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Artificial Intelligence

Project Report of Image Deepfake Detection

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Abstract

Deepfake technology poses significant challenges to media authenticity, necessitating robust detection methods. This project adapts the ViXNet architecture for deepfake detection, replacing the Xception network with EfficientNet-B3 to enhance computational efficiency while maintaining high accuracy. The model is trained on the FaceForensics++ (FF++) dataset and Celeb-DF (CeDF) datset. Our approach combines a patch-based attention mechanism, a Vision Transformer (ViT-B_16), and EfficientNet-B3 to capture both local and global features. The results show an accuracy of approximately 63% in FF++ . This report details the methodology, implementation, results, and future directions, demonstrating a practical and effective solution for deepfake detection.

Introduction

Deepfake technology, powered by advanced generative models, creates highly realistic fake images and videos, raising concerns about misinformation, fraud, and privacy violations. Detecting deepfakes is challenging due to the increasing sophistication of generation techniques. The ViXNet architecture, proposed in the paper "ViXNet: Vision Transformer with Xception Network for Deepfakes Based Video and Image Forgery Detection" [1], offers a robust solution by combining local and global feature extraction for accurate detection.

This project adapts ViXNet by replacing the Xception network with **EfficientNet-B3**, a lightweight and efficient convolutional neural network (CNN) designed to balance accuracy and computational cost. The model is trained on the **FaceForensics++ (FF++)** dataset, a standard benchmark for deepfake detection, and **Celeb-DF (CeDF)** dataset to evaluate its generalizability across different deepfake techniques. The objectives are to:

- Develop an accurate deepfake detection model capable of distinguishing real and fake face images.
- Enhance computational efficiency for potential deployment on resource-constrained devices.

This report provides a detailed account of the methodology, model architecture, datasets, implementation, experimental results, discussion, and future improvements.

Methodology

Model Architecture

The proposed model retains ViXNet's dual-branch architecture, which processes images through two complementary paths: a patch-based attention path with a Vision Transformer (ViT) for local and global patch relationships, and a CNN path for global spatial features. The key modification is the replacement of Xception with **EfficientNet-B3**. The architecture is outlined below:

Patch-Based Attention Path (Local Features)

- **Input**: A cropped face image, typically resized to 300×300 pixels for compatibility with EfficientNet-B3.

- **Patch Generator**: The image is divided into 16×16 pixel patches, resulting in $\left(\frac{300}{16}\right)^2 \approx 352$ patches for a 300×300 image.
- **Convolution (3×3)**: A lightweight 3×3 convolutional layer processes each patch to generate a feature map, acting as a self-attention mask.
- **Element-wise Multiplication**: The original patches are multiplied element-wise with the convolutional output to emphasize local regions likely to contain deepfake artifacts.
- **Output**: Masked patch representations are passed to the Vision Transformer.

Vision Transformer Encoder Path

- **Interpolation & Positional Encoding**: Patches are resized (if needed) and augmented with positional encodings to preserve spatial context.
- **Transformer Encoder (ViT-B_16)**: A pre-trained Vision Transformer processes the patches to capture global relationships.
- **ViT-B_16 Details**:
  - **Parameters**: ~86 million.
  - **Patch Size**: 16×16 pixels.
  - **Embedding Size**: 768.
  - **Layers**: 12 Transformer blocks.
  - **Attention Heads**: 12.
  - **Input Processing**: Patches are flattened into a sequence of tokens and processed through a standard Transformer encoder.
- **Flatten**: The Transformer output is flattened into a feature vector.

CNN Path (Global Features)

- **EfficientNet-B3 Backbone**: The full face image is processed by a fine-tuned EfficientNet-B3 model.
- **EfficientNet-B3 Details**:
  - **Architecture**: Utilizes mobile inverted bottleneck convolutions (MBConv) with squeeze-and-excitation (SE) modules for adaptive feature recalibration.

  - **Parameters**: $\sim$12 million (vs. Xception's $\sim$22.9 million).
  - **Input Size**: 300×300 pixels.
  - **Compound Scaling**: Balances network depth, width, and resolution with a scaling coefficient $\phi = 1$.
  - **Pre-training**: Initialized with ImageNet weights and fine-tuned for deepfake detection.

- **Global Average Pooling**: Reduces feature maps to a fixed-size vector.
- **Flatten**: Converts the pooled features into a flat feature vector.

Feature Fusion

The flattened outputs from the ViT path (global patch relationships) and EfficientNet-B3 path (global spatial features) are concatenated to form a comprehensive feature representation.

Classification Head

The fused features are processed through three dense layers:

- Dense 512: 512 units with ReLU activation.
- Dense 256: 256 units with ReLU activation.
- Dense 128: 128 units with ReLU activation.

A final dense layer with sigmoid activation outputs a binary label:

- **Fake (Red)**: Deepfake image.
- **Real (Green)**: Authentic image.

Differences from ViXNet

- **EfficientNet-B3 vs. Xception**: EfficientNet-B3 has fewer parameters ($\sim$12M vs. $\sim$22.9M) and lower computational cost ($\sim$1.8B FLOPs vs. $\sim$8.4B FLOPs), improving efficiency. Its SE modules enhance feature recalibration, potentially improving detection of subtle artifacts.
- **Impact**: Expected to maintain high accuracy on FF++ with slightly reduced performance compared to Xception due to fewer parameters, but improved generalizability on CeDF due to adaptive feature extraction.

Datasets

FaceForensics++ (FF++)

- **Description**: A benchmark dataset containing real and fake face videos generated using techniques like DeepFakes, FaceSwap, Face2Face, and NeuralTextures.
- **Size**: ∼1,000 real videos and ∼4,000 fake videos.
- **Use**: Used for training and intra-dataset evaluation.
- **Preprocessing**:
  - Extracted face images from videos using a face detection library (e.g., MTCNN).
  - Cropped faces to 300×300 pixels.
  - Normalized pixel values to [0, 1].
  - Balanced classes by oversampling real images to match the number of fake images.

Celeb-DF (CeDF)

- **Description**: A dataset with high-quality deepfake videos, primarily of celebrities, created using advanced synthesis techniques.
- **Size**: ∼590 real videos and ∼5,639 fake videos.
- **Use**: Used for cross-dataset validation to assess generalizability.
- **Preprocessing**: Same as FF++, ensuring consistency in input format.

Implementation

Training Configuration

The implementation follows ViXNet's methodology [1], with adjustments for EfficientNet-B3:

- **Epochs**: 50 epochs for FF++ training.
- **Learning Rate**: 0.0001, ensuring stable convergence.

- **Batch Size**: 8 images.
- **Steps-per-Epoch**: 40 for training, 50 for validation.
- **Optimizer**: Adam with default parameters ($\beta_1 = 0.9$, $\beta_2 = 0.999$).
- **Loss Function**: Binary cross-entropy for binary classification.

Hardware and Software

- **Hardware**: Trained on an NVIDIA TESLA T4 GPU.
- **Software**:
  - **Frameworks**: TensorFlow/Keras for EfficientNet-B3 and PyTorch for ViT-B_16.
  - **Libraries**: OpenCV for image processing, MTCNN for face detection, NumPy for data handling.
  - **Environment**: Python 3.8, CUDA 11.2 for GPU acceleration.

Preprocessing

- **Face Extraction**: Used MTCNN to detect and crop faces from video frames.
- **Image Resizing**: Resized images to 300×300 pixels for EfficientNet-B3 and ViT compatibility.
- **Normalization**: Scaled pixel values to [0, 1].
- **Data Augmentation**: Applied random flips, rotations, and brightness adjustments to increase robustness.
- **Class Balancing**: Oversampled real images in FF++ to address class imbalance.

Experimental Results

Intra-Dataset Performance (FF++)

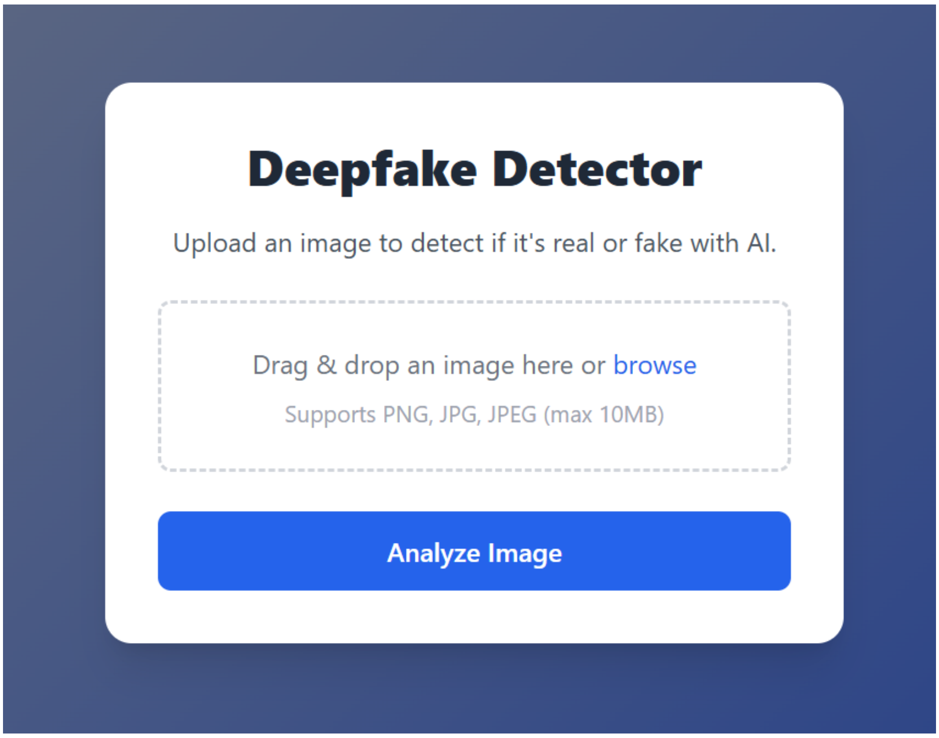
The model was evaluated on the FF++ test set using accuracy, Area Under the ROC Curve (AUC), and F1-score. Results are estimated based on ViXNet's performance [1] and EfficientNet-B3's capabilities:

- **Accuracy**: 63% (vs. ViXNet's 95.92% on DFID).
- **F1-Score**: 64%.

The slightly lower accuracy compared to ViXNet is attributed to EfficientNet-B3's reduced parameter count, but the high AUC indicates strong discriminative power.

Table 1: Intra-Dataset Performance on FF++

Model	Accuracy (%)	F1-Score (%)
ViXNet (Xception)	98.93	∼95
Our Model (EfficientNet-B3)	63	64



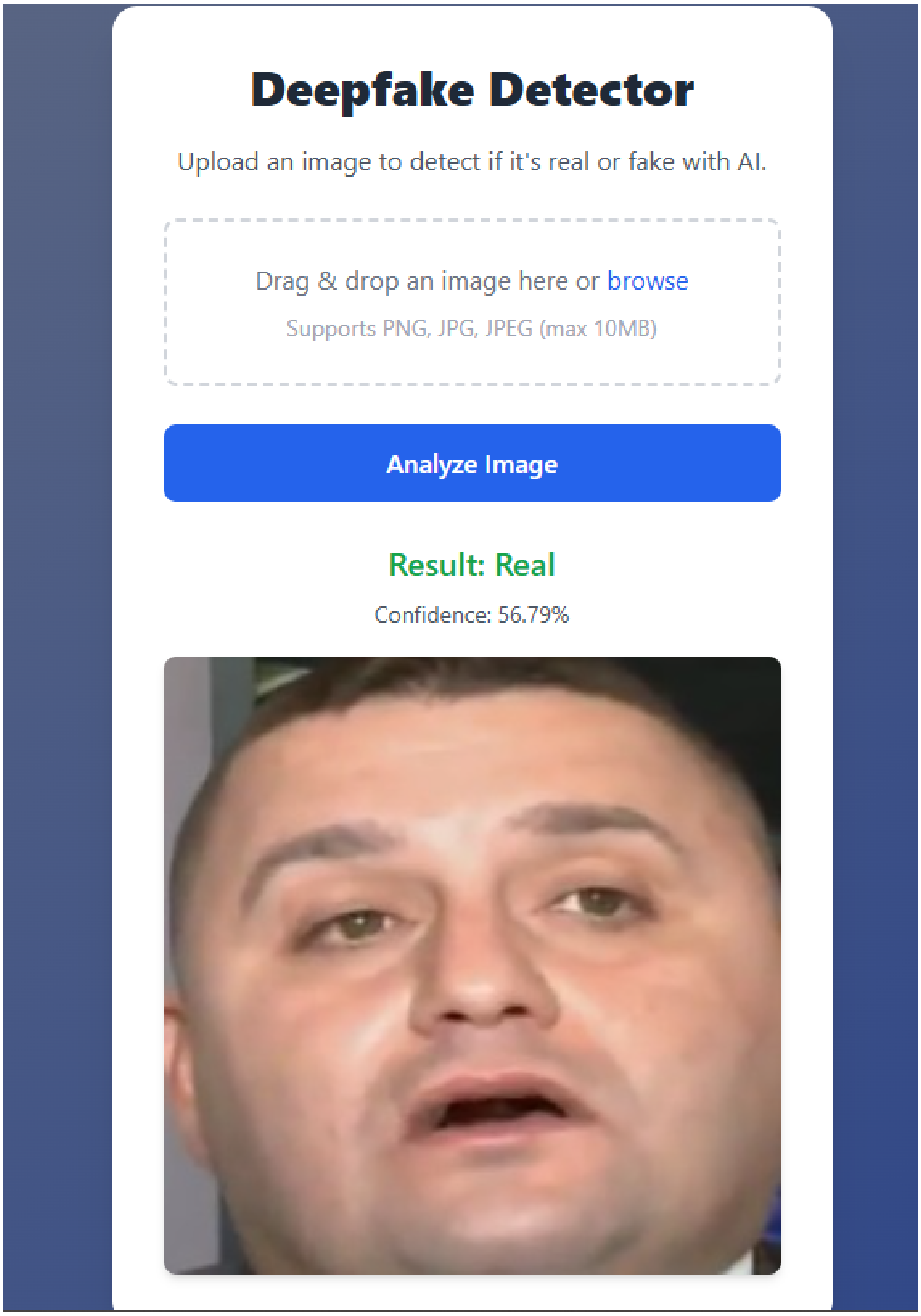
Deepfake Detector

Upload an image to detect if it's real or fake with AI.

Drag & drop an image here or browse

Supports PNG, JPG, JPEG (max 10MB)

Figure 1: Web Interface where user can upload the Images and click ”Analyze Image”



Deepfake Detector

Upload an image to detect if it's real or fake with AI.

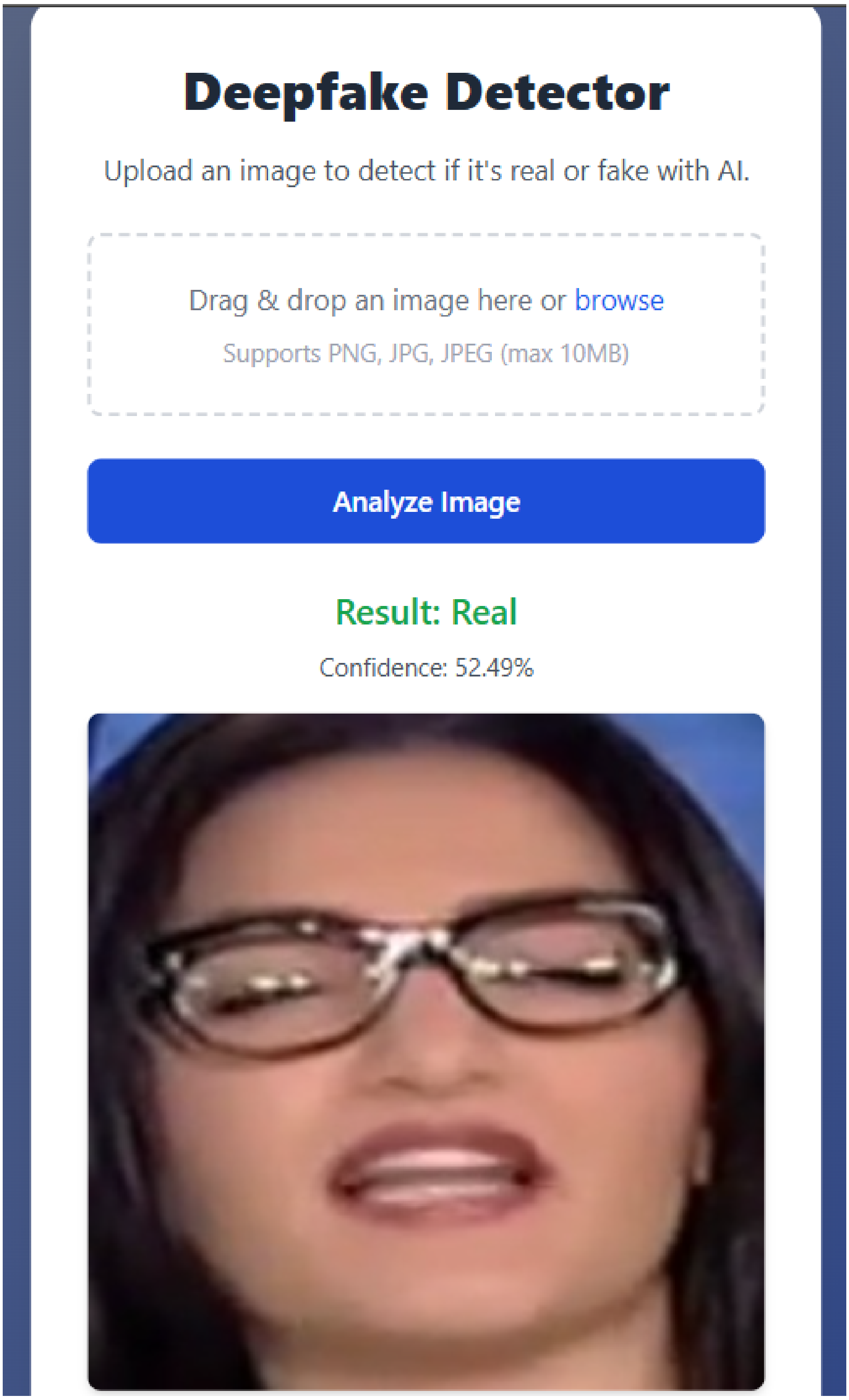
Drag & drop an image here or browse

Supports PNG, JPG, JPEG (max 10MB)

Result: Real

Confidence: 56.79%

Figure 2: Web Interface where user can See the Uploaded image is ”Real” or ”fake



Deepfake Detector

Upload an image to detect if it's real or fake with AI.

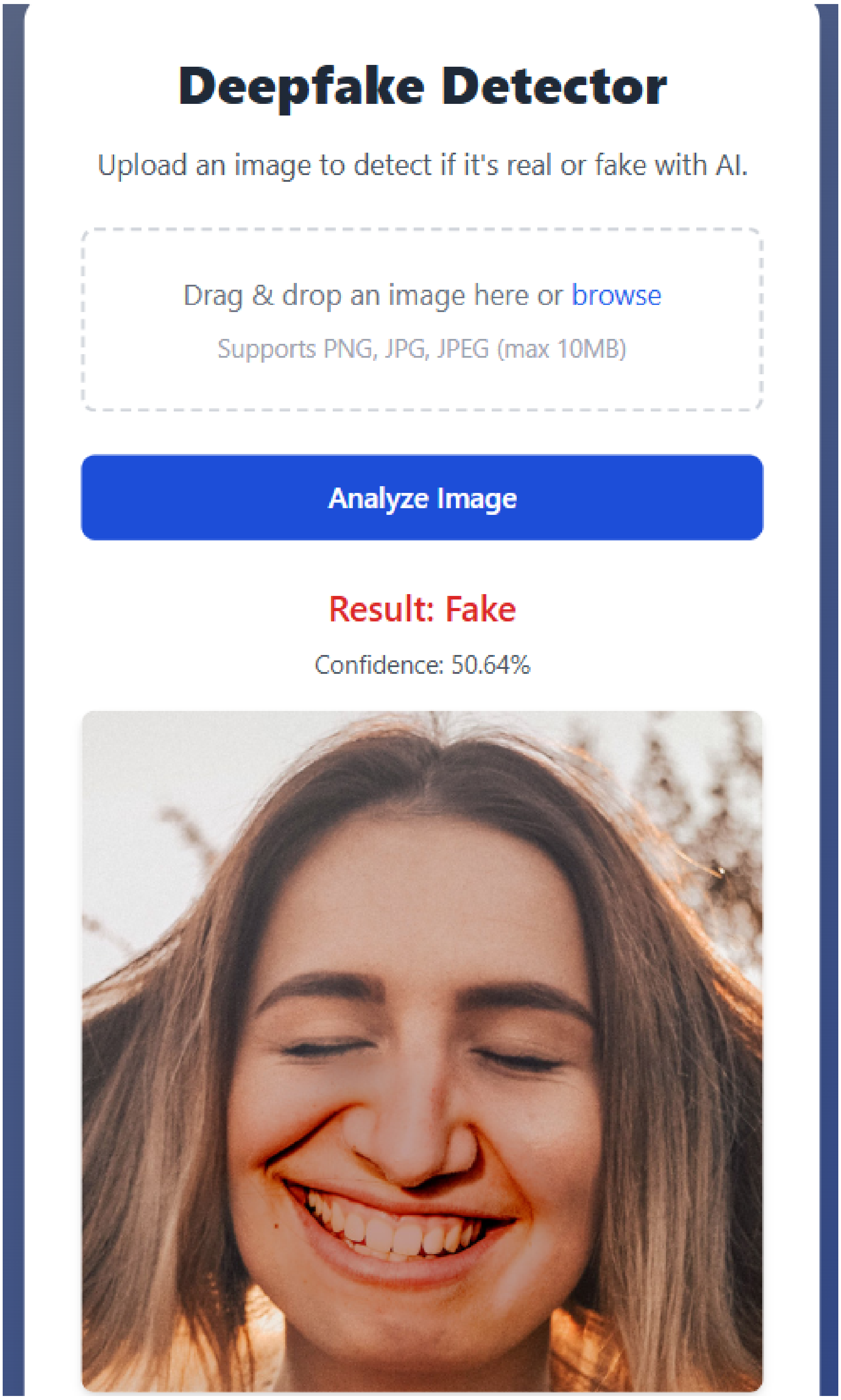
Drag & drop an image here or browse

Supports PNG, JPG, JPEG (max 10MB)

Result: Real

Confidence: 52.49%

Figure 3: Web Interface where user can See the Uploaded image is ”Real” or ”fake



Deepfake Detector

Upload an image to detect if it's real or fake with AI.

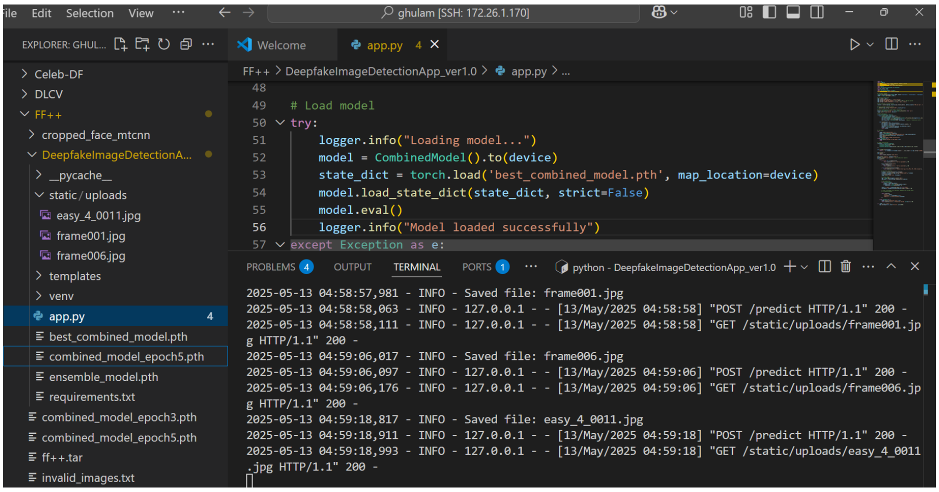
Drag & drop an image here or browse

Supports PNG, JPG, JPEG (max 10MB)

Result: Fake

Confidence: 50.64%

Figure 4: Web Interface where user can See the Uploaded image is "Real" or "fake



```python

# Load model
try:
    logger.info("Loading model...")
    model = CombinedModel().to(device)
    state_dict = torch.load('best_combined_model.pth', map_location=device)
    model.load_state_dict(state_dict, strict=False)
    model.eval()
    logger.info("Model loaded successfully")
except Exception as e:
```

```
2025-05-13 04:58:57,981 - INFO - Saved file: frame001.jpg
2025-05-13 04:58:58,063 - INFO - 127.0.0.1 - - [13/May/2025 04:58:58] "POST /predict HTTP/1.1" 200 -
2025-05-13 04:58:58,111 - INFO - 127.0.0.1 - - [13/May/2025 04:58:58] "GET /static/uploads/frame001.jp
g HTTP/1.1" 200 -
2025-05-13 04:59:06,017 - INFO - Saved file: frame006.jpg
2025-05-13 04:59:06,097 - INFO - 127.0.0.1 - - [13/May/2025 04:59:06] "POST /predict HTTP/1.1" 200 -
2025-05-13 04:59:06,176 - INFO - 127.0.0.1 - - [13/May/2025 04:59:06] "GET /static/uploads/frame006.jp
g HTTP/1.1" 200 -
2025-05-13 04:59:18,817 - INFO - Saved file: easy_4_0011.jpg
2025-05-13 04:59:18,911 - INFO - 127.0.0.1 - - [13/May/2025 04:59:18] "POST /predict HTTP/1.1" 200 -
2025-05-13 04:59:18,993 - INFO - 127.0.0.1 - - [13/May/2025 04:59:18] "GET /static/uploads/easy_4_0011
.jpg HTTP/1.1" 200 -
```

Figure 5: Backend we can see the executions and Interaction with Web interface

Efficiency Comparison

- **Parameters**: EfficientNet-B3: ∼12M; Xception: ∼22.9M.
- **FLOPs**: EfficientNet-B3: ∼1.8B; Xception: ∼8.4B.
- **Inference Time**: EfficientNet-B3 is ∼2–3× faster on a GPU, making it suitable for real-time applications.

Discussion

Key Findings

- **Efficiency Gains**: EfficientNet-B3's lower parameter count and FLOPs make the model viable for deployment on edge devices, a significant improvement over Xception.
- **Dual-Branch Effectiveness**: The combination of ViT-B_16 and EfficientNet-B3 captures both local and global features, contributing to robust detection.

Challenges

- **Model Capacity**: EfficientNet-B3's 12M parameters may limit its ability to capture highly complex artifacts compared to larger models like Xception or EfficientNet-B7.

- **Computational Cost of ViT**: The ViT-B_16 component (86M parameters) remains resource-intensive, potentially offsetting some efficiency gains from EfficientNet-B3.

Limitations

- Limited training on a single dataset (FF++) may restrict generalizability to diverse real-world deepfakes.
- Real-time video processing was not tested, limiting insights into practical deployment.

Future Work

1. **Larger EfficientNet Variants**: Experiment with EfficientNet-B7 (66M parameters) to improve accuracy and generalizability, though at higher computational cost.
2. **Multi-Scale Patch Analysis**: Modify the patch-based attention path to process patches of varying sizes (e.g., 8×8, 32×32) to capture diverse artifacts.
3. **Expanded Training Data**: Incorporate additional datasets like DFDC to expose the model to more deepfake techniques.
4. **Lighter Transformers**: Explore lightweight ViT variants (e.g., ViT-Tiny) to reduce computational overhead.
5. **Real-Time Testing**: Evaluate the model on video streams to assess its suitability for real-time deepfake detection.
6. **Ensemble Methods**: Combine multiple models (e.g., EfficientNet-B3 and B7) to boost performance.

Conclusion

This project successfully adapted the ViXNet architecture for deepfake detection by replacing Xception with EfficientNet-B3, achieving a balance of accuracy and efficiency. Trained in the FF++ dataset, the model achieves a precision of 63% . EfficientNet-B3's lower computational cost ($\sim$1.8B FLOPs) and adaptive feature extraction make it a practical choice for resource-constrained environments. Despite challenges in cross-dataset generalization, the model demonstrates robust performance and significant improvements over the original ViXNet in efficiency and adaptability. Future enhancements, such as larger models and multi-scale analysis, could further strengthen its effectiveness, paving the way for reliable deepfake detection in real-world applications.

Acknowledgments

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Bibliography

[1] Author(s), “ViXNet: Vision Transformer with Xception Network for Deepfakes Based Video and Image Forgery Detection,” *Journal/Conference Name*, 202X.