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An all-inclusive study on identification of fake multimedia content using Machine Learning approaches: A survey

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Abstract: With the rapid progress of technologies like Artificial Intelligence (AI), deep learning, and Machine Learning(ML), the ability to manipulate and modify images has become more accessible. This has led to the emergence of a concerning phenomenon known as deepfakes, where criminals can generate deceptive videos, images, or audio content. In addressing this growing challenge, the present study introduces a comprehensive literature review on numerous approaches including Residual Networks (ResNet), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) with reference to identification of fake content. The survey reviews popular research outcomes from the year 2017 to the current year. This work is useful in identifying research gaps in the area of fake content identification which can be useful to both experts and future enthusiastic. Despite being a preliminary study in this area, the authors propose this study as a valuable resource which can be used for years ahead.

Keywords*:* Deepfake, Deceptive content, ResNet, LSTM, and CNN.

I. INTRODUCTION

In this rapidly advancing tech era, manipulating images, videos, and audios through AI and ML has become surprisingly simple. This not only jeopardizes privacy but also opens the door to serious issues like shaping public opinion, spreading fake news, and even allowing criminals to create misleading impressions. Tackling this challenge requires a united front involving tech experts, policymakers, and society as a whole. Striking the right balance between innovation and ethical considerations is pivotal in finding effective solutions. Efforts are needed to create reliable detection tools and authentication protocols, especially to safeguard legal proceedings from the potential use of manipulated media as false evidence. Collaborative initiatives, bringing together tech companies, legal experts, and ethical hackers, are key to staying one step ahead of deceptive techniques and safeguarding against the misuse of transformative technologies.

Deepfakes are AI generated synthetic media that replace or overlay pre-existing information with freshly created, frequently faked content. A crucial step in the production of deepfakes is deep image generation.

A deep fake image is a digitally altered picture generated using sophisticated artificial intelligence, often indistinguishable from authentic images. ResNet50 and LSTM combined can assist to take use of each architecture's advantages and increase the detection accuracy of deepfake movies, particularly for those that contain both sequential and image-based data [1]. Through [2] rigorous training and evaluation against baseline models like CNN, the study contributes to the creation of automatic and precise deep fake detection systems to tackle the challenges posed by deceptive synthetic media.

Deepfake audio is the term for the application of AI and deep learning methods to produce synthetic audio files that accurately mimic the voice of a particular individual. It is possible to create authentic-sounding, modified audio recordings that may imitate several features of the target person's voice, such as speech patterns, intonations, and other vocal characteristics. Constant-Q Transform for spectrogram generation and a Vision Transformer Network for classification to detect whether an audio file is genuine or spoofed [3].

A deepfake video is a manipulated or fabricated video created using artificial intelligence, particularly deep learning techniques. These videos use algorithms to alter or replace the visual and auditory elements of the original content, often resulting in highly realistic simulations of individuals. Xception and MobileNet, two deepfake detection technologies employing neural networks, for classification tasks. These models are trained on FaceForensics++ datasets generated by different deepfake technologies, achieving high accuracy [4].

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The main objective of this article is to provide an in-depth understanding of deepfakes and the challenges they pose in the context of image, audio, and video manipulation using artificial intelligence and machine learning techniques. The aim of this research paper is to explore the risks associated with the widespread use of deepfake technology, including threats to privacy, potential manipulation of public opinion, dissemination of fake news, and the creation of misleading impressions. Additionally, the paper seeks to emphasize the importance of a collaborative approach involving tech experts, policymakers, and society to address these challenges.

Backpropagation minimizes loss in Neural Networks, but vanishing gradients in deep layers are addressed by ResNet, using skipping connections. Combining LSTM-CNN enhances deepfake detection, leveraging temporal and spatial analysis. The system initializes parameters individually, enabling rapid training with minimal images. The surge in realistic fake facial media from AI, exemplified by DeepFake, poses challenges due to potential social disturbances.

II. RELATED WORKS

It is evident from the literature that numerous strategies have already been used by researchers to build an effective DF detection system. Despite the variety of approaches, the fundamental ideas behind most of them stay the same, emphasizing the use of inconsistencies and manipulation traces left by GAN tools during the generation network.

In one study [1], various strategies are employed, emphasizing inconsistencies and manipulation traces for an effective DF detection system.

An extensive examination [2] focuses on datasets and techniques, with an emphasis on multimodal data to enhance the precision of detecting misleading audio-visual content.

In yet another exploration [3], the challenges posed by deepfakes are discussed, comparing model performance on the FaceForensics++ dataset. Observations and potential directions for advancing deepfake detection technology are explored in the conclusion.

A study [4] on "Multimodaltrace" presents a deepfake detection method achieving 92.9% accuracy on FakeAVCeleb. It performs well across datasets (83.61% and 70% on the World Leaders and Presidential Datasets, respectively), utilizing both IEML and IAML. Insights are gained through integrated gradient analysis.

In a unique investigation [5], the "Deepfake Video Detection System" utilizes CNNs and RNNs in a temporal-aware pipeline for automatic deepfake video detection. The system demonstrates effectiveness against various deepfake videos, even with its simplicity.

Another study [6] suggests that Deepfakes erode trust in ALL social media news, but skepticism doesn't stop specific deceptions. This widespread doubt actually fuels other misinformation dangers by making people less sure of all online resources.

An enhanced study [7] on D-CNN architecture addresses inter-frame dissimilarities, achieving high accuracy in robust deepfake image detection. The model, trained on various datasets, produces impressive results: 98.33% in AttGAN and 99.17% in real and deepfake images from StarGAN.

In a comprehensive survey [8] on DeepFake detection for human face photos and videos, the emphasis is on the realism achievable by generative deep learning algorithms. The goal is to advance deep learning applications in face image and video DeepFake detection by classifying detection methods, investigating creation techniques, and reviewing datasets.
In a proposal [9], a method Deep Vision was introduced for detecting Deepfakes by analysing changes in human eye blinking patterns. It achieves 87.5% accuracy across various videos.

Another work [10] utilizes enhanced-GAN, a better PGGAN version, to address the scarcity of medical imaging data for DEEPFAKE image synthesis. U-net metrics demonstrate that Enhanced-GAN performs better in segmentation tasks than PGGAN.

Amidst rising skepticism due to deepfakes, this study [11] identifies a troubling paradox: while general trust in social media news plummets, specific deepfake deceptions can still land. This highlights the need for AI-powered detection, currently promising with 90% accuracy, to continuously adapt and outsmart evolving fake video technology.

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Deep learning techniques, as explored in a study [12], investigate deepfake production and detection in great detail. The paper provides insightful information on the most recent approaches, assisting scholars in comprehending and contrasting developments in the detection of deepfake photos and videos in social media material.

In a comprehensive survey [13], techniques classified into deep learning, statistical, blockchain based, and traditional machine learning, all show persistent superiority over other approaches.

A unique deepfake detector with a CNN-LSTM backbone and two-stream network is presented in a noteworthy study [14], highlighting its strong, universal effectiveness across modalities. Cross-modal testing on FaceForensic++ that is successful is a major advancement in the fight against deepfake deception.

Using the Fake-or-Real dataset, machine learning and deep learning—more specifically, MFCCs—are used in one study [15] to detect deepfake audio. Remarkably, SVM works well on certain datasets, but in a different examination on the for-original dataset, the VGG-16 model performs better than other methods.

Another study [16] investigates GAN-based deepfake threats and improves detection by evaluating the significance of facial regions and utilizing video temporal information. Results using CelebDF and FaceForensics++ show that the additional temporal dimension significantly improves performance.

Another pivotal study [17] presents a strong face forensics framework that performs exceptionally well at detecting manipulation, particularly when dealing with different video compression levels. It visualizes class activation maps to identify important facial features and show tampering traces using convolutional neural networks.

One more work [18] investigates the generation and identification of deepfake images via the lens of deep learning applications. Stressing security and privacy issues, it recommends using deep learning techniques for picture augmentation to improve the quality of deepfakes that are produced.

Yet another study [19] suggests a hybrid face forensics framework that combines convolutional and general-purpose neural network techniques and exhibits exceptional robustness and accuracy. It outperforms earlier approaches on different datasets and offers insights into important face components and hidden tampering traces using class activation maps.

A comprehensive study [20] evaluates deep face recognition's prowess in pinpointing deepfakes. Utilizing diverse loss functions and deepfake techniques, it achieves a remarkable 0.98 AUC and 7.1% EER on Celeb-DF, surpassing traditional two-class CNNs and ocular approaches. Notably, Deep Face recognition excels at adapting to evolving deepfake methods, ensuring its effectiveness against future threats.

This section is concluded by Table-I, which highlights contribution of researchers in the field of DeepFake.

Table 1**:** Deepfake approaches towards next analysis.

Sl. No	Year of Publication	Title of paper	Description
1.	2023	Deep Fake Generation and Detection:Issues, Challenges, and Solutions	This article explores the challenges of detecting deepfake audio and video, emphasizing the potential harm in various contexts. It provides an overview of existing detection models, datasets, challenges, and opportunities.
2.	2023	A Comparative Study: Deepfake Detection Using Deep-learning	The study compares four deep learning models-VGG16,MobileNetV2, XceptionNet and InceptionV3—that were trained on the FaceForensics++ dataset in an effort to improve deepfake detection.
3.	2023	Multimodaltrace: Deepfake Detection using Audiovisual Representation Learning	This paper introduces "Multimodaltrace," a novel multimodal framework for detecting deepfakes by integrating audio and visual cues.

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4.	2023	Deepfake Video Detection System Using Deep Neural Networks	In order to increase accuracy, this study investigates deepfake detection using a hybrid architecture that incorporates ResNet50 and LSTM.
5.	2023	Deep learning based DeepFake video detection	In order to distinguish between real and fake movies, this study proposes a deep learning model based on transfer learning from the VGG16 neural network, which tackles the growing threat posed by DeepFake face-swapping technology. detection algorithms in the face of developing DeepFake technology.
6.	2023	Artificial Intelligence into Multimedia Deepfakes Creation and Detection	The commercial viability of deepfakes, facilitated by artificial intelligence, has led to a paradox where people are less likely to believe social media news but are more prone to skepticism than outright deception by deepfakes.
7.	2023	An Improved Dense CNN Architecture for Deepfake Image Detection	In order to address the issue of inter-frame dissimilarities that are frequently disregarded by current methods, this study presents an enhanced deep-CNN (D-CNN) architecture for deepfake detection.
8.	2022	DeepFake Detection for Human Face Images and Videos: A Survey	This article delves into DeepFake technology, covering its basics, risks, and GAN-based applications. It emphasizes the challenges in current detection methods and the ongoing need for improved data integrity measures.
9.	2022	DeepVision: Deepfakes Detection Using Human Eye Blinking Pattern	This study presents DeepVision, an algorithm utilizing changes in eye blinking patterns to detect GANs-generated Deepfakes with an 87.5% success rate.
10.	2022	Deepfake video detection using InceptionResnetV2	The need to distinguish real from false videos has increased due to the increasing ubiquity of deepfake face-swapping technologies, which has sparked research into deep learning model creation.
11.	2022	DEEPFAKE Image Synthesis for Data Augmentation	Enhanced-GAN excels in DEEPFAKE image generation, surpassing PGGAN in AM and Mode scores. Combined with real data, its synthesized DEEPFAKE data enhances U-net segmentation model performance in Schema-C.
12.	2022	Deepfake Detection in Videos and Picture: Analysis of Deep Learning Models and Dataset	With deep learning serving as the central technique, this study explores the critical need of deepfake identification as these altered graphics become more common. In response to the demand for reliable algorithms, the research investigates several techniques—such as Generative Adversarial Nets (GANs)—and offers a comparative analysis to improve the effectiveness of deepfake detection and prevention.
13.	2022	Deepfake Detection: A Systematic Literature Review	The methodology for the systematic literature review (SLR) on Deepfake detection involves three main stages: Planning the Review, Conducting the Review, and Reporting the Review.
14.	2022	Generalized Deepfake Video Detection Through Time-Distribution and Metric Learning	In this paper, a time-distributed network that uses a two-stream network with a CNN-LSTM backbone to use spatial and temporal information is presented as a generalized deepfake detector.

15.	2022	Deepfake Audio Detection via MFCC Features Using Machine Learning	This study employs deep learning and machine learning techniques to identify deepfake audio. Specifically, it applies the Mel-frequency cepstral coefficients (MFCCs) technique on the Fake-or-Real dataset. Experimental results suggest that the VGG-16 model surpasses other state-of-the-art methods, demonstrating its usefulness in deepfake audio detection, while the support vector machine (SVM) excels in accuracy on particular datasets.
16.	2021	Deepfake Video Detection with Facial Features and Long-Short Term Memory Deep Networks	This research addresses the dynamic landscape of generative models by investigating how temporal information from videos might be used to improve state-of-the-art deepfake detection techniques.
17.	2021	Detecting Deepfakes Using Deep Learning	This work presents an improved model that uses Deep Learning, CNN, and Error Level Analysis (ELA) to precisely identify modified facial photos produced by AI, especially GAN-generated images.
18.	2021	Exposing Fake Faces Through Deep Neural Networks Combining Content and Trace Feature	The paper introduces a robust fake face detection model using multi-channel constrained convolution, achieving high accuracy against Face2Face and DeepFake manipulations.
19.	2021	DeepFake Creation and Detection:A Survey	The phrase "DeepFake," which refers to multimedia content produced with realistic deep learning technology, presents serious risks to national security and privacy since it allows for the unapproved exchange of faces and aids in the dissemination of false information.
20.	2021	An Experimental Evaluation on Deepfake Detection using Deep Face Recognition	This work provides a thorough assessment of deep face recognition's performance in detecting deepfakes using a range of loss functions and deepfake creation methods. With a maximum Area Under Curve (AUC) of 0.98 and Equal Error Rate (EER) of 7.1% on Celeb-DF.
21.	2020	Manipulation Classification for JPEG Images Using Multi-Domain	MCNet excels in classifying manipulation algorithms in JPEG compressed images, utilizing spatial, frequency, and compression domain features. Its superior performance makes it promising for real-world applications, including DeepFake detection and integrity authentication.
22.	2020	DeepVision: Deepfakes Detection Using Human Eye Blinking Pattern	Our technology, DeepVision, which uses patterns in the blinking of the eyes, identified Deepfakes in 87.5% of the videos. Although encouraging, it has drawbacks when it comes to people who have mental health problems, which emphasizes the necessity for continuous advancements in cybersecurity techniques.
23.	2019	Combating Deepfake Videos Using Blockchain and Smart Contracts	The solution utilizes a decentralized system with IPFS, Ethereum, and a reputation system to verify the authenticity of digital videos, providing a robust method to counter deepfake content.
24.	2019	An Adversarial Approach to Few-Shot Learning	I suggest a system that handles few-shot learning problems using the conceptually straightforward and universal MetaGAN framework.

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25.	2018	A novel contrast enhancement forensics based on convolutional neural networks	First- and second-order statistics can be used to create relatively simple handcrafted characteristics for Contrast Enhancement (CE) forensic approaches, yet these methods have had trouble identifying contemporary counter-forensic attacks.
26.	2018	Fake Face Detection Methods: Can They Be Generalized?	The current advancements in computer vision technologies have made it possible to create fake faces through the use of fresher, alternative techniques. A group of CNN-based systems and Local Binary Patterns (LBP) are taken into consideration.
27.	2018	A Large-scale Video Dataset for Forgery Detection in Human Faces	Recent developments in deep learning have made it feasible to use Face2Face, Computer Generated Face picture (CGFI), Snap-Chat, picture morphing, Generative Adversarial Networks (GAN), and Snap-Chat to create modified photographs and videos in real-time.
28.	2018	Data Augmentation Generative Adversarial Networks	Even in target domains with limited data, the Data Augmentation Generative Adversarial Network (DAGAN) facilitates efficient neural network training. Moving data points to other points of equivalent class, the DAGAN captures the cross-class transformations because it is not dependent on the classes themselves.
29.	2018	Anatomically-aware Facial Animation from a Single Image	In addition to creating new expressions, the StarGAN architecture may alter the appearance of age, gender, and hair color on the face. Despite its generality, StarGAN can only modify one specific face characteristic out of a limited set of attributes determined by the dataset's annotation granularity.
30.	2018	Deepfake Video Detection Using Recurrent Neural Networks	In order to automatically recognize deepfake films, this study presents a temporal-aware pipeline that uses a convolutional neural network (CNN) to extract frame-level characteristics. The suggested approach shows competitive results in identifying edited videos from several sources by combining these features with a recurrent neural network (RNN), demonstrating effectiveness with a simple design.
31.	2018	Deep Learning Algorithms for Detecting Fake News in Online Text	This study addresses the pervasive problem of fake news on social media, emphasizing how it shapes events and societal opinions. The study finds that GRU is the most successful RNN model (vanilla, GRU, LSTM). This leads to additional investigation into a hybrid GRU and CNN model to improve accuracy on the LAIR dataset.
32.	2017	Detecting Computer Generated Images with Deep Convolutional Neural Networks	This research presents a novel method that uses transfer learning and a deep convolutional neural network based on ResNet-50 to recognize computer-generated images.
33.	2017	Discrimination Between Genuine Versus Fake Emotion Using Long-Short Term Memory with Parametric Bias and Facial Landmarks	This article presents a novel method that combines deep recurrent networks, namely long-short term memory (LSTM) with parametric bias (PB), and mirror neuron modeling to distinguish between real and artificial emotions.

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III. CONCLUSION

In conclusion, this study emphasizes the vital need to address the threats posed by deepfakes, fueled by advancements in AI and ML. The combination of ResNet50 and LSTM shows promise in enhancing detection accuracy, and collaborative efforts are crucial to stay ahead of deceptive techniques. As it navigates this landscape, the ongoing development of reliable detection tools is paramount to preserve societal trust in the digital era.

Furthermore, the evolution of deepfake technology demands continuous vigilance and adaptation of detection mechanisms to counter increasingly sophisticated manipulations. Collaborative interdisciplinary research, incorporating expertise from technology, law, and ethics, is essential to effectively mitigate the multifaceted challenges posed by synthetic media in this ever-changing digital landscape.

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