Truth in Motion: Depth and Flow Enhanced DeepFake Detection

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Outline

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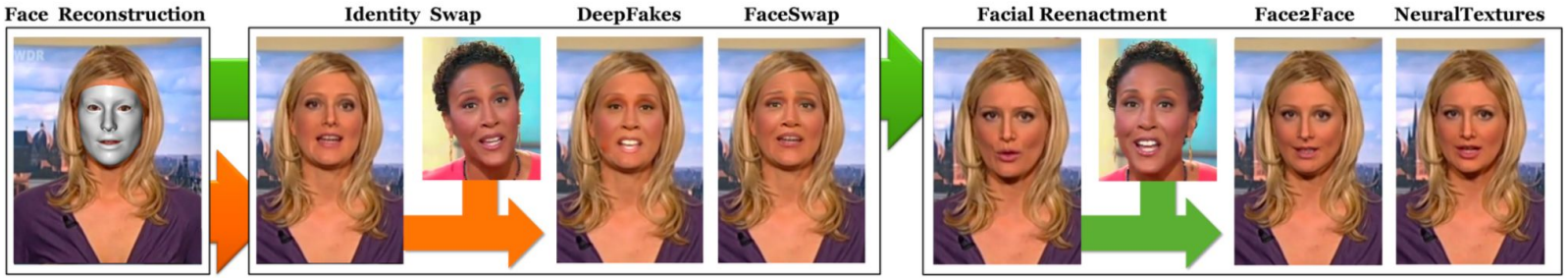
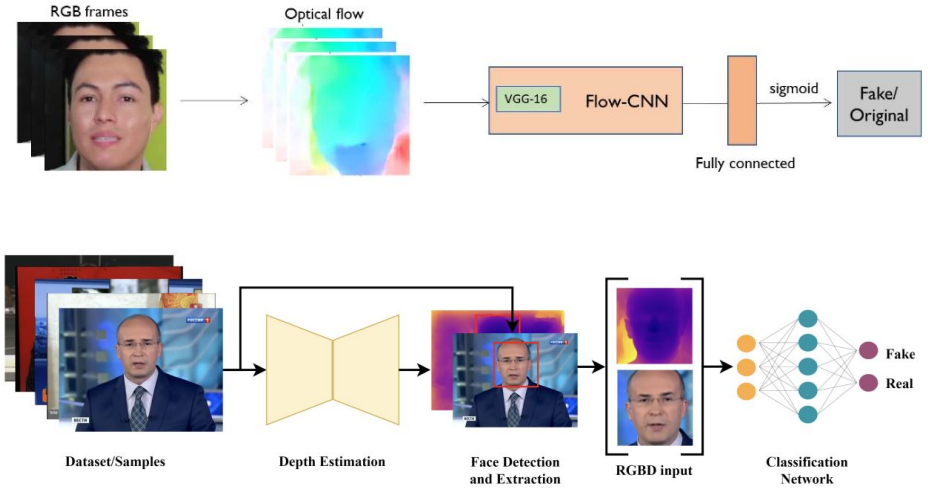
1. Problem Statement

- AI-driven methods have made the production of fake and manipulated videos simpler than ever [1]
- DeepFakes can be used to harm reputations and alter public opinions
- Accurately separating authentic videos from fake ones is crucial to preserve data integrity
- Also important to correct balance between detection efficacy and computational efficiency



2. State of the Art

- Steganalysis features with SVMs [1]
- Learned features with CNNs [1]
  - Flows [2, 3]
  - Depths [4]
- Transformers vs CNNs



3. Dataset

- FaceForensics++ [1]
  - 1000 original videos from Youtube manipulated with DeepFakes, Face2Face, FaceSwap, NeuralTextures, and FaceShifter
  - Also includes the original and manipulated videos from the DeepFake Detection Dataset hosted by Google and Jigsaw

4. Proposed Method

- Pre-processing
- Feature extraction generation
  - Flow using PWC-Net [5,6]
  - Depth using Depth-v2 [7]
- Training
  - Dino v2 [8]
- Compression
  - Quantization
  - Distillation

5. Experimental Setup

- Python scripts for pre-processing and feature extraction generation
- Jupyter Notebooks for training and compression locally and on Google Colab
- Combined all code into one notebook

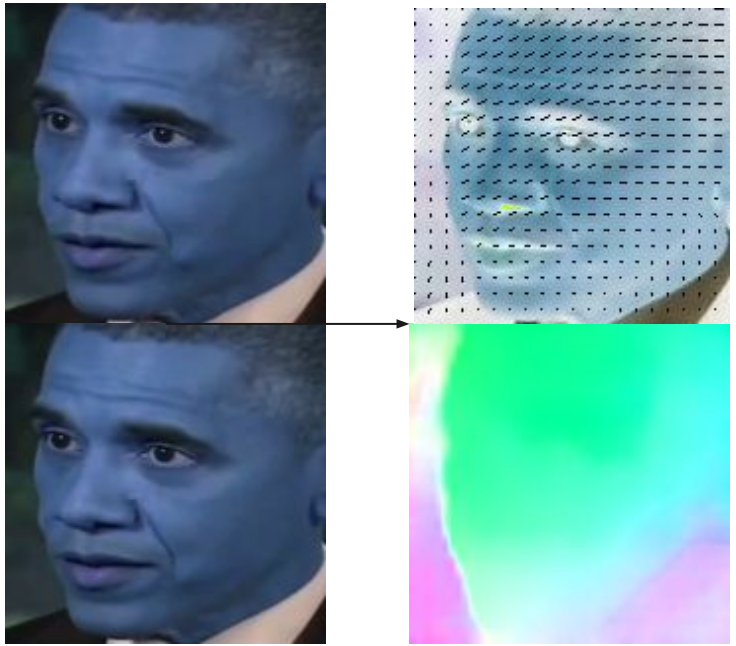
5.1 Pre-processing

- Downloaded dataset using script from authors
- Used OpenCV [9] to process videos and MTCNN [10] to extract faces from video frames
- Saved frames as 160 x 160 BGR images

5.2 Feature Extraction Generation

Flows

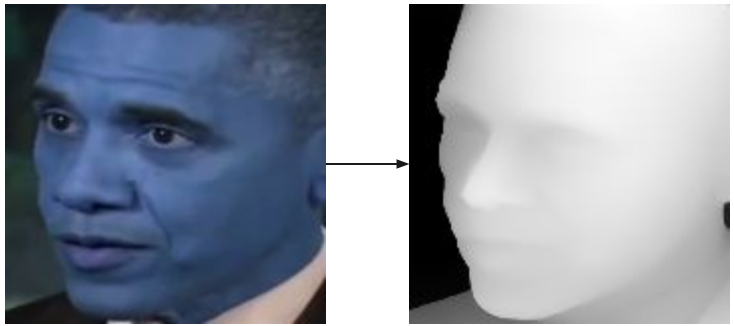
- Used PWC-Net [5,6] to extract flows from consecutive video frames
  - Output two channels (horizontal and vertical flows)
- Converted flows to RGB images where colour represents direction and saturation represents magnitude



5.2 Feature Extraction Generation

Depths

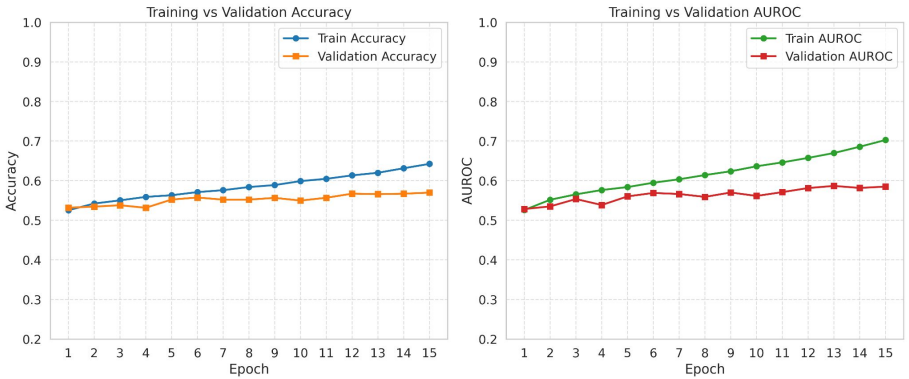
- Used Depth Anything V2 [7] to estimate depths from video frames
  - Output one channel (depths)
- Converted depths to grayscale images
  - Used grayscale to prevent introducing artefacts with colour maps



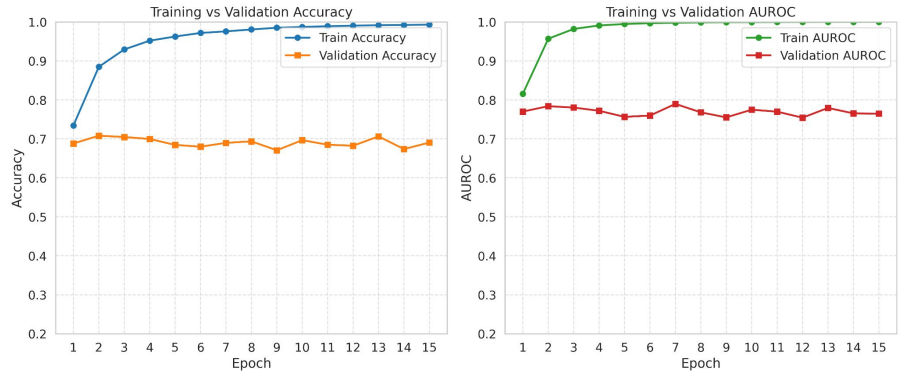
5.3 Training

- Dino v2 [8] takes 224 x 224 RGB images as input
  - Images resized to correct dimensions
  - Depths also replicated three times to generate pseudo-RGB images
- Last encoder layers and classification head parameters are trainable everything else is frozen

Dino-v2 base fine tuned on flow data



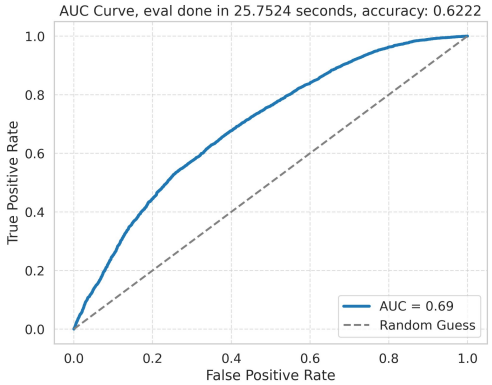
Dino-v2 base fine tuned on depth data

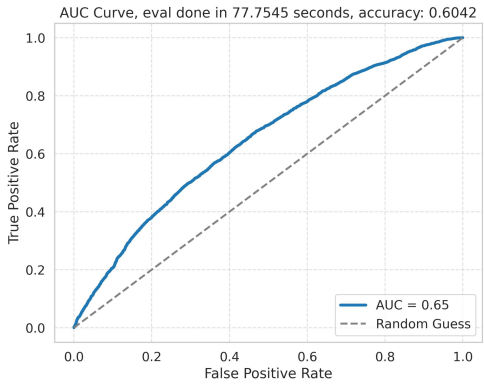


5.4 Compression

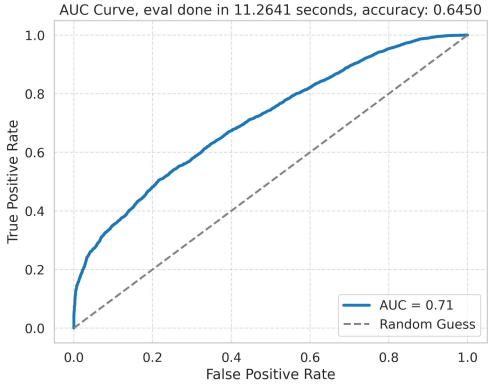
- Quantization:
  - Using float 16 instead of float 32
  - Done with autocast
- Distillation
  - KL divergence between final encoder representation of teacher and learner model
  - Because of different embedding sizes first project cls_token

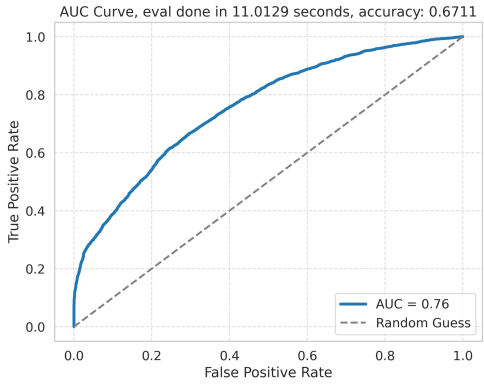
Dino-v2 base fp16 vs fp32





Dino-v2 small vs small distilled





6. Model Evaluation

	Accuracy	AUROC	Avg. Time / Epoch
Flow based fp16 model - Dino v2 base	0.5347	0.54	26.6
Depth based fp32 model - Dino v2 base	0.6042	0.65	77.75
Depth based fp16 model - Dino v2 base	0.6222	0.69	25.75
Depth based fp16 model - Dino v2 small	0.6450	0.71	11.26
Depth based distilled model - Dino v2 small	0.6711	0.76	11.01
Amerini et al. Flow & VGG16 [2] [a]	0.8161	-	-
Nassif et al. Flow & VGG16 [3] [b]	0.7584	0.8215	-
Maiono et al. Depth & XceptioNet [4]	0.9193	-	-

[a] Only Face2Face [b] Only DeepFake and Face2Face

7. Conclusions

- Final considerations
  - Overfitting
  - Depth worked considerably better than flows
- Future Work
  - Pre-process images to correct dimensions for transformers
  - Train on larger portion of the dataset
  - Potentially combining both depth and flow methods
    - Concat cls_token from the two transformer models

8. References

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Thanks! Questions?