

## FedLANE: a federated U-Net architecture for lane detection

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### ABSTRACT

Lane detection is a crucial module for today's autonomous driving cars. Detecting road lanes is a challenging task as it varies in color, texture, boundaries and markings. Traditional lane detection techniques detect the lane by applying a model trained with centralized data. As roads vary in urban and rural areas, a more localized and decentralized training technique is desired for accurate and personalized lane detection. Federated learning has recently proved to be a promising technology that trains and prunes the model using local data. Applying federated learning-based lane detection improves the accuracy of detection and also ensures the security and privacy of autonomous cars. This paper proposes FedLANE, a federated learning-based lane detection technique. U-Net, U-Net long short-term memory (LSTM) and AU-Net architectures were explored using a federated learning approach. Experimental analysis using TuSimple and CuLane dataset shows that the FedLANE based lane detection performs similar to that of the traditional deep learning lane detection models.

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## 1. INTRODUCTION

Driving accidents occur due to driver's drowsiness, usage of smartphones and incomplete judgment. This accounts for a total of 94% of accidents. According to a survey, it is reported that 80% of accidents can be reduced by introducing intelligence into vehicles [1]. Lane detection is one of the important environment perception modules for the advanced driver assistance system (ADAS) that detect lane markings and roads. With the recent development of high-definition cameras and high computing devices, real-time lane detection for driving assistance is possible. This also contributes highly to the development of semi-autonomous and fully autonomous self-driving cars [2]. High-definition cameras and light image detection and ranging (LIDAR) is used to capture lane images and techniques viz., feature-based lane detection technique, a mathematical model-based lane detection and machine learning and deep learning (ML/DL) based technique has been used to detect lane on real-time and guide the driver and the car.

Due to the growth of high computed devices, machine learning and deep learning architectures have been explored for lane detection. Researchers thrive to gratify the accuracy of lane detection by proposing various architectures. However, most of these architectures proposes centralized processing of the data using a single model [3]. Recently federated learning-based decentralized architectures have proved to show improved accuracy and efficiency [4]. In traditional centralized lane detection techniques, the following concerns have to be addressed; i) the model's training and testing employing a centralised design produce biased results under a variety of environmental and road conditions, ii) data gathered from self-driving and autonomous vehicles should be kept secret, because sending data to a testing server at a centralised location

compromises privacy and uses more network capacity, and iii) the real-time performance of ADAS is impacted by the centralised lane marking analysis delay. Considering these concerns, a FedLANE federated learning-based decentralized lane detection technique has been proposed. The clients are trained on various conditions and the aggregate server combines the output to provide pruned lane detection output. This improves accuracy, preserves data privacy and also saves bandwidth.

On lane detection methods, many works of literature have been proposed. Borkar *et al.* [5] proposed techniques such as RANSAC and Kalman filter for real-time lane recognition of highway with an accuracy of 88%. However, these methods have low accuracy under different lane detection scenarios. Apostoloff and Zelinsky [6] techniques like color cue and bar filtering have been suggested for the hough transform. However, it only gives results with 80% accuracy. Finding the boundary point on the edge map using the euclidean distance transform [7]. However, this is not reliable for lane prediction. Traditional methods were used in a lot of initiatives in the past, which led to erroneous results. Deep learning methods are now applied in this field. In comparison to traditional methods, segmentation, one of the deep learning techniques, generates results with good accuracy. Zou *et al.* [8] analysed numerous frames of a scene using a hybrid deep architecture that included recurrent and convolutional neural networks. The outcomes will be greater if they incorporate the lane fitting into the framework, though. Zhang *et al.* [9] observed that federated learning will increase the accuracy of steering angle prediction however, it surpassed the traditional method.

Zhang *et al.* [10] suggested this model's U-Net architecture for route extraction, deep neural networks can be trained by adding residual units. Additionally, the network features a large number of skip connections that disseminate data and permit the construction of networks with fewer parameters for better performance. This model, meanwhile, might not be applicable in remote areas. Manias and Shami [11] utilized federated learning to handle the difficulties of scalability, high availability, and data protection. They used the multi-view encoder framework in conjunction with SLU benchmark datasets, according to [12]. Using federation improved intent detection accuracy by 1.53%, according to the results. LaneNet have been proposed [13], although they only provide 86% accuracy. LaneNet is one such real-time lane detection system. U-Net's accuracy is 90%, whereas SegNet's accuracy is 89%. Kim [14] combined a Markov-style process sensor-fusion algorithm and a likelihood-based object recognition algorithm effectively for enabling in merging of lane and obstacle detection results using vision-based sensors. Never depend solely on sensors. Teng *et al.* [15] utilized particle filtering technique to integrate multiple cues for lane tracking.

Kumar and Simon [16] used lane recognition and tracking method, it was found that it is easy to recognise lanes using eyesight. However, because to the variety of lane conditions, lane identification and tracking can still be improved. Li *et al.* [17] structured visual detection approach that leverages the power of deep neural networks and accounts for structural cues combing convolutional network and recurrent neuron layer. Li *et al.* [18] suggested sensitive data such as medical records, company data, and client data need to be secured, as they can be exposed when used in other training models. However, using federated learning can solve this problem, according to the researchers. However, they also show that a large dataset without any outliers can improve the accuracy of end-users. Combining the algorithms with federated learning [19] will yield results that are more accurate than those from the classic algorithm technique. Analyses have been done on many enhanced deep learning-based models in [20]. All of these architectural designs have undergone centralization experiments.

Lane recognition is a crucial part of sophisticated driver support systems in self-driving and autonomous vehicles, therefore real-time performance with minimal latency and bandwidth usage is required. Furthermore, it is necessary to protect the user's privacy. Due to its ability to increase privacy, reduce latency, and consume less bandwidth, federated learning has recently been touted as a potential method for real-time applications. Self-driving automobiles gather private road images in the federated learning environment and analyse them to recognise the lane markings using the local model. This protects the user's location's privacy. Local processing of the data minimises latency and enables real-time lane recognition.

## 2. METHOD

Federated learning developed by google involves collaborative learning from distributed devices and consolidating the results with a central aggregation server. It was developed in 2016 to predict user text input in mobile devices. Further variants of federated learning (FL) have been used for emoji prediction, human trajectory prediction, and human behavior prediction [21]. It has its application in the areas of unmanned ariel vehicles, text analysis and sentiment analysis. It is also widely used in healthcare for diagnostic and predictive healthcare applications. The working of FL is shown in Figure 1.

For example, application of FL in self-driving cars can be explained as Figure 1 The global model is initially downloaded as local models to the set of chosen self-driving cars. The downloaded local model is used by the cars as it performs lane detection. The central server receives the local updates. The server updates the

local model, notifies the self-driving cars of the model updates, and then update their local model. In this way, the data is secured locally and privacy is retained. Communication cost decreases as the storage-intensive images are not transferred from self-driving cars to the global server. The next section explains the FL-based lane detection technique.

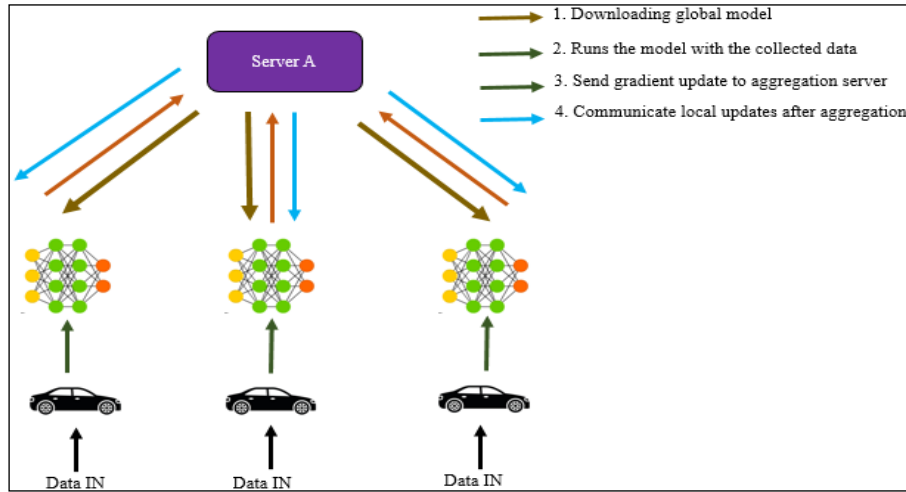


Figure. 1 Working of FL

**2.1. Federated lane detection**

Federated lane detection technique has experimented with U-Net, U-Net scanning tunneling microscopy (STM) and AU-Net. The U-Net architecture has been proved to be an efficient architecture in capturing finer details of the scene for better detection and classification. It has been widely used in medical and transport data analysis [22]. Variants of U-Net have also been proposed for improving accuracy. However, lane detection using static frames is affected by variable weather conditions and irregular road marking. Hence lane detection from the continuous driving scene is desirable. To keep the features of the previous frame fused with the current frame long short-term memory (LSTM) may be introduced. A hybrid architecture using a combination of U-Net and LSTM has been proposed. To provide accurate feature extraction attention blocks are interleaved between the convolutional block to form attention-based deep neural architecture. The input image is subjected to channel attention block and spatial attention block. The result of both the attention mechanism is fused using a weighted sum. The feature map extracted is subjected to binary and instance segmentation which results in an appropriate classification output [23], [24]. The deep learning architecture U-Net, U-Net LSTM and AU-Net have been explored using a federated learning approach.

The steps in the federated learning approach are given below. Initially, the global model  $M_g$  is downloaded to the set of selected self-driving cars as local models  $M_g \rightarrow M_g^i$ , where  $i$ , stands for a selected set of clients from 1 to  $i$ . The cars experiment with lane detection on the downloaded local model as  $M_g^i(Data IN)$ . The local updates are communicated to the central server as  $M_g^i(w_k)$ , where  $w_k$  is the new set of updated gradients. The server updates the local model and communicates the model updates  $M_{g_{new}}$ , to the self-driving cars. The self-driving cars then update their local model  $M_g^i \rightarrow M_{g_{new}}^i$ . The steps shown in the Algorithm 1 executes the federated learning approach. As pruned model trained with local data corrects the global model, the model becomes more accurate for lane detection.

**Algorithm 1. Federated learning U-Net approach**

- Step 1 – Given generic model  $M_g(I, w)$ ,  
 $I$  denotes the input images,  $w$  denotes the initial weights  
 $M_g = \{U - Net, U - Net LSTM, AU - Net\}$
- Step 2 – for (epochs = 0 to  $k$ )  
 $\{train \rightarrow M_g(I, w)\}$
- Step 3 – download  $M_g \rightarrow M_g^i, M_g^i$  denotes local model in client  $i$ .
- Step 4 – for (epochs = 0 to  $k$ )  
 $\{prune \rightarrow M_g^i(I_{test}, w), I_{test}, real\ time\ test\ data\}$
- Step 5 – obtain Parameters  $w \rightarrow w_{new}$
- Step 6 – send  $w_{new}$  to global server.

Step 7 – for (epochs = 0 to k)

{train →  $M_g(I, w)$ }

Step 8 – download  $M_{g_{new}} \rightarrow M_{g_{new}}^i, M_{g_{new}}^i$  denotes updated local model in client i.

Repeat from step 4.

### 3. RESULTS AND DISCUSSION

#### 3.1. Datasets

The proposed technique has been analyzed using two datasets [25] viz., the TuSimple dataset and the CuLane dataset. The TuSimple dataset has 6,408 road images with 1,280×720 resolution. The images were captured on US highway roads. In these 3,626 images are used for training and 2,782 images are used for testing purposes. The dataset was collected under medium and good weather conditions at different day times and traffic conditions. The CuLane dataset was framed from a video taken for 55 hours from six cities. The dataset holds 88,880 images for training and 34,680 for testing purposes. Annotations are included using curved splines and are context-based. This dataset also captures the road condition on various conditions viz., normal, crowded, night, shadow and arrow.

#### 3.2. Performance analysis

For analyzing the performance of the proposed technique, two approaches;

- Centralized learning approach: the datasets are analyzed in a single server using attention-based U-Net architecture.
- Federated learning approach: the datasets are analyzed in the client location and combined using an aggregation server. In all the analyses attention-based U-Net architecture is used.

The experiment is performed in Google Collaboratory using Python libraries viz., NumPy, pandas, Keras and TensorFlow. For the centralized approach, the U-Net, U-Net LSTM and AU-net deep learning architectures are executed and the results are recorded. Similarly, for the federated learning approach, U-Net, U-Net LSTM and AU-net deep learning architectures are executed. In the FL model, three set of clients viz., K=5, K=10, K=15 is selected, data is distributed and the results are aggregated using the aggregation server. Data is distributed using independent and identical distributed data (IID) and non-independent and identical distributed data (Non-IID). The model is executed for 50 rounds to ensure better results. FedAvg, federated averaging where the global model is updated by averaging the received gradient updates from the local model. The performance metrics evaluated are as follows [25].

##### 3.2.1. Accuracy

The accuracy is the ratio between the number of correctly classified instances and the total number of instances. The formula for accuracy is given in (1);

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

the terminologies associate with the metric are:

- True-positives (TP): true positives are cases in which true cases are correctly predicted as true.
- True-negative (TN): true negatives are cases when actual false cases are correctly predicted as false.
- False-positive (FP): false positives are cases in which actual false cases are wrongly predicted as true.
- False-negatives (FN): false negatives are cases in which true cases are wrongly predicted as false.

##### 3.2.2. Precision

Precision is a measure of correctly classified cases among the total number of cases, and it is calculated using (2). The quality of a positive prediction that the model makes is referred to as precision. It refers to the ratio of true positives to the sum of true positives and false positives.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

##### 3.2.3. Recall

A recall is a ratio between the correctly classified cases with that of correctly classified and true and wrongly classified, and it is calculated using (3). It is measured as the ratio of TP to the sum of TP and FN. The recall measures how well the model can identify positive samples.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

**3.2.4. F1-score**

F1-score is the mean of precision and recall, and the formula to calculate F1-score is given in (4). F1-score is a machine learning evaluation metric that measures a model's accuracy. The accuracy metric computes how many times a model made a correct prediction across the entire dataset. It is calculated as the ratio of two times the precision and recall to the sum of precision and recall.

$$F1\_Score = \frac{2*precision*recall}{precision+recall} \tag{4}$$

The experiment is performed in Google Collaboratory using Python libraries viz., NumPy, pandas, Keras and TensorFlow. For the centralized approach, the U-Net, U-Net LSTM and AU-net deep learning architectures are executed and the results are recorded. Similarly, for the federated learning approach, U-Net, U-Net LSTM and AU-net deep learning architectures are executed. In the FL model, three set of clients viz., K=5, K=10, K=15 is selected, data is distributed and the results are aggregated using the aggregation server. Data is distributed using independent and identical distributed data (IID) and non-independent and identical distributed data (Non-IID). The model is executed for 50 rounds to ensure better results. FedAvg, federated averaging where the global model is updated by averaging the received gradient updates from the local model.

**3.3. Result analysis of the centralized approach**

The centralized approach executes three deep learning architectures viz., U-Net, U-Net LSTM and AU-Net. Figure 2, shows the accuracy comparison of the centralized approach for the TuSimple dataset and CuLane dataset. From the Figure 2, it is evident that the higher accuracy of 97% is achieved with AU-Net and the lowest accuracy of 94% is achieved with U-Net architecture using the TuSimple dataset. When experimented with the CuLane dataset highest accuracy of 97.22% is obtained with AU-Net and the lowest accuracy of 94.78% is achieved with U-Net architecture. Table 1 tabulates the performance analysis of the centralized approach with three deep neural architectures. Performance metrics viz., precision, recall and F1-score have been measured for three architectures with TuSimple and CuLane datasets.

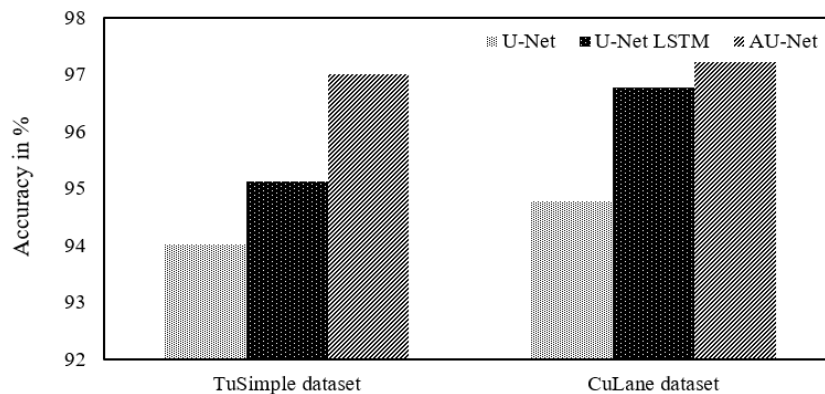


Figure 2. Accuracy of the centralized model

Table 1. Performance results of centralized approach

Dataset	Deep learning architecture	Precision (%)	Recall (%)	F1-score (%)
TuSimple dataset	U-Net	92	91	93
	U-Net LSTM	94	95	92
	AU-Net	97	98	97
CuLane dataset	U-Net	93	91	93
	U-Net LSTM	94	96	96
	AU-Net	97	96	97

**3.4. Result analysis of federated learning approach**

A federated learning approach was executed using the Tusimple dataset and CuLane dataset on U-Net, U-Net LSTM and AU-Net. The IID and Non-IID data are used for evaluation for 50 rounds. The data is compared for K=5, K=10 and K=15. Figure 3 shows the accuracy score for the centralized approach compared with the federated approach for U-Net, U-Net LSTM and AU-Net using IID data applying the

TuSimple dataset. From the Figure 3, it is depicted that the federated learning technique could achieve accuracy similar to the centralized approach. Figure 4 shows the accuracy score for the centralized approach compared with the federated approach for U-Net, U-Net LSTM and AU-Net using IID data applying the CuLane dataset. Similar to the TuSimple dataset, the federated learning technique could achieve accuracy similar to the centralized approach.

Figure 5 and Figure 6 show the accuracy score for the centralized approach compared with the federated approach for U-Net, U-Net LSTM and AU-Net using non-IID data applying TuSimple and CuLane dataset. Due to the non-IID nature of the data, there was a slight depression inaccuracy. However, the federated learning approach is near the accuracy level of the centralized approach. Further pruning of the federated learning approach can achieve better accuracy than the centralized training approach.

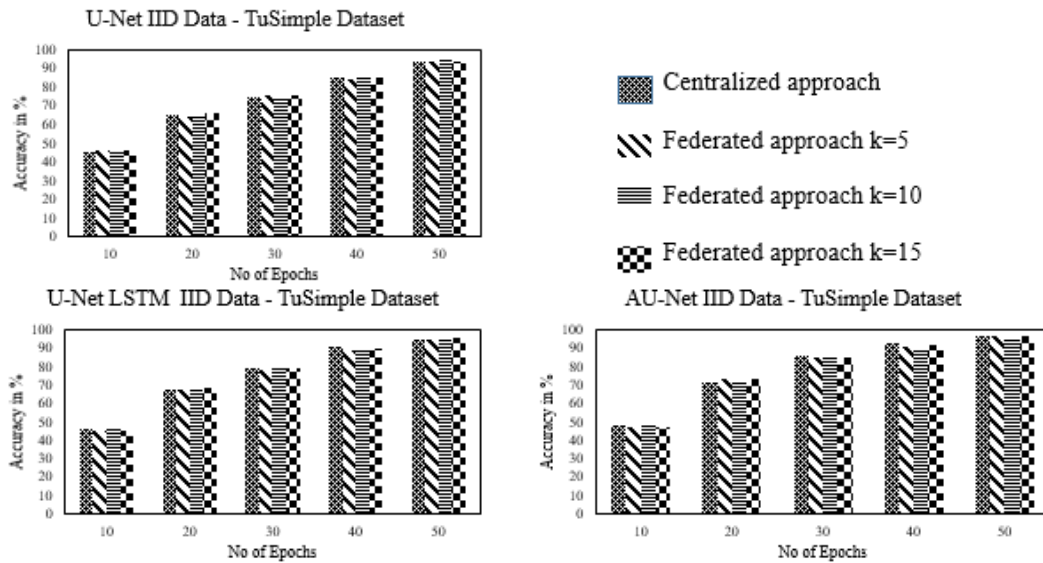


Figure 3. Accuracy score of centralized approach compared with federated approach IID data-TuSimple dataset

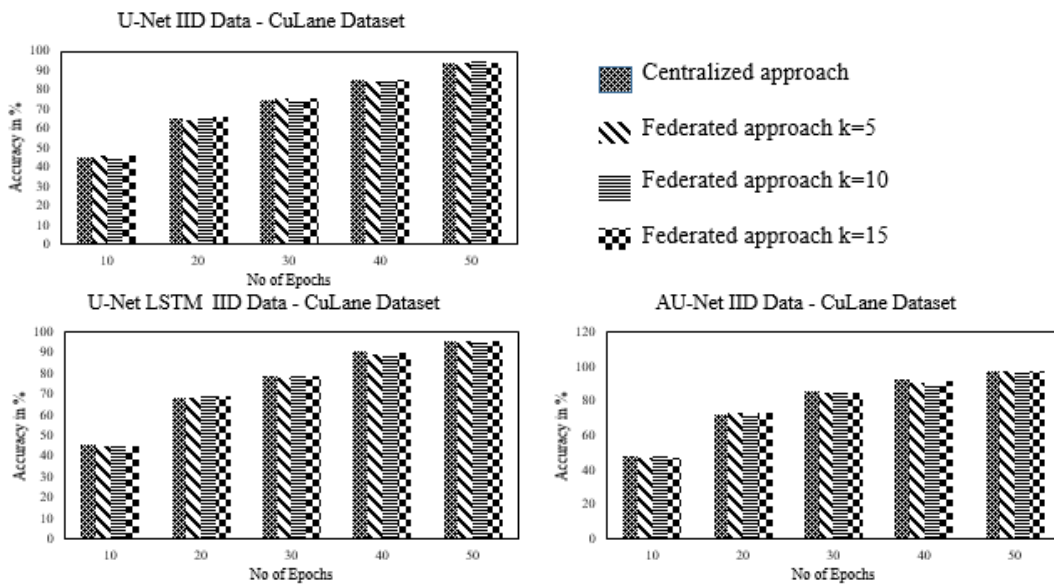


Figure 4. Accuracy score of centralized approach compared with federated approach IID data-CuLane dataset

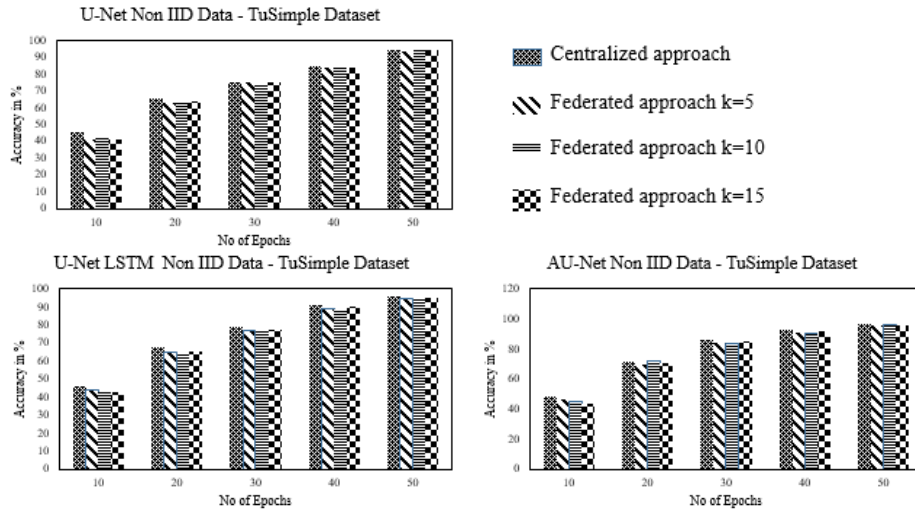


Figure 5. Accuracy score of centralized approach compared with federated approach Non-IID data-TuSimple dataset

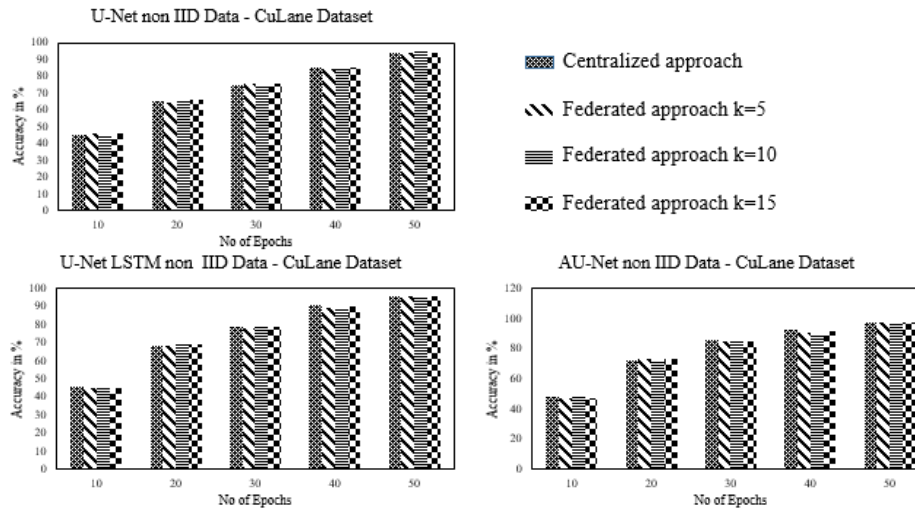


Figure 6. Accuracy score of centralized approach compared with federated approach Non-IID data-CuLane dataset

#### 4. CONCLUSION

For sophisticated driver assistance systems in self-driving cars, lane detection has become a crucial environment perception technology. In the past, lane detection has been investigated utilising deep learning, machine learning, mathematical models, and image processing. Models developed using a preset dataset are insufficient owing to variable weather and traffic conditions. The security of the user is significantly compromised while sending real-time lane data to a centralised server for model training. Federated learning-based deep learning architectures have been studied in order to enable privacy and real-time output from lane detecting systems. The TuSimple dataset and CuLane dataset have been used to evaluate the proposed FedLANE detection method for K=5, 10 and 15 clients over a total of 50 epochs. For both IID and Non-IID data, performance indicators such as accuracy, precision, recall, and F1-score have been calculated. Evaluation of performance demonstrates unequivocally that in many instances, the federated learning model performs similarly to the centralised learning strategy, and in a select few instances, it performs better. This demonstrates that the federated learning model may be used when data privacy is an issue and the system demand real-time operation with a minimum amount of latency. In the future, federated learning categories such as vertical federated learning, horizontal federated learning and federated transfer learning can be explored with lane detection applications. The selection of users and improvised aggregation in the server can further be explored.

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