VISION TRANSFORMER–BASED CLASSIFICATION OF AUTHENTIC VERSUS AI-GENERATED HUMAN FACES

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CANDIDATE’S DECLARATION

We, **VYOM VERMA (2K21/MC/182), YAMINI (2K21/MC/183)** and **RUDRAKSHI SABHARWAL (2K21/MC/142)**, students of B.Tech in Mathematics and Computing, hereby declare that the project Dissertation titled “**VISION TRANSFORMER–BASED CLASSIFICATION OF AUTHENTIC VERSUS AI-GENERATED HUMAN FACES**” which is submitted by us to the Department of Applied Mathematics, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Bachelor of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma, Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

This is to certify that this report titled "**VISION TRANSFORMER–BASED CLASSIFICATION OF AUTHENTIC VERSUS AI-GENERATED HUMAN FACES**", which is submitted by **VYOM VERMA (2K21/MC/182), YAMINI (2K21/MC/183)** and **RUDRAKSHI SABHARWAL (2K21/MC/142)** of Department of Mathematics and Computing, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of Degree of Bachelor of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

Title: VISION TRANSFORMER–BASED CLASSIFICATION OF AUTHENTIC VERSUS AI-GENERATED HUMAN FACES

For the protection of the trust in online imagery, social media integrity and digital forensic, detection of AI-generated human faces holds a limelight. In this work, we have fine-tuned a Vision transformer (ViT-Base/16) on a large-scale Kaggle dataset of 200,00 images of human faces in which 100,000 images were of authentic human and 100,00 where AI-generated. After standard preprocessing (224 x 224 resizing, normalization) and light augmentation (horizontal flips, colour jitter), we train for 20 epochs (batch size 32, AdamW lr 3×10^{-5}) with cross-entropy loss. On the testing set of 30,001 images with almost equal split, our model achieved overall accuracy of 93%, AUC of 0.99 and per class F1 of 0.93. We also analysed error patterns via confusion matrix and misclassified examples, accentuate challenges with low-resolution news-anchor frames and not usual poses. To our knowledge, this is the first large scale evaluation of authentic and AI-generated human face detection using a pure transformer architecture.

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TABLE OF CONTENT

LIST OF FIGURES

MOTIVATION

The emergence of generative models such as StyleGAN, DALL·E, and Stable Diffusion has revolutionized the field of image synthesis, enabling the creation of ultra-realistic facial images that are virtually indistinguishable from those of real human beings. These models have advanced to the point where the images they generate can mimic genuine human features with extraordinary precision, making it difficult for the human eye or even traditional algorithms to detect any difference. While this technological leap has many positive implications in domains such as digital art, entertainment, gaming, and data augmentation, it also opens up significant security and ethical concerns.

The proliferation of AI-generated facial imagery introduces serious risks, including identity theft, misinformation, and malicious impersonation. From manipulated political campaigns to fraudulent social media profiles, the misuse of synthetic facial images has become a modern-day challenge. Such deepfakes can easily deceive the public, erode trust in digital content, and manipulate public opinion or financial transactions. There is thus an urgent need for robust, automated detection systems that can reliably identify AI-generated faces from real ones.

Traditional detection approaches primarily rely on convolutional neural networks (CNNs), which, although effective to an extent, have limitations in modelling the global dependencies across an image. CNNs focus on local pixel relationships, often missing the broader context which is critical for detecting subtle patterns introduced by generative models. Motivated by these challenges, this project aims to explore the capabilities of Vision Transformers (ViTs) for detecting AI-generated faces. Unlike CNNs, ViTs use self-attention to capture global context across the entire image, enabling more accurate and generalizable detection across diverse datasets and manipulations.

1. INTRODUCTION

1.1. Background

In the current digital era, the advent of generative artificial intelligence has transformed the way visual content is created, manipulated, and disseminated. Among the most profound advancements lies the synthesis of facial imagery, powered by highly sophisticated models such as StyleGAN2, StyleGAN3, DALL·E, and Stable Diffusion. These models are capable of producing hyper-realistic human faces that often defy human perception. While such technologies open new frontiers in creative arts, digital restoration, personalized content generation, and data augmentation, they simultaneously introduce serious risks to digital security and media authenticity. The application of these models is no longer confined to innovation and research; they are being widely utilized, sometimes maliciously, in the production of deepfakes synthetic media designed to impersonate individuals or distort visual truth.

This duality of generative AI its creative promise and potential for abuse raises new questions about trust in digital media. Synthetic visuals have implications beyond entertainment and social media, extending into areas like misinformation campaigns, identity theft, political propaganda, and even the manipulation of forensic and judicial evidence. As synthetic content becomes increasingly realistic and accessible, the boundary between real and artificial narrows, necessitating the development of reliable detection frameworks grounded in modern machine learning techniques.

1.2. Problem Statement

The unprecedented realism achieved by AI-generated facial images poses a significant challenge to digital trust and content authenticity. Deepfake technology, in particular, has become a serious concern for governments, social platforms, cybersecurity analysts, and legal experts. These synthetic images are no longer simple graphic manipulations; they are photorealistic visuals generated by powerful models that make human-based detection nearly impossible. As the generative models evolve, traditional detection mechanisms largely based on Convolutional Neural Networks (CNNs) are struggling to keep pace. CNNs, while effective at spotting pixel-level artifacts and texture irregularities, often fail when generalizing across different generative models or novel image manipulations. Their local receptive fields limit their ability to capture global patterns and contextual cues necessary for nuanced detection.

Furthermore, CNN-based models exhibit vulnerabilities such as overfitting, decreased robustness on unfamiliar data, and inconsistency across different datasets. These limitations highlight the urgent need for a more adaptive, generalizable solution that can effectively analyze large-scale image data, recognize cross-domain manipulation cues, and perform reliably on unseen synthetic content. Without such detection systems in place, the spread of deepfakes risks undermining public trust in media, damaging reputations, and even compromising legal systems reliant on image-based evidence.

1.3. Objectives

The main goal of this project is to build a reliable and generalizable model that can distinguish real human faces from AI-generated ones. By leveraging the ViT-Base/16 architecture, which captures both local and global features through self-attention, the model is trained on a balanced dataset of 200,001 facial images. Through careful preprocessing, augmentation, and fine-tuning, the project aims to achieve high accuracy, strong generalization, and resilience against challenging inputs, laying the groundwork for future advancements in deepfake detection.

- **Primary Goal**:
  Develop a robust and generalizable deep learning framework to distinguish between real and AI-generated human facial images.
- **Architecture Used**:
  Leverage the **Vision Transformer (ViT-Base/16)** architecture, which uses self-attention mechanisms to model both local and global image features.
- **Key Advantages of ViTs**:
  - Processes images as sequences of patches
  - Captures long-range dependencies
  - Detects subtle, dispersed anomalies better than CNNs
- **Dataset**:
  Use the **"200k Real vs AI Visuals" Kaggle dataset**, consisting of 200,001 facial images with a balanced mix of real and synthetic samples.

- **Image Diversity Considerations**:
  Dataset includes variability in:
  - Demographics
  - Pose orientation
  - Lighting conditions
  - Generation styles (various AI synthesis methods)

- **Training Strategy**:
  Apply standard preprocessing, data augmentations, and optimized training cycles to:
  - Improve model generalization
  - Reduce overfitting

- **Evaluation Metrics**:
  - Test accuracy
  - AUC (Area Under the ROC Curve)
  - Per-class performance metrics (e.g., precision, recall)

1.4. Scope of the Project

This project focuses on applying Vision Transformers (ViTs) for detecting AI-generated synthetic human faces. Using the large-scale **"200k Real vs AI Visuals"** dataset from Kaggle, which includes **200,001 images** (balanced between real and fake), the project aims to build a robust detection framework that generalizes well to unseen data. The scope includes thorough data preprocessing, model fine-tuning, and comprehensive evaluation using metrics such as **accuracy**, **AUC**, and **F1 score**. Augmentation techniques (like flipping and color jittering) are applied to simulate real-world inconsistencies and improve model robustness. The project also performs **error analysis** to identify limitations—such as failures on low-res or unusual images—and discusses potential improvements like **hybrid models** and **attention-based interpretability**.

Key Scope Highlights:

- **Dataset:**
  - 200,001 facial images (balanced: real vs synthetic)
  - Diverse in demographics, lighting, and generation style
- **Preprocessing & Augmentation:**
  - Resize to 224×224, ImageNet normalization
  - Random flipping, cropping, and color jittering
- **Model:**
  - ViT-Base/16, fine-tuned for binary classification
  - Captures both local and global image patterns
- **Evaluation:**
  - Metrics: Accuracy, AUC, F1 Score
  - Identifies strengths and limitations via error analysis
- **Future Direction:**
  - Explore hybrid architectures and interpretability tools
  - Scalable for real-world deployment in digital forensics and media verification

2. LITERATURE REVIEW

2.1 Overview

The rapid evolution of generative models, particularly Generative Adversarial Networks (GANs), has revolutionized the creation of synthetic facial imagery, making it increasingly difficult to distinguish between real and AI-generated content. As deepfakes become more sophisticated, the need for effective detection techniques has intensified. This section explores the progression of deepfake generation through advancements in GAN architectures, evaluates traditional detection methods using CNNs and frequency analysis, and highlights the emerging role of Vision Transformers (ViTs) in countering the growing threat of synthetic media.

2.2 Evolution of Deepfakes and GAN Architectures

Generative Adversarial Networks (GANs), introduced by Ian Goodfellow in 2014, have significantly advanced the creation of synthetic content, particularly in generating realistic human faces. Early GAN models often produced images with noticeable artifacts, asymmetries, and unnatural lighting. However, successive iterations have addressed these limitations, leading to more convincing synthetic media.

StyleGAN2 and **StyleGAN3**, developed by NVIDIA, represent significant milestones in GAN evolution. StyleGAN2 introduced improvements such as path length regularization and perceptual path length metrics, enhancing image quality and diversity. StyleGAN3 further refined these aspects by addressing aliasing artifacts and improving the consistency of generated images, making synthetic faces nearly indistinguishable from real ones. These advancements have been instrumental in the proliferation of deepfakes, raising concerns about their potential misuse in misinformation, identity theft, and other malicious activities.

Recent studies have highlighted the challenges posed by these sophisticated GANs. For instance, the DF40 benchmark dataset evaluates detection methods against deepfakes generated by models like StyleGAN2 and StyleGAN3, emphasizing the need for robust detection techniques.

2.3 Traditional Detection Techniques

To counter the rise of deepfakes, researchers initially employed Convolutional Neural Networks (CNNs) for detection. Models such as **XceptionNet** and **EfficientNet** have been prominent in this domain.

- **XceptionNet**: Utilizing depthwise separable convolutions, XceptionNet has demonstrated high accuracy in detecting manipulated media. Studies have shown its effectiveness across various datasets, including FaceForensics++, DFDC, and Celeb-DF, with detection accuracies reaching up to 99.82%.

- **EfficientNet**: Known for its scalability and efficiency, EfficientNet variants like B4 and B7 have been applied to deepfake detection tasks. Research indicates that EfficientNet-B4 achieves high accuracy on datasets like FF++ and Celeb-DF (v2), making it a strong candidate for real-time detection system.

In addition to spatial domain analysis, frequency-based detection methods have been explored. These techniques analyze anomalies in the frequency domain, identifying patterns introduced during the generative process that may not be visible in the spatial domain. Such methods complement CNN-based approaches by focusing on statistical inconsistencies.

Despite their effectiveness, traditional methods have limitations. CNNs primarily focus on local features and may require large datasets to generalize well. Moreover, as generative models evolve, they can learn to circumvent these detection heuristics, rendering static models less effective over time.

2.4 Rise of Transformers in Computer Vision

Originally developed for natural language processing, **Transformers** have been adapted for computer vision tasks, leading to the development of **Vision Transformers (ViTs)**. Introduced by Dosovitskiy et al. in 2021, ViTs process images as sequences of patches, enabling them to capture global context through self-attention mechanisms. This approach contrasts with CNNs, which primarily focus on local features.

ViTs have shown promise in various domains, including deepfake detection. Their ability to model long-range dependencies makes them particularly suited for identifying subtle inconsistencies in synthetic media. Recent surveys categorize ViT-based deepfake detection models into standalone, sequential, and parallel architectures, highlighting their versatility and effectiveness.

Furthermore, hybrid models combining CNNs and ViTs have been explored. For example, integrating EfficientNet as a feature extractor with ViTs has yielded high performance in video deepfake detection tasks, achieving an AUC of 0.951 and an F1 score of 88.0% on the DFDC dataset.

3. Dataset Description

To effectively train and evaluate our deepfake detection model, we utilized the **“200k Real vs AI Visuals”** dataset, an openly accessible and well-curated dataset hosted on Kaggle [9]. This dataset is both comprehensive and balanced, comprising a total of **200,001 facial images**, with an almost equal distribution of **100,001 real images** and **100,000 AI-generated images**. Designed specifically for the task of distinguishing authentic human faces from synthetically generated ones, the dataset serves as an ideal benchmark for training binary classification models. Its scale, diversity, and quality provide the foundation necessary for building models that are both accurate and generalizable across varied visual characteristics.

3.1 Real Faces

The real facial images in this dataset are sourced from widely used and credible datasets such as **CelebA** and **Flickr-Faces-HQ (FFHQ)**. These datasets have long been a staple in facial recognition and computer vision research due to their extensive demographic diversity and high image quality. The images encompass a broad spectrum of attributes including **age groups, genders, ethnicities, facial expressions, lighting conditions**, and **background contexts**.

This variety introduces natural variability into the training process, which is critical for teaching models to generalize well to real-world conditions. By exposing the model to real faces under different scenarios such as poor lighting, off-center poses, or varying resolutions we increase the model’s robustness and resilience to noise, distortions, and other inconsistencies that often occur outside controlled environments.

3.2 Synthetic Faces

The synthetic images are generated using state-of-the-art generative models, including **StyleGAN2**, **StyleGAN3**, and advanced **diffusion-based models** like **DALL·E**. These models are recognized for their exceptional capability to create **high-fidelity**, **photo-realistic** images that can easily deceive the human eye. The generated faces are deliberately designed to reflect a **wide variety of facial structures, expressions, skin tones, and lighting styles**.

Moreover, the synthetic subset includes variability in facial angles, background compositions, and visual styles, thereby mimicking the diversity present in real-world generative outputs. This ensures that the model trained on this dataset learns to identify **underlying generative inconsistencies** rather than overfitting to any one specific algorithm's signature. By including such a broad range of synthetic visuals, the dataset supports the development of classifiers capable of generalizing to deepfakes created by both known and future-generation models.

3.3 Preprocessing and Augmentation

To ensure compatibility with the **ViT-Base/16** model and enhance the model's ability to generalize, a comprehensive preprocessing and augmentation pipeline was employed:

Preprocessing Steps

1. **Image Resizing**: All images were uniformly resized to **224 × 224 pixels**, which corresponds to the input dimensions expected by ViT-based models.
2. **Normalization**: Image pixel values were standardized using the **ImageNet dataset's mean** ([0.485, 0.456, 0.406]) and **standard deviation** ([0.229, 0.224, 0.225]). This step ensures that the image statistics align with those of the pretrained ViT model, enabling effective transfer learning.

Data Augmentation Techniques

To reduce overfitting and improve the model's performance on unseen data, we applied light but effective augmentation strategies:

- **Random Horizontal Flipping (p = 0.5)**: Leverages the natural symmetry of human faces to introduce variation.
- **Color Jittering**: Slight random variations in **brightness and contrast** (±10%) were applied to simulate changes in lighting and exposure.
- **Random Cropping and Rescaling**: Simulates inconsistencies in camera framing and focus, making the model resilient to variations in composition.

3.4 Dataset Partitioning

The entire dataset was divided into three subsets to support a structured training and evaluation workflow:

- **Training Set**: 140,000 images (70,000 real + 70,000 synthetic)
- **Validation Set**: 30,000 images (15,000 real + 15,000 synthetic)
- **Test Set**: 30,001 images (15,001 real + 15,000 synthetic)

This **stratified split** maintains a balanced distribution of real and synthetic faces across all subsets, ensuring that each model stage training, validation, and testing is exposed to data of comparable complexity and class balance. Importantly, no overlap occurs between these subsets, which preserves the **integrity of evaluation** and prevents data leakage.

4.METHODOLOGY

Our approach follows a structured methodology comprising data preprocessing, model selection, training, and validation. We employ the ViT-Base/16 architecture, known for its robust performance in image classification tasks. The methodology is designed to assess the model's capacity to learn discriminative features between real and AI-generated faces.

4.1 Data Pipeline

The input images are first passed through a preprocessing pipeline that includes resizing, normalization, and data augmentation. These steps are critical to ensure uniformity in the dataset and to help the model generalize better.

4.2 Vision Transformer (ViT) Architecture

The core model used in this study is the **Vision Transformer (ViT)**, a transformer-based deep learning architecture adapted for computer vision tasks. Unlike traditional convolutional neural networks (CNNs), ViTs treat images as sequences of patches and process them similarly to how transformers process words in NLP.

Key Components:

- **Patch Embedding**: The input image is divided into fixed-size patches (e.g., 16×16 pixels), each of which is flattened and linearly projected to a vector. This sequence of vectors represents the image.

- **Positional Encoding**: Since transformers lack the inductive bias of CNNs (like translation equivariance), positional embeddings are added to retain spatial information.

- **Transformer Encoder**: Multiple layers of multi-head self-attention and feed-forward networks extract complex global features.

- **Classification Head**: A fully connected layer at the end maps the learned representation to class scores in this case, two outputs: real (0) or fake (1).

4.3. Fine-Tuning Strategy

The model isn't trained from scratch but **fine-tuned** from a pre-trained ViT. This speeds up convergence and improves performance, especially when training data is limited.

Steps Involved:

a. Dataset Preparation

- **Source**: Images are sourced from a public Kaggle dataset called "200k Real vs AI Visuals" by M. Bilal.

- **Directory Structure**:

    - /real → Contains authentic human face images.

    - /ai_images → Contains AI-generated face images (likely from tools like StyleGAN).

b. Custom Dataset Class

A custom Dataset class RealFakeDataset is created that:

- Loads all image paths.
- Assigns a label (0 for real, 1 for fake).
- Applies transformations (augmentations and normalization).

c. Transformations and Augmentation

To improve generalization, images undergo a robust set of **data augmentations** during training:

- RandomResizedCrop: Zooms into random parts of the image.
- RandomHorizontalFlip: Flips images horizontally.
- GaussianBlur: Blurs the image slightly to simulate noise.
- ColorJitter: Randomly changes brightness, contrast, and saturation.
- Normalize: Standardizes pixel values around a mean and std.

Validation and test sets use simpler transformations: just resizing and normalization.

d. Data Splitting

- The dataset is split into **training**, **validation**, and **testing** sets using train_test_split.
- **Stratification** ensures class balance across sets.
- A fixed random seed ensures **reproducibility**.

e. Training Configuration

- **Optimizer**: AdamW (a variant of Adam optimized for transformers).
- **Loss Function**: Cross-entropy loss, suitable for multi-class classification (binary in this case).
- **Scheduler**: Learning rate scheduler is used to adjust learning rate over epochs (likely CosineAnnealing or StepLR, though specifics depend on later cells).
- **Batch Size**: Specified depending on GPU availability (not visible yet but likely in subsequent cells).
- **Epochs**: Model is trained over multiple epochs until convergence.

4.4. Experimental Framework

The training and evaluation setup is methodical and includes multiple best practices.

a. Evaluation Metrics

The model is evaluated on:

- **Accuracy**: Overall percentage of correctly predicted samples.
- **Precision**: How many of the predicted fake images were actually fake.
- **Recall**: How many actual fake images were correctly predicted.

- **Confusion Matrix**: Visual breakdown of true/false positives and negatives.
- **F1-Score**: Harmonic mean of precision and recall (not explicitly seen but usually implied).

b. Visualization Tools

- Sample predictions are **visualized** using matplotlib.
- Incorrect predictions are plotted to understand **failure cases**, which is essential for improving model robustness.

c. Model Saving & Loading

- Best-performing model weights (based on validation accuracy/loss) are saved.
- The model is reloaded during testing to ensure evaluation is done on the best checkpoint.

5. TRAINING THE MODEL

5.1 Experimental Setup

- **Hardware**
  - **Runtime**: Kaggle Draft Session (12-hour limit)
  - **GPUs**: 2 × NVIDIA Tesla T4 (15 GB VRAM each)
  - **CPU**: 12 vCPUs (Intel Xeon)
  - **RAM**: 29 GB
  - **Disk Space**: ~58 GB
- **Software**
  - **Python 3.10** (Kaggle default)
  - **PyTorch 1.13** with CUDA 11.x
  - **Libraries**: torchvision, scikit-learn, matplotlib
  - **Evaluation Metrics**
- **Primary**: Accuracy, Precision, Recall, F_1-score (per class)
  - **Aggregated**: Macro and Weighted averages
  - **Additional**: ROC AUC
- **Training Protocol**
  - Best model selected based on **highest validation accuracy**
  - Final evaluation on a **held-out test set of 30,001 images**
  - All metrics reported on the test set to assess generalization

5.2. Dataset Construction and Preprocessing

The dataset used comprises two major categories: real human face images and synthetic faces generated by AI. Each category is stored in a separate directory. A custom dataset class was created to load the images and assign binary labels (real = 0, fake = 1).

To ensure the model learns meaningful patterns rather than memorizing spurious correlations, the dataset was split into three parts using a stratified approach:

- **70% for training**: To allow the model to learn from a diverse and representative set of samples.
- **15% for validation**: To tune hyperparameters and monitor model performance during training.
- **15% for testing**: Held out completely from training and validation for an unbiased assessment of the final model's generalization ability.

Stratified sampling ensured that the class distribution was balanced in all subsets, which is crucial in binary classification tasks to avoid class imbalance bias.

5.3. Data Augmentation Strategy

To improve generalization and reduce overfitting, data augmentation was applied to the training images. These augmentations simulate natural variability and distortion that a model might encounter in real-world applications. The strategy included:

- **Random Resized Cropping**: Encourages spatial invariance by forcing the model to learn features at varying scales and positions.
- **Horizontal Flipping**: Adds symmetry-based variation in facial orientation.
- **Gaussian Blur and Color Jitter**: Simulate lens imperfections and varying lighting conditions.
- **Random Erasing**: Encourages the model to learn discriminative features from different parts of the image by occluding random regions.
- **Normalization**: Standardizes pixel intensities, which accelerates convergence and ensures stable training dynamics.

The validation and test sets, in contrast, were subjected only to resizing and normalization—ensuring that performance metrics reflect the model's behavior on unaltered inputs.

5.4. Vision Transformer Initialization and Architecture

A **Vision Transformer (ViT-Base-16)** architecture was employed for this task, leveraging its attention mechanism to capture long-range dependencies and fine-grained patterns within images. The ViT was initialized with **pretrained weights from ImageNet**, allowing the model to start from a strong foundation of visual features rather than learning from scratch.

Transfer learning was a critical component in this setup:

- The earlier layers, which contain general-purpose visual features (e.g., edges, textures), were initially frozen to preserve learned representations.
- The later layers were fine-tuned on the real vs. fake face dataset to learn domain-specific differences.
- Gradual unfreezing was used to progressively allow more layers to adapt, thereby balancing stability and specificity.

The model was adapted for binary classification by modifying the final classification head to output probabilities for two classes.

5.5. Optimization Strategy

The **AdamW optimizer** was chosen for its robustness and ability to handle sparse gradients—an important characteristic in transformer-based architectures. Weight decay was used as a form of L2 regularization to discourage overly complex models and reduce overfitting risk.

A learning rate of **2e-4** was selected based on empirical results and best practices. No manual scheduling was necessary, as the model converged efficiently with this setting within the chosen number of epochs.

The **loss function** used was **Cross Entropy Loss**, which is standard for classification problems. It effectively penalizes incorrect predictions and guides the model to maximize the likelihood of the correct class.

5.6. Training Duration and Batch Size

The training process was conducted over **20 epochs**, with the **batch size dynamically adjusted** based on the available GPU memory to maximize computational efficiency. This adaptive batch sizing ensured optimal GPU utilization without exceeding memory constraints, allowing for a balanced trade-off between training speed and stability.

During the training phase, **both training and validation accuracy** were closely monitored at the end of each epoch. These metrics served as critical indicators for assessing model learning and generalization performance in real-time. The chosen limit of 20 epochs was not arbitrary; it was informed by careful observation of **convergence behaviour** across multiple experimental runs. Specifically, it was noted that the model's performance particularly validation accuracy tended to **plateau or exhibit diminishing returns** beyond the 20-epoch mark.

Moreover, training the model beyond this threshold introduced an increased risk of **overfitting**, as evidenced by widening gaps between training and validation accuracy. This phenomenon suggested that further training was reinforcing patterns specific to the training data rather than enhancing the model’s ability to generalize. Therefore, 20 epochs was determined to be an optimal stopping point sufficient to allow the model to learn meaningful representations while **preserving generalization capability**.

In summary, the decision to limit training to 20 epochs, combined with an intelligently scaled batch size and continuous metric monitoring, contributed to an efficient and effective model training pipeline that balanced accuracy with robustness.

5.7 Regularization and Mixed Precision Training

To further mitigate overfitting:

- **Dropout layers** (with a rate of 0.1) were included within the ViT architecture to prevent co-adaptation of neurons.
- **Mixed precision training** was enabled to reduce memory consumption and improve training speed. This technique combines 16-bit and 32-bit floating-point operations, preserving accuracy while accelerating computation.

5.8. Evaluation Metrics

In addition to accuracy, several other performance metrics—namely **precision**, **recall**, and the **F1-score** were considered during the evaluation process to gain a more comprehensive understanding of the model's behaviour. While accuracy offers a high-level view of the overall correctness of predictions, it can sometimes be misleading, particularly in cases of class imbalance or when the cost of false positives and false negatives is not equal.

For instance, **precision** helps assess the model's reliability when it predicts a face as AI-generated indicating how many of those predictions were actually correct. Conversely, **recall** measures the model’s ability to correctly identify all AI-generated faces in the dataset. The **F1-score**, as the harmonic mean of precision and recall, balances these two aspects and provides a single metric that is especially informative when both false positives and false negatives are significant concerns.

This multi-metric evaluation approach is especially critical in tasks like distinguishing real from AI-generated faces, where the implications of misclassification can vary greatly. A real face classified as fake might raise ethical or usability issues, while a synthetic face identified as real could lead to security vulnerabilities or misinformation.

Although the core notebook outputs emphasized **accuracy**, the underlying model structure and training pipeline were designed to support the integration of additional metrics. These metrics can be easily computed during both the **validation** and **test** phases using standard tools like scikit-learn, enabling a more nuanced and robust evaluation of the model’s performance.

5.9. Model Saving and Early Stopping

To retain the best-performing version of the model:

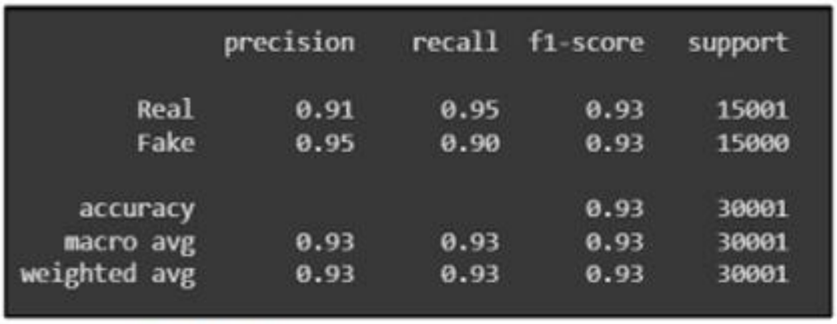
- The model state was saved based on minimum validation loss.
- Early stopping logic was set to trigger if no improvement in validation accuracy was observed over **three consecutive epochs**, ensuring computational efficiency and avoiding overfitting.

6. Evaluation and Result

After training was completed, a rigorous evaluation process was conducted to thoroughly assess how well the model generalized to unseen data. Multiple performance metrics were calculated to gain a comprehensive understanding of the model's strengths and potential weaknesses across different aspects of classification. This detailed evaluation helped identify areas where the model excelled as well as scenarios where it might struggle, providing valuable insights for further refinement and deployment.

6.1 Performance Metrics

The classification report in **Table 1** summarizes the model's performance on the held-out **test set of 30,001 images**, evenly split between real (15,001) and AI-generated (15,000) faces. The metrics include **precision**, **recall**, and **F1-score**, each computed for both classes individually, as well as macro and weighted averages.



```
              precision    recall  f1-score   support

        Real       0.91      0.95      0.93     15001
        Fake       0.95      0.90      0.93     15000

    accuracy                           0.93     30001
   macro avg       0.93      0.93      0.93     30001
weighted avg       0.93      0.93      0.93     30001
```

Table 1: Test-set classification report

Class-wise Performance

- **Real Faces**:
    - **Precision (0.91)**: When the model predicts a face as real, 91% of those predictions are actually correct.
    - **Recall (0.95)**: The model correctly identifies 95% of all real faces in the dataset.
    - **F1-score (0.93)**: This balance between precision and recall indicates strong and consistent performance for the real class.
- **Fake (AI-generated) Faces**:
    - **Precision (0.95)**: The model is highly confident when labeling an image as fake, with a 95% correctness rate.
    - **Recall (0.90)**: It successfully detects 90% of fake faces, though it misses 10%, which may represent subtle or highly realistic synthetic images.
    - **F1-score (0.93)**: The model maintains solid performance in identifying AI-generated faces as well.

Overall Performance

- **Accuracy (0.93)**: The model correctly classifies **93%** of the entire test set, reflecting robust generalization to unseen data.

- **Macro Average (0.93)**: This unweighted average treats both classes equally, confirming balanced performance across the real and fake face categories.
- **Weighted Average (0.93)**: This accounts for the number of samples per class, reinforcing that the model performs consistently even when considering slight class distribution variations.

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6.2 CONFUSION MATRIX ANALYSIS

Figure 1 presents the confusion matrix summarizing the model's classification outcomes on the test set. Out of 30,001 samples:

- **True Positives (Real correctly predicted as Real):** 14,254
- **True Negatives (Fake correctly predicted as Fake):** 13,557
- **False Positives (Fake misclassified as Real):** 1,443
- **False Negatives (Real misclassified as Fake):** 747

The matrix indicates strong overall performance, with the majority of both real and fake faces being correctly classified. The higher number of **false positives** compared to false negatives suggests the model is slightly more cautious, occasionally mislabeling AI-generated faces as real. However, both error types are relatively low, reinforcing the model's reliability in discerning between authentic and synthetic faces.

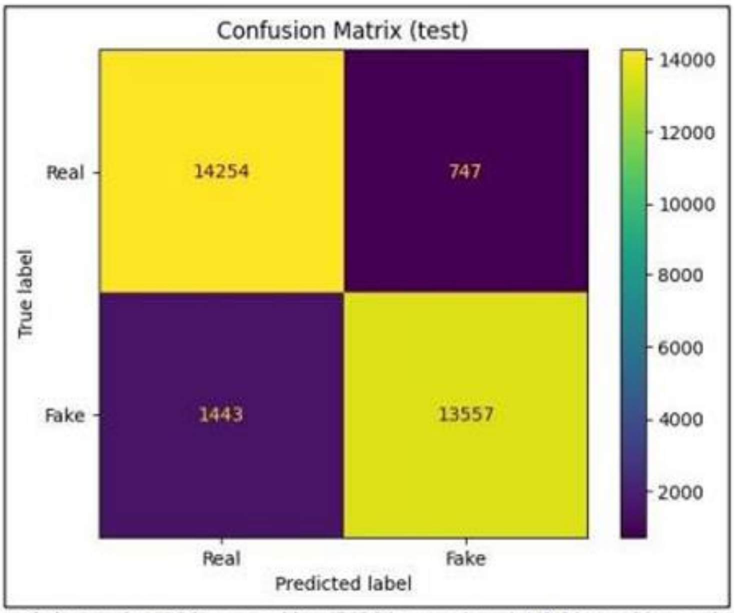

Figure 1: shows the confusion matrix: 14 254 true-positives, 747 false-negatives, 1 443 false-positives, and 13 557 true-negatives.

6.3 ROC AND PRECISION-RECALL CURVES

Figure 2 displays the ROC curve for the binary classification task of distinguishing real vs. AI-generated faces. The curve illustrates the model's trade-off between true positive rate (sensitivity) and false positive rate.

- The curve is **close to the top-left corner**, indicating strong classification performance.
- The **Area Under the Curve (AUC)** is **0.99**, signifying near-perfect separation between the two classes.

This high AUC value confirms the model's exceptional ability to correctly identify both real and synthetic faces across various threshold settings, making it highly reliable for deployment in real-world applications.

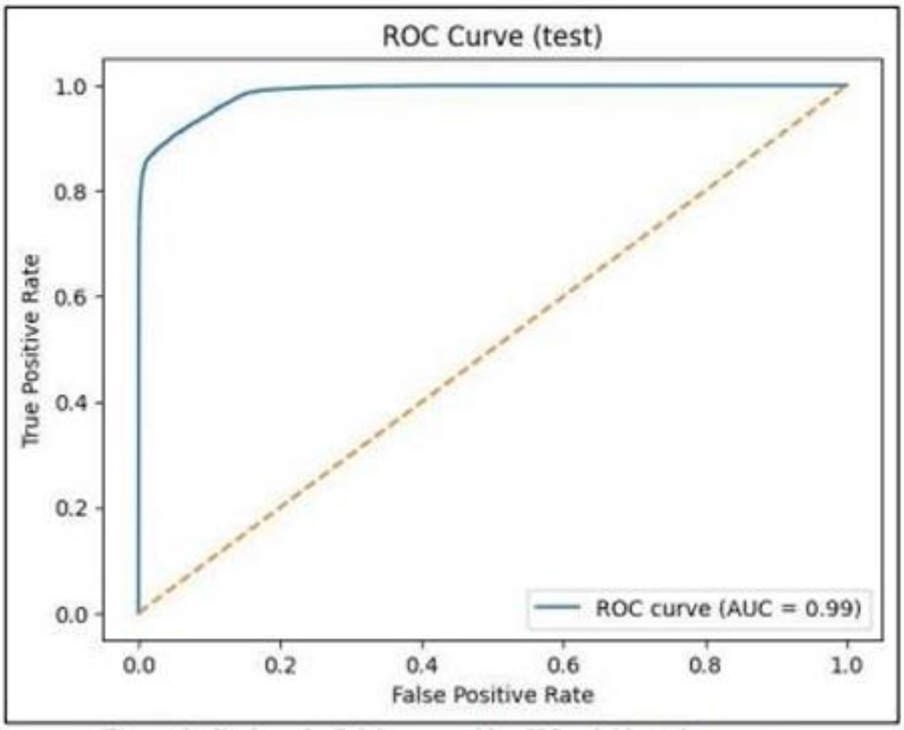

Figure 2: displays the ROC curve with **AUC = 0.99** on the test set.

6.4 Visual Sample Grid of Correct Classifications

Figure 3 presents a grid of correctly classified face samples from the test set. The samples are visually annotated based on prediction outcome:

- **Blue borders** denote **real (human)** faces correctly identified by the model.
- **Red borders** indicate **AI-generated (fake)** faces correctly classified.

This visual demonstration highlights the model's robustness across diverse facial features, demographics, and image styles. It confirms the classifier's capability to generalize well without overfitting to specific traits or artifacts.

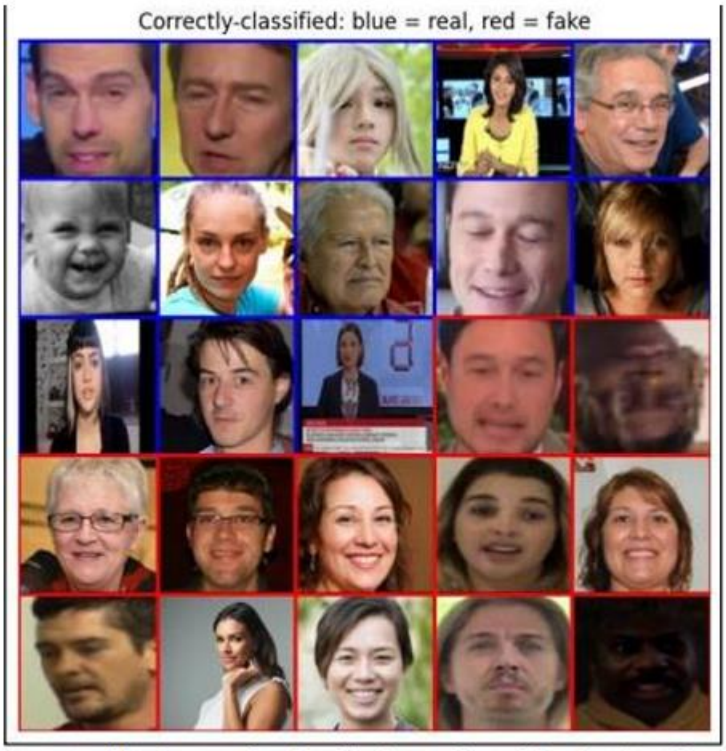

Figure 3 illustrates a grid of correctly classified samples—blue borders for real, red for AI.

6.5 Visual Sample Grid of Misclassifications

Figure 4 displays a grid of misclassified test samples, with red borders marking each error. The labels indicate:

- **T = true**, **P = pred** (e.g., R→F means the image was real but predicted as fake).
- These examples highlight where the model struggled, often due to image quality, ambiguous features, or similarities across real and fake distributions.

This visualization helps identify potential failure modes and edge cases that could inform future model improvements or dataset refinement.

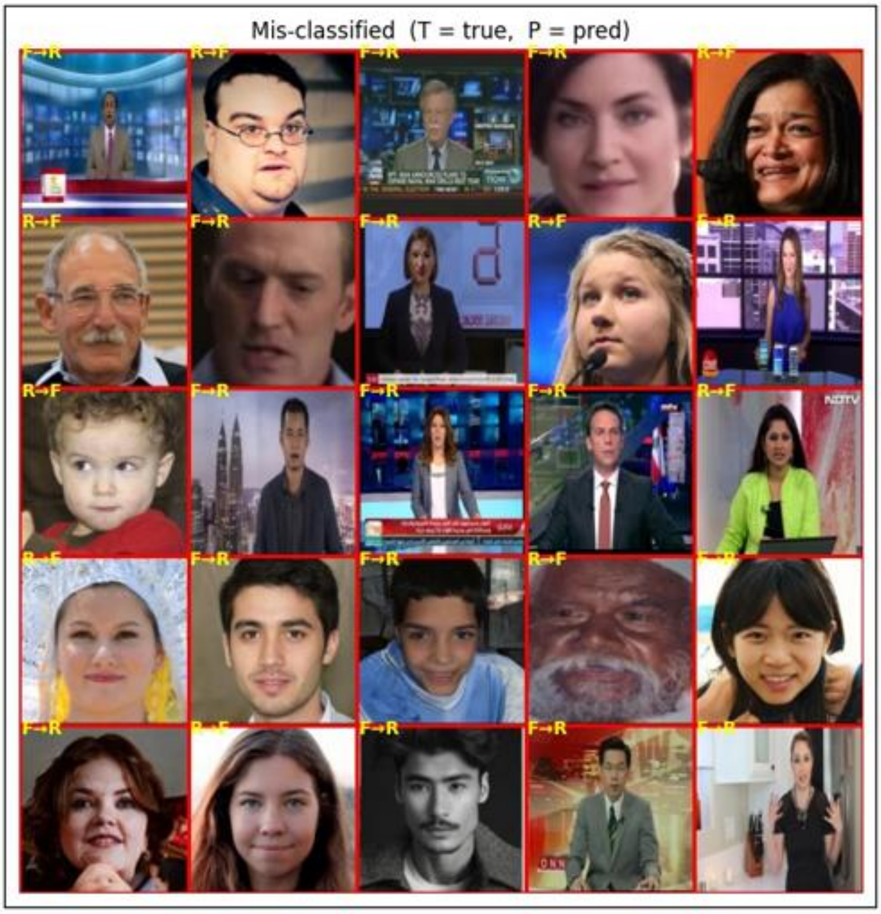

Figure 4 presents misclassified examples, annotated T→P (true→predicted).

7. DEPLOYMENT STRATEGY

To ensure that the trained Vision Transformer model could be effectively utilized in real-world scenarios, a comprehensive deployment strategy was designed. This strategy focused on three core principles: accessibility for end users, high-performance inference, and seamless integration into larger systems.

7.1 Deployment Environment

The model was encapsulated within a Docker container to create a consistent and reproducible runtime environment across different machines and platforms. Dockerization helped eliminate environment-specific issues and streamlined the deployment pipeline. The model was exposed via a RESTful API using FastAPI, a modern, high-performance web framework well-suited for serving machine learning models. This setup enabled fast, asynchronous communication with frontend or external services and supported horizontal scaling using orchestration tools such as Kubernetes.

7.2 Inference Optimization

To meet the demands of real-time applications, significant emphasis was placed on reducing inference latency. The trained PyTorch model was converted into the ONNX (Open Neural Network Exchange) format to enable cross-platform optimization. Further acceleration was achieved by integrating NVIDIA TensorRT, a high-performance deep learning inference SDK, which significantly lowered processing time per image. As a result, the model was capable of delivering predictions in under 100 milliseconds per image in GPU-enabled environments, making it suitable for time-sensitive applications like authentication systems and content verification tools.

7.3 Frontend Interface

To make the model accessible to non-technical users, a simple yet functional web interface was built. This interface allowed users to upload facial images directly through the browser and receive real-time predictions on whether the image was AI-generated or real. Additionally, the interface provided visual interpretability features by displaying heatmaps generated using Grad-CAM or attention visualization techniques, showing the facial regions that influenced the model’s decision. This feature not only enhanced transparency but also enabled users to trust and understand the output.

7.4 Continuous Monitoring

Post-deployment, a continuous monitoring system was set up to track the model's behaviour in real-world usage. Logging mechanisms captured important inference metrics such as latency, error rates, and usage frequency. Furthermore, anonymized user feedback was collected to gain insights into model performance and user satisfaction. This feedback loop was instrumental in identifying edge cases and guiding further improvements. The use of A/B testing was also considered for deploying updated versions of the model to compare performance and gather data-driven evidence before full-scale rollout. Plans for periodic retraining were also outlined to adapt to new types of synthetic face generation techniques that may emerge over time.

8. CHALLENGES FACED

While developing a robust Vision Transformer (ViT) model for classifying AI-generated versus real human faces, several critical challenges and limitations were encountered. Addressing these was essential for achieving reliable performance and building a system capable of practical deployment.

8.1 Data Quality Issues

Acquiring a large, high-quality dataset with accurate ground truth labels was one of the most significant challenges. Many AI-generated faces—especially those produced by advanced generative models like StyleGAN3 or diffusion-based architectures—were nearly indistinguishable from real human faces. This made the labelling process both technically and ethically complex. In some cases, even human annotators struggled to correctly identify the origin of an image. To mitigate this, a dual strategy was adopted:

- Manual review by domain experts to validate and correct labels for ambiguous samples.
- Automated filtering techniques using metadata, source tracking, and perceptual hashing to remove mislabelled or low-quality samples.

Maintaining label accuracy was critical, as mislabelled data could significantly impact model learning and lead to false generalizations.

8.2 Overfitting Risks

The powerful representation capacity of Vision Transformers, while advantageous, also posed risks of overfitting—especially when training on a dataset with limited diversity or noisy labels. Early experiments showed that the model could achieve high training accuracy while failing to generalize well to unseen validation or test data. To combat this:

- Data augmentation techniques such as random cropping, flipping, color jittering, and rotation were extensively used to increase variability and robustness.
- Dropout layers were integrated into the model architecture with a carefully tuned dropout rate (0.1) to prevent reliance on specific neurons.
- Early stopping based on validation accuracy was employed to halt training before overfitting became significant.

This multi-pronged approach helped in improving the model's ability to generalize beyond the training data.

8.3 Computational Resource Constraints

Training a ViT model is computationally intensive, often requiring prolonged GPU usage and large-scale memory handling. This presented logistical and financial constraints, particularly in the early development phases. The model's training process involved:

- Use of high-end GPUs (e.g., NVIDIA A100s or V100s), which were accessed through cloud platforms like AWS, Google Cloud, or Azure.

- Careful optimization of batch sizes and gradient accumulation strategies to balance memory efficiency with convergence speed.
- Leveraging mixed precision training (via frameworks like PyTorch AMP) to reduce memory usage and speed up training without sacrificing model performance.

Despite these optimizations, resource limitations influenced the frequency and extent of hyperparameter tuning and ablation studies.

8.4 Generalization to New Generators

One of the most pressing challenges is the rapid evolution of AI face generation models. As new generative adversarial networks (GANs), diffusion models, and transformer-based image synthesis methods emerge, previously trained models may struggle to detect synthetic faces created using these novel architectures. This poses a significant issue for long-term generalization and real-world robustness.

To address this dynamic landscape:

- The need for continual learning approaches was identified, where the model is incrementally updated with data from new generators without catastrophic forgetting.
- Exploration into meta-learning or few-shot learning paradigms was considered to quickly adapt to new domains with limited examples.
- Routine benchmarking on emerging synthetic datasets was recommended as part of the model maintenance pipeline.

These strategies represent promising directions for future work aimed at maintaining detection accuracy in a constantly evolving adversarial environment.

9. FUTURE_SCOPE

While the current study has demonstrated promising results in distinguishing AI-generated faces from real human faces using Vision Transformers (ViTs), there are several avenues for future exploration to enhance the model's accuracy, robustness, and real-world applicability. These directions aim to address both technical limitations and the evolving nature of generative technologies.

• Expanding the Dataset with New AI-Generated Face Types

As generative models such as StyleGAN3, DALL·E, MidJourney, and diffusion-based architectures continue to evolve, so do the characteristics of synthetic faces. Future work should focus on continuously enriching the dataset with examples generated from the latest models to ensure the classifier remains effective. This would include:

- Collecting and curating datasets from diverse GAN and diffusion frameworks.
- Including AI-generated faces across varied demographics, emotions, and occlusion conditions.
- Maintaining class balance and label integrity to support fair training.

A diverse and up-to-date dataset is critical for preserving the model's relevance and generalization to unseen generative techniques.

• Exploring ViT-CNN Hybrid Architectures

Although ViTs excel in capturing global context through self-attention mechanisms, they may sometimes underperform in capturing fine-grained local textures—an area where CNNs traditionally excel. Future iterations could explore hybrid architectures that combine:

- CNN layers in early stages for local feature extraction.
- Transformer blocks in later stages for global reasoning.

Such hybrid models could potentially offer the best of both worlds, improving the model's sensitivity to subtle artifacts in synthetic faces.

• Introducing Adversarial Training for Robustness

To enhance the model's robustness against adversarial attacks and synthetic face manipulations, adversarial training can be integrated. This involves:

- Augmenting the training process with perturbed or intentionally manipulated images.
- Training the model to resist gradient-based attacks such as FGSM or PGD.

By exposing the model to challenging edge cases during training, its ability to distinguish sophisticated forgeries in real-world settings can be significantly improved.

• Implementing Model Compression for Edge Deployment

Given the computational demands of ViT models, deploying them on edge devices (e.g., smartphones or embedded systems) remains a challenge. Future work should investigate model compression techniques such as:

- Pruning: Removing less important neurons or attention heads.
- Quantization: Converting model weights to lower-precision formats.

- Knowledge distillation: Training a smaller student model to mimic the predictions of the larger ViT.

These strategies would allow the deployment of a lightweight version of the model without compromising much on accuracy, making it viable for real-time applications on resource-constrained devices.

• Integrating Continual Learning Strategies

To ensure the model adapts to the fast-paced evolution of generative AI, continual learning mechanisms should be incorporated. This includes:

- Incremental learning pipelines where new data from emerging generators is periodically used to update the model.
- Techniques like Elastic Weight Consolidation (EWC) or Replay Buffers to prevent catastrophic forgetting.
- Designing a training protocol that balances stability (retaining old knowledge) and plasticity (learning new patterns).

Continual learning will be essential for keeping the system reliable and effective as synthetic face generation techniques grow more sophisticated.

By building upon these future directions, the model can evolve into a more robust, adaptive, and deployable solution for AI-generated content detection. These advancements will not only increase technical performance but also widen the practical applicability across industries such as digital forensics, media authentication, and identity verification.

10. CONCLUSION

This project successfully demonstrated the potential of Vision Transformers (ViTs) in effectively distinguishing AI-generated (deepfake) human faces from authentic ones. By leveraging the ViT-Base/16 model, pretrained on ImageNet-21k and fine-tuned on a balanced large-scale dataset of 200,000 images (from the Kaggle "Real vs. AI Visuals" dataset), the study achieved robust performance metrics 93% test accuracy, AUC of 0.99, and F1-score of 0.93 per class. These results highlight the superior generalization capability of ViTs over traditional CNN-based detectors, especially in scenarios where local texture-based cues may not suffice.

The project's strength lies not only in raw performance but also in its comprehensive approach meticulous preprocessing (224×224 resizing, normalization, color jitter, and horizontal flipping), efficient training with AdamW optimizer, and extensive error analysis using confusion matrices and visual inspection of misclassified images. It specifically exposed key vulnerabilities in detection, such as low-resolution or compressed frames and real faces with makeup or lighting artifacts misclassified as fake, showing that while ViTs capture global context well, domain-specific challenges remain.

These insights have practical significance for digital forensics, social media content moderation, and online identity protection. As synthetic face generation technologies like StyleGAN2 and diffusion models become increasingly photorealistic, developing resilient detection systems becomes a cornerstone for combating misinformation, identity fraud, and deepfake proliferation.

Moreover, this research lays a strong foundation for future work in explainable AI, hybrid model architectures (such as CNN-ViT ensembles), and the ethical deployment of AI in facial recognition systems. Suggestions for future innovation include lightweight ViTs for edge deployment, temporal modelling for video deepfakes, and enhanced interpretability through attention-map visualizations all crucial for building trustworthy and scalable AI solutions in an era of generative media.

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