCC-COA method increasing the weights and lessening the classifier error under both data. The outcome identifies a perfect understanding of the OFLCC-COA method associated with the TRA data, underlining its efficiency in capturing patterns. Considerably, the OFLCC-COA technique incessantly improves its parameters in decreasing the variances among the predictive and actual TRA classes.

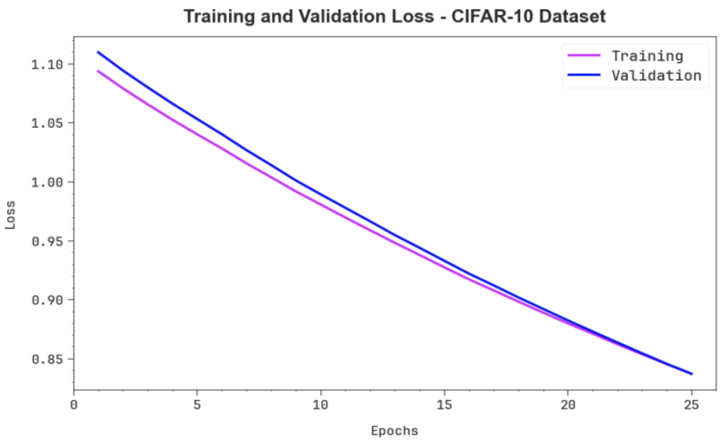

Figure 5. Loss curve of the OFLCC-COA algorithm under CIFAR10 dataset

Table 2 and Fig. 6 examine comparative $accu_y$ outcomes of the OFLCC-COA model at the MNIST dataset. These simulation findings indicate that the OFLCC-COA system gains successful performance over numerous epochs. According to 10 epochs, the OFLCC-COA method provides boosted $accu_y$ of 56.93% whereas the QMAMCC-FL, ACO-FED, GWO-FED, CSO-FED, and TFL techniques acquire minimized $accu_y$ values of 51.62%, 12.89%, 19.91%, 19.90%, and 25.87%, respectively. Additionally, based on 50 epochs, the OFLCC-COA algorithm gives an increased $accu_y$ of 86.49% but, the QMAMCC-FL, ACO-FED, GWO-FED, CSO-FED, and TFL systems get lesser $accu_y$ values of 80.83%, 63%, 66.97%, 67.13%, and 79.05%. Besides, with 100 epochs, the OFLCC-COA algorithm gives a greater $accu_y$ of 90.20% although, the QMAMCC-FL, ACO-FED, GWO-FED, CSO-FED, and TFL techniques obtained the diminished $accu_y$ values of 84.97%, 65.08%, 71.86%, 76.99%, and 79.05%.

Table 2: $Accu_y$ outcome of the OFLCC-COA method with recent algorithms under the MNIST database

Accuracy (%); MNIST Dataset						
No. of Epochs	OFLCC-COA	QMAMCC-FL	ACO-FED	GWO-FED	CSO-FED	Traditional Federated Learning
10	56.93	51.62	12.89	19.91	19.90	25.87
20	70.47	65.84	25.22	40.01	35.51	57.25
30	86.60	80.83	39.62	54.19	50.68	75.53
40	87.46	81.86	54.80	62.41	62.59	78.23
50	86.49	80.83	63.00	66.97	67.13	79.05
60	87.32	81.67	64.67	70.24	72.86	79.45
70	85.04	80.42	64.02	71.66	72.87	79.86
80	87.11	81.65	64.86	71.88	74.31	79.27
90	87.83	83.09	64.92	71.24	75.77	79.66
100	90.20	84.97	65.08	71.86	76.99	79.05

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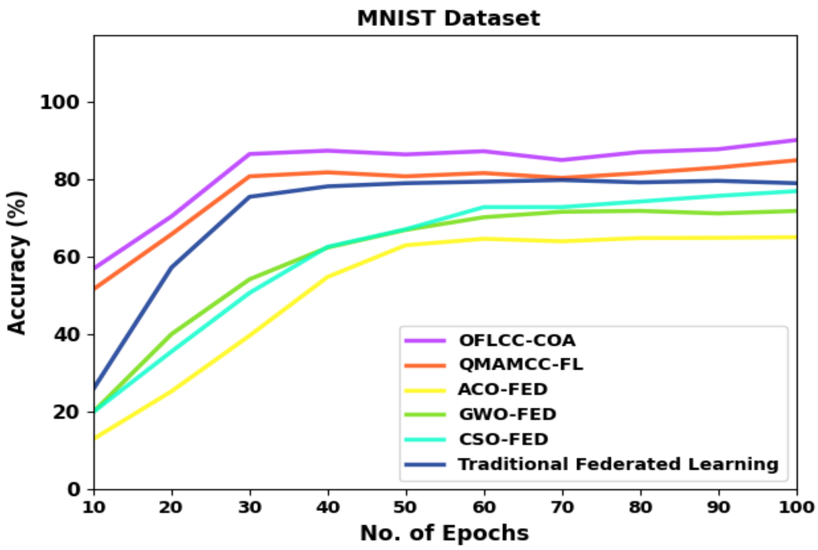

Figure 6. $Accu_y$ Outcome of the OFLCC-COA system at MNIST dataset

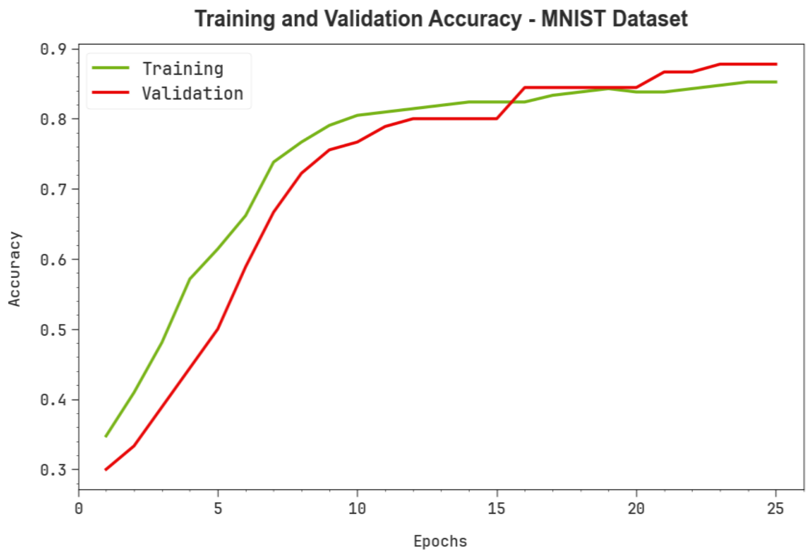

Figure 7. $Accu_y$ Curve of the OFLCC-COA system at MNIST dataset

The efficiency of the OFLCC-COA model at the MNIST dataset is graphically demonstrated in Fig. 7 in the procedure of TRAAC and VALAC curves. This outcome exhibits a useful analysis of the behavior of the OFLCC-COA technique over different epochs, demonstrating its learning method and generalized abilities. Predominantly, the figure undertakes a continuous enhancement in the TRAAC and VALAC with development in epoch counts. It confirms the adaptive aspect of the OFLCC-COA system in the pattern detection method with both data. The increased trends in VALAC outline the proficiency of the OFLCC-COA technique to adapt to the TRA data and also to provide precise classification on hidden data, displaying strong generalized capabilities.

Fig. 8 illustrates a detailed view of the TRALS and VALLS results of the OFLCC-COA system at the MNIST dataset over distinct epochs. The progressive reduction in TRALS highlights the OFLCC-COA technique growing the weights and lessening the classifier error on both data. The outcome states a perfect knowledge of the OFLCC-COA model related to the TRA data, highlighting its efficiency in capturing patterns. Considerably, the OFLCC-COA methodology incessantly increases its parameters in reducing the variances between the predictive and real TRA classes.

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Figure 8. Loss curve of the OFLCC-COA model on the MNIST dataset

The communication cost (CC) results of the OFLCC-COA technique are compared with existing models in Table 3. In Fig. 9, the comparative outcome of the OFLCC-COA technique with respect to CC has been given under the CIFAR10 database. These results show that the CSO-FED model reaches worse outcomes with an increased CC of 89.68%. Along with that, the QMAMCC-FL, ACO-FED, GWO-FED, and TFL algorithms gain moderately closer CC of 69.25%, 79.94%, 75.64%, and 78.87%, respectively. However, the OFLCC-COA technique demonstrates better performance with the least CC of 48.12%.

Table 3: CC outcome of the OFLCC-COA method under two datasets

Communication Cost (%)		
Methods	CIFAR10 Dataset	MNIST Dataset
OFLCC-COA	48.12	56.89
QMAMCC-FL	69.25	71.25
ACO-FED	79.94	87.86
GWO-FED	75.64	85.76
CSO-FED	89.68	80.19
Traditional Federated Learning	78.87	89.39

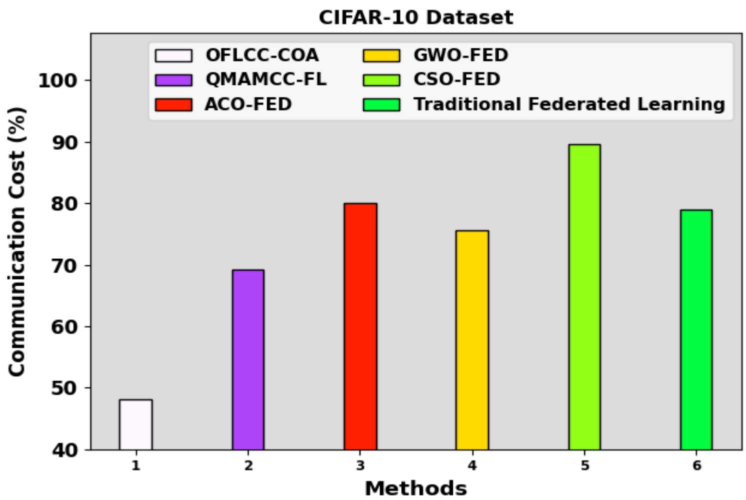

Figure 9. CC result of the OFLCC-COA system at CIFAR10 dataset

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A comprehensive comparative result of the OFLCC-COA method with respect to CC is provided with the MNIST dataset and reported in Fig. 10. These experimentation outcome values presented that the TFL technique gets poorer outcomes with a higher CC of 89.39%. Moreover, the CSO-FED, QMAMCC-FL, ACO-FED, GWO-FED, and systems are acquired reasonably nearer CC of 80.19%, 71.25%, 87.86%, and 85.76%. Nevertheless, the OFLCC-COA algorithm shows excellent performance with a decreased CC of 56.89%, respectively.

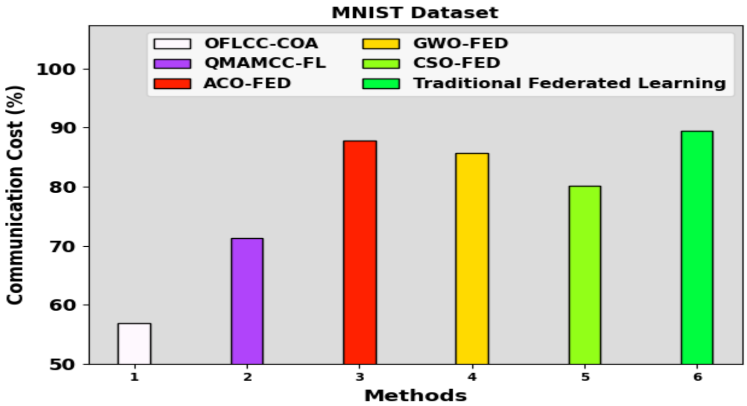

Figure 10. CC result of the OFLCC-COA method at MNIST dataset

In conclusion, the test accuracy (TACC) result of the OFLCC-COA technique is compared with other algorithms on two datasets in Table 4. Fig. 11 represents the comparative TACC outcome of the OFLCC-COA method with the CIFAR10 database. These experimentation outcome values indicate that the ACO-FED, GWO-FED, CSO-FED, and TFL methods indicate lower TACC values of 61.04%, 66.89%, 63.31%, and 65.78%. Concurrently, the QMAMCC-FL technique resulted in considerable $accu_y$ of 74.73%. However, the OFLCC-COA technique highlighted superior performance with a maximum TACC of 81.90%.

Table 4: TACC outcome of the OFLCC-COA system on two datasets

Test Accuracy (%)		
Methods	CIFAR10 Dataset	MNIST Dataset
OFLCC-COA	81.90	83.23
QMAMCC-FL	74.73	76.43
ACO-FED	61.04	61.82
GWO-FED	66.89	60.28
CSO-FED	63.31	67.36
Traditional Federated Learning	65.78	68.18

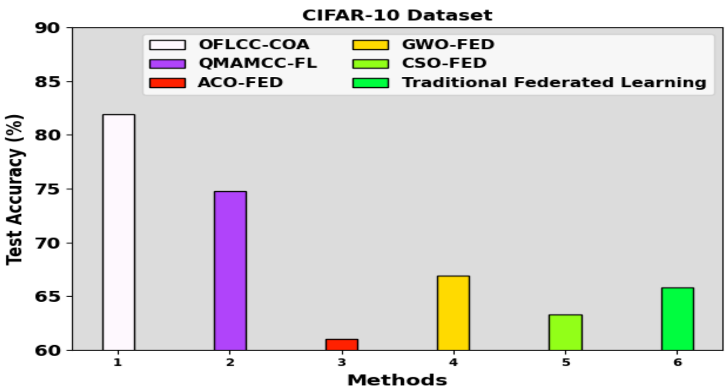

Figure 11. TACC analysis of the OFLCC-COA model on the CIFAR10 dataset

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Fig. 12 signifies the comparative TACC outcomes of the OFLCC-COA system on the MNIST dataset. These experimentation findings point out that the ACO-FED, GWO-FED, CSO-FED, and TFL techniques get minimized TACC values of 61.82%, 60.28%, 67.36%, and 68.18%, respectively. Similarly, the QMAMCC-FL method provides a significant $accu_y$ of 76.43%. However, the OFLCC-COA technique emphasized higher performance with an increased TACC of 83.23%.

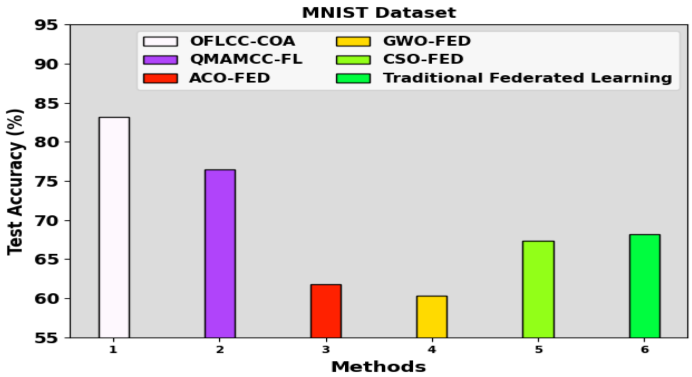

Figure 12. TACC outcome of the OFLCC-COA technique under the MNIST dataset

Thus, the OFLCC-COA model is used for effectual optimization of communication cost in the FL model.

5. Conclusion

In this work, we have developed an OFLCC-COA technique. The OFLCC-COA model is mainly applied for effectually optimizing the communication process in the FL to minimize the data transmission cost with the guarantee of enhanced model accuracy. The OFLCC-COA technique enhances the robust performance in unsteady network environment via the transmission of score values instead of large weights. Besides, the OFLCC-COA technique improves the communication efficiency of the network by transforming the form of data that clients send to servers. The performance analysis of the OFLCC-COA model occurs utilizing different performance measures. The simulation outcomes indicated that the OFLCC-COA model obtains superior performances over other methods in terms of distinct metrics.

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