Predicting Heart Rate Variations of Deepfake Videos using Neural ODE

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Abstract

Deepfake is a technique used to manipulate videos using computer code. It involves replacing the face of a person in a video with the face of another person. The automation of video manipulation means that deepfakes are becoming more prevalent and easier to implement. This can be credited to the emergence of apps like FaceApp and FakeApp, which allow users to create their own deepfake videos using their smartphones. It has hence become essential to detect fake videos, to avoid the spread of false information. A recent study shows that the heart rate of fake videos can be used to distinguish original and fake videos. In the study presented, we obtained the heart rate of original videos and trained the state-of-the-art Neural Ordinary Differential Equations (Neural-ODE) model. We then created deepfake videos using commercial software. The average loss obtained for ten original videos is 0.010927, and ten donor videos are 0.010041. The trained Neural-ODE was able to predict the heart rate of our 10 deepfake videos generated using commercial software and 320 deepfake videos of deepfakeTIMI database. To best of our knowledge, this is the first attempt to train a Neural-ODE on original videos to predict the heart rate of fake videos.

1. Introduction

Deepfake is an artificial intelligence method of video manipulation, which involves replacing the face of a person in a video with another person's face [1]. To create deepfake videos, an auto-encoder is trained using an input of a large collection of photos and condensing the photos into specific data points. A second auto-encoder performs the same condensing on stills of the face to be replaced in the video. The data points of the input photos are superimposed onto the data points from the video to replace the heads, based on each specific feature [2]. Deepfakes are becoming more prevalent and easier to implement, with the emergence of apps like FaceApp [3] and FakeApp [4] applications.

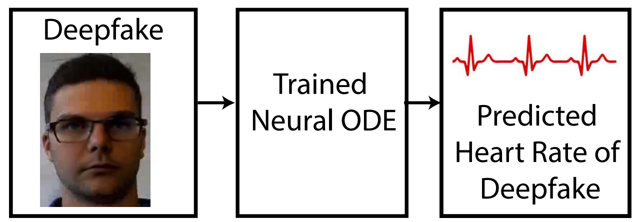


Figure 1: Neural-ODE prediction of heart rate variations

There are some valid concerns raised about the potentially damaging consequences of deepfake videos. First, while some applications of deepfake are harmless enough, it is increasingly being used to overlay unrelated faces onto the actors of pornographic videos [5]. Another danger of deepfake videos is the spread of false information and manipulated news through the Internet and specifically, social media [2]. With the large amount of false news already being spread via social media, it's important to identify further manipulations of the truth. Finally, scenes captured on video have long been accepted forms of evidence in legal proceedings; the increasing prevalence of deepfake videos has called into question the suitability of depending on video evidence to make legal verdicts [1]. To enable us to sort through original and fake videos, we must focus on developing sophisticated artificial intelligence methods for detecting deepfakes.

A recent study shows that the heart rate of fake videos can be used to distinguish original and fake videos [6]. However, obtaining a heart rate directly from fake videos is a time-consuming task. In this paper, we use the state-of-the-art Neural Ordinary Differential Equation (Neural-ODE) [7] solver to predict the heart rate of fake videos trained on original videos.

To the best of our knowledge, this is the first attempt to use state-of-the-art Neural-ODE solver to predict the heart rates variations of fake video obtained from commercial website [8].

2. Related Work

Forgeries and image spoofing have been traditionally studied by analyzing the pixels and frequencies of visual artifacts. With the advent of deep learning and generative adversarial networks, it has become easy to create dystopian situations related to fake images and videos.

2.1. Manipulating Faces in Videos

Face manipulation in videos was first introduced in the 90's. Video Rewrite was the first facial-animation based system, introduced by Bregler et al [9] in the late 1990's. It had the capability of automating the labeling and assembling tasks required to resync current footage with a new audio track. Koopman et al. [1] extracted the video frames containing the subject's face and split them uniformly into eight groups. An average value of photo response non uniformity (PRNU) [10] patterns were calculated for each of the eight groups. The PRNU patterns of the first group were compared with the PRNU patterns of the other seven groups, and the normalized cross-correlation scores were calculated for each video. The authors tested their methods on a small dataset, noting that the approach must be validated on a wider dataset before being widely accepted.

Recently, several techniques have been proposed using Generative Adversarial Networks (GANs) for generating fake faces in videos [11]. GANs are also used to alter the age [12]and skin color of a face [13], and facial hair and mouth expressions can be altered using feature interpolation [14]. GANs have also been used in several image synthesis techniques [15, 16, 17], and in the synthesis of high-quality images from low-resolution images [18]. The recent advancements in GANs have contributed to the development of deepfakes.

2.2. Image and Video based Digital Forensics

Traditionally, image inconsistencies are detected by finding compression artifacts [19] and distortions [20], as well as assessing image quality [21]. The color and noise distributions in original images can be investigated using specific networks [35, 48]. However, it is hard to find distortion, compression artifacts, and noises in synthetic images due to non-linearity [22]. Hence, feature-based techniques [23, 24] and convolutional neural networks (CNNs) [25] are used to find the authenticity of digital images. CNNs have been used to detect morphed facial images [26]. Recently, feature-based face detection was proposed by Thies et al. [27] on the dataset created by Rssler et al. [28], which contains around half a million edited images. Video manipulations are usually detected by finding duplicated or dropped frames [29], or copy and move manipulations [30].

2.3. Biological Signals

Subtle motion and color variations within videos can be observed [31, 32],enabling remote photoplethysmography (rPPG) [33, 34] and ballistocardiogram (BCG) [35] techniques for heart rate detection from facial videos. rPPG has proven to be more robust compared to BCG. There are several proposed methods for using rPPG, including using optical properties [36], Kalman filters [37], and extracting signal information from different facial areas [38, 39, 40, 33].

2.4. Recurrent Neural Network

Long Short Term Memory (LSTM) networks are the most popular recurrent neural networks (RNNs), introduced by Schmidhuber et al. [41]. They have been used for temporal analysis by Gera et al. [42], and in CNNs extracting frame features. Pre-processing is done by subtracting the mean and then resizing the frame to 299x299. The features from multiple frames are concatenated and given to LSTM for temporal analysis. However, missing data is a major issue in time series analysis. Typically it is addressed using generative models [43, 44], concatenating time stamp information of the input to RNN [45, 46, 47], or data imputation [48].

In this paper, we used Neural ODE, which is a recent generative approach for modeling time series. In this model, each time series is represented by a latent trajectory. The latent model was trained using a variational autoencoder [49, 50] by considering sequence-valued observations. We first created deepfake videos using the commercial deepfake video generating website, deepfakeweb.com [8]. The average loss obtained using deepfakeweb.com for ten original videos was 0.010925, and ten donor videos were 0.010041. Heart rate from original videos were extracted using three well known approaches: facial skin color variation [51], average optical intensity in the forehead [52], and Eulerian video magnification [31]. The Neural-ODE was trained using the heart rate obtained from the original videos. It was then used to predict the heart rate of deepfake videos obtained from deepfakeweb.com [8] and a publicly available DeepfakeTIMI database [53].

The key contributions of the paper are listed below.

- A new deepfake database was created using the commercial website [8] by considering ten original videos and ten donor videos from the COHFACE database.
- Predicting heart rate variations of deepfake videos using Neural-ODE trained on original videos from the COHFACE and publicly available VidTIMIT database.

To the best of our knowledge, this is the first attempt to use state-of-the-art Neural-ODE solver to predict the heart rates variations from deepfake videos [8].

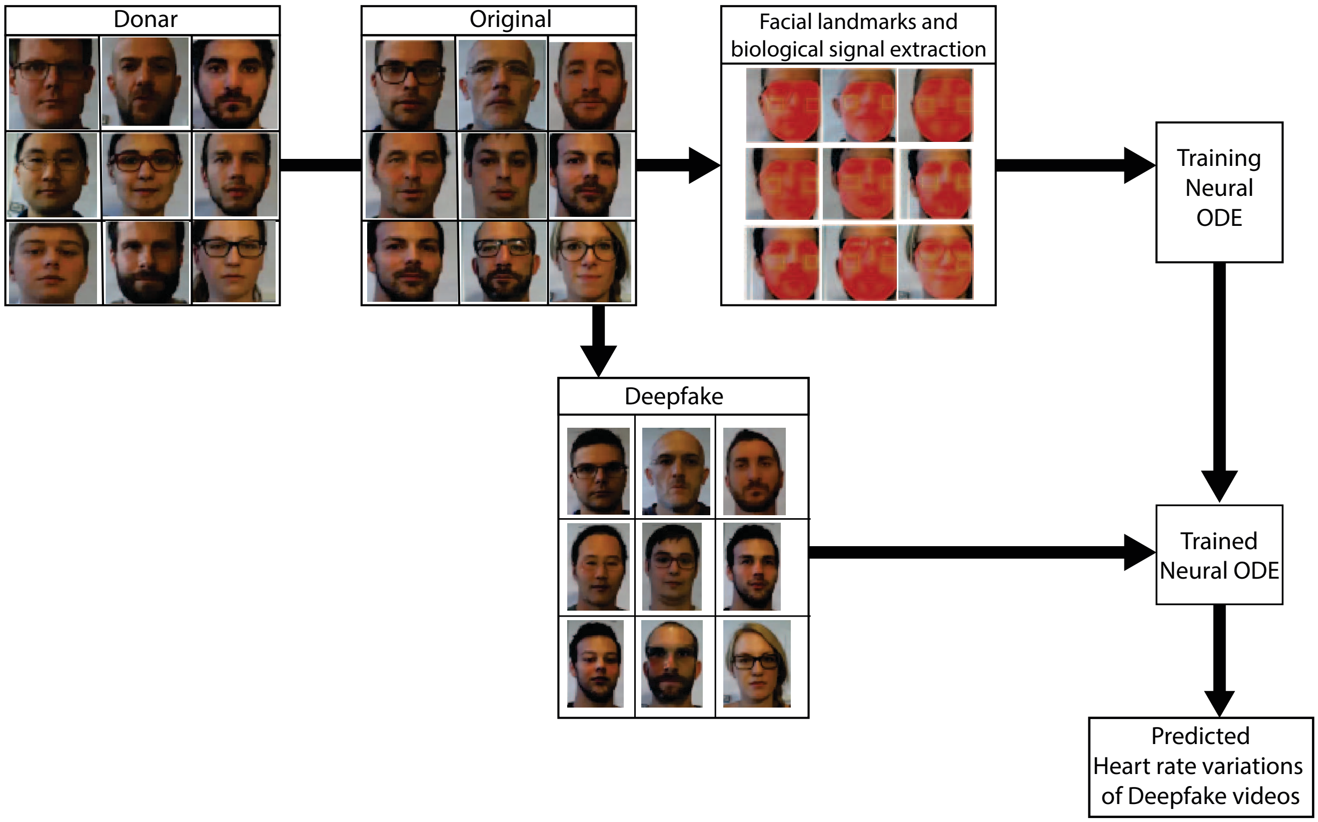


Figure 2: Block diagram of the proposed system used to predict the heart rate of deepfake videos using Neural-ODE

3. Proposed System

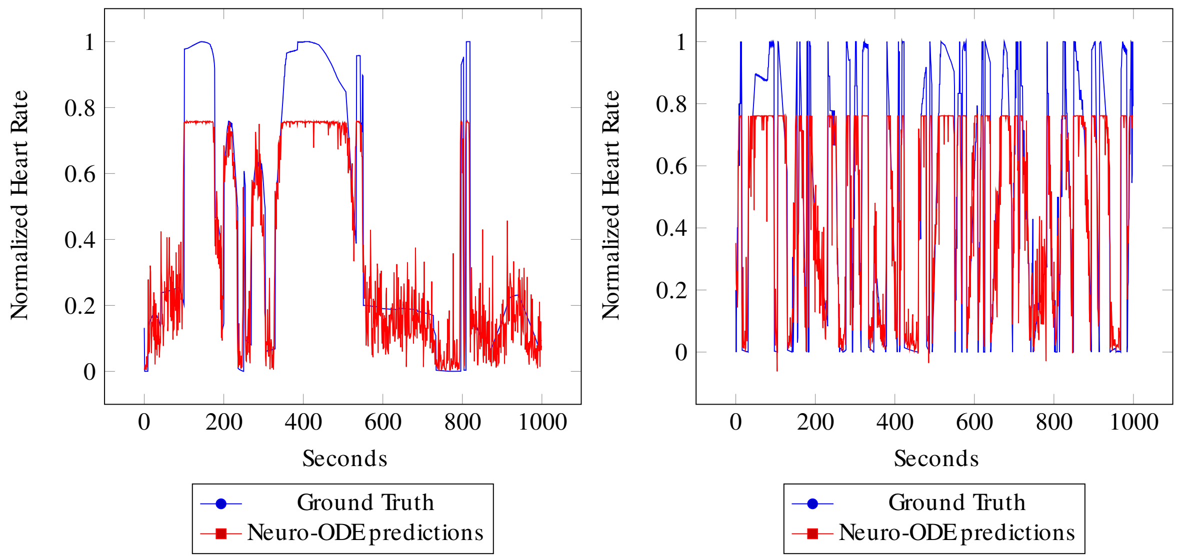
The four main steps are (i) Creating a deepfake dataset using a commercial website [8] (ii) Extracting heart rate from facial videos (iii) Training Neural-ODE using heart rate from original videos (iv) Predicting heart rates of deepfake videos using trained Neural-ODE.

3.1. Deepfake Databases

We considered twenty videos from the COHFACE database and uploaded them to commercial website [8] to create ten deepfake videos. Each deepfake video was created by considering an original video and a donor video. The resolution of the original video was 640x480 pixels, and the frame rate was 20Hz. The original and donor inputs and deepfake output from deepfakesweb.com are shown in Fig. 6. We also considered DeepfakeTIMI database [53], containing 320 videos from 32 subjects (10 videos per subject). The image resolution for videos was 128x128. The corresponding 320 original videos were constructed by concatenating the frames from VidTIMIT database.

3.2. Detecting Heart Rate from Facial Videos

We extracted the heart rates from the original videos using three known approaches: (i) measuring facial skin color variation caused by blood flow [51]; (ii) measuring average optical intensity in the forehead [52]; and (iii) magnifying and processing temporal changes in the color using Eulerian method [31]. In the facial skin color variation approach, the facial landmarks were detected using dlib [54], and ROI was obtained. Average RGB values for all the frames containing the ROI was obtained. Fast Fourier Transform was applied to obtain the heart rate [51]. In the optical intensity approach, the forehead region was isolated from the face, and the average optical intensity [52] in this region was used to detect the heart rate. With standard lighting conditions and considerably less noise caused by motion, a stable heart rate was obtained after 15 seconds. After the stable heart rate was obtained, phase variation with respect to frequency was computed. In Eulerian method, the color values at a given spatial location is amplified within a specific range of temporal frequency band. The amplification indicates that the changes in the redness are more significant as the blood flows into the facial region.



(a) (b)

Figure 3: Min-max normalized heart rate obtained from skin color variation (ground truth) and Neural-ODE (predictions) on: (a) Our deepfake videos (b) DeepfakeTIMI database videos

3.3. Training Neural-ODE

The heart rates obtained from the original videos using the three approaches discussed in section 3.2 were normalized using min-max normalization and applied to Neural-ODE for training. The Neural-ODE was trained separately using the ten original videos from COHFACE and the 320 original videos from VidTIMIT. Among the 320 original videos from VidTIMIT database, the videos of poor quality were automatically discarded. The steps involved in training the NeuralODE are listed below:

- The training data was split using the sliding window approach with time steps of 5.
- The RNN encoder was executed over the time series data of the heart rate, obtained from optical intensity and skin color variation approaches.
- For the posterior, validate the parameters over.

$$q\left(\boldsymbol{z}_{t_0} | \{\boldsymbol{y}_{t_i}, t_i\}_i, \phi\right) = \mathcal{N}\left(\boldsymbol{z}_{t_0} | \mu_{\boldsymbol{z}_{t_0}}, \sigma_{z_0}\right) \quad (1)$$

  where, $\mu_{\boldsymbol{z}_0}, \sigma_{z_0}$ are from the hidden states of $RNN\left(\{y_{t_i}, t_i\}, \phi\right)$.

- The isotropic unit Gaussia was sampled using the reparameterization trick.
- The variational autoencoder was built with Adam optimizer having learning rate of 0.00001.

3.4. Predicting the Heart Rate of Deepfake Videos using NeuralODE

For prediction of heart rate from deepfake videos, the trained Neural-ODE is given our 10 deepfake videos and 320 deepfake vidoes from the DeepfakeTIMI database. Among the 320 deepfake videos from the DeepfakeTIMI database, the videos of poor quality were automatically discarded. The layers in the encoder, decoder models of LSTM and variational autoencoder (VAE) of our prediction network are tabulated in Table 1.

Model	Layers
Encoder	Input Layer
	LSTM-1
	Dense Layer
Decoder	Input Layer
	RepeatVector
	LSTM-1
	LSTM-2
VAE	Input Layer
	LSTM-1
	Dense Layer-1
	Dense Layer-2
	LSTM-3
	LSTM-4

Table 1: Encoder, Decoder Layers of LSTM and VAE

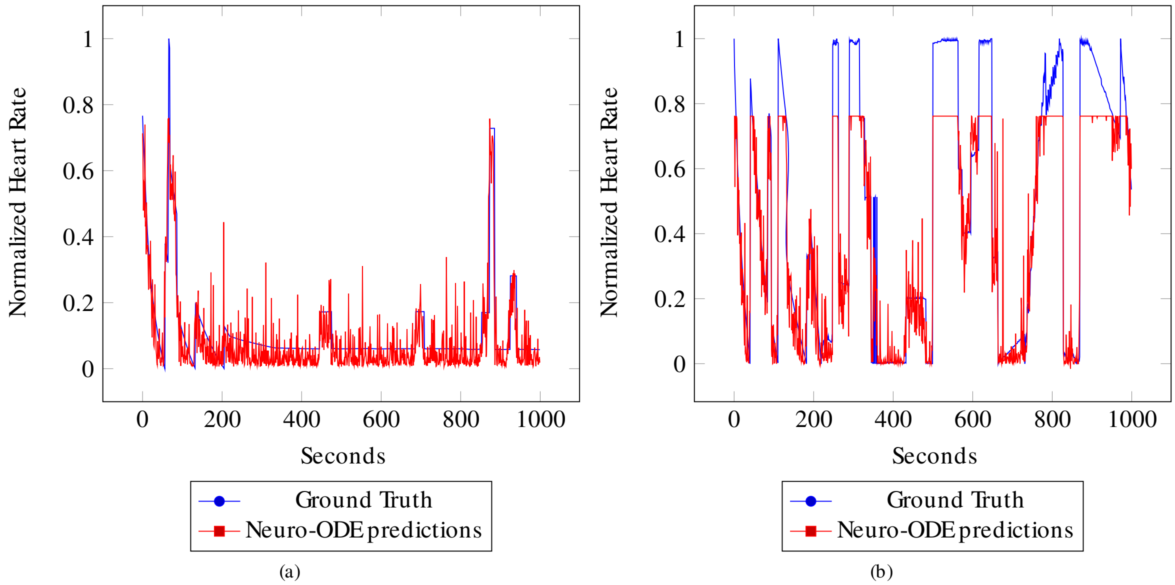


Figure 4: Min-max normalized heart rate obtained from optical intensity (ground truth) and Neural-ODE (predictions) on: (a) Our deepfake videos (b) DeepfakeTIMI database videos

4. Results and Discussions

4.1. Detecting Heart Rate from Facial Videos

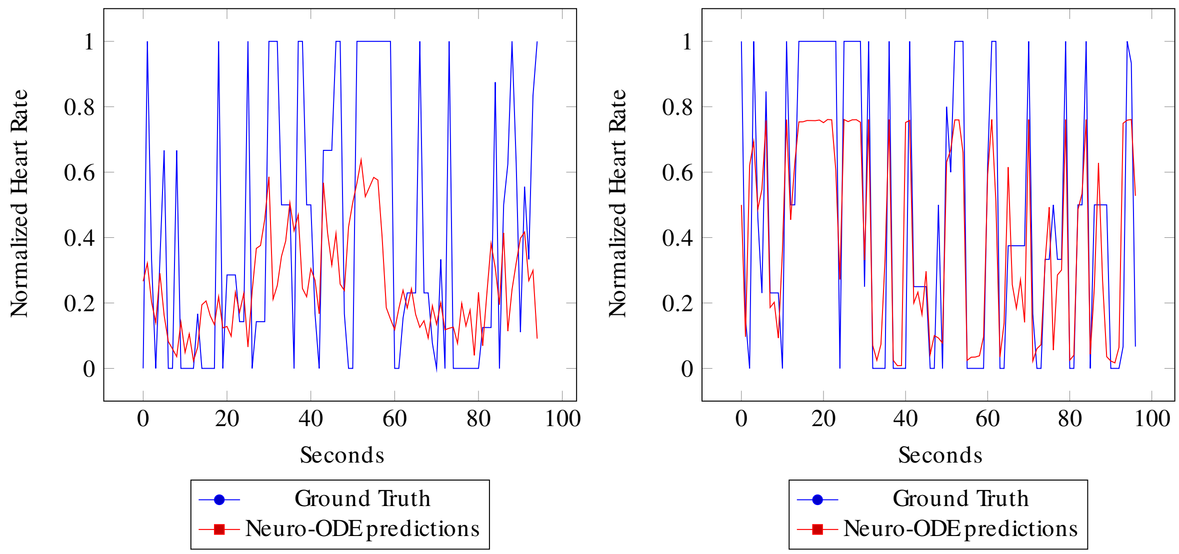
We considered 20 videos from the COHFACE dataset. This included ten original videos and ten donor videos. The 20 videos were uploaded to commercial deepfake video generating website [8]. To obtain the deepfake videos, 4 hours of GPU cloud usage was purchased. The losses obtained for the ten original and ten donar videos are tabulated in Table 2. The average loss obtained for ten original videos was 0.010927, and for the ten donor videos, 0.010041. Three well known approaches: facial skin color variation, average optical intensity and Eulerian video magnification are used to extract the heart rate of original videos. The Neural-ODE is trained using the min-max normalized heart rate obtained from the three approaches for 10 original videos from COHFACE database and 320 original videos of VidTIMIT database. To obtain the ground truth, the min-max normalized heart rate is again obtained using the three approaches for our 10 deepfake videos and 320 deepfake videos from the DeepfakeTIMI database. Among the 320 original videos from VidTIMIT database and 320 deepfake videos from DeepfakeTIMI database, the videos of poor quality were automatically discarded. The training loss values for Neural-ODE on original videos using the three approaches: facial skin color variation, average optical intensity and Eulerian video magnification on original videos from COHFACE database and VidTIMIT database are tabulated in Table 3.

Subject	Original video loss	Donor video loss
1	0.01179	0.00979
2	0.0113	0.0097
3	0.0085	0.00981
4	0.00962	0.01132
5	0.00924	0.01118
6	0.01056	0.0097
7	0.01071	0.00745
8	0.01433	0.00986
9	0.01153	0.01268
10	0.01169	0.00892

Table 2: Loss values for 10 original and donor videos obtained from commercial deepfake website [8]

Heart rate extraction techniques	Database	Loss
Skin color variation	COHFACE	0.0189
	VidTIMIT	0.0401
Optical intensity	COHFACE	0.0166
	VidTIMIT	0.0261
Eulerian magnification	COHFACE	0.1254
	VidTIMIT	0.0727

Table 3: Training loss values for Neural-ODE on original videos from COHFACE and VidTIMIT databases.



(a) (b)

Figure 5: Min-max normalized heart rate obtained from Eulerian magnification (ground truth) and Neural-ODE (predictions) on: (a) Our deepfake videos (b) DeepfakeTIMI database videos

4.2. Predicting the Heart Rate of Deepfake Videos using Neural-ODE

The ground truth heart rate prediction obtained from the three approaches: facial skin color variation, average optical intensity and Eulerian video magnification are min-max normalized and compared with Neural-ODE. The loss values for Neural-ODE on fake videos are tabulated in Table 4.

Heart rate extraction techniques	Database	Loss
Skin color variation	Our fake videos	0.0215
	DeepfakeTIMI	0.0327
Optical intensity	Our fake videos	0.0154
	DeepfakeTIMI	0.0252
Eulerian magnification	Our fake videos	0.0353
	DeepfakeTIMI	0.0565

Table 4: Loss values for Neural-ODE on Deepfake videos

The Neural-ODE is trained for 5000 epochs using the min-max normalized heart rate obtained using skin color variation, and optical intensity and 10000 epochs using Eulerian video magnification. The learning rate is 0.0001 and Adam optimizer is used. The prediction result obtained from Neural-ODE using skin color variation, average optical intensity, and Eulerian video magnification on our 10 fake videos and 320 fake videos from DeepfakeTIMI database are shown in Fig. 3, Fig. 4 and Fig. 5 respectively.

5. Conclusion and Future Work

Neural-ODEs have lead a revolution in the area of deep neural networks. They combine traditional theory of differential equations and numerically stable forward simulation [7]. In this paper, we have developed a novel approach to predict the heart rates of deepfake videos using state-of-the-art Neural-ODE. The Neural-ODE is trained using min-max normalized heart rate obtained from original face videos using three well-known approaches: skin color variation, average optical intensity, and Eulerian video magnification.

The significant contributions of our paper are listed.

- Created a new fake video database using commercial deepfake video generating website [8].
- Predict the heart rate of the deepfake videos generated using commercial websites and other fake datasets.

To the best of our knowledge, this is the first attempt to detect heart rate of deepfake videos using Neural-ODE. In the future, we will optimize the network to implement it on low-power/cost single-board computer [55, 56, 57].

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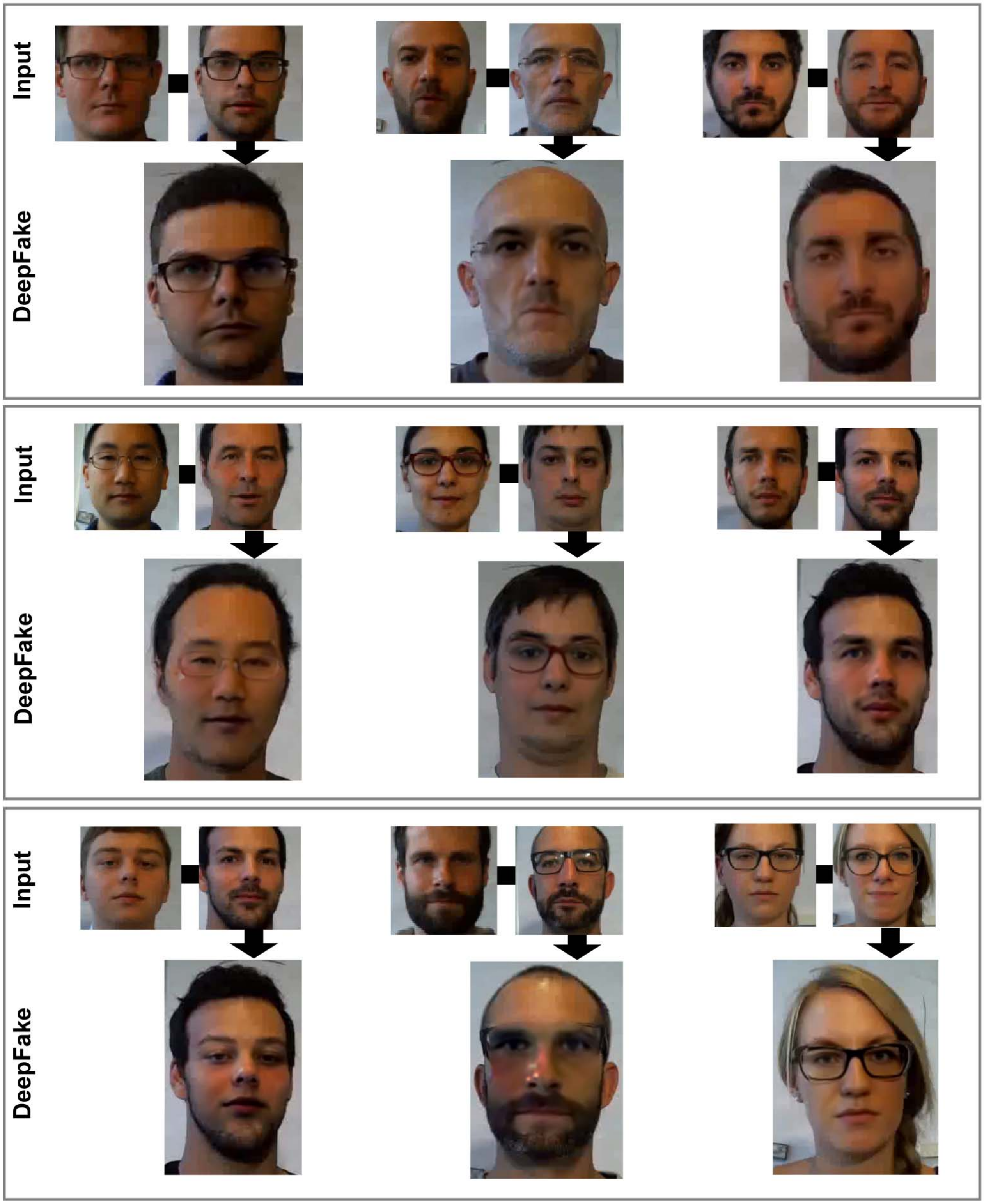

Figure 6: Original, donar, and deepfake video frame generated using commercial deepfake website [8]

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