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Federated transfer learning for distributed drought stage prediction

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Abstract
Due to the uncertain nature of drought, it is one of the most menacing natural disasters. Drought modeling (Prediction, Detection, Forecasting, and Stage Prediction) is very essential for efficient policy making. But one of the key problems with drought modeling is the limited availability of centralized datasets. To address this problem, we are a novel proposing federated learning based transfer learning models for the prediction of drought stages. In this study, satellite image dataset was collected from the Tharparkar district (prone to drought) of Pakistan. We trained the dataset using traditional and federated learning approaches, comparing centralized ML models, pre-trained models, and their respective federated learning models (FL-ResNet, FL-DenseNet, FL-MobileNet). The development of these models is the novel aspect of the study specifically for the use case of drought stage prediction. Based on the final evaluation, FL-MobileNet achieved 82% precision while baseline MobileNet scored 68%. The results show the effectiveness of novelty (federated learning), that our proposed framework improves the performance of the drought stage classification task.

Keywords Satellite images · Remote sensing · Transfer learning · Federated learning · Distributed learning

1 Introduction

Drought is among the most cataclysmic natural events. Drought has a consequential impact on the environment and society. In drought-stricken areas, all human livelihoods are affected, including agriculture [1], water resources [2], and ecosystems [3]. These regions often exacerbate food insecurity, economic instability, and health crises [4]. One such area is the Tharparkar district in Pakistan. Tharparkar has been designated a drought-calamity area fifteen times [5]. Tharparkar is the region of interest in this study. In order to create proactive plans to minimize and mitigate these negative effects and enable prompt interventions such as policymaking, agricultural planning, and water conservation drought stage classification is essential.

Although accurate drought stage classification is desperately needed, traditional centralized Machine Learning (ML) approaches are fraught with difficulties. For drought modeling (drought prediction and forecasting), large amounts of data, including soil moisture index, hydrological, and meteorological measurements, are frequently collected at one site

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for classification approaches [6]. This method presents two main problems: data privacy and infrastructure scalability. Data privacy issue arises because it is not possible to transfer regional or local data without privacy concerns [7]. Furthermore, because centralized systems need a lot of infrastructure and processing power to handle the increasing amount and complexity of climate data, they may not be scalable. Other strategies, like distributed machine learning (federated learning, edge learning, etc.), are emerging as a solution to these problems because of their capacity to solve scalability and data privacy bottlenecks in drought modeling research.

To overcome these constraints, novel approaches that put privacy protection, scalability in machine learning models with distributed datasets are required. The solution to this problem comes from new developments in machine learning, especially in the paradigms of distributed and federated learning. These paradigms allow collaborative ML across several datasets without transferring actual raw data by maintaining privacy and facilitating the inclusion of geographically or logically diverse datasets. These techniques are not fully utilized for the task of classification of drought stages, which presents a significant research gap.

To achieve a precise and privacy-preserving classification, we use the advantages of Transfer Learning [8] combined with Federated Learning (FL) in this study. Transfer Learning is ideal for analyzing raw satellite images of drought stages, as pretrained models can adapt their deep feature extraction capabilities to the domain specific task of drought stage classification. In order to address privacy concerns and facilitate collaborative learning across dispersed datasets, we combine TL with FL to ensure that sensitive regional data remains decentralized. This innovative method guarantees scalability and adaptability, which are essential to address the difficulties presented by various climatic and geographical conditions, in addition to improving the contextual relevance of the classification results.

The purpose of this study is to fill existing gaps by introducing a new concept that combines federated learning with Transfer Learning, specifically tailored for drought stage classification. We used the DenseNet [9], ResNet [10] and MobileNet [11] models in this this study. The pictorial presentation of proposed framework is shown in Fig. 1. The following are the main contributions of this study.

- Developed a new federated learning framework for drought stage classification that employed transfer learning. The accuracy of the federated learning approach increased from 68% in traditional methods to 82%.
- Using proposed approach we were able to achieve privacy preservation while maintaining a high average F1 score of 82% with FL-MobileNet, the top-performing model.
- Other Federated learning models (FL-DenseNet and FL-ResNet) demonstrated significant gains over their centralized counterparts with F1 scores of 73.62% and 71.13%, respectively.

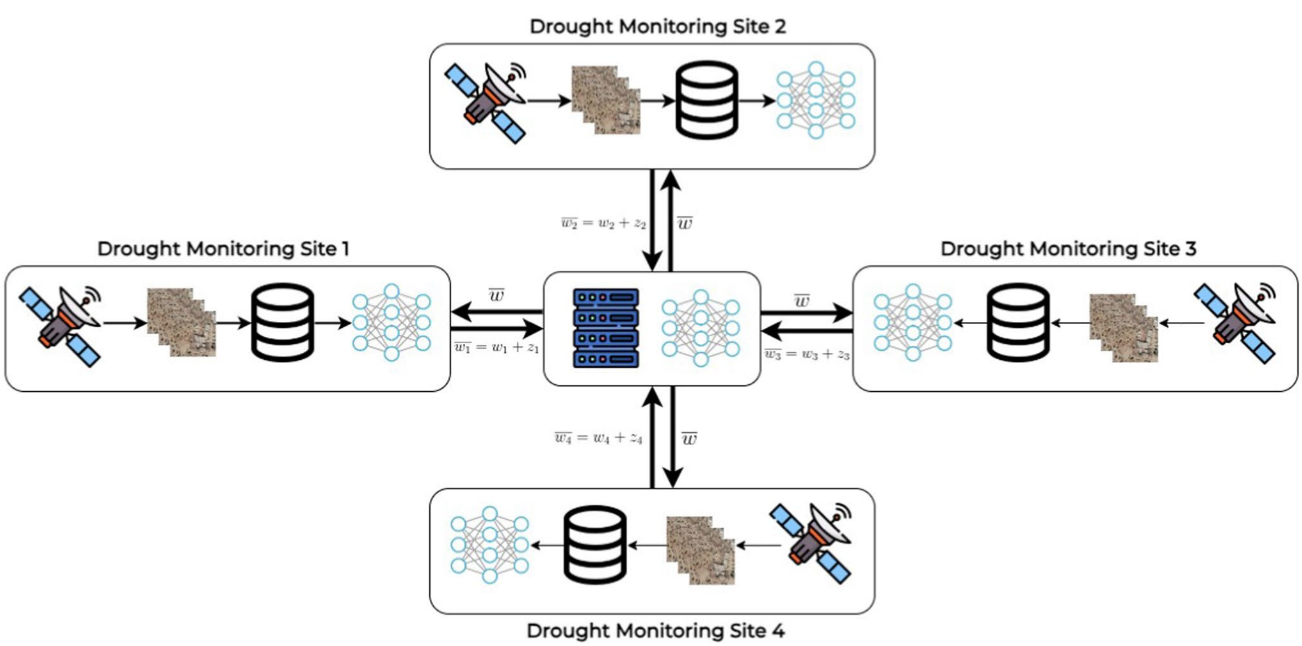


Fig. 1 Proposed federated learning framework for drought stage classification

2 Literature review

Given the intricate interactions between several contributing factors, drought is the natural disaster with the least amount of understanding. It can go on for months or even years, and it is difficult to tell when it will end [12]. Drought modeling is essential for the sustainability of water resources and the creation of effective mitigation strategies [13]. Traditionally, drought modeling is done using remote sensing indexes such as the SPI (Standardized Precipitation Index), the EVI (enhanced vegetation index) and PDSI (Palmer's Drought Severity Index). Although these indicators offer valuable information on the intensity of drought, they frequently do not capture the spatial variability and intricate dynamics of drought, specifically in areas like Tharparkar, which are vulnerable to frequent drought occurrences.

Satellite imagery can now be used for fine-grained, large-scale drought monitoring thanks to recent developments in remote sensing technologies. Google Earth Engine (GEE) and other platforms have made it easier to obtain high-resolution environmental data, providing previously unheard of opportunities to examine drought trends and their changes [14]. Remote sensing has been shown to be very useful in predicting drought using remote sensing indexes such as NDVI (Normalized Vegetation Index), EVI (Enhanced Vegetation Index) and many others [15]. Researchers in ref. [16] used SPEI (standardized precipitation evapotranspiration index) for the prediction of the drought index, [17] used NDVI (normalized difference vegetation index) and SMI (sol moisture index) for the prediction of drought, [18] used NDVI (normalized difference vegetation index), TCI (temperature condition index), VCI (vegetation condition index) and EVI2 (2 band enhanced vegetation index (EVI2) for the prediction of drought. The problem with these techniques is combining these indexes from multiple sources and maintaining consistency across the spatial and temporal scale.

Machine learning models have the ability to identify patterns and relationships in high-dimensional data, It has been applied in numerous use cases such as ref. [19] where it is used to predict the COVID spread or as in ref. [20] researcher have used it for early detection of potato disease. Machine learning attracted a lot of interest environmental modeling particularly in drought modeling. In ref. [21] used machine learning models like support vector machines (SVMs) and random forests (RFs) to predict drought severity. In ref. [22] applied random forest on remote sensing based drought condition spectral indices. In [23] researcher are using Partial Least Square (PLS) and Support Vector Machine (SVM) integerated with remote sensing indexes. Machine learning models perform really well but these model depend on centralized data and have issues with privacy and scalability [24].

One of the key step in machine learning is feature extraction, automatic feature extraction is very important to extract spatial features from satellite imagery and Convolutional Neural Networks (CNN) can play a very important role in this [25]. Pretrained Deep learning models are implemented for variety of task as in ref. [26] researcher have used pretrained model for Potato Blight Detection. In the study [27] researchers have used pretrained deep learning models such as ResNet and XceptionNet to predict if there is drought using raw satellite images. This study shows the efficiency of deep learning models for drought prediction. Apart from this there are several studies performing drought prediction such as refs. [28– 30], in these studies different classes of deep learning models such as CNN, long short term memory (LSTM), Deep neural networks (DNN) are used with diverse source of data.

There has been shift towards collaborative learning in distributed data environments due its improved performance and scalability. Currently, the medical drought modeling uses a centralized machine learning (ML) architecture to create drought prediction models [25]. This centralized strategy involves transferring data to the cloud to build an ML model. Transmitting data from heterogeneous site to a server in a centralized machine learning configuration can lead to major privacy breaches.

This study proposes a federated learning framework integrated with transfer learning for prediction of drought stages. This solution fills two main gaps from literature one is data privacy second is scalability. This study offers a novel approach to the drought stage prediction model for Tharparkar district. Satellite images data are provided to the federated learning framework that applied distributed transfer learning on satellite images to predict drought stages.

3 Methodology

Fig. 2 presents the methodology for this study. There are two subsection as shown in Fig. 2. (1) Data collection and sharding in this section satellite images from Tharparkar, which is a drought-prone district, were gathered using Google Earth Engine. The images were categories into four 4 classes which represent a drought stage(no drought (ND), before drought (BD), drought (DO), and after drought (AD)). 2) Modeling and evaluation where federated learning was applied using transfer learning on the data set. The pretained models used in this study are DenseNet, ResNet, and MobileNet. Lets discuss each step in details.

3.1 Dataset and dataset sharding

The dataset used in this study is acquired using GEE (Google Earth Engine), a comprehensive geospatial analysis tool that offers environmental data and satellite imagery. The dataset is collected from the Tharparkar district in Pakistan. Tharparkar is one of the most drought-prone regions, since 1968, Tharparkar has been identified as drought calamity area fifteen times, most recently in the years 2013, 2014, and 2018. In this dataset we have 4 classes drought stages: no drought (ND), before drought (BD), drought (DO), and after drought (AD). These labels are assigned to the images on the basis of the image timestamp. There is no preprocessing applied to these images to test the models or raw satellite images. The distribution of training and validation samples of the dataset can be seen in Table 1. While the validation

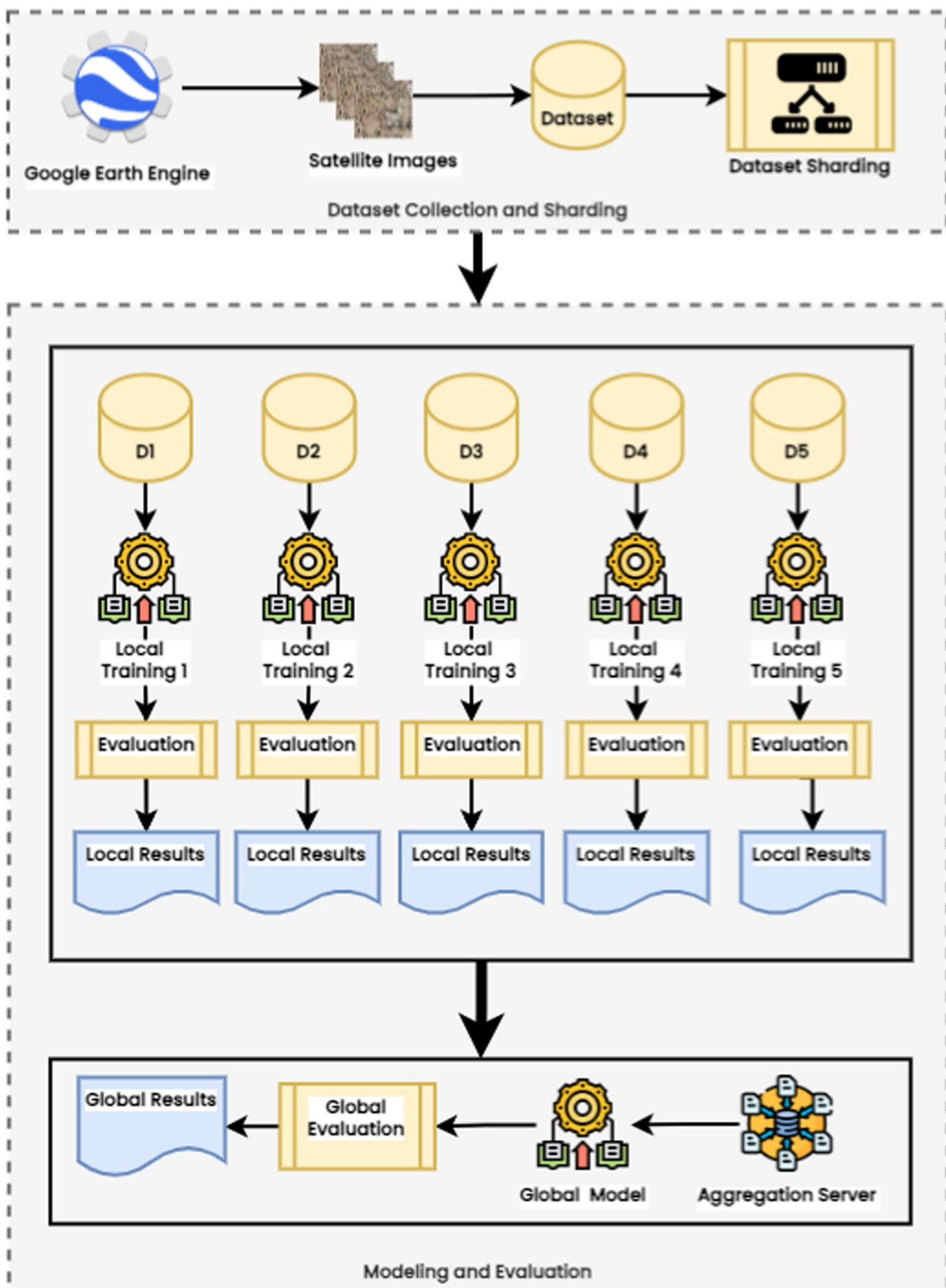


Fig. 2 Step-by-step representation of the proposed federated learning based drought stage classification process

set consists of 3,074 samples, with 614-618 samples per client, each client has an equal portion of the training data. This guarantees equitable training and assessment.

For feature selection in machine learning models these images are converted into bag of pixels (3D array of number representing pixel values). For deep learning CNN based automatic feature selection technique is applied. Figure 3 shows the sample of images from the dataset from all 4 classes.

This dataset collection methodology can be applied to any region globally. Because historical images from different timezone collected where there was drought or no drought. The collected data doesn't depend on any specific climate type. The given data set can be represented by Eq. 1

$$D = \{(x_i, y_i) \mid 1 \le i \le N\} \tag{1}$$

where x_i shows the image instance and $y_i \in \{0, 1, 2, 3\}$ denotes the drought class. The total dataset is partitioned into $K = 5$ client datasets using Eq. 2:

$$D = D_1 \cup D_2 \cup D_3 \cup D_4 \cup D_5 \tag{2}$$

where $D_k \cap D_j = \emptyset$ for $k \ne j$ and $|D_k| \approx \frac{N}{K}$.

The partitioning ensures that each client holds approximately $\frac{N}{K}$ samples, preserving class distributions across clients to maintain an Independent and Identically Distributed (IID) setting.

The class distribution per client $P_k(c)$ is calculated by Eq. 3:

$$P_k(c) = \frac{1}{|D_k|} \sum_{(x_i, y_i) \in D_k} 1(y_i = c) \tag{3}$$

where $c \in \{0, 1, 2, 3\}$ and $0(y_i = c)$ is an function that returns 0 if $y_i = c$, and 1 otherwise.

The partitioning methodology accounts for class imbalance by randomly splitting the data, reducing the likelihood of over-representation of any single drought stage in one client.

3.2 Modeling and evaluation

In this section, local and global models are integrated to investigate modeling and evaluation of deep learning models. Lets discuss each of the section in details.

3.2.1 Client model training (local update rule)

In the federated learning (FL) setup, each one of client c trains the local model on its own subset of the dataset. Here, the goal is to minimize the local loss function so client are good on their own. The categorical cross-entropy loss is employed here, the function is represented as Eq. 4:

$$L_c = -\sum_i y_i \log(p_i) \tag{4}$$

y_i represents the correctly predicted label and p_i shows the probability of the predicted class i. The given output is derived from the softmax function.

Table 1 Distribution of training and validation samples across clients for each class label

Class label	Training C_1	Training C_2	Training C_3	Training C_4	Training C_5	Validation
After drought	143	126	125	145	143	682
Before drought	140	150	172	155	169	786
Drought	179	163	153	165	156	816
No drought	152	175	164	149	150	790
Validation per client	614	614	614	614	618	3074

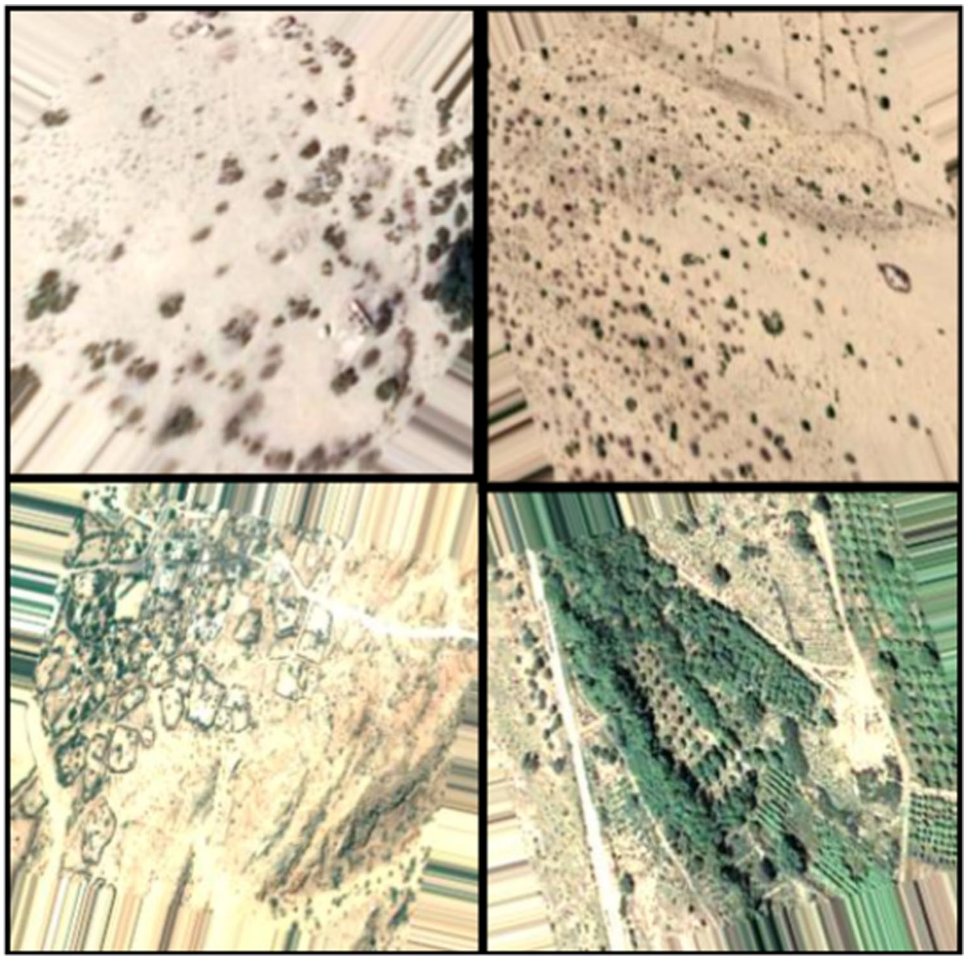


Fig. 3 Sample images from the dataset with drought classes

After the computation of loss for each clients using SGD (stochastic gradient descent) weights are update. The update rule for each client c is given as Eq. 5:

$$W_c \leftarrow W_c - \eta \nabla L_c \tag{5}$$

where η shows the learning rate, and ∇L_c denotes the loss function gradient with respect to the model parameters. This iterative process refines the local model by adjusting the weights towards the decreasing loss, thereby improving its performance on the local dataset.

The local training phase plays a critical role in federated learning by making models to change based on client-specific data distributions, preserving privacy by keeping data decentralized. After a set number of local epochs, the updated weights are sent to the aggregation server for averaging, contributing to the global model's convergence.

In this study, we employ DenseNet, ResNet, and MobileNet as the backbone models, leveraging the principles of transfer learning to achieve an effective classification of drought stages. Transfer Learning allows for fine-tuning pre-trained models optimized for big datasets (e.g., ImageNet) for specific applications like drought classification. We selected ResNet, DenseNet, and MobileNet because these model provide a balance between performance and efficiency. The mathematical formulations for each model are described as follows: DenseNet is distinguished by its dense connection, with each layer connected to the next layer, ensuring feature reuse and efficient gradient flow. Mathematically, the transformation at the l-th layer is expressed as Eq. 6:

$$H_n^{(l)} = \sigma\left(W^{(l)}\left[H_n^{(0)}, H_n^{(1)}, \dots, H_n^{(l-1)}\right]\right), \tag{6}$$

where:

- $H_n^{(l)}$ represents l-th layer output,

- $W^{(l)}$ represents l-th layer's weight matrix,
- σ denotes the activation function, typically ReLU,
- $[H_n^{(0)}, H_n^{(1)}, \dots, H_n^{(l-1)}]$ represents the concatenation of outputs from all previous layers.

ResNet introduces residual connections to mitigate the problem of vanishing gradients by learning residual mappings. The transformation in the l-th layer is given by Eq. 7:

$$HH_n^{(l+1)} = \sigma\left(HH_n^{(l)} + F\left(HH_n^{(l)}, W^{(l)}\right)\right), \tag{7}$$

where:

- $HH_n^{(l)}$ shows the l-th layer input,
- $F(H^{(l)}, W^{(l)})$ is the residual function parameterized by the weight matrix $W^{(l)}$,
- σ is the activation function (e.g., ReLU).

MobileNet is designed for computational efficiency, employing depthwise separable convolutions. This process is mathematically described as Eq. 8:

$$HH_n^{(l)} = \sigma\left(W_{\text{depth}}^{(l)} * X + W_{\text{point}}^{(l)} * X\right), \tag{8}$$

where:

- $W_{\text{depth}}^{(l)}$ and $W_{\text{point}}^{(l)}$ are the depthwise and pointwise convolution filters, respectively,
- $*$ denotes the convolution operation,
- X is the input feature map,
- σ represents the activation function.

In all three models, the final fully connected layer is replaced to match the number of drought classes, ensuring task-specific adaptation. In DenseNet, the output of the concatenated layers is passed through a task-specific fully connected layer. Mathematically it is represented by Eq. 9

$$\hat{y} = \text{Softmax}(W_{\text{fc}} HH_n^{(L)} + b), \tag{9}$$

where $HH_n^{(L)}$ is the final features vector, W_{fc} is the weights matrix, b is the bias term, and $\hat{y}$ is the predicted class distribution. In ResNet, the final residual output is similarly passed through a modified fully connected layer. MobileNet, the lightweight architecture ensures computational efficiency while adapting the classifier to the drought classes.

3.2.2 Federated learning process

The federated learning process follows an iterative communication framework between clients and a central server. In federated learning, the central server plays a critical role in aggregating locally trained models from participating clients. This aggregation step forms the backbone of the global model update, allowing decentralized knowledge to be integrated efficiently. Let C represent the total number of clients participating in the training process at each communication cycle. The server averages the local model weights, which can be stated as Eq. 10

$$W_s = \frac{1}{C} \sum_{c=1}^{C} W_c \tag{10}$$

where W_s represents the global model's weight after aggregation, and W_c corresponds to the model parameters from client c. This decentralized technique allows for collaborative training across multiple clients without exposing sensitive data. The complete training cycle can be broken down into three core steps: local model updates, server-side aggregation, and global model distribution.

During each communication round t, clients perform local training on their respective datasets. Each client c minimizes the loss function L_c using stochastic gradient descent (SGD) or its derivatives. The local model updating rule can be represented as Eq. 11:

$$W_c(t+1) = W_c(t) - \eta \nabla L_c \tag{11}$$

where $W_c(t)$ represents the model weights at round t, η is the learning rate, and ∇L_c denotes the gradient of the loss function with respect to the model parameters. This step allows clients to learn independently, adapting their models to the local data distribution.

Upon completion of local training, each client transmits its updated model to the server. The server aggregates these models by averaging the weights, ensuring that the global model benefits from the collective knowledge of all clients. The aggregation is performed using Eq. 12:

$$W_s(t+1) = \frac{1}{C} \sum_{c=1}^{C} W_c(t+1) \tag{12}$$

where C denotes the total number of clients, and $W_s(t+1)$ represents the aggregated global model weights at round $t+1$. This federated averaging scheme enhances generalization by mitigating overfitting to any specific client's data.

Following aggregation, the updated global model is redistributed to all clients using Eq. 13:

$$W_c(t+1) = W_s(t+1) \tag{13}$$

This ensures that each client begins the next communication round with the same global model, promoting alignment across the decentralized network.

The federated learning process iterates over multiple rounds t, allowing the global model to gradually converge. By leveraging graph structures and distributed data, federated learning integrated with pretrained deep learning models can capture spatial dependencies and enhance predictive performance in complex environments such as drought stage classification.

Evaluating the performance of federated learning models, particularly in multiclass classification tasks, requires extending standard metrics such as accuracy, precision, recall, and F1 score to account for multiple classes. The following metrics are computed to assess the model's effectiveness across all classes:

Accuracy: Overall accuracy measures the proportion of correctly classified samples is shown using Eq. 14

$$Accuracy = \frac{\sum_{i=1}^{K} TP_i}{\sum_{i=1}^{K} (TP_i + FP_i + FN_i)} \tag{14}$$

where TP_i, TN_i, FP_i, and FN_i represent the true positives, true negatives, false positives, and false negatives for class i, and K is the total number of classes.

Precision (Macro-averaged): Precision measures the ability of the model to avoid false positives, averaged across all classes, It is represented by Eq. 15

$$Precision = \frac{1}{K} \sum_{i=1}^{K} \frac{TP_i}{TP_i + FP_i} \tag{15}$$

Recall (Macro-averaged): Recall evaluates the model's capacity to correctly identify all positive samples, computed as Eq. 16:

$$Recall = \frac{1}{K} \sum_{i=1}^{K} \frac{TP_i}{TP_i + FN_i} \tag{16}$$

F1 Score (Macro-averaged): The F1 score balances precision and recall, providing a harmonic mean. It is calculated using 17

$$F1 = \frac{1}{K} \sum_{i=1}^{K} \frac{2 \times Precision_i \times Recall_i}{Precision_i + Recall_i} \tag{17}$$

4 Results

4.1 Experimental settings

Table 2 shows the experimental setting used to train traditional and federated learning models. All transfer learning models are trained on 10 epochs with a learning rate of 0.01 and a batch size of 32. The hyperparameter for machine learning and deep learning models were kept on default. For federated leanring number of clients is 5 and number of rounds is also 5. The platform for training and evaluating these models is Google Colab. The ram used by the notebook is 32 GB and storage is 128 GB.

The table 3 compares the performance of different machine learning and deep learning models under traditional centralized and distributed Federated Learning approaches. The four evaluation parameters are taken to assess the model: accuracy, precision, recall, and F1 score. Among decentralized machine learning models, SVM achieves the best results with an F1 score of 63.57%. Among deep learning models, MobileNet outperformed ResNet and DenseNet in decentralized setting with an F1 score of 68%.

The federated learning variants of ResNet, DenseNet and MobileNet (FL-ResNet, FL-DenseNet and FL-MobileNet) consistently achieved better results. In particular, FL-MobileNet is the best performing model, it achieved a precision of 82. 89% and an F1 score of 82.93%. Significant improvements are also demonstrated by FL-ResNet and FL-DenseNet when compared to their non-federated counterparts. From these results it is observed that federated learning enhanced the performance of machine learning models, this shows its potential for better generalization in scenarios where data is distributed.

The accuracy and loss trends for the models based on federated learning (FL-DenseNet, FL-ResNet, and FL-MobileNet) over five rounds are shown in Fig. 4. For every model as the rounds go on, accuracy rises and loss falls. This shows that the models are successful in adapting and optimizing, learning from the data more effectively, and reducing errors with each iteration.

The average F1 score for each round for each model is shown in Fig. 5, demonstrating that the performance improves with the number of rounds. The best performing model is MobileNet, which consistently achieved the highest F1 score in all rounds. Followed by DenseNet that performs moderately well in all rounds. All models exhibit a positive trend, with accuracy increasing with each iteration, and it is noteworthy as it shows that the models are getting better at learning and adapting.

The averages of F1 scores per client for different federated learning models are shown in Fig. 6. The performance of FL-DenseNet, FL-ResNet, and FL-MobileNet is compared on five clients. Performance varies from client to client. For all three models, client 5 achieved the highest accuracy because of more balanced local data. Although Client 1, have lower scores, which is due to an imbalance in the dataset. These results show the importance of high-quality local data. Balanced local datasets result in better performance on local level which eventually results in improvement of global model.

The confusion matrices in Fig. 7 show that when it comes to drought condition classification, FL-MobileNet performs noticeably better than the baseline MobileNet. Higher accurate classifications are obtained by FL-MobileNet in every category, especially when it comes to differentiating "drought" (753 vs. 213) and "before drought" (544 vs. 444), while minimizing incorrect classifications. An example of the model's improved handling of class imbalance is the better

Table 2 Summary of experimental settings

Setting	Description
Number of rounds	5
Clients participating per round	5
Learning rate	0.01
Optimizer	Adam
Number of epochs	10
Loss function	Cross-Entropy Loss
Batch size	32
Platform	Google Colab
RAM	32 GB
Storage	128 GB

Table 3 Comparative analysis of performance metric under centralized and distributed settings

Model performance using traditional and distributed approach (federated learning)				
Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Logistic Regression	62.72	63.03	63.24	63.11
SVM	63.33	63.50	63.85	63.57
Random Forest	59.35	59.93	59.66	59.51
Gradient Boosting	62.07	63.00	62.32	62.50
k-NN	55.61	56.26	56.59	54.62
ResNet	61.83	64.14	62.27	61.05
DenseNet	65.93	68.38	65.93	66.26
MobileNet	68.21	70.32	69.22	66.80
FL-ResNet	71.44	79.33	72.47	71.13
FL-DenseNet	73.23	77.11	73.58	73.62
FL-MobileNet	**82.89**	**83.64**	**83.24**	**82.93**

Bold values indicate the highest performance amongst models

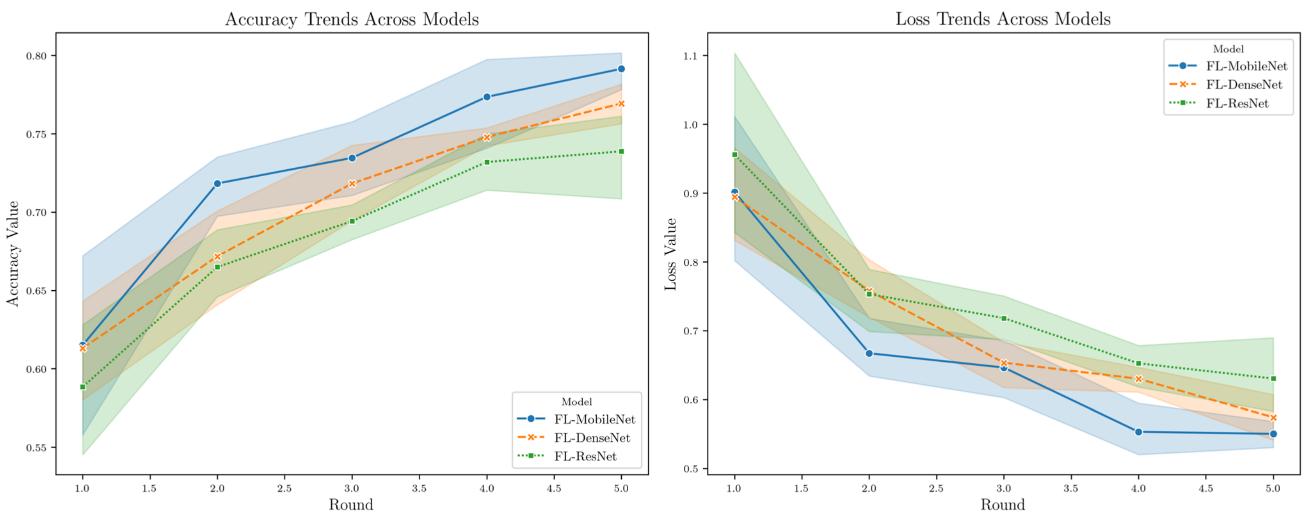


Fig. 4 Accuracy and Loss Trends across the Federated Learning Based Models

Fig. 5 Avergae F1 score per round for all the models

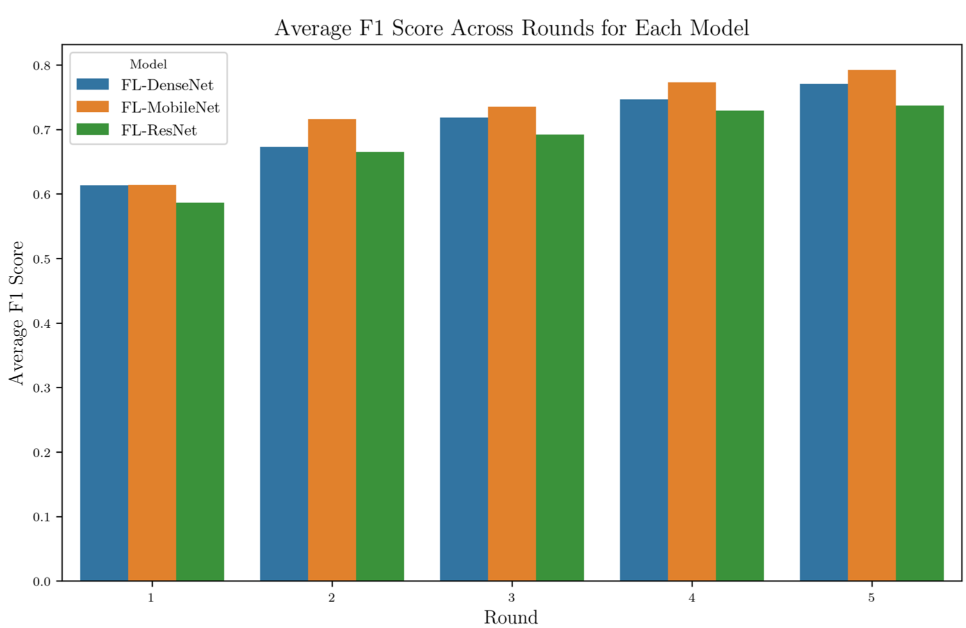
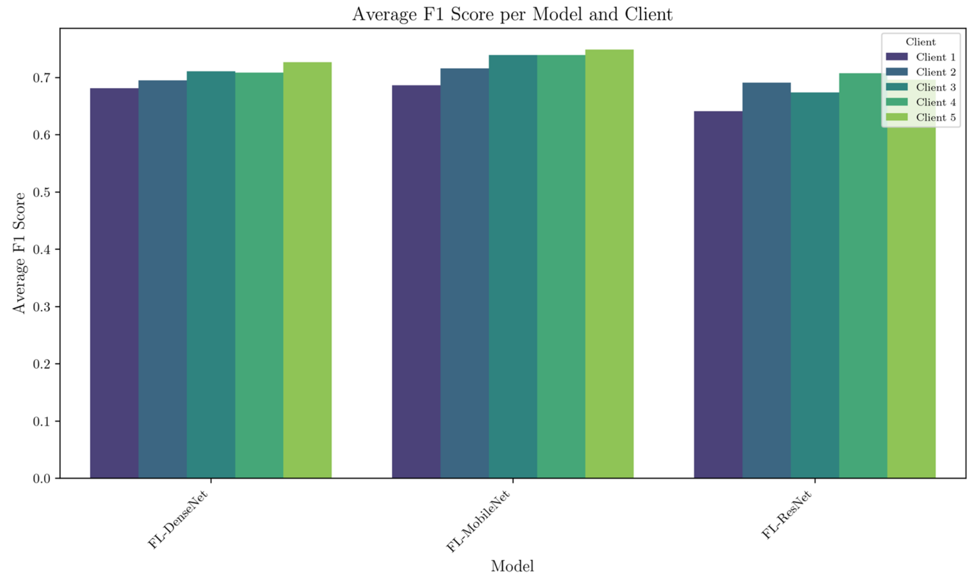


Fig. 6 Avergae F1 score per client for all the models



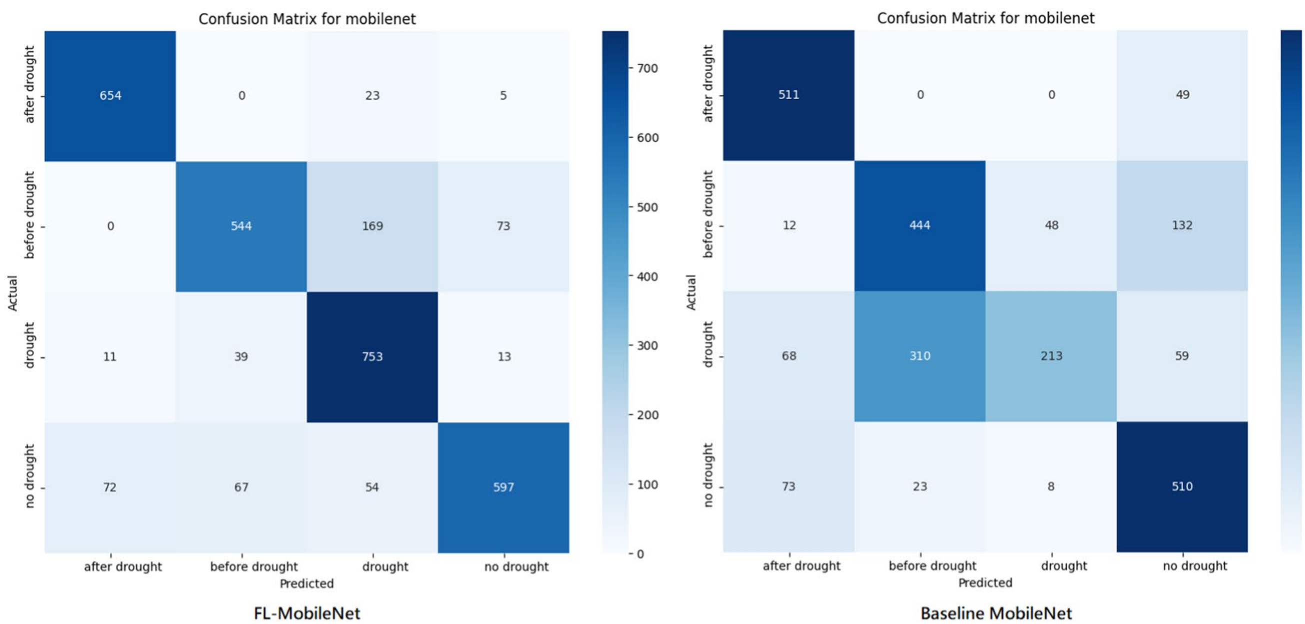


Fig. 7 Comparative Confusion Matrices for MobileNet and FL-MobileNet

classification of "after drought" (654 vs. 501) and "no drought" (597 vs. 510). FL-MobileNet outperforms MobileNet in terms of generalization, reducing errors and improving classification accuracy.

5 Conclusion

In this study, we focus primarily on the privacy-protected satellite image classification for the prediction of drought stages. Drought stage prediction have a problem of limited availability of centralized data. This study uses transferlearning with federated learning to predict drought stages. A custom data set for this task is gathered using the Google Earth engine. Traditional and distributed federated machine learning techniques are applied on this dataset. Based on the results, the traditional approach was able to score as high as 68%, on the other hand, with federated learning, we were able to achieve an accuracy of 82%. This improvement is measure of explicit comparison, their significance is not measured by any test. This increase in precision underscores the importance of federated learning. From the results, it is noted that federated learning combined with transfer learning can create more generalized and robust machine learning models for scenarios where limited data is available. The model trained on this study are on modest parameters such as 10 epochs, 5 rounds, and 5 clients, in future studies these parameters will be increased to create even better models. This approach can be scaled to other regions by adapting the model to local conditions, as the models used in this study use transfer learning, which makes them highly adaptable while maintaining privacy, allowing accurate prediction of the drought stage in diverse regions without compromising data security.

One the main challenge of this study is when scaling it to large number of clients it will increase network overhead and result in slower model convergence which will be addressed in extended work by including more efficient aggregating algorithms such as FedProx, FedAvgM, etc.

The main objective was not to maximize absolute performance but to show how federated learning outperforms traditional models. More modern architectures, like EfficientNet, will be investigated in future extensions to improve model efficiency and accuracy even more. To ensure better performance and efficiency in federated learning based drought classification, future research will investigate grid search and Bayesian optimization as an approach to methodically validate and optimize model settings.

By utilizing satellite imagery, remote sensing, and Internet of Things sensors, the suggested model can be integrated with current drought monitoring systems. With cloud computing, edge processing, and adaptive learning, major deployment issues like data heterogeneity and real-time processing can be resolved for greater usefulness.

Policymakers can benefit from the proposed Federated Learning (FL) and Transfer Learning (TL)-based model, which allows for decentralized, data-driven drought monitoring across regions. This method facilitates collaborative, privacy-preserving learning from a variety of datasets, which helps with quicker and more accurate decision-making. Without sacrificing sensitive data, the model can assist in optimizing resource management and drought mitigation tactics by utilizing local data.

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Author contributions O.R, A.U, and J.R developed the methodology and performed the experiments. O.R and A.U developed the initial Manuscript. T.A and S.A prepared the figures and tables from experimental results. J.R finalized the manuscript. T.A and S.A formatted and converted the manuscript into publication format. In the end all author reviewed the final manuscript.

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Data availability Dataset created or analyzed in this study can be provided by the corresponding author based on an appropriate request.

Declarations

Ethics approval and consent to participate Authors declare no human or animal subject or any biological material was used in the study.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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