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A Comprehensive Review on Deepfake Generation, Detection, Challenges, and Future Directions

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Abstract: In a world with more watchful eyes and advanced technology, where the whole world is crazy about social media, deepfakes have been recently taking over the world with their popularity having both pros and cons, and have become the main controversial issue to date. Deepfake, with its enormous benefits such as entertainment, marketing, and many more, has also become a scary tool between reality and fiction, misleading information and propaganda, introducing fear and confusion to society, targeting mainly celebrities and politicians with its manipulated, high-quality, realistic content. Various detection methods have been developed to combat such manipulated multimedia. This paper provides a systematic literature review on the current state-of-the-art deepfake and their generation technique. It also summarizes deepfake detection methods in images, videos, and audio on the grounds of their technique, methodology used, performance, accuracy, and detection techniques such as existing algorithms. It also discusses in-depth publicly available benchmark datasets for multimedia. Considering current deepfake detection faces, it also provides a detailed overview of the current challenge and future research directions. This paper presents current achievements and displays the current research status of state-of-the-art deepfake detection for multimodal.
Keywords: Deepfake, SLR, Multimodal Deepfake, Forgery Detection.

I. INTRODUCTION

With the rapid advancement and development of new technology, creating highly realistic fabricated synthetic media (video, audio, image, and text) can be easily process by anyone with just cheap smartphones and electronics due to the availability of user-friendly software packages for easy editing [1], which poses a great threat to society by spreading misinformation, blackmail, cybersecurity, identity fraud, and political propaganda [2]. Deepfake was first created for entertainment purposes as a playful tool to swap out actors' faces in classic movies for amusement, and later became a weapon for people with evil intentions, creating deepfake pornography [3]. Now it has become a popular tool for malicious evil intentions, fraud [4] and revenge porn [5]. On 25 September at Meta Connect 2024, CEO of Meta Mark Zuckerberg announced about Meta AI tool's ability for image editing, voice interaction, and video translation on Instagram and Facebook, which poses a concern to society [6]. The hyper-realistic nature of deepfakes casts a shadow over reality, deceiving numerous people. Deepfake made by the combination of two words, "deep learning" and "fake" [7]. Deepfakes are a type of synthetic media that use machine learning (ML) and artificial intelligence (AI) to create, manipulate, or enhance digital images, videos, and sound that seem convincing and authentic but are entirely fabricated [8]. A deepfake video was also shared on Twitter in March 2022, about President Vladimir Putin of Russia declaring peace and to surrender which was untrue [9]. On 16 August 2024, Donald Trump posted on Truth Social falsely claiming Taylor Swift had endorsed him for his 2024 presidential campaign, which was an AI-generated image of her in an Uncle Sam outfit, accompanied by young women wearing T-shirts "Swifties for Trump" [10]. The growing danger of deepfakes is getting out of hand and has become a global issue. The truth is buried with the image created by the shadow, and this reality has led us to analyse the impact and challenges of how important it is to have real-time deepfake detection models. In this paper, we'll talk about the main types of deepfakes and their detection, which are videos, audio, and images. This study employs both ML-based approaches and DL-based approaches. This study also presents a systematic literature review (SLR) to analyse the overview of past and latest research work done in deepfake, which will be a great source for researchers who are interested in this magnificent and challenging topic. The significant contributions of this work include:

- It provides in-depth details about deepfake generation and detection.
- It provides an updated overview of recent popular tools, techniques, and public datasets.
- It provides a comprehensive overview of the recent works of literature review in deepfake creation and detection.
- It also provides challenges and breakthroughs in deepfake creation and detection.

The outline structure of the paper is as follows: Section 2 concisely summarizes the literature survey. Deepfake Generation and detection will be briefly discussed in Section 3. Section 4 introduces the collection of popular deepfake detection datasets. Section 5 summarizes the overall observation of current challenges of the past and recent deepfakes. Section 6 presents the conclusions.

II. LITERATURE SURVEY

The perils posed by deepfakes made researchers and scholars aware of the threat and research on this topic. Tao Zhang (2022) [11] presented an overview on state-of-the-art deepfake face generation focusing on two methods, i.e., swapping of face and reenactment. They also presented detection methods based on features and Machine learning-based detection methods, and also provide in detail about the current datasets. They also point out the challenges faced and the future scope that should be explored. Momina Masood et al. (2022) [12] discuss a survey in depth about video and audio-based deepfake generation and detection based on machine learning methods. They provide brief details about categories of deepfakes. Visual in four ways: (i) face swap or identity swap, (ii) lip-syncing, (iii) face-reenactment or puppet-mastery, iv) entire face synthesis and v) facial attribute manipulation and audio deepfake in two ways: I) text-to-speech synthesis and II) voice conversion along with its counter-measures. It also provides existing tools, a popular dataset, and is presented in a systematic detail about the trends, drawbacks, current challenges, and future directions, which will be helpful to other researchers and developers. Md Shohel Rana et al. (2022) [13] provides a synopsis in deepfake detection where detection was grouped in four categories: deep learning-based techniques, classical machine learning-based methods, statistical techniques, and blockchain-based techniques from 2018 to 2020 concisely consisting of 112 related published articles comprising certain methods concluding that deep learning-based methods outshine other methods in Deepfake detection. Yogesh Patel et al. (2023) [14] presented a board overview on deepfake generation and detection for multi-modal, published in the year 2019 to 2023 with 111 articles based on ML/DL approaches. They also presented incompatibility between multiple modes (IBMM). Arash Heidari et al. (2023) [15] provide a comprehensive review on deepfake generation and detection. The deepfake detection are selected from that have publish from 2018 to 2021, selecting 32 articles which fits the criteria of their choice for four techniques: video, image, audio, and hybrid multimedia detection based on DL-Based algorithms classifying them in terms of their application which concludes that Convolutional Neural Networks (CNN) was most favour and used by researchers. Vishal Kumar Sharma et al. (2024) [16] presented a precise overview on deepfake pointing out with a research question. The deepfake detection is based on three techniques: ML, DL, and statistical-based techniques consisting of 81 published papers from January 2018 to August 2023, exploring the current research gaps and presenting in detail the challenges it faces. It also presented an open issue and publicly available dataset with future direction, giving insights to other fellow researchers. Peter Edwards et al. (2024) [17] presented a comprehensive survey summarizing and comparing SOTA research papers based on DL technique on image and video detection, where literature review consists of 10 papers published in the year 2022 and 2023, and 29 papers published in 2023 were chosen for deepfake detection analysis. They also go into details about current open issues and future directions, detection methods and datasets, presenting its strength and weaknesses. Gan Pei et al. (2024) [18] provide a recap on literature survey on deepfake generation and detection, classifying the detection into four techniques related to facial attributes: face swapping, face reenactment, talking face generation, and facial attribute editing, as well as forgery detection. They also proposed current datasets, metrics, and losses used in this field, providing current challenges and future directions with the latest trends and technology. Anukriti Kaushal et al. (2024) [19] presented a bibliometric analysis from the year 2012 to September 2023 selecting 621 papers from Web of Science (WoS) using keyword-based search. They presented in-depth about striking sources of publications, distinguished institutions, excellent countries/regions that have done comprehensive Literature surveys on deepfake generation and detection, giving insights to researchers. They also provide mapping using VOSviewer about top countries which have produced the most in this field every year, or top authors and respective countries, to which in 2023, the People's Republic of China emerges as the top contributor. Using Citespace, they also present the period of popularity for prominent articles in this field. With the problem and numerous challenges face by present deepfake detection Tianyi Wang et al. (2024) [20] presented a comprehensive survey focusing on their reliability addressing on three challenges: transferability, interpretability, and robustness in which these challenges were address by a model reliability study metric using statistical random sampling along with publicly available benchmark datasets.

III.DEEPFAKE GENERATION AND DETECTION

A. Deepfake Generation

In 2014, Deepfake made a breakthrough by Ian Goodfellow which introduce ML concept known as generative adversarial networks (GANs) [21] and came into light in the late 2017 when a Reddit user created a subreddit "r/deepfakes" for deepfake pornographic videos where he faces-swaps onto actresses' photo [22], and by 2019 deepfake got more popularized and attention from viewers about U.S House Speaker Nancy Pelosi [23].

Deepfake can be differentiated into audio and visual deepfake, and its generation mechanism comes in many forms which can be face swapping [24], facial reenactment [25], Lip-syncing [26], Voice cloning [27]-[28], Attribute manipulation (AM) [29], and Textual deepfake such as Voice conversion(VC) and Text to speech (TTS) [30] which are possible with the rapid advancement in neural network architectures such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), Transfer learning, Explainable AI (XAI) coming into light and many more. Some popular enhanced versions of deepfake software tools are DeepSwap, FaceSwap, SoulGen, DeepFaceLab, DeepNudeNow, DeepfakesWeb, FaceApp, Zao [31], Resemble.ai, Descript, Cereproc [32], which are some swift progresses in deepfake creation accessible for producing deepfake synthesized media. The most notable architecture used for deepfake generation will be Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs).

Variational Autoencoders (VAEs) are a type of autoencoder neural network architecture that provides a probabilistic manner to generate realistic fake images. It consists of an encoder and decoder. The encoder maps each image to a distribution within the latent space. The decoder map from the latent space to the input space can produce a diverse range of images, but the quality of the generated images is often blurred as compared to GANs [33]-[34]. The breakthroughs in deepfake technology are the application of generative adversarial networks (GANs) [35]. Generative Adversarial Networks (GANs) are a popular type of deep learning that can produce high-resolution, realistic images. GANs consist of two neural networks: a generator and a discriminator. The generator generates realistic fake images or videos, and the discriminator detects the fake from real images or videos. During the training process, the discriminator is trained on both the real and fake images, distinguishing the real from the fake. This process is repeated until the images or videos become undistinguishable by the discriminator [36]. StyleGAN, second version (StyleGAN2) and third version (StyleGAN3) [37], CycleGAN [38] for generating realistic images, LipGAN for lip sync speech generation [39] are some of the popular approaches of GANs architecture for generating high resolution undistinguishable realistic images and has become a powerful tool for manipulation and face swapping that greatly improve the quality of the synthesized media.

B. *Deepfake Detection*

In this section, we'll be discussing in-depth the multimodal deepfakes detection along with its methodology used and efficiency.

1) *Deepfake Video Detection:* One of the most contributing deep learning technique developed so far to detect manipulated fake videos in still images will be taken up Singh et al.(2020) using a Convolutional Neural Network (CNN) architecture such as EfficientNet-B1, EfficientNet-B3, XceptionNet, and InceptionV3 combined in a time-distributed layer and the output was fed into an LSTM layer to learn spatio-temporal features using Deep Fake Detection Challenge dataset in which EfficientNetB1 gives the best result with an accuracy of 97.6% [40]. A new method for detecting deepfakes was introduced by Aya Ismail et al. (2021) called YOLO-CNN-XGBoost (you only look once–convolutional neural network–extreme gradient boosting) with CelebDF-FaceForencics++ (c23) dataset. Extraction of face region from video frames is done by YOLO face detector and InceptionResNetV2 CNN-derived features from these faces, then fed into XGBoost, which achieved 90.73% of accuracy [41]. Rana et al. (2020) proposed a Realtime Deepfake detector to detect the manipulated videos/images called DeepfakeStack combined with a base learner on the FF++ dataset, among which the DFC (Deepfake Classifier) model shows the best performance that predicts accuracy of 99.65% [42]. Marwa Elpeltagy el at. (2023) introduced multimodal deepfake detection, which occurs in three steps; video frames, audio modalities, and the whole video using an upgraded XceptionNet model, modified InceptionResNetV2, and Gated RecurrentUnit (GRU), which used FakeAVCeleb multimodal videos dataset with accuracy of 98.51% [43]. Resnext CNN and LSTM were used by Shilpa B et al. (2023) for detecting deepfake voice detection that gives authenticity to a given video [44]. Wodajo et al. (2021) proposed Convolutional Vision Transformer (CViT) a hybrid between Convolutional Neural Network (CNN) added to Vision Transformer (ViT) to detect Deepfake videos that learn both local and global features building a relationship between features and used DeepFake Detection Challenge Dataset (DFDC) achieving 91.5 % accuracy [45]. Shahroz Tariq et al. (2020) developed a Convolutional LSTM based Residual Network (CLRNet) using FaceForensics++ dataset. The input is taken as a sequence of consecutive frames from the video, detecting spurious present in the frames exceeding 5, previously proposed same state-of-the-art methods by introducing better generalizability [46]. Ahmed Hatem Soudy et al. (2024) employ CNN combined with a vision transformer based on three sub-models for three features, i.e., entire face, eyes, and nose, generating individual predictions using FaceForensics++ in which CNN achieved an accuracy of 97%, while the CViT 85% [47]. Trevine Oorloff et al. (2024) propose Audio-Visual Feature Fusion (AVFF) that focuses on audio and visual modalities for deepfake detection, giving 98.6% accuracy with FakeAVCeleb dataset outperforming the current state-of-the-art method [48]. Supervised learning being prone to adversarial attacks as they require a large sample of accurate labels for training, Tong Qiao et al. (2024) proposed a fully unsupervised Deepfake detector which are more exceptional than current state-of-the-art methods and even complementary to supervised methods. They used a

pseudo-label generator to extract label training data and fed it into an enhanced contrastive learner, which refined the features iteratively. Their approach was observed on various datasets such as FF++, Celeb-DF, DFD, DFDC, and UADFV and resulted in a robust, effective method [49].

2) *Deepfake Image Detection:* Tracking the traces left by GANs, which is Convolutional Traces (CT) and putting to its advantage, Luca Guarnera et al. (2020) proposed Expectation-Maximization algorithm to extract unique fingerprint from images to detect deepfake achieving robustness state [50]. A novel common fake feature network (CFFN) a deep learning-based approach with DenseNet as its base, based on a pairwise learning approach was proposed by Chih-Chung Hsu et al. (2020) for detecting the fake images by using the contrastive loss, a GAN generated fake image including which are not even in the training period [51]. A comparative study was done by Hasin Shahed Shad et al. (2021) using 8 different CNN models and 5 evaluation metrics along with a custom model that integrates methods such as dropout and padding and trained their model using the Kaggle dataset which achieved an accuracy of 99% [52]. Ali Raza et al. (2022) proposed novel DFP (deepfake predictor), a hybrid of VGG16 and CNN for deepfake detection and later compared with some Transfer learning (TL) techniques which achieved 94% accuracy and surpass TL techniques and other current state- of -art method using deepfake dataset available on Kaggle [53]. Most CNN does not give generalizability, to solve this, Yogesh Patel et al. (2023) proposed deep-CNN (D-CNN) architecture using 5 datasets for deepfake and 2 datasets for real images, which achieves well-balanced performance and generalizability over all datasets and even has a threshold frequency for the label's class [54]. A hierarchical multi-level approach was proposed by Luca Guarnera et al. (2024) that identifies images generated by 9 different GANs and 4 diffusion models (DMs) introducing reliability to attack such as JPEG compression and resize, improving the deepfake detection on average by about 2% [55]. With the wrecking in real-time deepfake detection, R. Uma Maheshwari et al. (2024) introduced a biosensor system combining advanced plasmonic resonance with machine learning. The biosensor captures the subtle changes in amplifying signals and was then fed to CNN, presenting as a security measure against deepfake [56]. Ahmed Hatem Soudy et al. (2024) using FaceForensics++ and DFDC dataset, employ CNNs to detect deepfake to eye and nose and CViT for face and breaking down into three sub-models, based on different features and focusing on majority voting by merging their result, arising three different predictions leading to high accuracy and high reliability [57]. With the surge of online frauds, becoming the biggest threat, Zong Ke et al. (2025) use generative adversarial networks (GANs) for detection of synthetic and deceitful activities in online payments using real-world online payment images and AI-generated deepfake images achieving an accuracy of above 95% [58].

3) *Deepfake Audio Detection:* Janavi Khochare et al. (2021) proposed a feature-based approach and an image-based approach using ML and Temporal Convolutional Network (TCN) and Spatial Transformer Network (STN), a DL based approach, which TCN achieved 92 % comparable to traditional CNN using the Fake or Real (FoR) dataset [59]. Ameer Hamza et al. (2022) used the Fake-or-Real dataset by extracting features using the Mel-frequency cepstral coefficients (MFCCs) technique for detecting audio deepfake, where they employed ML and DL-based approaches outperforming another feature-based approach. SVM model outperforms other ML models with 98.83% for-rerec dataset [60]. Most deepfake audio often struggles with unseen data; keeping this in mind, Alessandro Pianese et al. (2022) explore the use of speaker verification systems to identify deepfake audio that extracts only the biometric characteristics of the speaker, assessing inconsistencies in speaker characteristics [61]. With every person having a unique pattern, Davide Cozzolino et al. (2023) proposed a person-of-interest (POI) audio-visual deepfake detector with contrastive learning that identifies face and audio fragments, giving a good result even in manipulated or low-quality [62]. Being feature extraction is a great step for audio deepfake detection, Nidhi Chakravarty et al. (2024) implement modified ResNet50 where features were extracted from audio Mel spectrogram which then apply Linear Discriminant Analysis (LDA) technique for dimensionality reduction and a machine learning classifiers later to the extracted features, achieving an accuracy of 99.7% and Equal Error Rate (EER) of only 0.4% [63]. The same process as Nidhi Chakravarty et al. (2024) was also proposed by Lam Pham et al. (2024), which presented a deep-learning-based approach, where audio was transformed into spectrograms by Short-time Fourier Transform (STFT), Constant-Q Transform (CQT), and Wavelet Transform (WT), then fed to three deep learning approaches and applied transfer learning, which achieved an Equal Error Rate (EER) of 0.03 using the ASVspoofing 2019 challenge [64]. To enhance the sensitivity in deepfake audio features, Qishan Zhang et al. (2024) [65] employ the pre-trained XLS-R framework that integrates an SLS (Sensitive Layer Selection) module capturing diverse audio features and sensitive contextual information contributing to audio deepfake detection. Influenced by environmental factors such as direct and reverberant sounds, Gunwoo Lee et al. (2025) presented a novel dual-channel deepfake audio detection method using a self-collected dataset called the Sports Press Conference dataset (SPC), which presented an effective and robust detection [66].

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IV. DATASETS

A countermeasure is needed with the rapid emergence of real-world deepfakes. To develop effective deepfake detectors, we need a robust, challenging dataset. Large-scale datasets for training and testing are vital for efficient deepfake detection.

Some popular publicly available datasets are given below:

A. Video Datasets

1) FaceForensics [67] (2018): They consist of 500,000 manipulated images extracted from 1004 videos using Face2Face approach, to which the videos were taken from YouTube. These consist of two types of reenactment dataset: Source to video and Self reenactment for detecting forgeries in videos and images.
2) FaceForensics++(FF++) (2019) [68]: This dataset is the updated version of FaceForensics dataset consisting of 1.8 million fake images from 1000 video sources for facial forgeries detection, which makes researchers train Neural network-based approaches in supervised learning using four approaches: Face2Face, Deepfakes, Faceswap, and NeuralTextures.
3) Celeb-DF (CDF) V2 (2020) [69]: A revised version of CDF V1 dataset and it consists of 590 real videos and 5,639 manipulated videos where the videos source is taken from interviews of 59 celebrities found in YouTube with 56.8 % male,43.2% females and age from below 30 to above 60 years old from three different race Asians, African Americans and Caucasians. The deepfake videos were generated using a novel DeepFake synthesized method, i.e. by swapping faces.
4) DeeperForensics-1.0(DF-1.0) (2020) [70]: This dataset contributes to real-world facial manipulation detection consisting of 17.6 million frames from 60,000 videos. Selecting only those that satisfy three criteria: 1) Quality, 2) Scale, 3) Diversity for this dataset. 100 actors, i.e. 53 males, 47 females from 27 countries with different skin tones as white, black, yellow and brown, ranging from 20 to 45 years old, were paid with consent and captured various angles and expressions to be used as in the original and manipulation of their face. Along with that, they also presented a novel face swapping framework, DeepFake Variational Auto-Encoder, to which seven types of perturbations at five different levels were employed, all together 35 perturbations have been performed.
5) The DeepFake Detection Challenge (DFDC) (2020) [71]: This acted as the turning point for the dataset in deepfake detection. It was published by Facebook AI, a large-scale face swap video dataset to test deepfake detection methods. It consists of 960 paid actors and actresses with their consent for their face to be manipulated by a computer vision algorithm producing a cropped image resolution of 256 x 256 pixels. Multiple face-swapping techniques were employed such as Deepfake Autoencoder (DFAE), MM/NN face swap, NTH, FSGAN, and StyleGAN out of which DFAE performed the best as compared to GAN-like. As compared to previous published datasets, DFDC made a major contribution as this involves a large public competition to train on the full DFDC dataset, also allowing the use of a free additional external dataset by the participants. Through these, it came to light how well the dataset is effective in deepfake detection.
6) WildDeepfake (2021) [72]: This dataset consists of 707 videos collected from the internet, providing 1,180,099 images of 7,314 face sequences. This could be used as an additional to the existing dataset because it consists of various scenes, faces, and different background collected from the web. Moreover, it also proposed two Attention-based Deepfake Detection Networks (ADDNets): ADDNet-2D and ADDNet-3D to exploit the attention mask to differentiate the real/fake for better deepfake detectors.
7) Korean DeepFake Detection Dataset (KoDF) (2021) [73]: A large-scale facial manipulation dataset that surpassed DF-1.0[61] containing 175,776 deepfake and 62,166 real image of 403 paid subjects composing of East Asian and Southeast Asian where majority is Korean using six different approaches to generate deepfake: FaceSwap, DeepFaceLab, FSGAN, First Order Motion Model (FOMM), Audio-driven Talking Face Head Pose (ATFHP) and Wav2Lip. Unlike another existing dataset, Augmentation was exempted from this dataset, making other researchers apply their approaches, providing a good insight into deepfake methods, also with high quality of the real clips and the manipulated clips. It also yields a good performance when combined with another existing dataset such as DFDC [62] and FF++ [59].
8) DeepFake MNIST+ (2021) [74]: This paper provided a first large-scale dataset for face animation videos dataset for human facial animation presenting us about advanced detection models for preventing spoofing. It consists of 590 real videos available in YouTube, also 10,000 face animation videos in ten different actions, and 10,000 real face videos selected from VoxCeleb1 for supervised detector training. Siarohin's framework was used for generating face animation videos.
9) Gender Balanced DeepFake Dataset (GBDF) (2022) [75]: This dataset consists of 10,000 videos with 5000 each for both males and females created from existing datasets such as FF++ [59], Celeb-DF [60], and DF-1.0 [61] where videos were synthesis using two deepfake generation techniques: Identity Swapping and Expression swapping. This dataset was presented to promote

gender fairness in deepfake detectors and provide a gender-balanced and annotated gender deepfake dataset, also irregular swaps were exempted in this paper.

10) DF-Platter (2023) [76]: A large-scale deepfake dataset consisting of 764 source videos from YouTube with 454 different subjects comprising 133,260 videos containing both high (HR) and low-resolution (LR) generated using FSGAN, FaceShifter and FaceSwap techniques, belonging to Indian ethnicity with balanced resolution and gender also containing various age, skin tone and occluded facial and evaluated using three metrics: Set A, Set B, and Set C It employed six deepfake detection models to benchmark the dataset.
11) Deepfake Face Mask Dataset (DFFMD) (2023) [77]: This dataset presented 2000 videos of people with face masks, women with hijab/Saudi niqab, and men with Ghutrah/Lithamah around their faces collected from ten open-source websites, and YouTube channels, comprising of 1000 fake and 1000 real videos generated using FOMM model. It uses three deepfake detection models such as VGG19, InceptionResNetV2, and proposed CNN models of which InceptionResNetV2 achieved the highest accuracy of 99.39%. But this dataset is composed of medium-quality faces in synthesized videos, and the removal of audio after deepfake generation was seen.
12) DF40 (2024) [78]: A large-scale face deepfake detection dataset consisting of 40 distinct deepfake techniques approaches using four different types of protocols: face-swapping (FS), face-reenactment (FR), entire face synthesis (EFS), and face editing (FE) where source video was collected from existing datasets: FF++ and CDF. 8 deepfake detection methods was used, resulting to 7 new notable observations. They also provide four open issues for forthcoming analysis.
13) INDIFACE (2024) [79]: The first deepfake dataset comprising of entirely with Indian ethnics, composing of 62 source videos from YouTube that’s with open Creative Commons licenses are selected with different skin tones and facial shape and further undergo three different pre-processing methods: Gaussian Blur, Salt and Pepper Noise and Random Shifting Brightness resulting to 404 real videos consisting of 101 original clips and 1668 fake videos generated using SimSwap and Ghost. Selim's implementation of EfficientNet and Cross Efficient ViT was used for deepfake detection. This paper presented that separate probing is vital for Indian ethnic as they are to be fine-tuned to be detected by deepfake detection models.

B. Audio Datasets

1) LJSPEECH (2017) [80]: This dataset comprises 13,100 audio clips, each in 16-bit PCM wav format of a real speech database reading 7 non-fiction books by a single speaker and was recorded by the LibriVox project in 2016-17.
2) M-AILabs Speech Dataset (2019) [81]: This dataset is presented for speech recognition and speech synthesis, consisting of 9265 real and 806 fake samples, and the data is based on LibriVox and Project Gutenberg and was recorded using the LibriVox project.
3) ASVspoof 2019 (Automatic Speaker Verification) [82]: ASVspoof 2019 a public challenge dataset focusing on assessment of tandem systems presented two different spoofing scenarios: LA (Logical access) constituting voice cloning and voice imitation speech data generated using TTS and VC and PA (Physical access) consists of replay spoofing to improve the performance generated by simulation where both are derived from VCTK corpus, which consists of 107 speakers comprising of 46 males and 61 females. This paper presented three different spoofing attacks: synthetic, converted, and replayed speech.
4) FakeorReal (FoR) (2021) [83]: A large-scale dataset consisting of 198,000 audios presented for speech synthesis and synthetic speech detection mainly for machine learning techniques where they provided synthetic utterances similar to human speech generated using TTS methods comprising of 87,000 synthetic audio and 111,000 real audios where it was collected from existing datasets namely Arctic Dataset, LJSPEECH, and Arctic Dataset also from educational videos such as TED, online courses, and tutorials. They presented in four versions: for-original, for-norm, for2seconds, and for-rerecorded.
5) WaveFake (WF) (2021) [84]: A large-scale audio dataset consisting of 117,985 manipulated audio clips in 16-bit PCM wav format collected from existing datasets LJSPEECH and JSUT, where ten sample sets from six different TTS generative models were collected from each of the two datasets. This dataset also has several limitations, such as difficulties in obtaining realistic data.
6) The Diffusion and Flow-Matching Based Audio Deepfake Dataset (DFADD) (2024) [85]: This dataset was presented for an anti-spoofing speech dataset, which was collected based on three advanced Diffusion and two Flow-matching TTS models. The data were collected from VCTK, which consists of 109 speakers generating 163,500 synthesis audio clips using TTS, consisting of two stages: input selection and text-to-speech synthesis.
7) The Multi-Language Audio Anti-Spoofing Dataset (MLAAD) (2024) [86]: A large-scale dataset for Audio Anti-Spoofing detection comprising 154,000 utterances where data were collected from MAILABS Speech Dataset, comprising eight

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languages, where it was generated with Neural Machine Translation into 38 languages in MLAAD, and later the audio clips were synthesized by 82 TTS models, constituting 33 different architectures outperforming InTheWild or FakeOrReal dataset on generalization and various other existing datasets.

8) Codecfake Dataset (2025) [87]: A large-scale dataset for detection of Audio Language Model (ALM) based deepfake audio, where fake audio was constructed using seven representative codec synthesis methods. It comprises millions of audio samples and various test conditions in two languages: English and Chinese.

C. Audio-Visual Datasets

1) FakeAVCeleb (2022) [88]: An Audio-Video Multimodal Deepfake Detection dataset for both video and audio deepfakes with accurate lip-sync taken from 500 videos belonging to different ages, genders, and races from the VoxCeleb2 dataset of YouTube videos. SV2TTS, a Transfer learning-based real-time voice cloning tool, was used to generate fake audio where MFCC features were computed. To generate deepfake videos, Face-swapping methods such as Faceswap and FSGAN were employed, and later Wav2Lip was applied for accurate reenactment of the videos. Eight different deepfake detection methods were employed and compared with seven existing datasets to show the high complexity of detecting detected by the model.
2) AV-Deepfake1M (2024) [89]: A large-scale audio-visual deepfake dataset designed for temporal deepfake localization comprising 1,886 hours of audio-visual data from 2,068 unique subjects collected from the Voxceleb2 dataset, pre-processed where audio is generated using FFmpeg and Whisper-based real transcript generation. As of now, AV-Deepfake1M is the largest audio-visual deepfake dataset.
3) Hindi audio-video-Deepfake (HAV-DF) (2024) [90]: The first Hindi language content audio-video Deepfake dataset containing 508 source videos based on front view, lone in the video, with explicit audio and occluded facial, composing of 200 real and 308 fake clips collected from YouTube with different race, gender, and age. The fake contents were generated using faceswap, lip-sync, and voice cloning methods. Due to its complication of linguistic distinction, they concluded that HAV-DF faces bigger hurdles in deepfake detection as compared to English-centric datasets.

V. DISCUSSION

In this section, we discuss open challenges and future directions on deepfake detection.

A. Open Challenges

1) Quality of deepfake dataset and Adversarial Attacks: Technological advancement has made rapid evolution of numerous tools for generating high-quality deepfakes with ease, where anyone can generate synthesis clips or audio effortlessly with diffusion models or advanced GANs, making detection models difficult, elusive, and outdated promptly. To confront this, we need a large-scale, robust, high-quality dataset. Real-world datasets with high quality are limited, and most existing datasets are label imbalanced, such as DFDC [71], DF-1.0 [70], FoR [83], and suffer from biases in model predictions, which also reduces generalization. Most datasets are prone to adversarial attacks, such as low-quality resolution, including mismatched face or blurred face, spatial-temporal patterns, Gaussian noise, mismatched colour, inconsistency in facial movement, which can be easily detected. However, high-quality deepfakes that deceive human eyes are rarely detected by detectors. Also, not being detected by the models doesn't always mean it is an authentic multimedia.
2) Generalization: Detection models often struggle with a lack of generalization, struggling with unseen datasets or techniques, overfitting of the training data across different datasets, and generative models are often seen quite commonly. Some progress is seen recently in detection models, but mostly it suffers from cross-dataset detection. A need for developing advanced detection models that can effectively identify distinct types of deepfakes across disparate platforms and modalities. Many detection models were ineffective across different types of deepfakes.
3) Robustness: Most detection models are susceptible to adversarial attacks. With the rapid evolution of deepfake generation, generating extremely realistic multimedia doesn't take much effort. To counter the evolving deepfake technology, robustness becomes a challenging issue for detecting real-world scenarios to accurately detect deepfakes.
4) Lack of diversity: Most publicly available datasets are mainly in English; we don't see much of Mandarin Chinese being the most native language, followed by Hindi, Spanish, and Arabic. Due to this linguistic distinction, it became a big challenge. MLAAD [86] with 38 different languages for audio anti-spoofing used TTS to generate, which was not spoken by a native speaker. Creating a dataset with multilingual data would help out in speech recognition or deepfake detection. Not just languages, we also see limited diversity in terms of the diversity of faces, the present dataset focusing on just a couple of faces and specific races, genders, and demographics.

B. Future Research

1) Improved detection approach: Current detection can be enhanced by introducing various technique such as hybrid methods, Explainable AI (XAI), and Real-time Detection which can be developed by combining multiple modalities approach for detection using AI, blockchain and watermarking for more generalisation, accuracy, detection in real time and adversarial robustness threshold determination that can counter GANs and Diffusion Models combating adversarial attacks for improving robustness and generalization of deepfake detection method. Improving detection methods not just for image or video but also for Deepfake Audio is indispensable to avoid fraud and skepticism.
2) Multi-Modal approach: Combining multi-modal features can contribute to the robustness of the deepfake detection by leveraging the inconsistencies within them, enhancing detection performance. Deepfake generation techniques leave some inconsistency of artifact features, and by focusing on that can improve the current detection methods [91]-[93].
3) Biometric approach: Biometric-based forensic techniques can be of great help for detecting deepfakes based on facial recognition with temporal features, such as facial expressions, blinking eyes, fingerprint recognition, voice recognition, and head movements, which will enhance the integrity and authenticity of biometric data [94]-[96].
4) Datasets: To have a robust, generalizable, and efficient deepfake detection, we need a high-quality, large-scale dataset, which is fit for real-time detection with diversity of language, age, race, and gender.
5) Integrity: Introduction of an authenticated solution for media integrity, such as AI-based verification, digital watermarking, provenance, and so on.

VI. CONCLUSION

Deepfakes being the spotlight in this present generation, and which will get more treacherous in the future, is vital for a novel approach to detection to protect from this perilous tool. This paper presents the latest survey on state-of-the-art deepfakes, discussing deepfake technologies, their generation, detection methods, and relevant datasets. It presented some of the breakthroughs in deepfake detection, summarizing all four types of deepfake generation, including visual and textual. Deepfakes with many applications have helped out humans in numerous ways, and in addition, their darkness has overshadowed a lot, exploited, and manipulated. Generation and detection should go hand in hand, being a rivalry. However, deepfake generation is evolving at high speed, and we face more challenges for deepfake detection, with a lack of high-quality datasets and benchmark assessment methods. A need for robust, generalised detection is necessary. we also summarize the current challenges and future research directions for this field. We also discuss combining multi-modal features, and with the advancement in technology, upgraded detection, such as combining multi-modal features, can be developed to be leveraged fully.

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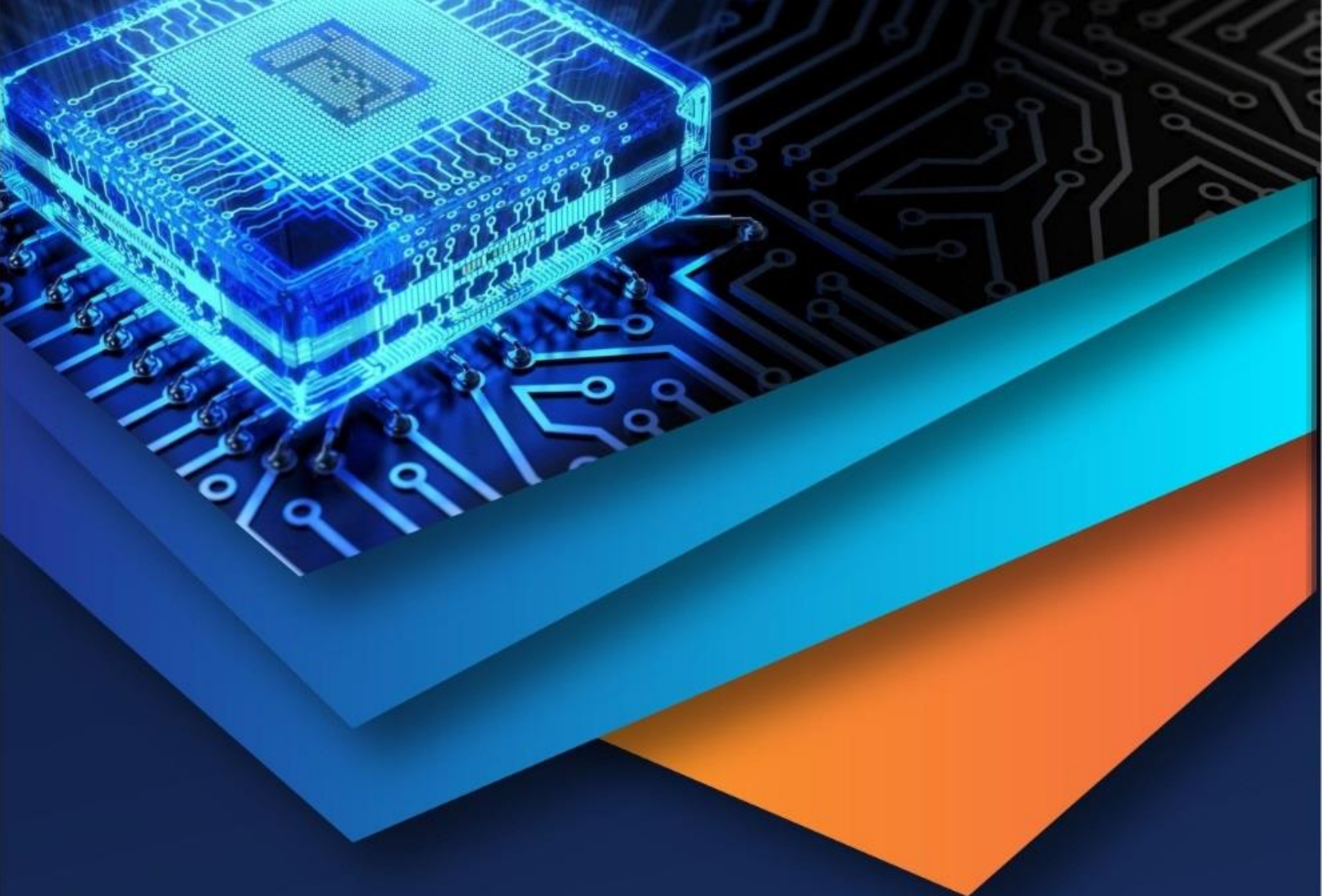

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