WORKSHOP Face Image Manipulation & Detection

European Association for Biometrics
eab
Human Identity in Europe

12 & 13 July

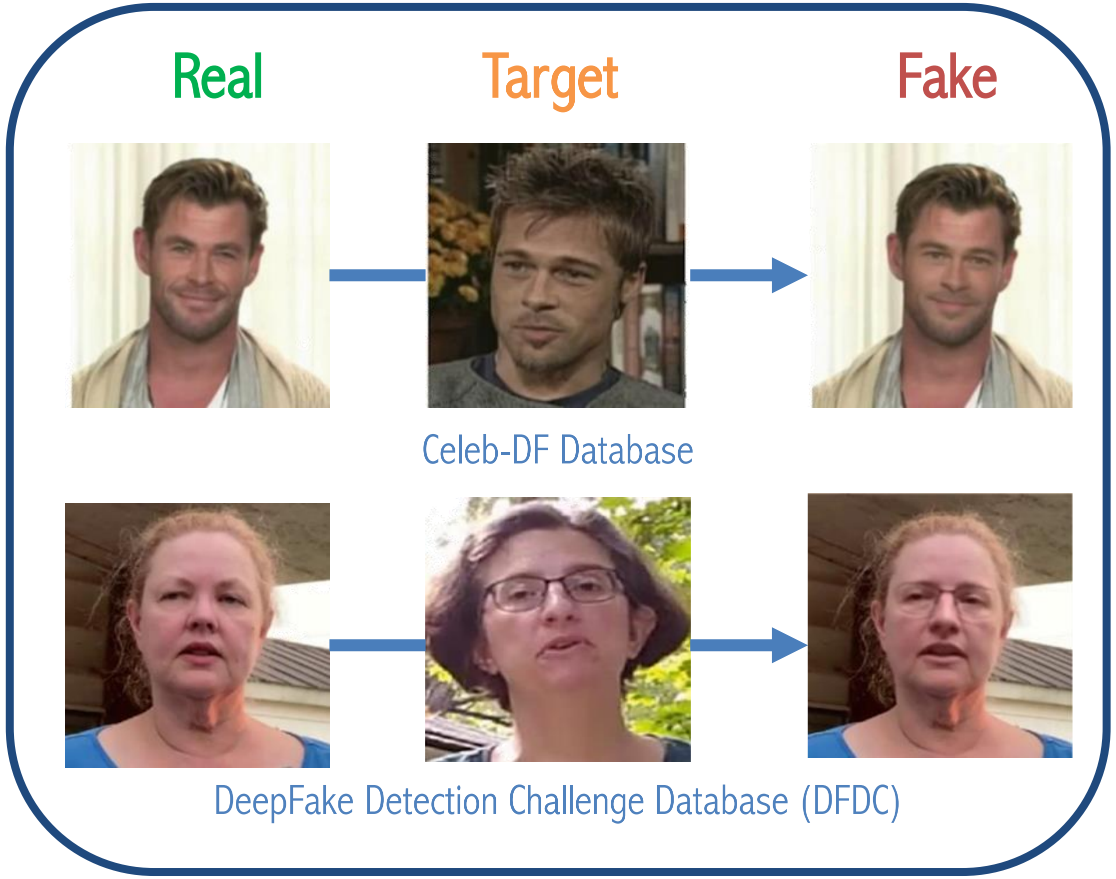
DeepFakes Detection Based on Heart Rate Estimation

Single- and Multi-Frame

Julian Fierrez

Introduction

- DeepFake (Identity Swap) is referred to a deep learning based technique able to create fake videos by swapping the face of a person by the face of another person [1].



[1] Tolosana, R.; Vera-Rodriguez, R.; Fierrez, J.; Morales, A.; and Ortega-Garcia, J. 2020. **"DeepFakes and Beyond: A Survey of Face Manipulation and Fake Detection"**. *Information Fusion* 64: 131–148.

Introduction

- **Face manipulation techniques:** mostly based on AutoEncoders (AE) [2] and Generative Adversarial Networks (GAN) [3].
- **Very realistic visual results**: specially in the latest generation of public DeepFakes [4].

Real Video
(Robert de Niro)

DeepFake Video
(Al Pacino)

[2] Kingma, D. P.; and Welling, M. 2013. "Auto-Encoding Variational Bayes". In *Proc. Int. Conf. on Learning Represent.*
[3] Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.;Warde-Farley, D.; Ozair, S.; Courville, A.; and Bengio, Y. 2014. "Generative Adversarial Nets". In *Proc. Advances in Neural Information Processing Systems.*
[4] Tolosana, R.; Romero-Tapiador, S.; Fierrez, J.; and Vera-Rodriguez, R. 2020. "DeepFakes Evolution: Analysis of Facial Regions and Fake Detection Performance". In *Proc. International Conference on Pattern Recognition Workshops* .

Introduction

- **Face Recognition Presentation Attack:** using photographs, videos, and masks [5].

- **3D Masks :** somehow similar to DeepFake digital manipulations.
  - Physical vs digital mask over the real face.
- **Texture and shape**-based techniques **not efficient** against hyperrealistic 3D Masks [6].
  - Same with realistic DeepFake methods.
  - Other approaches are necessary → Physiology.

[5] Hernandez-Ortega, J.; Fierrez, J.; Morales, A.; and Galbally, J. 2019. **"Introduction to Face Presentation Attack Detection"**. In *Handbook of Biometric Anti-Spoofing*, 187–206. Springer.
[6] Erdogmus, N.; and Marcel, S. 2014. **"Spoofing Face Recognition with 3D Masks"**. *IEEE Transactions on Information Forensics and Security* 9(7): 1084–1097.

Introduction

- **3D Masks do not emulate the physiology of human beings** [6], i.e. HR, blood oxygen, breath rate.
    - **Estimating them** is a powerful tool for 3D Masks detection.

- **Do DeepFake manipulations consider the physiological aspects in the synthesis process?**

- Detection based on pulse detection → **Remote Photoplethysmography** [7], used in:
    - E-learning [Hernandez-Ortega *et al.* 2020].
    - Health Care [Mc-Duff *et al.* 2015].
    - Human-Computer Interaction [Tan and Nijholt 2010].
    - Security [Marcel *et al.* 2019].

[7] Hernandez-Ortega, J.; Fierrez, J.; Morales, A.; and Tome, P. 2018. **"Time Analysis of Pulse-Based Face Anti-Spoofing in Visible and NIR"**. In *Proc. IEEE Conf. on Comp. Vision and Pattern Recognition Workshops*.

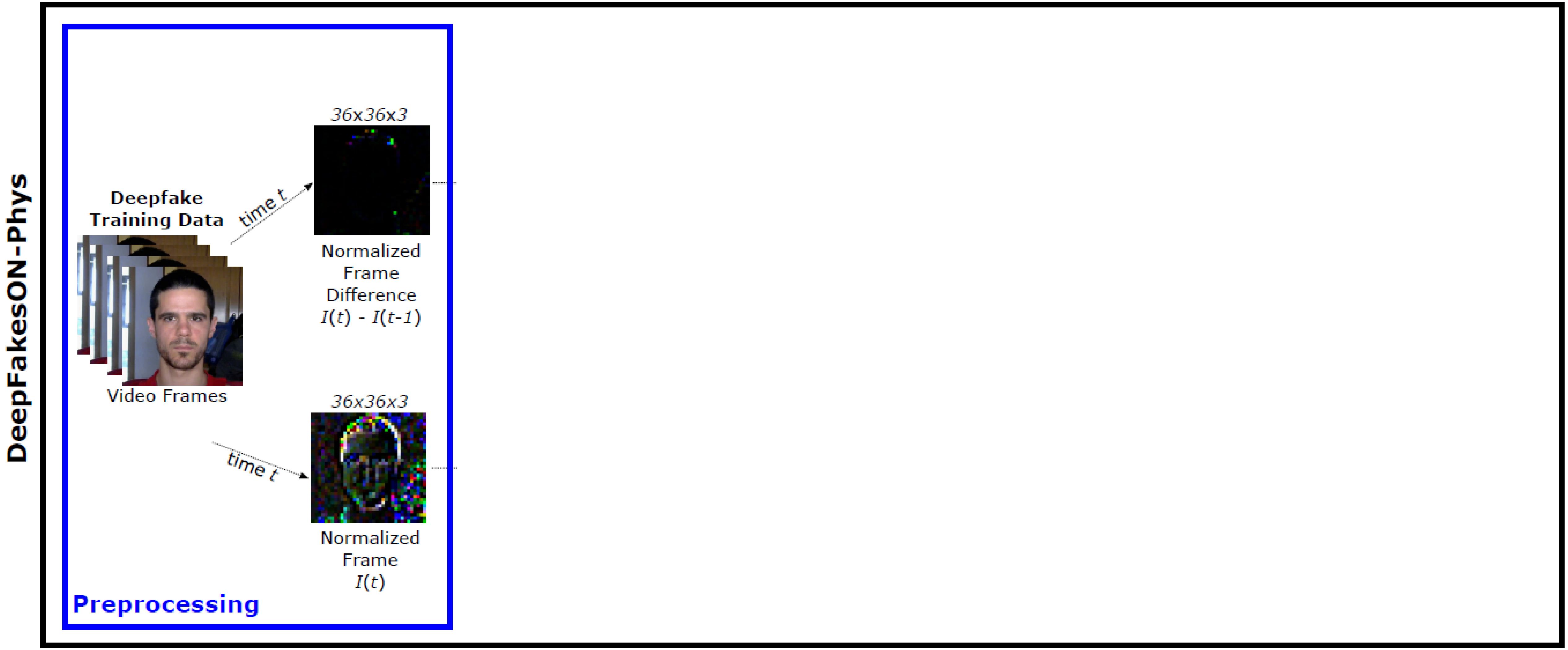
Contributions

- DeepFake detector based on physiological measurement: DeepFakesON-Phys.
  - Based on Deep Learning.
  - rPPG features pretrained for heart rate estimation.
  - Adapted using knowledge transfer.
  - Information related to the heart rate → Real or Fake.

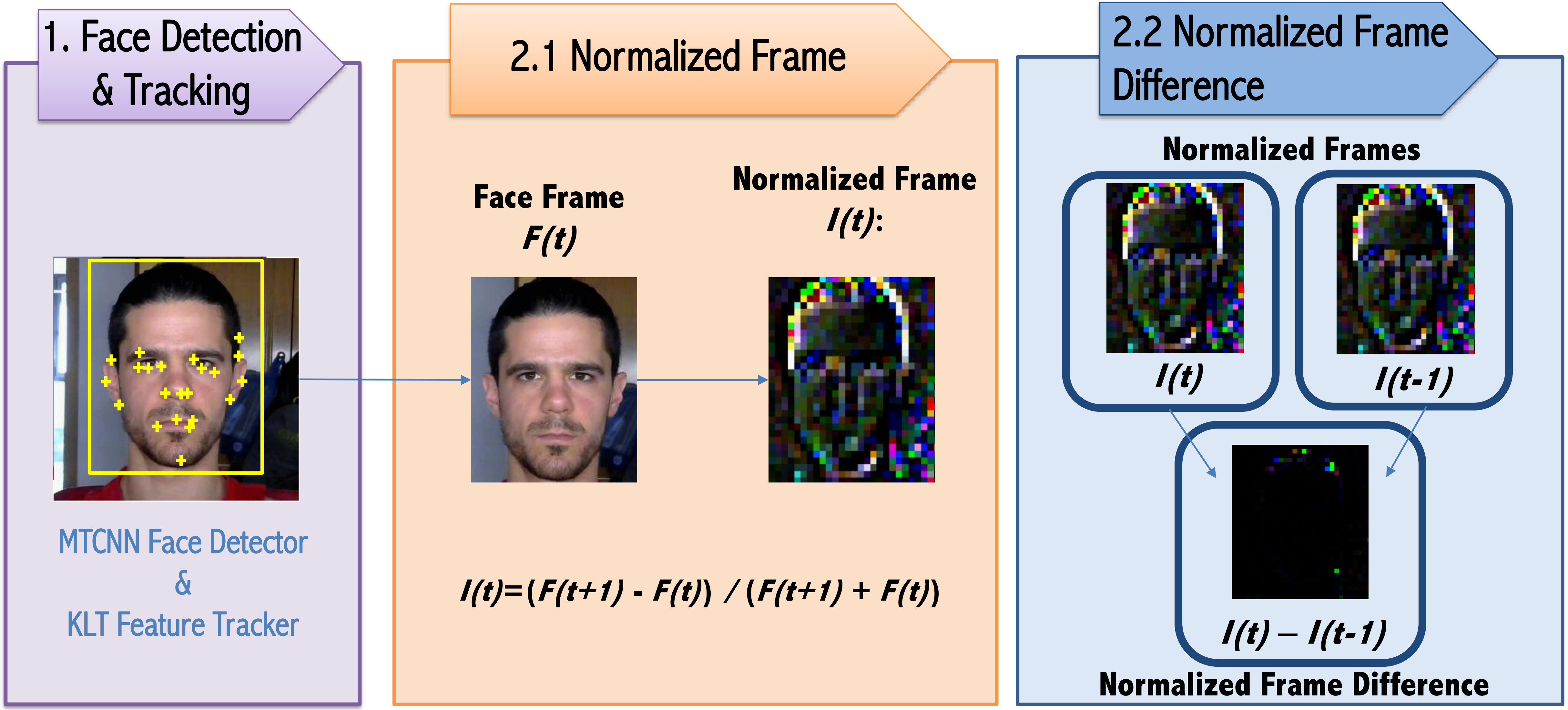
- Trained and tested with 2nd generation DeepFake DBs:
  - **DFDC Preview.**
  - **Celeb-DF v2.**

DeepFakesON-Phys → solution to the weaknesses of detectors based on the visual artifacts and fingerprints inserted during the synthesis process.

Proposed Framework



Preprocessing



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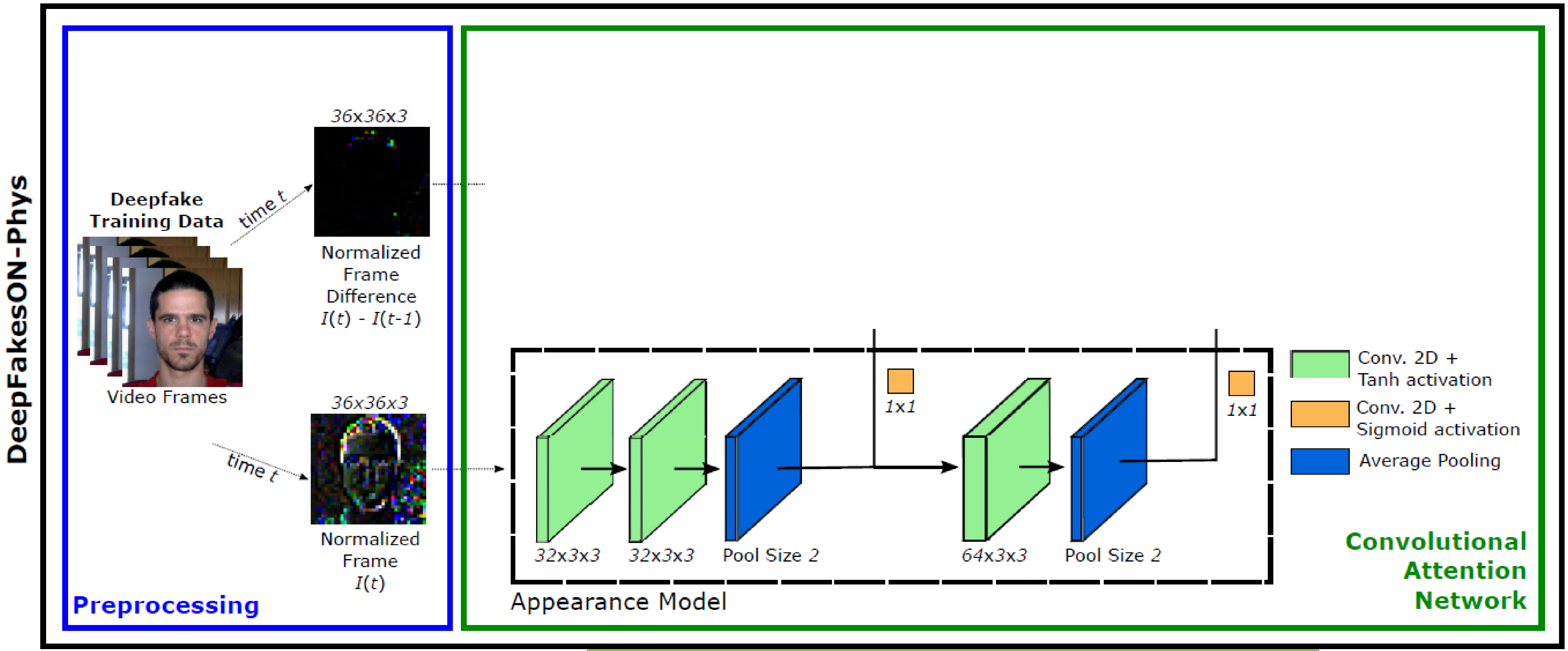
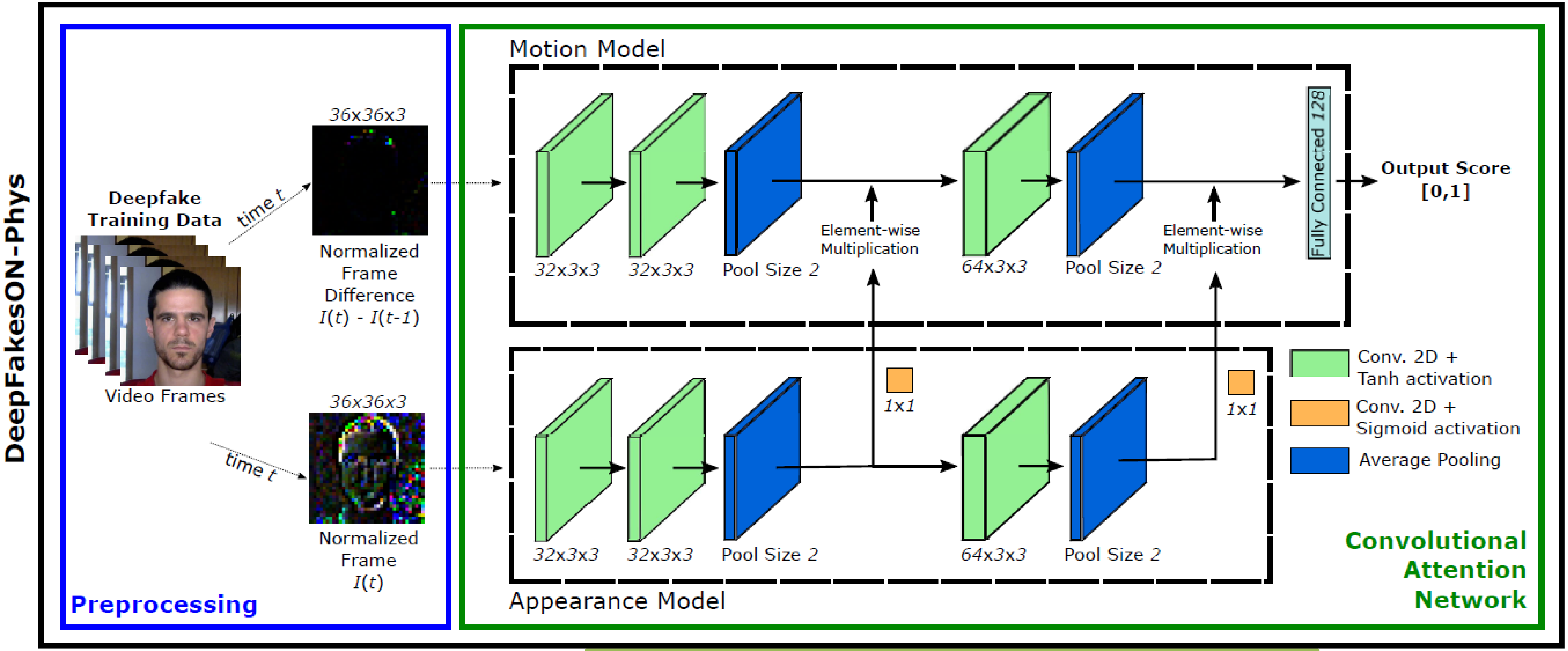


Appearance model: static information → Attention

Proposed Framework

Motion model: temporal information + attention



Appearance model: static information → Attention

Databases – 2nd Generation

Celeb-DF v2 [9]

- 590 real (Youtube)
- 5,639 fake videos (Deep Learning)

DFDC Preview [10]

- 1,131 real (Actors)
- 4,139 fake videos (Various)

[9] Y. Li, X. Yang, P. Sun, H. Qi, and S. Lyu. 2020. "Celeb-DF: A LargeScale Challenging Dataset for DeepFake Forensics". In *Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition (CVPR).*

[10] B. Dolhansky, R. Howes, B. Pflaum, N. Baram, and C. C. Ferrer. 2019. "The Deepfake Detection Challenge (DFDC) Preview Dataset". *arXiv preprint.:1910.08854.*

DeepFakesON-Phys: Development

1) Model based on DeepPhys [11] (Heart rate from facial video) → Not public.

[11] W. Chen, and D. McDuff. 2018. "**Deepphys: Video-based Physiological Measurement using Convolutional Attention Networks**". In *Procs. of the European Conf. on Computer Vision (ECCV).*

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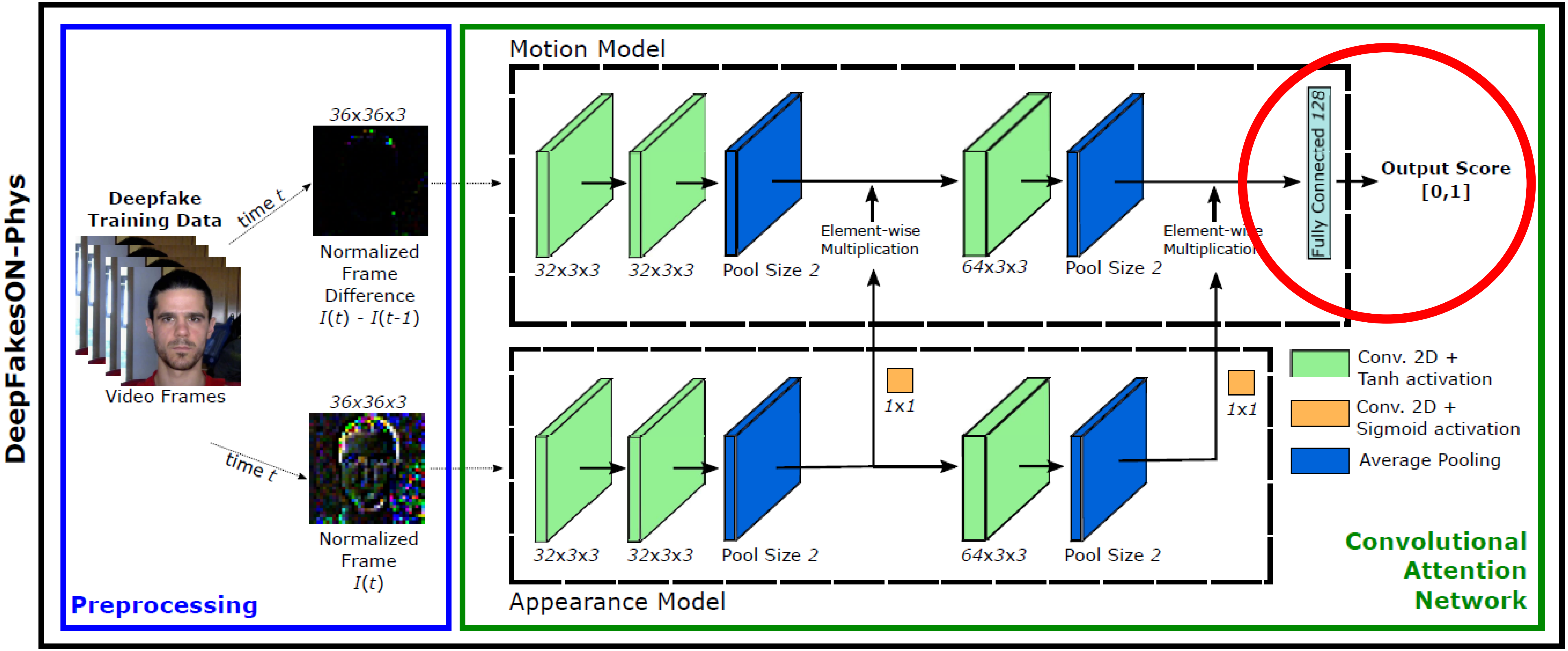
DeepFakesON-Phys: Development and Evaluation



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3) Celeb-DF v2 and DFDC Preview split into 2 non-overlapping datasets: dev. and eval.
4) Changed the last FC and the output layers of the former model (two classes, real or fake).
5) Fixed all weights up to the final fully-connected layer.
6) Trained the network for 100 more epochs and choose the best performing model based on validation accuracy.
   - One model per training database.

[11] W. Chen, and D. McDuff. 2018. "Deepphys: Video-based Physiological Measurement using Convolutional Attention Networks". In *Procs. of the European Conf. on Computer Vision (ECCV).*
[12] J. Hernandez-Ortega, *et al.* 2020. "A Comparative Evaluation of Heart Rate Estimation Methods using Face Videos". In *Procs. of the Computers, Software, and Applications Conf. (COMPSAC).*

Experimental Results

Evaluation Metrics→ Area Under the Curve (AUC) and Accuracy (Frame level).

Celeb-DF v2

Study	Method	Classifier	AUC (%)
Yang, Li, and Lyu 2019	Head Pose	SVM	54.6
Li *et al*. 2020	Face Warping	CNN	64.6
Afchar *et al*. 2018	Mesoscopic	CNN	54.8
Dang *et al*. 2020	Deep Learning	CNN + Attention	71.2
Tolosana *et al*. 2020a	Deep Learning	CNN	83.6
Qi *et al*. 2020	Physiological	CNN + Attention	-
Ciftci, Demir, and Yin 2020	Physiological	SVM/CNN	Acc. = 91.5
DeepFakesON-Phys [Ours]	Physiological	CNN + Attention	$\boxed{99.9 \; \text{Acc.} = 98.7}$

Experimental Results

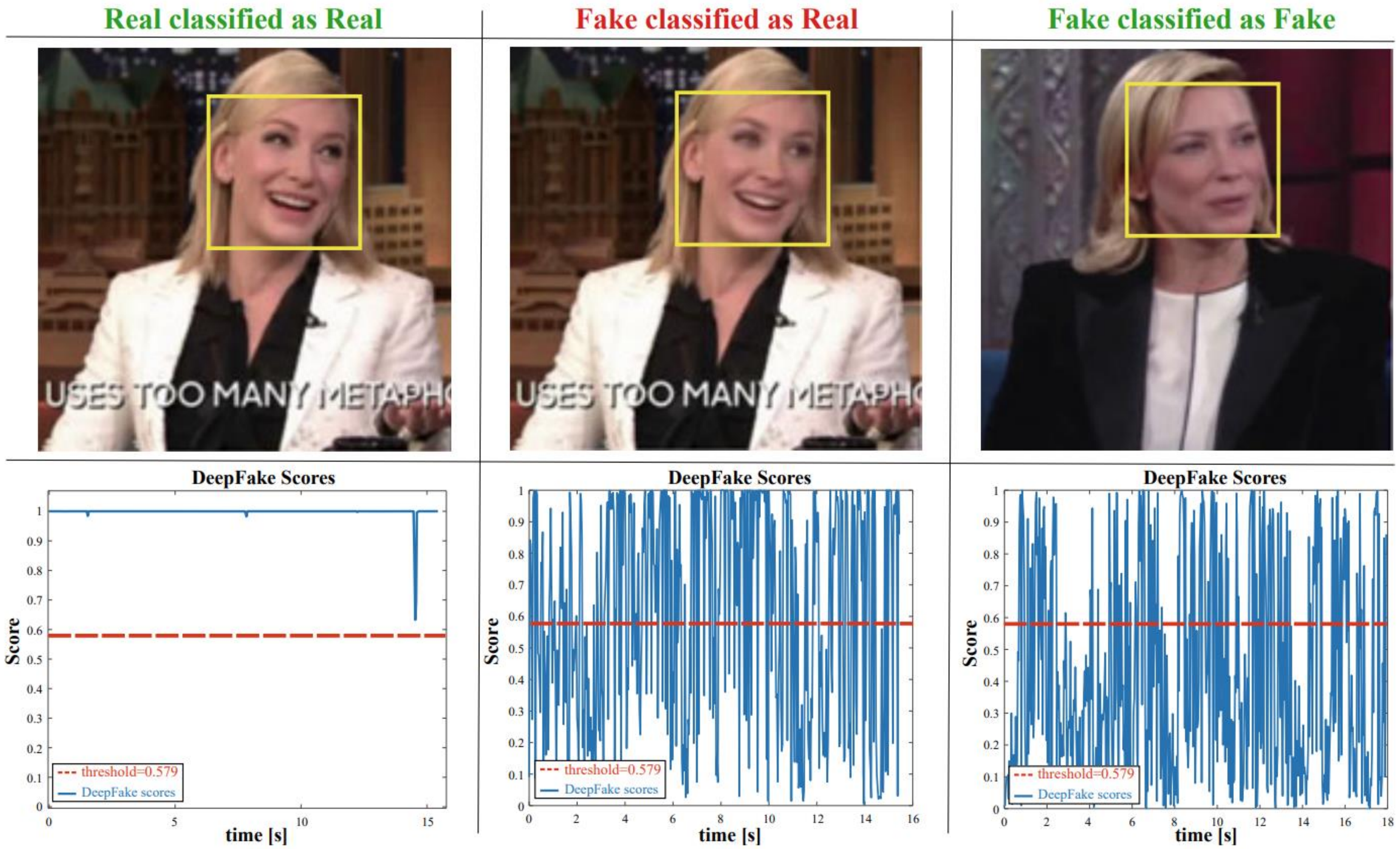
Evaluation Metrics→ Area Under the Curve (AUC) and Accuracy (Frame level).

DFDC Preview

Study	Method	Classifier	AUC (%)
Yang, Li, and Lyu 2019	Head Pose	SVM	55.9
Li *et al*. 2020	Face Warping	CNN	75.5
Afchar *et al*. 2018	Mesoscopic	CNN	75.3
Dang *et al*. 2020	Deep Learning	CNN + Attention	-
Tolosana *et al*. 2020a	Deep Learning	CNN	91.1
Qi *et al*. 2020	Physiological	CNN + Attention	Acc. = 64.1
Ciftci, Demir, and Yin 2020	Physiological	SVM/CNN	-
DeepFakesON-Phys [Ours]	Physiological	CNN + Attention	98.2 Acc. = 94.4

Detection at Short-Term Video Level

To detect the type of errors illustrated in Fig. (**oscillating scores**)



Detection at Short-Term Video Level

Combination of the frame-level scores inside a temporal window of variable length T.

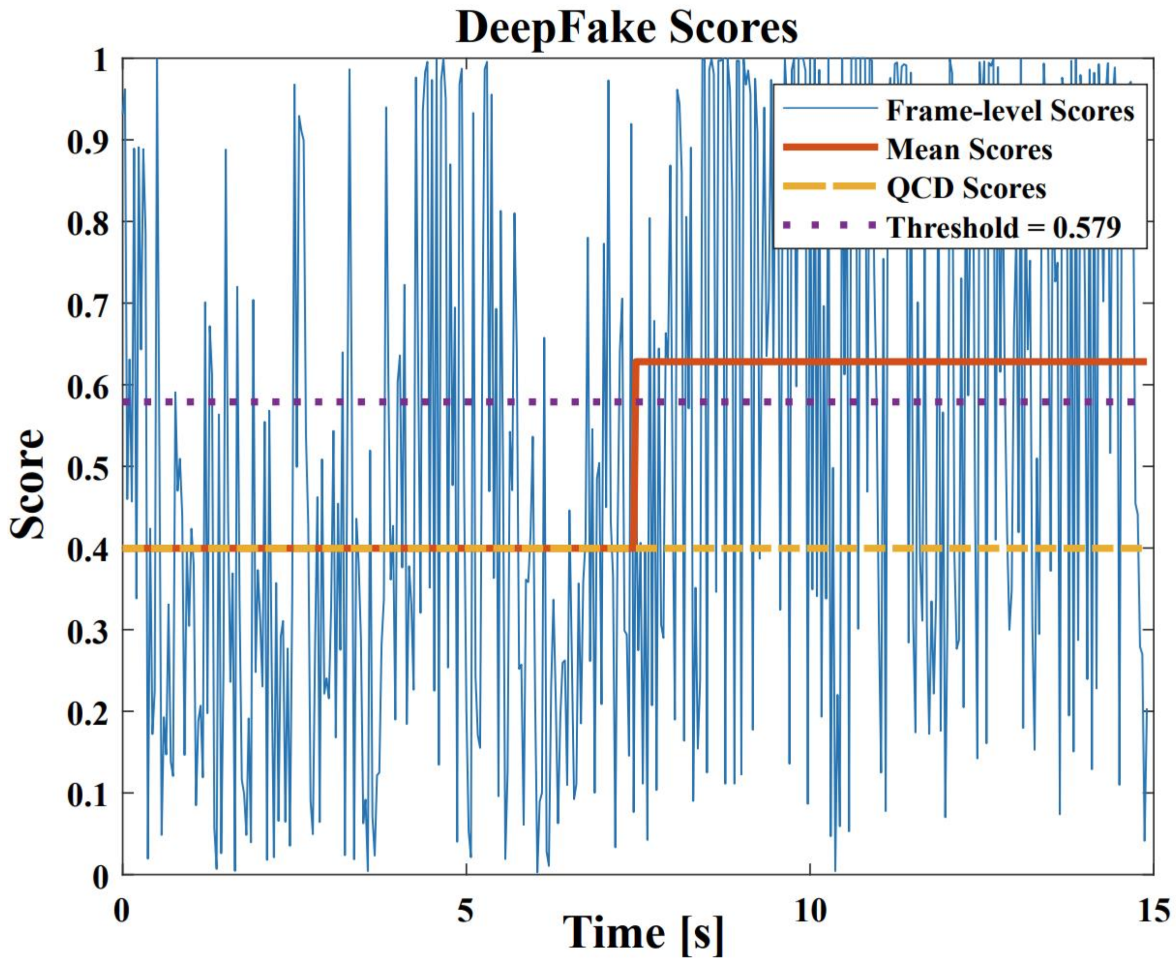
Three different combination strategies:

- Mean score
- Median score
- QCD score

Output for each one of these combinations → individual DeepFake detection score.

T going from 5 to 15 seconds.
Video segments not overlapped: decision will be generated with a delay of T secs.

Detection at Short-Term Video Level



The figure shows the single scores, the mean scores, and QCD integrated scores (T = 7 sec.) for a DeepFake video of Celeb-DF v2.

Mean score is under the threshold for the first temporal window (successful DeepFake detection), but for the second window, the score crosses the threshold causing a false acceptance.

Detection at Short-Term Video Level

Table 12.3 DeepFakes Detection at Short-Term Video Level. The study has been performed on Celeb-DF v2, changing the length of the time window T of the video sequences analyzed. Values are in %. The highest values of AUC for each type of combination of score are highlighted in bold

Mean score

Window Size T[s]	5	6	7	8	9	10	11	12	13	14	15
AUC [%]	99.97	99.98	**99.99**	99.97	99.98	99.96	99.97	99.98	99.97	99.97	99.93
Acc. [%]	99.24	99.47	99.47	99.24	99.46	99.15	99.32	99.63	99.14	99.06	99.37

QCD score

Window Size T[s]	5	6	7	8	9	10	11	12	13	14	15
AUC [%]	99.97	**100.0**	99.98	99.96	99.98	99.96	99.97	99.98	99.97	99.97	99.93
Acc. [%]	99.49	100.0	99.73	99.24	99.46	99.15	99.32	99.63	99.14	99.06	99.37

Detection at Short-Term Video Level

Temporal integration of scores can reduce the shakiness of the single scores.

Improved AUC and accuracy rates.

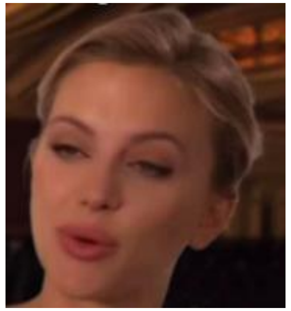
QCD obtained the best performance → but needs prior information.

Mean scores also obtain the same stability benefits → not needing any previous knowledge.

Conclusions

Two 2nd generation DeepFake databases

Celeb-DF v2



DFDC Preview

Two of the latest and most challenging DeepFake video databases.

DeepFakesON-Phys:

Outperformed other **state-of-the-art fake detectors** based on face warping and pure deep learning features, among others.

Revealed that **current DeepFake techniques do not pay attention to** the heart-rate-related or blood-related **physiological information**.

BiDA Lab

Biometrics & Data Pattern Analytics Lab

UAM Universidad Autónoma de Madrid

Know More:

R. Tolosana, R. Vera-Rodriguez, J. Fierrez, A. Morales and J. Ortega-Garcia, "**DeepFakes and Beyond: A Survey of Face Manipulation and Fake Detection**", *Information Fusion*, 2020.

J. C. Neves, R. Tolosana, R. Vera-Rodriguez, V. Lopes, H. Proenca and J. Fierrez, "**GANprintR: Improved Fakes and Evaluation of the State of the Art in Face Manipulation Detection**", *IEEE Journal of Selected Topics in Signal Processing*, 2020.

J. Hernandez-Ortega, *et al*. "**Time Analysis of Pulse-based Face Anti-spoofing in Visible and NIR**“. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 2018.

J. Hernandez-Ortega, *et al*. "**Introduction to Presentation Attack Detection in Face Biometrics and Recent Advances**" *Handbook of Biometric Anti-Spoofing,* Springer, 3rd Ed., 2022.

http://biometrics.eps.uam.es

Funding: This work has been supported by projects: PRIMA (ITN-2019-860315), TRESPASS-ETN (ITN-2019-860813), and BBforTAI (PID2021-127641OB-I00 MICINN/FEDER). J. H.-O. is supported by a PhD fellowship from UAM.

TReSPAsS-ETN

Privacy Matters

European Commission

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