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SURVEY ON DETECTION METHODSFOR DEEPFAKE VIDEOS

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Abstract

In recent times, deepfake videos, created through advanced deep learning algorithms, have garnered significant attention. This technology enables hyper realistic face manipulations. The internet has seen a proliferation of deepfake videos, predominantly targeting celebrities and politicians due to the extensive online presence of their visual content. These videos often serve the purpose of tarnishing the reputation of public figures and influencing public opinion, posing a substantial threat to societal stability. While the deepfake algorithm itself lacks inherent moral attributes, its widespread application has predominantly been for negative ends. In response to this, various research initiatives have been launched to counteract the potential harm, focusing on the development of detection methods and the establishment of comprehensive benchmarks. This review seeks to outline the current state of research in deepfake video detection, encompassing the generation process, diverse detection methods, and existing benchmarks. It is evident that existing detection techniques still fall short when applied in real-world scenarios. Consequently, future research efforts should prioritize enhancing the generalization and robustness of these methods.

Keywords: Deepfake, detection, research, face manipulation

1.Introduction

Deepfakes, a form of synthetic media , while deepfake technology could be used for positive purposes, such as film-making and virtual reality, it is still heavily applied for malicious uses media[17], utilize deep learning, a subset of artificial intelligence, to generate fabricated images and videos depicting false events. This process involves superimposing a target individual's face onto a source video, creating a seemingly authentic portrayal of the target engaging in actions or uttering statements from the source material. Unfortunately, deepfake technology has been misused, such as in the swapping of celebrities' faces onto bodies in explicit content. The inception of deepfakes dates back to 2017, marked by the emergence of a video where a celebrity's face was substituted with that of a porn actor

This misuse of deepfakes holds the potential to manipulate public opinion, influence election outcomes, and even disrupt financial markets through the dissemination of fake news. Moreover, deepfakes could be employed to create deceptive satellite images, introducing non-existent structures or objects to confuse military analysts and misguide troops in strategic operations, exemplified by the fabrication of a fictitious bridge across a river in a military scenario.

Over the last two years, substantial advancements have been made in the creation of novel detection techniques. To begin with, the number of video data-sets built for deepfake detection tasks is growing. From small datasets (such as DeepFake-TIMIT and UADFV) in an early stage, to large-scale datasets (such as FaceForensic++ , Celeb-DF , DFDC and DeeperForensic), the number of datasets that can be used for training has increased.

In this review, our emphasis will be on the current detection strategies tailored for deepfake videos, aiming to encourage advancements in the field of deepfake video detection.

There have been numerous methods proposed to detect deepfakes. Most of them are based on deep learning, and thus a battle between malicious and positive uses of deep learning methods has been aris-ing.[18]

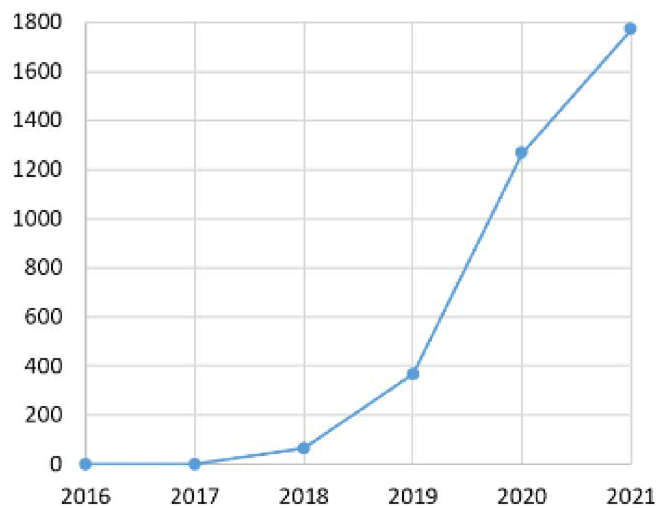

Fig 1 Number of papers related to deepfakes from years 2016 to 2021 with a search of keyword “deepfake”.[18]

2. Deepfakes Creation

Deepfakes employ an autoencoder, a type of neural network. An encoder condenses an image into a lower-dimensional latent space, while a decoder reconstructs the image from this latent representation. In the context of Deepfakes, this involves encoding a person into the latent space using a universal encoder, capturing essential characteristics of their facial features and body posture in the latent representation. Subsequently, a model, specifically trained for the target, decodes this information. In essence, the target's distinctive features are overlaid onto the latent space's inherent facial and body traits from the original video.

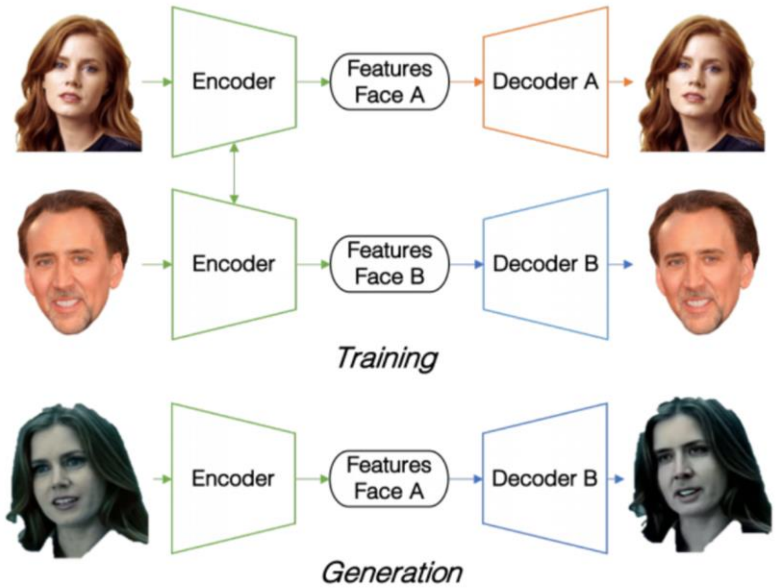

Fig 2 A deepfake creation model using an encoder-decoder pair [20]

The incorporation of a generative adversarial network (GAN) into the decoder represents a widely adopted enhancement to the previously mentioned architecture. In the context of an adversarial relationship, a GAN simultaneously trains a generator (the decoder) and a discriminator. The generator creates novel images based on the latent representation of the source material, while the discriminator assesses whether the image is authentic or generated. Consequently, the generator strives to produce images closely mirroring reality, as any deviations would be identified by the discriminator. In this zero-sum game, both algorithms evolve over time. The continual evolution of Deepfakes poses a challenge for counteraction, as they consistently adapt; any identified flaws can be promptly rectified.

3. DETECTION METHODS

TABLE 1 Classification of detection methods

SR NO	METHODS	DESCRIPTION
1.	CNN	A deep learning architecture designed for image processing tasks, particularly effective in feature extraction.
2.	RNN	A type of neural network designed to process sequential data, allowing for information persistence over time.
3.	LSTM	A specialized RNN variant, designed to address the vanishing gradient problem and capture long-term dependencies in data.
4.	FTCN (Fully temporal convolution network)	A convolutional neural network with fully trainable parameters, providing flexibility in feature learning.
5.	ResNext	A deep learning architecture that enhances traditional residual networks by introducing grouped convolutions for improved efficiency.

6.	UCL (Unsupervised Contrastive Learning)	A prominent research institution, often associated with cutting-edge developments in various fields, including deep learning.
7.	Face warping artifacts detection	Detection of distortions in facial features resulting from image warping, often associated with deepfake generation.
8.	MesoNet	A deep learning network designed specifically for detecting deepfake images, focusing on mesoscopic properties.
9.	MesoInception	An enhanced version of MesoNet, incorporating inception modules for improved feature representation in deepfake detection.
10.	Convolutional Traces	Techniques involving convolutional operations to trace and analyze patterns in data, often used in image processing.
11.	Key Video Frame Extraction	The process of identifying and extracting crucial frames from videos, often used for summarization or analysis purposes.
12.	TTN	Improves temporal pattern capture in sequential data through dynamic attention mechanism adjustments.

4. Literature Review

Various techniques and prediction models used by various researchers, the algorithms they used, and the ways they followed for their systems, of them are described below.

4.1 ResNext, CNN and LSTM Models [2]

Publication: Deep Fake Video Detection Using ResNext CNN And LSTM
Author: S Jeevidha, S. Saraswathi, Kaushik J B, Preethi K, Nallam Venkataramaya
(2023)

In this paper, a method for detecting deep fake videos is proposed. The authors utilize a combination of ResNext CNN and LSTM models to identify manipulated videos. The approach aims to address the growing concern of deep fake videos, which are digitally altered videos that can deceive viewers. By leveraging deep learning techniques, the authors propose a solution to detect and mitigate the spread of such videos.

4.2 Hybrid CNN-LSTM Models by Leveraging Optical Flow Features [3]

Publication: A Hybrid CNN-LSTM model for Video Deepfake Detection by Leveraging Optical Flow Features
Author: Pallabi Saikia, Dhwani Dholaria, Priyanka Yadav, Vaidehi Patel, Mohendra Roy
(2022)

In this paper, a novel approach to detect deepfake videos is proposed. The authors introduce a hybrid model that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. They leverage optical flow features, which capture the motion information in videos, to enhance the detection accuracy. By training the hybrid model on a large dataset of both real and deepfake videos, the authors demonstrate its effectiveness in accurately identifying manipulated videos. The proposed approach contributes to the ongoing efforts in combating the spread of deepfake videos by providing a robust and reliable detection method.

4.3 Temporal Coherence [4]

Publication: Exploring Temporal Coherence for More General Video Face Forgery Detection
Author: Yinglin Zheng, Jianmin Bao, Dong Chen, Ming Zeng, Fang Wen (2021)

This paper focuses on improving video face forgery detection. The authors propose a method that leverages temporal coherence, which refers to the consistency of facial movements over time, to enhance the accuracy of detecting manipulated videos. By analyzing the temporal information in videos, the proposed approach can effectively distinguish between real and forged facial expressions. The authors conduct experiments on various datasets and demonstrate the effectiveness of their method in detecting different types of face forgery techniques. The research contributes to the advancement of video face forgery detection by considering the temporal aspect and improving the overall detection performance.

4.4 Examination of Fairness of AI Models [5]

Publication: An Examination of Fairness of AI Models for Deepfake Detection
Author: Loc Trinh, Yan Liu (2021)

In this paper, the predictive performance of popular deepfake detectors on racially aware datasets balanced by gender and race was thoroughly measured. This paper echoes the importance of benchmark representation and intersectional auditing for increased demographic transparency and accountability in AI systems.

4.5 Machine Learning based Approach through Key Video Frame Extraction [6]

Publication: A Machine Learning based Approach for DeepFake Detection in Social Media through Key Video Frame Extraction
Author: Alakananda Mitra, Saraju P. Mohanty, Peter Corcoran, Elias Kougianos
(2021)

This paper presents a machine learning approach for detecting DeepFake videos in social media platforms. The authors propose a method that focuses on extracting key frames from videos and utilizing machine learning algorithms to analyze and classify them as real or manipulated. By identifying and analyzing specific frames, the proposed approach aims to detect DeepFake videos more accurately. The authors evaluate their method on various datasets and demonstrate its effectiveness in detecting DeepFake videos in social media. The research contributes to the field of DeepFake detection by providing a machine learning-based approach that leverages key frame extraction for improved accuracy.

4.6 Unsupervised Contrastive Learning [8]

Publication: DeepfakeUCL: Deepfake Detection via Unsupervised Contrastive Learning
Author: Sheldon Fung, Xuequan Lu, Chao Zhang, Chang-Tsun Li (2021)

In this paper, the deepfake detection is done via unsupervised contrastive learning. The model first generates two different transformed versions of an image and feeds them into two sequential sub-networks, i.e., an encoder and a projection head. The unsupervised training is achieved by maximizing the correspondence degree of the outputs of the projection head. To evaluate the detection performance of the unsupervised method, unsupervised features are used to train an efficient linear classification network.

4.7 Convolutional Neural Network (CNN) [7]

Publication: Deepfake Video Detection Using Convolutional Neural Network
Author: Aarti Karandikar, Vedita Deshpande, Sanjana Singh, Sayali Nagbhidkar, Saurabh Agrawal (2020)

This paper focuses on detecting deepfake videos using Convolutional Neural Networks (CNN). The authors propose a method that utilizes CNNs to analyze and classify videos as real or manipulated. By training the CNN model on a dataset of both real and deepfake videos, the authors demonstrate its effectiveness in accurately detecting deepfake videos. The research contributes to the field of deepfake detection by leveraging the power of CNNs to address the growing concern of manipulated videos and provide a reliable detection method.

4.8 Convolutional Traces [9]

Publication: DeepFake Detection by Analyzing Convolutional Traces (2020)
Author: Luca Guarnera, Oliver Giudice, Sebastiano Battiato

Idea of the proposed approach is that the local correlation of pixels in Deepfakes is dependent exclusively on the operations performed by all the layers present in the GAN which generate it; specifically the (latter) transpose convolution layers. This detection method is based on features extracted through the EM algorithm. The underlying fingerprint has been proven to be effective to discriminate between images generated by recent GANs architectures specifically devoted to generating realistic people's faces.

4.9 Capsule Networks with LSTM [10]

Publication: Deepfake Detection using Capsule Networks with Long Short-Term Memory Networks (2020)

Author: Akul Mehra

This model exploits the inconsistencies and identifies real and fake videos and is our contribution toward deepfake detection. Capsule Network is introduced to detect spatial inconsistencies in a single frame and then combined with LSTM to detect the Spatio-temporal inconsistencies across multiple frames

4.10 Face warping artifacts detection [11]

Publication: Methods of Deepfake Detection Based on Machine Learning (2020)
Author: Artem A. Maksutov; Viacheslav O. Morozov; Aleksander A.

In this work, they've described a summary of indicators that can be used to decide whether video or photo was changed. Their choice of building model is facing warping artifacts detection which is one of the best indicators of fake video/photo right now. A great part of present deepfake algorithms can synthesize only low-quality resolution faces. Such transformations leave distinctive artifacts that can be detected.

4.11 CNN and LSTM [1]

Publication: The Deepfake Challenges and Deepfake Video Detection (2020)
Author: Worku Muluye Wubet

This paper proposes deepfake video detection using CNN and LSTM based on eye blinking rate tested on UADFV publicly available dataset.The VGG16 and ResNet-50-based CNN models are trained on a training dataset that contains open and closed eyes regions. The eye blinking rate enables detection of fake videos from real videos.

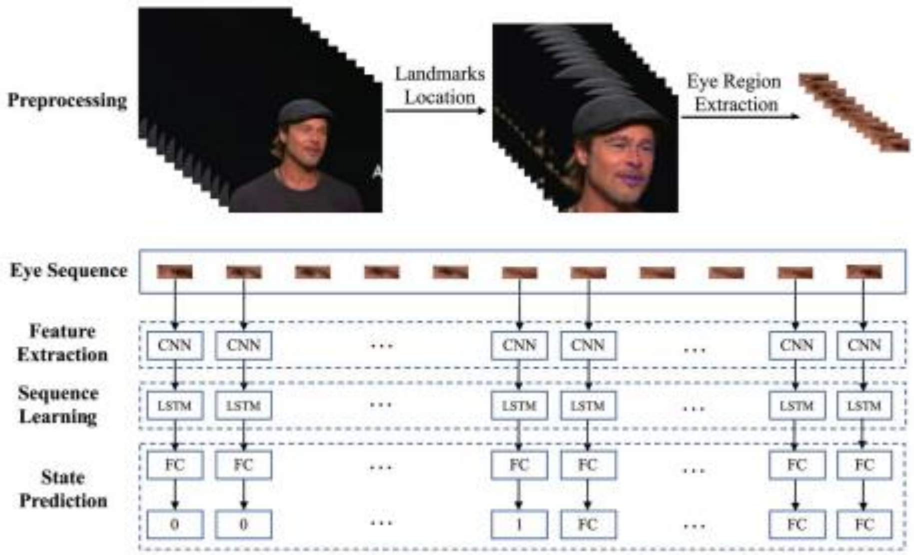

Fig 3 This figure depicts the preprocessing and feature extraction of eye blinking rate [19]

4.12 Deepfake Video Detection using Neural Networks [12]

Publication: Deepfake Video Detection using Neural Networks
Author(s): Abhijit Jadhav, Abhishek Patange, Jay Patel, Hitendra Patil, Manjushri Mahajan (2020)

Detecting the DF using CNN and RNN. The system uses a Convolutional Neural network (CNN) to extract features at the frame level.These features are used to train a recurrent neural network (RNN) which learns to classify if a video has been subject to manipulation or not and is able to detect the temporal inconsistencies between frames introduced by the DF creation tools.

4.13 FaceForensics++: Learning to Detect Manipulated Facial Images[13]

Publication: FaceForensics++: Learning to Detect Manipulated Facial Images
Author(s): Andreas Rössler, Davide Cozzolino, Luisa Verdoliva, Christian Riess, Justus Thies, Matthias Nießner (2019)

This research paper shows different methods how manipulated images can be detected using trained forgery detectors.

4.14 CNN and LSTM [14]

Publication: Deepfake Video Detection Using Recurrent Neural Networks (2018)
Author: David Guera Edward J. Delp

This research paper presents a temporal-aware system to automatically detect deepfake videos.It proposes a two-stage analysis composed of a CNN to extract features at the frame level followed by a temporally-aware RNN network to capture temporal inconsistencies between frames introduced by the face-swapping process. A simple convolutional LSTM structure is used which can accurately predict if a video has been subject to manipulation or not with as few as 2 seconds of video data.

4.15 MesoNet [15]

*Publication***:** MesoNet: a Compact Facial Video Forgery Detection Network (2018)
Author: Darius Afchar, Vincent Nozick, Junichi Yamagishi, Isao Echizen

In this research paper the method to detect forged videos was placed at a mesoscopic level of analysis. The architecture is based on well-performing networks for image classification that alternate layers of convolutions and pooling for feature extraction and a dense network for classification.

Table 2 Literature survey summary

Sr. No	**Publication (Year) and Author**	**Technique/Algorithm**	**Advantages**	**Disadvantages**
1	Deep Fake Video Detection Using ResNext CNN And LSTM [2] **Author:** S Jeevidha, S. Saraswathi, Kaushik J B, Preethi K, Nallam Venkataramaya (2023)	ResNext, CNN and LSTM	This research suggests that the proposed method can be integrated into popular applications like WhatsApp, Facebook, and Instagram for easy pre-detection of fake/morphed videos before sharing with other users.	The proposed method uses a smaller sample size of ≤ 150 frames for training and evaluation.
2	A Hybrid CNN-LSTM model for Video Deepfake Detection by Leveraging Optical Flow Features [3] **Author:** Pallabi Saikia, Dhwani Dholaria, Priyanka Yadav, Vaidehi Patel, Mohendra Roy (2022)	CNN-LSTM	By utilizing optical flow, the model is able to extract temporal features and identify inconsistencies in the motion of the subject's face, enhancing the classification accuracy of deepfakes.	The research acknowledges that the model's performance due to computational constraints, was performed on a subset of frames, potentially limiting its accuracy.
3	Exploring Temporal Coherence for More General Video Face Forgery Detection	Fully temporal convolution network (FTCN),	The proposed framework achieves impressive results without relying on pre-	The research paper does not provide a detailed evaluation of its

	Author: Yinglin Zheng, Jianmin Bao, Dong Chen, Ming Zeng, Fang Wen [4] (2021)	Temporal Transformer network	training knowledge or hand-crafted datasets.	performance in real-world scenarios or discuss potential challenges and limitations that may arise in practical applications.
4	An Examination of Fairness of AI Models for Deepfake Detection [5] **Author:** Loc Trinh, Yan Liu (2021)	Survey	The study examines the bias present in deepfake datasets and detection models across different racial subgroups. This analysis sheds light on the disparities in predictive performances across races, providing insights into potential discrimination and fairness issues.	Through research the dataset bias may limit the generalizability of the findings to other racial groups and could introduce biases in the deepfake detection models.
5	A Machine Learning based Approach for DeepFake Detection in Social Media through Key Video Frame Extraction [6] **Author:** Alakananda Mitra, Saraju P. Mohanty, Peter Corcoran, Elias Kougianos (2021)	Key Video Frame Extraction	The key video frame extraction technique significantly reduces the computational burden, making the approach more efficient. The model is designed to detect deepfake videos in highly compressed social media videos, which is a common scenario in real-world applications.	The model may not produce accurate results for hazy fake videos, as the training dataset did not have sufficient examples of such videos.
6	DeepfakeUCL: Deepfake Detection via Unsupervised Contrastive Learning [8] **Author:** Sheldon Fung, Xuequan Lu, Chao Zhang, Chang-Tsun Li	Unsupervised Contrastive Learning	DeepfakeUCL utilizes unsupervised contrastive learning, which allows it to learn separable features without the need for labeled data. This is advantageous as it eliminates the need for manual labeling, which can be	Although the document mentions that DeepfakeUCL can detect various manipulation techniques, it does not provide detailed information on the specific techniques tested or the system's performance against each technique.

	(2021)		time-consuming and costly.	
7	Deepfake Video Detection Using Convolutional Neural Network [7] **Author:** Aarti Karandikar, Vedita Deshpande, Sanjana Singh, Sayali Nagbhidkar, Saurabh Agrawal (2020)	Convolutional Neural Network	The model uses a pre-trained VGG-16 model for feature extraction, which has shown excellent properties in image and video processing tasks.	Low Resolution Images: The model's accuracy decreases with low-quality images, indicating that it may struggle to detect deepfakes in such cases.
8	DeepFake Detection by Analyzing Convolutional Traces [9] **Author:** Luca Guarnera, Oliver Giudice, Sebastiano Battiato (2020)	Convolutional Traces	The system is designed to work in an "almost-in-the-wild" scenario, meaning it can detect Deepfakes without prior knowledge of the specific generation process. This adaptability makes it suitable for real-world applications where Deepfakes can be encountered in various contexts.	The system's effectiveness is tested on specific image sizes used by the considered GAN architectures. It may not perform as well on images of different sizes or resolutions.
9	Deepfake Detection using Capsule Networks with Long Short-Term Memory Networks [10] **Author:** Akul Mehra (2020)	Capsule Networks with LSTM	1)Improved Performance: The spatio-temporal hybrid model achieves an accuracy of 83.42% in detecting deepfakes, This indicates that the model is effective in identifying inconsistencies in videos and distinguishing between real and fake videos.	The model's performance is sensitive to the selection of frames, which may require careful consideration and optimization as the choice of frame selection technique has a significant impact on the performance of the model.

10	Methods of Deepfake Detection Based on Machine Learning [11] **Author:** Artem A. Maksutov; Viacheslav O. Morozov; Aleksander A. (2020)	Face warping artifacts detection	1) It does not require training datasets of deepfake videos, as it relies on face detection and affine transformations. This makes it easier to implement and use. It uses DenseNet169 as the model architecture has shown good results in terms of accuracy.	The proposed system focuses on detecting face swapping algorithms and may not be as effective in detecting other types of deepfake techniques such as lip-sync or puppet-master.
11	The Deepfake Challenges and Deepfake Video Detection[1] **Author:** Worku Muluye Wubet (2020)	CNN and LSTM	By focusing on the eye blinking rate, the system leverages a natural and involuntary behavior that is difficult for deepfake creation tools to replicate accurately. This makes it a potentially reliable feature for detecting deepfakes.	The system relies on the UADFV dataset for training the detection model. The dataset does not adequately represent the range of deepfake variations, the system's accuracy may be compromised.
12	Deepfake Video Detection using Neural Networks [12] **Author(s)**:Abhijit Jadhav, Abhishek Patange, Jay Patel, Hitendra Patil, Manjushri Mahajan (2020)	ResNext CNN and LSTM	The use of ResNext CNN for feature extraction helps in accurately detecting frame-level features, enhancing the overall detection accuracy.	The method is trained on noiseless and simulated datasets, which may not fully capture the complexities and variations present in real-time data. This could potentially affect the performance on real-world deepfake videos.
13	FaceForensics++: Learning to Detect Manipulated Facial Images[13] **Author:** Andreas Rössler, Davide Cozzolino, Luisa Verdoliva, Christian	Survey	The survey system covers various facial manipulation methods, including facial expression manipulation and facial identity manipulation. It includes state-of-the-art techniques such as	While the system achieves high accuracy in detecting manipulations within the evaluated dataset, its performance on unseen or novel manipulation techniques may be limited.

	Riess, Justus Thies, Matthias Nießner (2019)		Face2Face, FaceSwap, DeepFakes, and NeuralTextures, providing a comprehensive evaluation of detection methods.	
14	Deepfake Video Detection Using Recurrent Neural Networks[14] **Author:** David Guera Edward J. Delp (2018)	CNN and LSTM	It uses a two-stage analysis approach, combining a convolutional neural network (CNN) for frame-level feature extraction and a temporally-aware recurrent neural network (RNN) for capturing temporal inconsistencies introduced by the face-swapping process. This allows the system to effectively detect deepfake manipulations in videos.	The paper does not discuss the limitations or potential vulnerabilities of the proposed system and does not provide detailed information about the computational requirements and efficiency of the system.
15	MesoNet: a Compact Facial Video Forgery Detection Network[15] **Author:** Darius Afchar, Vincent Nozick, Junichi Yamagishi, Isao Echizen (2018)	MesoNet	By utilizing deep learning networks, the system can capture and analyze the mesoscopic properties of images, which is crucial for detecting face tampering in videos.	The system focuses on detecting two specific face tampering techniques, Deepfake and Face2Face. It may not be as effective in detecting other types of video forgeries.

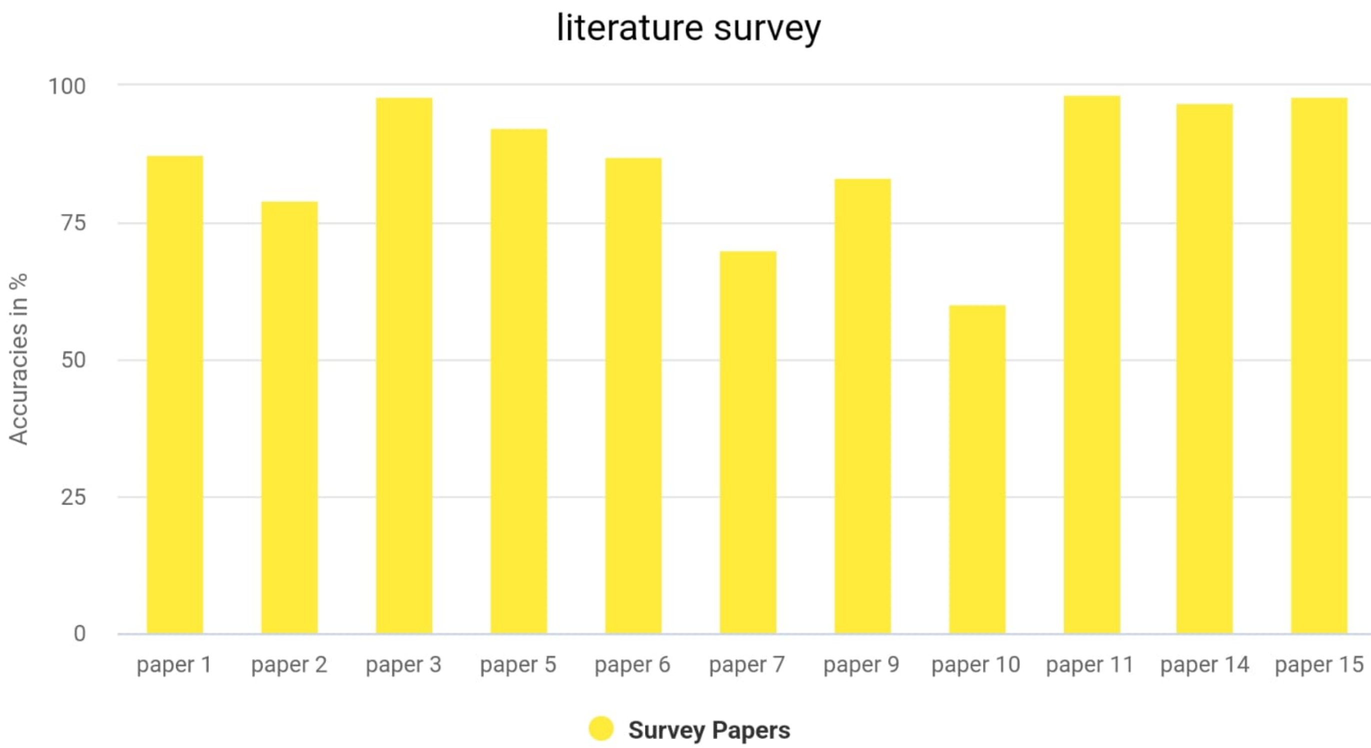

Fig 4 The above graph varies the average accuracies of the models trained on the the datasets namely Celeb DF FaceForensic++, Deepfake Detection Challenge ,Face2face, identified in different research paper serially given in the Table 2 Literature survey summary ; whereas the papers 4, 8, 12 and 13 are based on the algorithms specified in the table w.r.t. surveys conducted.

4. DISCUSSIONS

Deepfake videos have gained attention in the last two years, presenting a significant threat to societal security. Consequently, extensive research has been conducted, leading to notable advancements. While recent detection algorithms demonstrated nearly 100% accuracy in early deepfake datasets, their performance is less than ideal in newly developed datasets. In the recent DFDC competition, the average accuracy of proposed detection approaches was only 65.18%, indicating that current methods fall short of meeting practical scene requirements. Simultaneously, contemporary research leans towards employing intricate network structures for abstract feature extraction. Although this enhances detection performance, the heightened network complexity results in increased computational costs.

5. CONCLUSION

In recent years, there has been an unprecedented advancement in deepfake technologies, driven by deep learning. The rapid dissemination of maliciously manipulated videos, created through deepfake algorithms, poses a global threat to social stability and personal privacy via the widespread reach of the Internet. In response, both commercial entities and research groups worldwide are actively engaged in mitigating the adverse effects of deepfake videos on individuals. This article sequentially addresses the generation technology of deepfake videos, evaluates current detection methods, and explores future research directions. The review underscores prevalent issues in existing detection algorithms while emphasizing the importance of generalization and robustness. This comprehensive overview aims to assist researchers in the field of deepfake detection and contribute to the mitigation of the negative impacts associated with deepfake videos.

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