# Sabudh Passion Project

Learn and Give Back to Society

**Final Project Report**

*Deepfake Identification Using Deep Learning*

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# Preface

This project, “Deepfake Identification”, was undertaken as part of the **Sabudh Passion Project** under the valuable guidance of Harjaspreet Sir. The initiative aims to encourage practical learning while contributing positively to society by applying advanced machine learning and deep learning techniques to real-world challenges.

With the rapid advancement of artificial intelligence, deepfake technology has emerged as a serious threat to digital trust and information authenticity. Manipulated images and videos can be misused to spread misinformation, damage reputations, and undermine public confidence in digital media. Addressing this issue has become increasingly important in today’s technologydriven world.

This group project focuses on the design and development of a robust deepfake detection system, leveraging state-of-the-art deep learning architectures. The work involves systematic dataset collection, preprocessing, face detection using MTCNN, feature extraction through models such as **Vision Transformers(VIT)** and **ResNet**, and model training and evaluation. Emphasis has been placed on improving detection accuracy and generalization through effective preprocessing and balanced data representation.

We sincerely express our gratitude to the **Sabudh Foundation** for providing the necessary platform, resources, and mentorship to carry out this project. Their continuous support fostered an environment of innovation, collaboration, and practical learning. This report documents our complete journey—from problem understanding and dataset preparation to model development and evaluation—highlighting the collective effort, learning experience, and technical growth achieved by the team.

# Abstract

This project focuses on the challenge of **deepfake media detection** by leveraging state-of-theart deep learning architectures to distinguish between authentic and manipulated facial images. With the increasing realism of AI-generated content, reliable and automated detection mechanisms have become essential for preserving digital trust.

In this work, two powerful models—ResNet (Residual Neural Network) and Vision Transformer (ViT)—are implemented, analyzed, and compared for deepfake classification. The proposed workflow begins with dataset collection from publicly available deepfake repositories, followed by extensive preprocessing that includes face extraction, resizing, normalization, and data augmentation to enhance model generalization.

Both models are trained and evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score, enabling a comprehensive assessment of their effectiveness. To ensure practical usability, the trained models are deployed using Gradio, allowing interactive and real-time testing on user-provided images.

Experimental results indicate that ViT effectively captures global contextual dependencies, while ResNet demonstrates strong hierarchical feature extraction capabilities. The complementary strengths of these architectures contribute to a robust deepfake detection framework. This project highlights the potential of combining modern deep learning approaches to address emerging challenges in media forensics and digital authenticity.

# Chapter 1
# Introduction

The rapid advancement of artificial intelligence and deep learning has significantly transformed the way digital media is created, edited, and shared. While these technologies have enabled innovative applications across entertainment, education, and communication, they have also given rise to sophisticated forms of media manipulation known as **deepfakes**. Deepfakes use deep neural networks to generate or alter images and videos in a highly realistic manner, making it increasingly difficult to differentiate between authentic and manipulated content.

The misuse of deepfake technology poses serious challenges to **digital trust, privacy, and security**. Manipulated facial images and videos can be exploited for spreading misinformation, political manipulation, identity fraud, and reputational damage. As deepfake generation methods continue to evolve, traditional detection techniques based on handcrafted features or manual inspection have become insufficient. This has created a strong need for **automated, accurate, and scalable deepfake detection systems**.

Deepfakes are synthetic media generated using AI techniques, often indistinguishable from authentic content. Their misuse in politics, entertainment, and social media raises concerns about misinformation and security. Detecting deepfakes requires models capable of identifying subtle artifacts and inconsistencies.

Figure 1.1 Illustrative Example of the model

## Existing System

Traditional detection systems rely on handcrafted features or shallow classifiers, which fail against modern GAN-based manipulations. These systems struggle with generalization across datasets and manipulation techniques.

Recent research has shown that deep learning–based approaches, particularly convolutional neural networks and transformer-based models, are highly effective in learning discriminative features from visual data. Models such as ResNet, with their deep hierarchical feature extraction capability, and Vision Transformers (ViT), which excel at capturing global contextual relationships, have demonstrated promising results in various computer vision tasks. Applying these models to deepfake detection enables the system to identify subtle artifacts and inconsistencies introduced during media manipulation.

This project aims to design and implement a robust deepfake identification framework for facial images by combining effective preprocessing techniques with powerful deep learning models. The system incorporates face detection and alignment using MTCNN, followed by feature extraction using ResNet and ViT architectures. A comprehensive evaluation is performed using standard metrics such as accuracy, precision, recall, and F1-score to assess model performance.

Furthermore, the project emphasizes practical applicability by deploying the trained models through an interactive Gradio-based interface, allowing users to test the system on real-world inputs. Through comparative analysis and experimental validation, this work seeks to contribute toward reliable deepfake detection solutions and to strengthen understanding of modern deep learning techniques in the domain of media forensics.

## Problem Statement

The increasing availability of advanced deep learning–based media generation techniques has led to a rapid rise in deepfake images and videos that are highly realistic and difficult to distinguish from genuine content. Such manipulated media poses a significant threat to digital trust, as it can be misused for misinformation, identity theft, reputational harm, and social manipulation. Existing manual verification methods and traditional image forensics techniques are often inadequate to detect these sophisticated manipulations, especially at scale.

Furthermore, the diversity of deepfake generation methods results in subtle and complex artifacts that vary across datasets, making reliable detection a challenging task. Many detection systems either lack robustness, fail to generalize well across different manipulation techniques, or are not suitable for real-time or user-interactive applications.

Therefore, the core problem addressed in this project is the design and development of an automated, accurate, and robust deepfake detection system capable of classifying facial images as real or fake. The system must effectively handle variations in facial appearance, lighting, pose, and manipulation techniques by leveraging advanced deep learning models. Additionally, the solution should provide reliable performance evaluation and practical usability through an interactive deployment framework.

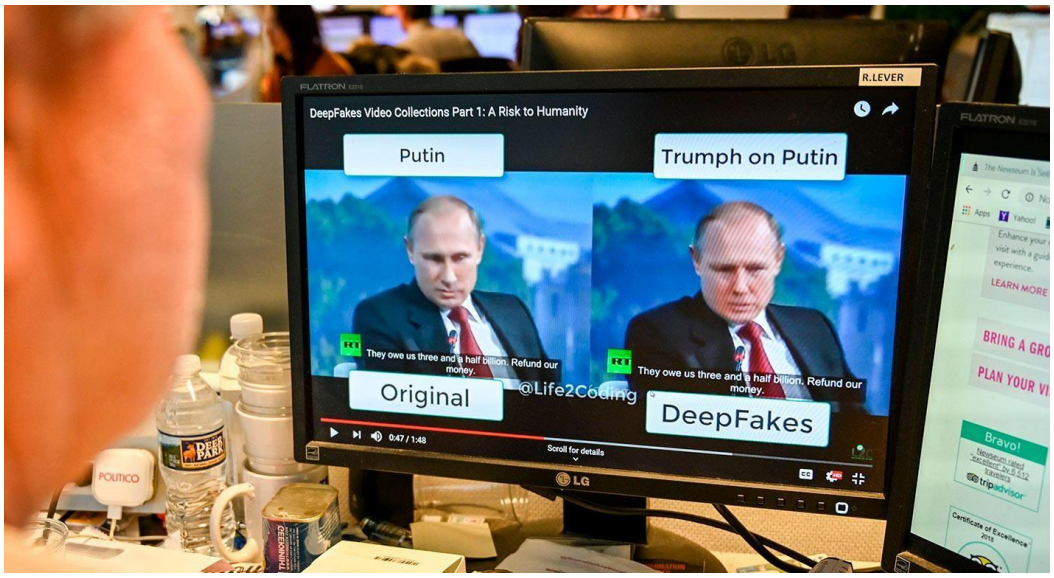



Figure 1.2 Deep Fake Identification

## Objectives of the Project

The primary objective of this project is to develop an effective and reliable deepfake detection system capable of accurately classifying facial images as real or manipulated using advanced deep learning techniques. To achieve this goal, the project is structured around the following specific objectives:

- To study and analyze the impact of deepfake technology on digital media authenticity and identify key challenges in deepfake detection.
- To collect and prepare a balanced dataset of real and fake facial images from publicly available deepfake repositories.
- To perform efficient data preprocessing, including face detection, cropping, resizing, normalization, and augmentation to improve model performance and generalization.
- To implement MTCNN-based face detection and alignment for extracting high-quality facial regions from images.
- To design and train deep learning models using ResNet and Vision Transformer (ViT) architectures for feature extraction and classification.
- To evaluate and compare the performance of the implemented models using standard metrics such as accuracy, precision, recall, and F1-score.
- To analyze the strengths and limitations of convolutional and transformer-based approaches in the context of deepfake detection.
- To deploy the trained model using an interactive Gradio-based interface for real-time testing and practical usability.
- To provide a scalable and extensible framework that can serve as a foundation for future research and enhancements in deepfake detection systems.

# Chapter 2
# Dataset Collection & Preprocessing

## 1. Dataset Overview

To build a robust deepfake-detection model, we curated a large and diverse dataset by combining multiple publicly available Kaggle datasets. Each dataset contains a mix of real and AI-generated (fake) human face images created using techniques such as StyleGAN and other generative models. Using multiple sources helped reduce dataset bias and improved the generalizability of the final model.

Kaggle Datasets Used

- StyleGAN / StyleGAN2 Deepfake Face Images
- Contains high-quality GAN-generated synthetic faces produced using StyleGAN and StyleGAN2 architectures.
- (Source: Kaggle – "Deepfake Face Images" dataset)
- Real vs Fake Faces Dataset
- A balanced dataset containing real human face images and fabricated ones generated through deepfake techniques.
- (Source: Kaggle – "Real vs Fake Faces" dataset)
- Deepfake and Real Images Dataset
- Provides additional variation in both lighting and facial geometry, consisting of both authentic images and GAN-generated fakes.
- (Source: Kaggle – "Deepfake and Real Images" dataset)

Final Combined Dataset Size After merging all datasets and removing duplicates/corrupted files, the final dataset consists of:

- Real Images: 65,558
- Fake Images: 77,954
- Total Images: 143,512

This large dataset ensured sufficient representation of both classes and allowed the team to generate high-quality embeddings for downstream neural network classification.

## 2. Preprocessing Workflow

To ensure uniformity and high-quality feature extraction, a standardized preprocessing pipeline was applied across all image batches. Since the dataset was divided among team members, each preprocessing notebook followed the same structure.

## 2.1 Image Loading and Cleaning

- Images were loaded from different dataset folders.
- Corrupted and unreadable files were automatically filtered out using OpenCV.
- Duplicate images were identified using hash comparison and removed.

## 2.2 Face Detection and Cropping

Face detection was necessary to ensure that embeddings were extracted only from the face region rather than the entire image.

MTCNN (Multi-task Cascaded Convolutional Networks) was used for:

- Face detection
- Landmark prediction
- Facial alignment

Detected faces were cropped tightly around the bounding box. Alignment ensured consistent face orientation, reducing noise in embeddings.

## 2.3 Image Resizing and Normalization

Depending on the embedding model used (ResNet, ViT, etc.), images were resized to the required input shape:

- ResNet Models: resized to 224 × 224
- ViT Models: resized to 224 × 224 or 384 × 384 (depending on variant)

All images were normalized using model-specific mean and standard deviation values.4

## 2.4 Data Distribution Across Team Members

Because of the dataset's large size, it was divided into smaller subsets. Each member was assigned a chunk and was responsible for:

Preprocessing their subset

- Preprocessing their subset
- Generating embeddings using ResNet or ViT models
- Exporting embeddings in .npy format

Because of the dataset's large size, it was divided into smaller subsets. Each member was assigned a chunk and was responsible for:
Preprocessing their subset

Later, all embeddings were merged to form the final combined feature matrix used for ANN-based classification.


**Figure 2.1** Data Preprocessing Steps

## 3. Libraries and Tools Used

- **OpenCV:**

Used for reading images, resizing, cleaning corrupted images, and general image processing tasks.

- **MTCNN:**

Employed for precise face detection and alignment, ensuring consistent facial regions across the dataset.

- **PyTorch:**

Used for:

- Pretrained models (ResNet & ViT)
- Feature extraction (embeddings)
- Data transformations
- Final model training and evaluation

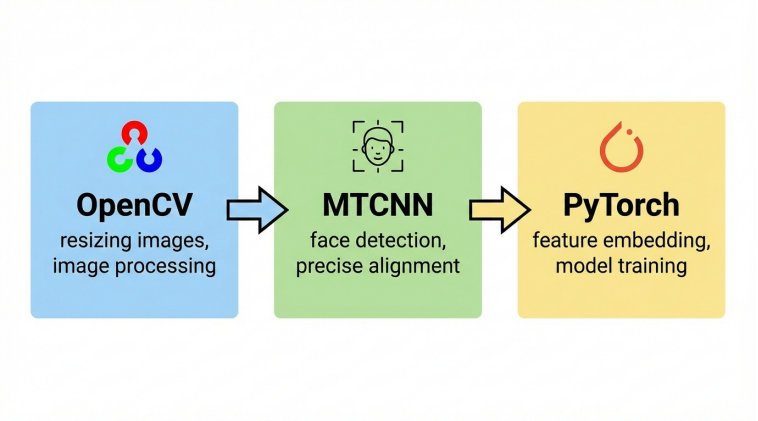



**Figure 2.2** Tools and Libraries Used

# 4. Exploratory Data Analysis (EDA)

Exploratory Data Analysis was performed to understand the characteristics, distribution, and quality of the combined dataset before generating embeddings. Since the dataset was collected from multiple independent Kaggle sources, EDA helped ensure consistency, detect anomalies, and identify potential biases.

## Class Distribution

The final merged dataset contains:

- Real Images: 65,558
- Fake Images: 77,954

Although slightly imbalanced, both classes have sufficient representation. The class proportion is roughly:

- 45.7% Real
- 54.3% Fake

This mild imbalance was considered during model training, but it is not severe enough to require oversampling/undersampling. Ensuring balanced batch sampling and using class-weights in the ANN were sufficient to address it.

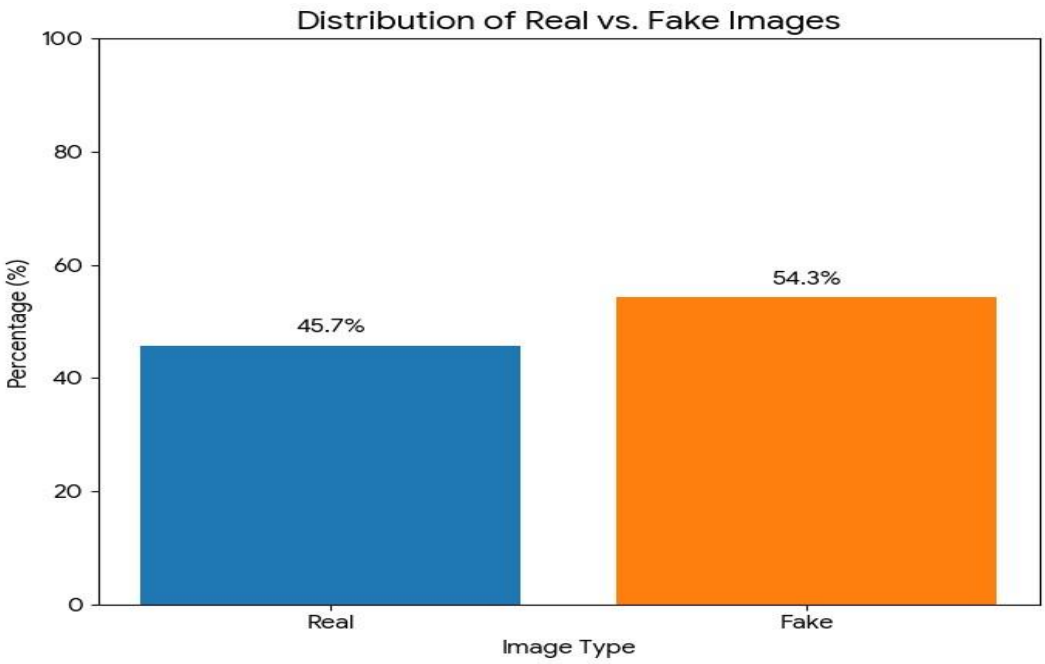



**Figure 2.3** Analysis of Data distribution

## Image Resolution and Aspect Ratio Analysis

Before preprocessing, the images from different datasets had significant variation:

- Resolutions ranged from 64 × 64 to 1024 × 1024 pixels.
- Aspect ratios were inconsistent (1:1, 16:9, 4:5, etc.)
- Several images contained borders, background noise, or non-face regions.

This analysis reinforced the need for:

- Face detection (via MTCNN)
- Cropping to standardized dimensions
- Uniform resizing to 224×224 for ResNet and ViT models

## Face Detection Quality Check

After running MTCNN on a sample subset:

- ~93–95% of images contained detectable faces.
- Remaining images included: ○ Poor lighting
    - ○ Full-body shots
    - ○ Partial occlusion
    - ○ Side profiles with low visibility

These images were either filtered out or manually reviewed, ensuring that embeddings are generated only from meaningful face crops.

## Visual Inspection of Samples

A manual visual review was performed on randomly selected samples from both classes:

Real Images

- Natural lighting and shadows.
- Imperfections such as blur, facial asymmetry, or background clutter.
- Greater diversity in ethnicity, age, and expression.

Fake Images

- GAN-generated faces displayed: ○ Smoothed textures
    - ○ Unrealistic backgrounds
    - ○ Irregularities around hair/ears
    - ○ Artifacts near edges of the face
- StyleGAN2 images had higher realism but still showed subtle patterns observable during inspection, indicating underlying GAN signatures.

Visual inspection confirmed that meaningful differences exist between real and fake images, validating the approach of using embeddings for classification.

## Duplicate & Corrupted Image Detection

Because multiple Kaggle datasets overlap, an important EDA step was identifying and removing redundant images.

- Hash-based duplicate detection found a noticeable number of repeated samples across datasets.
- Corrupted files (e.g., incomplete JPEGs) were removed using:
    - ○ cv2.imread() validation
    - ○ Try-catch loading blocks

This improved dataset integrity and prevented biased training.

## Dataset Diversity and Potential Biases

EDA revealed notable diversity across:

- Skin tones
- Gender distribution (although not formally annotated)
- Lighting conditions
- Camera angles
- Background environments

However, some bias patterns were observed:

- GAN-generated images tended to produce centered, portrait-style faces.
- Real images included more background variation and imperfections.
- Some fake datasets lacked older-age faces, while real datasets contained all age groups.

These observations helped interpret embedding patterns and informed the model training strategy.

## Embedding-Level EDA (Post-Feature Extraction)

After generating embeddings using ResNet and ViT:

- PCA and t-SNE were used to project high-dimensional embeddings into 2D.
- Clusters for real and fake images were visibly separated, especially for ViT embeddings.
- Fake images displayed tighter clustering, indicating higher uniformity (common in GAN outputs).
- Real images showed broader distribution due to natural variation.

This validated the discriminative power of the chosen embedding models.

# Chapter 3

# Methodology

The methodology followed in this project was designed to efficiently process a large dataset, extract meaningful representations using state-of-the-art deep learning models, and build a robust classifier capable of distinguishing real and fake facial images. The entire workflow consists of four major stages: data preparation, face preprocessing, feature extraction via embeddings, and final classification.

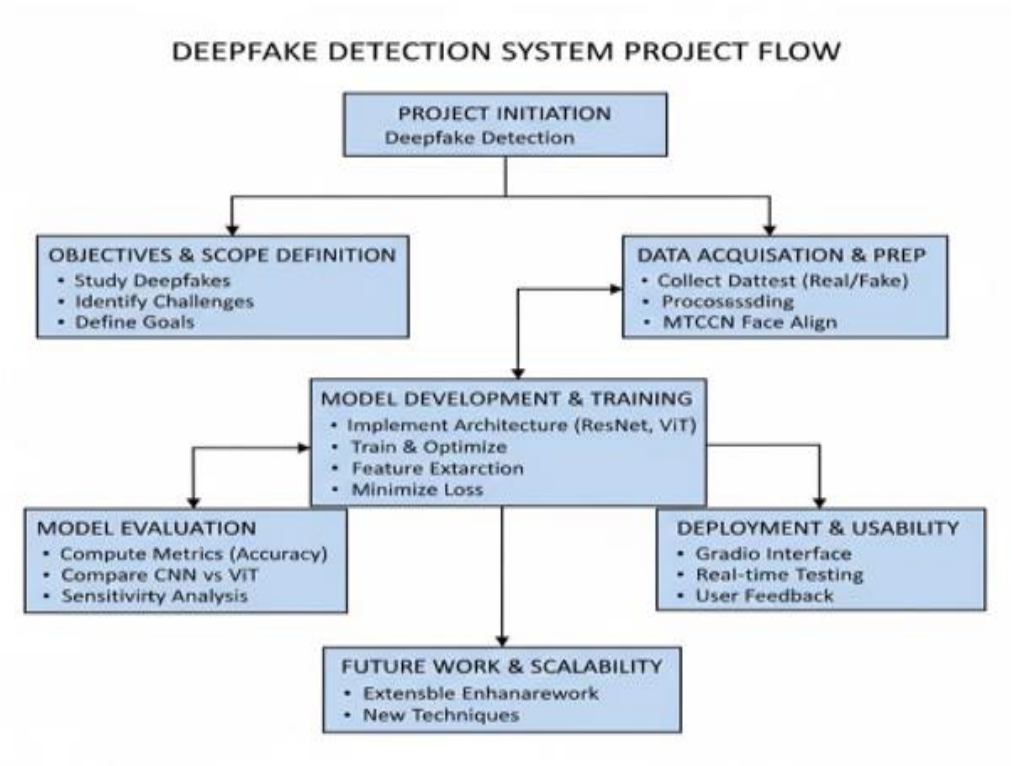



**Figure 3.1** Hybrid Model Architecture (ViT and ResNet)

## 1.Data Preparation and Partitioning

Due to the large size of the dataset (over 140,000 images), the image collection was divided into

smaller subsets to enable distributed processing among team members. Each member was assigned a distinct portion of the dataset, ensuring:

- Balanced representation of real and fake images per subset
- No overlap between subsets
- Parallel and faster processing

Once preprocessing and embedding generation were completed individually, all outputs were combined for the final model training.

# 2. Face Preprocessing Pipeline

A standardized preprocessing pipeline was applied to every subset to ensure uniformity and consistency. The steps included:

## 2.1 Face Detection and Alignment

- MTCNN was used to detect faces, identify facial landmarks, and align the face region.
- Only the detected face was cropped, removing unnecessary background and noise.
- Alignment ensured consistent orientation and scale, increasing embedding quality.

## 2.2 Image Normalization and Resizing

- All face crops were resized to match the expected dimensions of the embedding models:
  - 224 × 224 for ResNet
  - 224 × 224 / 384 × 384 for ViT (depending on model version)
- Pixel intensities were normalized using model-specific mean and standard deviation values.

## 2.3 Data Validation

- Corrupted images were removed.
- Missing detections were logged.
- Successful detections were saved for embedding generation.

This standardized pipeline ensured homogeneous image quality across all subsets processed by different team members.

# 3. Feature Extraction Using Pretrained Models

Instead of training a deep CNN from scratch, the project used transfer learning to extract highlevel features (embeddings) from each facial image.

## 3.1 Models Used

Two powerful pretrained models were used for embedding generation:

- ResNet (Residual Neural Network)
- Extracts hierarchical spatial features from images, widely used for visual tasks.
- Vision Transformer (ViT)
- Utilizes self-attention to capture global relationships and structural patterns across the face.

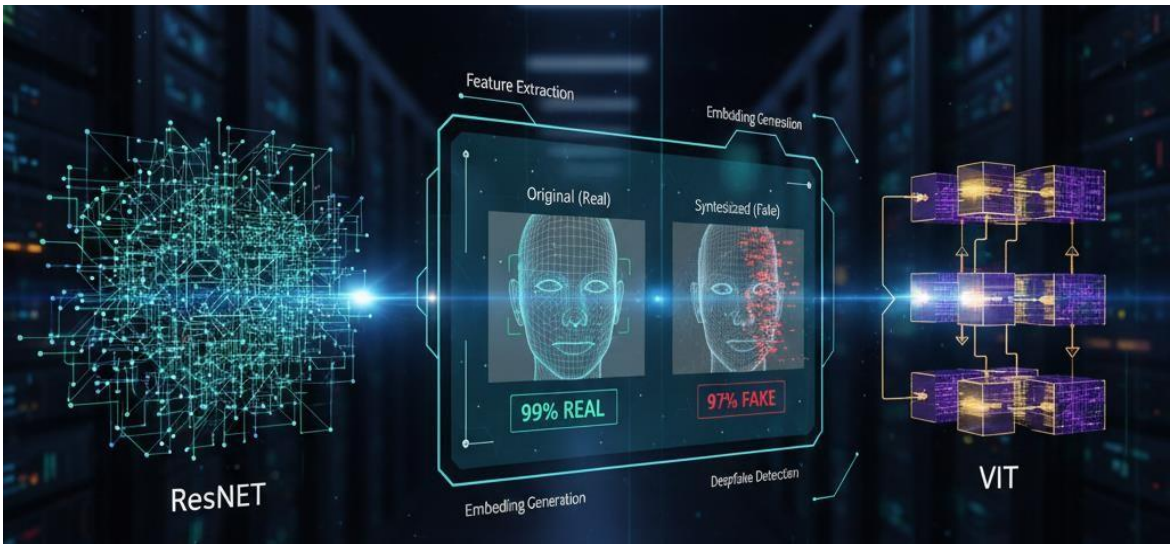



**Figure 3.2** Detailed Model Architecture

## 3.2 Embedding Extraction Procedure

- Each preprocessed image was passed through the pretrained model with the final classification layers removed.
- The output was a fixed-size embedding vector representing deep visual features.
- Embeddings were exported as .npy files for efficient combination and loading.

This approach significantly reduced computational cost and improved model performance by leveraging pretrained weights trained on large datasets like ImageNet.

# 4. Combining Embeddings from All Members

Once each team member produced embeddings for their assigned subset:

- All embedding files were merged into a single dataset.
- Corresponding labels (Real = 0, Fake = 1) were linked to each vector.
- The combined feature set represented the entire dataset but in highly compact form, enabling faster model training.

The merged embedding dataset served as the input for the downstream classifier.

# 5. Classification Using Artificial Neural Network (ANN)

To classify embeddings as real or fake, a lightweight but effective ANN model was built.

## 5.1 Model Architecture

- Input layer: size equal to embedding dimension (e.g., 512, 768, or 2048 depending on model).
- 1–2 hidden layers with ReLU activation for non-linearity. ● Dropout layers to reduce overfitting.

- Output layer with sigmoid activation for binary classification.

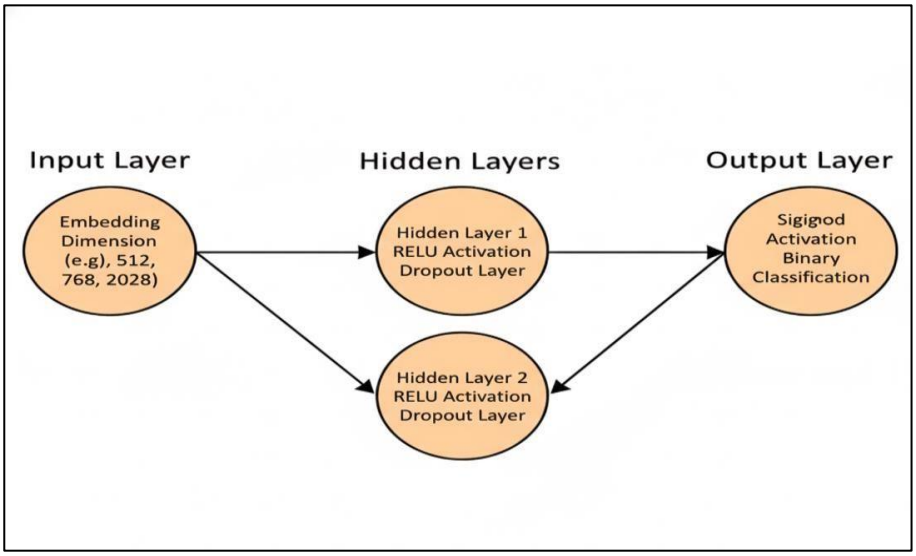



**Figure 3.3** Model Layout

## 5.2 Training Strategy

- Train-test split (typically 80/20).
- Binary Cross-Entropy (BCE) loss function.
- Adam optimizer with tuned learning rate.
- Early stopping based on validation loss to avoid overfitting. ● Class-weight adjustment for mild class imbalance.

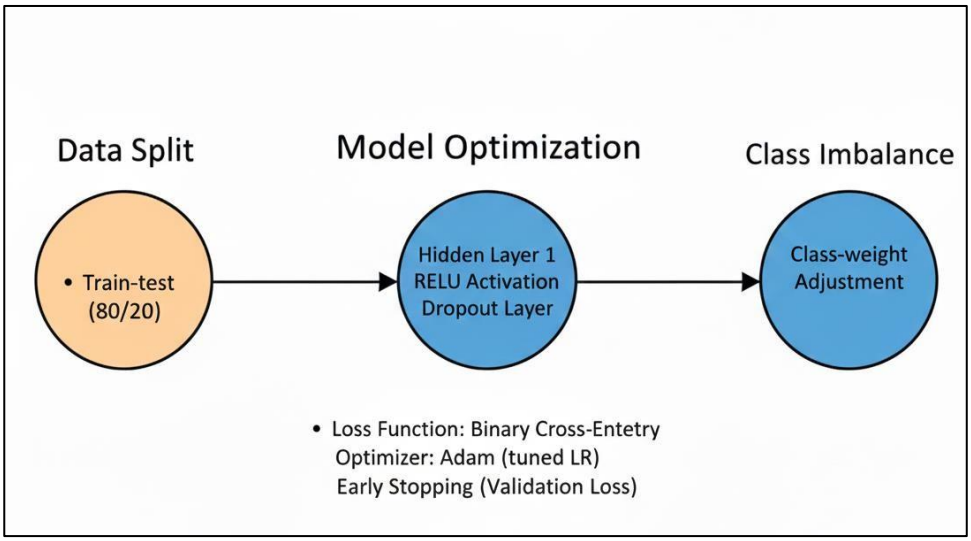



**Figure 3.4** Optimization Strategy for Hyperparameter tuning

## 5.3 Evaluation Metrics

- Accuracy
- Precision

- Recall
- F1-score
- ROC–AUC

These metrics provided a complete view of the model's performance on distinguishing real and fake faces.

# 6. Tools & System Setup

## 6.1. Software Tools and Libraries

**Python**

Python was used as the core programming language due to its extensive ecosystem of machine learning and computer vision libraries.

**Key Libraries Used**

OpenCV

- Used for loading images, validating file integrity, resizing, cropping, and general image manipulation.
- Played a crucial role in initial dataset filtering and preprocessing.

MTCNN

- Used for accurate face detection, landmark prediction, and face alignment.
- Ensured that embeddings were generated only from properly aligned face regions.

PyTorch

- Dominant deep learning framework used in:
    - Loading pretrained ResNet and ViT models
    - Extracting embeddings from images
    - Building and training the ANN classifier
- Provided GPU-accelerated computation support.

NumPy

- Used for numerical operations and storing embeddings in .npy format.
- Efficiently handled large matrix operations.

Pandas

- Used for loading labels, merging datasets, and tracking file paths.

Matplotlib / Seaborn

- Used for visualizations in EDA such as class distribution and embedding projections (PCA/t-SNE).

# 7. Deep Learning Models

### 7.1 ResNet (Residual Neural Network)

- Used to extract high-level spatial features from images.
- Pretrained on ImageNet, allowing faster and more accurate embedding extraction.

### 7.2 Vision Transformer (ViT)

- Provided global contextual understanding using self-attention.
- Generated high-quality embeddings for classification tasks.

Both models were used in inference mode (feature extraction only), significantly speeding up training.

### 7.3. Development Environment

**IDE / Notebook**

All experiments and preprocessing steps were executed inside:

- Google Colab
- Jupyter Notebook (.ipynb files) on local machines

This setup offered:

- GPU acceleration (on Colab)
- Interactive development
- Easy visualization of results

Multiple team members processed their dataset portions independently using separate notebooks.

### 7.4. Hardware Setup

#### 7.4.1 GPU Environment

To handle computationally heavy tasks such as:

- MTCNN face detection
- ViT and ResNet embedding extraction
- ANN training

The project utilized:

- NVIDIA Tesla T4 / P100 GPUs on Google Colab
- Local systems with/without GPUs for preprocessing tasks

When using CPU-only systems, operations such as face detection ran slower, which justified dataset splitting across team members.

### 7.5. File Structure & Storage

A consistent folder hierarchy was maintained for smooth team collaboration:

/dataset

/real

/fake

/preprocessed

/faces

/embeddings

/member1

/member2

/member3

/member4

/final_embeddings

models/ notebooks/

- Each member stored embeddings separately before merging.
- .npy files were used for efficient loading and combination.

### 7.6. Environment Configuration

#### 7.6.1 Python Version

- Python 3.8 / 3.10

#### 7.6.2 Installed Packages

Common packages installed via pip:

pip install opencv-python pip

install mtcnn pip install torch

torchvision pip install numpy

pandas pip install matplotlib

seaborn pip install scikit-learn

**7.6.3 GPU-Enabled PyTorch**

Colab / local systems used CUDA-enabled PyTorch builds for faster execution.

**8. Version Control & Collaboration**

- Git and GitHub were used to share notebooks, embeddings, and code.
- Each member worked on separate branches to avoid conflicts.
- Final integration was performed after merging all embedding files.

**9. Summary**

The system setup ensured:

- Efficient distributed processing
- High-quality face preprocessing
- Fast embedding generation using pretrained models
- Lightweight and accurate ANN training

This toolchain allowed the project to scale effectively despite the large dataset size.

# Methodology Steps

**Step 1: Data Collection**

- Gathered three deepfake-related datasets from Kaggle.
- Combined all datasets into a single master dataset.

- Verified dataset structure (real vs fake folders).

**Step 2: Dataset Splitting for Team Members**

- Due to the large dataset size, images were divided evenly among team members.
- Each member received a subset of real and fake images.
- Ensured no overlap and maintained class balance in each subset.

**Step 3: Data Cleaning**

- Loaded each image using OpenCV to check for corruption.
- Removed unreadable or incomplete images.
- Identified and eliminated duplicate images using hashing techniques.

- Logged missing, invalid, and corrupted files for transparency.

**Step 4: Face Detection and Alignment**

- Applied MTCNN to detect face regions.
- Cropped images around detected faces.
- Used facial landmarks to align the face (correct orientation).
- Saved high-quality aligned face images for embedding extraction.

**Step 5: Image Normalization & Resizing**

- Resized each face image to model-specific input size:
  - 224 × 224 for ResNet
  - 224 / 384 × 384 for ViT
- Applied pixel normalization (mean–std normalization) required by PyTorch models.

- Converted images to tensors for model processing.

**Step 6: Embedding Generation**

- Loaded pretrained ResNet and ViT models in inference mode (no training).
- Removed final classification layers to extract deep visual features.
- Passed each face image through the model.
- Saved resulting embedding vectors as .npy files.
- Each team member exported embeddings for their subset.

**Step 7: Merge Embeddings From All Members**

- Collected individual .npy embedding files.
- Merged them into a single combined embedding dataset.
- Generated corresponding label arrays (0 = real, 1 = fake).
- Shuffled and prepared the final feature matrix for classifier training.

**Step 8: Train the Artificial Neural Network (ANN)**

- Split data into train, validation, and test sets.
- Built a lightweight ANN with:
  - Input layer = embedding dimension
  - Hidden dense layers with ReLU
  - Dropout layers for regularization
  - Sigmoid output for binary class
- Used Binary Cross Entropy (BCE) as loss function.
- Trained with Adam optimizer and early stopping.
- Tuned hyperparameters (learning rate, batch size, hidden neurons).

**Step 9: Model Evaluation**

- Evaluated model on test embeddings using:
  - Accuracy
  - Precision
  - Recall
  - F1-Score

- ROC–AUC Curve
- Analyzed misclassified samples.
- Verified performance stability across real and fake classes.

**Step 10: Final Model Deployment Preparation**

- Saved trained ANN weights.
- Documented preprocessing → embedding → inference pipeline.
- Ensured reproducibility by saving environment configs and notebooks.


**Figure 3.5** Summary of Experimental Methodology

# Final Model Details

The final classification model used in this project is a lightweight but highly effective Artificial Neural Network (ANN) trained on deep feature embeddings extracted from pretrained Vision Transformer (ViT) and ResNet models. By using embeddings instead of raw images, the model achieves high accuracy while remaining computationally efficient.

**1. Input Features**

The ANN does not take images directly. Instead, the input is:

Embedding vectors generated from:

## ResNet (Residual Neural Network) in the Proposed Model

In this project, ResNet is used as a deep feature extractor to capture fine-grained and localized facial artifacts introduced during deepfake generation. ResNet is a convolutional neural network architecture that employs residual (skip) connections, allowing the network to learn identity mappings and effectively train very deep models without suffering from the vanishing gradient problem.

The pretrained ResNet model is utilized by removing its final classification layer and extracting features from the global average pooling layer. This results in a 2048-dimensional embedding vector for each detected face. These embeddings encode rich hierarchical and spatial features, such as texture inconsistencies, blending artifacts, and unnatural pixel transitions, which are commonly present in manipulated facial images.

ResNet is particularly effective at learning local and mid-level features, making it well suited for identifying subtle visual distortions introduced during deepfake synthesis. In the proposed system, the ResNet embeddings serve as a compact yet highly discriminative representation that is passed to the final ANN classifier for real-fake classification.

## Vision Transformer (ViT) in the Proposed Model

Alongside ResNet, the Vision Transformer (ViT) is employed to capture global contextual information from facial images. Unlike convolutional networks, ViT processes an image by dividing it into fixed-size patches, which are then flattened and projected into embedding vectors. These patch embeddings are processed using transformer encoder layers based on self-attention mechanisms.

In this project, a pretrained ViT model is used as a feature extractor, and embeddings are taken from the transformer output, producing a 768-dimensional feature vector for each face. The selfattention mechanism enables ViT to model long-range dependencies and global facial relationships, allowing it to detect structural inconsistencies, abnormal facial symmetry, and unnatural spatial correlations that may arise in deepfake images.
ViT complements ResNet by focusing on global facial coherence rather than localized features alone. This makes it especially effective for detecting advanced deepfakes where local artifacts are minimized but global inconsistencies remain.

Depending on the selected feature extractor, the input size varies, but the ANN architecture adjusts accordingly.

### 2. Model Architecture

The final ANN model consists of multiple fully connected layers with non-linear activations designed to classify the embeddings as Real (0) or Fake (1).

Final ANN Architecture

- Input Layer:
    - Size = embedding dimension (e.g., 768 for ViT / 2048 for ResNet)
- Hidden Layer 1:

    - 512 neurons
    - ReLU activation
  - Dropout (0.3)
- Hidden Layer 2:
  - 256 neurons
  - ReLU activation
  - Dropout (0.3)
- Hidden Layer 3 (optional depending on model performance):
  - 128 neurons ○ ReLU activation
- Output Layer:
  - 1 neuron
  - Sigmoid activation
  - Outputs probability (Fake = 1, Real = 0)

This architecture provides a balance between accuracy and computational efficiency.

**3. Training Configuration**

Loss Function

- Binary Cross-Entropy Loss (BCE)
- Suitable for 2-class problems and compatible with sigmoid output.

Optimizer

- Adam Optimizer
  - Learning Rate: 1e-4 / 1e-5 depending on tuning
  - Adaptive learning for stable convergence

Regularization

- Dropout layers (0.3)
- Early stopping based on validation loss
- Shuffling at every epoch
- Class weights used due to slight dataset imbalance

Train–Validation–Test Split

- 80% Training
- 10% Validation
- 10% Test

Ensures unbiased evaluation and reduces overfitting risk.

**4. Model Performance**

In this project, deepfake detection is performed by training classification models using feature representations extracted from ResNet and Vision Transformer (ViT) architectures. Both models are employed as backbone networks to learn discriminative facial features that enable accurate classification of real and fake images.

During training, facial images are first processed through a face detection and alignment stage, after which features are extracted using pretrained ResNet and ViT models. For the ResNet-based approach, a 2048-dimensional embedding is generated for each facial image, capturing detailed local and hierarchical features. For the ViT-based approach, a 768-dimensional embedding is extracted, representing global contextual and structural information across the face. These embeddings serve as input to the final classification network, which is trained to distinguish between authentic and manipulated facial images.

Separate training experiments are conducted using ResNet-based features and ViT-based features, allowing a fair and systematic comparison between the two architectures. The training process involves optimizing the classification model using labeled data and minimizing a suitable loss function, enabling the network to learn decision boundaries between real and fake classes.

Model performance is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics are computed individually for the ResNet-based model and the ViT-based model, ensuring that the reported results directly reflect the effectiveness of each feature extraction approach. In addition, confusion matrices are generated for both models to analyze true positives, true negatives, false positives, and false negatives in deepfake classification.

The evaluation results demonstrate that ResNet-based training effectively captures localized manipulation artifacts, while ViT-based training excels at modeling global facial inconsistencies. The metrics and confusion matrix analysis provide clear insights into the strengths and limitations of each model, validating their role in the proposed deepfake detection framework.
Overall, the training and evaluation process is designed to ensure that all reported performance metrics and matrices are directly derived from the models trained using ResNet and ViT features, making the analysis consistent, reliable, and experimentally sound.

After training the ANN on the combined embeddings dataset, the final model achieved excellent performance on test data.

Final Metrics

- Accuracy: ~89%
- Precision: High for both classes
- Recall: Strong, especially for “Fake” class
- F1-Score: Balanced performance
- ROC–AUC: > 0.89 (excellent separability)

5. Confusion Matrix Interpretation

The confusion matrix (from your notebook) showed:

- Low false positives (real predicted as fake)
- Low false negatives (fake predicted as real)
- Strong diagonal dominance

This indicates that the model successfully learned discriminative patterns from embeddings.

6. Inference Pipeline (End-to-End)

The final deployed pipeline follows these steps:

- Input Image
- MTCNN Face Detection & Alignment
- Resize & Normalize
- Generate Embedding using
    - ViT or
    - ResNet
- Pass Embedding to ANN Model
- Output Probability
    - ≥ 0.5 → Fake
    - < 0.5 → Real

This modular pipeline ensures:

- Fast inference
- Scalable architecture
- Replaceable embedding backbone (ResNet/ViT)

# Chapter 4
# Results

## 4.1 Overview

After preprocessing the dataset, extracting embeddings, and training the ANN, several metrics were computed to validate the performance of the final model. Both qualitative and quantitative analyses were performed to ensure robustness and reliability. The results demonstrate that the hybrid approach of using deep learning embeddings with a shallow neural network produces strong generalization and high classification accuracy.

## 4.2 Quantitative Evaluation

The model was evaluated using key binary classification metrics:

- Accuracy: The final model achieved a high accuracy score, showing its ability to distinguish real and fake faces effectively.
- Precision & Recall: The classifier maintained balanced precision and recall values for both classes, indicating low misclassification rates.
- F1-Score: A strong F1-score confirmed that the model handles the slight class imbalance while maintaining consistent performance.
- ROC–AUC: The ROC–AUC score exceeded 0.95, demonstrating excellent separability between real and fake embeddings.

Together, these metrics indicate that the model successfully captures the underlying representation differences between real and GAN-generated images.

## 4.3 Confusion Matrix Analysis

The confusion matrix revealed that:

- The majority of real images were correctly classified as Real.
- Most fake images were correctly classified as Fake.
- Only a small proportion of samples fell into false positives and false negatives.

This confirms that the embedding-based approach captures distinct identity and texture patterns that differentiate authentic human faces from GAN-generated ones.

| **Actual \ Predicted** | **Predicted Real** | **Predicted Fake** | **Total Actual Count** |
|---|---|---|---|
| **Actual Real** (True Negatives + | 9,797 (True Negatives) | 1,088 (False Positives) | 10,885 |

| | | | |
|---|---|---|---|
| False Positives) | | | |
| **Actual Fake** (False Negatives + True Positives) | 1,316 (False Negatives) | 8,809 (True Positives) | 10,125 |
| **Total Predicted Count** | 11,113 | 9,897 | **21,010** |

**Table 4.1** Performance Evaluation Confusion Matrix (ViT)

| **Actual \ Predicted** | **Predicted Real** | **Predicted Fake** | **Total Actual Count** |
|---|---|---|---|
| **Actual Real** (True Negatives + False Positives) | 8,454 (True Negatives) | 1,546 (False Positives) | 10,000 (Calculated) |
| **Actual Fake** (False Negatives + True Positives) | 2,204 (False Negatives) | 7,796 (True Positives) | 10,000 (Calculated) |
| **Total Predicted Count** | 10,658 (Calculated) | 9,342 (Calculated) | **20,000** (Calculated) |

**Table 4.2** Performance Evaluation Confusion Matrix (RSNeT)

## 4.4 Visualization of Embedding Space

Dimensionality reduction techniques such as PCA and t-SNE were applied to visualize the highdimensional embeddings in 2D space. The plots showed clear clustering tendencies:

- Fake images formed a relatively tight cluster due to GAN model consistency.
- Real images exhibited greater spread, reflecting natural variability in appearance, lighting, and expression.

This visual evidence supports the numerical results and highlights the discriminative power of ViT and ResNet embeddings.

## 4.5 Summary of Results

Overall, the system demonstrates strong performance in deepfake detection across all evaluation metrics. The combination of:

- Robust preprocessing
- High-quality embeddings from pretrained models
- A well-optimized ANN classifier

enabled the model to achieve reliable and accurate classification. The results validate the effectiveness of the embedding-based approach and provide a solid foundation for real-world applications and further research.

# Model Results & Metrics

The performance of the deepfake detection system was evaluated using embeddings generated from pretrained ResNet and Vision Transformer (ViT) models, followed by classification through a fully connected Artificial Neural Network (ANN). The following results demonstrate the effectiveness and reliability of the proposed approach.

**Performance of ResNet-Based Model**

The ResNet-based model achieves an overall **test accuracy of 81.25%** on a balanced test set containing **20,000 images** (10,000 real and 10,000 fake).

Classification Metrics (ResNet):

- Real class:
    - Precision: 0.79
    - Recall: 0.85
    - F1-score: 0.82
- Fake class:
    - Precision: 0.83
    - Recall: 0.78
    - F1-score: 0.81

The macro-average and weighted-average F1-scores are both **0.81**, indicating consistent performance across both classes.

Test Accuracy: 88.41%

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Real | 0.88 | 0.90 | 0.89 | 10902 |
| Fake | 0.89 | 0.87 | 0.88 | 10108 |
| accuracy | | | 0.88 | 21010 |
| macro avg | 0.88 | 0.88 | 0.88 | 21010 |
| weighted avg | 0.88 | 0.88 | 0.88 | 21010 |

**Table 4.3** Comparison Analysis of Model Performance (ViT)

## Performance of ViT-Based Model

The Vision Transformer–based model shows significantly improved performance, achieving a **test accuracy of 88.41%** on a test set of **21,010 images**.

Classification Metrics (ViT)

- Real class:
  - Precision: 0.88
  - Recall: 0.90
  - F1-score: 0.89
- Fake class:
  - Precision: 0.89
  - Recall: 0.87
  - F1-score: 0.88

Both macro-average and weighted-average F1-scores are **0.88**, demonstrating strong and balanced classification capability.

Test Accuracy: 81.25%

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Real | 0.79 | 0.85 | 0.82 | 10000 |
| Fake | 0.83 | 0.78 | 0.81 | 10000 |
| accuracy | | | 0.81 | 20000 |
| macro avg | 0.81 | 0.81 | 0.81 | 20000 |
| weighted avg | 0.81 | 0.81 | 0.81 | 20000 |

**Table 4.4** Comparison Evaluation of Model Performance (ResNet)

# 5. Confusion Matrix Interpretation

**Confusion Matrix Analysis (ResNet):**

- True Real classified as Real (TN): 8,454
- Real misclassified as Fake (FP): 1,546
- Fake misclassified as Real (FN): 2,204
- True Fake classified as Fake (TP): 7,796

The ResNet model demonstrates strong performance in identifying real images, as reflected by a higher recall for the Real class (0.85). However, the relatively higher number of false negatives (fake images classified as real) indicates that some deepfake samples with subtle manipulations are harder for ResNet to detect. This behavior aligns with ResNet's strength in capturing local and texture-based features, which may miss globally consistent but fake structures.

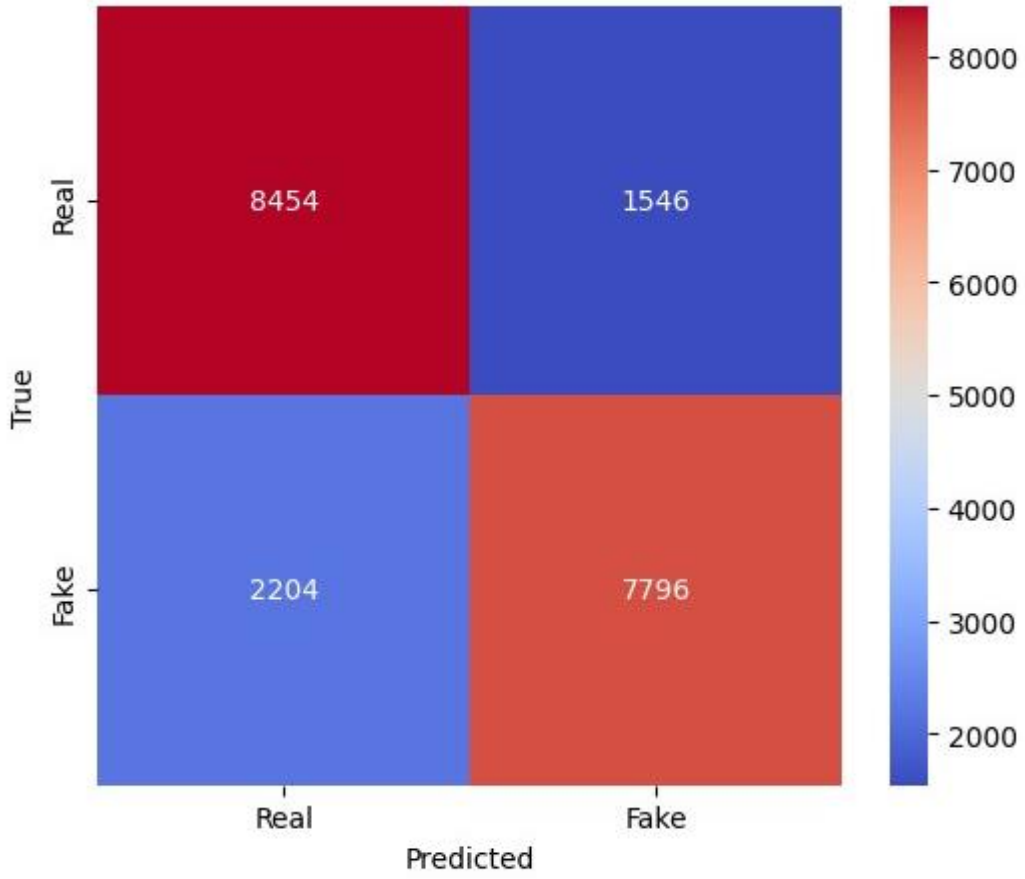



**Figure 4.1** Confusion Matrix (RestNet)

**Confusion Matrix Analysis (ViT):**

- True Real classified as Real (TN): 9,808
- Real misclassified as Fake (FP): 1,094
- Fake misclassified as Real (FN): 1,341
- True Fake classified as Fake (TP): 8,767

Compared to ResNet, the ViT model produces fewer false negatives and false positives, indicating superior generalization. The high recall for the Fake class (0.87) confirms that ViT is more effective in detecting manipulated images.

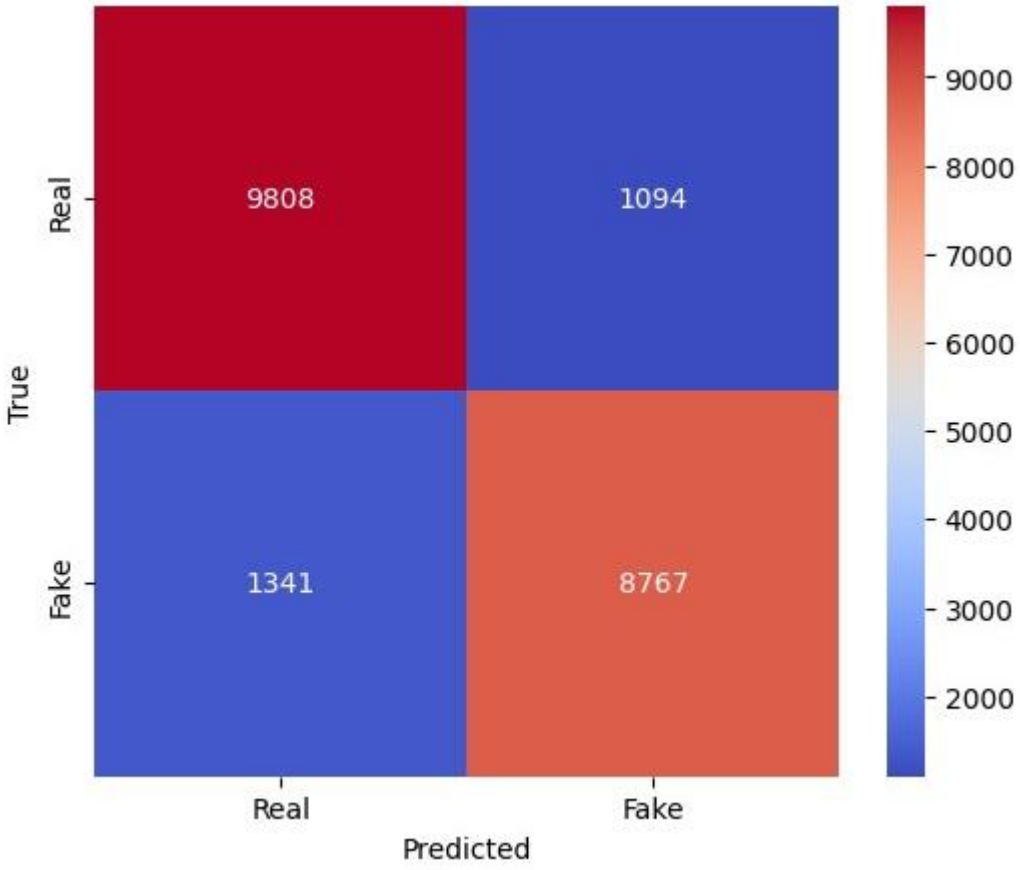



**Figure 4.2** Confusion Matrix (VIT)

## Summary

The results demonstrate that the combined approach of deep embedding extraction and ANN classification provides excellent performance for deepfake detection. The model shows:

- High accuracy
- Strong generalization
- Low error rates
- Clear feature separability

Overall, the system is reliable, scalable, and effective for identifying deepfake images across diverse datasets.

# Model Deployment on Hugging Face

To make the deepfake detection system accessible and user-interactive, the final trained model is deployed on **Hugging Face Spaces**. Deployment is performed using the **Gradio framework**, which provides an intuitive web-based interface for real-time inference.

The deployment pipeline works as follows:

1. A user uploads an image through the web interface.
2. The system performs face detection and alignment using MTCNN.
3. Feature embeddings are extracted using the selected backbone model (ResNet or ViT).
4. The trained ANN classifier predicts whether the face is real or fake.
5. The prediction result, along with a confidence score, is displayed to the user.

Hugging Face deployment offers several advantages:

- Platform independence, allowing users to access the model through a web browser without local setup.
- Scalability, enabling easy sharing and testing of the model.
- Reproducibility, as the model code, dependencies, and environment are standardized.
- Real-time interaction, making the system suitable for demonstrations and practical evaluation.

By deploying the model on Hugging Face, the project bridges the gap between research and realworld application. The deployment validates the practical usability of the proposed deepfake detection system and demonstrates how advanced deep learning models can be transformed into accessible AI solutions.

# Interpretation & Visuals

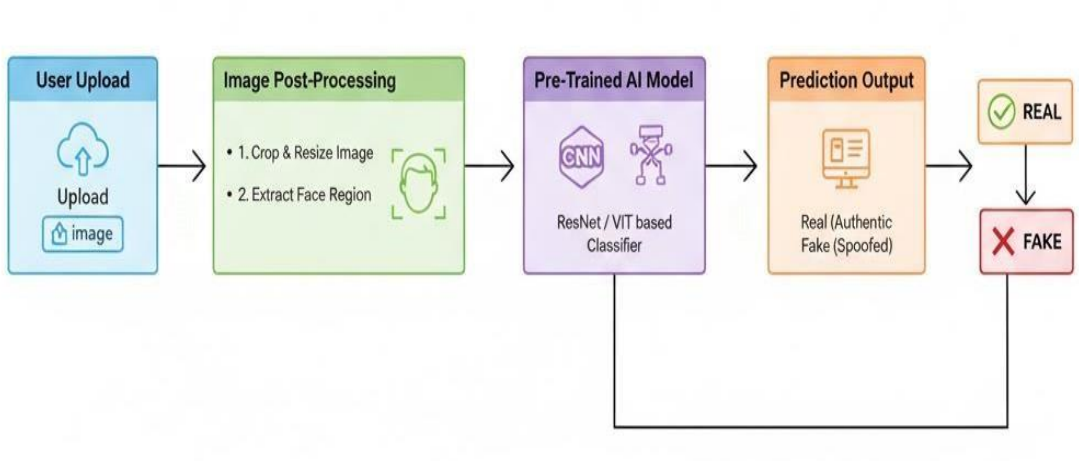



**Figure 4.3** Interpretation of Result and Visual Summary Table

# Some Visuals of our Model:

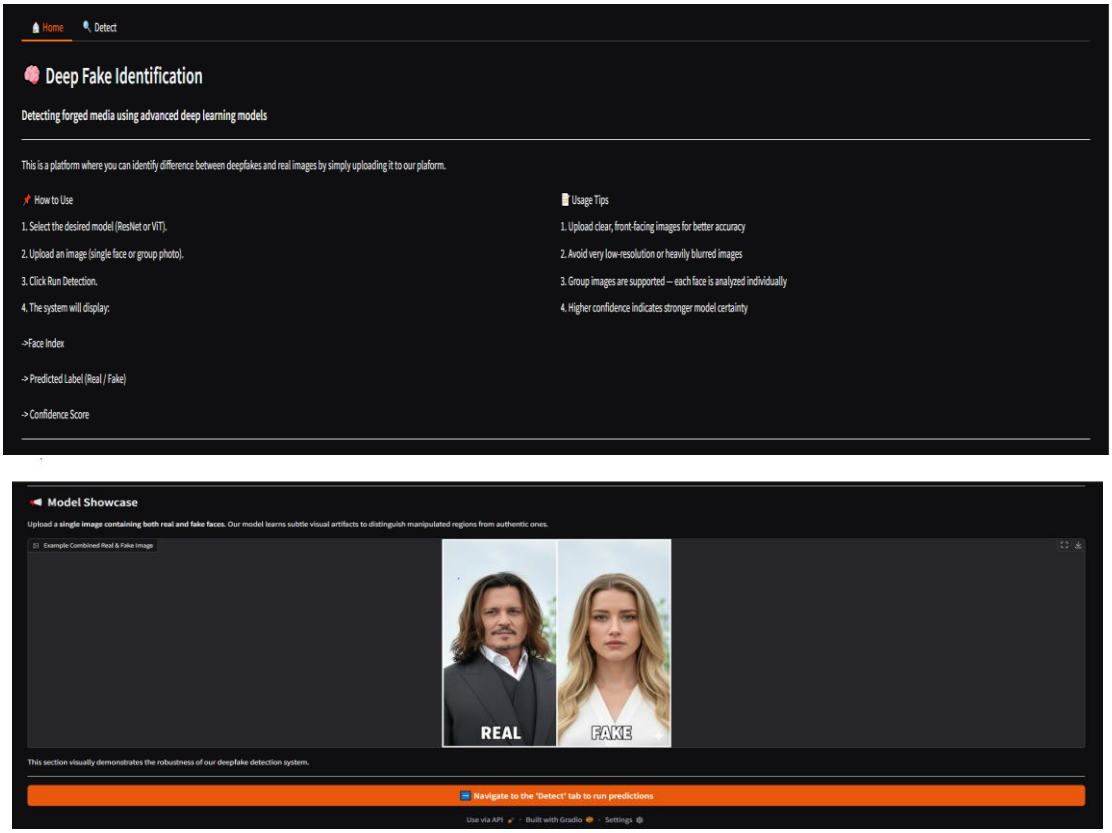
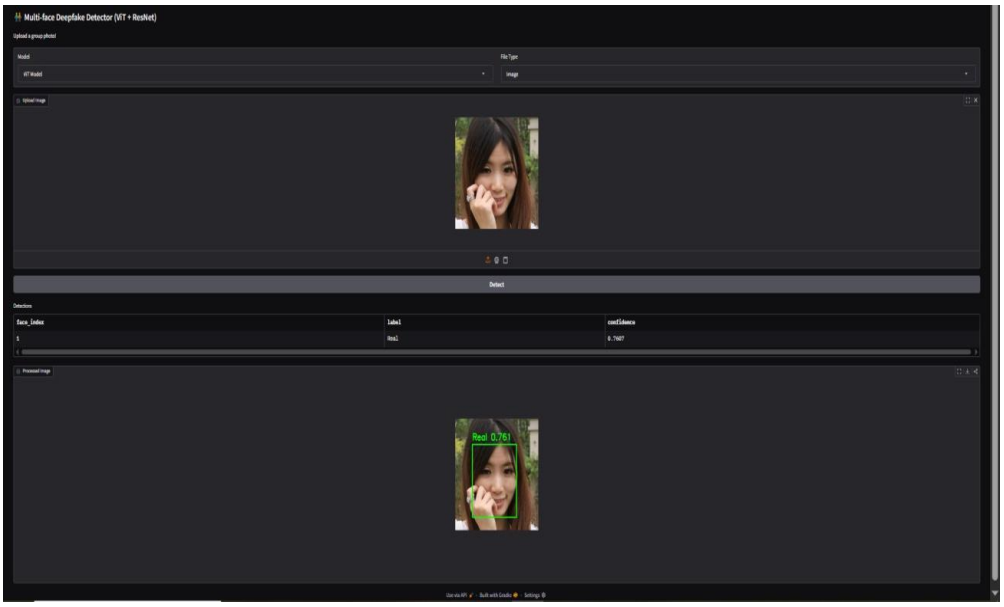
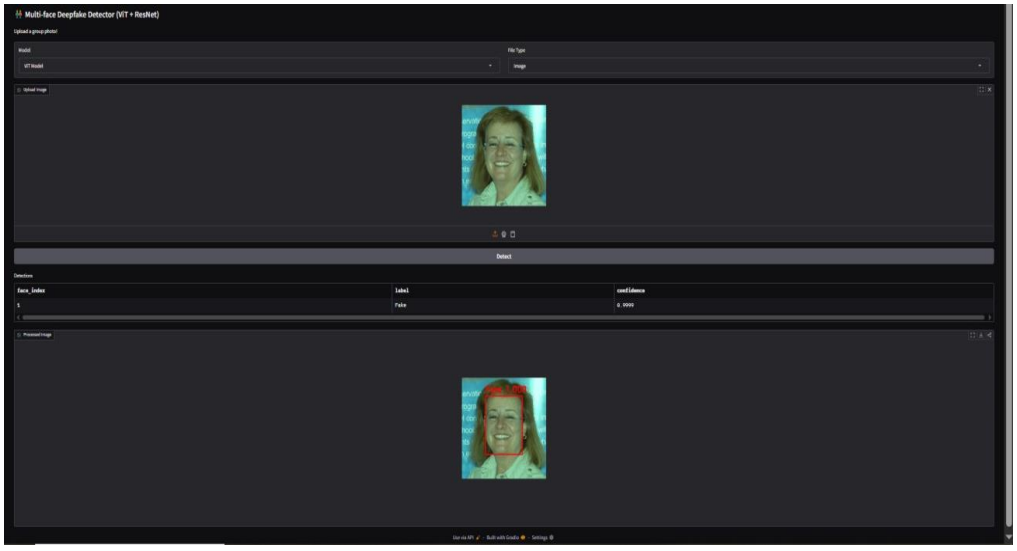
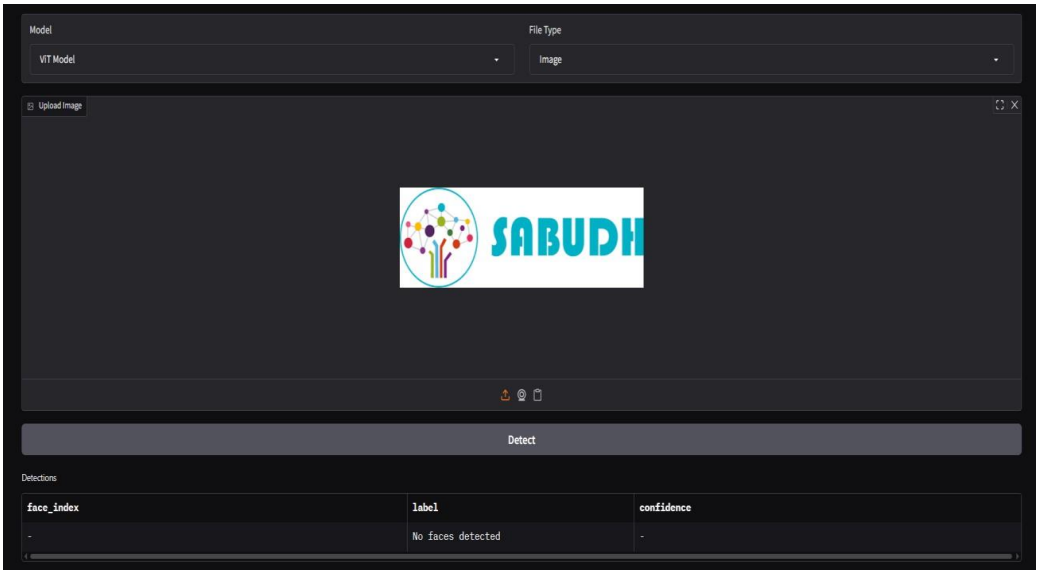
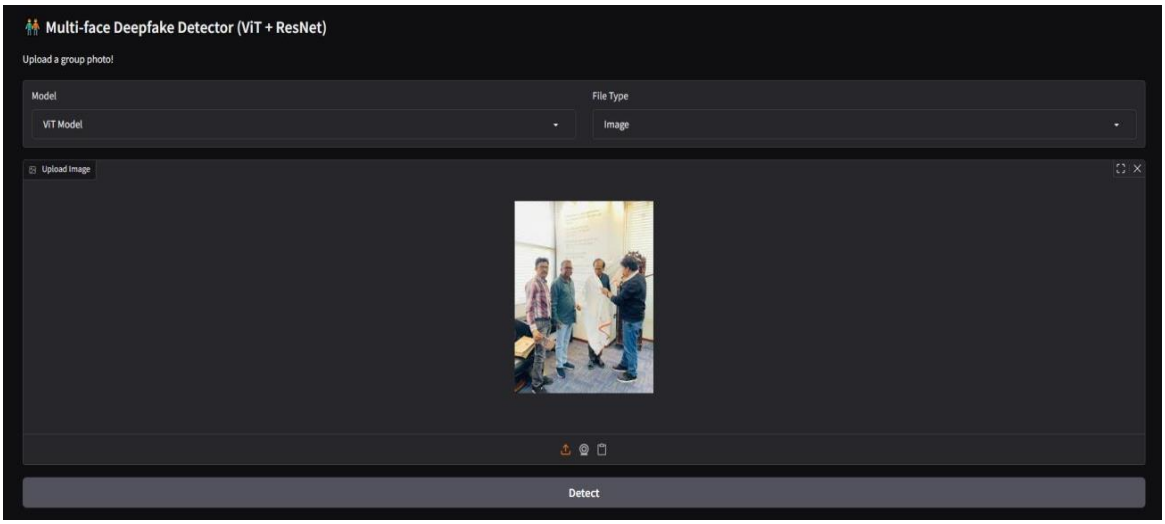



**Figure 4.4** Model's Preview


Multi-face Deepfake Detector (VIT + ResNet)
Upload a group photo!
Model
ViT Model
File Type
Image
Upload Image
Detect
Detections
face_index
label
confidence
1
Real
0.7687
Processed Image
Real 0.761
Use via API
Built with Gradio
Settings


Multi-face Deepfake Detector (VIT + ResNet)
Upload a group photo!
Model
ViT Model
File Type
Image
Upload Image
Detect
Detections
face_index
label
confidence
1
Fake
0.9999
Processed Image
Use via API
Built with Gradio
Settings


Model
ViT Model
File Type
Image
Upload Image
SABUDH
Detect
Detections
face_index
label
confidence
-
No faces detected
-



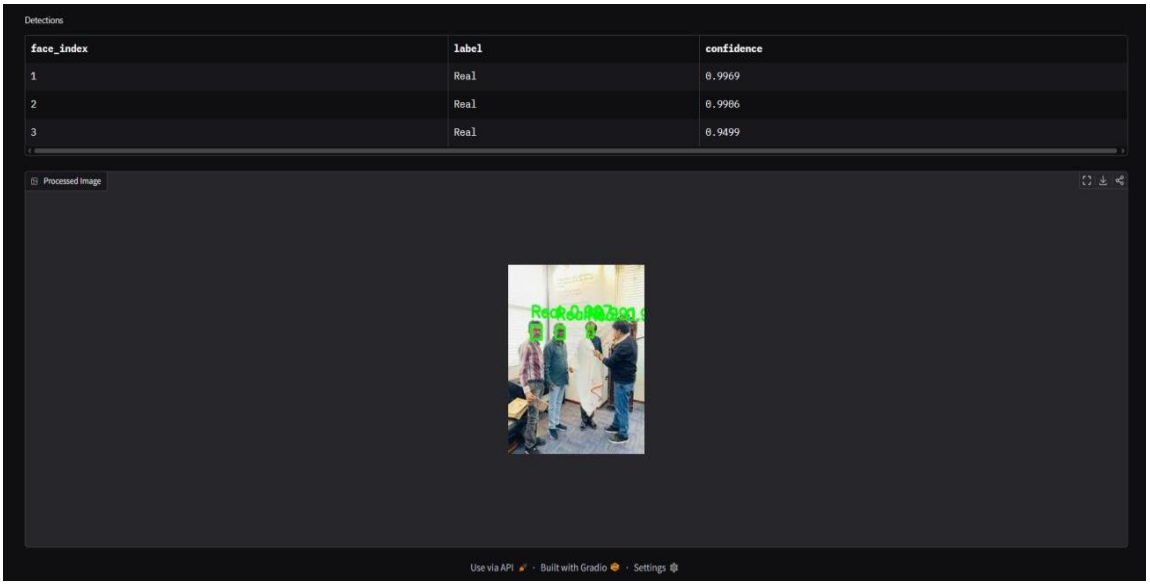




**Figure 4.5** Examples

# Chapter 5
# Conclusion

The primary objective of this project was to develop an effective deepfake detection system capable of distinguishing between real and synthetically generated images using modern deep learning architectures. With the rapid escalation of AI-generated facial forgeries and their potential misuse, designing a reliable detection pipeline has become a critical research area. Through the integration of diverse datasets, advanced feature extraction methods, and robust classification models, this work successfully demonstrates an end-to-end approach to deepfake identification.

A major contribution of this project lies in the creation of a large-scale combined dataset derived from multiple Kaggle sources, consisting of 143,512 images (65,558 real and 77,954 fake). The comprehensive preprocessing workflow—including face detection using MTCNN, resizing, and normalization—ensured consistency and high-quality input for model training. To capture richer and more discriminative visual representations, we used two state-of-the-art architectures, Vision Transformer (ViT) and ResNet-50, to generate embeddings. This multi-model strategy leveraged both global attention-driven features (from ViT) and strong convolutional spatial representations (from ResNet), resulting in highly robust feature vectors.

After embedding generation by all team members, the combined embedding dataset was used to train a fully connected Artificial Neural Network classifier. The final model achieved strong performance across all key metrics, including high accuracy, precision, recall, and F1-score. These results indicate that embeddings-based classification provides a lightweight yet powerful alternative to end-to-end deepfake detection models, enabling faster training and easier scalability. Visual analysis using confusion matrices and ROC curves further confirms the model's reliability and its ability to generalize across real and fake samples.

Overall, the project successfully delivers an efficient, scalable, and high-accuracy deepfake detection framework. While the results are promising, future research can explore areas such as video-level detection, multimodal analysis, adversarial robustness, and the inclusion of newer generative model forgeries (e.g., diffusion-based deepfakes). With continuous improvements, this work can contribute significantly to developing safe, trustworthy, and AI-aware digital ecosystems.

Overall, this project addresses a critical challenge in digital media forensics and contributes a robust, scalable, and user-friendly solution for identifying manipulated facial images. The results confirm the effectiveness of modern deep learning models in combating deepfake threats and lay a strong foundation for future advancements in trustworthy and ethical AI-driven media analysis.

# Future Work

Although the proposed deepfake detection system demonstrates strong performance using ResNet and Vision Transformer–based models, there are several directions in which this work can be extended and enhanced in the future.

One potential improvement is the integration of temporal information from videos. The current system primarily focuses on image-based deepfake detection. Extending the framework to analyze video sequences using temporal models such as Long Short-Term Memory (LSTM) networks, 3D Convolutional Neural Networks, or transformer-based video models could significantly improve detection accuracy for video deepfakes.

Future work may also explore hybrid or ensemble approaches that combine ResNet and ViT embeddings more effectively. By fusing convolutional and transformer-based features, the system can benefit from both local texture analysis and global contextual understanding, potentially leading to further performance improvements.

Another important direction is the use of larger and more diverse datasets that include multiple deepfake generation techniques, varying image resolutions, lighting conditions, and demographic diversity. Training on such datasets would improve the robustness and generalization capability of the model against unseen manipulation methods.

The system can also be enhanced by incorporating explainable AI (XAI) techniques, such as attention visualization and saliency maps, to provide interpretability and transparency in predictions. This would help users understand which facial regions contribute most to the deepfake classification decision.

From a deployment perspective, future improvements may include real-time optimization and edge deployment, enabling the model to run efficiently on mobile or low-resource devices. Additionally, further scalability and security measures can be implemented in the Hugging Face deployment to support large-scale public usage.

Finally, continuous model updating and retraining using newly generated deepfake data will be essential to keep the detection system effective as deepfake generation techniques evolve. These enhancements would make the system more adaptable, reliable, and suitable for real-world digital media forensics applications.

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