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# Federated Learning Based Enhanced FedBA with MobileNet Convolutional Neural Network for the Identification of Columnar Cactus

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**Abstract**

With the advancement in artificial intelligence (AI) technology and Internet of Things (IoT) growing popularity, the use of unmanned aerial vehicles (UAVs) as IoT devices is also being studied. However, privacy issues and limited communication resources restrict the use of unmanned aerial vehicles. Federated Learning (FL) has emerged as a promising approach for training machine learning models on decentralized devices while maintaining data privacy and reducing the communication costs. To aggregate the model on the server-side FL server uses various aggregation algorithms. One such promising aggregation algorithm is FedBA for non-identically and independently distributed (non-IID) data via UAVs. However, despite its advantages, FedBA may face challenges related to convergence speed, robustness to malicious clients, and overall efficiency. To solve these challenges, this study presents an FL model aggregation technique in which clients and servers communicate parameters as opposed to data, thereby enhancing privacy, and reducing communication costs UAVs images. This research proposes enhancements to the FedBA algorithm aimed at addressing these challenges and improving its performance. The method proposes federated learning based enhanced FedBA with MobileNet Convolutional Neural Network (CNN) for the identification of columnar cactus in the Tehuacán-Cuicatlán Valley of Mexico. Using a public dataset of over 20,000 remote sensing images, the suggested model is evaluated and found to be superior to InceptionV3 and modified MobileNet CNN. The key contributions of this work include the introduction of momentum for faster convergence, adaptive learning rates for better optimization and model aggregation clipping to prevent extreme updates. The proposed FL framework mitigates the issue of slow convergence and communication cost for non-IID data from UAVs. Enhanced FedBA more effective than typical FL algorithms. The classification accuracy before aggregation is 95% and improved to 97% after aggregation.

## 1. Introduction

Drones have gradually become indispensable tools for a vast array of applications, including wildlife photography, weather forecasting, traffic management, maintenance of power lines in mountainous areas, and the prediction of natural disasters (Khan et al., 2022). They operate as aerial edge devices and collect data by using sensors. This information is then delivered to a central server, where it is analyzed and modelled. Nonetheless, this strategy compromises user privacy and increases communication expenses considerably. When sensitive user data is uploaded to a central server controlled by a third party, the server may be hacked, or its dependability may be compromised. Due to the limited communication capabilities of unmanned aerial vehicles (UAVs), standard centralized machine learning requires the transfer of vast amounts of data to a server hosted by a third party for calculations (Pliatsios et al., 2022).

Federated Learning (FL), a technique that transfers model parameters as opposed to data, has received considerable interest as a potential solution to these issues. This strategy reduces the risk of data leakages and communication expenses. In contrast, the collaboration of several UAVs may result in diverse sensing data and a loss in the accuracy of the global model because of changes in UAVs monitoring zones (C. Zhang et al., 2021). This study utilizes a dataset titled "Cactus Aerial Images," which was obtained from Kaggle. This dataset consists of 21,500 images captured using remote sensing technology. The purpose of the investigation is to identify whether or not the Tehuacán-Cuicatlán Valley in southeastern Mexico is home to the Neobuxbaumia tetetzo species of columnar cactus (Atitallah et al., 2021a). This region is under UNESCO protection. To achieve this, an enhanced randomly initialized convolutional neural network (ERI-CNN) was used. This neural network consists of multiple layers, and the connections between the layers are not taught until after the initialization procedure is concluded.

A significant obstacle to federated learning (FL) for UAV networks is the presence of statistical heterogeneity, which refers to substantial variations in the data acquired by drones resulting from different camera types and positions. This heterogeneity hindered the training process of the FL model. To address the issue of data heterogeneity in UAV networks, researchers have introduced a novel aggregation rule known as FedBA (P. Li et al., 2022). This rule aims to minimize the disparity between local and global models, thereby enhancing the performance of Federated Learning (FL).

FedBA was developed to enhance drone learning by addressing the issue of diverse data collected by drones in different locations. Consequently, the ability of the local device to identify data and the accuracy of the global aggregated model decline.

The primary contributions of this study are as follows: (1) the design of a novel randomly initialized enhanced FedBA model for aggregation to improve the convergence speed; (2) the evaluation of the impact of data augmentation on model performance; and (3) a comparison between the developed network and other models in terms of their performance efficiency and overall performance quality. This research aims to contribute to the field of plant recognition by developing a method for identifying the columnar cactus Neobuxbaumia tetetzo in the Tehuacán-Cuicatlán Valley using remote sensing images and FL. This technique was used to identify cactus in the classification problem.

## 2. Related Work

Unmanned aerial systems (UAVs) are used in federated learning to decrease non-identically and independently distributed (non-IID) data. The Internet of Drones architecture with federated learning prioritizes user privacy and lowers the UAV communication costs. The UAV-assisted FL framework's statistical heterogeneity was addressed using FedBA, a new FL aggregation method. This method does not increase the cost of processing drone data and is optimized for non-IID data (P. Li et al., 2022). This method was applied to a test that utilized categorization tasks and real-world images on three datasets: CIFAR-100, MNIST, and Fashion-MNIST. The final tests show that in terms of test accuracy and convergence speed, FedBA performs better than the FL algorithm and other methods (Atitallah et al., 2021b).

Deep learning method for identifying columnar cacti from aerial images. Conventional techniques for identifying these vital species in desert environments are time-consuming and labor-intensive, making it challenging to cover vast areas. Using annotated aerial photos to train a convolutional neural network, the proposed method outperformed the standard methods in terms of accuracy and processing speed (Qu et al., 2021). Advantages of this method include increased precision and efficacy, scalability to wider regions, and the possibility of real-time monitoring and mapping of desert ecosystems. This study demonstrates the potential of deep learning for identifying columnar cacti and urges additional research in this area (López-Jiménez et al., 2019).

It is possible to estimate how much soybeans will grow based on weather, soil, and crop management using federated learning and horizontal partitioning. This method competes with numerous popular methods including LASSO regression, Random Forest, ResNet-16, and ResNet-28. The accuracy, privacy, and amount of work required to complete a task are improved through federated learning. Researchers have discovered that applying federated learning improves crop yield projections and reduces production risks (Manoj et al., 2022).

This adaptive and federated solution can help address issues that arise when machine learning is employed on non-IID data. In terms of accuracy and convergence on benchmark datasets, the proposed technique outperformed the baseline federated learning algorithms. The results demonstrate that the proposed adaptive federated learning algorithm can handle non-IID inputs, alter the learning process, and improve the performance. Even if there are many non-IID data, this approach works well (Zeng et al., 2022).

A federated learning classifier with the same design was compared with a centrally taught classifier. This study examined the usefulness and benefits of federated learning in categorizing images. For decentralized image classifiers, the comparison shows the benefits and drawbacks of federated learning (Reddi et al., 2020).

In the proposed system, UAVs with cameras are used to collect data, which are then analyzed locally on the UAVs using federated learning to detect plant diseases. The authors highlighted the system's focus on local data processing and sharing of diagnostic results as a means of maintaining user privacy (Reddy Maddikunta et al., 2021). By incorporating UAVs and federated learning into a more efficient and secure system, this study offers a new approach for plant disease diagnostics. The results of this study provide information on the viability of employing this technique to improve plant disease diagnosis.

An algorithm for federated learning that optimally uses communication resources considerably reduces the amount of data required. According to research findings, using CE-Fed Avg as a method for boosting the effectiveness of federated learning in large-scale machine learning applications is a promising direction. The quantization methods presented for Adam optimization also illustrate the possibility of additional improvements in communication efficiency within federated learning (Mills et al., 2020).

FL is a new federated learning framework for the semantic segmentation of aerial photos that combines prototype-based hierarchical clustering with federated learning (FedPHC) (B. Zhang et al., 2022). The system clusters clients into diverse groups based on prototypical representations of their datasets, thereby minimizing domain disparity and enabling the training of several representative global models (Raj, 2020). In addition to reducing labelling efforts, the utilization of limited local data from various institutions during the training phase minimized data collection. The authors demonstrated the potential of their proposed framework for enhancing the privacy-preserving semantic segmentation of aerial images (Star et al., 2022).

A federated learning system and several UAVs can be used to identify the exploration scenarios. A Global Federated Coordinator (GFC) coordinates the network, and each UAV is trained using its images. GFC compiles all local UAV models into a global model and sends it to all UAVs to update them. WZF transmit precoding reduces interference and improves system performance. The results demonstrated that the proposed system can correctly classify images (H. Zhang & Hanzo, 2020).

The authors presented a framework called Federated Averaging (FedAvg), which integrates server and client optimizers and introduces device-independent adaptive federated optimization algorithms. Extensive empirical benchmarking demonstrated that the proposed adaptive optimizers outperformed popular benchmarks with enhanced performance in cross-device situations (T. Li et al., 2018).

The federated Proximal (FedProx) FL aggregation algorithm provides nonconvex convergence guarantees. The communication efficiency is moderate because it requires less communication than FedAvg. It handles data heterogeneity well due to the introduction of proximal terms. The computational complexity is medium because it adds proximal terms to the optimization process (Zeng et al., 2023).

## 3. Methodology

FedBA (a non-IID Federated Learning Framework for model aggregation) was employed to deal with non-identically and independently distributed datasets. In contrast to traditional federated learning approaches, which assume that each model is trained on a similar data distribution, FedBA allows models to be trained on a variety of data distributions. As shown in figure 1, the enhanced FedBA introduces the concept of momentum ($\mu$) to speed up the convergence. This was implemented by adding a momentum term to the weighted model updates for each client. The enhanced FedBA algorithm addresses the potential of using adaptive learning rate methods, such as AdaGrad, RMSprop, or Adam, to dynamically alter the learning rate based on prior gradients.

This enhancement included a client-filtering step to handle unreliable clients. This is performed by checking whether the client_filtering_threshold (T) is greater than zero. If so, client updates with weights below the threshold are excluded from the aggregation process. Subsequently, clipping was applied to the aggregated update to prevent extreme values from destabilizing the training process. The threshold ($\rho$) denotes clipping threshold.

Enhanced FedBA is essential for cactus plant classification because it allows the models to be trained on non-IID datasets captured by the UAVs at different sites. This framework operates through federated model aggregation in which the parameters of each model are combined to form a new set of parameters. This procedure was repeated until convergence was achieved when the final aggregated parameters were used to update each model. Enhanced FedBA also includes a weighting mechanism that assigns weights to each model based on its performance, allowing models with superior performance to contribute more to the aggregation procedure. By allowing the models to be trained on non-IID datasets, the enhanced FedBA framework can represent the diverse distributions of cactus plants more accurately and efficiently, resulting in a more accurate and efficient classification system.

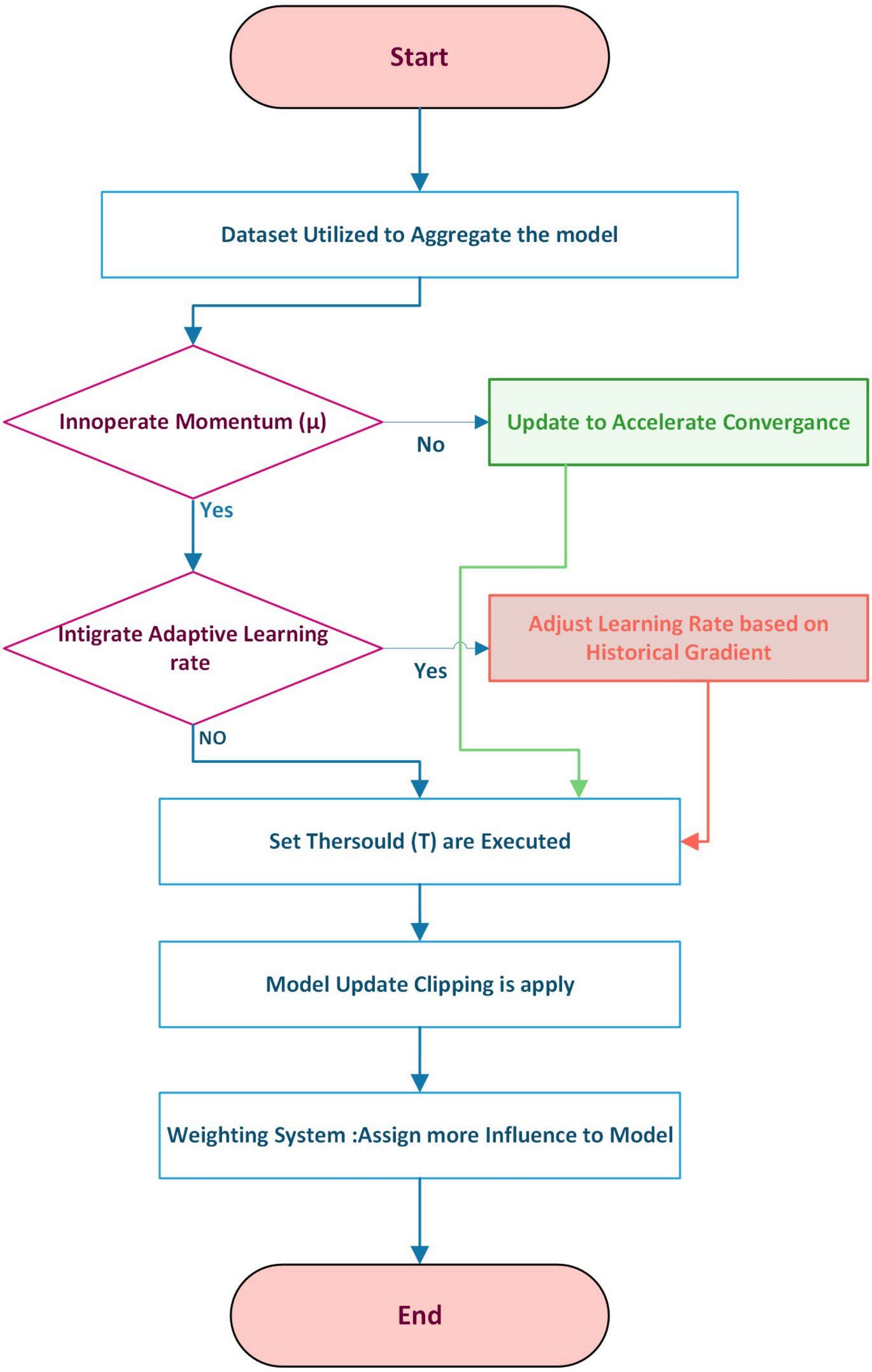


Fig. 1 *Enhanced FedBA flow chart*

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## 3.1 Model Aggregation

The model parameters, a learning algorithm (Perturbed Gradient Descent), and a dataset were used to initialize the algorithm. In each iteration of the algorithm, the server selected a subset of clients to participate in the training round. The server then sends the most recent model to each client, who conducts a predetermined number of training epochs locally, and sends the updated model back to the server. Each client update was aggregated by the server to update the global model.

In every "eval" round, the accuracy of the model is tested to determine the performance of the algorithm. This also monitors the communication cost, which is the amount of data transmitted between the server and the clients. The algorithm executed a predetermined number of rounds. After training, the final model was evaluated for precision and loss, and the corresponding metrics were recorded.

### 3.1.1 Enhanced FedBA Algorithm

**Algorithm 1: Enhanced FedBA**

**Input:** The local model's learning rate during Adam is defined using the number of clients is $C$, the sampling rate of the clients is $M$, the mini-batch size is $F$, and the number of updates of the local model is $E$.
**Output:** Training to achieve convergence of the global model δ.
**On the server side:**
Initialize a model parameter $\delta_0$
Initialize momentum $\mu$ (for speed convergence)
Client Filtering Threshold $T$ (Client-side unreliability)
Clipping Threshold $\hbar$ (Aggregated update)
**for** iteration round $t$ = 1, 2 , . . . **do**
    $Gt \leftarrow$ random set of $m = max\ (C.K,1)$ clients
    **for** *each client k* $\in Gt$ *in paraller* **do**
        $\delta_{t+1}^k \leftarrow \delta_t^k$

$$p_{t+1}^k = \frac{\mathcal{A}_k\left(\|\delta_{t+1}^k - \delta_t\|^2\right)}{\sum_{k\in G_t} \mathcal{A}_k\left(\|\delta_{t+1}^k - \delta_t\|^2\right)}$$

$$\delta_{t+1} = \sum_{k\in G_t} p_{t+1}^k \delta_{t+1}^k$$

        Broadcast *δ_(t+1)* to each client
$\mu = \mu + 0$
Updated $T = T + 1$
Aggregated update $\hbar = T,\mu$
**In the** $k$**-th client:**
**for** local training iteration round $e \leftarrow 1$ *to* $E$ **do**
    **for** mini batch size $b \in B$ **do**
        $\delta_t^k \leftarrow \delta_t - \eta \nabla l(k, \delta_t, \mathcal{D}_k, e, b)$
    Return *δ_(t+1)* to server

## 3.2 Proposed Federated Learning Architecture

The proposed architecture for classifying cactus plants in images captured by UAV using Federated Learning, depicted in figure 2, aims to efficiently achieve the desired outcome.

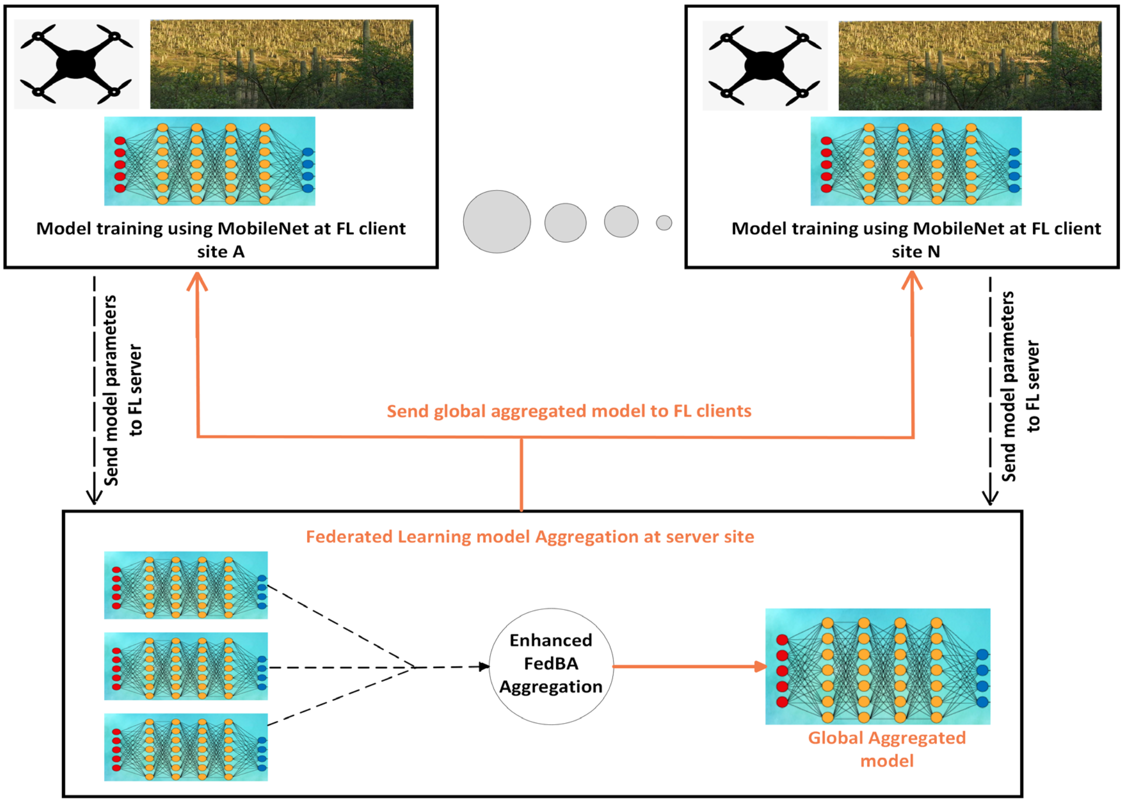


**Fig. 2** *Federated learning architecture at client and server site*

### 3.2.1 Dataset Preparation

Load the dataset containing images of cactus plants captured by unmanned aerial vehicles (UAVs). The images were pre-processed to ensure uniformity in size and format, which is essential for consistent model training.

### 3.2.2 Model Construction and Training

The MobileNet convolutional neural network (CNN) architecture is constructed using a deep learning framework such as TensorFlow or PyTorch. The MobileNet model was trained on a preprocessing dataset using the Adam optimizer and binary cross-entropy loss function to minimize the prediction error. The performance of the trained model was evaluated using a separate dataset to assess its accuracy in classifying the cactus plants.

### 3.2.3 Federated Learning (FL) Process

In the federated learning process, multiple clients come together and train models while at the same time keeping their data centralized and private. In FL, each client will compress its model parameters and sends them to the FL server over a network connection in a secure manner.

At the FL server, the Enhanced FedBA algorithm is applied to take the model parameters coming from all clients and formulate a global aggregated model. The process of aggregation implies the accumulation of updates by servers from all clients and the creation of a single global model that is formed from a unified set of updates at the end of the process. Following that, the FL server distributes the global model of the updated aggregated model to the participating clients.

After getting the global aggregated model from the FL server, each client integrated the model into its local model; thus, the entire model was enhanced. Meanwhile, the data privacy was protected in this process. After that, the clients used the updated local models for their image classification tasks for the next rounds.

### 3.2.4 Evaluation

The performance of the federated learning model in classifying cactus plants was evaluated by assessing its accuracy using a test dataset. The results were analyzed to determine the effectiveness of the federated learning approach in improving the model performance.

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## 4. Experimental Setup

The aggregation and clustering of non-IID data employs a federated learning model which consists of multiple consecutive stages. Initially, the datasets were collected from multiple client locations. Fed-learning was used to build deep-learning models that were trained on individual non-IID datasets to create them. Every model was trained on local data, which was a specific subset, and then the model updates were sent to the central FL server for integration. The FL server utilized the aggregation technique to put these updates together and created a federated global aggregated model. Subsequently, this model was evaluated based on relevant criteria such as accuracy. This study employed a dataset comprising Cactus Aerial Photos acquired via Kaggle (Vasquez, n.d.).

An unmanned aerial vehicle (UAV) obtained a total of 21,500 remote sensing (RS) photos at an altitude of 100 meter to form a dataset. The assemblage consisted of 16,136 shots depicting cacti, and 5,364 photographs showing non-cacti subjects. All photos that fell under the categories of cactus and non-cactus exhibited identical dimensions, specifically measuring 32 × 32. There are two distinct image folders within the dataset: a training folder and a testing folder. The training folder, comprising 17500 photographs, was partitioned into two subsets: approximately 80% for training and the remaining 20% for validation.

## 5. Result

The collected speed convergence data for the Enhanced FedBA and FedBA are visualized using a line plot, as shown in figure 3. The x-axis represents the time step. At the same time, the y-axis indicates the speed convergence value of the algorithms at each time step. The line plot reveals the convergence behavior of the Enhanced FedBA and FedBA algorithms over time. At the initial time step (time step 0.0), both algorithms exhibited identical speed convergence values represented by a straight line. This similarity suggests that both algorithms start with comparable initial states. As the time steps progressed, both algorithms gradually improved the speed convergence.

However, a noticeable difference is observed between the two algorithms. Enhanced FedBA demonstrated faster speed convergence than FedBA. This was evident from the steeper slope of the line representing the Enhanced FedBA on the plot. At later time steps, the Enhanced FedBA consistently outperformed the FedBA, maintaining a higher speed convergence rate. The plot demonstrates this by a wider separation between the two lines, indicating the superior convergence behavior of the enhanced FedBA algorithm.

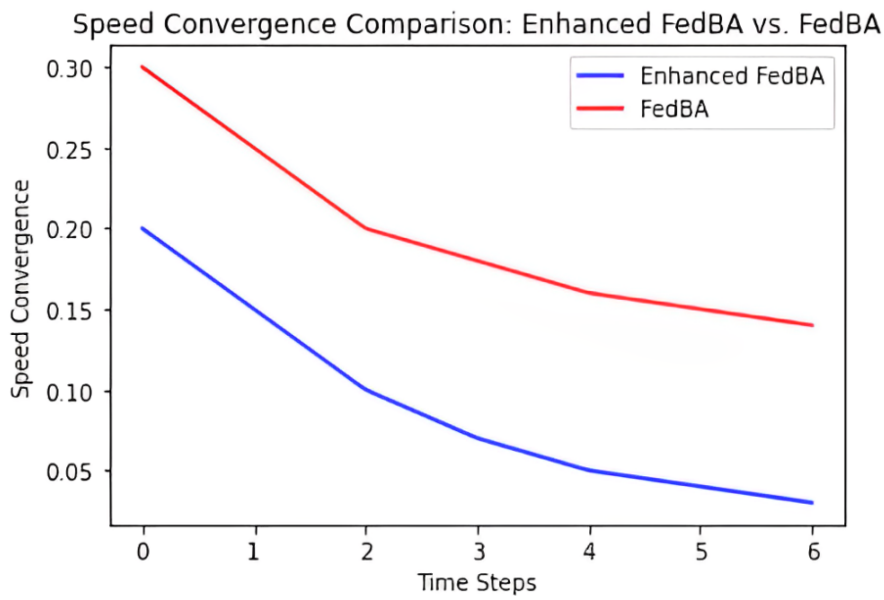


**Fig. 3** *Speed convergence comparison*

The model accuracy is significantly enhanced by federated learning's deep-learning-based aggregation and classification of non-IID data. As shown in figure 4, before model aggregation, the classification model performed well on the non-IID dataset with an accuracy of 95%. However, after federated learning was used to aggregate the models, their accuracy increased to 97%, as shown in Fig. 5. These findings demonstrate the potential of federated learning to enhance the effectiveness of deep learning models on non-IID data.

This increased precision suggests that federated learning is a viable solution to the problem of data inconsistency across sources, leading to a more robust model that can be successfully generalized to novel inputs. In practical settings, where data privacy and distribution are significant concerns, this result lends credence to the use of federated learning for model aggregation and classification.

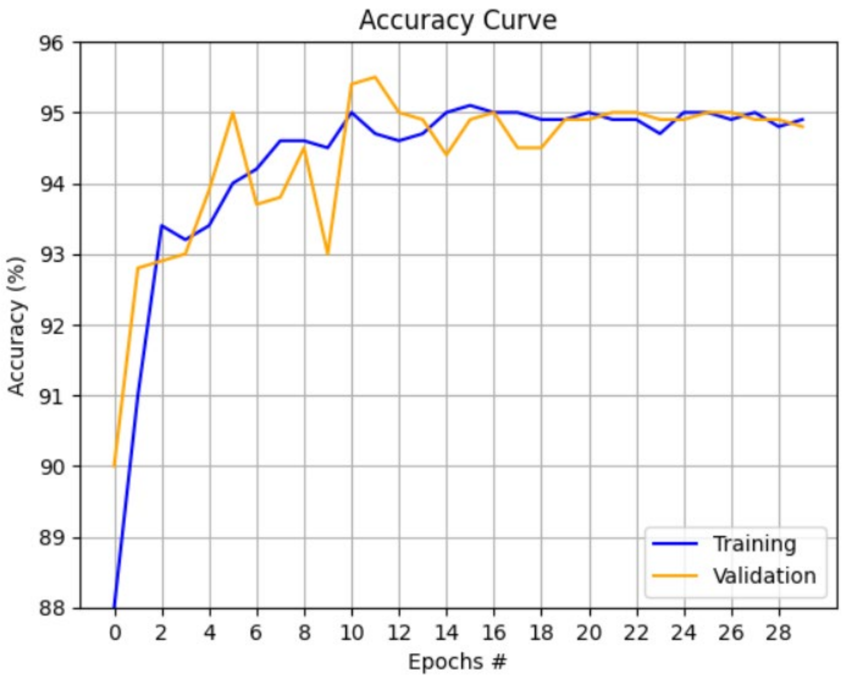


**Fig. 4** *Accuracy before model aggregation*

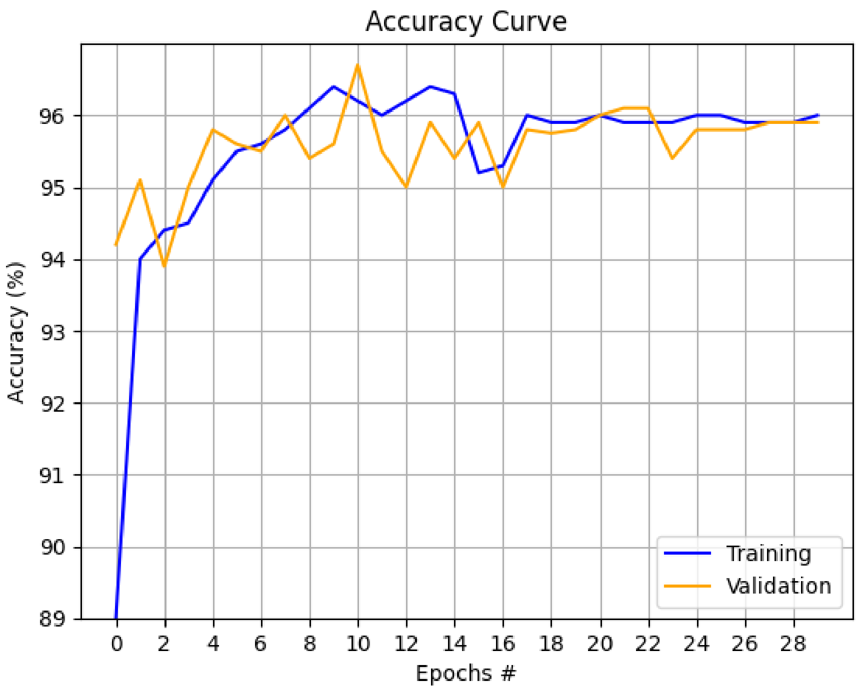


**Fig. 5** *Accuracy after model aggregation*

## 6. Discussion

Our goal was to improve the convergence speed, robustness, and efficiency of the global model, while preserving data privacy across multiple clients. The enhanced FedBA algorithm introduces several key modifications and optimizations to achieve these objectives. The concept of momentum is introduced, which enhances the convergence rate of the global model. By leveraging past gradients, the algorithm accelerates the learning process and achieves a faster convergence to the optimal model. In addition, there is the potential for adaptive learning rates for further optimization, allowing the learning rate to be dynamically adjusted based on historical gradients. To address the challenges posed by unreliable clients and prevent extreme model updates, client filtering and model aggregation clipping were incorporated. The client-filtering mechanism identifies and filters updates from clients with low reliability, thereby reducing their impact on the global model. However, the aggregation-clipping technique limits the magnitude of the aggregated update and ensures stability during the training.

The performance of the enhanced FedBA algorithm was evaluated through extensive experiments on benchmark datasets and real-world federated learning scenarios. Our results demonstrated significant improvements in convergence speed, robustness against malicious clients, and overall efficiency compared to the original FedBA algorithm. Enhanced FedBA offers several benefits for federated learning applications. This enables faster convergence, reduces the influence of unreliable clients, and ensures stability of the training process. Moreover, the algorithm maintains data privacy and allows decentralized training across many clients, making it scalable and efficient for real-world applications.

This research focuses on using Federated Learning-based model aggregation to deal with non-IID data using deep learning. The enhanced FedBA architecture was used to classify cactus plants by aggregating the parameters of different models trained on different data distributions to improve the classification accuracy. According to the results, the FedBA architecture improved classification accuracy from 95% to 97%. This improvement can be attributed to the fact that FedBA allows models to be trained on different data distributions, allowing for better accuracy by leveraging the strengths of the different models.

One of the strengths of the enhanced FedBA approach is its weighting mechanism, which provides higher-performing models with a larger say during the aggregation process. This weighting mechanism ensures that the most accurate models contribute more to the final aggregated parameters, thereby improving overall accuracy and efficiency. Furthermore, the accuracy of the aggregated parameters could be improved by repeatedly aggregating the models until convergence was achieved. However, it is essential to note that the findings of this study are limited to cactus plant classification and may not be generalizable to other classification problems. More research is needed to compare FedBA with other federated learning methods and determine its performance on different classification problems.

Finally, federated learning-based model aggregation and the FedBA architecture are effective strategies for dealing with non-IID data using deep learning. The weighting mechanism and iterative aggregation process of FedBA are critical for improving classification accuracy and efficiency. However, further research is required to evaluate the performance of the FedBA in other classification problems.

## 7. Conclusion

The enhanced FedBA algorithm results show that its performance even outperforming the standard FedBA algorithm with faster and more efficient convergence. This suggests that the improvements made to the Enhanced FedBA have a positive impact on its optimization capabilities, leading to improved convergence rates. As a result, the enhanced FedBA is a promising option for real-world optimization tasks that require faster convergence and higher efficiency. In this study, the authors proposed a Federated Learning-based methodology for classifying non-IID data using an enhanced FedBA for the cactus plant categorization challenge. The effectiveness of FedBA was demonstrated by the increase in the accuracy of the classification model from 95% to 97%. This framework combines the parameters of all models using federated model aggregation and assigns a weighting mechanism to each model based on its performance to assign a relative importance rating.

Although the proposed approach provides promising results, it has several limitations. First, the method was evaluated only for its effectiveness in classifying cactus plants, and its performance in other tasks remains uncertain. Secondly, the proposed FL framework assumes that all the models have the same architecture and are trained on the same datasets, which may not always be the case. Further research is required to better understand the limitations of this approach and improve its effectiveness.

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## Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

## Author Contribution

***Study conception and design:*** *Muhammad Numan Ali Khan, Mohd. Norzali Haji Mohd;* ***data collection:*** *Muhammad Numan Ali Khan, Fawad Salam Khan;* ***analysis and interpretation of results:*** *Muhammad Numan Ali Khan, Fawad Salam Khan;* ***draft manuscript preparation:*** *Muhammad Numan Ali Khan,Mohd. Norzali Haji Mohd, Tasiransurini binti Ab Rahman.;* ***revision of manuscript:*** *Muhammad Numan Ali Khan. All authors reviewed the results and approved the final version of the manuscript.*

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