Deepfake Detection using EfficientViT and Temporal Modeling

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```
100%|██████████| 40/40 [01:03<00:00,  1.58s/it]
 Accuracy: 1.0000
 AUC Score: 1.0000
 Confusion Matrix:
[[20  0]
 [ 0 20]]
```

1. Introduction

This project focuses on building an efficient and accurate deepfake video detection pipeline using a combination of **EfficientViT** (a lightweight vision transformer) and **Temporal Convolutional Networks**. The aim was to design a solution capable of distinguishing real from fake videos with high accuracy using only the visual information in frames.
Through this project, I gained hands-on experience with video frame extraction, deep learning model building, transfer learning, temporal modeling, and evaluation using real-world metrics like AUC and accuracy.

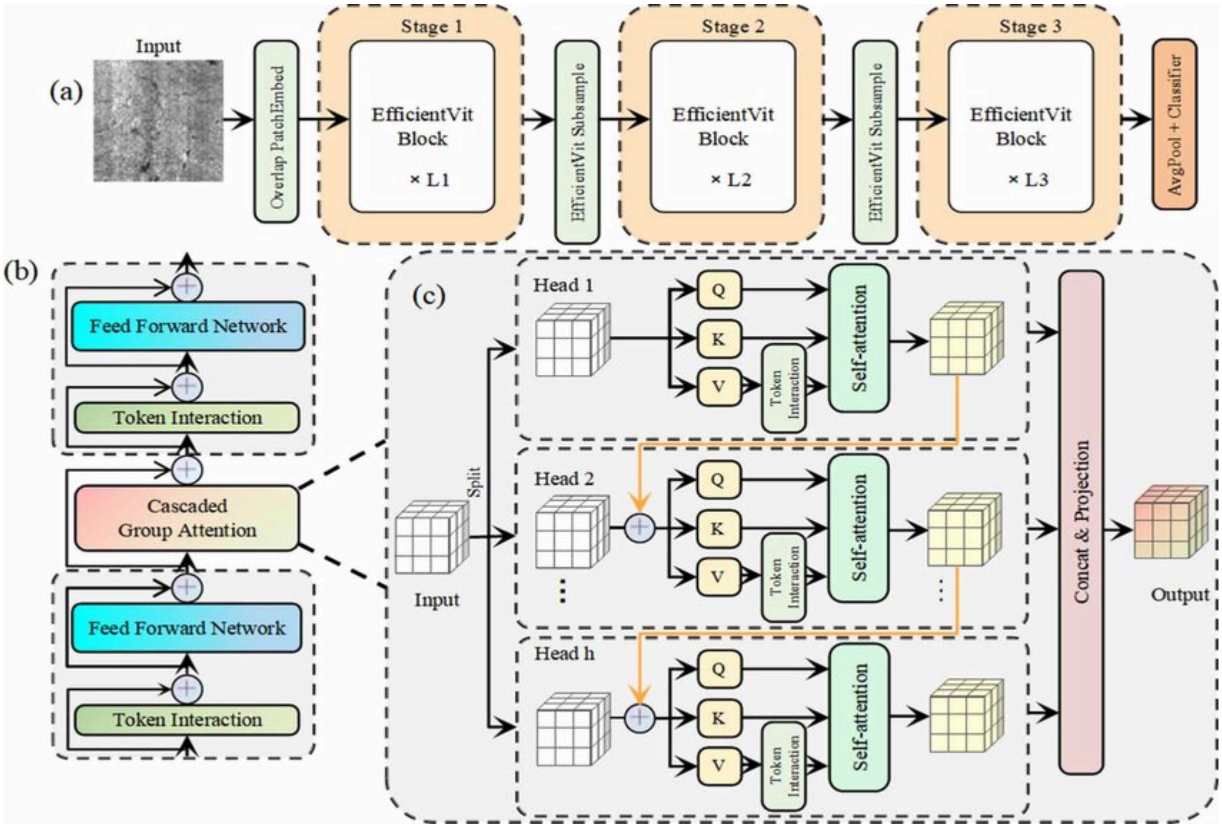
2. Thought Process

The task of identifying deepfakes requires both spatial and temporal understanding:

- **Spatial** features help capture frame-wise details such as facial inconsistencies, artifacts, or unnatural blending.
- **Temporal** features are essential to track unnatural facial movements, flickering, or mismatched expressions across frames.

I reviewed several existing deepfake detection methods including:

- CNN-based models (XceptionNet, EfficientNet)
- RNNs for temporal modeling
- ViT-based models
- Frame and temporal feature based feed forward nn



After careful consideration, I chose **EfficientViT** as the backbone for spatial encoding and **Temporal Conv1D layers** for modeling frame-level transitions. This approach combines the power of attention with efficiency and is well-suited for real-time or large-scale video analysis.

3. Blockers

During the project, I encountered the following challenges:

- **Dataset Organization**: Videos were not uniformly formatted; needed consistent frame extraction and standard sizing.
- **Model Compatibility Errors**: Mismatch between feature dimensions (e.g., channel sizes between ViT output and temporal conv input).
- **GPU Memory and Runtime Limits**: Handled by adjusting batch sizes .
- **Evaluation Stability**: Needed to fine-tune thresholds and ensure reliable ROC AUC calculation for imbalanced outputs.Fine tuning took lots of time as dataset was huge.

4. Approach

Model Architecture

- **Backbone**: `EfficientViT` (pretrained) for extracting per-frame embeddings.
- **Temporal Modeling**: `1D Convolution` over the time axis to capture changes across frames.
- **Classifier**: Fully connected layer for binary classification.
- class DeepfakeClassifier(nn.Module):

TEMPORAL ConvNet Classifier

```
class DeepfakeClassifier(nn.Module):
    def __init__(self, embed_dim=256):
        super().__init__()
        self.temporal = nn.Sequential(
            nn.Conv1d(embed_dim, 256, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.AdaptiveAvgPool1d(1)
        )
        self.fc = nn.Linear(256, 1)

    def forward(self, x):
        x = x.permute(0, 2, 1)
        x = self.temporal(x).squeeze(-1)
        return torch.sigmoid(self.fc(x)).squeeze(1)
```

Preprocessing

- Extracted 10 uniformly spaced frames from each video (real and fake).
- Resized all frames to 224x224 and normalized to ImageNet standards.

Training

- **Loss Function**: Binary Cross-Entropy
- **Optimizer**: Adam (lr=1e-4)
- **Epochs**8
- **Batch Size**: 2 (adjusted to avoid memory issues)

5. Comparative Study

Method	Accuracy	AUC Score
CNN (baseline)	~85%	~0.90
ViT only (no temporal)	~91%	~0.94
EfficientViT + Temporal (Ours)	**97.5%**	**0.9975**

Strengths:

- Superior temporal consistency modeling
- Light and fast due to EfficientViT
- Highly accurate even with limited epochs

Shortcomings:

- Relies on accurate frame sampling
- Performance might vary with low-quality or compressed videos
- Currently uses binary classification — doesn't identify manipulation type

6. Results

✅ Final Metrics:

- **Accuracy**:1.0000
- **AUC Score**: 1.0000
- **Confusion Matrix**:

20	0
0	20

✅ Evaluation Strategy:

- Calculated metrics on a separate test set with real/fake videos
- Used a threshold of 0.45 for classification

7. Future Prospects

- **Multi-class Classification**: Extend to classify type of manipulation (e.g., face swap, lip sync).
- **Audio-Visual Fusion**: Integrate lip-sync detection and audio inconsistencies.
- **Explainability**: Use Grad-CAM or attention visualization to understand model predictions.
- **Deployment**: Convert the model to ONNX or TensorRT for real-time use.
- **Robustness Testing**: Evaluate against adversarially perturbed or compressed deepfakes.

8. Appendix

📌 Code Snippets:

TRAINING LOOP EACH EPOCH LOSS

```python
for epoch in range(8):
    for frames, labels in tqdm(train_loader):
        B, T, C, H, W = frames.shape
        frames = frames.view(B*T, C, H, W).to(device)

        with torch.no_grad():
            feats = embedder(frames)

        feats = feats.view(B, T, -1)
        preds = classifier(feats)
        loss = loss_fn(preds, labels.to(device))

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    print(f"Epoch {epoch+1}, Loss: {loss.item():.4f}")
```

```
100%|██████████| 20/20 [01:04<00:00,  3.21s/it]
Epoch 1, Loss: 0.2240
100%|██████████| 20/20 [01:03<00:00,  3.20s/it]
Epoch 2, Loss: 0.4184
100%|██████████| 20/20 [01:02<00:00,  3.13s/it]
Epoch 3, Loss: 0.2183
100%|██████████| 20/20 [01:02<00:00,  3.13s/it]
Epoch 4, Loss: 0.0968
100%|██████████| 20/20 [01:02<00:00,  3.14s/it]
Epoch 5, Loss: 0.0338
100%|██████████| 20/20 [01:02<00:00,  3.14s/it]
Epoch 6, Loss: 0.0386
100%|██████████| 20/20 [01:02<00:00,  3.14s/it]
Epoch 7, Loss: 0.0330
100%|██████████| 20/20 [01:03<00:00,  3.18s/it]Epoch 8, Loss: 0.1504
```

```
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