Enhanced Decentralized Federated Learning based on Consensus in Connected Vehicles

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Abstract: Advanced researches on connected vehicles have recently targeted to the integration of vehicle-to-everything (V2X) networks with Machine Learning (ML) tools and distributed decision making. Federated learning (FL) is emerging as a new paradigm to train machine learning (ML) models in distributed systems, including vehicles in V2X networks. Rather than sharing and uploading the training data to the server, the updating of model parameters (e.g., neural networks’ weights and biases) is applied by large populations of interconnected vehicles, acting as local learners. Despite these benefits, the limitation of existing approaches is the centralized optimization which relies on a server for aggregation and fusion of local parameters, leading to the drawback of a single point of failure and scaling issues for increasing V2X network size. Meanwhile, in intelligent transport scenarios, data collected from onboard sensors are redundant, which degrades the performance of aggregation. To tackle these problems, we explore a novel idea of decentralized data processing and introduce a federated learning framework for in-network vehicles, C-DFL (Consensus based Decentralized Federated Learning), to tackle federated learning on connected vehicles and improve learning quality. Extensive simulations have been implemented to evaluate the performance of C-DFL, that demonstrates C-DFL outperforms the performance of conventional methods in all cases.

1 INTRODUCTION

A new technical analysis by the National Highway Traffic Safety Administration (NHTSA) states that human error is to blame for 94% percent of traffic accidents[1]. Autonomous driving vehicles (AVs) with V2X links can also free labor from simple, repetitive driving by relying on artificial intelligence, visual computing, radar, surveillance devices, and global positioning systems to work together to allow computers to operate motor vehicles autonomously, which can prevent accidents caused by human driving errors. The AVs are expected to perceive the surroundings with data captured by a variety of onboard sensors in near-real-time [2]. However, the increasing data collected by AVs become an issue holding back the development of self-driving technology. The emergence of distributed deep learning (DML) will alleviate this situation.

Distributed Machine Learning is currently one of the most popular research fields in machine learning. Due to the good flexibility and scalability of DML, single-machine resources can be effectively combined. Hence, connected automated driving (CAD) ushered in a new development. Cooperative multi-vehicle control and planning strategies are the emphasis of the CAD functions [3]. Nevertheless, distributed training on autonomous driving vehicles is limited by the following problems. The first is the huge burden that the Internet brings to the backbone network to transmit raw data. Furthermore, it is impossible to share such vast amounts of data.

Federated Learning (FL), which offers improved privacy-preserving functions in comparison to DML systems [4], has been developing in recent years to handle large-scale distributed training across numerous linked devices or agents. Furthermore, FL has recently started to gain attention in connected automated driving applications. With FL, autonomous vehicles send model updates to a so-called parameter server rather than sharing raw sensor data with the server training the model [5]. FL avoids the need for the data to leave the edge devices (refers to the base station in this paper), improving privacy, lowering the computational burden for the server, and decreasing the communication overhead when the model update is smaller than the data to be transmitted per iteration. In early FL implementations, research of FL focuses on Centralized Federated Learning (CFL). However, this approach comes with significant drawbacks [6–8] and scaling issues for increasing V2X network size. Not only does a parameter server create a single point of failure vulnerable to crashes or hacks, but it can also become a performance bottleneck as the number of devices pushing model updates increases, which makes it difficult for autonomous driving to process data in real-time.

This drives researches on decentralized federated learning (DFL) in AVs (as depicted in Fig.1). Decentralized solutions to FL based on a distributed implementation of SGD [9] have been thus proposed. As shown in the example of Fig.1, base station 1 receives the model updates parameters from the neighbors base station 2 and base station 3. Then, it upgrades the local parameters. Models are trained using a decentralized topology and the parameter server is removed with DFL. With DFL, base stations rely on local cooperation with neighbors, each base station is connected to a subset of the other base stations in the network from which it receives incoming models and to which it pushes its updated models. DML solves the communication bottleneck to a certain extent. Decentralized solutions are therefore favored in intelligent transport scenarios, and local processing makes it possible to accelerate the learning process. Additionally, the AV’s perceive the surroundings via analyzing a large amount of data captured by a variety of onboard sensors in near-real-time. More especially, data collected by onboard sensors may be redundant, which affects the performance of aggregation.

To solve the aforementioned problem, we should constitute a new aggregation strategy to train a model with data from sensors. In this work, we propose C-DFL, a novel idea of decentralized data processing and federated learning framework for in-network vehicles, which...
considers redundant data. The main contributions are summarized as follows:

(1) To satisfy new intelligent transport scenarios, we propose a decentralized federated learning framework, C-DFL, for distributed environment understanding of in-network vehicles.

(2) Considering the redundant data collected from vehicles, we explore a novel aggregation paradigm of local model updates, by mapping data into a compact representation as a record of local data distribution. Through exchanging this type of compact representations, base stations can filter redundant data and thus speed up local updating and update aggregation.

(3) Using two real-world datasets, we implement our method and baselines on an NS-3-based simulation platform. Extensive simulations demonstrate that our method outperforms all baselines in terms of accuracy as well as convergence speed.

This paper is organized as follows: We review the related work about DFL in Section 2, and detail the system model of decentralized FL training in Section 3. In Section 4, a decentralized federated learning framework is proposed with a novel aggregation paradigm of local model updates to reduce the impact of redundant data to different local models. Two real-world datasets is used to demonstrate the proposed framework outperforms the state of the art in a V2X scenario. Finally, we conclude this work in Section 6.

2 RELATED WORK

New types of decentralization are anticipated to support next-generation networks. Devices can work together directly over device-to-device (D2D) spontaneous connections thanks to these networks, which are created without the assistance of a central coordinator. D2D techniques bring further advances for Decentralized FL. Instead of depending on centralized solutions, collaborating devices in Decentralized FL share model parameters via D2D connections and set a consensus policy into place. Edge nodes don’t need to rely on a central server for fast training parameters feedback, reducing the communication bottleneck of the FL.

Devices sample, convergence, and stochastic heterogeneity are the three basic difficulties in DFL design [10–13]. Reduced FL process convergence times are crucial, especially in mobility scenarios involving autonomous vehicles.

To reduce the communication bottleneck of the FL, some studies focus on decentralized FL. Lan et al. [14] provided a decentralized stochastic algorithm. Sirb and Ye [15] gave an asynchronous decentralized stochastic algorithm. However, those algorithms are provided not accelerated. For the purpose of improving the communication efficiency of FL, Gossip-based protocol for distributed learning has been explored in the data center setting as an alternative to the parameter-server approach [16]. However, when the communication speed of the nodes and the heterogeneity of the data are related, the GL cannot converge. Later, Guha et al. [17] addressed a decentralized FL based on segmented gossip. Lu et al. [18] applied the decentralized FL to electronic health records. These studies demonstrate how, under certain circumstances, transitioning from a centralized sharing scheme to a decentralized one might enable models to establish a consensus at the global minimum while avoiding server node-related communication delays. In [19], a segmented gossip aggregation is proposed. However, it’s extremely application dependent and not suitable for more general ML contexts. More recently, Savazzi et al.[20] proposed a consensus-based FedAvg-inspired algorithm (referred to as CFA), supposing sparse connectivity. Consensus-driven FL (C-FL) [21], developed by Luca Barbieri et al. It is a decentralized, modular approach to learning FL which is suitable for Point Net compatible deep Systems and Lidia point cloud processing for road actor categorization. [22] proposed fully decentralized paradigms driven by consensus methods.
Gradient Descent (SGD): 

In general, the task initialization is implemented in each client. 

By alternately optimizing a local model at each client and the 

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local model optimization and aggregation steps, training is repeated 

of a weighted sum of the input values in each layer. The function of 

layers, including the input layer, hidden layers, and 

output layer. The model iteratively computes a nonlinear function 

N

w

encapsulates model parameters including Neural Networks weights 

n
 Meanwhile, in other layers \((n = 1, \ldots, N - 1)\) , the function is depicted in 

and \(h_{N-1}\) is an output of the last layer, while for \(n = 0\) , we have 

in the DFL, the parameters \(W\) can be learned by applying 

minimizing a global loss function \(L(W)\): 

With \(L_k\) being the local loss function observed by client \(k\) and 

being the size of the \(k\)-th data set under the non-IID assump- 

by alternately optimizing a local model at each client and engaging in a round of neighborhood communication to acquire an updated global model, DFL was able to tackle this problem iteratively. In general, the task initialization is implemented in each client at \(t = 0\). At iteration \(t > 0\), each client sends local model parameters to their neighbors. Then, every client updates the local model by aggregating the local model parameters and neighborhood parameters at \(t - 1\). This is solved by gradient methods, such as Stochastic Gradient Descent (SGD): 

\[ W_{t+1} = W_t - \mu_s \times \nabla L(W_t) \]  

Where \(\mu_s\) is the learning rate of SGD, and \(\nabla\) is the gradient of the loss by backpropagation. Considering the above described local model optimization and aggregation steps, training is repeated until each model converges to, or the desired training accuracy is obtained.

### 3 The Decentralized Federated learning

Decentralized FL approaches enable the sharing and synchronization of the local model parameters over networking with neighbors without relying on the servers. The proposed DFL approaches combine local models with neighboring ones by algorithms. After that, they update the models using local data and other’s parameters. When local models converge to satisfy a target loss or accuracy, the DFL process typically concludes after a number of communications rounds.

DFL aims to learn every local model \(\hat{y}(W)\), with matrix \(W\) encapsulating model parameters including Neural Networks weights \(w_N\) and biases \(b_N\) and \(x\) is the input data. A deep Neural Network is composed of \(N\) layers, including the input layer, hidden layers, and the output layer. The model iteratively computes a nonlinear function of a weighted sum of the input values in each layer. The function of the last layer is defined as:

\[ \hat{y}(W(N)); x = f_N(w_N x + b_N) \]  

Meanwhile, in other layers \((n = 1, \ldots, N - 1)\), the function is depicted in 

\[ f_n(w_n h_{n-1} + b_n) \]  

and \(h_{N-1}\) is an output of the last layer, while for \(n = 0\), we have \(h_0 \equiv x\). In the DFL, the parameters \(W\) can be learned by applying a minimization a global loss function \(L(W)\):

\[ \min_w L(W) = \min_w \sum_{k=1}^{K} \frac{E_k}{E} \times L_k(w) \]  

4 THE METHOD

#### 4.1 Overall Design

In this section, we propose C-DFL, a decentralized federated learning framework with a novel aggregation paradigm of local model updates to reduce the impact of redundant data on different local models. Specifically, in Section 4.2, we explore a novel redundant data processing solution by mapping data into a compact representation as a record of local data distribution. In Section 4.3, we propose a decentralized federated learning framework, C-DFL, for distributed environment understanding of in-network vehicles.

The proposed algorithm designs the aggregation paradigm of local model updates by mapping data into a compact representation as a record of local data distribution. Through exchanging this type of compact representations, base stations can filter redundant data and thus speed up local updating and update aggregation. The C-DFL algorithm mainly includes two parts: the processing of redundant data and local model training. In the following, this paper details the redundant data processing and model training in section 4.2 and section 4.3.

#### 4.2 Redundant Data Processing

In reality, the V2X network can generate a large amount of data. The data are collected by the camera on vehicles. Then vehicles send them to a nearby base station by V2X, which can lead to the base station having a lot of duplicate data captured by nearby vehicles. Thus, that can affect the accuracy and convergence speed of model training. Therefore, we design CND, a method that maps data into a compact representation.

A detailed description of the CND is provided in Algorithm 1. On line 2, a new item is hashed, and the generated hash value. By different hash functions, we can obtain different bitmaps. To obtain the estimation result, we search the number of “1” in all the bitmaps (line 6) and calculate the arithmetic mean of these numbers, obtaining the cardinality estimation of the dataset (line 9). Specifically, in the hash, we have considered features (separated by semicolon) in each item as tokens and assigned weights to features (lines 11-12). For generating an n-bit simple hash (line 15), we have used an n-bit Jenkins hash function. For each item, weighted all feature vectors, in accordance with the calculation rules, it encounters a hash value and weight, encountering 0 hash values and weight negative multiplication (line 16-20). The weighting result of the various feature vectors is accumulated, and there is only one sequence string (lines 24-25).

#### 4.3 Model Training

This section mainly introduces the algorithm for model training, and the proposed method allows the base station to rely on cooperation with neighbor base stations and local intranet processing to learn model parameters. We construct a ring network topology \(G = (V, E)\) with the set of base stations \(V = 1, 2, \ldots, k\) and edges (links) \(E\). The \(K\) distributed base stations are connected through a decentralized communication architecture based on V2X communications. The neighbor set of base station \(k\) is denoted as \(N_k\), with cardinality \(|N_k|\). Notice that we include base station \(k\) in the \(N_k\) while \(N_k = \emptyset\) does not. As introduced in the previous section, each base station has a database \(E_k\) of examples \((x_k, y_k)\) that are used to train a local NN model \(W_{k,t}\) at some epoch \(t\). The model maps input features \(x\) into outputs \(y(W_{k,t}; x)\) as in (1). A cost function, generally non-convex, as \(L_k(W_{k,t}; x)\) in (3), is used to optimize the weights \(W_{k,t}\) of the local model.

First, initialize the parameters \(w_{0,k}\) and compute the bitmaps of local data by CND (lines 2-5) at time \(t = 0\) for each base station. After a certain round of local training time \(t > 0\), base station \(k\) sends its model updates \(w_{t,k}\) and bitmaps of the dataset to its neighbors by the V2X network. Meanwhile other base stations \(k\) receive weights and bitmaps from neighbors \(w_{t,k}, i \in N_k\). On the received bitmaps, the base station \(k\) uses the local data set to continue to calculate the hash value by CND. After the above processing, the
Algorithm 1 Counting Non-repeated data (CND)

Require:
T: a new item;
Bitmap: vector of size n, initialized to 0;

Ensure:
avg: the estimation of cardinality of the items;
1: for each i ∈ [0, 2] do
2: while the sampling period is not end do
3: hash ← hash_{i}(item);
4: Bitmap[hash] ← 1;
5: end while
6: count[i] ← Search the number of the 1 bit in the bitmap;
7: return count[i];
8: end for
9: avg ← (count[0] + count[1] + count[2]) / 3;
10: begin hash_{i}(item);
11: feature[i] ← tokenize;
12: weight[i] ← assign weights to features;
13: v = vector of size n, initialized to 0;
14: for each feature i in an item do
15: feature_hash_make_n-bit hash(feature);
16: for i = 1 to n do
17: if ith bit of feature == 1 then
18: v[i] ← v[i] + weight(feature);
19: else
20: v[i] ← v[i] - weight(feature);
21: end if
22: end for
23: end for
24: bit_vector = vector of size n, initialized to 0
25: for i = 1 to n do
26: if v[i] > 0 then
27: bit_vector[i] = 1
28: end if
29: end for
30: return bit_vector to decimal

Algorithm 2 C-DFL

Require:
T: Dataset;
Ensure:
Category:
1: initialize w_{0,k} ← base station k
2: for round t ∈ [1, n] do
3: receive w_{t,i}(i ∈ N_k), bitmaps
4: for all base stations i ∈ N_k do
5: for all base stations k ∈ N_k do
6: Ψ_{t,k} ← w_{t,k}
7: end for
8: w_{t+1,k} = ModelUpdate (Ψ_{t,k})
9: send (w_{t+1,k}), bitmaps
10: begin ModelUpdate (Ψ_{t,k})
11: B ← mini-batches of size B
12: m_{t+1,i} ← β_1 m_{t,i} + (1 - β_1) ∇ L_{t,i} (Ψ_{t,i})
13: v_{t+1,i} ← β_2 v_{t,i} + (1 - β_2) ∇^2 L_{t,i} (Ψ_{t,i})
14: end for
15: w_{t+1,k} ← Ψ_{t,k} - (1 - β_1) · m_{t+1,i} / ψ_{t,i}
16: end return (w_{t,k})
17: end ModelUpdate (Ψ_{t,i})

base station k calculates the number of different data between it and other neighbor base stations. Then, it obtains the weight of the model aggregated based on the number of different data. Finally, it updates its model w_{t,k} at time t.

\[ \psi_{t,k} = \eta_i \psi_{t,k} + \gamma t \sum_{i \in N_k} \eta_{k,i} (W_{t,i} - W_{t,k}) \] (5)

Where \( \gamma_t \) is the consensus step size and \( \eta_{k,i} \) is the mixing weights for the models which are stetted as:

\[ \eta_{k,i} = \frac{\sum_{k \in N_t} E_k}{\sum_{k \in N_t} E_k} \]

(6)

\[ E_k = E_k W_{t,k} \]

(7)

where \( E_k \) is the size of the dataset on base station k and \( E_{t,k} \) is the number of the dataset processed by the CND, where the mixing weights \( \eta_{k,i} \) are adapted on each epoch \( t \) based on current validation accuracy or loss metrics. The consensus step size \( \gamma_t \) can be chosen as \( \gamma_t \in (0, 1/\nabla) \), and \( \nabla = \max_k (\sum_{i \in N_k} \eta_{k,i}) \).

Once the consensus process is completed, the base station i sends the parameters \( w_{t,k} \) and runs a local optimizer to minimize local loss L (3). Considering Adam is an optimizer, this last stage is implemented as \( W_{t+1} = W_t - \mu \times \nabla L(W_t) \) with:

\[ \Delta \psi_{t,i} = \mu t \frac{1 - \beta_1}{1 - \beta_1^t} \cdot m_{t+1,i} \frac{1 - \beta_2}{1 - \beta_2^t} \]

\[ m_{t+1,i} = \beta_1 m_{t,i} + (1 - \beta_1) \nabla L_{t,i} (\psi_{t,i}) \]

\[ v_{t+1,i} = \beta_2 v_{t,i} + (1 - \beta_2) \nabla^2 L_{t,i} (\psi_{t,i}) \]

5 EXPERIMENTAL EVALUATION

We report experiments conducted on two real-world datasets, which are: MINIST[27] and BIRD-400[28] to validate our proposed C-DFL approach.

5.1 Simulation Setup

In order to validate our method, we simulate the experiment with MLP and VGG on Sim4DistrDL[29]. We choose the common edge network topology (as depicted in Fig.4). The topology used in the simulation process is a ring topology. It includes four connected base stations and their adjacent end vehicles. The connection between vehicles and base stations via V2X. The ML model’s parameters are exchanged through V2X communications. The base stations and vehicles are connected through wireless links. The vehicles are used for capturing data, while base stations are used for training models. The data required for model training are all released by the nearby vehicles. The base station uses the received parameters and the data received by vehicles to train DNN models in a collaborative way.

As can be seen from the above topology diagram, the neighbor of 4-edge base station sets consists of \( N_T = \{4, 2\}, N_7 = \{1, 3\}, N_7 = \{2, 4\}, \) and \( N_T = \{3, 1\} \). Each kth base station has a database of \( E_k \) local training data.
5.2 Datasets

Our experiments are performed on two datasets for classification, MNIST and BIRDS 400. The MNIST consists of 10 classes (from 0 to 9) with the dimension of 786 (28x28x1), respectively. BIRD consists of 400 bird species, and all images are 224x224x3 color images in jpg format.

5.3 Baseline Models

We consider three baseline algorithms: (1) Consensus-Based FA (CFA)[13], (2) Consensus-driven federated averaging (C-DFA)[21] (3) Consensus-Driven FA (CDFA) [7]. The training of the above algorithms is based on decentralized federated learning. Specifically, the C-DFA algorithm is implemented by applying the federated optimization to a variable number $Q \leq N$ of layers (FC and CN layers) in the NN. More specifically, performances are analyzed by varying the fraction $M = Q/N$ of the layers subject to the C-FL process. We consider C-DFA $M = 100\%$ as a baseline. For CDFA, we don’t consider encoding and decoding, and use it as another comparison scheme.

5.4 Experimental Results

In this section, we give the numerical results for the evaluation of the proposed C-DFL. The method is evaluated in terms of loss and accuracy using the previously mentioned network topology configuration. In the following, Sec. 5.4.1 details the results of the MLP model based on MINIST, Sec. 5.4.2 describes the results of the VGG model based on BRID-400 and illustrates the more accurate comparison of the two models.

5.4.1 MINIST: The MNIST consists of 10 classes (from 0 to 9) of signals with a dimension of 786 (28x28x1). In this work, we consider solving a 10-label classification problem with data federation formed between different vehicles. In our setting, each base station collects 320 training samples (including 10 categories) and 80 testing samples (see fig4 for the data distribution). Each base station utilizes local neural networks that have one hidden layer with...
30 units to learn input samples. We set learning rate = 0.0001, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\delta = 1e-7$ and batch size = 32. Each base station sends and aggregates the learned weights and biases of neural networks with its neighbors via the V2X network.

Fig. 5 reports the loss of C-DFL (our method) and baselines on each base station, while Fig. 6 presents the corresponding test accuracy for our method and baselines. It can be seen from Fig. 5 that the baseline algorithms converge very slowly due to redundant data. On the other hand, our method can provide highly accurate results outperforming baselines. It outperforms Consensus-Driven FA [25] and CDFA significantly and outperforms CFA by a large margin (see Figure 6).

5.4.2 BIRD-400: This Dataset contains 58388 training images and 2000 test images of 400 categories with a shape of 224×224×3. This is an extremely high-quality dataset where each image only contains one bird, and the bird usually occupies at least 50% of the image’s pixels. Each base station has 120 training samples (including 5 categories and redundant data) and 30 testing samples (the data distribution as depicted in Fig7). Each base station uses one local Visual Geometry Group (VGG) model to learn from training images and test images of 400 categories with a shape of 224×224×3.

Each base station sends and aggregates the learned weights and biases of the model with the in-network vehicles. From Fig.8 and...
Fig 9, we have the following observations. Our scheme is obviously faster than CDFA and C-DFA in terms of convergence speed and also has some improvement over CFA. This suggests that, the baseline algorithms are poorly adapted to redundant data. Table 1-4 shows the training rounds to achieve a specific accuracy (about 80 percent) in terms of different algorithms. C-DFL outperforms the baselines in the data processing period. This demonstrates that filtering redundant data brings great benefits for improving the accuracy and convergence speed of federated learning models. Our method achieves 80 percent accuracy in about 8 epochs, whereas other methods only achieve 50 accuracy in 100 epochs. While using the VGG model, C-DFL reduces convergence delay by half compared with C-DFA and CDFA. In addition, compared with the CFA algorithm, our scheme also has a significant improvement. Results also indicate that, the reduction process of the impact of redundant data at local is essential to improve aggregation performance among the base stations.

### Table 1: The Epoch and the Test accuracy

| Base station | 1 (Our) | 1 (CFA) | 1 (C-DFA) | 1 (CDFA) |
|--------------|---------|---------|-----------|----------|
| MLP          | 9(0.86) | 100(0.54) | 100(0.45) | 100(0.44) |
| CNN (VGG)    | 19(0.86)| 19(0.86) | 27(0.81)  | 47(0.81)  |

### Table 2: The Epoch and the Test accuracy

| Base station | 2 (Our) | 2 (CFA) | 2 (C-DFA) | 2 (CDFA) |
|--------------|---------|---------|-----------|----------|
| MLP          | 9(0.88) | 100(0.58) | 100(0.31) | 100(0.45) |
| CNN (VGG)    | 18(0.86)| 28(0.85) | 52(0.82)  | 43(0.80)  |

### Table 3: The Epoch and the Test accuracy

| Base station | 3 (Our) | 3 (CFA) | 3 (C-DFA) | 3 (CDFA) |
|--------------|---------|---------|-----------|----------|
| MLP          | 10(0.84)| 100(0.4) | 100(0.15) | 100(0.44) |
| CNN (VGG)    | 18(0.87)| 15(0.86) | 37(0.8)  | 43(0.82)  |

### Table 4: The Epoch and the Test accuracy

| Base station | 4 (Our) | 4 (CFA) | 4 (C-DFA) | 4 (CDFA) |
|--------------|---------|---------|-----------|----------|
| MLP          | 7(0.84) | 100(0.58) | 100(0.6) | 100(0.61) |
| CNN (VGG)    | 17(0.83)| 19(0.86) | 30(0.83) | 47(0.87) |

### 6 Conclusion

We addressed a novel idea of decentralized data processing with a federated learning framework based on consensus in vehicles. To satisfy concerns of edge-cloud cooperation for new intelligent transport scenarios, we explore a decentralized aggregation paradigm of local model updates. Extensive simulations on NS-3 demonstrate that through efficient cooperation at the edge. The evaluation has also shown that this is useful to reduce the learning time and meet the challenging requirements foreseen for full self-driving scenarios. Finally, although this paper addressed a classification task as an application of connected vehicles, the proposed framework can be generalized to perform a wider range of tasks.

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Fig. 7: The Cross-Entropy Loss of CNN (VGG)

Fig. 8: Test accuracy (%) comparison of C-DFL to CFA and CDFA on BRID-400 (VGG)
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