COMBINING EFFICIENTBET AND VISION TRANSFORMERS FOR VIDEO DEEPFAKE DETECTION

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신우정

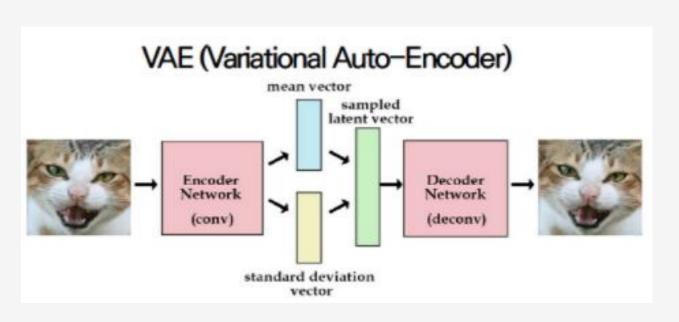
Deepfake



1. GAN (Generative Adversarial Network)

Generator z Fake Discriminator Fake Real

2. VAE (Variational AutoEncoder)

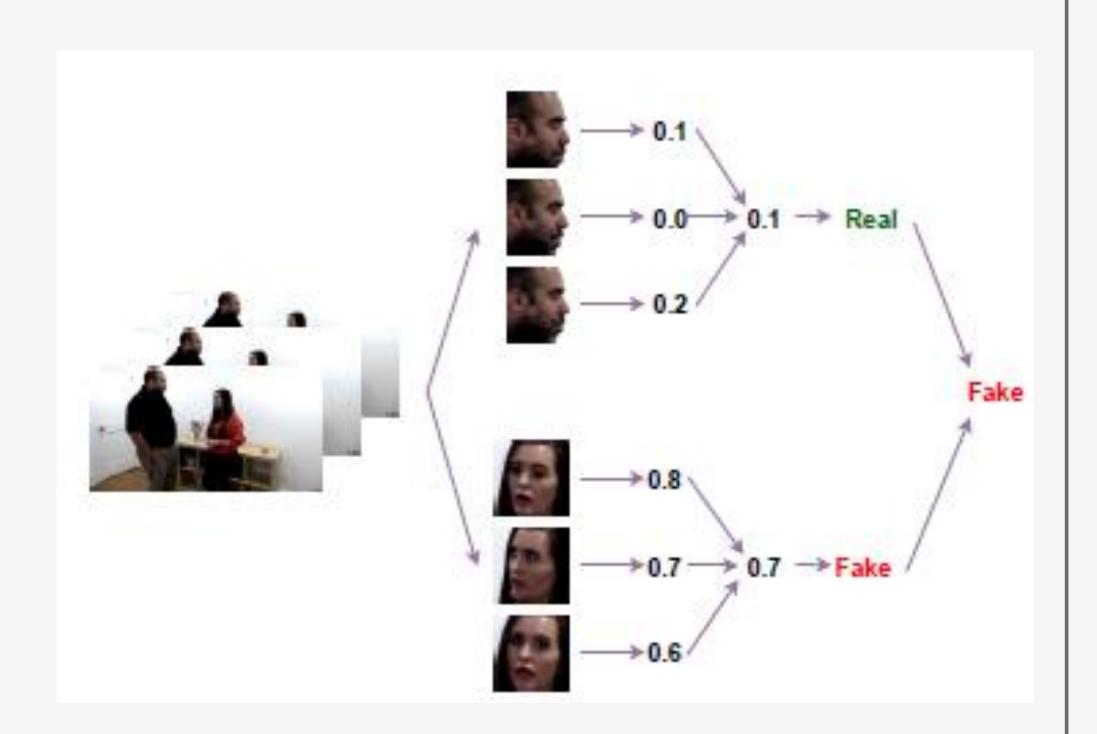


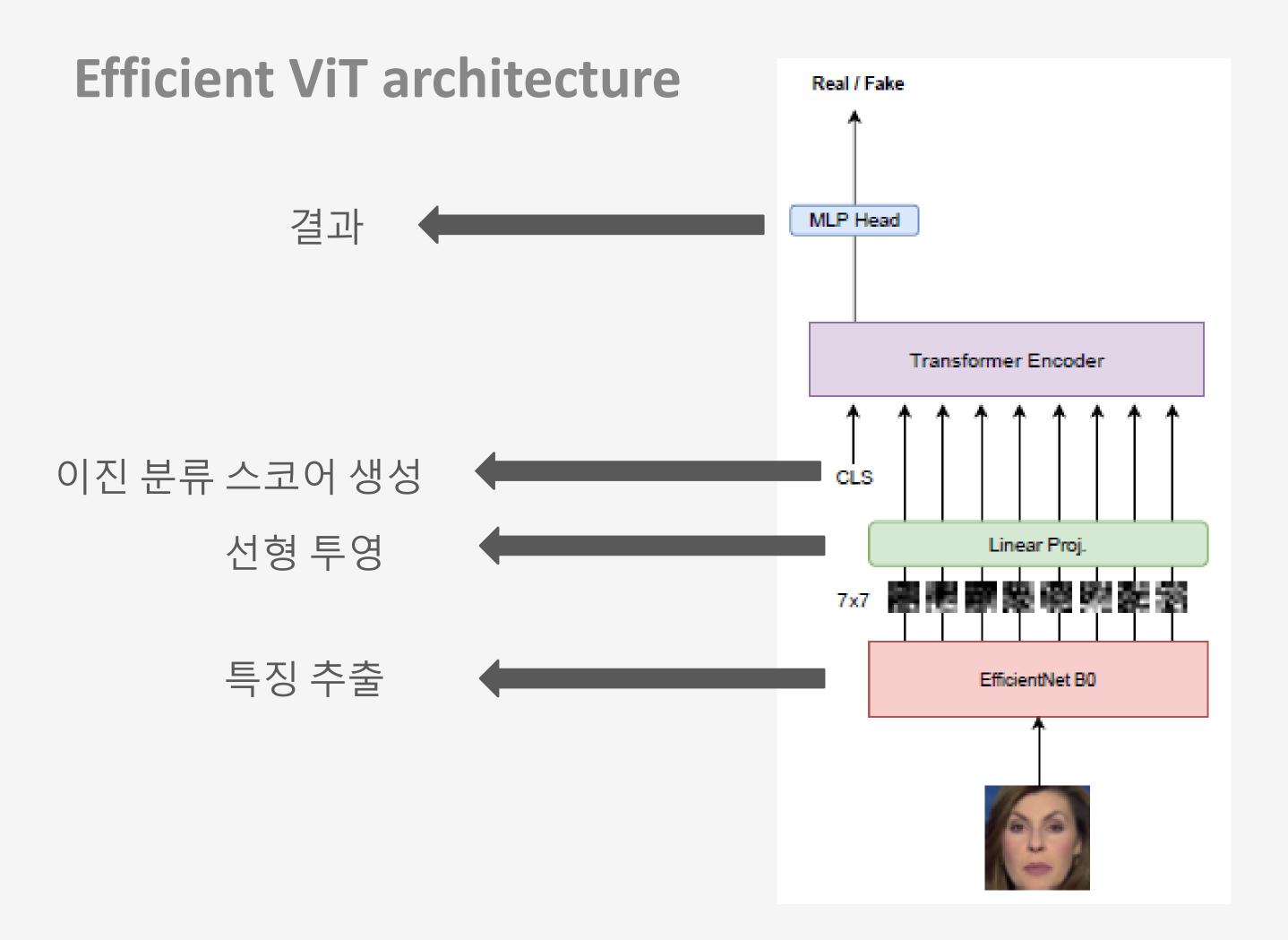
https://www.creativebloq.com/features/deepfake-examples https://ratsgo.github.io/generative%20model/2017/12/20/gan/ https://velog.io/@ohado/%EB%94%A5%EB%9F%AC%EB%8B%9D-%EA%B0%9C%EB%85%90-1.-VAEVariational-Auto-Encoder

Experiments

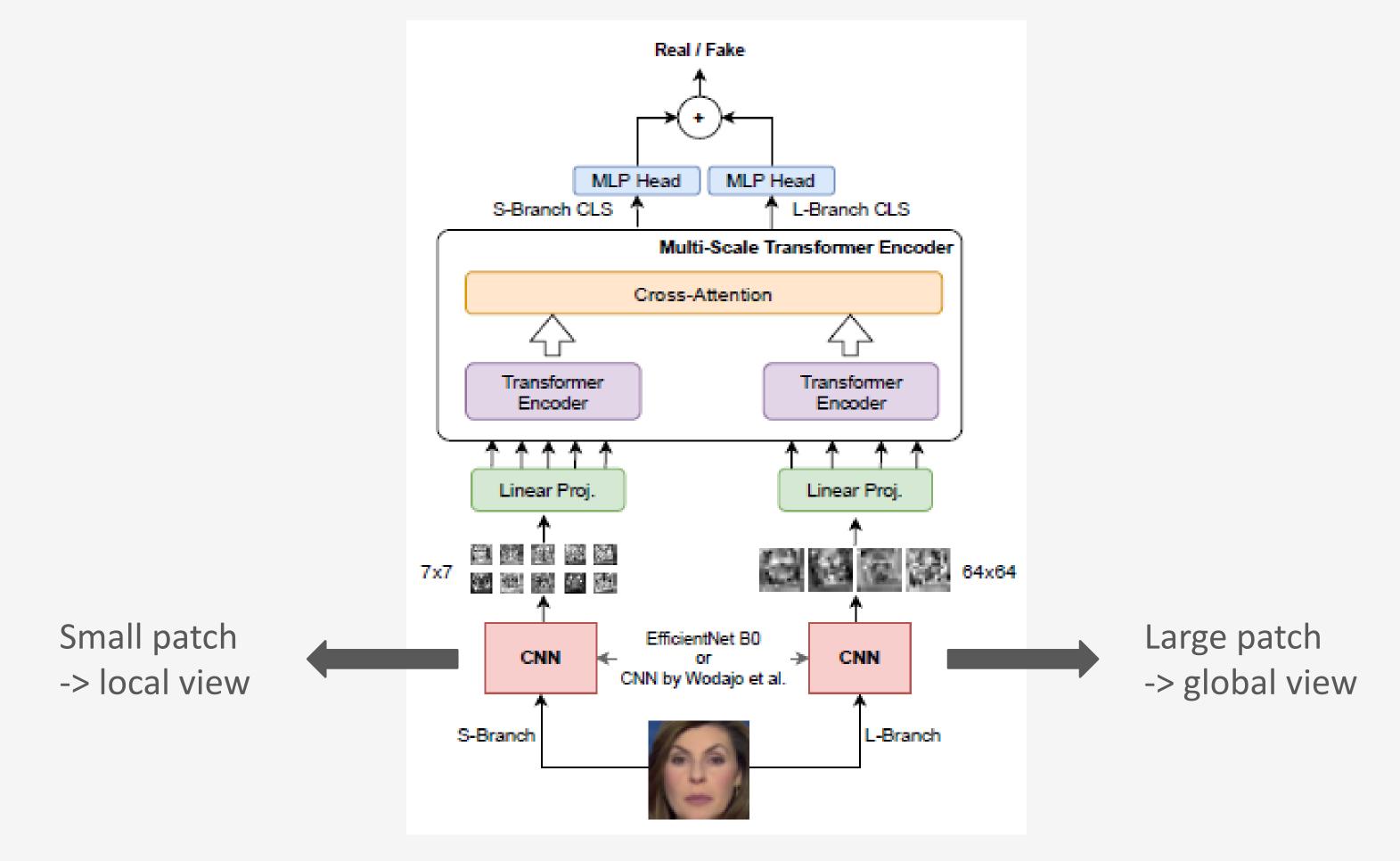
- <Dataset>
- FaceForensics++
- DFDC dataset
- <Training>
- SGD optimizer
- Learning rate -> 0.01

<Inference>
Real/Fake threshold -> 0.55





Convolutional Cross ViT architecture



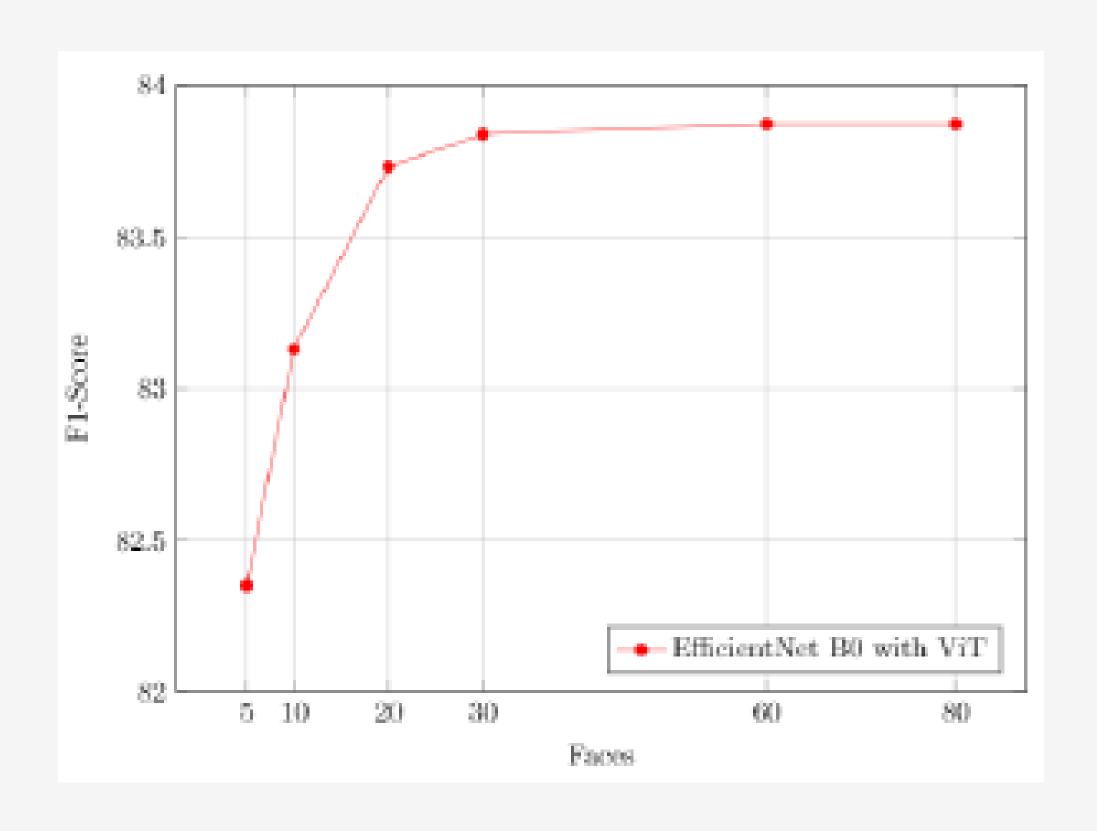
Results

Table 1: Results on DFDC test dataset AUC Mode1 F1-score ViT with distillation [Heo et al., 2021] 91.9% 0.978 Selim EfficientNet B7 Seferbekov, 2020 0.97290.6% Convolutional ViT 0.84377.0% Efficient ViT (our) 0.919 83.8% 84.5% Convolutional Cross ViT (our) 0.925Efficient Cross ViT (our) 88.0% 0.951

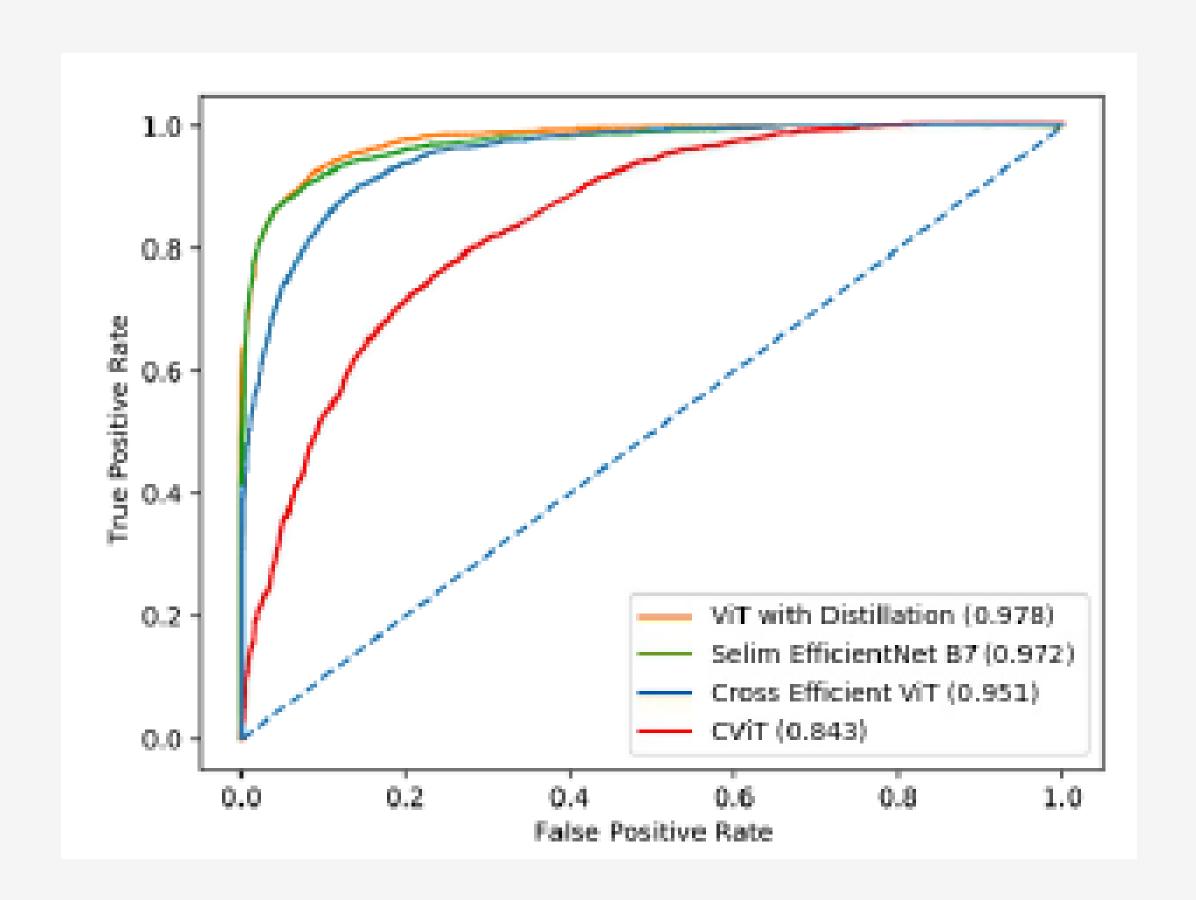
Table 2: Models accuracy on FaceForensics++

Model	Mean	FaceSwap	DeepFakes	FaceShifter	NeuralTextures
Convolutional ViT Wodajo and Atnafu, 202	1 67%	69%	93%	46%	60%
Efficient ViT (our)	76%	78%	83%	76%	68%
Convolutional Cross ViT (our)	76%	81%	83%	73%	67%
Efficient Cross ViT (our)	80%	84%	87%	80%	69%

F1-score versus the number of extracted faces



ROC Curves comparison



감사합니다