Deepfake Face Detection using ResNet18 Architecture

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*Abstract*—Deepfake technology has been increasing rapidly, threatening digital content privacy. Misusing deepfake images poses challenges such as spreading misinformation, privacy violations, identity theft, and threats to digital security. In this regard, a deepfake face image detection framework has been proposed using a fine-tuned ResNet18 model. The model is trained and evaluated using a variety of datasets, such as DeepFakeDetection, FaceForensics++, and Celeb-DF. These different data sources contain millions of real and manipulated images produced using various successful deepfake technologies. By further exploiting ResNet18's architecture, which is efficient in extracting features, this fine-tuning and transfer learning process has targeted hidden artifacts and/or inconsistencies characteristic of deepfake images. The entire training has been subjected to extensive augmentation of data and hyperparametric optimization to make it optimally robust and generalize over unseen deepfake generation methods and multiple datasets. The experimental results show that the ResNet18 model with custom classification head produces good classification accuracy, which demonstrates its power in detecting deepfake face images. Thus, it can emerge as a scalable plus reliable route in fighting the stealthy menace of deepfake intervention, for example, as a part of media authentication and cybersecurity.

Keywords—Deepfake technology, privacy violations, digital security, face image detection, ResNet18 model, DeepFake detection.

# Introduction

Deepfake technology has progressed quickly in a short time, such that it can create very realistic and convincing images and videos for presentations in the media and entertainment industries. It can offer creative options but then raises concerns about misinformation, privacy invasion, and identity fraud. There are many concerns, such as for law enforcement, journalism, and social media, about the possibility of deceiving an audience with fake content. With new advances in the generation methods of creating deepfakes, indeed, there comes a requirement for reliable systems capable of detecting them. In this regard, the detection of deepfake faces will be highly useful, as they are more likely to be used for political manipulation and social media misinformation campaigns [1].

Conventional image forgery detection mechanisms had normally been based upon pixel-wise data inconsistencies that include unnatural artifacts and compression discrepancies, leading to their unsatisfactory performance. Recent studies showed that the traditional image analysis-based deepfake detection systems were no longer valid for the high-tech techniques employed by the most recent deepfake generators [2]. Therefore, there is an urgent challenge for the development of remarkably well-generalized detection systems against various deepfake generation schemes and datasets.

There have been several applications of deep learning methods that seem to hold promise in solving this problem. Some of these applications include using convolutional neural networks (CNN) and some other deep learning methods for deepfake detection. A good number of these applications are among pre-trained architectures such as ResNet. They are particularly ideal in the consideration that they successfully extract hierarchical features from images while also making it easier for one to address challenges like the vanishing gradient through residue learning. The fine-tuning of already trained models such as ResNet to cater to specific tasks like deepfake detection results in a significant improvement in the accuracy and robustness of these models [3]. Other processes being tested against a variety of data sources as a tool to improve model performance in detecting deepfakes include data augmentation, weighted random samplers, and transfer learning [4].

In this work, we present a different approach toward deepfake face image detection by fine-tuning ResNet18 with an added linear layer on top that would classify the images into various classes. The model trains on a huge dataset consisting of real and deepfake images coming from different sources: DeepFakeDetection, FaceForensics++, and Celeb-DF. Also, some techniques of data augmentation would be induced, as well as a weighted random sampler during training to overcome class imbalance and facilitate better generalization by model.

Our experimental results indicate that the fine-tuning ResNet18 model achieves reasonably good rates of accuracy for deepfake face image detection. Therefore, it heralds a potentially important step in the broader arena of real-world applications, such as media authentication, cybersecurity, and digital forensics.

# LITERATURE REVIEW

Real and fake image classification research has significantly developed through numerous deep learning models, datasets, and techniques aimed at challenges increasingly created by synthetic media, says J. Anil et al. [5] emphasised the effectiveness of deep learning models like ResNet50, VGG16, and MobileNet, showcasing ResNet50's superior testing accuracy of 99% for classifying real and fake images, thereby underscoring its reliability in tasks involving intricate image features. S. Kumar et al. [6] performed a comparison study on ResNets and Variational Autoencoders (VAEs) that showcased the effectiveness of ResNets in identifying AI-generated images, thus providing a useful resource for model architecture choice in this application domain. K. Sharma et al. [7] introduced the CIFAKE dataset, which specifically targets the classification of real versus AI-generated images using CNNs, providing high classification accuracy with a benchmarking future research direction. M. Roy et al. [8] aimed at detecting fake images produced by GANs through error-level analysis, which provided a novel approach to identifying manipulation artifacts that other traditional methods may miss. In the same direction, P. Zhang et al. [9] worked on global tampering detection in generative models to address the problems of advanced synthetic image generation through new approaches. A. Gupta et al. in [10] showed the importance of feature extraction in image classification. Tailored feature engineering improves the performance of a model significantly. L. Chen et al. [11] enhanced detection accuracy by using unique natural traces of real images by including features in model training. Li et al. [12] conducted an effective study on benchmarking human and AI capabilities in synthetic image detection emphasizing the need for effective, robust detection systems concerning the rapid evolution of the synthetic media. N. Kumar et al. [13] presented the FLORIDA dataset containing real images with fake-like appearances and introduced methodologies to deal with the subtlety of distinguishing these images from their synthetic counterparts.  In this regard, the work of H. Wang et al. [14] provide forensic insights into the properties of synthetic images created by GANs and diffusion models while suggesting methods for improving detection accuracy.

Our work is based on these foundations and the ResNet18 architecture to classify real and fake images in real time. The imbalanced datasets challenge was recognized, and weighted random sampling techniques were used, with weights calculated and saved for effective integration into the training pipeline. Hyperparameter optimization was carried out using Optuna, which found the optimal configuration for the classification head: a simplified transformation from 512 by 2 linear layers, which is efficient and accurate for classification. Our approach also includes data augmentation for training data and ensures effective transformations for validation and testing, which makes it suitable for real-world applications. In contrast to more general research efforts that focus on model comparisons or dataset creation, our study focuses on lightweight, robust solutions tailored for deployment in practical scenarios, offering significant contributions to the field of synthetic image detection.

# METHODOLOGY

This section describes the methodology adopted in each phase, from data collection to analysis. Python and PyTorch were used for the entirety of this process.

## Dataset

The dataset has images for both images segregated into train and valid folders. Each of the two folders have images further categorized as Fake and Real by dividing them into real and fake folders. There are:

 42,690 real instances for training.

 219,470 fake instances for training.

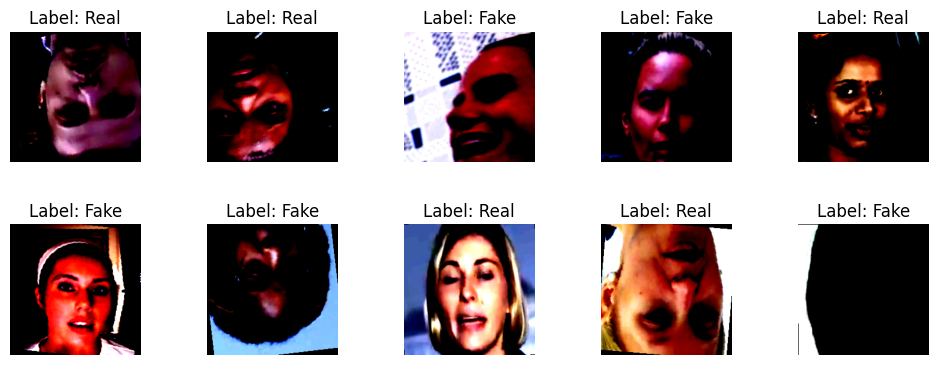
1,548 real instances for validation.

1,524 fake instances for validation.

All images are in .png format with a resolution of 256x256 pixels. They have been extracted from videos and uniformly post-processed using an identical algorithm. The sample images are shown in Figure 1.

A small portion of the training dataset (5%) has been extracted and has been used as the validation dataset during the training phase of the model. The validation dataset in the original dataset has been used as the testing dataset.

## Data Transformations

Each image has been resized to 224x224 pixels size and normalized before feeding them to the model. Specifically for the training data, to help the model generalize better, random transformations (Random Crop, Random Horizontal Flip, Random Vertical Flip and Random Rotation up to 15 degrees) have been applied to the images to perform Data Augmentation. Only resize and normalize transformations were applied to the validation and test images.

## Handling Class Imbalance

The training dataset is heavily biased towards fake images. There are 219,470 fake images but only 42,690 real images. To handle the class imbalance between the real and fake instances, we used Weighted Random Sampling. To assign them to the WeightedRandomSampler of PyTorch, we assigned each image its class weight. The weights for each image have been stored in a JSON file to avoid recalculation of each image weight everytime.

## Resnet18

We used Resnet18 [15] as our base model for the task. The model is not too small to underfit the data and not too large to take too much time to process one image. Resnet18’s Final Fully Connected Network is a Linear Layer mapping 512 Convolutional Layer Outputs to 1000 Class Prediction Outputs. We replace that with our custom classification head which forward passes those 512 Convolutional Outputs to get our classification output for the 2 classes, real and fake.

## Choosing the classification head

We used the Python Module Optuna to decide on the number of layers and number of units in each layer of our classification head. The suggestion for number of layers has been given a range of integers between 0 and 5 (both inclusive). The Number of units in each layer will be suggested between 128 and 512. The learning rate suggestions will range from 1e-4 to 1e-1. After 100 trials, we concluded that a direct Linear mapping of the 512 CNN layer outputs to the 2 class outputs work the best with a learning rate of 0.001.

## Hyperparameters

For the loss function we have used Cross Entropy Loss. The learning rate is 0.001. The optimizer used is Adam. The batch size of the train, validation, and test datasets is 32. The model will be evaluated against the validation dataset every 2 epochs. The Stopping Criteria employed is Early Stopping, albeit the training of the model doesn’t immediately stop, once the model’s loss reaches a better minimum it is stored. If the model’s loss stays the same or increases that model is not stored. This can be viewed as a softer implementation of early stopping.

## Training the Model

We trained the same model twice with the same hyperparameters for this experiment. Once with the Resnet18’s Convolutional Layers frozen with Pretrained weights, and only optimizing the Classification Head Parameters. The other trial with Resnet18’s Pretrained weights loaded but none of the parameters are frozen. All the parameters are trained. The Resnet18 Convolutional Layers have 11,176,512 parameters in total. Our custom classification head has a total of 1026 parameters.

For the model with the convolutional layers frozen, the trainable parameters are only 1026. But for the model with no layers frozen, the trainable parameters are 11,177,538. The training process consists of forward passing, back propagation and optimization step. Even though we are not freezing any convolutional layers in the second model, we still load the pretrained weights for the resnet18 model to achieve faster convergence.

# Results and discussions

After this experiment, we have seen that the Resnet18 Model with no parameters frozen works much better than the model with the convolutional layers frozen.

The loss curve of the model with the convolutional layers frozen is shown in figure 2. We can see that the running loss curve is almost linear and very little variation. But the validation loss has huge variation. This may indicate underfitting during training. This behaviour may be explained by the possibility of the Resnet18 Pretrained Convolutional Layers not being able to pick up more relevant features from the training images to be able to properly classify the images. The real and fake images fundamentally are similar in nature. Thus, only optimizing the classification head may not yield the desired results.

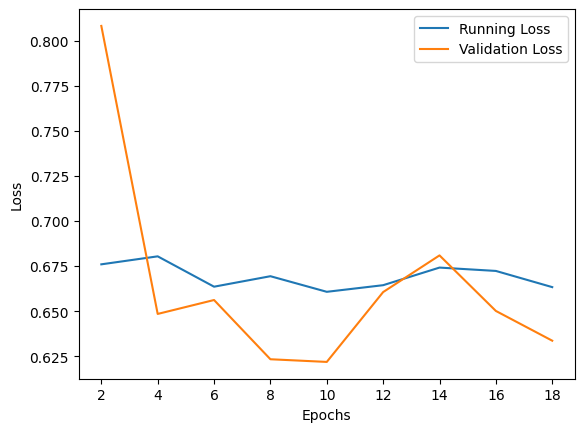


Figure 2: Loss Curve of Resnet18 Model with frozen CNN Layers

The loss curve of the model with the pretrained Resnet18 without any frozen parameters is shown in figure 3. Here, we see that the running loss and validation loss both decrease steadily. The validation loss jumps up at some epochs but ultimately goes down. The performance of this model being better might be due to the convolutional layers extracting the necessary features from the images, even if the images are similar. Also, because the model was initialized with Pretrained weights from ImageNet dataset instead of initializing them at random, the model may be converging faster to better performance.

The model achieves an accuracy of 94.97% on the validation dataset. The model achieves a good accuracy of 85.51% on the test dataset. The model performance indicates that the generalizing capabilities of the model are great. The best model was saved and the models in the following epochs where the validation loss increased were ignored. The model is able to process 3072 images in 18 seconds. Which averages to 0.0059 seconds for processing each image. Which signifies that our model achieves good accuracy and also can process images very quickly.

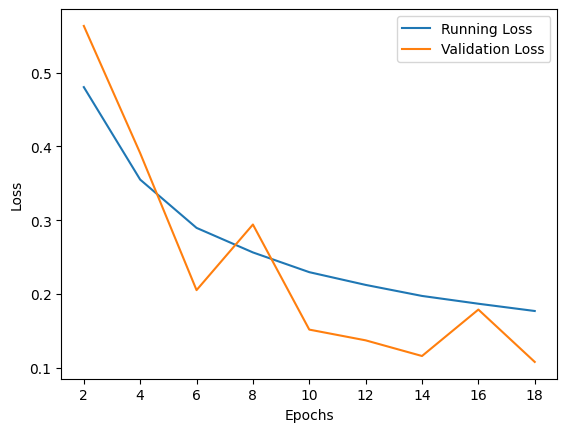


Figure 3: Loss Curve of Pretrained Resnet18 Model with no frozen parameters

# conclusion

Adding up, the deepfake facial image detection framework, which considers ResNet18 architecture-based model, takes care of many critical challenges posed by deepfake technology on real-world levels. This model has an accuracy of 85.51%, making it a formidable tool to detect manipulated faces, thus coping with a wide variety of deepfake effects. This type of model makes a significant impact on the fight against fake news in today's society by guarding the privacy of many individuals against identity thieves. Moreover, the model secures digital safety conditions through safety sheets, which aim at preventing spoofing attacks and ensuring the media's purity in journalism and legal applications. By way of illustration, this solution sets a scalable and dependable course of renewing the risks related to deepfake technologies in the long run. It offers some significant benefits in the areas of media authentication, cybersecurity, and the protection of digital content.

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