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Research Article

Exploring the Deepfake Dilemma and the Evolution of Detection Techniques

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ABSTRACT

Deep learning generative models have seen a rise in their usage by technology experts and cybercriminals alike. It has become a big social issue, and its significance is expected to grow exponentially in upcoming times. As a result, the need for investment in Deepfake detection techniques is imperative. Specifically, image manipulation using deepfake techniques is easier and has a wider impact on the digital world. This paper aims to review currently available technology to deal with this pressing issue. We report the details of examined works and shortcomings. Furthermore, various research is reviewed, relevant to the topic dealt with in this paper.

Keywords: Deepfake Image Detection, Deep Learning, Machine learning, Fake Image

INTRODUCTION

In the current generation, visual content dominates the digital world. However, the rise of deepfake technology presents a considerable challenge to the authenticity and trustworthiness of the content, especially images. Synthetic images created using deep learning algorithms tend to be visually indistinguishable from the original content. Such unprecedented accuracy presents a major challenge to various aspects of society including journalism, entertainment, politics, and cybersecurity.

Considerable resources have been put in place for the detection of deepfakes amidst the growing influence of deepfakes on society. It's a complicated and sophisticated task with a considerable requirement of domain expertise. This review aims to summarize the current techniques and research available for the detection of deepfakes, specifically deepfake images.

Over the years, the influence of deepfakes on various aspects of society has skyrocketed and now it has reached an all-time high. Every day, news reports include mentions of fraud happening around with the use of manipulated media, especially images, through the use of deep learning techniques, making it harder for the general population to notice the difference between original and fake.

While there are policies in place to deter fraud through deepfake, detection is important for those laws to be useful. In this tug of war, creators of deepfake media have an upper hand due to the increasing efficiency of Machine Learning and deep learning algorithms. To stay in this war, detection algorithms and techniques need to evolve as well to catch up with the evolving deepfake generation techniques.

The rise of powerful deep learning algorithms has made it considerably easier to generate very realistic and convincing fake images. Deepfake was recognized as a technology as early as 2012 but its effects were unclear until 2018. In 2018, the rise of deepfake technology unveiled its potential for unethical and malicious applications, such as spreading misinformation, impersonating political leaders, and defaming innocent individuals [1].

Deepfakes refer to manipulated or synthetic media, such as images, videos, or audio, that are created using deep learning algorithms to generate realistic-looking content [2]. This new technology has gained prominence due to the availability of convenient tools and techniques for generating realistic-looking fake multimedia content.

The primary factor responsible for the rise in deepfake technology is the growth fueled by advancements in deep learning, specifically the use of Generative Adversarial Networks(GAN) and auto encoders [3]. While deepfake may have a few valid use cases, the harmful effects of this technology have far outgrown its proper use. Moreover, visually identifying deepfakes is very difficult, so we can only rely on technology itself for detection purposes.

Deepfakes have become a major challenge to society as a whole due to its recent advancements. It has the potential to greatly undermine trust in visual content. The growing quality of deepfakes makes it very difficult for the general population to discern between real and fake images. This has significant implications for the spread of misinformation, as deepfakes can be used to create realistic-looking fake images that appear genuine and can mislead viewers [4]. Deepfakes also pose a significant threat to the privacy of individuals as they can be used to create counterfeit content featuring individuals without their consent. Its political implications are dangerous as they can be utilized to create fake images of political leaders, featuring them in inappropriate activities.

We aim to provide an overview of literature from various sources focused on the detection of deepfake images. Moreover, we traverse the dynamic terrain of deepfake research from the researchers' point of view, while also exploring different approaches to the problem inclusively.

In this review, we provide an insight into the current scenario of deepfake detection while comparing different techniques available. We also take a look at the machinery behind the detection tools and techniques in brief.

METHODOLOGY

A proper review demands an apt search of resources, specifically research papers and articles that have been published in the required domain. To carry out this review, we have gathered research papers and articles from various sources using some general keywords.

Fig. 1. Methodology for selecting relevant studies.

The following are the steps involved in selecting the studies:

1.1. Search Keywords

The following keywords were used while searching the relevant material: "deepfake images", "deepfake media", "deep learning", "machine learning", "fake image detection", "fake media detection", "convolutional neural network", "recurrent neural network", "generative adversarial network", "machine learning".

1.2. Research Databases

The material used in this review was taken from the following databases: IEEExplore, ResearchGate, ScienceDirect, Google Scholars, ACM Digital Library, Web of Science, arXiv

1.3. List of Articles

A list of relevant articles was prepared after the first two steps. These were to undergo further filtering in the upcoming steps.

1.4. Selection Criteria

The selection criteria for appropriate articles involved the following considerations:

- **Relevance:** Articles have been chosen in such a way that they were highly relevant to the topics included in the review. They were directly focused on deepfake image detection techniques and tools to be included in our review.
- **Publication Date:** Articles that were published after 2018 were included since deepfake gained popularity and more significance around this time.
- **Peer reviews:** Those articles that have been highly appraised by the peer community were given priority. Being featured in highly revered conferences and talks was a primary factor in selecting the articles.
- **Experimental validation:** Articles including appropriate experimental results and reviews were preferred over those with none.
- **Comparative Analysis:** The papers precisely dealing with comparative analysis of various algorithms and techniques were also taken. These were used to identify the strengths and weaknesses of individual tools.
- **Ethical implications:** Those papers were sought that discussed ethical implications of deepfake detection including issues related to privacy, consent, misinformation, and impact on the society.
- **Quality and Citations:** Articles with high citation counts and those published in reputable journals and conferences were prioritized.

1.5. Selected studies

The articles that satisfied the given steps were taken. Further, the redundant articles were removed for an efficient overview and to avoid clumsy writing. After all the mentioned steps, the articles and papers mentioned in the "References" section were selected to be used as a reference.

EVOLUTION OF DEEPFAKE IMAGE CREATION

There has been considerable evolution in deepfake image creation techniques in recent years. Generative deep learning algorithms like Generative Adversarial Networks(GAN) and auto-encoders have contributed significantly to the advancement of deepfake technology [5]. These algorithms are trained using large datasets of real images to learn underlying features and patterns necessary for generating fake images that look real to the naked eye [6]. Due to these algorithms, deepfake image creation has become more sophisticated which makes it difficult to distinguish between real and fake images, not only for a human but also for detection algorithms [7].

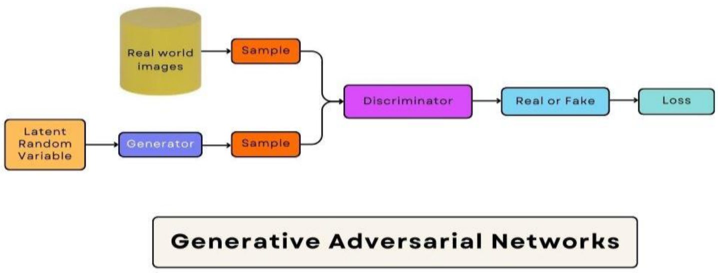

Fig. 2. Generative Adversarial Network

One of the most popular approaches is using a Generative Adversarial Network (GAN) which consists of two neural networks: a Generator and a Discriminator [8]. The Generator network produces fake images while the discriminator network tries to distinguish between real and fake images at the same time. The generator network learns to create more realistic images through an iterative process to deceive the discriminator network.

A Generative Adversarial Network (GAN) is trained using a dataset consisting of real images of individuals. The Generator improves through training and becomes better at creating more convincing fake images that relate to the characteristics of input data. The Generated deepfake is visually indistinguishable from a real image which makes it challenging to detect such deepfake images.

During training, the generator and the discriminator compete against each other like rivals in a game. While the generator aims to create more realistic fake images, the discriminator works to get better at distinguishing real images from fake ones. This makes it very challenging for humans as well as simple computer programs to identify deepfake images or discern them from real ones.

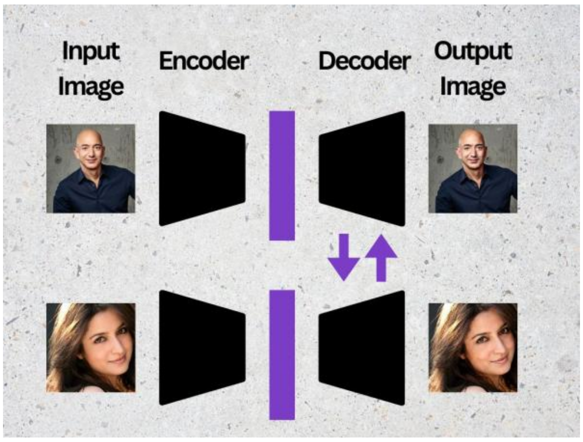

Fig. 3. Auto-encoder illustration

Using auto-encoders is another approach for generating deepfake images. Auto-encoders are neural networks that are designed to learn a compressed version of input data. It is trained using a large dataset of real images and then it learns to encode the essential features of these images into representation in lower dimensions. This lower-dimensional representation is then used to generate fake images by decoding it back into real image space [9].

Generally, two auto-encoders are trained for deepfake creation. One is trained with the images or videos of the target person, and the other is trained in the images or videos of another person whose facial expressions or gestures need to be imitated.

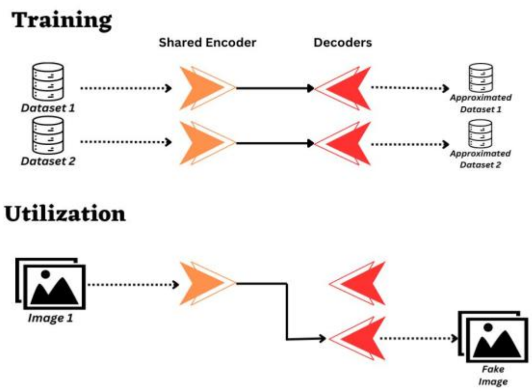

Fig. 4. Shared encoders

A shared encoder may be used to encode core facial features into the latent space. Using this, we can superimpose more detailed information about the target onto another person's expressions [10]. STo enhance the realism of the deepfake, the reconstructed output can be processed through a Generative Adversarial Network (GAN). It refines the images to make them look more realistic and undetectable to the naked eye.

ADVANCEMENTS IN DEEPFAKE IMAGE DETECTION TECHNIQUES

To mitigate harm caused by deepfake images, the first step is to detect them accurately. Spreading of deepfake can be very harmful for the masses and may have lasting effects. So, several techniques have been put forth by the scientific community and technology developers for the detection of deepfake images.

Fig. 5. Illustration of Deepfake Image Detection

One approach that has been developed for detection is to analyze the anomalies and artifacts that are present in deepfake images which are typically not found in real images. These anomalies include unnatural facial movements and expressions, inconsistency in lighting and shadows, and mismatches in facial features [11].

Another approach that can be used for deepfake image detection is analyzing the inconsistencies in visual and statistical features of the images. It involves examination of variations in color, texture, and noise patterns that are characteristic of deepfake images [12]. Researchers have considered using machine learning algorithms for deepfake image detection purposes. These algorithms are trained using large datasets consisting of both real and deepfake images. This allows them to learn the patterns and features that discern deepfake images from the real ones [13].

Among the most used machine learning techniques for deepfake detection is the Convolutional Neural Network (CNN). The specialty of Convolutional Neural Networks is that they are efficient and applicable for image classification tasks. Convolutional Neural Networks consist of several layers of interconnected nodes known as neurons, which perform various operations on input data to extract relevant features and make further predictions. In the case of deepfake image detection, Convolutional Neural Networks are used to learn the features that discern fake images from real ones [14].

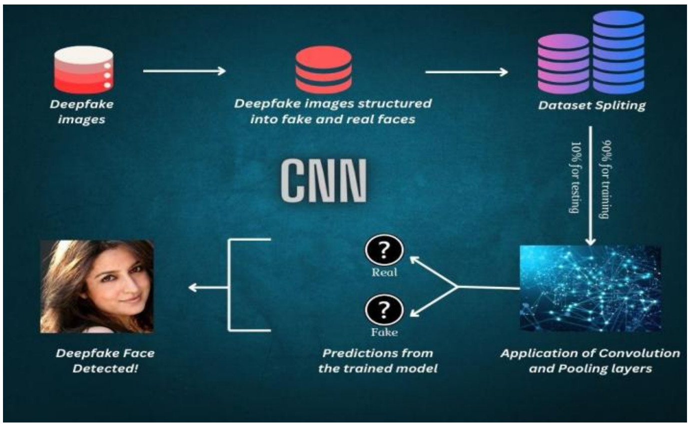

Fig. 6. Deepfake Image Detection using CNN

Convolutional Neural Network (CNN) is a type of deep learning algorithm that has been widely used in distinguishing between real and fake images. This method depends upon labeled data for training i.e. the labeled data is divided into two categories, Real and Fake. In the training phase, the neural network analyzes unique patterns and features associated with the images. Recent research has revealed that the performance of Convolutional Neural Networks (CNN) can be improved by using advanced architectures like Inception-ResNet-v2 [15] and XceptionNet [16]

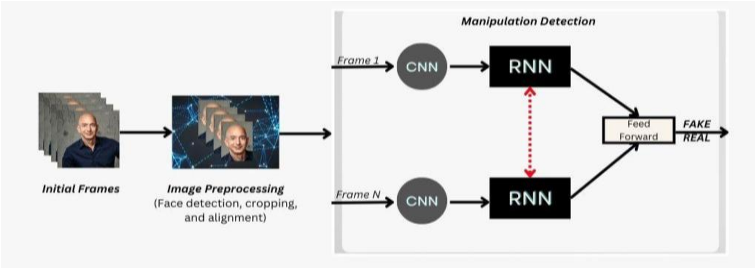

Fig. 7. Deepfake detection using RNN

Another technology that can be utilized for deepfake image detection is Recurrent Neural Network (RNN). They can process sequential data which makes them suitable for analysis of fake features in videos. These approaches involve using a combination of Convolutional Neural Network (CNN) layers to extract features and Recurrent Neural Networks (RNN) to analyze the sequential patterns, thereby working together for effective deepfake detection [17]. This shows how different deepfake detection techniques need not always be mutually exclusive and can be used together to produce better results.

COMPREHENSIVE OVERVIEW OF DEEPFAKE DETECTION TECHNIQUES

The Rise of deepfake technology has fueled the need for more investment in terms of time, money, and research into the field of deepfake detection and identification of manipulated media, especially images. Various methods have been proposed by several researchers all around the world, addressing the challenges and efforts behind deepfake image detection. One of the most commonly used approaches is the utilization of deep learning techniques like Convolutional Neural Networks (CNN) which have proved to be highly efficient in detecting deepfake images to a great extent and considerable accuracy [18].

Convolutional Neural Networks are very well suited for the detection of deepfake images due to their effectiveness in extracting relevant information from image data. Training of this network is carried out by feeding it labeled data that contains two types of images, namely, real images and deepfake images. The datasets that are used for this purpose are made through two steps. The first step is obtaining real images from reliable sources and the second step is to use deepfake generation techniques like Generative Adversarial Network (GAN) to generate deepfakes of these sample images. They are then combined into a single dataset and ready to be used for training a deepfake detection model [19].

Various studies have been put forth dealing with the use of different techniques and architectures to improve the accuracy of deepfake images as well as their efficiency. One such study by Singh et al.. 2021, mentions the use of deep learning-based Convolutional Neural Network (CNN) architectures such as Inception-Resnet-v2 and XceptionNet, for efficient detection of deepfake images [20]. These prove to be very powerful in terms of accuracy and efficiency. Upon introduction, they turned out to be way ahead of existing deepfake detection techniques around that time.

A similar approach was proposed by Karandikar et al.,2020, which used a Convolutional Neural Network for deepfake video detection rather than being limited to image detection. It uses temporal sequence between the frames which means it uses the relevant details and the magnitude of change in further frames in the sequence to discern real videos from deepfake videos with a good amount of efficiency [21].

Other than CNN-based approaches, other approaches have also been explored by researchers, particularly, the use of Recurrent Neural Networks (RNN) for deepfake image detection. Guera and Delp put forth a temporal-aware pipeline for automatic detection of deepfake videos, thereby minimizing human dependence and going a step further. This pipeline uses a combination of Convolutional Neural Networks (CNN) for extraction of frame-level features to detect whether a video has been tampered with and manipulated or not [22].

Using deep learning techniques for deepfake detection has so far been a successful endeavor for researchers across the globe. It is important however to realize that as the deepfake detection techniques get better, the deepfake creation techniques continue to grow at a great speed with increasingly realistic images being generated in large quantities. So the significance of good datasets can't be ignored. Large-scale datasets which include both real images and deepfake-generated images form a crucial part in training powerful detection models. Recent studies have given importance to the size of datasets for training detection models as well as their diversity.

Aspects	**Details**
Significance of Deepfake Detection	Rising need for investment in time, money and research, also identification of manipulated media like images is critical.
Primary Approach	Utilization of deep learning techniques, particularly Convolutional Neural Networks (CNNs)
Effectiveness of CNNs	Highly efficient in extracting relevant information from images. Trained using labeled datasets containing real and deepfake images.
Dataset creations for CNN training	1) Real images obtained from reliable sources. 2) Deepfake images generated using techniques like Generative Adversarial Networks (GANs) 3) Combined into a dataset for training detection models
Advanced CNN architectures	Inception ResNet V2 and XceptionNet are efficient detection of deepfake images with superior accuracy and efficiency.
Video detection techniques	RNN explored for deepfake image detection. Guera and Delp's temporal-aware pipeline combines CNNs for frame-level feature extraction and RNNs to detect manipulated videos.[17]
Importance of datasets	Large-scale, diverse datasets of real and deepfake images are crucial. Diversity and size of datasets are critical for training robust detection models.
Key studies and contributions	Highlighted advanced CNN architectures for images detection. [15][21] Focused on video detection using CNNs and temporal analysis [22] Developed a pipeline combining CNNs and RNNs for video manipulation detection.[23]

Table 1: Structured and systematic overview of deepfake detection techniques.

ANALYZING THE EFFECTIVENESS OF DEEPFAKE IMAGE DETECTION METHODS

Various deepfake detection methods have been developed using artificial intelligence algorithms to detect manipulated media, particularly images. A common and comparatively simple method in this case is the visual characteristics-based approach. It focuses on the extraction and analysis of visual features [23]. A different approach to the detection of deepfake images is the local characteristic-based approach which focuses on detecting inconsistencies in specific regions or areas within the image [24].

The deep learning-based models are more advanced than the previous models in the detection of deepfake images as well as more sophisticated. It utilizes deep learning-based models to extract deep-level features and patterns from the image and then uses them to train itself thereby making it possible in the future to detect deepfake images more accurately and efficiently. The temporal feature-based approach is another method that is used primarily for video detection in which manipulated sequences act as an indicator of deepfake content [25].

The effectiveness of deepfake image detection methods can be evaluated based on the following factors:

- **Accuracy**: The correctness of a deepfake detection algorithm or method in distinguishing between real and deepfake generated images can be termed as its accuracy. According to the available studies, major deepfake detection methods currently have accuracy between 75% and 99%, depending on what algorithm is being discussed and what dataset was used to train the algorithm. For example, Korshunov et al. [26], conducted a study in which the accuracy of different deepfake detection methods was evaluated on a public dataset. It was found that the best-performing algorithms had an average accuracy of 94.3%.
- **Robustness**: The robustness of any deepfake detection method means its capability to accurately detect various types of deepfake manipulations without considering the techniques or models used for this purpose. Since deepfake technology tends to evolve continuously at a rapid pace, the robustness of any deepfake detection method is a major challenge. Researchers around the world have made considerable efforts to develop detection methods that can be adaptable to different types of deepfake generation models and identify manipulated content with decent accuracy. For example, Rössler et al. revealed a study that evaluated the robustness of deepfake detection methods against various types of deepfake techniques and found that some algorithms achieved high detection accuracy rates across different types of deepfake models. This indicates that they were effective in detecting a wide range of manipulations [27].

- **Generalizability:** The ability of a deepfake image detection model to detect deepfake images in samples that it has not been trained in before is known as Generalizability. It is an important aspect of deepfake image detection because deepfake images constantly and rapidly evolve, which means that new techniques keep emerging. As a result, a detection model that isn't doesn't perform well in the unknown waters may have less practical use. For example, a study by Matern et al. [28] deals with the evaluation of the generalizability of deepfake detection methods by testing their performance on new deepfake images and it was found that a few algorithms were able to achieve higher detection rates which is a direct indicator of their capability to adapt to the ever changing scene of deepfake media.

Comparative Analysis of Deepfake Image Detection Techniques

Deepfake detection techniques can be broadly classified into two main approaches: traditional approach and deep learning-based approach. Traditional methods are dependent upon visual anomalies that are characteristic of manipulated media like deepfake images. These methods primarily involve a thorough examination of inconsistencies in facial expressions. However, it may also consider other factors that hint towards manipulation [29]. For example, one traditional method compares the displacement and rotation of facial landmarks and then uses it to detect whether the image has been manipulated.

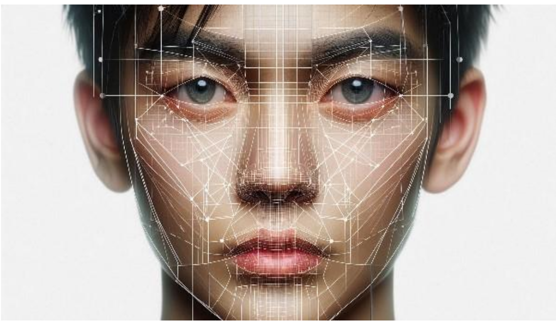

Fig. 8. Using facial landmarks for deepfake image detection

On the other hand, deep learning-based methods primarily use neural networks to independently learn and detect patterns and characteristics from deepfake image samples and then use them to detect deepfake images from test samples. Generally, Convolutional Neural Networks (CNN) or Recurrent Neural Networks (RNN) are used to train models for deepfake image detection as they prove to be highly reliable and robust in the deepfake image detection landscape [30]. For example, a neural network may be trained upon a large dataset consisting of both deepfake and real images. It may help the neural network learn the differences between real and deepfake images.

Generative Adversarial Networks (GAN) are another class of deep learning-based methods capable of using competitive components competing against one another, one generating better deepfake images while the other is busy getting better at detecting them. The generative component is named the Generator which creates fake images and the other component is named the Discriminator which tries to figure out deepfake images. The purpose of the generator network is to fool the discriminator network [31].

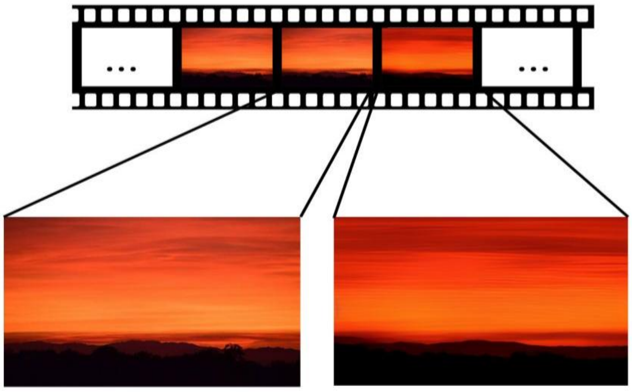

Fig. 9. Optical flow analysis

Yet another deep learning technique focuses on optical flow analysis which tries to interpret motion flow patterns in videos to filter out deepfake image frames. It is usually done by analyzing the visual features of the video or the flow of pixels between consecutive frames [32]. Inconsistent flow or motion patterns often hint towards image manipulation in the frames.

CONCLUSIONS AND FUTURE SCOPE

Upon analyzing various methods and approaches to deepfake image detection techniques, deep learning-based methods are far ahead of their traditional competitors. Convolutional Neural Networks (CNN) form a strong base for detection purposes as their special flexibility and suitability for images and pixels give them an edge over other common algorithms.

Detection of deepfake images is a critical area in the research community due to its increasing influence over important factors of society. Existing deepfake detection methods have made considerable progress, which is primarily driven by advancements in deep learning techniques and the availability of large, high-quality datasets.

However, there are a lot of areas and challenges that need to be thoroughly addressed by the research community like the detection of non-face-swapping deepfake images and the adaptation to the emerging deepfake generation techniques. The rapid evolution of deepfake generation techniques demands focused research efforts into detection methods to stay up to date with the latest developments in the field. Through this literature review, we have tried to provide a comprehensive overview of trends and developments in the field of deepfake image detection while also detailing the advantages and disadvantages of various detection approaches and discussing the challenges that arise. We strongly recommend further research in this challenging and evolving field.

REFERENCES

[1] N. Sontakke, S. Utekar, S. Rastogi, and S. Sonawane, “Comparative analysis of Deep-Fake algorithms,” arXiv (Cornell University), Sep. 2023, doi: 10.48550/arxiv.2309.03295.

[2] Y. Mirsky and W. Lee, “The creation and detection of deepfakes,” ACM Computing Surveys, vol. 54, no. 1, pp. 1–41, Jan. 2021, doi: 10.1145/3425780.

[3] D. Pan, L. Sun, R. Wang, X. Zhang and R. O. Sinnott, "Deepfake Detection through Deep Learning," 2020 IEEE/ACM International Conference on Big Data Computing, Applications and Technologies (BDCAT), Leicester, UK, 2020, pp. 134-143, doi: 10.1109/BDCAT50828.2020.00001.

[4] S. Lyu, “DeepFake Detection: current challenges and next steps,” arXiv (Cornell University), Mar. 2020, doi: 10.48550/arxiv.2003.09234.

[5] M. M. Patel, A. Gupta, S. Tanwar, and M. S. Obaidat, “Trans-DF: A Transfer Learning-based end-to-end Deepfake Detector,” 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA), pp. 796–801, Oct. 2020, doi: 10.1109/ICCCA49541.2020.9250803.

[6] N. Krueger, M. Vanamala, and R. Dave, “Recent advancements in the field of deepfake detection,” arXiv (Cornell University), Aug. 2023, doi: 10.48550/arxiv.2308.05563.

[7] A. Borji, “Qualitative failures of image generation models and their application in detecting deepfakes,” arXiv (Cornell University), Mar. 2023, doi: 10.48550/arxiv.2304.06470.

[8] Y. Rodríguez-Ortega, M. Ballesteros, and D. Renza, “Copy-Move Forgery Detection (CMFD) using deep learning for image and video forensics,” Journal of Imaging, vol. 7, no. 3, p. 59, Mar. 2021, doi: 10.3390/jimaging7030059.

[9] H. A. Khalil and S. A. Maged, “Deepfakes Creation and Detection Using Deep Learning,” 2021 International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC), pp. 1–4, doi: 10.1109/MIUCC52538.2021.9447642.

[10] K. N. Ramadhani and R. Munir, "A Comparative Study of Deepfake Video Detection Method," 2020 3rd International Conference on Information and Communications Technology (ICOIACT), Yogyakarta, Indonesia, 2020, pp. 394-399, doi: 10.1109/ICOIACT50329.2020.9331963.

[11] S. S. Zotov, P. Дремлюга, A. Borshevnikov, and K. Krivosheeva, DeepFake Detection Algorithms: A Meta-Analysis. 2020. doi: 10.1145/3421515.3421532.

[12] T. T. Nguyen et al., “Deep learning for deepfakes creation and detection: A survey,” Computer Vision and Image Understanding, vol. 223, p. 103525, Oct. 2022, doi: 10.1016/j.cviu.2022.103525.

[13] Y. Tu, Y. Liu, and X. Li, Deepfake Video Detection by Using Convolutional Gated Recurrent Unit. New York, NY, United States of America: Association for Computing Machinery, 2021. doi: 10.1145/3457682.3457736.

[14] S. Zobaed et al., “DeepFakes: Detecting forged and synthetic media content using machine learning,” arXiv (Cornell University), Sep. 2021, doi: 10.48550/arxiv.2109.02874.

[15] R. R. Rajalaxmi, S. P. P, R. A. M, P. S, D. P and G. E, "Deepfake Detection using Inception-ResNet-V2 Network," 2023 7th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2023, pp. 580-586, doi: 10.1109/ICCMC56507.2023.10083584..

[16] V. L. L. Thing, “Deepfake Detection with Deep Learning: Convolutional Neural Networks versus Transformers,” arXiv (Cornell University), Apr. 2023, doi: 10.48550/arxiv.2304.03698.

[17] J. Pu et al., “Deepfake Videos in the Wild: Analysis and Detection,” arXiv (Cornell University), Mar. 2021, doi: 10.48550/arxiv.2103.04263.

[18] A. A. Ismail, M. S. Elpeltagy, M. S. Zaki, and K. A. ElDahshan, “Deepfake video detection: YOLO-Face convolution recurrent approach,” PeerJ. Computer Science, vol. 7, p. e730, Sep. 2021, doi: 10.7717/peerj-cs.730.

[19] Y. Shah, P. Shah, M. Patel, C. Khamkar and P. Kanani, "Deep Learning model-based Multimedia forgery detection," 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India, 2020, pp. 564-572, doi: 10.1109/I-SMAC49090.2020.9243530.

[20] R. K. Singh, P. V. Sarda, S. Aggarwal and D. K. Vishwakarma, "Demystifying deepfakes using deep learning," 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2021, pp. 1290-1298, doi: 10.1109/ICCMC51019.2021.9418477.

[21] A. Karandikar, “Deepfake video detection using convolutional neural network,” International Journal of Advanced Trends in Computer Science and Engineering, vol. 9, no. 2, pp. 1311–1315, Apr. 2020, doi: 10.30534/ijatcse/2020/62922020.

[22] D. Güera and E. J. Delp, "Deepfake Video Detection Using Recurrent Neural Networks," 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), Auckland, New Zealand, 2018, pp. 1-6, doi: 10.1109/AVSS.2018.8639163.

[23] B. F. Nasar, S. T and E. R. Lason, "Deepfake Detection in Media Files - Audios, Images and Videos," 2020 IEEE Recent Advances in Intelligent Computational Systems (RAICS), Thiruvananthapuram, India, 2020, pp. 74-79, doi: 10.1109/RAICS51191.2020.9332516.

[24] S. Liu, Z. Lian, S. Gu, and X. Liang, “Block shuffling learning for Deepfake Detection,” arXiv (Cornell University), Feb. 2022, doi: 10.48550/arxiv.2202.02819.

[25] J. Mallet, R. Dave, N. Seliya, and M. Vanamala, “Using deep learning to detecting deepfakes,” arXiv (Cornell University), Jul. 2022, doi: 10.48550/arxiv.2207.13644.

[26] P. Korshunov and S. Marcel, “Deepfake detection: humans vs. machines,” arXiv (Cornell University), Sep. 2020, doi: 10.48550/arxiv.2009.03155.

[27] A. Rössler, D. Cozzolino, L. Verdoliva, C. Rieß, J. Thies, and M. Nießner, “FaceForensics++: Learning to Detect Manipulated Facial Images,” arXiv (Cornell University), Jan. 2019, doi: 10.48550/arxiv.1901.08971.

[28] F. Matern, C. Riess and M. Stamminger, "Exploiting Visual Artifacts to Expose Deepfakes and Face Manipulations," 2019 IEEE Winter Applications of Computer Vision Workshops (WACVW), Waikoloa, HI, USA, 2019, pp. 83-92, doi: 10.1109/WACVW.2019.00020.

[29] S. A. Buo, “The emerging threats of deepfake attacks and countermeasures,” arXiv (Cornell University), Dec. 2020, doi: 10.13140/rg.2.2.23089.81762.

[30] M. A. Younus and T. M. Hasan, "Abbreviated View of Deepfake Videos Detection Techniques," 2020 6th International Engineering Conference “Sustainable Technology and Development" (IEC), Erbil, Iraq, 2020, pp. 115-120, doi: 10.1109/IEC49899.2020.9122916.

[31] N. Anantrasirichai and D. Bull, “Artificial intelligence in the creative industries: a review,” Artificial Intelligence Review, vol. 55, no. 1, pp. 589–656, Jul. 2021, doi: 10.1007/s10462-021-10039-7.

[32] Y. S. Chernyshova, M. Sh. Aliev, E. Gushchanskaia, and A. Sheshkus, Optical font recognition in smartphone-captured images and its applicability for ID forgery detection. 2019. doi: 10.1117/12.2522955..