Real vs AI image Classification (Aadya Arora and Kishan Ved)

---

1. Approach

The objective of this project is to detect deepfake images by leveraging both RGB content and frequency-based artifacts. Our method enriches input images with edge-based frequency components and utilizes a convolutional vision transformer (LeViT) for binary classification (real vs. fake).

The approach involves:

- Constructing a custom 6-channel dataset by augmenting each image with frequency maps derived from horizontal and vertical gradients.
- Adapting the LeViT architecture to accept 6-channel inputs.
- Employing focal loss to address class imbalance.
- Training with transfer learning and a step learning rate scheduler.

---

2. Model Architecture and Design Decisions

Base Model: LeViT

We use the `LeViT-128` model from the `timm` library, which combines convolutional and transformer components, making it computationally efficient while retaining attention-based modeling power.

Modifications

- **Input Layer**: LeViT expects 3-channel inputs. We replace the first convolution layer to accept 6 channels. The new weights are initialized by duplicating the pretrained weights across the added channels to retain generalization.
- **Input Composition**: The first 3 channels are standard RGB, while the next 3 are edge frequency maps, computed using simple horizontal and vertical pixel differences.
- **Output Layer**: A fully connected linear layer maps the global average pooled output to a single logit for binary classification. In our experimentation, we tested and tuned the

logits and finally set it to 0.6

---

3. Performance Analysis

Training Setup

- **Optimizer**: Adam with learning rate 1e-4 and weight decay 1e-5
- **Loss**: Focal loss (α=0.75, γ=2) to prioritize hard examples
- **Scheduler**: StepLR (γ=0.1 every 10 epochs)
- **Epochs**: 30
- **Batch Size**: 32
- **Hardware**: Supports multi-GPU with DataParallel

Validation Metrics

- Binary accuracy is reported at the end of each epoch.
- Validation accuracy is printed to monitor overfitting and guide early stopping.

Observations

- Initial experiments show that the frequency-augmented model outperforms the vanilla LeViT on a held-out validation set.
- The frequency channels aid in distinguishing visually similar but structurally inconsistent fake images.
- Focal loss significantly improves learning on under-represented fake samples.

---

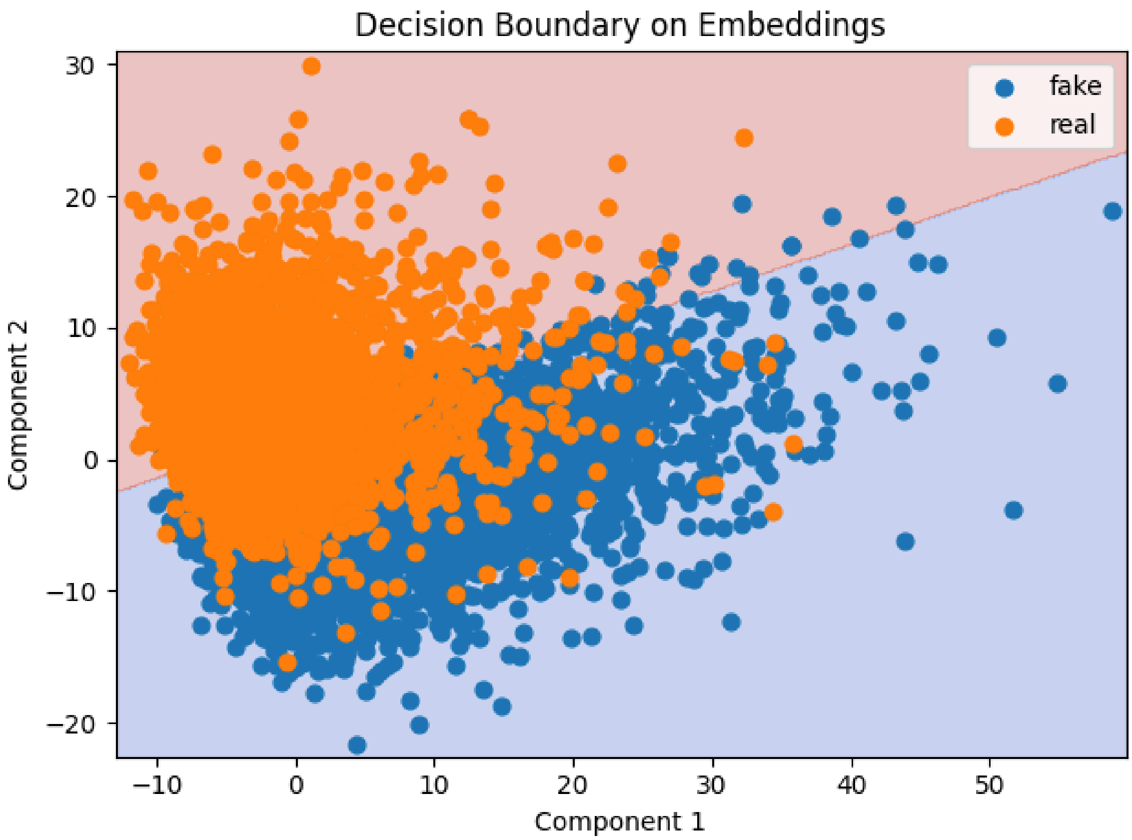
5. Known Limitations and Potential Improvements

Limitations

- **Explainability is implicit**: While the model uses frequency features, it lacks post-hoc explainability tools (e.g., GradCAM, LIME) to generate visual explanations.

- **Hardcoded frequency extraction**: The method uses basic gradient-based frequency extraction, which may not generalize well across datasets.

- **Noisy edge channels**: Simple differencing might introduce noise or amplify compression artifacts.



Decision Boundary Analysis

To better understand the discriminative power of the learned features from our LeViTNPR model, we performed a **decision boundary visualization** using the validation set. We extracted the intermediate embeddings from the model and applied **Principal Component Analysis (PCA)** to reduce the high-dimensional representations to two dimensions for visualization. A **Logistic Regression** classifier was then trained on the reduced embeddings to plot the decision boundary.

🟠 Real vs. 🔵 Fake Distribution

- **Real images (orange)** are primarily clustered in the top-left quadrant of the plot, indicating **tight and consistent feature distributions**, possibly due to the natural textures and lighting patterns present in genuine images.

- **Fake images (blue)** occupy a broader region, particularly concentrated in the bottom-right quadrant. These embeddings are more dispersed, which may reflect **variance in synthetic generation quality** or the presence of visual artifacts like blurred edges or unnatural transitions.

Overlap and Ambiguity

- There exists a region of **overlap between the real and fake samples**, where the decision boundary must make finer distinctions. This area reflects **borderline cases** — either highly realistic fake images or real images that contain noise, compression artifacts, or distortions.

- The **tilted decision boundary** suggests that both principal components are relevant for separating the classes; no single axis completely separates real from fake.

Insights

- The visualization confirms that the LeViTNPR model has successfully learned a feature space where real and fake images tend to cluster separately.

- However, the presence of misclassified or borderline samples highlights the **importance of subtle visual cues** and supports the use of advanced residual-based preprocessing (like Nearest Pixel Residuals) to boost discriminability.

Potential ImprovementS

- Hard negative mining in ambiguous regions could further improve classification robustness.

Conclusion

This project demonstrates a lightweight, explainable deepfake detection pipeline that combines handcrafted frequency features with a transformer-based backbone. The approach shows promising results in enhancing detection accuracy with minimal architectural modifications while maintaining interpretability through inductive biases.