Deepfake Video Classifiers – Capture Images and Texts from Deepfake & Real YouTube Videos as Features

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INTRODUCTION

Motivation

Deepfake Videos may fool people nowadays and they are causing trouble.

Contributions

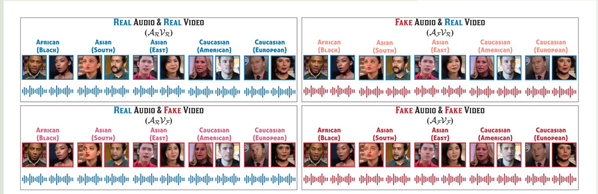
1. I successfully extract two important video features: images and texts. Then, I concatenate them as a data frame for model training.
2. I construct two different classification models to classify Deepfake videos with 97 % and 88 % accuracy scores.

Keywords

Computer Vision, Natural Language Processing, Machine Learning, Neural Network

FakeAVCeleb DATASET

The authors propose a novel Audio-Video Deepfake dataset (FakeAVCeleb [1]) that contains not only deepfake videos but also respective synthesized lip-synced fake audios. FakeAVCeleb is generated using recent most popular deepfake generation methods. To generate a more realistic dataset, the authors selected real YouTube videos of celebrities having four racial backgrounds (Caucasian, Black, East Asian, and South Asian) to counter the racial bias issue.



pc: FakeAVCeleb

Dataset	Real-Audio	Fake-Audio
Real-Video	VoxCeleb2	RTVC
Fake-Video	FSGAN,Faceswap	FSGAN,Faceswap
	DeepFaceLab,Wav2Lip	DeepFaceLab,Wav2Lip,RTVC

pc: FakeAVCeleb

I choose RTVC as the fake subset in terms of real-video and fake-audio
I choose FSGAN as the fake subset in terms of fake-video and real-audio
I choose Faceswap as the fake subset in terms of fake-video and fake-audio
I choose VoxCeleb2 as the real subset in terms of real-video and

DATA PREPROCESSING

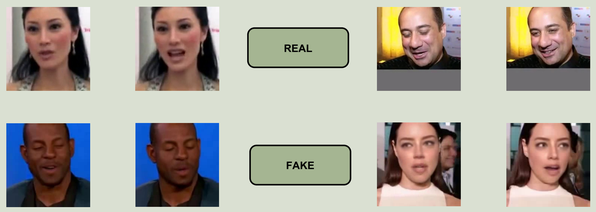
1. Capture Images from Videos

Fake Images :

- RTVC: 360 videos x 4 frames = 1440 frames
- FSGAN: 1884 videos x 2 frames = 3768 frames
- Faceswap: 2256 videos x 2 frames = 4512 frames

Real Images:

- VoxCeleb2 : 390 videos x 25 frames = 9750 frames



2. Capture Audios from Videos and then Transfer Them to Texts

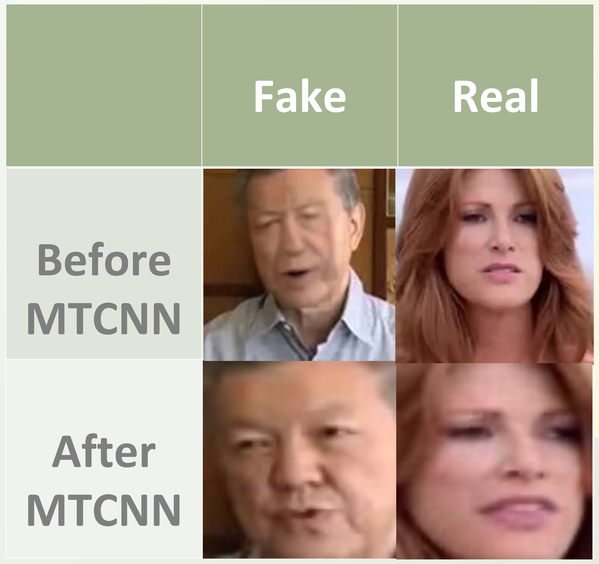
Leverage the *SpeechRecognition* package to covert audios to texts.

Fake Texts: "*it's just be widespread casted like 12 cast members", "attraction carries not that she's being that and then that's address and everything*"

Real Texts: "*beautiful I love the weather here I love like the warm climate I've loved every everywhere we go out to eat and", "I said that you know God so had this plan where he thought I want*"

3. Extract Facial Features Using a Pre-Trained MTCNN Model

MTCNN (Multi-Task Cascaded Convolutional Neural Networks) is a type of neural network that recognizes faces and facial landmarks in images. It was published by Zhang et al. in 2016. MTCNN is a good face detector that provides exactly pixel positions of precise nose, mouth, left eye, right eye, and face boundary. Thanks for the prior research, I can now simply install a `MTCNN` package to capture the facial features.



My task for this session is to save each image as a one-dimensional array. The images are three-dimensional in nature (RGB channels). I need to change the dimensions from 64 x 64 x 3 to 1 x 12288. I flatten each pixel as 1D array to each observation. Also, all data points have normalized from 0-255 to 0-1.

3. Vectorize Texts Using a Pre-Trained word2vec Model

After tokenizing, converting to lowercase, and removing stop words and numbers, the texts now are cleaned. I keep punctuation and emoticon symbols since they might be necessary for the vectorization procedure that follows. A popular pre-trained option is the Google News dataset model, containing 300-dimensional embeddings for 3 millions words and phrases. For constructing vector representations of words, this tool provides an efficient implementation of the continuous bag-of-words and skip-gram designs. A single video of texts is now a 1 x 300 array after vectorization.

4. Concatenate Image Feature and Text Features

Finally, I column-wise concatenate image and text features and save them as a new data frame from which we will begin building the models.

EXPLORATORY DATA ANALYSIS

X Features

Data dimension: 19470 rows x 12288 columns

- 9720 observations from the fake set, 9750 observations from the real set
- 12288 features from the images, 300 features from the texts

Y Labels

Label 0 as fake videos, label 1 as real videos. Because each observation is labeled, this is supervised learning.

MACHINE LEARNING MODEL

Random Forest

- Train-test split: 80 % training, 20 % testing
- Cross validation: (1) K-fold cross-validation, k = 5
  (2) Utilize bootstrap samples to build trees

Why Random Forest

1. It can handle large features efficiently
2. It can reduce computation time

Hyperparameters Tuning the Random Forest Model

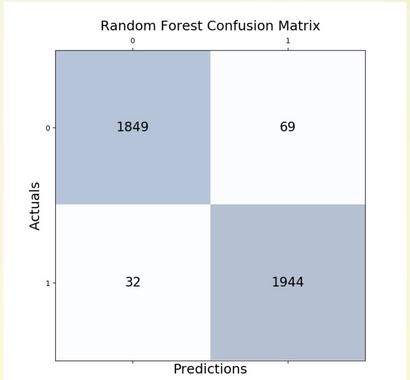
I leverage grid search in training set, the selected parameters are:

- grid['n_estimators'] = [100, **500**]
- grid['max_depth'] = [5, 10, 50, **100**]

Random Forest Model Results

Testing Accuracy: 97.41%

Random Forest Model Confusion Matrix



Random Forest Model Classification Report

	precision	recall	F1-score	support
fake	**0.98**	**0.96**	**0.97**	**1918**
real	**0.97**	**0.98**	**0.97**	**1976**
accuracy			**0.97**	**3894**
macro avg	**0.97**	**0.97**	**0.97**	**3894**
weighted avg	**0.97**	**0.97**	**0.97**	**3894**

DEEP LEARNING MODEL

Why Deep Learning

I would like to experiment with incrementally learning high-level features from data in order to capture more underlying relationships in the data.

Neuron Network Architecture

Model: "sequential"

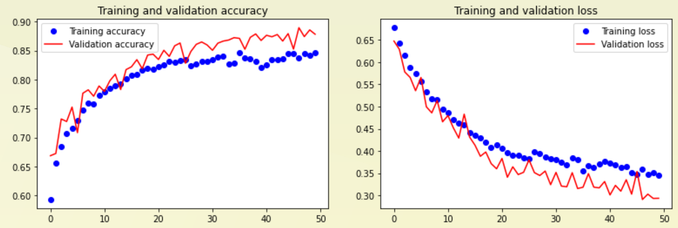
Layer (type)	Output Shape	Param #	Activation
dense (Dense)	(None, 8192)	103129088	[relu]
dropout (Dropout)	(None, 8192)	0	
dense_1 (Dense)	(None, 4096)	33558528	[relu]
dropout_1 (Dropout)	(None, 4096)	0	
dense_2 (Dense)	(None, 1024)	4195328	
dense_3 (Dense)	(None, 512)	524800	[sigmoid]
dense_4 (Dense)	(None, 256)	131328	[softmax]
dense_5 (Dense)	(None, 64)	16448	
dense_6 (Dense)	(None, 1)	65	[sigmoid]

Total params: 141,555,585
Trainable params: 141,555,585
Non-trainable params: 0

Hyperparameters Tuning the Deep Learning Model

- Train-test split: 80 % training, 20 % testing. I also use the testing set for validation during training.
- Learning Rate: 0.0001
- Optimizer: Adam
- Loss Function: Binary Crossentropy
- Grid Search: batch size = [**64**, 128], epochs = [10, 20, **50**], 3-fold cv

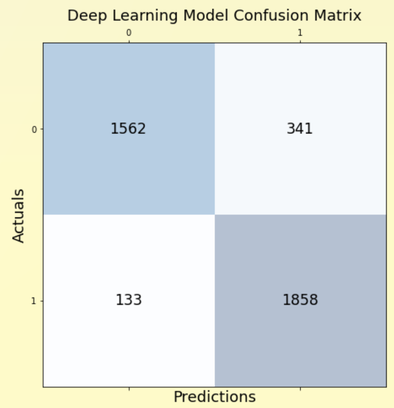
Training and Validation



Deep Learning Model Results

Testing Accuracy: 87.83%

Deep Learning Model Confusion Matrix



Deep Learning Model Classification Report

	precision	recall	F1-score	support
fake	**0.92**	**0.82**	**0.87**	**1903**
real	**0.84**	**0.93**	**0.89**	**1991**
accuracy			**0.88**	**3894**
macro avg	**0.88**	**0.88**	**0.88**	**3894**
weighted avg	**0.88**	**0.88**	**0.88**	**3894**

IMPROVEMENTS AND FURTHER WORKS

Require More HPC Resources

So far, I use *@zorro.american.edu* to implement the experiments. If I submit my code to high performance computing (HPC) for more than two days, the submission would be automatically canceled.

Tuning More Hyperparameters of Estimators

If I have an abundance of computation resources, I will use grid search to find the best estimators in both models.

Source Code

Please refer to my GitHub repo: *twyunting/Deepfake_Video_Classifier2.0*

[1] Khalid, H., Tariq, S., Kim, M., & Woo, S. S. (2021). FakeAVCeleb: A Novel Audio-Video Multimodal Deepfake Dataset. *arXiv preprint arXiv:2108.05080.*
[2] Kastrati, Z., Imran, A. S., & Kurti, A. (2019). Integrating word embeddings and document topics with deep learning in a video classification framework. *Pattern Recognition Letters, 128,* 85-92.