

Project Report – Privacy-Preserving and Explainable Federated Learning for Robust Digital Forensics

Advanced Research Topics in IT Security (ARTIS)

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January 13, 2026

1. Introduction

Electronic devices are now involved in 85% of all criminal investigations. Each device generates and stores data, leaving behind a digital footprint. This footprint can be used as evidence in subsequent investigations and consists of GPS coordinates, text messages, wearables and more. In the age of big data, the amount of data is growing exponentially, making it much more difficult to search for important evidence and human capacity is not sufficient. Machine learning (ML) is intended to remedy this lack of capacity and the increasing complexity of data. ML models can be used to search for complex patterns and anomalies in large data sets. However, privacy and data security are also playing an increasingly important role. In 2018, the GDPR was published in Europe to protect the data of individuals. Data may not be shared between organizations without consent in order to train ML models. This leads to data islands, which are a problem for classic ML models that require a large data set for the training process. Federated learning aims to counteract these data islands by pursuing a decentralized approach to training an ML model. Each client owns a portion of the data and trains an ML model locally. After the training phase, all clients send their learned parameters to a server, which aggregates these parameters from all clients. This method allows ML models to be trained in a decentralized manner without having to share client data. However, this method also has vulnerabilities that can be exploited by attackers. Attackers can attempt to disrupt the training process or draw conclusions about training data by reading the clients' parameters.

The DF has a multimedia division that specializes in image forgery. This also includes the detection of fake faces. Training a fake face detection model requires real faces, which constitute sensitive data and cannot be shared without further ado. That is why a decentralized approach using FL is one way to connect the data islands between organizations.

The contributions of our project are as follows:

1. We want to analyze existing forensic ML models in the field of fake face detection and reimplement one of them in an FL architecture without reducing accuracy.
2. We want to develop a XAI module that provides insights into the model's decisions. This should reveal whether FL leads to different decisions being made.
3. The FL model should be protected against attackers by integrating robust defense mechanisms.

The rest of the project report is structured as follows. Section 1 provides an overview of existing central ML models in the field of fake face detection. The following section 2 introduces the

basic concepts. This is followed by a description of an ML model and how it is converted into FL, as well as the presentation of a simulation to simulate the training process. Section 4 presents the results, which are then discussed and classified in section 5.

2. Related Work

In the literature, there are various types of approaches to fake face detection without FL. The first group of literature uses CNNs as feature extractors and trains ML models with these features for the classification task. In [1], the authors use the VGG16 as a model and initialize it with the weights trained on ImageNet. The VGG16 consists of 13 convolutional layers, which extract the features of the input image. The output of the 13th layer is flattened and consists of 73984 features, which represent the high-level features of the image. The 140-real-fake-faces dataset is used as input and the features are extracted for each image. These features are then used to train various ML models such as logistic regression, K-means (KNN), decision trees, artificial neural networks (ANN) and random forests (RF). RF performs best with an accuracy of 78.6%, 76% precision, 79% recall and an F1 score of 77.4%.

In [11], the authors use the same approach, but the GoogLeNet, ResNet18, and SqueezeNet models are used to extract the features. In addition, the authors use the 140k-real-fake-faces-with-ELA dataset, in which all images have undergone an additional preprocessing step. This step is error level analysis (ELA), which is a forensic technique for examining image segments for varying compression levels that arise during digital editing of the image. The models again extract the high-level features of the images, which are used to train KNN and Support Vector Machine (SVM) models. The combination of ResNet18 and SVM performs best in fake face detection with an accuracy of 88.6%, 88.5% precision, 89% recall and 85% f1-score.

The second group of fake face detection approaches does not use CNNs as feature extractors, but trains them and uses them for classification. Almost all of the papers mentioned use the 140k real-fake-faces dataset, which makes comparison easier.

In [5], the authors developed a very lightweight fake face detection system that uses LightFDDNetv1 and v2, which contain 3 and 5 convolutional layers and one output layer, respectively. These models contain very few parameters so that they can be used on edge devices. Both models were trained using transfer learning. LightFDDNetv1 achieved a test accuracy of 69.9%, 62% precision, 85% recall and an f1-score of 71.2% after 10 epochs and LightFDDNetv2 accuracy of 71.2%, 78.2% precision, 71% recall and an f1-score of 74.5%.

In [12], the authors used the stacking ensemble learning method, in which several models are trained separately from each other on the same dataset and the predictions are combined during the prediction process. The models used were EfficientNetB0, MobileNetv1 and MobileNetv2, which were trained on the FFHQ dataset using transfer learning. This enabled the authors to achieve an accuracy of 96.4%, 97.8% precision, 97.4% recall and 97.6% f1-score.

In [6], the authors use EfficientB0 with transfer learning. They use a learning rate scheduling technique to adjust the learning rate based on the training epoch. This allows them to achieve an accuracy of 99.06% and a loss of 0.057.

3. Background

3.1. Digital Forensics and the use of Machine Learning

A perpetrator always leaves traces of evidence of their involvement at the crime scene, as described by Dr. Edmond Locard in his exchange principles, which are used in forensic science [2].

The landscape of forensic science has changed due to the rise of electronic devices, which play an increasingly important role in our daily lives and are often connected to the internet and accessible from anywhere. The field has expanded since the early 2000s with digital forensics

(DF), which specializes more in the growing number of cybercrimes. However, even crimes that are not classified as cybercrime are becoming increasingly digital in most modern crime scenes. According to the EU, digital evidence is involved in 85% of criminal investigations. This evidence consists of data generated in our daily lives through the use of digital devices, leaving behind a digital footprint. The footprint consists of data generated by wearable devices, emails, cloud service providers, online payments and other sources [3].

The field of digital forensics can be divided into seven identifiable sub-areas, namely blockchain, networks, mobile, cloud, IoT, file systems & data storage and multimedia. This project is limited to the sub-area of multimedia, which specializes in image forger [3].

A major challenge in this field is dealing with large, complex data sets and classifying them. This problem can be addressed by machine learning (ML), whose techniques have expanded and improved in recent years. ML techniques search through the data and look for anomalies and patterns in the investigation process. The largest area for ML in DF is image forensics, accounting for 62.7%. In the field of image forensics, convolutional neural networks (CNNs) are typically used to recognize such complex patterns in the data, which is why this approach was pursued in the project. [9]

3.2. CNNs for face fake detection

3.2.1 Fundamentals

In recent years, there has been intensive research into CNNs in the areas of image classification, facial recognition and facial expressions, resulting in significant improvements. However, with the emergence of increasingly sophisticated deepfakes, it is becoming more and more difficult to distinguish between real and fake faces [6]. During the training process, CNNs learn complex patterns and can provide information about whether an input image is fake or real. Among CNN architectures, EfficientNet is one of the most modern models, as it is faster, has fewer parameters and has more capabilities for extracting features than other CNN models. These parameters are also called weights and can be learned by the model during the training process. During the training process, the model is shown many input images of positive (real faces) and negative (fake faces) [14]. The model independently learns complex patterns in the form of weights over several iterations (epochs) in order to distinguish positive from negative examples in the case of a binary classifier, or to assign probabilities to classes in the case of a multiple classifier system. [7][4]. What is special about CNNs are the convolutional layers, which reduce the resolution of the images and extract the spatial local features through weighted convolutions. Such local features can be low-level features such as edges, end points and corners in the first convolutional layers and complex high-level features in the last layers. In the final layers, the high-level features (3D vector) are combined into a fully connected layer (1D) to make a classification decision. In this project, the output consists of two output nodes with probabilities indicating whether the input image is a fake or real face [14].

3.2.2 Transfer Learning

To avoid training a model from scratch for a task, a pre-trained model can be reused and retrained for a new task. This process is called transfer learning. To do this, the fully connected layers are replaced with the number of nodes required for the new task. In the case of fake face detection classification, two nodes are required for the probabilities of the image being a real or fake face. Furthermore, the weights in the first layers (close to the input) are frozen so that the parameters are not changed during the training process. These weights represent what has been learned from the original model and should remain as consistent as possible. The weights in the back layers can then be adjusted to the new task during training by fine-tuning [6].

3.2.3 Model Explainability using SHAP

TBD

3.3. Federated Learning

3.3.1 Fundamentals

In the age of big data, data privacy and security are becoming increasingly important and are receiving more attention. The in 2018 published GDPR aims to protect individuals' data, users of services should be able to have their data deleted at any time and data may not be used for training ML models without consent. This leads to a problem in training classical ML models, as large amounts of data form the basis for them. However, the data volumes are now not stored centrally in a single data set but scattered across data islands. Federated learning addresses this problem by training ML models with data from data islands without moving the data from the islands, thereby preserving privacy. [15]

To perform FL, three main steps must be carried out, as described in [8].

- 1 - Model selection: A global model must be selected, which is initialized with pre-trained weights to speed up the learning process. The global model is located on a central server.
- 2 - Model training: The parameters of the global model are distributed to all clients. Each of the clients owns a portion of the data for the training process. The clients initialize their local model with the parameters of the global model and train it for several epochs.
- 3 - Parameter aggregation: All clients send their local parameters to the server. The server updates the global model with an algorithm that incorporates the local updates from the clients into the global model.

The last two steps are repeated until a specified number of epochs or a desired accuracy has been achieved.

3.4. The Flower Federated Learning Framework

Flower is an open-source framework designed for FL applications. It provides a flexible and extensible architecture that enables machine learning across decentralized data while maintaining data privacy on client devices.

Key Advantages

1. **Framework Agnosticism:** Flower supports many ML frameworks such as PyTorch, TensorFlow, JAX and scikit-learn. This allowed us freedom in development without compatibility issues.
2. **Low Learning Curve and Ease of Use:** Flower is specifically designed with developer experience in mind. Its clean, minimal API allows for quick prototyping—a working FL system can be implemented with just a few lines of code. Compared to alternatives like TensorFlow Federated (which requires learning specialized abstractions) or PySyft (with its complex privacy-preserving cryptography integration), Flower offers a more intuitive approach that reduces the barrier to entry for both researchers and practitioners.
3. **Scalability:** The framework supports deployments ranging from small-scale simulations to production systems with hundreds of clients. This scalability enables both algorithm development in simulated environments and real-world deployment across distributed devices.
4. **Production Readiness:** Beyond research use cases, Flower includes features necessary

for production deployment, including fault tolerance, client management and monitoring capabilities. This makes it suitable for both experimental validation and real-world applications.

3.4.1 Attack Vectors in FL

Attack vectors on FL are divided into two large groups, which are described in [10]. On the one hand, there are model performance attacks, which focus on damaging the training process in various ways. These include data poisoning attacks, in which the training data is modified by replacing images or labels before the training. Model poisoning attacks, in which the gradients of the locally trained model are altered. Free-riding attacks, in which the model is only used without adding value to the global model. On the other hand, there are privacy attacks that attempt to draw conclusions about training data from the local parameters of clients or the global parameters of the global model. These include model inversion and gradient inference attacks, as well as GAN reconstruction attacks, in which private training data is to be reconstructed.

4. Methodology

4.1. Experimental Setup

A fake face detection model is developed using federated learning (FL) to distinguish between real and fake faces. First, a centrally trained model without FL is implemented and used as a baseline for performance comparison. Second, a decentralized fake face detection model is trained using FL in a simulated multi-client environment.

4.1.1 Dataset

The well-known 140k real-fake faces dataset was used, which consists of 70,000 real faces and 70,000 fake faces with a image size of 256px [13]. The fake faces were generated using StyleGAN, a generative adversarial network developed by NVIDIA that is capable of producing highly photorealistic synthetic facial images.

4.1.2 Model

The base model chosen is EfficientNet-B0, a convolutional neural network (CNN), which was also used by Khudeyer et al. [6]. The authors trained a fake face detection model using transfer learning. For this purpose, the model was initialized with the pretrained weights of EfficientNetB0 on the ImageNet dataset. A lightweight head was attached to the pre-trained base model, consisting of global average pooling, a 256-dimensional fully connected layer with ReLU activation, batch normalization, and dropout, followed by a 2 dimensional softmax output layer. The output is a 2-dimensional vector with probabilities indicating whether the input image is a fake or real face. The model was optimized with binary cross-entropy loss and the Adam optimizer. All input images for training were resized to 244px.

4.2. Centralized Fake Face Detection Model

The authors of [6] developed a method for fake face detection using CNN, which achieves an accuracy of 99.06%. This approach is used as a benchmark for comparing central fake face detection with fake face detection using FL. This work was reimplemented for verification purposes in order to ensure a meaningful comparison.

The dataset was divided into 100.000 training images, 20.000 test images, and 20.000 validation images. EfficientNetB0 with the hyperparameters of section 4.1.2 is used. Training was

Epoch	Learning rate
$epoch \leq 2$	0.01
$2 < epoch \leq 15$	0.001
$epoch > 15$	0.0001

Table 1: Adjustment of the learning rate during training.

performed with a batch size of 32 over 30 epochs with early stopping to reduce training time. The paper presented a learning rate scheduler that adjusts the learning rate during training based on the epoch, as shown in Table 1. The learning rate scheduler ensures that significant weight adjustments are made early in training. Furthermore, in later iterations, a strong adjustment is prevented by the decreasing learning rate. This leads to faster convergence in early epochs, while weight optimizations can be performed in later iterations. Due to time constraints, the model was only trained once, as training was very computationally intensive due to the large amount of data.

4.3. Decentralized Fake Face Detection Development

The transition from a centralized to a decentralized model was conducted in two phases: an initial implementation using an automated framework, followed by a custom-built manual Federated Learning (FL) system to accommodate specific security requirements.

4.3.1 Phase 1: Automated FL via Flower Framework

Initially, the decentralized model was implemented using the *Flower* framework. This phase served to validate the feasibility of training EfficientNet-B0 in a multi-client environment. However, during development, significant technical challenges arose regarding the integration of custom encryption layers within the Flower abstraction. This limitation necessitated the development of a more transparent, manual FL pipeline.

4.3.2 Phase 2: Manual FL with Weight Encryption

To ensure full control over the aggregation process and security protocols, a manual FL simulation was developed. The environment simulates a global server and five distinct participants (clients). Each client is allocated a shard of the dataset (approximately 20,000 images) using *tf.data.shard* to maintain memory efficiency.

Training Loop: The global model is initialized with ImageNet weights. In each of the 10 federated rounds:

1. The server broadcasts the current global weights to all active clients.
2. Each client performs 3 local epochs of training using a categorical cross-entropy loss and the Adam optimizer.
3. Clients serialize their local weight updates into byte streams.
4. These updates are encrypted using AES-128 via the Fernet symmetric encryption library before being transmitted back to the server.

Secure Aggregation: Upon receiving the encrypted updates, the server performs decryption and updates the global model using a *Weighted Federated Averaging* (FedAvg) algorithm. The

contribution of client k is weighted by its sample size n_k relative to the total samples N :

$$W_{global} = \sum_{k=1}^K \frac{n_k}{N} W_k$$

This ensures that the global model converges effectively while preserving the privacy of the local data through the encryption of model parameters during transit.

4.3.3 Threat Model and Privacy

The primary attack vector addressed in this architecture is the interception of model weights during transmission. By implementing Fernet-based encryption, we ensure that even if a third party captures the packets between the client and the server, the underlying gradients—which could potentially be used for reconstruction attacks—remain inaccessible without the shared secret key.

4.4. Explainability using SHAP

In order to analyze the centrally trained model and the decentralized trained model, the decisions made by the models should be compared for individual inputs. The aim is to clarify whether the models have developed differently as a result of the different training processes and whether they focus on different details when making decisions. The SHAP method is used for this purpose.

5. Results

In this section, we evaluate the performance of our digital forensics model across three development phases: the centralized baseline, the Flower-based Federated Learning (FL) implementation, and our custom Manual FL implementation designed for encryption integration.

5.1. Performance Metrics Comparison

The performance of each iteration was measured using Accuracy, Precision, Recall, F1-score, and ROC-AUC. Table 2 summarizes these metrics.

Table 2: Performance Comparison of Model Versions

Model Version	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Baseline (Centralized)	0.8256	0.7747	0.9184	0.8404	0.9279
Flower Framework FL	0.7412	0.6658	0.9686	0.7891	0.9211
Manual FL (Encrypted)*	0.0000	0.0000	0.0000	0.0000	0.0000

*Note: Results for Manual FL with encryption are pending final computation.

As shown in Figure 1, the baseline model maintains the highest overall accuracy, whereas the Flower framework shows a significant increase in Recall (0.9686), indicating a high sensitivity in detecting "Real" faces, albeit with a trade-off in "Fake" face precision.

5.2. Confusion Matrix Analysis

To better understand the classification behavior, we compare the confusion matrices of the models (see Figure 2).

The Flower framework implementation exhibited a tendency to misclassify "Fake" samples as "Real" (4,862 instances), which explains the lower precision. In contrast, our Baseline model showed a more balanced distribution, correctly identifying 7,329 "Fake" samples compared to Flower's 5,138.



Figure 1: Comparison of evaluation metrics across the three model versions.

6. Discussion

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7. Conclusion

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your_confusion_matrix_filename.png

Figure 2: Side-by-side comparison of Confusion Matrices for the Baseline and Flower-based models.

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