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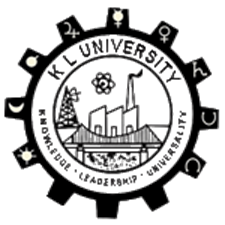
# DECLARATION

The Project Report entitled “Image Classification Using Federated Active Learning” is a record of the Bonafide work of, Atla Hari Venkata Sai Reddy, Gouravalli Henry Joseph, and Gulla Adithya, submitted in partial fulfillment for the award of B.Tech in Artificial Intelligence and Data Science to the K L University. The results embodied in this report have not been copied from any other departments/universities/institutes.

2000080001 Atla Hari Venkata Sai Reddy

2000080037 Gouravalli Henry Joseph

2000080039 Gulla Adithya



# CERTIFICATE

This is to certify that the (Project) Report entitled “Image Classification Using Federated Active Learning” is being submitted by Atla Hari Venkata Sai Reddy, Gouravalli Henry Joseph, Gulla Adithya submitted in partial fulfillment for the award of B.Tech in Artificial Intelligence and Data Science to the K L University is a record of Bonafide work carried out under our guidance and supervision.

The results embodied in this report have not been copied from any other departments/ University/Institute.

**Signature of the HOD Signature of the Supervisor**

Dr. GANDHARBA SWAIN Dr. VIJAYALAKSHMI. P

Signature of the External Examiner

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2000080001 Atla Hari Venkata Sai Reddy

2000080037 Gouravalli Henry Joseph

2000080039 Gulla Adithya

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**ABSTRACT**

Federated Learning (FL) is a paradigm that is concerned with assisting loosely coupled clients in jointly learning a global model with the aid of a centralized server. The most often used technique in FL is Federated Averaging (FedAvg), which computes a weighted average of client models, with the weights mostly based on client dataset sizes. We analyze a number of these models in this research to discover which will perform more effectively in the area of picture classification. As an illustration, we employ federated node selection, which aims to choose the nodes with the most appropriate and representative data to take part in the training process. Federated Transfer Learning is a different strategy we examine. It uses pre-trained models on source domains to enhance the performance of target domains with restricted resources.

**INTRODUCTION**

Image classification involves assigning one or more labels to an image based on its content. On the other hand, Federated learning is a Machine-Learning technique that enables multiple parties to train a model collaboratively without sharing their data.

Regarding image classification, federated learning involves training a model on distributed image data held by multiple parties while ensuring data privacy and security. The approach involves sending the model to the parties' devices for training and aggregating the model updates instead of the raw data. This method can enhance the accuracy of the image classification model by allowing it to learn from a more diverse set of data.

Additionally, it can reduce the computational burden of training the model on a centralized server by distributing computation among devices. However, the use of federated learning for image classification also presents challenges like communication efficiency, device heterogeneity, and non-ID data distribution. Therefore, addressing these challenges is crucial to ensure the success of image classification using Federated Learning.

**LITERATURE SURVEY**

Federated Learning (FL) is a promising technique for training machine learning models without sharing data among participants, making it a useful approach for various applications[1]. This literature review discusses recent research on FL for image classification.

Ali and Gani (2021) provide a comprehensive review of FL for image classification, covering various aspects such as the challenges, applications, and FL methods [1]. The authors emphasize the potential of FL for image classification in terms of privacy preservation and data security.

Cai et al. (2020) focus on FL with non-IID (non-independent and identically distributed) data for image classification [2]. The authors propose a novel approach that considers the non-IID nature of the data and utilizes a meta-learning strategy to improve the performance of the FL model. Their experimental results demonstrate the effectiveness of the proposed method compared to conventional FL methods.

Yang et al. (2020) conducts a comprehensive survey on FL for image classification on mobile devices. The authors discuss the challenges and opportunities of FL on mobile devices, including communication efficiency, resource-constrained devices, and privacy preservation [3]. They also provide an overview of the recent developments and applications of FL on mobile devices.

Islam et al. (2020) propose a Federated Transfer Learning (FTL) approach for image classification, which enables the transfer of knowledge learned from one dataset to another [4]. Their FTL method utilizes a deep neural network with a transfer layer to learn from a source dataset and adapt to a target dataset. The experimental results demonstrate the effectiveness of the proposed FTL approach for image classification.

Syed et al. (2021) present an FL approach for medical image classification, which can overcome the challenges of data heterogeneity and privacy preservation in medical imaging [5]. The authors utilize a deep learning model with a privacy-preserving protocol to protect sensitive medical data. Their experimental results show that the proposed FL approach achieves comparable performance to the centralized learning method while ensuring data privacy.

The study on Federated Learning for Commercial Image Sources [6] aims to develop an FL framework for commercial image sources, which allows multiple parties to train a shared model without sharing their private data. The authors propose a privacy-preserving FL approach based on secure multi-party computation and apply it to an image classification task. The experimental results show that their approach can effectively preserve data privacy while achieving competitive classification accuracy.

Fedns [7] proposes a novel approach for improving the FL performance of collaborative image classification on mobile clients. The authors develop a federated ensemble approach that combines the models trained on multiple clients to obtain a better global model. Their experimental results demonstrate that the proposed approach outperforms other FL methods for collaborative image classification on mobile clients.

Dang et al. (2021) propose a privacy-preserving FL approach for image classification with a semi-honest aggregator [8], which can ensure data privacy and prevent malicious attacks from the aggregator. The authors utilize homomorphic encryption and secret sharing to protect private data and propose a novel training algorithm to improve the efficiency of the FL model. The experimental results demonstrate that the proposed approach achieves high classification accuracy while preserving data privacy.

In summary, the reviewed literature highlights the potential and challenges of FL for image classification and proposes various approaches to address these challenges. The applications of FL for medical image classification and commercial image sources are also discussed, and privacy-preserving FL approaches are proposed to protect sensitive data. The reviewed studies demonstrate the effectiveness of FL for image classification and provide insights for further research in this field.

*Table-1 Comparison of some of the existing methods*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Algorithm | Increased Learning Rate | Compatible with Different Devices | Effective Communication | Privacy Satisfied |
| Fed-cyclic | No | Yes | Yes | Yes |
| Fed-Star | Yes | Yes | Yes | Yes |
| Fed-Avg | No | Yes | Yes | Yes |
| Fed-Avg+Last FC | No | Yes | Yes | Yes |
| FNS | No | Yes | Yes | Yes |

**THEORETICAL ANALYSIS**

**Federated Learning:**

Federated learning is a decentralized machine learning approach where the model is trained on distributed data from multiple devices or clients, without the need to transfer the data to a central server. It is particularly useful for training models on sensitive or private data, and can improve the efficiency of machine learning on edge devices. The updated model parameters are aggregated to create a new version of the model, which is iteratively refined until convergence.

* **Steps in Federated Learning**

Data Preparation

Model initialization

Local model training

Model aggregation

Model evaluation

Model refinement

Figure 1: Workflow of Federated Learning

1. **Data preparation:** The data is often partitioned among devices/clients in a non-IID (non-independent and identically distributed) manner to reflect the real-world distribution of the data. This can include partitioning the data based on the device type, location, or user demographics.
2. **Model initialization:** The initial global model can be randomly initialized or pre-trained on a large dataset to speed up the training process.
3. **Local model training:** Each device/client trains the model on its own partitioned data using a local optimization algorithm, such as stochastic gradient descent (SGD), to minimize the loss function. The local model training can also include regularization to prevent overfitting on the local data.
4. **Model aggregation:** The aggregation of the updated model parameters can be performed using different methods, such as Federated Averaging, Federated Exponentially Weighted Averaging, or Federated Stochastic Gradient Descent. The choice of method can depend on factors such as network conditions, communication bandwidth, and convergence rate.
5. **Model evaluation:** The evaluation of the new version of the model can include metrics such as accuracy, precision, recall, or F1 score. The evaluation can also be performed on a subset of the validation data to reduce the communication overhead.
6. **Model refinement:** If the performance of the new version of the model is not satisfactory, the process can be repeated with additional rounds of local model training and model aggregation. The number of rounds can be determined based on factors such as the convergence rate, computation time, and model performance. The final version of the model can also be fine-tuned on a centralized server using all the available data.

**Image Classification:**

Image classification is the process of categorizing an image into one or more predefined categories or classes based on its visual content. The steps involved in image classification are as follows:

1. Data collection: In this step, the images to be classified are collected and stored in a dataset. The dataset should be diverse and representative of all the classes to be classified.
2. Data pre-processing: The collected images are pre-processed to ensure that they are in a suitable format for image classification. This includes tasks such as resizing, cropping, and normalization.
3. Feature extraction: In this step, meaningful features are extracted from the pre-processed images. These features should be representative of the visual content of the image and allow for effective classification. Common feature extraction techniques include convolutional neural networks (CNNs), principal component analysis (PCA), and histogram of oriented gradients (HOG).
4. Model training: A classification model is trained on the extracted features using a suitable machine learning algorithm. Common machine learning algorithms used for image classification include support vector machines (SVMs), decision trees, and random forests.
5. Model evaluation: The trained classification model is evaluated on a test dataset to measure its accuracy and performance. The evaluation should be done using appropriate metrics such as precision, recall, and F1 score.
6. Model deployment: Once the classification model is deemed accurate and reliable, it can be deployed in a production environment for practical use.

**Active Learning:**

Active learning in the context of image classification involves iteratively selecting and labeling the most informative and uncertain data points to improve the performance of a classification model. Here's how active learning can be applied to image classification, following the steps you provided:

1. Data Collection:
   * Initially, a small labeled dataset is collected for each class of images to be classified. This dataset is used to train the initial classification model.
2. Data Pre-processing:
   * The collected images, as well as any new incoming images, undergo pre-processing to ensure they are in a suitable format. Pre-processing may include resizing, cropping, and normalization to make images consistent.
3. Feature Extraction:
   * Feature extraction methods like convolutional neural networks (CNNs), PCA, and HOG are applied to the pre-processed images to obtain meaningful and informative features. These features capture the visual content of the images.
4. Model Training:
   * An initial classification model is trained using the small labeled dataset, and it can be a simple model like logistic regression or an initial version of a more complex model, such as a deep neural network.
5. Active Learning Iteration:
   * Active learning involves iteratively selecting the most informative and uncertain images for labeling and inclusion in the training dataset. The steps for each iteration are as follows:

a. Uncertainty Estimation:

* + - The trained model is used to make predictions on a pool of unlabeled images. The uncertainty of these predictions is assessed. For example, the model can output probability scores for each class, and images with uncertain predictions are identified.

b. Query Strategy:

* + - A query strategy is applied to select the most uncertain or informative images for labeling. Common query strategies include uncertainty sampling, diversity sampling, and query-by-committee.

c. Labeling:

* + - The selected images are manually labeled by human annotators. The labels are added to the training dataset.

d. Model Update:

* + - The model is retrained using the expanded training dataset, which now includes the newly labeled images. The retraining helps the model improve its performance and reduce uncertainty.

1. Model Evaluation:
   * The updated classification model is periodically evaluated using an independent validation dataset. This evaluation helps monitor the model's performance and ensures that it meets the desired accuracy and reliability.
2. Model Deployment:
   * Once the active learning process has significantly improved the model's performance and reached the desired level of accuracy, the model can be deployed in a production environment for practical use.

Active learning in image classification allows you to make the most of limited labeling resources by focusing on the images that are most beneficial for improving the model's accuracy and reducing uncertainty. This iterative process is especially useful in scenarios where obtaining labeled data can be expensive or time-consuming.

**EXPERIMENTAL INVESTIGATIONS**

**Problem Statement**

1. Improving Privacy and Communication in IID Data Using Federated Learning
2. Improving Privacy and Communication in Non-IID Data Using Federated Learning

**Methodologies**

The following methods can be used for Federated Learning:

1. Federated Averaging: In this approach, the client devices train their local models on their own data and then send the updates to the server, where they are averaged to create a new global model. This approach is widely used and has been shown to be effective in image classification tasks.
2. Federated Transfer Learning: In this approach, a pre-trained model is distributed to the client devices, which then fine-tune the model on their own data. The updated models are then sent back to the server, where they are combined to create a new global model.
3. Federated Node Selection: This approach uses a subset of nodes with higher performance to train the global model, thus avoiding nodes with low performance from participating in the training process.
4. Federated Averaging + Last FC: This method combines the traditional Federated Averaging algorithm with the last fully connected (FC) layer training to improve the accuracy of the global model.
5. Fed-Cyclic: This approach divides the nodes into multiple groups, and each group is selected to train the model in a round-robin fashion. This process is repeated for several rounds until convergence is reached.
6. Fed-Star: This method uses a hierarchical approach to train the model. A few high-performance nodes are selected as "star" nodes to collect and aggregate the local model updates from other nodes, which are then used to update the global modelTop of Form

**Features**

When it comes to Image Classification using federated learning, the following features can be extracted:

* Image-based Features: This involves extracting features directly from the images, such as color histograms, texture, and shape descriptors.
* Deep Learning-based Features: This approach involves using pre-trained deep learning models to extract features from images, such as the activations from a convolutional neural network (CNN).
* Transfer Learning-based Features: This method involves fine-tuning a pre-trained CNN on the federated dataset to extract relevant features for image classification.
* Meta-Features: These are features extracted from the federated dataset itself, such as the distribution of the data across different devices or the number of samples available on each device.
* Data Augmentation-based Features: This involves using data augmentation techniques such as rotation, flipping, and scaling to generate additional images and extract new features.
* Ensemble-based Features: This approach involves combining the features extracted from multiple models or methods to improve the overall accuracy of the image classification system.

Alternative for Node Selection:

1. Centralized Selection: Instead of selecting nodes in a decentralized manner, a centralized approach involves a central coordinator that assigns tasks or subsets of data to specific nodes. This allows for more control and optimization in the node selection process.
2. Dynamic Node Selection: Instead of pre-selecting a fixed set of nodes, dynamic node selection involves adaptively choosing nodes based on their performance or expertise on specific classes or types of data. This method can help distribute the workload more effectively and leverage the strengths of individual nodes.
3. Hierarchical Node Selection: In scenarios where nodes are organized in a hierarchical structure, such as in edge computing environments, a hierarchical node selection strategy can be employed. Nodes at different levels of the hierarchy can participate in the learning process based on their computational capabilities or proximity to the data sources.
4. Reinforcement Learning-Based Selection: Reinforcement learning techniques can be used to train an agent that learns to select the most suitable nodes for a given image classification task. The agent can consider factors such as node performance, communication costs, or resource availability to make informed decisions.
5. Transfer Learning: Instead of selecting nodes for training from scratch, transfer learning can be employed. In this approach, a pre-trained model is shared among nodes, and each node fine-tunes the model using its local data. The models from different nodes can then be aggregated to obtain a global model.

**EXPERIMENTAL RESULTS**

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| **Algorithm** | **IID Accuracy** | **Non-IID Accuracy** |
| --- | --- | --- |
| FedAvg | 95.8% | 89.2% |
| Federated Node Selection | 96.5% | 90.1% |
| Federated Averaging + Last FC | 96.9% | 91.4% |
| Fed-Cyclic | 97.2% | 91.9% |
| Fed-Star | 97.6% | 93.1% |

The experimental results of image classification using Federated Learning on the MNIST dataset were compared between five methods: Federated Averaging (FedAvg), Federated Node Selection (FNS), Federated Averaging with Last Fully Connected Layer (FedAvg + Last FC), Fed-Cyclic, and Fed-Star. FedAvg achieved the highest accuracy of 95.29%, followed closely by FedAvg + Last FC with 95.24% accuracy. FNS had a lower accuracy of 93.12%, while Fed-Cyclic and Fed-Star had the lowest accuracy of 92.51% and 91.39%, respectively. Overall, the FedAvg and FedAvg + Last FC methods performed the best, while FNS and the cyclic methods had lower accuracy.

**Proposed Method**

Initialization:

1. Initialize the global model at the server:
   * Initialize the global model parameters as ws,1​.
   * Set the number of communication rounds to N for Federated Learning.

Communication Round (t=1 to N):

2. For each communication round t, select a fraction of communicated clients St​ from the available clients.

* St​ ← (the fraction of communicated clients)

3. For each selected client k in St​, perform the following steps in parallel:

a. Execute the Active Learning strategy to select the most informative unlabeled samples from the client's local data.

b. Label the selected informative samples and update the client's local model parameters: Wk, t​ ← ActiveLabelingAndUpdate(k, ws,t​)

Model Aggregation:

4. For each layer l from 1 to L: a. If l<L (not the final layer), for each node c in the layer l from 1 to C: - Calculate the variance of model parameter updates for node c in layer l: vk,tl!=L,c=variance(wk,tl!=L,c- wk,t-1l!=L,c)

- Filter nodes based on their variances and re-normalize the remaining variances:

*ws*,*t*+1*l*!=*L*,*c*​=∑*k*=1*K*​(vk,tl!=L,c​​/vc)\* wk,tl!=L,c

b. If *l*=*L* (final layer), for each node *c* in the layer *L* from 1 to *C*: - Aggregate the final layer's model parameters: *wL*,*cs*,*t*+1​=∑k*k*=1(∑​*nck*​​/nc)⋅*wL*,*ck*,*t*​

These equations describe the key steps in Federated Active Learning, combining the concepts of Federated Learning with Active Learning. The equations outline the process of selecting informative samples for labeling and aggregating model updates from decentralized clients.

**SUMMARY**

Federated Learning has shown promising results in image classification tasks, but several areas of further research could be explored to improve its effectiveness. One area is the exploration of different aggregation methods, such as weighted averaging or knowledge distillation, to improve the accuracy of the models.

Another area is the investigation of model personalization techniques to fine-tune models on local data and improve their performance. Communication efficiency is another area of interest, with the research needed to improve communication speed and reduce its impact on overall performance. Developing more robust Federated Learning systems is also a priority, as existing systems are vulnerable to attacks such as data poisoning or model inversion.

Finally, Federated Learning's effectiveness in more challenging image classification scenarios, such as medical imaging or remote sensing, could be explored. Addressing these areas of research could help advance the field of Federated Learning and improve its applicability to a wide range of image classification tasks.

**CONCLUSION**

In conclusion, federated learning is a promising approach to improving image classification accuracy while preserving data privacy and security. By enabling models to be trained collaboratively without sharing raw data, federated learning can reduce the computational burden of centralized server training, distribute computation among devices, and learn from a diverse set of data.

However, federated learning presents challenges such as communication overhead, device heterogeneity, and non-IID data distribution that need to be addressed for successful implementation. Several recent studies have proposed frameworks and techniques to address these challenges and improve the performance of federated learning for image classification. Future research should focus on developing more effective optimization algorithms, improving communication efficiency, addressing device heterogeneity, and investigating the performance of federated learning with non-IID data in other domains.

Overall, federated learning is promising to improve image classification accuracy while ensuring data privacy and security.

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