

A Review of Deep Learning-based Approaches for Deepfake Content Detection

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Abstract

Recent advancements in deep learning generative models have raised concerns as they can create highly convincing counterfeit images and videos. This poses a threat to people's integrity and can lead to social instability. To address this issue, there is a pressing need to develop new computational models that can efficiently detect forged content and alert users to potential image and video manipulations. This paper presents a comprehensive review of recent studies for deepfake content detection using deep learning-based approaches. We aim to broaden the state-of-the-art research by systematically reviewing the different categories of fake content detection. Furthermore, we report the advantages and drawbacks of the examined works and future directions towards the issues and shortcomings still unsolved on deepfake detection.

Keywords: Fake Content, Machine Learning, Deep Learning, Security

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1. Introduction

One of the major global concerns of modern society regards the development and rapid dissemination of fake information through fast-content consumption platforms, such as TikTok, Twitter, Facebook, and Instagram [1, 2, 3, 4]. Such
5 content may vary from text-based messages to, most recently, image and video automatic manipulation using a family of machine learning (ML)-based approaches called deep learning.

Deep learning techniques usually stack a set of simpler ML models and apply successive operations to extract intrinsic information from data. Such
10 approaches gathered extreme popularity in the last decade, for they achieved state-of-the-art results in virtually any field of science. Among them, deepfake content became famous in social media due to its ability to stimulate one’s imagination by creating surreal and fanciful events, like presenting David Beckham speaking several languages ¹ (which he actually do not speak) or bringing
15 Salvador Dalí to host visitors of Dalí Museum ². Deepfake uses artificial intelligence to change people’s faces in images and videos, synchronizing lip, eyes, and other facial expressions, as well as body movements [5]. The technique is powerful enough to convey some comfort and raise nostalgic feelings by bringing some beloved people and celebrities “back to life”, like Freddie Mercury ³.
20 Last but not least, it also became a meme factory and source of entertainment, empowering people to “make” their friends and relatives to sing ⁴ and dance [6], among other activities [7, 8].

The deepfake concept spread so fast that, nowadays, anyone equipped with a smartphone and internet access can download and manage straightforward tools
25 to manipulate videos in any context and create realistic deepfake videos. Such a readiness raised several concerns worldwide due to the potentially negative

¹<https://variety.com/2019/biz/news/ai-dubbing-david-beckham-multilingual-1203309213/>

²<https://www.theverge.com/2019/5/10/18540953/salvador-dali-lives-deepfake-museum>

³<https://nerdist.com/article/freddie-mercury-deepfake/>

⁴<https://www.wombo.ai/>

consequences regarding unethical and malicious aspects. To cite some examples, one can find celebrities with their faces swapped with porn actresses⁵ or tampered politicians' speeches⁶.

30 Such a negative potential caught the attention of many researchers world-wide, proposing thousands of papers toward effective deepfake content detection using deep learning approaches. Nonetheless, a few works summarized the main challenges and technologies employed for the deepfake content detection. Nguyen et al. [9] excerpted the most relevant approaches for deepfake
35 creation and detection. Later on, Tolosana et al. [10] provided a review on face manipulation and deepfake detection, and more recently Juefei-Xu et al. [11] provided a deepfake-related study exposing the battleground between deepfake generation and detection and some insights regarding tendencies and future work. Finally, Mirsky et al. [12] presented an illustrated catalog of the deepfake
40 network architectures, also exploring the current status and tendencies of the attacker-defender game. Table 1 provides a comparison among recent surveys on deepfake detection, .

These works show that efficient deepfake detection tools are crucial, and such studies contribute to a brand new ground for research, whose demand grows to
45 the same degree as manipulating software becomes more popular and easier to handle, leading to an increase in the number of deepfake cases and bringing several consequences to people, governments, and companies. Therefore, this survey provides an overview of the progress associated with deepfake detection techniques. It explains deepfake detection methods based on machine learning,
50 among other intelligent systems, and also elaborates on the architectures and frameworks employed for face swapping. Further, it offers the reader a base of knowledge available in the current literature, being useful as a new source for researchers involved in image detection and security issues. Additionally, it presents a precise vision of recent research's potential challenges and the latest

⁵<https://www.vice.com/en/article/gydydm/gal-gadot-fake-ai-porn>

⁶<https://ars.electronica.art/center/de/obama-deep-fake>

Table 1: Comparison of recent surveys on deepfake detection. Notice that the number of models studied regards detection tasks only and does not consider works related to deepfake creation.

Reference	Year	Review Period	Papers Reviewed	Dataset Coverage	Models studied: Traditional/ Deep Learning	Papers discussed: Traditional/ Deep Learning	Future Directions
[10]	2020	2016-2020	34	Yes	Yes/Yes	9/25	Yes
[12]	2021	2017-2020	54	No	Yes/Yes	10/44	Yes
[11]	2021	2017-2020	97	Yes	Yes/Yes	28/69	Yes
[13]	2022	2017-2021	64	Yes	Yes/Yes	12/52	Yes
[14]	2022	2018-2020	91	Yes	Yes/Yes	21/70	No
[9]	2022	2017-2021	24	No	Yes/Yes	7/17	Yes
[15]	2022	2018-2020	25	No	No/Yes	0/25	Yes
Ours	2023	2018-2023	89	Yes	No/Yes	0/89	Yes

research guidelines. Moreover, one of the main differences and contributions is a detailed and illustrated presentation of the datasets used for detection tasks. The contributions of this work are listed below:

- It provides an updated and comprehensive review of the most recent works toward deepfake creation and detection;
- It exposes the most recent advances, main challenges, and tendencies of the field;
- It presents a detailed description of the most recent and popular architectures and frameworks for deepfake creation;
- It supplies the reader with an illustrated catalog of datasets employed for deepfake detection.

This work is organized as follows: Section 2 introduces the survey methodology, search strategy, and work selection criteria employed to produce this review article. Section 3 presents a collection of works on deepfake creation and detection, discussing each method’s relevance and contributions, while Section 4

addresses the most recent and popular datasets used in deepfake detection re-
 search. Section 5 discusses the opportunities and challenges faced by the works
 considered in this survey. Finally, Section 6 presents conclusions and future
 research possibilities on deepfake detection.

2. Review methodology

The foremost step towards a literature review is the search for the proper
 studies which comprise the subject of interest. In this sense, meaningful and
 recent research must be selected for a complete analysis aiming at categorizing
 and exploring the essential works revealing the deepfake analysis and detec-
 tion. The methodology employed in this review includes the steps depicted in
 Figure 1. The following sections describe each step in detail.

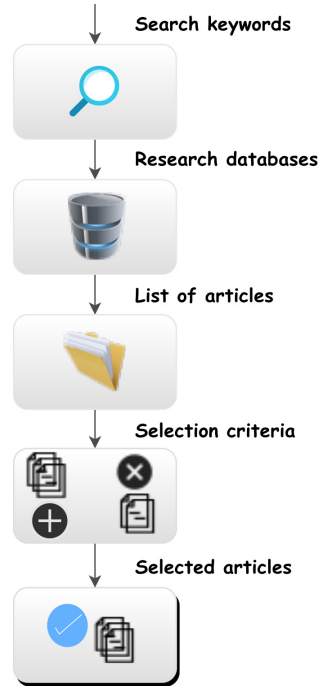


Figure 1: Proposed methodology for the literature review.

2.1. Search Keywords

The following keywords were considered for searching the eligible articles: “deep learning”, “convolutional neural network”, “deepfake detection”, “deepfake dataset”, “tampering video detection”, and “fake video detection”. Moreover, we combine the previous keywords with “recurrent neural network”, “LSTM”, and “GRU” for a broader tracking of works in the temporal learning domain. A joint of keywords was used to assemble the following command search:

```
$ ("deep learning" OR "convolutional neural network" OR  
"LSTM" OR "GRU") AND ("deepfake detection" OR  
"deepfake dataset" OR "tampering video detection" OR  
"fake video detection")
```

2.2. Research Databases

The works described and analyzed in this survey were obtained through a search ranging from 2018 to the current date in the following scientific article databases: IEEEExplore, ScienceDirect, ACM, Taylor & Francis Online, and Web of Sciences.

2.3. Selection Criteria

The selection criterion relied on the appraisal of the title and the abstract’s content to properly examine the key features which reveal the studies focusing on deepfake creation and detection. Further, some works were left aside since they didn’t fit the survey’s scope in terms of application or architecture. In this context, Rezende et al. [16], for instance, employs a shallow model, i.e., the Support Vector Machines (SVM) for classification purposes, while [17, 18, 19, 20, 21] presents different methods for fake image classification using distinct feature extraction techniques. Additionally, the work of Birunda et al. [22], which addresses deepfake detection using the Flood Fill algorithm, can be included in this list. In summary, the works selection was based on the following inclusion standards enumerated in order of importance:

- Studies that provide public datasets containing real and forged faces;
 - 110 • Studies comprising different methods for face manipulation on images, videos, and a joint of audio and video information;
 - Studies applying classical machine learning algorithms;
 - Studies applying recent deep learning models on the spatial or temporal learning domain.
- 115 The exclusion of unrelated articles was based on the following criteria:
- Records related to books and conference proceedings;
 - Systematic reviews and surveys;
 - Studies reporting a general approach to detect any fake content in images rather than only face forgery detection;
 - 120 • Studies reporting only the audio fake detection;
 - Studies comprising fake news detection;

2.4. *Selected studies*

The search strategy yielded a total of 856 reports. After removing repeated records, the selected studies were eligible for the task regarding the selection cri-

125 teria described in Section 2.3. An initial set of 742 articles was seen as potential works in the deepfake creation and detection context. The next step involves removing the documents related to books, conference proceedings, systematic reviews, and survey articles from the document set. After examining each of the remaining 658 studies, we found 101 relevant articles meeting the standards

130 for a full analysis and inclusion in this review.

3. Deepfake Detection Methods Review

This section provides a literature review of the most recent studies containing deep learning-based approaches for deepfake detection. We categorize the works by deep learning approaches for better comprehension, i.e., Convolutional Neural Networks (CNNs) with Fully Connected Network (FCN) or hybrid approaches combining classical machine learning algorithms, Generative Models, like Autoencoder and Generative Adversarial Networks (GAN), and Recurrent Neural Networks (RNN) like Long-Short Term Memory (LSTM), Gated Recurrent Unit (GRU) and Transformer. Figure 2 depicts the taxonomy of the deep learning approaches reported in the literature. In summary, we can establish two main categories for deepfake detection research: spatial learning and temporal analysis.

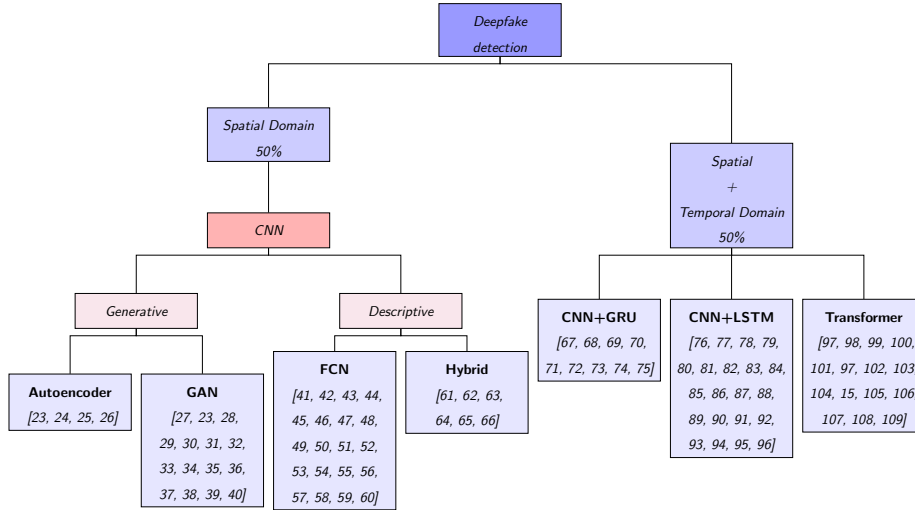


Figure 2: Taxonomy of the deepfake detection methods.

Spatial learning is designed to seek evidence of facial manipulation in images and videos by using feature extraction from all video frames individually. For feature extraction, deep CNNs are usually employed to capture the feature representation of each frame in the video. Subsequently, a classification model is trained on the feature vectors for further deepfake detection at a frame-level.

based approach. Eventually, the predictions are combined to determine the presence of face manipulation for the entire video. Regardless, spatial analysis
150 usually fails to capture unnatural artifacts at the frame-dependence level along the video composition.

Unlike spatial properties, which usually capture the forgery evidence within a single image or video frames individually, temporal properties are gathered to explore inconsistencies in the video stream using the spatial features extracted
155 from a sequence of frames, thus revealing the intercorrelation among the frames' components over time. In this sense, recurrent models have been designed to learn information dependence using a sequence of intercorrelated features, thus meeting the standards for deepfake detection via frame analysis.

3.1. Convolutional Neural Networks

160 The developed works described below use similar architectures, such as Alexnet and VGG. The authors achieve significant results even with discreet architectures and different dataset changes.

Sengur et al. [41] used AlexNet and VGG16 to extract features from faces to identify fake content evidence. The proposed approach imports the trained
165 weights via transfer learning and neglects the fine-tuning procedure, replacing the dense layer with an SVM to perform false or legit face classification. Moreover, the authors proposed combining the features obtained from both nets, providing more information and improving prediction effectiveness. The integrated features delivered the highest model performance, delivering an accuracy
170 of 94.01% on the CASIA dataset.

Meanwhile, Khodabakhsh [43] addressed the ability of some deep learning models to cope with the counterfeit face detection in images acquired from Youtube videos. The proposed study aims to appraise the model's generalizabil-
175 ity in non-public datasets. To this extent, the authors used a dataset composed of 53,000 images acquired from 150 YouTube videos related to forged faces generated by CGI (Computer-Generated Imagery) and tampering methods like FakeApp and face replacement. The authors used the following popular CNN

architectures: AlexNet, VGG19, ResNet, Xception, and Inception, trained on the Imagenet dataset. Despite the high accuracy obtained from Imagenet test images, the model effectiveness is severely reduced in test images of the new proposed dataset, indicating the difficulty of predicting the newly introduced artifacts.

Gowda and Thillaiarasu [48] alerted the threat of fake images and videos on various social platforms. Their work detects deep counterfeit images and videos using modified CNN models such as ResNext, Xception, and Ensemble from ResNeXt and Xception. The method achieved 80% accuracy with ResNeXt, 78% with Xception, and 93% with the ensemble method.

Amerini et al. [47] presented a deepfake detection approach using optical flow vectors, calculated from two consecutive frames using a CNN-based method. The model relies on possible disorders observed in such vectors due to manipulations performed in the video. Further, the flow vectors are converted to 3-channel color images so that VGG16 and ResNet-50 models extract features to predict a video as either real or fake.

Other approaches that use CNN models address the identification of noise, incompatibilities, and other features of the face to improve deepfake detections.

The work of Ivanov et al. [44] focused on the classification of counterfeit content proposing a method based on deep learning and super-resolution algorithms to expose deepfakes based on the incompatibility between the different regions of the face and the head position.

Still Li et al. [45] developed a deep learning-based approach that aims at exposing deepfake videos by detecting face warping artifacts. The main difference from this method is that it does not require deepfake generated images as negative training examples since it targets such artifacts as the distinctive feature to detect real and fake images. The approach was evaluated over two public datasets and presented very effectively in practice.

Agarwal et al. [49] proposed a biometric-based forensic technique for deepfake detection with static facial recognition, temporal behavior observed in facial expressions, and head movements. A CNN learns the behavioral incorporation

using a metric-learning objective function. In a similar work [50], the authors
210 focused on a forensic technique for lip-sync deepfake detection. Even though the
mouth shape’s dynamics are sometimes inconsistent with the spoken phoneme,
the method obtained state-of-the-art results.

Mittal et al. [54] presented a quantum-inspired evolutionary-based feature
selection method (IQIEA-FS) to classify fake-face images. The method employs
215 AlexNet to extract features from images and a feature selection model to dis-
criminate the images as real and fake faces using the best features selected from
the image feature vector.

Qurat et al. [59] compared several deep CNN architectures for face forgery
detection using the Real and Fake Face detection dataset [110]. The work
220 comprises image normalization and preprocessing using Error Level Analysis
for further training and finetuning of different deep-learning models.

With a focus on detecting video tampering, the authors Afchar et al. [46]
introduces the Mesonet, an efficient network designed to detect deepfake and
Face2Face-tampered videos. The network is composed of a few layers and fo-
225 cuses on the mesoscopic properties of images. Experimental results show a very
successful detection rate for both tasks.

Along the same lines, the work of Zi et al. [55] addressed deepfake detection
in videos using an attention-based convolutional neural network. The model
comprises 2D and 3D networks designed to use attention masks on real and ma-
230 nipulated faces. Moreover, the authors proposed the WildDeepfake in the very
same work. In similar work, Ciftci et al. [56] proposed the Fakecatcher, a deep-
fake detection network that employs biological signals as an implicit descriptor
of authenticity. The work presented outstanding results over several public
datasets, i.e., FaceForensics [111], FaceForensics++ [112], and Celeb-DF [113],
235 as well as a private set of data from videos in the wild.

Still Wang and Dantcheva [57] compared three distinct 3D-CNN models,
namely I3D, ResNet 3D, and ResNeXt 3D, for deepfake detection in videos.
The authors considered four video manipulation techniques, providing consis-
tent results on specific training and testing scenarios. Wodajo and Atnafu [58]

240 combined a CNN model with a Vision Transformer (ViT) architecture to detect videos with evidence of face manipulation. The authors rely on the VGG-16 CNN model for feature extraction from the video frames and the ViT model on such feature maps to classify the video as real or fake, obtaining significant results over the DFDC dataset.

245 Awotunde et al. [60] addresses the considerable increase in fake videos appearing genuine thanks to advances in deepfake production tools. This investigation suggests five-layer CNNs for a DeepFake detection and classification model. ReLU-enhanced CNN extracts feature from these faces, as the model extracted the face region from the video frames. The proposed model was tested 250 using Face2Face and DeepFake first-order motion datasets. Experimental results demonstrated that the proposed model has an average prediction rate of 98% for DeepFake videos and 95% for Face2Face videos in real network diffusion cases. Compared with techniques like Meso4, MesoInception4, Xception, EfficientNet-B0, and VGG16 that use CNN, the proposed model produced the 255 most promising results with an accuracy rate of 86%.

Mitra et al. [63] addressed the fake face classification in videos using a simple but effective end-to-end, fully connected deep learning architecture. The proposed method used an XceptionNet CNN as the feature extractor from the video frames. Moreover, a fully connected layer is proposed for predicting a 260 video as authentic or fake following the fact that if one of the frames is denoted as counterfeit, the proposed method considers the entire video as deep faked. The proposed network was trained with medium compressed videos (c23 compression level) of the FaceForensics++ dataset. However, predictions on highly compressed videos showed remarkable accuracy of 93%, while the performance 265 on the videos with intermediate compression quality attained 96% accuracy. However, the authors did not present the model’s effectiveness on the different fake face manipulation techniques of the FaceForensics++ dataset.

Edge descriptors have also been reported as useful features for deepfake classification in videos. In this sense, Wang, Li and Zhao [66] proposed capturing 270 the edge information from video frames for deepfake prediction using a com-

bined approach based on CNN for image feature extraction and the SVM as
 the underlying classification algorithm. Six edge filters based on four Sobel
 and two Laplacian operators are applied to the grayscale image of the face.
 Then, image feature extraction is achieved by using a ResNet-50 model in each
 275 image obtained by each edge operator. The feature maps resulting from each
 CNN model are concatenated and fed to a fully connected layer so that a 500-
 dimensional feature vector is obtained. As the final step, the SVM is used for
 classifying the frame as real or fake based on the 500-dimensional feature vector.
 The method achieved the highest AUC values against the four baseline meth-
 280 ods used for comparison. Moreover, the authors showed the best performance
 attained by using the feature vector of the edge details of the frames with the
 SVM as the underlying classifier. In this case, the method showed an AUC of
 89.3% on the Celeb-DF dataset. However, most of the tests were performed
 using the Celeb-DF dataset as the underlying data for training and evaluation
 285 of the proposed approach. Though, the method also achieved a satisfactory
 performance on the UADFV and FaceForensics++ when the Celeb-DF dataset
 was used to train the models in a cross-dataset experiment.

Recent works also highlight the detection of Deep fakes by comparing frames.
 El Rai et al. [51] describes a deepfake detection approach through CNN and
 290 residual noise. The authors hypothesize that the residual noise obtained from
 the difference between an original frame and its denoised counterpart possesses
 strong indicators in deepfake contexts. After applying a Wavelet Transform as
 the denoising filter, the residual noise is computed and further used as input
 to an InceptionResNetV2 CNN model to detect whether the whole video is
 295 fake or not. The authors reported similar performance with two baselines in
 the FaceForensics dataset, thereby confirming the good effectiveness of residual
 noises in deepfake identification.

Furthermore Patel et al. [64] proposed an end-to-end method combining fea-
 tures extracted by several CNN models for detecting deepfake videos on a frame-
 300 level-based approach. Using videos of the DFDC dataset, the authors processed
 the frames of the videos as individual images for further feature extraction and

deepfake classification by the Random Forest classifier. The authors attained the best accuracy of 0.902 with the features extracted by the MobileNet CNN. The method is proposed for deepfake detection in a frame-level-based approach. Therefore, the temporal inter-frame correlation is not considered for the entire video classification.

Besides, a study conducted by Rafique et al. [65] addressed fake face detection in images by using two machine-learning algorithms for predicting counterfeit faces based on features extracted by AlexNet and ShuffleNet CNNs. Moreover, the authors presented a new image descriptor to strengthen the prediction capability of the proposed network. The authors assume there is a difference in compression levels of authentic and counterfeit images. In this sense, the proposed approach evaluates the difference between the original image and its counterpart version with an 85% of compression level. The method is called Error Level Analysis (ELA), which produces an image with lossy details resulting from the compression level. The ELA image is then fed to the AlexNet and the ShuffleNet CNNs for the image feature extraction. The produced feature vector is used for the final classification as authentic or fake by SVM and k -NN classifiers. From experiments performed on the Real and Fake Face Detection dataset, ShuffleNet attained the highest accuracy when used as the feature extractor from the images. Moreover, combined with the k -NN classifier, the model provided the best-performing accuracy of 88.2% against 87.9% when the SVM is used as the underlying classifier.

Applicable Techniques and methods such as Transfer Learning, Generative Networks, and Fine Tuning are gaining prominence in Deepfake detection.

Malolan et al. [52] explored interpretable and easily explainable models to detect deepfake videos using a deep learning-based approach. The authors trained a CNN model in a face database and applied two explainable AI techniques to visualize the image’s protruding regions, i.e., the Layer-Wise Relevance Propagation (LRP) and Local Interpretable Model-Agnostic Explanations (LIME). Further, the authors presented a collection of explainable results for the model’s predictions regarding heat maps, image slices, and input perturbation, indicat-

ing the model’s rotational invariance and robustness to deepfake image detection.

335 Ranjan et al. [53] analyzed three public deepfake datasets, i.e., Deepfake Detection Challenge (DFDC) [114], Celeb-DF [113], and DeepfakeDetection (DFD) [115], which is now part of FaceForensics++ [112], as well as a custom high-quality deepfake dataset. The work explores real-world usage scenarios through transfer learning and a deepfake detection approach based on CNNs.
340 The authors attained 95.86% accuracy.

Many works have applied GANs as an excellent and promising technique to detect deepfake in images and videos. In this sense, the study of Varun et al. [37] explores several deepfake detection systems containing GAN with CNN to detect fake images. The authors report the latest methods to detect
345 deep fakes made on the Internet over the years. Deep fakes are identified by training the data on two datasets. Their model achieved an accuracy of 74% and validation accuracy of 63% using a lightweight model.

Mo et al. [42] proposed to detect fake faces using a simple CNN model based on three groups of convolutional and max-pooling layers. The authors used a set
350 of spatial high pass filters, which perform spatial operations for highlighting fine details on images, amplifying the image’s noise as a consequence. The residual noise constitutes the input features used in the proposed CNN architecture. The authors reported accuracy of 99.4% in legit images of the CELEBA-HQ dataset, augmented using synthetic faces generated using a GAN-based approach [116].

355 Other studies were also proposed towards the use of hybrid approaches combining classical machine learning algorithms with features extracted by CNN models for deepfake prediction in images and videos. Das et al. [61] reported a frame-level-based approach for deepfake detection in videos using a hybrid strategy for feature extraction by CNN models, feature selection, and classification
360 by a machine learning algorithm. After performing the face detection and cropping, each video frame is fed to the model for feature extraction and further classification using a classical machine learning algorithm. From each video frame used as the input image, the method combines the image features obtained

by three CNN models into a feature vector that is further used for feature selection and dimensionality reduction by the Principal Component Analysis (PCA).
365 Afterward, an SVM performs the frame classification as authentic or fake. The method attained 96.50% accuracy on the DFDC dataset using ten components selected by PCA. It performed significantly better than the baselines end-to-end CNN models trained on the same version of the deepfake dataset. The highest score is probably due to combining feature vectors with a feature selection
370 approach. However, the method used a reduced version of the DFDC dataset for experiments and performance evaluation. Therefore, it may not capture the variability of the deepfake traits in the full DFDC dataset.

The study of Masood et al. [62] exploits the combination of CNN models and an SVM classifier for fake face prediction in videos. The proposed method
375 considers a sequence of 20 video frames to perform the feature extraction and deepfake classification. The authors explored several CNN architectures in order to pick the one that performs well with the underlying classification algorithm in the feature vectors of the video frames. At last, the fake face prediction is performed by an SVM on the features extracted by the best-performing CNN
380 model. The authors reported the highest accuracy of 98% attained by the DenseNet-169 and the SVM classifier. Moreover, the same combination also achieved the highest values of precision, recall, and F1-Score.

Table 2 presents the summary of the methods described in this section, i.e.,
385 which considers Convolutional Neural Networks for deepfake detection. Notice that Tables 2-6 consider the best result reported in each paper, following the best evaluation measure and the dataset whose effectiveness was the highest among the other ones.

Table 2: Sumarized works considering CNN sorted by year and alphabetical order.

Convolutional Neural Networks					
Ref.	Year	Technique	Dataset	Input	Best result
[46]	2018	CNNs	Private data	Videos	Accuracy: 98%
[43]	2018	CNN	Fake Face in the Wild	Videos	Accuracy: 99.60%
[45]	2018	CNN	UADFV, Deepfake-TIMIT	Videos	AUC: 0.999
[42]	2018	CNN	CELEBA- HQ [116]	Fine details from high pass filters	Accuracy: 99.40%
[41]	2018	AlexNet, VGG16	NUAA [117], and CASIA-FASD [118]	Images	Accuracy: 94.01%
[47]	2019	CNN	FaceForensics++	Optical Flow from frames	Accuracy: 81.61%
[49]	2020	CNN	FaceForensics++, DFDC, Celeb-DF, WLDR [119], and DFD [115]	Videos	Accuracy: 98.90%
[50]	2020	CNN	Private data	Lip-sync, Audio-to-video, Text-to-video	Accuracy: 99.60%
[56]	2020	Traditional operator+CNN	FaceForensics, FaceForensics++, Celeb-DF, and private data	Images and Videos	Accuracy: 96%
[51]	2020	CNN	FaceForensics and DFDC	Residual noise	Accuracy: 93.00%
[44]	2020	CNN + super-resolution algorithms	UADFV	Videos	Accuracy: 95.5%
[52]	2020	LRP, LIME	FaceForensics	Faces, Images	Accuracy: 94.33%
[63]	2020	XceptionNet	FaceForensics++	Videos	Accuracy: 96%
[54]	2020	IQIEA-FS	Real and Fake Face Detection	Images	Mean normalized accuracy: 0.583
Continued on next page					

Table 2 – continued from previous page

Ref.	Year	Technique	Dataset	Input	Best result
[64]	2020	MobileNet + Random Forest	DFDC	Videos	Accuracy: 90.2%
[53]	2020	CNNs	DFD, Celeb-DF, DFDC, and private data	Images and Videos	Accuracy: 95.86%
[55]	2020	CNNs	WildDeepfake, DFD [115], Deepfake-TIMIT, and FaceForensics++	Images and Videos	Accuracy: 99.82%
[62]	2021	DenseNet-169 + SVM	DFDC	Videos	Accuracy: 98%
[59]	2021	VGG-16	Real and Fake Face Detection	Images	Accuracy: 92.09%
[65]	2021	ShuffleNet + k -NN	Real and Fake Face Detection	Images	Accuracy: 88.2%
[66]	2021	ResNet-50 + SVM	UADFV, FaceForensics++ and Celeb-DF	Videos	AUC: 89.3%
[57]	2021	3D-CNN	FaceForensics++	Videos	TCR: 87.43%
[58]	2021	CNNs and Vision Transformers	DFDC	Images and Videos	Accuracy: 91.5%
[48]	2022	CNN	DFDC	Videos	Accuracy 93%
[61]	2023	CNN + PCA + SVM	DFDC	Videos	Accuracy: 96.50%
[60]	2023	Fiver-layer CNN	DeepFake, Face2Face and First-Order Motion	Videos	Accuracy: 98.6% [‡]

[‡]Maximum score when the specified datasets are tested individually.

390 3.2. Generative Models

This section covers two generative models, the Autoencoder and Generative Adversarial Network.

Maksutov et al. [23] proposed a method to detect deepfake videos considering an artificial dataset created using GANs and autoencoders. The technique
395 computes face features using the encoders and classifies such features using the decoders and CNNs, obtaining satisfactory values of AUC and accuracy.

Along the same lines, the work carried out by Venkatachalam et al. [26] proposed a two-level deepfake detection in which the first phase concerns the task of extracting feature frames from the forged image using a sparse autoen-
400 coder enhanced by a graph long-short term memory and in the second phase fed the extracted features as input to a capsule network. Experiments were conducted using Flickr-Faces-HQ (FFHQ), 100K-Faces, Celeb-DF, and WildDeepfake datasets demonstrating good generalization and effectiveness in detecting deepfake images.

Khalid and Woo [24] proposed a Variational Autoencoder (VAE) architecture to predict fake face images in the context of one-class anomaly detection. Instead of using the binary classification task, the so-called OC-FakeDect model is trained on images of true faces that are subsequently used to predict unseen fake face images as possible anomalies. Moreover, the authors proposed a second
405 VAE version comprising an encoder layer after the image reconstruction layer for further comparison with the latent space of the original input image’s encoder. As reported in the study, the OC-FakeDect model produced better results than the binary classification task performed by the state-of-the-art Xception CNN architecture over the DFD dataset.

Du et al. [25] motivated by the degrading generalizability of deepfake detection models, they proposed a Locality-Aware AutoEncoder in which the model is forced to focus on correct forgery regions to make detection predictions. The model avoids capture dataset biases by augmenting the model with local interpretability and extra pixel-wise forgery ground truth regularization. Three types
420 of deepfake detection tasks are proposed to evaluate the model’s performance face swap manipulation, facial attributes manipulation, and inpainting-based manipulation.

Regarding Generative Adversarial Network, the work of Hsu et al. [27] com-

bined CNN models with the contrastive loss function to cope with fake image
 425 detection. The authors combined features extracted from real and counterfeit
 images for the subsequent prediction by a fully connected layer attached to the
 feature extraction network. In the context of fake image detection, the con-
 trastive loss may learn important aspects related to any image manipulation
 by comparing the features of real and forged images. Once the deep learning
 430 model is trained, it can handle the fake spots in the images' feature representa-
 tion, thus achieving a high performance even in fake images generated by five
 GANs' architectures. The authors reported an average precision and recall of
 0.88% and 0.87%, respectively, and a maximum precision and recall of 0.947%
 and 0.922%, respectively, using the Least Squares GAN (LSGAN) for fake image
 435 generation. Later on, the same authors [28] extended the work to recognize gen-
 erated fake images effectively and efficiently by integrating the Siamese network
 with the DenseNet and contrastive loss to improve the model's performance.
 In this scenario, the model attained 0.968% and 0.906% of precision and recall,
 respectively, and maximum precision and recall of 0.988% and 0.948%, respec-
 440 tively, using the Progressive Growth of GANs (PGGAN) fake image generation
 network.

Further, Korshunov and Marcel [29] reported the vulnerability of state-of-
 the-art face recognition systems to expose deepfake videos efficiently and effec-
 tively. The authors considered several baseline approaches conducted over a
 445 custom dataset named VidTIMIT ⁷. They found the best-performing methods
 based on visual quality metrics, often used in presentation attack detection.
 They also show the challenges in detecting deepfake videos produced by GANs
 using standard face recognition systems. Besides, they state the worst-case
 scenarios due to the advances of new deepfake technologies.

450 Besides, Yang et al. [30] developed a generative neural network-based method
 that splices synthesized face regions into original images, which introduces er-
 rors revealed when distinct head poses are estimated using 3D models. Such

⁷<https://conradsanderson.id.au/vidtimit/>

a model produces a set of features used to feed an SVM classifier for further distinguishing between real and fake images. Frank et al. [31] proposed a study
455 that analyzes GAN’s generated images in the frequency domain. Experimental results identified severe artifacts caused by the upsampling operations found in current GAN architectures, indicating a structural and fundamental problem in GAN’s image generation procedure.

Guarnera et al. [33] extracted Deepfake fingerprints from images by training
460 an Expectation-Maximization algorithm. These fingerprints represent the Convolutional Traces left by GANs during image generation. The results demonstrated that the proposed method achieved high discriminative power and independence of image semantics considering deepfake from 10 different GAN architectures. Following the same idea, Giudice et al. [34] employed Discrete
465 Cosine Transform to detect the GAN-specific frequencies and used G-boost as a classifier, demonstrating the robustness and good generalization even in deepfake videos that were not used in the training phase.

Aduwala et al. [35] proposed an augmented ensemble of GAN discriminators to detect DeepFake videos. Concerning the architecture, both the GAN genera-
470 tor and discriminator are deep CNNs. The methodology employed consisted of a training step in which the discriminator is pre-trained, and then both the generator and the discriminator are trained together in the GAN. The experimental results demonstrated that the accuracy of the discriminator is low in unknown datasets, i.e., those datasets that did not participate in the training step. Thus,
475 it was concluded that a GAN discriminator is not viable for handling Deepfake videos.

Jeong et al. [36] designed a deepfake detector, called FrePGAN, to overcome the poor performance of GAN models on unseen data by generating frequency-level perturbation maps. These frequency-level perturbation artifacts cause the
480 generated images to be indistinguishable from real images. Thus, at the initial iterations, the model is trained to detect these frequency-level artifacts, and at the last iterations, the model considers image-level irregularities. They employed a VGG model for the perturbation map generator, DCGAN’s discriminator

for the perturbation discriminator, and a pre-trained ResNet for the deepfake
485 classifier. Experiments validated the FrePGAN as a generalized detection model
reducing domain-specific artifacts in generated images.

Preeti et al. [38] presented a study concerning methods employed to imple-
ment deepfake. Also, they discussed deepfake manipulation and detection tech-
niques. Furthermore, they suggested a Deep Convolution-based GAN model to
490 detect deepfake on Deepfake Detection Challenge. The proposed model, trained
in Celeb-A dataset [120], worked well in small and limited datasets achieving
higher detection capacity, i.e., telling which image is real or fake, as training iter-
ations progress, minimizing the discriminator loss and achieving 100% accuracy
in detecting fake images.

495 Since there is a certain difficulty for one GAN to detect deepfake images
generated by another type of GAN, Kanwal et al. [39] proposed a general solu-
tion by employing siamese network with triplet loss function to detect deepfake
images. Experiments were split into two cases: (i) training and test sets come
from the same dataset composed of real images taken from the FFHQ dataset
500 and fake images generated by StyleGAN; (ii) training and test sets come from
different datasets in which the model is trained on FFHQ dataset and Style-
GAN and evaluated on images generated by PGAN. The results prove that train
using contrastive loss or triplet loss instead of cross entropy or MSE improves
the generalization capacity.

505 In line with the previous research, Ciftci et al. [32] separated deep forgeries
from real videos and discovered the specific generator model behind deepfake
generation. The work suggests the generator’s residuals contain relevant infor-
mation to disentangle manipulated artifacts from biological signals. The study
uses 32 raw photoplethysmogram (PPG) signals from different face locations,
510 encoded along with their spectral density into a spatiotemporal block, i.e., the
PPG cell. The PPG cells are fed to an off-the-shelf neural network to recognize
distinct signatures from the source generative models.

Complementing the studies presented, there is the research developed by
Moritz [40] that presents a Wavelet-packet-based analysis of GAN-generated

515 images for deepfake analysis and detection. The authors concern the spatial-
frequency properties of GAN-generated content. The method finds differences
between real and synthetic images in the wavelet-packet mean and standard
deviation, with rising frequency and at the edges. This mention suggests that
GAN architectures must still thoroughly capture the backgrounds and high-
520 frequency information. The same authors also found that coupling higher-order
wavelets and CNN attained an improved and competitive performance compared
to a Discrete Cosine Transformer (DCT) approach or working directly on the
raw images, where combined architectures show the best performance.

Table 3 presents the summary of the methods described in this section, i.e.,
525 using generative models to deepfake detection.

Table 3: Sumarized works considering generative models sorted by year and alpha-
betical order.

Generative Models					
Ref.	Year	Technique	Dataset	Input	Best result
[27]	2019	CNN	CelebA [120]	Images	Precision: 94.70%
[29]	2019	VGG, Facenet	Deepfake-TIMIT	Videos	False Accep- tance Rate: 95%
[30]	2019	Generative neural net- works and SVM	UADFV and DARPA MediFor GAN Image/Video Challenge [121]	Images and Videos	AUC: 0.89
[32]	2020	CNN	FaceForensics, celeb-DF, UADFV, Deepfake-TIMIT	Videos	Accuracy: 93.69%
[31]	2020	GANs, CNN, k -NN	CelebA [120] and LSUN [122]	Images	Accuracy: 99.91%
[28]	2020	CFFN	CelebA [120]	Large pose variations, and back- ground clutter	Precision: 98.80%
[24]	2020	VAE	FaceForensics++	Images	Accuracy: 98.20%
Continued on next page					

Table 3 – continued from previous page

Ref.	Year	Technique	Dataset	Input	Best result
[21]	2021	GAN	Private data	Images	Accuracy: 98.40%
[25]	2020	Locality-aware AutoEncoder	Face Swap, Facial Attributes and Inpainting-based	Videos	Accuracy: 99.67% [‡]
[33]	2020	GAN fingerprint from Expectation-Minimization	Celeb-A	Videos	Accuracy: 93%
[34]	2021	Discrete Cosine Transform	Celeb-A	Images	Accuracy: 99.9%
[35]	2021	StyleGAN-discriminator	DFDC, Celeb-A, 70k ⁸ and 140k (StyleGAN) ⁹	Images	Accuracy: 92%
[36]	2022	Frequency Perturbation GAN	FaceForensics++ and Custom GAN-generated [123]	Images	Accuracy: 79.4%
[37]	2022	CNN+GAN	Celeb-A and Real and Fake Faces	Images	Accuracy: 63%
[26]	2022	Sparse Autoencoder	FFHQ, 100K-Faces, Celeb-DF and WildDeepfake	Videos	Accuracy: 97.78%
[38]	2023	Deep Convolution-based GAN	Celeb-A	Images	Accuracy: 100%
[39]	2023	Siamese Network	FFHQ and StyleGAN	Images	Accuracy: 94.80%
[40]	2023	Wavelet-packet	FFHQ, Celeb-A, Large-scale Scene Understanding (LSUN) and FaceForensics++	Images	Accuracy: 96.91%

[‡]Maximum score when the specified datasets are tested individually.

⁸<https://www.kaggle.com/c/deepfake-detection-challenge/discussion/122786>

⁹<https://www.kaggle.com/datasets/xhlulu/140k-real-and-fake-faces>

3.3. Recurrent Neural Networks

Deep learning models applied to spatial properties of the images and videos are usually unable to effectively capture the artifacts changes and inter-correlation among the frames sequence of the video. One strategy regards classifying each video frame individually and taking the most common class for the whole video classification as real or a forgery by manipulation. However, this approach may not find the connection among the aspects that lead to a deepfake generation in high-quality and realistic deepfake videos. In contrast to spatial learning performed by classical deep learning models, temporal learning provides a reasonable strategy for capturing the intrinsic aspects that compose the traits of face manipulation across a series of visual information. In this sense, temporal learning models like recurrent neural networks can handle the drawbacks of a single-frame classification and reach a consensus on the entire video classification. In this approach, each video frame is fed to a recurrent model for learning the dependency among the visual traits of the face in a sequence. Afterward, the outputted temporal representation is handed by a model for the final classification of the whole video. By doing so, we can achieve a more effective forgery identification than only using the spatial features from the video frames. Figure 3 depicts the general process of the temporal learning approach for deepfake classification in videos.

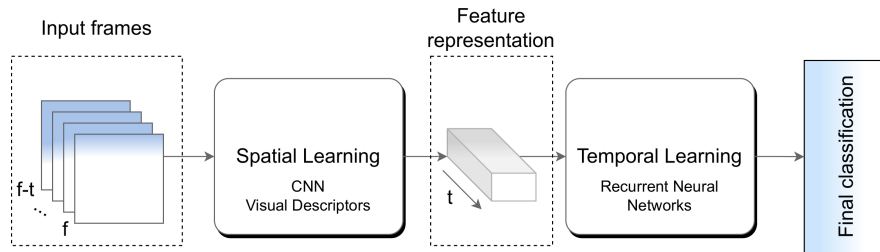


Figure 3: Illustration of the general strategy for the learning of temporal sequences of t frames in videos.

Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) are the two widespread structures for temporal learning in sequences of data. LSTM

is a special recurrent neural network model proposed to cope with the gradient vanishing in long-term dependency problems. The LSTM comprises three elements called gates: an input gate, a forget gate, and an output gate. The input gate receives the information and updates the current state of the model. The forget gate determines the irrelevant information that should be discarded, while the output gate provides the updated information. By doing so, LSTM can handle long-term sequences by deciding what information should be retained or updated. As a recurrent neural network-inspired model, GRU can also cope with long data series by combining resetting and updating mechanisms. However, unlike the LSTM structure, the GRU architecture incorporates only the update and reset gates. The update gate determines the portion of the past information that must be passed through the next layers. On the other hand, the reset gate is responsible for deciding the information that should be neglected. In this fashion, GRU reveals less number of parameters than LSTM.

Several studies have reported LSTM and GRU-based approaches as an alternative strategy to cope with the deepfake classification. The following sections describe the most recent studies proposed for classifying deepfake videos by combining spatial features and LSTM and GRU mechanisms for temporal learning.

3.3.1. LSTM

Güera and Delp [76] proposed a temporal-aware system for automatically detecting deepfake videos using CNNs for frame-level feature extraction and further feed a recurrent neural network for classification. The method is evaluated considering a large set of deepfake videos obtained from various websites, achieving competitive results for the task.

Similarly, Li et al. [77] described a method that exposes videos with fake faces generated from deep neural network models. This method detects the blink of an eye in videos, usually not treated in fake videos. The process combines Convolutional Neural Networks and Long-term Recurrent CNNs (LRCN) to distinguish between open and closed eye states.

False information provided through algorithmically modified footage, im-
580 ages, audio, and the emergence of misinformation from fabricated content re-
quires the development of anti-disinformation methods such as deepfake detec-
tion algorithms to verify the validity of digital content. To cope with such a
task, Chan et al. [78] proposed a blockchain Hyperledger Fabric 2.0 designed
with LSTMs for audio/video/descriptive captioning to combat deepfake media.
585 The framework combines various LSTM networks to trace and track digital
content’s historical provenance. As an outcome and contribution to cope with
deepfake scope, discriminative features created by a deep encoder allow proof of
authenticity (PoA) for digital media using a decentralized blockchain of multiple
LSTMs.

590 Considering the progressive quality of deepfake information created by deep
learning techniques, better algorithms to detect them are highly demanded. Al-
Dhabi and Zhang [79] then presented a solution based on a combination of CNN
and RNN, whose research highlights that using a CNN and RNN combined
architecture achieves promising results. From a pre-trained ResNeXt50, the
595 time of the model’s training is saved from scratch and used for feature extraction
from the video frames. The feature maps are then used to train the LSTM
blockchain. As the authors concluded, the CNN and RNN combination captures
the inter and intra-frame features to detect if a video is real or fake. Using a large
collection of deepfake videos gathered from various distribution sources, the
600 authors demonstrated their model’s performance with around 95.5% accuracy in
the positive deepfake detection, proposing competitive results when employing
a simplistic architecture.

From deep generative algorithms, such as GAN, Saikia et al.[93] proposed
an approach to synthesize pseudo-realistic videos that usually are very difficult
605 to distinguish. In most cases, CNN based discriminators are used to detect such
synthesized media. However, it primarily emphasizes the spatial attributes of
individual video frames, thereby failing to learn the temporal information from
their inter-frame connections. To cope with the hard task of learning temporal
information from video’s inter-frame relations, the authors employed an optical

610 flow-based approach to extract temporal features, then fed to a hybrid model
for classification composed of CNN and RNN architecture combination. Such a
hybrid model showed effective performance on the tested open source datasets,
such as DFDC, FF++, and Celeb-DF, with an accuracy of 66.26%, 91.21%,
and 79.49%, respectively, with a very reduced amount of samples (less than 100
615 frames), outperforming other works for the same fake detection modality.

To propose a new way of detecting deepfake in continuous frame video sam-
ples, Liu et al. [88] presented a robust deepfake video detection method, namely
EfficientNet-LSTM, based on steady frame face-swapping. From an in-house
face-swapping dataset with Delaunay triangulation and piecewise affine trans-
620 form (to ensure the continuous face-swapping fashion), the authors described
facial and background information using (i) EfficientNet to extract intra-frame
fusion features and (ii) LSTM to extract inter-frame time features, composing a
final mask fusion zone based on both. The cross-domain experiments highlight
that the proposed method outperforms previous ones, with higher AUC values
625 of 84.38%.

To introduce a fully-automatic and efficient approach to getting facial ex-
pressions in videos, Jolly et al. [84] proposed a model aiming to detect deepfake
or synthetic information from recorded frames. Employing the FaceForensics++
dataset for training the model composed of a Residual-Net as the backbone (fea-
630 ture extraction) and an LSTM module to build a temporal sequence for face
manipulation between frames, the authors achieved more than 99% successful
detection rate in Deepfake, Face2Face, FaceSwap, and neural texture. Thus,
the approach proposed by the authors is composed of (i) detecting the subject’s
existing facial region by extracting and processing features using a CNN and
635 LSTM combined model. Meanwhile, the Recycle-GAN was employed to merge
spatial and temporal data.

Lalitha and Kavitha’s work [87] proposed a robust neural network-based
method to identify deepfake videos. A model with a main goal of detecting
artifacts and composed of a CNN and a classifier layer based on GAN tech-
640 nology is designed, followed by a head of a Resnet, ResNeXt50, or LSTM in

favor to decide which structure to pair with the classifier while detecting the fake frames. The subsequent classifier network uses CNN’s feature vectors to categorize whether a video is fake or real. The dataset considered comes from DeepFake Detection Challenge. Compared to previous state-of-the-art studies,
645 the key video frame extraction method decreases computations by achieving 97.2% accuracy on the DeepFake Detection Challenge dataset.

To determine the rightfulness of a video, Saber et al. [91] used and compared several deepfake detection techniques to detect fake videos. By applying techniques such as YOLO-CRNN, LSTM, etc., the authors compared the models’ performances by employing EfficientNet-B5 to extract spatial features from
650 faces on video recordings, feeding them as a batch of input series into a two-way long- and short-term memory (BiLSTM). The proposed assessment is then tested on CelebDFFaceForencics++ (c23), a dataset based on a mash-up of two well-known records: FaceForencics++ (c23) and Celeb-DF. As a result, the authors achieved AUC outcomes of 89.35%, an accuracy of 89.38%, a recovery of
655 83.13%, and an F1-measure of 84.23% to insert data focus.

Patel et al. [89] proposed a joint spatial and temporal learning approach for deepfake detection in videos by combining a CNN model and an LSTM network to further detect the face as authentic or manipulated by generative models.
660 In their study, the authors proposed a new joint dataset comprising 50% real and 50% fake videos collected from YouTube and the FaceForensics++ dataset. The method considers up to 100 video frames for further feature extraction and temporal analysis by an LSTM layer. At last, a detection network predicts if the video is authentic or manipulated. The highest accuracy (91.50%) was
665 attained by using 80 sequences of video frames. Moreover, a web interface has been designed to upload the video for the subsequent deepfake prediction.

Kuang et al. [86] explored a dual-branch approach to capture inconsistencies from the sequence of video frames to detect deepfake manipulation in videos. The method comprises spatial and temporal branches for learning the spatial and temporal information from the input video. The authors used the
670 EfficientNet-B0 to capture the feature maps from the sequence of the video

frames in the spatial branch. Then, it is followed by a fully connected layer that predicts if the video is genuine or fake. At last, the method takes the average scores of all the video frames to compute the final prediction for the video. In the temporal branch, an EfficientNet and a Bidirectional LSTM layer are used to capture the spatial features and the temporal correlation from the sequence of optical flow frames computed from a gradient-based motion trajectory estimation. Optical flows regard the horizontal and vertical shifts of vector fields between pairs of video frames. In deepfake detection, it is important to capture the motion patterns of consecutive regions of the face. Finally, the spatial and temporal prediction scores are combined and passed to an SVM classifier for the final prediction of the video. The proposed model attained a maximum accuracy of 98.21% in detecting forgery faces produced by deepfake methods in the FaceForensics++ dataset. Moreover, experiments conducted on the Celeb-DF dataset also showed that the proposed model attained the best performance against the baseline models used for comparison, providing an accuracy of 98.93%.

In a similar study, Wang, Li and Zhao [95] proposed a dual-stream and a dual-utilization network that is firstly pre-trained on real and deepfake videos for the subsequent frame feature extraction and deepfake classification by an SVM classifier. In their work, dual-stream refers to the joint spatial learning and temporal learning used in combination for feature extraction from a sequence of video frames. A spatial branch was proposed to learn the edge information obtained by six edge operators applied to the video frames. Then, a binary classification is performed by a fully connected network to predict the video as authentic or manipulated. Dual-utilization is the process of training and learning the intrinsic features from the video frames in the dual-stream domain, followed by the subsequent feature extraction for further classification by the SVM classifier. The method achieved the highest accuracy of 96.2% against several baseline deep learning models adopted for comparison in deepfake detection. However, the accuracy decreases in a cross-dataset experiment in which the model’s training is applied to the FaceForensics++ dataset, and

the prediction performance is evaluated on the Celeb-DF dataset. By doing so, the model attained only 60.3% accuracy. Yet, it is higher than the accuracy
705 achieved by the baseline models. The drawback of the method is the requirement for a two-stage approach for the training of the deep learning models and the SVM classifier on the features extracted by the spatial and temporal models. Moreover, the authors selected a subset of 1000 fake videos of medium-quality compression from the FaceForensics++ dataset for performance evaluation of
710 the proposed method.

Shobha et al. [96] proposed using spatial learning and temporal analysis for deepfake detection by training the deep learning models on a large dataset of real and counterfeit videos. A comparative study of different models was evaluated using the Celeb-DF and Face Forensic++ datasets. The web-based
715 framework using Python is designed to upload a video and detect deep fakes by implementing deep neural networks. The ResNet-50 was used as the detection network for the actual training and verification. The proposed method categorizes videos more precisely to establish whether a video is real or fake. By combining ResNet-50 CNN and LSTM layers, the proposed method can help
720 leverage the strengths of both architectures and enhance the accuracy of deepfake detection by involving both image-based and sequential data. The proposed approach attained a maximum accuracy of 87.48% in 40 epochs for the model's training.

Pipin et al. [90] addressed the deepfake detection in videos by combining a
725 Deep Learning algorithm and Photo-Response Non-Uniformity pattern for the noise analysis of the video frames. Deep learning is modeled using ResNeXt-50 and LSTM and Photo-Response Non-Uniformity analysis (PRNU) to check the PRNU pattern of each frame in a video for deep fake prediction with high accuracy value reaching 97.89% using 100 input video frames of the FaceForensics++
730 dataset.

The paper of Stanciu et al. [80] proposed using a spatiotemporal CNN-LSTM approach for deepfake detection in videos using three selected facial regions. The study compares the model's performance in combined facial areas like the nose,

mouth, and eyes and the entire face on two datasets. The proposed approach
735 shows significant improvements when using a temporal network provided with 60
video frames as the input sequence for the deepfake detection; the method yields
a 13.46% increase in AUC for the Celeb-DF dataset (from 83.6% to 97.06%) and
a 99.95% AUC for the FaceForensics++ dataset.

Ilyas et al. [82] stated the challenges in detecting deepfake videos because
740 of the temporal features that might differ between the video frames. In addition,
frame-level visuals are becoming more realistic due to a tiny imperceptible
modification in each frame. Due to these aspects, the authors introduce a hybrid
deep learning model called InceptionResNet-BiLSTM, which employs the
customized InceptionResNetV2 as a front-end feature extractor and Bidirectional
745 Long-Short Term Memory (BiLSTM) network as a back-end classifier. The model
extracts the features from the frames of the videos by employing a customized
InceptionResNetV2 and then passes the feature vectors to the temporally aware
Bidirectional LSTM, which simulates the class dependency in forward and backward
directions. The authors attained an accuracy of 93.39%
750 in videos manipulated by deepfake techniques in the FaceForensics++ dataset.

Zhang et al. [81] presented a temporal learning strategy for coping with
deepfake detection in videos by using facial features and an LSTM network.
The authors proposed the Facial Alignment LSTM (FA-LSTM) and the Dense
Face Alignment LSTM (DFA-LSTM) to extract facial features from videos for
755 the subsequent classification as real or fake. The facial traits are based on
68 landmark points obtained from the facial alignment method and 3D dense
features extracted by the DFA method. Each facial component is independently
used to train a bidirectional LSTM model for the temporal learning of the
interconnection between the video frames. The authors reported 0.932 and
760 0.941 accuracies for the FA-LSTM and DFA-LSTM, respectively, on videos of
high-quality compression of the FaceForensic and FaceForensics++ datasets.
Although the lower accuracy values compared to the XceptionNet model, the
face descriptors methods performed a faster inference speed due to the low
complexity and avoidance of training of a CNN model for feature extraction

765 from the video frames.

Jalui et al. [83] proposed a method for deepfake detection in videos by using the ResNeXt-50 CNN and an LSTM layer for the spatial learning and the temporal analysis of the frame’s feature vectors. After extracting the features from the video frames, an LSTM layer receives the 2,048-dimensional feature
770 vectors to learn the visual sequences and further classify the video as authentic or fake. The authors used only 550 videos from the Deepfake Detection Challenge (DFDC) dataset to train and validate the proposed deepfake detection approach. The model achieved 96.36% accuracy on 110 samples of the test set. A correlation-based strategy was also employed to neglect similar frames from
775 the videos. However, the number of frames used as input by the LSTM model was not detailed in the study.

In a similar study conducted by Saraswathi et al. [94], a deepfake detection method was proposed by combining spatial learning and temporal analysis with a CNN and an LSTM network. In the proposed approach, a pre-trained
780 ResNeXt-50 CNN was also used for the feature extraction from each video frame. The authors used a sequence of 20 video frames for feature extraction and deepfake classification by an LSTM model. The feature vector received by the LSTM layer is 2,048 in dimensional size. Different from the study of Jalui et al. [83], the authors used a mixture of videos from Celeb-DF, FaceForensics++, and
785 Deep Fake Detection Challenge (DFDC) datasets for training and validating the proposed approach. The proposed method attained 90.37% accuracy on the test set of the created dataset.

Khedkar et al. [85] proposed a CNN-LSTM architecture for the deepfake classification in videos. The authors used four pre-trained CNN models, namely
790 VGG-19, ResNet-50 v2, Inception v3, and DenseNet-121, for feature extraction from 40 video frames before the temporal learning by two LSTM layers. Then, a dense layer is used for the final classification. The method was tested in the Face Forensic++ and DFDC datasets. The proposed model yielded 0.908 AUC and 90.7% accuracy with the frame’s spatial representation obtained by the
795 DenseNet-121 and two LSTM layers for temporal learning.

Saif et al. [92] proposed a method for face forgery detection in videos by a deep temporal learning architecture based on LSTM layers and the contrastive loss function. The authors used the contrastive loss function for the cross-learning aspects of pairs of real and faked video frames. Moreover, several CNN architectures were tested for feature extraction from the video frames. Efficient-Net B3 attained the highest accuracy when compared to the other CNN backbones for feature extraction, providing 97.3% accuracy on videos forged by deep-fake techniques and 91.36%, 91.85%, and 88.15% for FaceSwap, Face2Face, and NeuralTexture manipulation, respectively. However, it performed less than most baseline models on the entire FaceForensics++ dataset. Nonetheless, the model attained the best performance with 90.95% and 98.7% accuracy on videos with low and high-quality compression, respectively. Moreover, the authors show the challenges when a cross-method approach is tested with different forgery methods applied to the training and the validation of the temporal learning model. In such cases, the prediction capacity is decreased on videos trained using a manipulation technique and tested with another type of face forgery method. The best accuracy was attained by training and testing the model with the FaceSwap technique (97.3% accuracy).

Table 4 presents the summary of the methods described in this section, i.e., using LSTM to deepfake detection.

Table 4: Sumarized works considering LSTM sorted by year and alphabetical order.

CNN+LSTM					
Ref.	Year	Technique	Dataset	Input	Best result
[76]	2018	InceptionV3, LSTM	videos from multiple websites	Videos	Accuracy: 94.00%
[77]	2018	CNN and EAR	CEW [124] and EBV [77]	Videos	Accuracy: 99.00%
[78]	2020	Blockchain Hyperledger Fabric	N/A	Videos	N/A
Continued on next page					

Table 4 – continued from previous page

Ref.	Year	Technique	Dataset	Input	Best result
[79]	2021	ResNeXt50	DFDC, FaceForensics++ and Celeb-DF	Videos	Accuracy: 95.5%
[80]	2021	Xception	Celeb-DF and FaceForensics++	Videos	AUC: 99.95% [‡]
[81]	2021	Dense Face Alignment	FaceForensics and FaceForensics++	Videos	94.10% [‡]
[82]	2022	InceptionResNetV2	FaceForensics++	Videos	Accuracy: 93.39%
[83]	2022	ResNeXt-50	DFDC	Videos	Accuracy: 96.36%
[84]	2022	ResNet18	FaceForensics++	Videos	Accuracy: 99.26%
[85]	2022	DenseNet-121	DFDC and FaceForensics++	Videos	Accuracy: 90.7%
[86]	2022	EfficientNet-B0 + SVM	FaceForensics++ and Celeb-DF	Videos	Accuracy: 98.93% [‡]
[87]	2022	ResNeXt50	FaceForensics++ and DFDC	Videos	Accuracy: 97.2%
[88]	2022	Delaunay triangulation + Piecewise affine + EfficientNet	FaceForensics++ and Celeb-DF	Videos	AUC: 84.38%
[89]	2022	ResNeXt	FaceForensics++ and YouTube videos [†]	Videos	Accuracy: 91.50%
[90]	2022	ResNeXt-50 + PRNU	FaceForensics++	Videos	Accuracy: 97.89%
[91]	2022	EfficientNet-B5	FaceForensics++ and Celeb-DF [†]	Videos	Accuracy: 89.38%
[92]	2022	EfficientNet-B3	FaceForensics++	Videos	Accuracy: 97.3%
[93]	2022	Optical flow + VGG-16	DFDC, FaceForensics++ and Celeb-DF	Videos	Accuracy: 91.21% [‡]
[94]	2022	ResNeXt-50	Celeb-DF, DFDC and FaceForensics++ [†]	Videos	Accuracy: 90.37%
Continued on next page					

Table 4 – continued from previous page

Ref.	Year	Technique	Dataset	Input	Best result
[95]	2022	Edge de- scriptors + ResNet + SVM	FaceForensics++ and Celeb-DF [†]	Videos	Accuracy: 96.2%
[96]	2023	ResNet-50	Celeb-DF and Face- Forensics++	Videos	Accuracy: 87.48%

[†]Experiments conducted over a mash up of the specified datasets.

[‡]Maximum score when the specified datasets are tested individually.

3.3.2. GRU

In the work of Sabir et al. [67], a recurrent neural network approach was proposed to address the deepfake detection using CNN and GRU layers for feature
820 extraction and temporal learning of the video frames, respectively. Moreover, the authors addressed the face alignment among the video frames through a landmark-based alignment method and a spatial transformer network to learn the spatial parameters for the affine transformation and face alignment. The use of DenseNet CNN with face alignment and a GRU layer attained significant
825 improvements and the best prediction accuracy when Face2Face and FaceSwap manipulations were applied to the videos of the FaceForensics++ dataset. In contrast, the deepfake manipulation detection is slightly better when the three components are combined together, achieving 96.9% accuracy compared to the 96.7% accuracy provided by the DenseNet and the face alignment method with-
830 out the GRU layer. It shows the difficulty in predicting high-quality and sophisticated manipulation when deepfake methods are applied to the videos. Moreover, the landmark-based alignment strategy attained the best accuracy compared to the Spatial Transformer Network.

In the work of Montserrat et al. [68], face forgery recognition in videos is
835 proposed by using a weighting approach of the fake face probabilities in frames and a GRU layer for temporal learning of the frames' feature vectors. For each frame and face found in the video, the EfficientNet computes a weighted value and the logit value containing the probability of whether the face is real or

fake in the feature map resulting from the CNN model. All weights and logit
 840 values are then used to compute the forgery likelihood p_w for the entire video.
 The logit values, weights, and the final probability p_w are concatenated to the
 feature vectors for further analysis by a GRU layer and final prediction as a real
 or deepfake video. This approach is called Automatic Face Weighting (AFW).
 The proposed method with AFW and GRU layer achieved the best accuracy of
 845 91.88% on the test set samples of the Deep Fake Detection Dataset (DFDC).

In a similar study, Hao et al. [71] addressed detecting deepfake videos using
 a multimodality approach that relied upon visual and audio components of the
 video. For the visual classification, each video frame is fed to an EfficientNet-b5
 CNN for feature extraction and further classification of the face as real or a
 850 possible forgery by manipulation. The labels assigned to each video frame are
 then used to determine the probability of possible manipulation of the entire
 video. Then, the frames' feature vectors and the associated probabilities are
 combined and fed to a GRU layer to capture spatiotemporal properties and
 predict the video as real or fake. The authors presented a simple approach
 855 for the audio classification in which audio signals' spectrograms are fed to a
 customized CNN architecture for the subsequent classification as real or fake.
 Moreover, a multimodality approach based on audio and visual information
 from the video was also proposed to provide more discriminative features for
 the deepfake classification. Emotional features are also extracted from audio
 860 and visual components for further combination into a latent space of features
 for the final classification as a real or manipulated video. However, the authors
 did not present quantitative analysis or results achieved by the multimodality
 approach.

In the work of Jaiswal [69], a hybrid model combining LSTM and GRU
 865 layers was proposed to exploit the benefits of each type of recurrent model
 in the deepfake classification of video frames. The author presented a deep
 learning architecture in which two layers of each recurrent model are stacked
 together, followed by a single dense layer for binary classification of a video
 as real or deepfake. A customized CNN architecture was stacked before the

870 hybrid recurrent layers for temporal feature extraction from each video frame. The hybrid sequence of GRU layers followed by two LSTM layers attained the best accuracy against using only one type of recurrent model. The provided accuracy was 0.8165 for the GRU-LSTM layers in the Deep Fake Detection Challenge Dataset.

875 Tu et al. [70] addressed the problem of deepfake detection by using a Convolutional GRU (ConvGRU) architecture for temporal learning of feature maps produced by a pre-trained Resnet50 CNN on a sequence of 10 video frames. ConvGRU was used because it is less complex and has less parameters than Convolutional LSTM (ConvLSTM). The proposed method attained 89.3% AUC
880 and 94.56% accuracy on the celeb-DF(v2) dataset. The main drawback is the lack of important architecture information like the feature map's size resulting from both, ResNet50 and ConvGRU.

Ismail et al. [72] proposed a hybrid approach for face forgey classification in videos that integrates image features extracted from a modified Xception
885 Net architecture and spatial gradient directions computed from the Histogram of Gradient Oriented (HOG) method. Their strategy presented a customized CNN architecture that receives the image containing the gradient orientation calculated by the HOG method and produces a fixed-size output feature vector representation. Moreover, an improved Xception Net architecture is proposed to
890 extract the feature's vector representation directly from the input video frames. The feature vectors produced by the two CNN models are then fused and fed to a sequence of GRU layers for further classification of the video's authenticity. To capture discontinuities produced by processing each frame individually, the authors utilized eight sequences of GRU layers to extract the temporal features
895 of the video frames, which are then fed to a fully connected layer for the final video's classification as real or fake. The proposed method performed best compared to baseline CNNs, achieving 95.56% accuracy and 95.53% of Area Under the Receiver Operating Characteristic (AUROC) on the Celeb-DF and FaceForencics++ datasets.

900 Pu et al. [73] proposed a temporal learning-based method and a novel loss

function to handle deepfake detection in a class-imbalanced dataset. Using a video-level and a frame-level classification approach, the authors combined the feature maps extracted from 300 video frames with the temporal learning performed by GRU layers to classify real and fake faces in videos. ResNet50 has
905 been used to compute the features from each video frame. Also, the authors proposed a loss function that combines the binary cross entropy and AUC to efficiently cope with imbalanced class distribution at the video-level and frame-level classification. Experiments were performed using the Celeb-DF and FaceForensics++ datasets. Also, the authors used samples from the DFDC dataset with
910 different ratios of positive and negative instances to simulate an imbalanced data distribution. No data augmentation was used in this work. The proposed method attained the best performance at both the video-level and frame-level classification, even in skewed data distribution that promotes excessive samples for videos of real faces. The method achieved 96.5% accuracy and 98.9% AUC
915 in the imbalanced Celeb-DF dataset. Also, the performance increased as the combined loss was included in the model.

Elpeltagy et al. [74] addressed the ability of a multimodal-feature level approach for deepfake classification in videos. The proposed method is based on two modalities of features extracted from frames and the audio of the input
920 videos. Each video component, i.e., the visual and the audio, is fed to a different CNN architecture to obtain two feature vector representations. The two feature vectors are then fused and given to a GRU network to learn the video’s temporal properties. The real or fake video prediction is performed by a fully connected layer that receives the temporal features from the GRU model. From
925 experiments performed on the FakeAVCeleb dataset, the method attained the highest accuracy (97.52%) when compared to Xception and VGG16 employed for deepfake classification on spatial characteristics of the frames.

Sun et al. [75] designed a recent deepfake detection method to transform the task of detecting deep fake videos into a scheme of detecting multi-variable
930 time series anomalies to expose artifacts generated by facial manipulation in both temporal and spatial dimensions. The authors propose employing virtual-

anchor-based region displacement trajectory extraction to obtain the spatial-temporal representation of different facial areas. Furthermore, a fake trajectory detection network was constructed based on dual-stream spatial-temporal graph attention. A gated recurrent unit backbone converts the deep fakes detection task into a binary classification problem for a multi-variable time series. The samples from the Face-Forensics++ dataset were applied to carry out the method.

Table 5 presents the summary of the methods described in this section, i.e., using GRU to deepfake detection.

Table 5: Sumarized works considering GRU sorted by year and alphabetical order.

CNN+GRU					
Ref.	Year	Technique	Dataset	Input	Best result
[67]	2019	DenseNet + Face Alignment	FaceForensics++	Videos	Accuracy: 96.9%
[68]	2020	EfficientNet + AFW	DFDC	Videos	Accuracy: 91.88%
[69]	2021	CNN + GRU-LSTM	DFDC	Videos	Accuracy: 81.65%
[70]	2021	ConvGRU	Celeb-DF(v2)	Videos	Accuracy: 94.56%
[71]	2022	EfficientNet-b5	DFDC	Videos	AUC: 0.97
[72]	2022	XceptionNet + HOG	Celeb-DF and FaceForensics++	Videos	Accuracy: 95.56%
[73]	2022	ResNet-50	Celeb-DF	Videos	Accuracy: 96.5%
[74]	2023	XceptionNet + Inception-ResNet	FakeAVCeleb	Videos and Audio	Accuracy: 97.52%
[75]	2023	Trajectory of the Facial Region Displacement	FaceForensics++	Video	Accuracy: 99.5%*

*Maximum score obtained from the deepfake manipulation method of the FaceForensics++.

3.4. Transformer

Khan et al. [125] propose a video transformer with a face UV Texture Map for deepfake detection. The results on five public datasets show that the method
945 achieves better than state-of-the-art methods. That proposed segment embedding allows the network to extract more informative features, improving detection accuracy. The exhaustive experiments show that the model can reach suitable performance on an unexplored dataset while maintaining the performance on the previous dataset.

950 Cocomini et al. [98] investigate various solutions based on combinations of convolutional networks, mainly the EfficientNet-B0, with varying types of Vision Transformers and compare the results with the state-of-the-art. The proposed solution is designed to merge two visual transformer architectures which combine multi-scaled feature maps obtained by two pre-trained EfficientNet-B0 CNNs.
955 By combining feature representations of the transformer mechanism, the method can learn the deepfake aspects of the multi-scale feature representation of the face. Still is investigating some gains that can be made during generalization to achieve better and more stable results in video deepfake detection. The work employs a patch extractor based on EfficientNet. It is particularly effective even
960 just using the smallest network in this category. It led to better outcomes than an extractor with a generic convolutional network trained from scratch, thus achieving an AUC of 0.951 using the cross-visual transformer. Moreover, compared to state-of-the-art solutions, the method achieved the highest mean accuracy in the four face manipulation strategies of the FaceForensics++ dataset.

965 Heo et al. [106] proposed a DeepFake detection using a Vision Transformer Model, which has indicated good performance in recent image classifications and combined CNN and patch-embedding features during the input stage. The Robust Vision Transformer Model has shown efficiency compared with EfficientNet as the state-of-the-art model, which consists of a 2D CNN network. The state-
970 of-the-art obtained an AUC of 0.972, whereas the proposed work obtained 0.978 under identical conditions without an ensemble approach. The proposed method produced an F1 score of 0.919, whereas the state-of-the-art model achieved 0.906

under the same threshold condition of 0.55. Furthermore, the authors observed an AUC gain of up to 0.17 compared with a recent scheme. The proposed model
975 reached an AUC of 0.982 with the ensemble method, whereas the state-of-the-art model achieved 0.981.

The work developed by Xue et al. [100] proposes a transformer-based deepfake detection method for facial organs, which can effectively differentiate deepfake media. The authors highlight that deepfake detection on subtle-expression
980 manipulation, facial-detail modification, and smeared images has become a wide research hotspot. Also, complete that existing deepfake detection methods on the entire face are coarse-grained, where the details are missing due to the insignificant manipulated size of the image. To address the concerns, the authors created a transformer model for a deepfake detection method by organ. The
985 investigation reduces the detection weight of defaced or unclear organs to prioritize the detection of clear and undamaged organs. The study also implements a Facial Organ Forgery Detection Test Dataset (FOFDTD), which includes the images of the masked face, sunglasses face, and undecorated faces collected from the network. Experimental results verified the effectiveness of the proposed approach, which attained an AUC of 99.93%, 94.32%, 75.93%, and 82.43% in the
990 FaceForensics++, DFD, DFDC-P, and Celeb-DF datasets, respectively.

In their paper, Zhang et al. [101] propose the TransDFD, a transformer-based network for deepfake detection that learns discriminative and general manipulation patterns end-to-end. Their model introduces the spatial attention
995 scaling module, which emphasizes salient features while suppressing less important representations. It considers fine-grained local and global features based on intra-patch locally-enhanced relations. Additionally, it also finds inter-patch locally-enhanced global relationships in face images. Experiments conducted over several public benchmark datasets show that TransDFD can outperform
1000 state-of-the-art approaches in robustness and computational efficiency.

The work of Khan et al. [97] proposes a hybrid transformer network using a feature fusion strategy for deepfake video detection. The model employs XceptionNet and EfficientNet-B4 as feature extractors along with a transformer

architecture in an end-to-end manner on FaceForensics++ and DFDC benchmarks. The authors also proposed two augmentation techniques: face cut-out and random cut-out augmentations. The model achieved comparable results to more advanced state-of-the-art approaches, while the augmentation techniques improved the detection performance of the model and reduced overfitting.

Khormali et al. [102] proposed an end-to-end Transformers-based deepfake detection framework called DFDT, whose layers implement a re-attention mechanism instead of a traditional multi-head self-attention layer. The model learns hidden traces of perturbations from local image features and the global relationship of pixels at different forgery scales using four main components: patch extraction and embedding, multi-stream transformer block, attention-based patch selection, and a multi-scale classifier. The performance of the approach is accessed through a set of experiments on several deepfake forensics benchmarks, which results reached detection rate values of 99.41%, 99.31%, and 81.35% on FaceForensics++, Celeb-DF (V2), and WildDeepfake, respectively.

Coccomini et al. [103] considered the possibility of untying the deepfake detection to the methods used to generate the training samples. The authors compared Vision Transformer with an EfficientNetV2 on a cross-forgery context based on the ForgeryNet dataset [126], concluding that EfficientNetV2 has a greater tendency to specialize, often obtaining better results on training methods. At the same time, Vision Transformers exhibit a superior generalization ability, making them competent even on images generated with new methodologies.

The work of Wang et al. [104] proposed the Multi-modal Multi-scale TRansformer (M2TR), which aims to capture subtle manipulation artifacts at different scales using transformers. The model operates on patches of different sizes to detect local inconsistencies in images at different spatial levels, also learning to detect forgery artifacts in the frequency domain to complement RGB information through a cross-modality fusion block. Results show that the technique can outperform state-of-the-art deepfake detection methods by clear margins when applied to a novel large-scale deepfake dataset named Swapping and Reenact-

1035 ment DeepFake (SR-DF).

A more recent work [109] proposes a deep convolutional Transformer model that incorporates decisive image features locally and globally. The model applies convolutional pooling and re-attention to enrich the extracted features and image keyframes to improve the deepfake detection performance and vi-
1040 sualize the feature quantity gap between the key and normal image frames caused by video compression. The experiments conducted over several deepfake benchmark datasets show that the solution outperforms several state-of-the-art baselines considering both within- and cross-datasets.

Raza, Malik and Haq [105] propose a vision transformer architecture com-
1045 bining spatial, temporal and spatiotemporal features extracted from videos for deepfake classification tasks. Spatial feature extraction is achieved by two-dimensional convolutional layers applied to a single frame of the video. In contrast, temporal features are extracted using three-dimensional convolutions to a sequence of images comprising the difference between two consecutive video
1050 frames. Finally, 3D convolutions are applied directly to video frames to capture the spatiotemporal aspects of the face. The proposed strategy combines the transformer representations obtained from the spatial, temporal, and spatiotemporal feature maps into a single feature vector representation which is then fed to a fully connected layer. This strategy can capture evidence of possi-
1055 ble manipulations at different feature levels, i.e., spatial and temporal domains. Results show AUC scores of 0.926, 0.9624, and 0.9415 on the DFDC, Celeb-DF, and FaceForensics++ datasets, respectively. Moreover, the proposed method achieved the best accuracy in videos produced by the Neural Texture subset of the FaceForensics++ dataset.

1060 Feinland et al. [99] proposed merging two visual transformer architectures to combine multi-scaled feature maps obtained by two pre-trained EfficientNet-B0 CNNs. By combining feature representations in the attention mechanism, the method can learn important aspects at the multi-scale feature level of the face image. Moreover, the authors propose an inference approach ruled by the
1065 vote of predictions produced from each face detected per person in the video.

The entire video is considered a forgery if one person’s face is classified as fake. The method attained an AUC of 0.951 using the voting classification and the cross-visual transformer with EfficientNet-B0 as the backbone for feature extraction. Compared to state-of-the-art methods, the approach achieved the highest
1070 mean accuracy in the four face manipulation strategies of the FaceForensics++ dataset.

The work of Lin et al. [107] proposes a dual-subnet network that uses a transformer architecture to learn and extract multi-scale information and high-level features of the faces to cope with deepfake in videos. Using multi-scale information
1075 makes it possible to learn intrinsic aspects revealing possible manipulations at different regions of the target face. At the same time, high-dimensional features are extracted via an EfficientNet-B4 convolutional module with depthwise convolutions. The multi-scale and the high-dimensional features are combined and fed to a vision transformer module to learn more contextual relations among
1080 the image features, followed by the final classification of the video as real or fake. By exploiting features at different scales, the method achieved the best scores in all datasets and ablation scenarios, with the best accuracy of 99.80% on the Celeb-DF dataset. In comparison, the worst performance was attained on the WildDeepfake dataset (82.63%).

1085 Zhang et al. [15] employed a vision transformer architecture for the temporal analysis of faces’ random regions to cope with spatiotemporal inconsistencies indicating possible video manipulation. The method is called spatiotemporal dropout, which discards some facial frames and random patches of each frame based on a uniform distribution ruled by dropout rates. A bag of patches is
1090 then formed from the selected facial regions and fed to the vision transformer architecture to capture inconsistencies across the frames. A fully connected layer then uses the transformer representation to predict the video as real or fake. Since the counterfeit artifacts are mostly spread across some regions of the face, the model can capture more specific features which locally describe
1095 spatial inconsistencies. Results showed the best AUC scores compared to 25 state-of-the-art methods in all the deepfake datasets, achieving average scores

of 99.8%, 99.1%, and 97.2% in the FaceForensics++, DFDC, and Celeb-DF datasets, respectively. Moreover, the model was able to cope with the four facial manipulations of the FaceForensics++ dataset, thus achieving eminent performance with scores higher than 90% in all subsets of deepfake generation.

Khalid, Akbar, and Gul [108] created the Swin Y-Net Transformers architecture in which the encoder, composed of a swin transformer, divides the entire image into patches to extract details. In contrast, the decoder, composed of U-Net, creates a segmentation mask for further classification. Experiments conducted over Celeb-DF and FF++ datasets demonstrated the generalization capability of the proposed model and great capacity to identify videos created by DeepFakes, FaceSwap, Face2Face, FaceShifter, and NeuralTextures algorithms.

Table 6 presents the summary of the methods described in this section, i.e., using Transformers to deepfake detection.

Table 6: Sumarized works considering Transformers sorted by year and alphabetical order.

Transformer					
Ref.	Year	Technique	Dataset	Input	Best result
[97]	2022	UV Texture Map	FaceForensics++ and DFDC	Video	Accuracy: 99.79% [‡]
[98]	2022	EfficientNet-B0	FaceForensics++ and DFDC	Video	AUC: 0.951 [‡]
[99]	2022	EfficientNet-B0	FaceForensics++ and DFDC	Videos	AUC: 0.951
[100]	2022	CNN on multiple face organs	FaceForensics++, DFD, DFDC-P and Celeb-DF	Video	AUC: 99.93% [‡]
[101]	2022	VGG	FaceForensics++, DFDC and DFD	Video	AUC: 98.40%
[97]	2022	Face cut-out and Random cut-out	FaceForensics++ and DFDC	Video	Accuracy: 98.24% [‡]
[102]	2022	Patch extraction and embedding	FaceForensics++, Celeb-DF and WildDeepfake	Videos	Accuracy: 99.41% [‡]
Continued on next page					

Table 6 – continued from previous page

Ref.	Year	Technique	Dataset	Input	Best result
[103]	2022	Vision Transformer	ForgeryNet [126]	Images	Variance: 0.004
[104]	2022	CNN + Frequency Filter	FaceForensics++, Celeb-DF and SR-DF [‡]	Videos	AUC: 91.20% [§]
[15]	2022	Dropout rate to discard image patches	Celeb-DF, DFDC and FaceForensics++	Videos	AUC: 99.8% [‡]
[105]	2023	2D and 3D CNNs	Celeb-DF, DFDC and FaceForensics++	Videos	AUC: 0.9624 [‡]
[106]	2023	EfficientNet-B7	DFDC and Celeb-DF (v2)	Video	AUC: 0.982
[107]	2023	EfficientNet-B4	Celeb-DF, DFDC, Face-Forensics++, and WildDeepfake	Videos	Accuracy: 99.80% [‡]
[108]	2023	Encoder + Decoder - Transformer	Celeb-DF and FaceForensics++	Videos	AUC: 0.99 [‡]
[109]	2023	Local and global feature maps	FaceForensics++, Celeb-DF, DF-1.0 and DFDC	Videos	AUC: 97.66%

[‡]Maximum score when the specified datasets are tested individually.

[§]Score obtained from the novel SR-DF dataset used in the training and testing of the model.

1110

4. Datasets

This section presents the most recent and popular datasets generated with deep learning techniques for deepfake detection.

4.1. HOHA-based dataset

1115 Güera and Delp [76] provided a dataset composed of 300 videos randomly selected from the HOHA dataset [127], which comprises a realistic set of sequence samples from famous movies with an emphasis on human actions, as well as 300 other deepfake videos collected from multiple video-hosting websites, leading to

a total of 600 videos, usually presented in 360×240 format, with 24 frames per
 1120 second.

4.2. Faceswap-GAN

Korshunov and Marcel [29] proposed the first publicly dataset composed
 of deepfake videos created with GANs, i.e., the Faceswap-GAN database¹⁰.
 The dataset comprises low and high-quality videos with 64×64 and $128 \times$
 1125 128 pixels resolution, respectively. Each resolution comprises 320 samples with
 approximately 200 frames each. Finally, it is generated from 16 pairs of people
 manually selected from the VidTIMIT dataset.



Figure 4: Samples from Faceswap-GAN dataset. For each block, the left column denotes
 original images and the right column stands for synthetic instances. Adapted from [128].

4.3. UADFV

The UADFV [129] is a synthetic dataset provided by the University of Al-
 1130 bany with the primary objective of helping to detect fake face videos through
 physiological signals, i.e., eye blinking, a feature claimed by the authors as not
 well presented in synthesized videos. The dataset is composed of 49 fake videos
 generated through the FakeApp mobile application¹¹, where the individual's
 original faces are swapped with Nicolas Cage's face. Each sequence comprises
 1135 a 294×500 pixels resolution and 11.14 seconds on average. Figure 5 provides
 some samples of the original and their respective synthetic version.

¹⁰<https://github.com/shaoanlu/faceswap-GAN>

¹¹<https://fakeapp.softonic.com>



Figure 5: Sample frames from the UADFV dataset. The top row depicts original faces, while the bottom row stands for synthetic images. Adapted from [129].

4.4. Deepfake-TIMIT

The Deepfake-TIMIT [130] comprises 640 fake videos obtained from 10 image sequences of 32 people extracted from VidTIMIT dataset ¹², generated using a GAN-based face-swapping algorithm. The authors manually selected 16 pairs of individuals that shared some visual similarities and swapped their faces, as illustrated in Figure 6. The videos are divided into two main categories, i.e., low quality, which comprises 320 videos with approximately 200 frames of 64×64 pixels each, and high quality, composed of 320 image sequences with around 400 frames of size 128×128 pixels.

4.5. FaceForensics

FaceForensics dataset [111] comprises about a half-million manipulated images from 1,004 videos designed for benchmarking forensic purposes regarding classification and segmentation tasks at various quality levels, provided with ground-truth masks. The dataset is divided into two subsets created using Face2Face [131] reenactment approach such that the first, namely Source-to-Target Reenactment Dataset, performs the reenactment between two randomly chosen videos, as illustrated in Figure 7, and the second subset is the Self-Reenactment Dataset, which uses the same video as the source and the target

¹²<https://conradsanderson.id.au/vidtimit/>

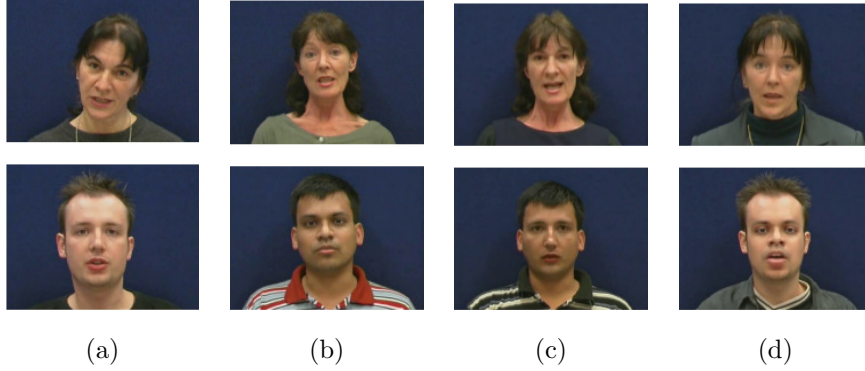


Figure 6: Sample frames from the Deepfake-TIMIT dataset: (a) original image A , (b) original image B , (c) swap $A \rightarrow B$, and (d) swap $B \rightarrow A$. Adapted from [130].

1155 video. The authors considered videos with 854×480 resolution or more from the
youtube and youtube8m datasets and extracted sequences containing at least
300 consecutive frames of the face. Finally, manual screening is performed to as-
1160 sure the videos' quality. The whole dataset comprises 1,408 videos for training,
300 for validation, and 300 for testing purposes, resulting in 732,391, 151,835,
and 156,307 images, respectively.

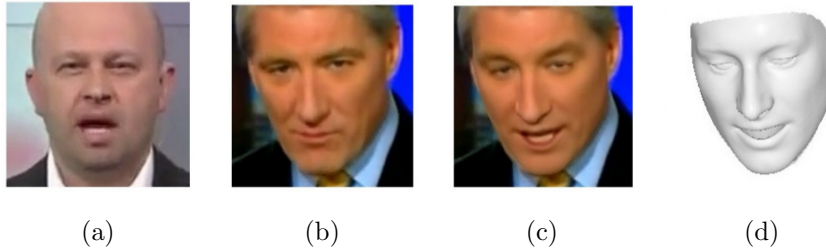


Figure 7: Faceforensics reenactment example: (a) original (source), (b) original (target), (c) manipulated, and (d) mask. Adapted from [111].

4.6. *Faceforensics++*

FaceForensics++ [112] is an extension of the FaceForensics dataset and de-
notes a public dataset proposed as a benchmark for realistic fake face image
detection. The set comprises 1,000 thoroughly selected videos, most of them
1165 from YouTube, such that approximately 60% of the individuals are male and the

remaining 40% are female. Concerning the resolution, approximately 55% are provided with 854×480 , i.e., Video Graphics Array (VGA) resolution, 32,5% in $1,280 \times 720$, i.e., high definition (HD), and 12,5% in $1,920 \times 1,080$ (full-HD) resolutions. Further, the authors performed a manual screening to ensure high-quality and avoid face occlusion, and exposed the videos to four face manipulation approaches, i.e., NeuralTextures [7], Face2Face [131], FaceSwap [131], and Deepfakes¹³. As an output, the model provides a manipulated video and a ground-truth mask indicating modified pixels for each input video to provide a more robust training data set. Figure 8 illustrates examples of face reenactment and replacement present in Faceforensics++ dataset.



Figure 8: Examples of Faceforensics++ approaches for face reenactment (a) and replacement (b). Adapted from [112]

4.7. Deepfake Detection Challenge

Facebook’s Deepfake Detection Challenge¹⁴ (DFDC) [114] dataset consists of 5,000 videos from actors with face likenesses manipulated. The dataset comprises 66 actors selected respecting the following proportions: 26% male and 74% female, 3% south-Asian, 9% west-Asian, 20% African-American, and 68% Caucasians. The manipulation was conducted considering two face swap approaches: method A, which produces higher swap quality images with faces closer to the camera, considering the source and swapped faces in the same proportions, and method B, which has lower quality swaps. In the end, we have a

¹³<https://github.com/deepfakes/faceswap>

¹⁴<https://ai.facebook.com/datasets/dfdc/>

dataset composed of 4,464 sample clips for training purposes and 780 for testing, each with 15 seconds length and different resolutions. Figure 9 provides some examples of the dataset.



Figure 9: Examples from DFDC dataset. Adapted from [114].

4.8. Celeb-DF

Celeb-DF [113] is a challenging large-scale deepfake video dataset generated using an improved synthesis process over celebrities’ videos available on YouTube. The dataset comprises 5,639 high-quality videos with more than two million frames of size 256×256 pixels each from 59 celebrities, comprising diverse ethnic groups (88.1% are Caucasians, 5.1% are Asians, and 6.8% are African Americans), ages (6.4% under 30 years, 28.0% between 30 and 40, 26.6% are 40s, 30.5% between 50 and 60, and 8.5% are of age 60 or above), and genders (56.8% male and 43.2% female). Each video has approximately 13 seconds with a standard frame rate of 30 frames-per-second and depicts diverse aspects such as lighting conditions, orientations, backgrounds, and subjects’ face sizes (in pixels). Figure 10 provides some dataset examples.

4.9. DeeperForensics-1.0

DeeperForensics-1.0 [132] is large-scale, high-quality, and rich-diversity dataset designed for forgery detection. It comprises 60,000 videos with $1,920 \times 1,080$ resolution, comprising 17.6 million frames of automatically generated swapped faces. The source videos were collected from 100 actors from 26 countries, distributed among males and females ranging from 20 to 45 years-old and diverse skin tones. Additionally, they were requested to perform eight natural



Figure 10: Celeb-DF dataset samples. Green-framed instances denote real images, while the red-framed ones stand for the corresponding fake samples generated through random donor individuals.

expressions, i.e., fear, disgust, anger, happiness, contempt, surprise, sadness, and neutral, in distinct angles ranging from -90° to $+90^\circ$, and simulated 53 other expressions from 3DMM blendshapes [133]. The dataset considers variations in the video footage to match real-world cases, such as transmission errors, compression, and blurry. Besides, it also provides special attention to expressions, poses, and lighting conditions on source images since they perform a critical role in the dataset’s quality. Figure 11(a) illustrates some examples of expressions (top row) and different lighting conditions (bottom row), while Figure 11(b) depicts some examples of 3DMM blendshapes simulations.

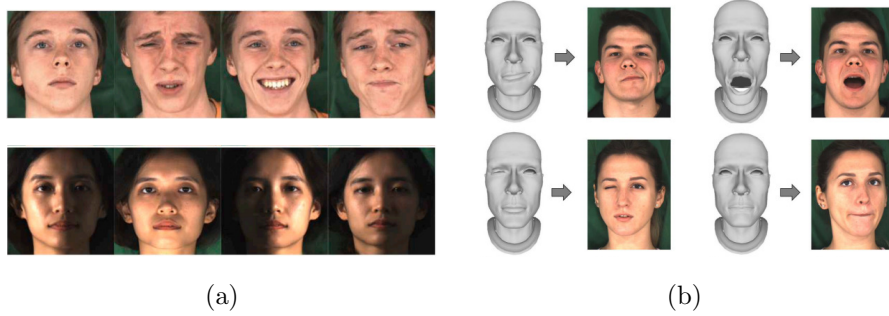


Figure 11: Samples from DeeperForensics-1.0 considering: (a) expressions and different lighting conditions for the top and bottom rows, respectively, and (b) 3DMM blendshapes simulations. Adapted from [132].

4.10. Real and Fake Face Detection

Real and Fake Face Detection¹⁵ [110] is a dataset created by the Computational Intelligence and Photography Lab from Yonsei University, which comprises high-quality photoshopped face images. The main idea of using expert-generated images instead of generative models is to provide an alternative dataset for forged faces with a completely different set of features. The authors claim that a classifier trained using deepfakes can learn intrinsic patterns between real and GAN-generated images. On the other hand, such patterns are not present in experts' designs, creating counterfeits in a completely different process. The dataset figures three categories, i.e., easy, mid, and hard. Moreover, it comprises 1,081 real and 960 fake images of size 600×600 pixels. Figure 13 illustrates some dataset examples.



Figure 12: Examples: (a) real and fake examples in (b) easy (nose), (c) mid (face), and (d) hard (both eyes). Adapted from [110].

4.11. WildDeepfake

WildDeepfake¹⁶ dataset [55] was proposed to better support real-world deepfake detection. The authors claim that deepfake datasets are usually filmed with a limited number of actors and scenes, and the videos are crafted using a few deepfake software, which impacts reduced effectiveness when detecting fake videos in the wild. In this context, WildDeepfake comprises 7,314 face

¹⁵<https://www.kaggle.com/ciplab/real-and-fake-face-detection>.

¹⁶<https://github.com/deepfakeinthewild/deepfake-in-the-wild>.

sequences of real and deepfake videos extracted from various sources on the Internet to provide a wide diversity of individuals, poses, and backgrounds. The data is divided into 6,508 sequences for training and 806 for testing purposes.

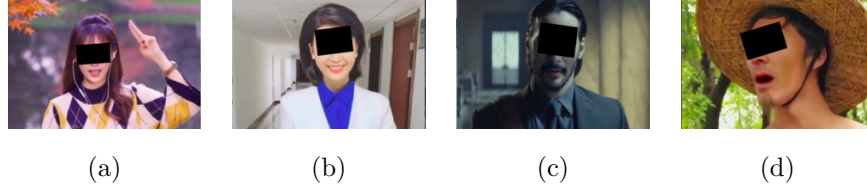


Figure 13: WildDeepfake dataset samples. The images comprise scene diversity to provide more realistic and real-world-like challenging scenarios. The authors block the eye regions due to privacy concerns. Adapted from [55].

4.12. Fake Face in the Wild

The Fake Face in the Wild (FFW) dataset [43] tries to simulate the performance of fake face detection methods in the wild. The dataset figures 150 videos extracted from YouTube. The selected videos denote fake content digitally created using GANs and CGI and manual and automatic image tampering techniques and their combinations. Moreover, each video length ranges from 2 to 74 seconds, with 854×480 resolution and 30 frames per second, ending up in 53,000 images. Figure 14 provides some examples of the dataset.

4.13. Dataset Summary

Table 7 introduces a summary of the datasets presented in this section.

5. Discussion and Open Issues

Recent advances in fake content generation methods have gained an ever-growing concern from several legislative and regulatory authorities because of the ill use of counterfeit multimedia for illegal and public opinion manipulation. Seeking and categorizing state-of-the-art methodologies for deepfake detection goals is critical to identify the most appropriate methods to predict the actions toward a dangerous political and social instability scenario. In this

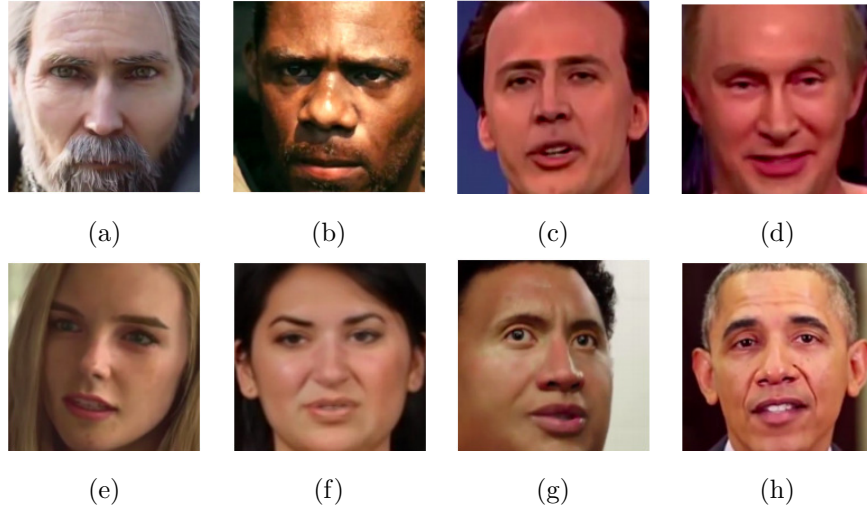


Figure 14: FFW dataset samples. Images (a) and (b) denote CGI full scenes, while (c) and (d) stand for deepfakes. Image (e) stands for head CGI, (f) represents face replacement, (g) denotes face CGI, and (h) represents part of face splicing. Adapted from [43].

sense, significant research has been reported to review and examine the well-
1255 established image and video manipulation approaches, namely those that rely
on deep learning-based methods, as stated in Section 1.

5.1. Recent Architectures Overview

We analyzed several novel studies concerning deepfake detection using the
most recent deep learning-inspired architectures, providing a more detailed
1260 start-of-the-art review.

Recent studies usually include several transfer learning-based approaches
to prevent the computational load of retraining the deep learning models in
massive amounts of deepfake images and videos. In this context, Sengur et
al. [41] attempted to capture the generalization of pre-trained AlexNet and
1265 VGG16 models without retraining them on new images of manipulated faces.
Despite the encouraging results presented in the study, fine-tuning the model's
parameters is often necessary to capture intrinsic aspects of new images to
improve the model's robustness on new collected features, thus increasing the

Table 7: Deepfake detection summarized datasets.

Ref.	Dataset name	Year	Modalities	Number of examples	Last work
[76]	HOHA-based	2018	Video	300 real and 300 fake videos.	[76]
[43]	Fake Face in the Wild	2018	Video	150 fake videos.	[43]
[111]	FaceForensics	2018	Video	2008 fake videos.	[81]
[112]	FaceForensics++	2018	Video	1,000 real and 4,000 fake videos.	[40] [96] [75] [109]
[129]	UADFV	2018	Video	49 real and 49 fake videos.	[66]
[29]	Faceswap-GAN	2019	Video	640 fake videos	[29]
[130]	Deepfake-TIMIT	2019	Video	320 real and 640 fake videos.	[55] [32]
[114]	DFDC-preview	2019	Video	5,244 fake videos.	[61] [109]
[110]	Real and Fake Face Detection	2019	Image	1,081 real and 960 fake images.	[59] [65]
[113]	Celeb-DF	2020	Video	590 real and 5,639 fake videos.	[96] [105] [106] [107] [108] [109]
[55]	WildDeepfake	2020	Video	3,805 real and 3,509 fake videos.	[107]

ability to recognize specific forged elements. Therefore, a more comprehensive
1270 analysis is required to compare the model’s effectiveness with and without fine-
tuning procedure.

Residual features are essential to improve deepfake detection. El Rai et
al. [51] proposed a novel approach to capture the potential noise disturbance
from any video manipulation procedure. Despite being a simple approach, the
1275 main drawback regards using a small number of videos for training and evaluat-

ing the CNN model. Moreover, since individual frames appear to be considered independently as input to the model, the final decision regarding the whole video’s authenticity remains unclear. Similarly, the work presented by Mo et al. [42] also comprised the residual features obtained from a single high pass filter applied to the images, thus differing from the former that computes the residual noise as the difference from the original and the corresponding smoothed images. Regardless, temporal analysis is still necessary for a broader analysis of the fake aspects’ interdependence across the sequences of video frames. As such, recurrent models appeared to gather the temporal data and transform them into a collection of time-series information to capture the forged sequence intercorrelation. In this context, Wang and Dantcheva [57] reported promising results considering the temporal analysis of the entire video. The authors emphasized the importance of 3D CNN models for capturing features that rely on the whole video’s motion sequence, thus increasing the ability to identify the evidence of any manipulation on specific frames. Despite the low performance on test videos from a different manipulation technique, the reported results confirmed the superiority of the 3D-CNN against the baselines used for comparison. Furthermore, recent studies reported outstanding results in temporal learning domain [92, 74, 75].

On the other hand, Wesselkamp et al. [134] provide evidence for developing robust and non-easily deceived models to detect deepfake images more effectively. The authors presented a new class of simple attacks to evade deepfake detection by removing GAN artifacts from the frequency spectrum of the images. The generative network may use one of the selected attacks to avoid detection depending on the combination of the dataset, GAN, and detection method. The authors showed a simple but effective procedure based on the image frequency domain to mislead the deepfake detection. It shows the main concerns regarding the system’s security toward an effective approach which may be deceived a priori using a new class of manipulative strategies aiming to refine the forgery of the faces and remove the evidence of possible manipulation. Therefore, it is an urge for novel research which may counteract deceived attacks and seek new

features of face manipulation using the frequency domain.

Vision Transformer (ViT) has shown a potential design for several image classification tasks. Based on its counterpart Transformer model initially proposed for Natural Language Processing tasks, the inherent sequential analysis used in the ViT architecture provides the local and global extraction of the features by combining the image patches in sequential order arrangement. An attempt to incorporate the ViT architecture into the deepfake detection context was presented by Wodajo and Atnafu [58], which used the feature maps provided by the convolutional layer of the VGG CNN architecture. By doing so, the vision transformer is not limited to the patch sizes described in the original work of Dosovitski [135], thus making the model more flexible for other CNN architectures with different output feature map sizes.

In social engineering, deepfake algorithms have raised new chances to earn unauthorized access to private and confidential information, leading to a pressing concern considering credentials manipulation. Despite being a recent form of attack, deepfake phishing proved to be a dangerous threat as a criminal instrument for obtaining financial benefits [136]. In biometric systems, deepfake may pose a significant threat to access control through spoofing of face biometrics, as pointed out by Wojewidka [137]. Although irrelevant to deepfake applications, fake content detection is critical to prevent several forms of credential tampering. Popular biometric systems often rely on fingerprint analysis, face identification, and iris features in modern applications. The work of Goel et al. [138] showed promising results for counterfeit fingerprint detection using a single deep-learning architecture. Despite the possible broadening investigation of spoofing techniques to other applications rather than the face point-of-view, we focused only on face forgery detection for their inherent application in the deepfake context.

5.2. Opportunities and Future Challenges

Regarding the final thoughts to complement this section, we present the following opportunities and future directions for further studies:

- Complexity and realism of deepfake methods are actively refined as a consequence of the advances in deep learning techniques. Therefore, it is highly desirable to follow the trends toward the analysis of large amounts of data and explore dynamic approaches to identify and extract additional features from recent sources of information;
- Deepfake generation is a constant process and continuously evolves due to social networks and the rapid spreading of new information. Therefore, more robust approaches based on unsupervised or semi-supervised learning are particularly essential to avoid the time-consuming and laborious manual annotation of massive amounts of new data;
- Regarding the cross-dataset and ablation experiments, most of the examined studies reported decreased performance when the models were trained and validated on different deepfake datasets. Moreover, there is a challenge in reaching the same best-performing accuracy for different fake production methods. Most related studies provided lower accuracy for the NeuralTextures and FaceShifter manipulation of the FaceForensics++ dataset [82, 92, 75]. It shows an urge to explore more complex forgery traits produced by several manipulation techniques and the challenges towards developing more accurate methods for fake face detection;
- There is a trend to combine visual and audio information to improve the accuracy of detecting forgery faces in videos. However, only a few studies have been explored to reveal the benefits of multimodality approaches [71, 74]. Therefore, more research is encouraged to assess the impacts of using audio characteristics on deepfake detection performance.
- Finally, recent advances in generating realistic images produced by diffusion models show promise even when compared to images generated by GANs. In a brief explanation, diffusion models [139, 140, 141] are governed by two processes. The forward process is described by a Markov chain in which Gaussian noise is gradually added to a given image at each

iteration. Moreover, the backward process involves learning the denoising process, i.e., from a noise-corrupted image to a clear image. Currently, there are still very few studies carried out in the sense of using diffusion models to generate deepfake [142, 143] and, in the same sense, few studies involving the detection of deepfake also generated by diffusion models.

6. Conclusions

This work highlights the most significant research in the last years regarding deepfake detection through deep learning techniques. Besides, it also presents the most relevant advances in the field and the main challenges and future trends. A brief analysis of the works presented in this study may deduce a correlation between fake news subjects and deepfake content, for deepfake production is intrinsically related to video manipulation, which denotes a complement to fake news content. Hence, it is necessary to investigate several studies that simultaneously merge fake news and deepfake.

An alarming concern regarding deepfake production regards the fast development of generative networks, implying more realistic and high-quality images. Such a tendency infers an increasing challenge, making detection even more difficult. The emergence of new intelligent algorithms and the evolution of existing ones may be the most plausible inclination to tackle the problem.

As stated in the last section, the field's future direction comprises more robust and dynamic approaches to deal with realistic deepfake content. Such models should identify and extract new features and analyze large amounts of data for better detection rates. Moreover, semi-supervised learning techniques should help to deal with the fast evolution of deepfake generators and the spread of their content in social networks. In this sense, future studies demand a more dynamic procedure or even the combination of supervised and unsupervised learning to rapidly identifying and actively tracking the patterns related to the modern and complex fake content production algorithms without requiring large amounts of data.

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References

- 1405 [1] K. R. K., A. Goswani, P. Narang, Deepfake: improving fake news detection using tensor decomposition-based deep neural network, in: The Journal of Supercomputing, Springer, 2020, pp. 1016–1038.
- [2] H. Susan, Deep fake and cultural truth - custodians of cultural heritage in the age of a digital reproduction, in: Culture and Computing, Springer 1410 International Publishing, 2020, pp. 65–80.
- [3] T. Kirchengast, Deepfakes and image manipulation: criminalisation and control, Information and Communications Technology Law 29 (3) (2020) 308–323.
- [4] J. Kietzmann, A. J. Mills, K. Plangger, Deepfakes: perspectives on the 1415 future “reality” of advertising and branding, International Journal of Advertising (2020) 1–13.
- [5] N. Liv, D. Greenbaum, Deep fakes and memory malleability: False memories in the service of fake news, AJOB Neuroscience 11 (2) (2020) 96–104.
- [6] C. Chan, S. Ginosar, T. Zhou, A. A. Efros, Everybody dance now, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 1420 2019, pp. 5933–5942.

- [7] T. Justus, Z. Michael, N. Matthias, Deferred neural rendering: Image synthesis using neural textures, *ACM Transactions on Graphics (TOG)* 38 (4) (2019) 1–12.
- 1425 [8] M. Kowalski, J. Naruniec, T. Trzcinski, Deep alignment network: A convolutional neural network for robust face alignment, in: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 2017, pp. 88–97.
- 1430 [9] T. T. Nguyen, Q. V. H. Nguyen, D. T. Nguyen, D. T. Nguyen, T. Huynh-The, S. Nahavandi, T. T. Nguyen, Q.-V. Pham, C. M. Nguyen, Deep learning for deepfakes creation and detection: A survey, *Computer Vision and Image Understanding* 223 (2022) 103525.
- 1435 [10] R. Tolosana, R. Vera-Rodriguez, J. Fierrez, A. Morales, J. Ortega-Garcia, Deepfakes and beyond: A Survey of face manipulation and fake detection, *Information Fusion* 64 (2020) 131–148.
- [11] F. Juefei-Xu, R. Wang, Y. Huang, Q. Guo, L. Ma, Y. Liu, Countering malicious deepfakes: Survey, battleground, and horizon, *arXiv preprint arXiv:2103.00218*.
- 1440 [12] Y. Mirsky, W. Lee, The creation and detection of deepfakes: A survey, *ACM Computing Surveys (CSUR)* 54 (1) (2021) 1–41.
- [13] J.-W. Seow, M.-K. Lim, R. C.-W. Phan, J. K. Liu, A comprehensive overview of deepfake: Generation, detection, datasets, and opportunities, *Neurocomputing*.
- 1445 [14] M. S. Rana, M. N. Nobi, B. Murali, A. H. Sung, Deepfake detection: A systematic literature review, *IEEE access* 10 (2022) 25494–25513.
- [15] D. Zhang, F. Lin, Y. Hua, P. Wang, D. Zeng, S. Ge, Deepfake video detection with spatiotemporal dropout transformer, in: *Proceedings of the 30th ACM International Conference on Multimedia*, 2022, pp. 5833–5841.

- 1450 [16] E. R. S. Rezende, G. C. S. Ruppert, T. Carvalho, Detecting computer generated images with deep convolutional neural networks, in: 30th Conference on Graphics, Patterns and Images, SIBGRAPI, 2017, pp. 71–78.
- [17] C. Shubham, S. Rashid, C. Nishita, A. Ritu, A comparative analysis of deep fake techniques, in: 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), 2021, 1455 pp. 300–303.
- [18] A. Shruti, F. Hany, Detecting Deep-Fake Videos from Aural and Oral Dynamics, in: IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2021, pp. 981–989.
- 1460 [19] H. A. Mohammad, F. Md Sadek, K. Mohsin, T. Sasu, Real, forged or deep fake? enabling the ground truth on the internet, IEEE Access 9 (2021) 160471–160484.
- [20] A. Atif, J. Yasir Khan, F. Zulqarnain, A. Munir, A. Naseem, A. Haitham, A. Ali, The threat of deep fake technology to trusted identity management, 1465 in: 2022 International Conference on Cyber Resilience (ICCR), 2022, pp. 1–5.
- [21] S. Agarwal, N. Girdhar, H. Raghav, A Novel Neural Model based Framework for Detection of GAN Generated Fake Images, in: 11th International Conference on Cloud Computing, Data Science Engineering (Confluence), 2021, pp. 46–51. 1470
- [22] S. S. Birunda, P. Nagaraj, S. K. Narayanan, K. M. Sudar, V. Muneeswaran, R. Ramana, Fake image detection in twitter using flood fill algorithm and deep neural networks, in: 12th International Conference on Cloud Computing, Data Science and Engineering (Confluence), 2022, 1475 pp. 285–290.
- [23] A. A. Maksutov, V. O. Morozov, A. A. Lavrenov, A. S. Smirnov, Methods of deepfake detection based on machine learning, in: IEEE Conference

of Russian Young Researchers in Electrical and Electronic Engineering (EIconRus), 2020, pp. 408–411.

- 1480 [24] H. Khalid, S. S. Woo, OC-FakeDect: Classifying Deepfakes Using One-class Variational Autoencoder, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, Vol. 2020-June, IEEE, 2020, pp. 2794–2803.
- 1485 [25] M. Du, S. Pentyala, Y. Li, X. Hu, Towards generalizable deepfake detection with locality-aware autoencoder, in: Proceedings of the 29th ACM International Conference on Information & Knowledge Management, CIKM '20, Association for Computing Machinery, New York, NY, USA, 2020, p. 325–334. doi:10.1145/3340531.3411892.
- 1490 [26] K. Venkatachalam, v. Hubálovský, P. Trojovský, Deep fake detection using a sparse auto encoder with a graph capsule dual graph cnn, PeerJ Computer Science (2022) e953doi:10.7717/peerj-cs.953.
- [27] C.-C. Hsu, C.-Y. Lee, Y.-X. Zhuang, Learning to detect fake face images in the wild, in: 2018 International Symposium on Computer, Consumer and Control (IS3C), IEEE, 2018, pp. 388–391.
- 1495 [28] C.-C. Hsu, Y.-X. Zhuang, C.-Y. Lee, Deep fake image detection based on pairwise learning, Applied Sciences 10 (1) (2020) 370.
- [29] P. Korshunov, S. Marcel, Vulnerability assessment and detection of deep-fake videos, in: International Conference on Biometrics (ICB), IEEE, 2019, pp. 1–6.
- 1500 [30] X. Yang, Y. Li, S. Lyu, Exposing deep fakes using inconsistent head poses, in: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 8261–8265.
- [31] J. Frank, T. Eisenhofer, L. Schonherr, A. Fischer, D. Kolossa, T. Holz, Leveraging frequency analysis for deep fake image recognition (2020).

- 1505 [32] U. A. Ciftci, I. Demir, L. Yin, How do the hearts of deep fakes beat? deep fake source detection via interpreting residuals with biological signals (2020).
- [33] L. Guarnera, O. Giudice, S. Battiato, Fighting Deepfake by Exposing the Convolutional Traces on Images, *IEEE Access* 8 (2020) 165085–165098. doi:10.1109/ACCESS.2020.3023037.
- 1510 [34] O. Giudice, L. Guarnera, S. Battiato, Fighting deepfakes by detecting gan dct anomalies, *Journal of Imaging* 7 (8). doi:10.3390/jimaging7080128.
- [35] S. A. Aduwala, M. Arigala, S. Desai, H. J. Quan, M. Eirinaki, Deepfake Detection using GAN Discriminators, in: 2021 IEEE Seventh International Conference on Big Data Computing Service and Applications (Big-DataService), 2021, pp. 69–77. doi:10.1109/BigDataService52369.2021.00014.
- 1515 [36] Y. Jeong, D. Kim, Y. Ro, J. Choi, FrePGAN: Robust Deepfake Detection Using Frequency-Level Perturbations, *Proceedings of the AAAI Conference on Artificial Intelligence* 36 (1) (2022) 1060–1068. doi:10.1609/aaai.v36i1.19990.
- 1520 [37] P. Varun, P. Gaurav, S. Samveg, P. Sakshi, Fakequipo: Deep fake detection, in: IEEE 3rd Global Conference for Advancement in Technology (GCAT), 2022, pp. 1–5.
- [38] Preeti, M. Kumar, H. K. Sharma, A GAN-Based Model of Deepfake Detection in Social Media, *Procedia Computer Science* 218 (2023) 2153–2162. doi:https://doi.org/10.1016/j.procs.2023.01.191.
- 1525 [39] S. Kanwal, S. Tehsin, S. Saif, Exposing ai generated deepfake images using siamese network with triplet loss, *Computing and Informatics* 41 (6) (2023) 1541–1562. doi:10.31577/cai_2022_6_1541.
- 1530 [40] W. Moritz, F. Blanke, R. Heese, G. Jochen, Wavelet-packets for deepfake image analysis and detection, *Applied Intelligence* 111 (2022) 4295–4327.

- [41] A. Sengur, Z. Akhtar, Y. Akbulut, S. Ekici, U. Budak, Deep Feature Extraction for Face Liveness Detection, in: 2018 International Conference on Artificial Intelligence and Data Processing (IDAP), IEEE, 2018, pp. 1–4.
- [42] H. Mo, B. Chen, W. Luo, Fake Faces Identification via Convolutional Neural Network, in: Proceedings of the 6th ACM Workshop on Information Hiding and Multimedia Security, ACM, 2018, pp. 43–47.
- [43] A. Khodabakhsh, R. Ramachandra, K. Raja, P. Wasnik, C. Busch, Fake face detection methods: Can they be generalized?, in: 2018 international conference of the biometrics special interest group (BIOSIG), IEEE, 2018, pp. 1–6.
- [44] N. S. Ivanov, A. V. Arzhskov, V. G. Ivanenko, Combining deep learning and super-resolution algorithms for deep fake detection, in: IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus), 2020, pp. 326–328.
- [45] Y. Li, S. Lyu, Exposing deepfake videos by detecting face warping artifacts, arXiv preprint arXiv:1811.00656.
- [46] D. Afchar, V. Nozick, J. Yamagishi, I. Echizen, Mesonet: a compact facial video forgery detection network, in: 2018 IEEE International Workshop on Information Forensics and Security (WIFS), IEEE, 2018, pp. 1–7.
- [47] I. Amerini, L. Galteri, R. Caldelli, A. Del Bimbo, Deepfake Video Detection through Optical Flow Based CNN, in: Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV) Workshops, 2019, pp. 1–3.
- [48] S. A. Gowda, N. Thillaiarasu, Investigation of comparison on modified cnn techniques to classify fake face in deepfake videos, in: 8th International Conference on Advanced Computing and Communication Systems (ICACCS), Vol. 1, 2022, pp. 702–707.

- [49] S. Agarwal, T. El-Gaaly, H. Farid, S. Lim, Detecting deep-fake videos from appearance and behavior, in: IEEE Workshop on Image Forensics and Security, IEEEExplore, 2020, pp. 1–12.
- 1565 [50] S. Agarwal, H. Farid, O. Fried, M. Agrawala, Detecting deep-fake videos from phoneme-viseme mismatches, in: IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2020, pp. 2814–2822.
- 1570 [51] M. C. El Rai, H. Al Ahmad, O. Gouda, D. Jamal, M. A. Talib, Q. Nasir, Fighting Deepfake by Residual Noise Using Convolutional Neural Networks, in: 3rd International Conference on Signal Processing and Information Security (ICSPIS), IEEE, 2020, pp. 1–4.
- 1575 [52] B. Malolan, A. Parekh, F. Kazi, Explainable deep-fake detection using visual interpretability methods, in: 3rd International Conference on Information and Computer Technologies (ICICT), IEEEExplore, 2020, pp. 289–293.
- [53] P. Ranjan, S. Patil, F. Kazi, Improved generalizability of deep-fakes detection using transfer learning based cnn framework, in: 3rd International Conference on Information and Computer Technologies (ICICT), 2020, pp. 86–90.
- 1580 [54] H. Mittal, M. Saraswat, J. C. Bansal, A. Nagar, Fake-face image classification using improved quantum-inspired evolutionary-based feature selection method, in: IEEE Symposium Series on Computational Intelligence (SSCI), 2020, pp. 989–995.
- 1585 [55] B. Zi, M. Chang, J. Chen, X. Ma, Y.-G. Jiang, Wilddeepfake: A challenging real-world dataset for deepfake detection, in: Proceedings of the 28th ACM International Conference on Multimedia, 2020, pp. 2382–2390.
- [56] U. A. Ciftci, I. Demir, L. Yin, Fakecatcher: Detection of synthetic portrait

videos using biological signals, IEEE Transactions on Pattern Analysis and Machine Intelligence.

- 1590 [57] Y. Wang, A. Dantcheva, A video is worth more than 1000 lies. Comparing 3DCNN approaches for detecting deepfakes, in: 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG), IEEE, 2020, pp. 515–519.
- [58] D. Wodajo, S. Atnafu, Deepfake video detection using convolutional vision
1595 transformer (2021). [arXiv:2102.11126](https://arxiv.org/abs/2102.11126).
- [59] Q. ul ain, N. Nida, A. Irtaza, N. Ilyas, Forged face detection using ela and deep learning techniques, in: 2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST), 2021, pp. 271–275. doi: 10.1109/IBCAST51254.2021.9393234.
- 1600 [60] J. B. Awotunde, R. G. Jimoh, A. L. Imoize, A. T. Abdulrazaq, C. Li, C. Lee, An enhanced deep learning-based deepfake video detection and classification system, Electronics 12 (1).
- [61] A. Das, L. Sebastian, A comparative analysis and study of a fast parallel
1605 cnn based deepfake video detection model with feature selection (fpc-dfm), in: 2023 Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA), IEEE, 2023, pp. 1–9.
- [62] M. Masood, M. Nawaz, A. Javed, T. Nazir, A. Mehmood, R. Mahum, Classification of deepfake videos using pre-trained convolutional neural networks, in: 2021 International Conference on Digital Futures and Transformative Technologies (ICoDT2), IEEE, 2021, pp. 1–6.
1610
- [63] A. Mitra, S. P. Mohanty, P. Corcoran, E. Koungianos, A novel machine learning based method for deepfake video detection in social media, in: 2020 IEEE International Symposium on Smart Electronic Systems (iSES)(Formerly iNiS), IEEE, 2020, pp. 91–96.

- 1615 [64] M. Patel, A. Gupta, S. Tanwar, M. Obaidat, Trans-df: a transfer learning-based end-to-end deepfake detector, in: 2020 IEEE 5th international conference on computing communication and automation (ICCCA), IEEE, 2020, pp. 796–801.
- [65] R. Rafique, M. Nawaz, H. Kibriya, M. Masood, Deepfake detection using
1620 error level analysis and deep learning, in: 2021 4th International Conference on Computing & Information Sciences (ICCIS), IEEE, 2021, pp. 1–4.
- [66] J. Wang, X. Li, Y. Zhao, A novel face forgery detection method based on
1625 edge details and reused-network, in: 2021 IEEE 9th International Conference on Computer Science and Network Technology (ICCSNT), IEEE, 2021, pp. 100–104.
- [67] E. Sabir, J. Cheng, A. Jaiswal, W. AbdAlmageed, I. Masi, P. Natara-
jan, Recurrent convolutional strategies for face manipulation detection in
videos, *Interfaces (GUI)* 3 (1) (2019) 80–87.
- 1630 [68] D. M. Montserrat, H. Hao, S. K. Yarlagadda, S. Baireddy, R. Shao,
J. Horváth, E. Bartusiak, J. Yang, D. Guera, F. Zhu, et al., Deepfakes de-
tection with automatic face weighting, in: *Proceedings of the IEEE/CVF
conference on computer vision and pattern recognition workshops*, 2020,
pp. 668–669.
- 1635 [69] G. Jaiswal, Hybrid recurrent deep learning model for deepfake video detec-
tion, in: 2021 IEEE 8th Uttar Pradesh Section International Conference
on Electrical, Electronics and Computer Engineering (UPCON), IEEE,
2021, pp. 1–5.
- [70] Y. Tu, Y. Liu, X. Li, Deepfake video detection by using convolutional
1640 gated recurrent unit, in: 2021 13th International Conference on Machine
Learning and Computing, 2021, pp. 356–360.

- [71] H. Hao, E. R. Bartusiak, D. Güera, D. Mas Montserrat, S. Baireddy, Z. Xiang, S. K. Yarlagadda, R. Shao, J. Horváth, J. Yang, et al., Deepfake detection using multiple data modalities, in: *Handbook of Digital Face Manipulation and Detection: From DeepFakes to Morphing Attacks*, Springer International Publishing Cham, 2022, pp. 235–254.
- [72] A. Ismail, M. Elpeltagy, M. S. Zaki, K. Eldahshan, An integrated spatiotemporal-based methodology for deepfake detection, *Neural Computing and Applications* 34 (24) (2022) 21777–21791.
- [73] W. Pu, J. Hu, X. Wang, Y. Li, S. Hu, B. Zhu, R. Song, Q. Song, X. Wu, S. Lyu, Learning a deep dual-level network for robust deepfake detection, *Pattern Recognition* 130 (2022) 108832.
- [74] M. Elpeltagy, A. Ismail, M. S. Zaki, K. Eldahshan, A novel smart deepfake video detection system, *International Journal of Advanced Computer Science and Applications* 14 (1).
- [75] Y. Sun, Z. Zhang, I. Echizen, H. H. Nguyen, C. Qiu, L. Sun, Face forgery detection based on facial region displacement trajectory series, in: *IEEE/CVF Winter Conference on Applications of Computer Vision Workshops (WACVW)*, IEEE Computer Society, Los Alamitos, CA, USA, 2023, pp. 633–642.
- [76] D. Güera, E. J. Delp, Deepfake video detection using recurrent neural networks, in: *15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*, IEEE, 2018, pp. 1–6.
- [77] Y. Li, M. Chang, S. Lyu, In ictu oculi: Exposing AI created fake videos by detecting eye blinking, in: *IEEE International Workshop on Information Forensics and Security (WIFS)*, IEEEExplore, 2018, pp. 1–7.
- [78] C. C. Ki Chan, V. Kumar, S. Delaney, M. Gochoo, Combating deepfakes: Multi-lstm and blockchain as proof of authenticity for digital media, in:

- 2020 IEEE / ITU International Conference on Artificial Intelligence for
 1670 Good (AI4G), 2020, pp. 55–62. doi:10.1109/AI4G50087.2020.9311067.
- [79] Y. Al-Dhabi, S. Zhang, Deepfake video detection by combining convolutional neural network (cnn) and recurrent neural network (rnn), in: 2021 IEEE International Conference on Computer Science, Artificial Intelligence and Electronic Engineering (CSAIEE), 2021, pp. 236–241. doi:10.1109/CSAIEE54046.2021.9543264.
 1675
- [80] D.-C. Stanciu, B. Ionescu, Deepfake Video Detection with Facial Features and Long-Short Term Memory Deep Networks, in: 2021 International Symposium on Signals, Circuits and Systems (ISSCS), IEEE, 2021, pp. 1–4.
- 1680 [81] Z. Zhang, C. Mal, B. Ding, M. Gao, Detecting manipulated facial videos: A time series solution, in: 2020 25th International Conference on Pattern Recognition (ICPR), IEEE, 2021, pp. 2817–2823.
- [82] H. Ilyas, A. Irtaza, A. Javed, K. M. Malik, Deepfakes examiner: An end-to-end deep learning model for deepfakes videos detection, in: 2022 16th International Conference on Open Source Systems and Technologies (ICOSST), 2022, pp. 1–6.
 1685
- [83] K. Jalui, A. Jagtap, S. Sharma, G. Mary, R. Fernandes, M. Kolhekar, Synthetic content detection in deepfake video using deep learning, in: 2022 IEEE 3rd Global Conference for Advancement in Technology (GCAT), IEEE, 2022, pp. 01–05.
 1690
- [84] V. Jolly, M. Telrandhe, A. Kasat, A. Shitole, K. Gawande, Cnn based deep learning model for deepfake detection, in: 2022 2nd Asian Conference on Innovation in Technology (ASIANCON), 2022, pp. 1–5. doi:10.1109/ASIANCON55314.2022.9908862.
- 1695 [85] A. Khedkar, A. Peshkar, A. Nagdive, M. Gaikwad, S. Baudha, Exploiting spatiotemporal inconsistencies to detect deepfake videos in the wild,

in: 2022 10th International Conference on Emerging Trends in Engineering and Technology-Signal and Information Processing (ICETET-SIP-22), IEEE, 2022, pp. 1–6.

- 1700 [86] L. Kuang, Y. Wang, T. Hang, B. Chen, G. Zhao, A dual-branch neural network for deepfake video detection by detecting spatial and temporal inconsistencies, *Multimedia Tools and Applications* 81 (29) (2022) 42591–42606.
- [87] L. S. K. Sooda, DeepFake Detection Through Key Video Frame Extraction using GAN, in: 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS), 2022, pp. 859–863. doi:10.1109/ICACRS55517.2022.10029095.
- 1705 [88] D. Liu, Z. Yang, R. Zhang, J. Liu, A robust deepfake video detection method based on continuous frame face-swapping, in: 2022 International Conference on Artificial Intelligence, Information Processing and Cloud Computing (AIIPCC), 2022, pp. 188–191. doi:10.1109/AIIPCC57291.2022.00048.
- [89] N. Patel, N. Jethwa, C. Mali, J. Deone, Deepfake video detection using neural networks, in: ITM Web of Conferences, Vol. 44, EDP Sciences, 2022, p. 03024.
- 1715 [90] S. J. Pipin, R. Purba, M. F. Pasha, Deepfake Video Detection Using Spatiotemporal Convolutional Network and Photo Response Non Uniformity, in: 2022 IEEE International Conference of Computer Science and Information Technology (ICOSNIKOM), IEEE, 2022, pp. 1–6.
- 1720 [91] A. M. Saber, M. T. Hassan, M. S. Mohamed, R. ELHusseiny, Y. M. Eltaher, M. Abdelrazek, Y. M. Kamal Omar, Deepfake video detection, in: 2022 2nd International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC), 2022, pp. 425–431. doi:10.1109/MIUCC55081.2022.9781791.

- 1725 [92] S. Saif, S. Tehseen, S. S. Ali, S. Kausar, A. Jameel, Generalized deep-fake video detection through time-distribution and metric learning, *IT Professional* 24 (2) (2022) 38–44. doi:10.1109/MITP.2022.3168351.
- [93] P. Saikia, D. Dholaria, P. Yadav, V. Patel, M. Roy, A hybrid cnn-lstm model for video deepfake detection by leveraging optical flow features
1730 (2022). arXiv:2208.00788.
- [94] R. V. Saraswathi, M. Gadwalkar, S. S. Midhun, G. N. Goud, A. Vidavaluri, Detection of synthesized videos using cnn, in: 2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), IEEE, 2022, pp. 01–05.
- 1735 [95] J. Wang, X. Li, Y. Zhao, D³: A novel face forgery detector based on dual-stream and dual-utilization methods, in: Advances in Artificial Intelligence and Security: 8th International Conference on Artificial Intelligence and Security, ICAIS 2022, Qinghai, China, July 15–20, 2022, Proceedings, Part I, Springer, 2022, pp. 413–425.
- 1740 [96] S. R. B. R, P. Kumar Pareek, B. S, G. G, Deepfake video detection system using deep neural networks, in: IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS), 2023, pp. 1–6.
- [97] S. A. Khan, D.-T. Dang-Nguyen, Hybrid transformer network for deepfake
1745 detection, in: Proceedings of the 19th international conference on content-based multimedia indexing, 2022, pp. 8–14.
- [98] D. A. Coccomini, N. Messina, C. Gennaro, F. Falchi, Combining efficientnet and vision transformers for video deepfake detection, in: Image Analysis and Processing (ICIAP 2022), Springer International Publishing, Cham, 2022, pp. 219–229.
1750
- [99] J. Feinland, J. Barkovitch, D. Lee, A. Kaforey, U. A. Ciftci, Poker bluff

- detection dataset based on facial analysis, in: International Conference on Image Analysis and Processing, Springer, 2022, pp. 400–410.
- [100] Z. Xue, Q. Liu, H. Shi, R. Zou, X. Jiang, A transformer-based deepfake-detection method for facial organs, *Electronics* 11 (24).
1755
- [101] Y. Zhang, T. Wang, M. Shu, Y. Wang, A robust lightweight deepfake detection network using transformers, in: Pacific Rim International Conference on Artificial Intelligence, Springer, 2022, pp. 275–288.
- [102] A. Khormali, J.-S. Yuan, DFDT: an end-to-end deepfake detection framework using vision transformer, *Applied Sciences* 12 (6) (2022) 2953.
1760
- [103] D. A. Coccomini, R. Caldelli, F. Falchi, C. Gennaro, G. Amato, Cross-Forgery Analysis of Vision Transformers and CNNs for Deepfake Image Detection, in: Proceedings of the 1st International Workshop on Multimedia AI against Disinformation, 2022, pp. 52–58.
- [104] J. Wang, Z. Wu, W. Ouyang, X. Han, J. Chen, Y.-G. Jiang, S.-N. Li, M2tr: Multi-modal multi-scale transformers for deepfake detection, in: Proceedings of the 2022 international conference on multimedia retrieval, 2022, pp. 615–623.
1765
- [105] M. A. Raza, K. M. Malik, I. U. Haq, Holisticdfd: Infusing spatiotemporal transformer embeddings for deepfake detection, *Information Sciences* (2023) 119352.
1770
- [106] Y. Heo, W. Yeo, B. Kim, Deepfake detection algorithm based on improved vision transformer, *Applied Intelligence* 53 (2023) 7512–7527.
- [107] H. Lin, W. Huang, W. Luo, W. Lu, Deepfake detection with multi-scale convolution and vision transformer, *Digital Signal Processing* 134 (2023) 103895.
1775
- [108] F. Khalid, M. H. Akbar, S. Gul, Swynt: Swin y-net transformers for deepfake detection, in: 2023 International Conference on Robotics and Au-

- tomation in Industry (ICRAI), 2023, pp. 1–6. doi:10.1109/ICRAI57502.2023.10089585.
- [109] T. Wang, H. Cheng, K. P. Chow, L. Nie, Deep convolutional pooling transformer for deepfake detection, *ACM Transactions on Multimedia Computing, Communications and Applications* 19 (6) (2023) 1–20.
- [110] Real and fake face detection, <https://www.kaggle.com/ciplab/real-and-fake-face-detection>, accessed: 2021-06-11 (2019).
- [111] R. Andreas, C. Davide, V. Luisa, R. Christian, T. Justus, N. Matthias, Faceforensics: A large-scale video dataset for forgery detection in human faces, *CoRR* abs/1803.09179.
- [112] A. Rossler, D. Cozzolino, L. Verdoliva, C. Riess, J. Thies, M. Nießner, Faceforensics++: Learning to detect manipulated facial images, in: *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2019, pp. 1–11.
- [113] L. Yuezun, Y. Xin, S. Pu, Q. Honggang, L. Siwei, Celeb-df: A large-scale challenging dataset for deepfake forensics, in: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 3207–3216.
- [114] B. Dolhansky, R. Howes, B. Pflaum, N. Baram, C. Canton-Ferrer, The deepfake detection challenge (dfdc) preview dataset, *ArXiv* abs/1910.08854.
- [115] N. Dufour, A. Gully, Contributing data to deepfake detection research, <https://ai.googleblog.com/2019/09/contributing-data-to-deepfake-detection.html>, accessed: 2023-06-12 (2019).
- [116] T. Karras, T. Aila, S. Laine, J. Lehtinen, Progressive growing of gans for improved quality, stability, and variation, *arXiv preprint arXiv:1710.10196*.

- [117] X. Tan, Y. Li, J. Liu, L. Jiang, Face liveness detection from a single image with sparse low rank bilinear discriminative model, in: European Conference on Computer Vision, Springer, 2010, pp. 504–517.
- [118] Z. Zhang, J. Yan, S. Liu, Z. Lei, D. Yi, S. Z. Li, A face antispoofing database with diverse attacks, in: 2012 5th IAPR international conference on Biometrics (ICB), IEEE, 2012, pp. 26–31.
- [119] S. Agarwal, H. Farid, Y. Gu, M. He, K. Nagano, H. Li, Protecting world leaders against deep fakes, in: CVPR Workshops, 2019, pp. 38–45.
- [120] Z. Liu, P. Luo, X. Wang, X. Tang, Deep learning face attributes in the wild, in: Proceedings of International Conference on Computer Vision (ICCV), 2015, pp. 3730–3738.
- [121] G. Haiying, K. Mark, R. Eric, L. Yooyoung, Y. Amy, D. Andrew, Z. Daniel, K. Timothee, S. Jeff, F. Jonathan, MFC datasets: Large-scale benchmark datasets for media forensic challenge evaluation, in: IEEE Winter Applications of Computer Vision Workshops (WACVW), IEEE, 2019, pp. 63–72.
- [122] F. Yu, A. Seff, Y. Zhang, S. Song, T. Funkhouser, J. Xiao, LSUN: Construction of a Large-scale Image Dataset using Deep Learning with Humans in the Loop (2016). [arXiv:1506.03365](https://arxiv.org/abs/1506.03365).
- [123] S.-Y. Wang, O. Wang, R. Zhang, A. Owens, A. A. Efros, Cnn-generated images are surprisingly easy to spot... for now, in: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2020, pp. 8695–8704.
- [124] F. Song, X. Tan, X. Liu, S. Chen, Eyes closeness detection from still images with multi-scale histograms of principal oriented gradients, Pattern Recognition 47 (9) (2014) 2825–2838.
- [125] S. A. Khan, H. Dai, Video transformer for deepfake detection with incremental learning, 9th ACM International Conference on Multimedia.

- [126] Y. He, B. Gan, S. Chen, Y. Zhou, G. Yin, L. Song, L. Sheng, J. Shao,
1835 Z. Liu, ForgeryNet: A Versatile Benchmark for Comprehensive Forgery
Analysis, in: 2021 IEEE/CVF Conference on Computer Vision and Pat-
tern Recognition (CVPR), IEEE Computer Society, Los Alamitos, CA,
USA, 2021, pp. 4358–4367. doi:10.1109/CVPR46437.2021.00434.
- [127] I. Laptev, M. Marszalek, C. Schmid, B. Rozenfeld, Learning realistic hu-
1840 man actions from movies, in: IEEE Conference on Computer Vision and
Pattern Recognition, IEEE, 2008, pp. 1–8.
- [128] faceswap-GAN Github, <https://github.com/shaoanlu/faceswap-GAN>, ac-
cessed: 2021-06-23 (2019).
- [129] L. Yuezun, C. Ming-Ching, L. Siwei, In ictu oculi: Exposing ai created
1845 fake videos by detecting eye blinking, in: IEEE International Workshop
on Information Forensics and Security (WIFS), IEEE, 2018, pp. 1–7.
- [130] P. Korshunov, M. Sébastien, Deepfakes: a new threat to face recognition?
assessment and detection, arXiv preprint arXiv:1812.08685.
- [131] T. Justus, Z. Michael, S. Marc, T. Christian, N. Matthias, Face2face:
1850 Real-time face capture and reenactment of rgb videos, in: Proceedings of
the IEEE conference on computer vision and pattern recognition, 2016,
pp. 2387–2395.
- [132] J. Liming, L. Ren, W. Wayne, Q. Chen, L. Chen Change, Deeperformer-
1.0: A large-scale dataset for real-world face forgery detection, in: Pro-
1855 ceedings of the IEEE/CVF Conference on Computer Vision and Pattern
Recognition, 2020, pp. 2889–2898.
- [133] C. Chen, W. Yanlin, Z. Shun, T. Yiyang, Z. Kun, Facewarehouse: A 3d
facial expression database for visual computing, IEEE Transactions on
Visualization and Computer Graphics 20 (3) (2013) 413–425.

- 1860 [134] V. Wesselkamp, K. Rieck, D. Arp, E. Quiring, Misleading Deep-Fake Detection with GAN Fingerprints, in: IEEE Security and Privacy Workshops (SPW), 2022, pp. 59–65.
- [135] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit,
1865 N. Houlsby, An image is worth 16x16 words: Transformers for image recognition at scale (2020). `arXiv:2010.11929`.
- [136] J. Loeffler, Deepfaked voice of ceo used to steal almost \$ 250,000 from company, <https://interestingengineering.com/deepfaked-voice-of-ceo-used-to-steal-almost-250000-from-company>, accessed: 2021-03-30 (2019).
- 1870 [137] J. Wojewidka, The deepfake threat to face biometrics, *Biometric Technology Today* 20 (2) (2020) 5–7.
- [138] G. Ishank, P. Niladri, M. Bappaditya, Deep convolutional neural network for double-identity fingerprint detection, *IEEE Sensors Letters* 4 (5) (2020) 17–20.
- 1875 [139] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, B. Ommer, High-resolution image synthesis with latent diffusion models, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 10684–10695.
- [140] J. Ho, A. Jain, P. Abbeel, Denoising diffusion probabilistic models,
1880 in: H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, H. Lin (Eds.), *Advances in Neural Information Processing Systems*, Vol. 33, Curran Associates, Inc., 2020, pp. 6840–6851.
URL https://proceedings.neurips.cc/paper_files/paper/2020/file/4c5bcfec8584af0d967f1ab10179ca4b-Paper.pdf
- 1885 [141] J. Sohl-Dickstein, E. Weiss, N. Maheswaranathan, S. Ganguli, Deep unsupervised learning using nonequilibrium thermodynamics, in: F. Bach,

D. Blei (Eds.), Proceedings of the 32nd International Conference on Machine Learning, Vol. 37 of Proceedings of Machine Learning Research, PMLR, Lille, France, 2015, pp. 2256–2265.

1890 [142] S. Mandelli, D. Cozzolino, E. D. Cannas, J. P. Cardenuto, D. Moreira, P. Bestagini, W. J. Scheirer, A. Rocha, L. Verdoliva, S. Tubaro, E. J. Delp, Forensic analysis of synthetically generated western blot images, IEEE Access 10 (2022) 59919–59932. doi:10.1109/ACCESS.2022.3179116.

1895 [143] Y. Jeong, D. Kim, Y. Ro, P. Kim, J. Choi, Fingerprintnet: Synthesized fingerprints for generated image detection, in: S. Avidan, G. Brostow, M. Cissé, G. M. Farinella, T. Hassner (Eds.), Computer Vision – ECCV 2022, Springer Nature Switzerland, Cham, 2022, pp. 76–94.

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