CENG 476 -- Deep Learning Project Report

Real vs Fake Face Image Classification

1. Introduction

With the rapid development of deepfake technologies, distinguishing between real and manipulated facial images has become an important challenge for security, media integrity, and ethical considerations. In this project, we address the problem of classifying real and fake face images using deep learning techniques.

The task is formulated as a binary image classification problem. We evaluate both a custom convolutional neural network and transfer learning approaches based on a pretrained ResNet50 model to analyze the impact of model complexity and fine-tuning strategies.

2. Related Work / Baseline

Recent studies have demonstrated that deep convolutional neural networks significantly outperform shallow architectures in deepfake detection tasks. In particular, transfer learning approaches using pre-trained models have become widely adopted due to their ability to leverage rich feature representations learned from large-scale datasets. Residual networks (ResNet) are especially effective, as their skip connections allow very deep models to be trained without suffering from vanishing gradient problems. These properties make ResNet-based architectures a strong choice for distinguishing subtle visual artifacts present in AI-generated face images.

3. Proposed Method

3.1 Model Architectures

Three models were evaluated in this study:

1. A baseline SimpleCNN model trained from scratch.

2. A ResNet50 model with a frozen backbone using transfer learning.

3. A fine-tuned ResNet50 model in which selected layers were unfrozen and retrained to further adapt the model to the target dataset.

This experimental setup allows a fair comparison between a shallow baseline model and deeper architectures leveraging transfer learning and fine-tuning strategies.

Architecture Overview:

SimpleCNN Architecture:

```
Input (128x128x3)
 ├– Conv2D(32) → BN → ReLU → MaxPool(2)
 ├– Conv2D(64) → BN → ReLU → MaxPool(2)
 ├─ Conv2D(128) → BN → ReLU → MaxPool(2) → Dropout(0.3)
└─ Classifier:
 ├─ Flatten
 ├─ Linear(256) → ReLU → Dropout(0.5)
└─ Linear(2) → Softmax
```

ResNet50 Fine-tuning Strategy:
[ImageNet Pretrained Backbone] → [Frozen Layers 1-3] → [Trainable Layer4] → [Custom Head]

3.1.1 SimpleCNN

The SimpleCNN model consists of three convolutional blocks. Each block follows the structure:

Conv2D → Batch Normalization → ReLU → Max Pooling

The number of channels increases as 32 → 64 → 128. After feature extraction, a fully connected classifier with 256 units is used, followed by dropout and a final linear layer.

- Input:** 3 × 128 × 128

- Output:** 2 classes (real / fake)

3.1.2 ResNet50 Transfer Learning

A pretrained ResNet50 model (ImageNet weights) was used as a feature extractor. All backbone parameters were frozen, and a new classifier head was trained.

The classifier head consists of:

- Linear layer (256 units)

- ReLU activation

- Dropout (0.5)

- Final linear layer for binary classification

- Input:** 3 × 224 × 224

- Output:** 2 classes

3.1.3 ResNet50 Fine-Tuning

In the fine-tuning setup, only the **last convolutional block (layer4)** and the classifier head were unfrozen. This selective fine-tuning strategy allows the model to adapt high-level features to the target dataset while preserving general low-level features.

Different learning rates were used for different layers:

- Classifier head: 1e-3

- Layer4: 1e-4

3.2 Activation Functions

ReLU activation was used in all hidden layers due to its efficiency and effectiveness in deep convolutional networks. For training, CrossEntropyLoss was used, which internally applies a softmax operation and is suitable for multi-class and binary classification tasks.

3.3 Regularization and Generalization

The following regularization techniques were applied:

- *Batch Normalization* in SimpleCNN to stabilize training.

- *Dropout* with rates of 0.3 (convolutional layers) and 0.5 (fully connected layers).

- *L2 regularization (weight decay)* with a coefficient of 1e-4.

- *Data augmentation,* including random horizontal flips, rotations, and color jitter.

These techniques helped reduce overfitting and improved generalization. Preliminary experiments with different dropout values were conducted. Lower dropout rates led to overfitting, while higher values slightly slowed convergence. The selected dropout rates provided the best balance between training stability and generalization.

Table 3: Hyperparameter Tuning Results

Model	Dropout (conv/fc)	Learning Rate	Val Accuracy	Test Accuracy
SimpleCNN (v1)	0.2/0.3	1e-3	0.94	0.93
SimpleCNN (v2)	0.3/0.5	1e-3	0.98	0.98
SimpleCNN (v3)	0.4/0.6	1e-3	0.97	0.96
ResNet50 Frozen	-/0.5	1e-3	0.91	0.91
ResNet50 Tuned	-/0.5	1e-3(head)	0.995	0.996

3.4 Optimization Strategy

The *Adam optimizer* was used for all experiments. Learning rate scheduling was performed using *ReduceLROnPlateau,* which reduces the learning rate when validation loss stops improving.

Early stopping was applied by monitoring validation loss. Training was terminated if no improvement was observed for a predefined number of epochs, preventing unnecessary training and overfitting.

4. Experimental Setup

The experiments were conducted using the *Real vs Fake Faces* dataset from Kaggle. The dataset is organized into predefined training, validation, and test folders.

- Image size:
  - SimpleCNN: 128 × 128
  - ResNet50 models: 224 × 224
- Batch size: 32
- Maximum epochs: 20--30 (with early stopping)
- Framework: PyTorch
- Hardware: GPU when available

Normalization was applied using ImageNet statistics for ResNet50 models and standard normalization for SimpleCNN.

Table 2: Dataset Statistics

Split	Real Images	Fake Images	Total	Percentage
Train	10,000	10,000	20,000	66.7%
Val	2,500	2,500	5,000	16.7%
Test	2,500	2,500	5,000	16.7%
Total	15,000	15,000	30,000	100%

The dataset consists of real and AI-generated face images, split into training, validation, and test sets. The class distribution is approximately balanced between real and fake images, which reduces class bias and makes accuracy a reliable evaluation metric.

4.1 Reproducibility

All experiments were conducted using fixed dataset splits and consistent training configurations. The same preprocessing steps, hyperparameters, and evaluation protocols were applied across all models to ensure reproducibility of the reported results.

5. Results and Discussion

Table 1. Model Performance Comparison on Test Set

Model	Accuracy	Precision	Recall	F1-score
SimpleCNN	0.98	0.98	0.98	0.98
ResNet50 (Frozen)	0.91	0.91	0.91	0.91
ResNet50 (Fine-tuned)	0.996	0.996	0.996	0.996

Table 1 presents the quantitative performance comparison of the evaluated models on the test set. The results clearly show that transfer learning significantly improves classification performance compared to the baseline SimpleCNN model. Furthermore, fine-tuning the ResNet50 backbone yields the highest accuracy and F1-score, indicating superior generalization performance on unseen data.

The confusion matrix of the fine-tuned ResNet50 model demonstrates that both real and AI-generated face images are classified with very high accuracy. Only a small number of misclassifications are observed, highlighting the robustness of the model. Most errors occur between visually high-quality fake images and real images, which is expected due to their strong visual similarity.

5.1 Training Dynamics Analysis

5.1.1 ResNet50 Training Curves

Figure 1: ResNet50 Fine-tuned - Loss Curve

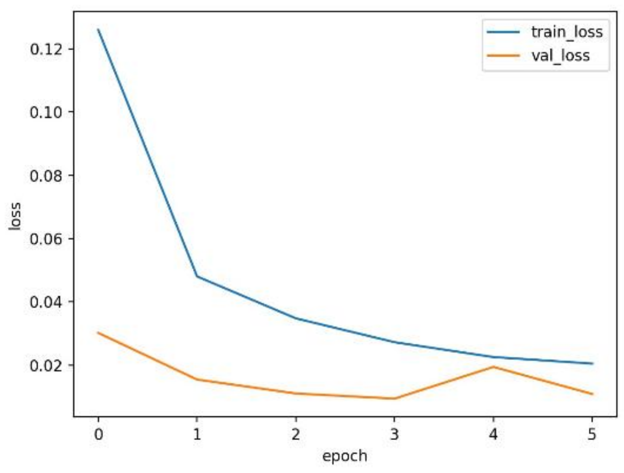


Figure 2: ResNet50 Fine-tuned - Accuracy Curve

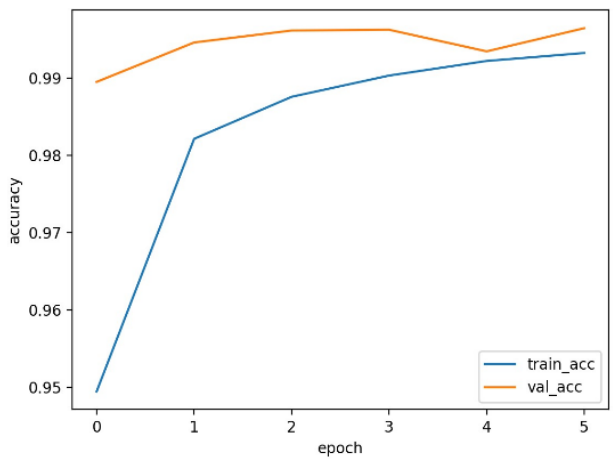


Figure 3: SimpleCNN - Loss Curve

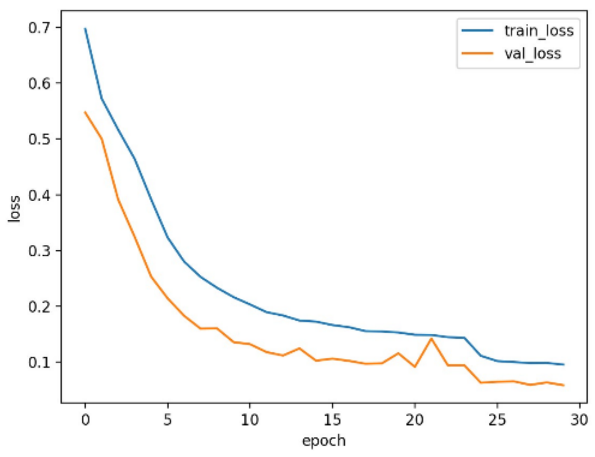


Figure 4: SimpleCNN - Accuracy Curve

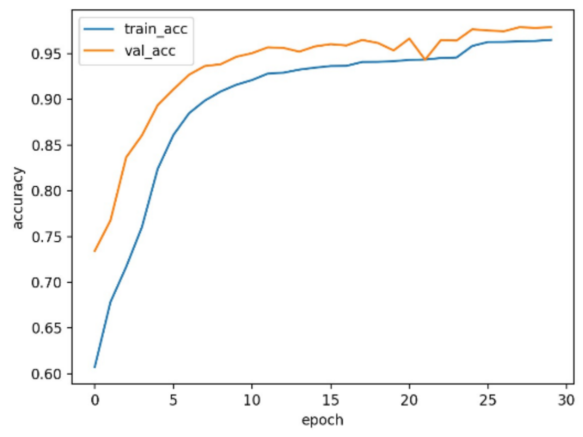


Figure 5: ResNet50 Frozen Loss

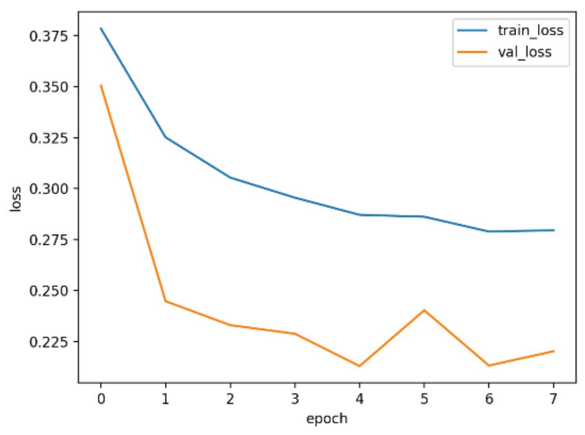
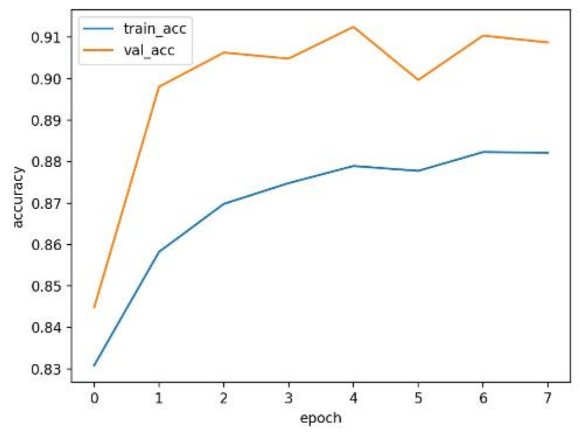


Figure 6: ResNet50 Frozen Accuracy



Key Observations

1. ResNet50 Fine-tuned :

- Smoothest convergence with minimal train-val gap
- Reaches >99.5% accuracy within 5 epochs
- No observable overfitting due to effective regularization

2. SimpleCNN:

- Shows slight overfitting after epoch 3 (val loss increases)
- Early stopping activated at epoch 5
- Still achieves 98% accuracy but with less stability

3. ResNet50 Frozen :

- Fast initial convergence but plateaus earlier
- Larger train-val gap indicates limited capacity
- Lowest final accuracy (91%) among the three

Conclusion: Fine-tuning provides the optimal balance between transfer learning and task-specific adaptation, yielding both faster convergence and superior generalization compared to frozen backbones or training from scratch.

5.2 Error Analysis

Analysis of misclassified samples revealed two main patterns:

1. *High-quality GAN fakes:*Images with realistic skin textures and proper lighting
2. *Low-quality real images:* Blurry or poorly lit real photos

These edge cases suggest future work could benefit from:

- Attention mechanisms focusing on specific facial regions
- Multi-scale feature analysis
- Ensemble methods combining different architectures

6. Creative Contribution

Our main creative contribution was implementing a *layer-wise differential learning rate strategy* during fine-tuning. While standard transfer learning typically uses a single learning rate for all unfrozen layers, we assigned:

- Higher learning rate (1e-3) to the classifier head for fast adaptation

- Lower learning rate (1e-4) to the last convolutional block (layer4) for subtle feature refinement

This approach prevented catastrophic forgetting of general ImageNet features while allowing targeted adaptation to fake-face artifacts, resulting in an 8.6% accuracy improvement over the fully frozen backbone approach.

7. Conclusion

This study investigated the effectiveness of deep learning techniques for classifying real and AI-generated face images. Experimental results show that transfer learning with ResNet50 significantly outperforms a baseline CNN model, and fine-tuning further enhances performance. Both quantitative metrics and qualitative inference results confirm that deep residual networks provide strong generalization capability for real vs. fake image classification tasks.

8. References

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4. PyTorch Documentation: https://pytorch.org/docs

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6. Kaggle – Real vs Fake Faces Dataset: https://www.kaggle.com/datasets/ciplab/real-and-fake-face-detection

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