TRUTH IN MOTION

DEPTH AND FLOW ENHANCED DEEPFAKE DETECTION

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WHAT IS A DEEPFAKE?

A *deepfake* is a type of media (video, audio, or image) altered using artificial intelligence to make it appear that someone said or did something they never actually did.

It uses neural networks, especially GANs, to realistically replace faces or voices.

Deepfakes can be used for satire, art, or, unfortunately, for manipulation and disinformation.

DEEPFAKE DETECTION: STATE OF ART

Deepfake Video Detection through Optical Flow based CNN

- optical flow fields
- CNN to highlight inter-frame motion inconsistencies

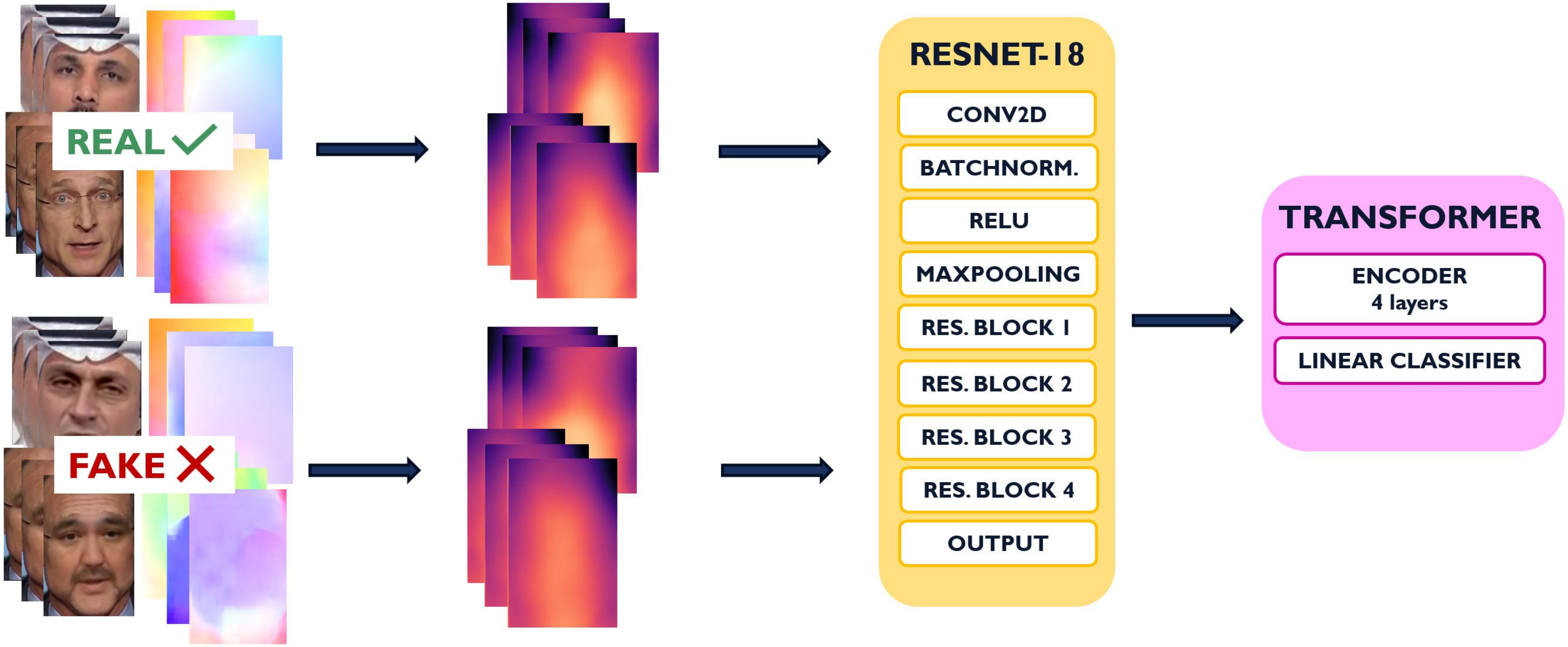
FaceForensics++: Learning to Detect Manipulated Facial Images

- large-scale benchmark
- deep learning detectors
- >99% accuracy on raw and >95% on compressed data

Improved Optical Flow Estimation Method for Deepfake Videos

- optical flow estimation
- CNN classifiers
- ~82% accuracyFaceForensics++: Learning to Detect Manipulated Facial Images

ENHANCED DEEPFAKE DETECTION



DATASET

The dataset used in this work is taken from FaceForensics++, using the raw videos. For manipulated samples, the following manipulation categories were selected: DeepFakes, Face2Face and FaceSwap

Real DeepFakes Face2Face FaceSwap

To build a balanced training dataset, the following videos were selected: 500 real videos and 166 manipulated videos per category. For the test set: approximately 100 real videos and 33 manipulated videos per category

FRAME EXTRACTION + OPTICAL FLOW

- **Face Detection & Cropping:**

  uses InsightFace for high-precision face detection, crops face regions from the central portion of each video (default 10s), applies letterbox resizing to standard size

- **Optical Flow Computation:**

  loads pretrained RAFT model, computes dense optical flow between pairs of cropped face frames, saves flow in .npy, .flo and .png for visualization

- **Optical Flow Normalization:**

  scans for all .npy flows to find the global minimum and maximum values of the flow data and applies min-max normalization

$$flow_{normalized} = \frac{flow - min_{global}}{max_{global} - min_{global} + \varepsilon}$$

DEPTH ESTIMATION

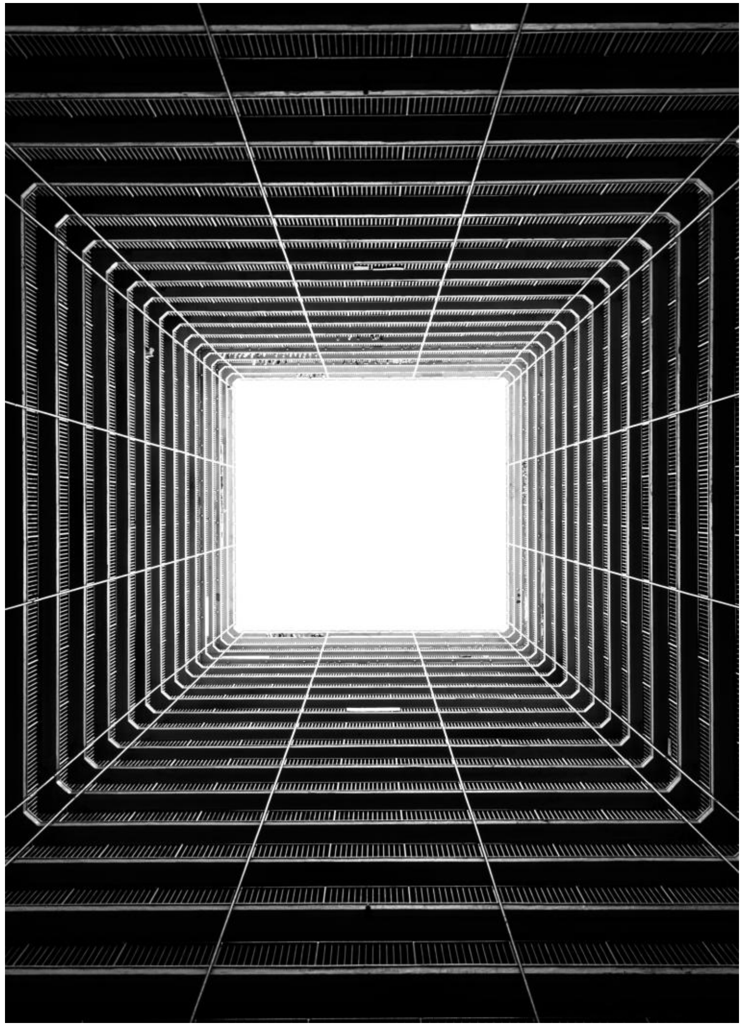
- **Depth Estimation Process:**

  loads the DPT_Large model, for each frame, predicts a dense depth map, uses bicubic interpolation to match input image size

- **Depth Normalization:**

  scans for all .npy depths to find the global minimum and maximum values and applies min-max normalization

$$depth_{normalized} = \frac{depth - min_{global}}{max_{global} - min_{global} + \varepsilon}$$



RESNET-18 + TRANSFORMER

❖**Dataset & Preprocessing:** a custom class loads 7 frames per sample and corresponding depths and optical flows

❖**CNN Backbone – Modified ResNet18:**

- accepts 6-channel input: RGB (3) + Flow (2) + Depth (1)
- outputs 512-dimensional feature vectors which encodes aspect, moving and depth

❖**Transformer Head:**

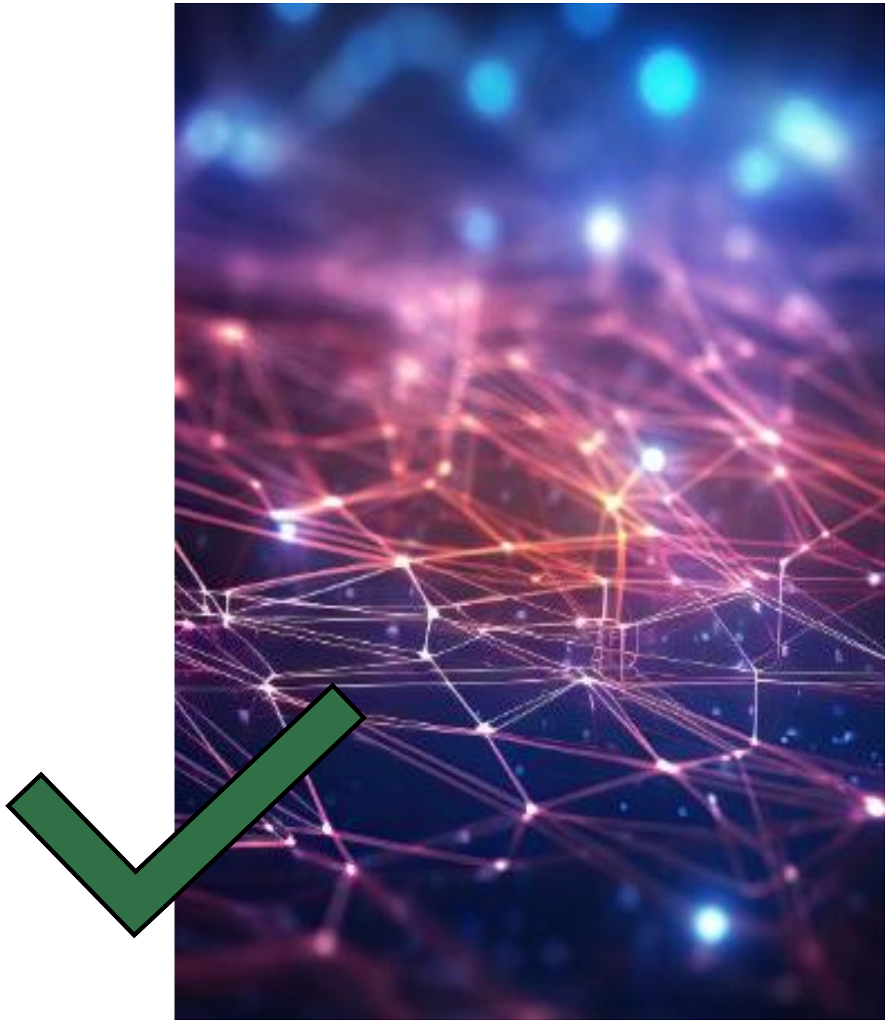
- capture long-range dependencies across frames
- analyzes how frames evolve trought time
- consists of 4 layers, 8 heads, outputs a binary prediction

RESNET-18 + TRANSFORMER: WHY COMBINE THEM?

- **The CNN specializes in local spatial analysis detecting within each frame:**
  - **visual artifacts**
  - **textures**
  - **fine details**

- **The Transformer excels at global temporal modeling understanding:**
  - **motion consistency**
  - **cross-frame anomalies**

Together, they allow the model to capture both the visual quality and temporal consistency of a video, leading to a more reliable and robust deepfake detection system.



PRUNING AND QUANTIZATION

- **Goal: reduce the size and computational cost of a pretrained DeepfakeDetector model**
- **Pruning:**
  - **applies 30% unstructured L1 pruning to all convolutional al linear layers**
  - **removes less important weights**
- **Fine-tuning after pruning:**
  - **uses 50% of the original dataset to re-train the pruned model for 3 epochs**
  - **stabilizes the model after pruning and recovers potential accuracy loss**
- **Quantization:**
  - **applies quantization-aware transformation to the final linear layer (classifier head)**
  - **converts model weights to 8-bit integers**
- **Testing:**
  - **loads the quantized model and runs inference on 10 random samples**
  - **prints predicted vs. true labels to verify correctness post-compression**

EXPERIMENTS AND PROBLEMS

- **Use of compressed videos**
- **Use flows and depth not normalized**
- **Use of Timesformer**
- **Use of Vit Transformer**
- **Use of transformer without the CNN as feature extractor**
- **Different type of algorithms for optical flow and depth**
- **Use of MTCNN and then RetinaFace for frames extraction**

The main problems were due to a large amount of time during training, the data that weren't normalized, the absence of a CNN as feature extractor and the combination of all of them

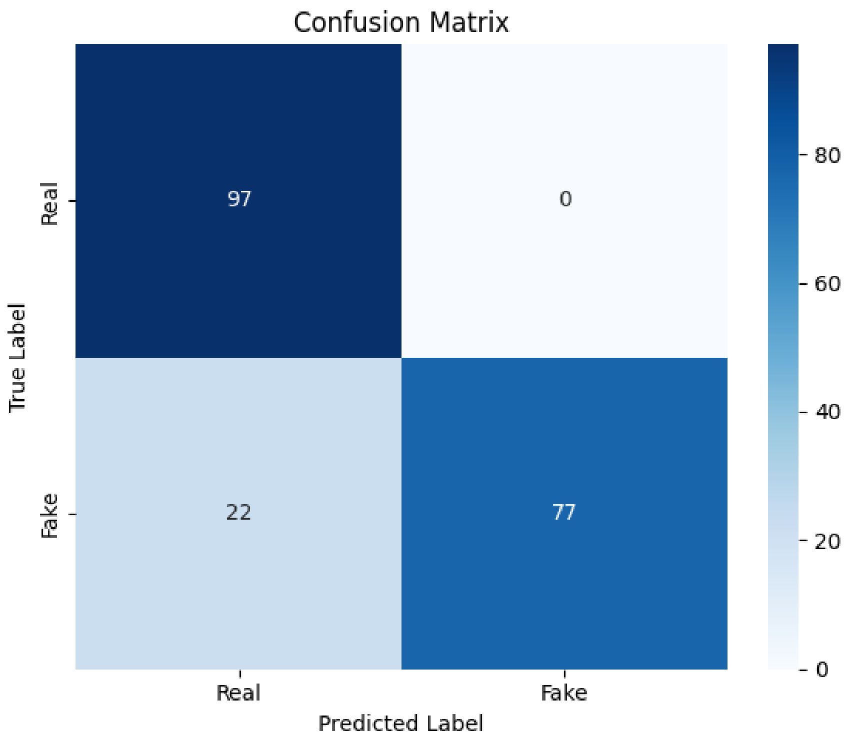
RESULTS OBTAINED

Classification report				
	Precision	Recall	F1-score	Support
Real	0.82	1.00	0.90	97
Fake	1.00	0.78	0.88	99
Accuracy			0.89	196
Macro avg	0.91	0.89	0.89	196
Weighted avg	0.91	0.89	0.89	196
General accuracy: 0.8878				
General F1-score: 0.8750				

The results shown here refer to the test phase performed on a balanced dataset composed of both original and manipulated videos

The model is perfect at recognizing real videos, while 22 fake videos were misclassified

Overall, the performance is very strong, with a total accuracy of 88.78% and a high general F1-score



CONCLUSIONS AND FUTURE WORK

- The model presented is good in real/fake discrimination
- The main errors involve fake videos that were not detected (22 out of 99), indicating room for improvement
- Explore the use of techniques to improve performance on unseen manipulation methods
- Integrate audio, metadata, and compression artifacts for more comprehensive detection

THANKS FOR THE ATTENTION