



DETECTING THE UNDETECTABLE: A REVIEW OF CUTTING-EDGE DEEP-FAKE DETECTION TECHNIQUES

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ABSTRACT

Nowadays, deep-fake technology has been seen as a powerful tool for producing very realistic but artificial media, thereby threatening privacy, digital security, and the authenticity of visual and audio material. The growing sophistication of Transformer-based models, Autoencoders, and Generative Adversarial Networks (GANs) has made it ever more challenging to distinguish genuine from edited material. Including Convolutional Neural Networks (CNNs), Bayesian Interface models, few shot Learning, and Self-Supervised Transformer Architectures, this review covers modern deep-fake detection methods in great detail. Highlighting their strengths, constraints, and practical utility, we examine the most recent techniques, benchmark data sets, and generalization challenges in deep-fake detection. Furthermore, we assess the effect of cross-dataset performance, adversarial resilience, and real-time detection on internet-of-things and edge devices. We consider the changing field of deep-fake research and suggest possible future courses to improve detection accuracy and resistance against adversarial assaults by comparing different detection methods. The results highlight the pressing need of AI-driven deep-fake detection systems that are adaptive, multimodal, and explainable to address the increasing abuse of synthetic media.



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I. INTRODUCTION

The rapid advancement of artificial intelligence (AI) has revolutionized various domains, including computer vision, biometrics, digital forensics, and media synthesis. Deep-fake technology, among one of the most debated advancements, uses deep learning algorithms to produce very synthetic fake media, therefore blending reality and artificial material. Created at first for entertainment and artistic purposes, deep-fakes are now a major worry given their capacity for fraud, information distortion, identity theft, and threats to national security. Over the last few years, the exponential growth in deep-fake research shows the need of fast creation of sophisticated detection techniques. As shown in Figure 1, the amount of works on deep-fake generation and detection has skyrocketed together with the rising complexity of synthetic media. Early detection techniques depended on handcrafted features and conventional forensic methods; present ones utilize CNN-based classifiers, GAN-generated anomaly detection, Bayesian inference models, and deep-fake identification networks based on Transformer. Though much headway has been made, deep-fake detection technologies present several major issues: adversarial resilience, real-time efficiency, explainability, and generalization to unobserved datasets. Current models sometimes overfit particular data sets, have poor cross-domain transferability, and still fall prey to attacks from adversaries that evade detection systems. Moreover, real-time detection becomes more challenging given the resource limitations of edge devices and Internet-of-Things technologies. The review offers a thorough analysis of deep-fake detection techniques, classifying them based on their underlying architectures and detection strategies. Among the cutting-edge approaches we examine are few-shot learning, data augmentation through data farming, spatial Bayesian inference weighting at frame level, and Vision Transformers (ViTs) powered self-supervised deep-fake detection. Rising use of deep-fake technology has driven a boom in study concentrated on both deep-fake making and sensing. Fast developments in Autoencoders, Generative Adversarial Networks (GANs), and Transformer-based models have greatly helped to grow the body of deep-fake-related publications and internet material.

The growth trend in deep-fake research is shown in figure 1, which shows the volume of publications on deep-fake generation, detection, and general deep-fake investigation over the past few years. A growing number of deep-fake-related studies are revealed by the data, with deep-fake detection research showing great advances in answer to mounting worries about fraud, privacy hazards, and misinformation. Research on deep-fakes has increased over time as well as shown in the graph in it. It compares the total amount of deep-fake creation, deep-fake detection, and deep-fake research works. The figures unambiguously indicate rising interest in deep-fakes as evidenced by more research paying on detecting them.

While deep-fake creation methods have improved, efforts to detect them have also grown significantly. This highlights the ongoing challenge of staying ahead of new techniques used to make deep-fakes more realistic. The steady rise in detection research shows that experts are actively working to find better ways to spot deep-fakes before they can be misused. As deep-fake technology advances, it becomes harder to detect fake media. This makes it crucial to develop smarter and faster detection methods to protect against its misuse, especially in areas like cybersecurity, media integrity, and online safety.

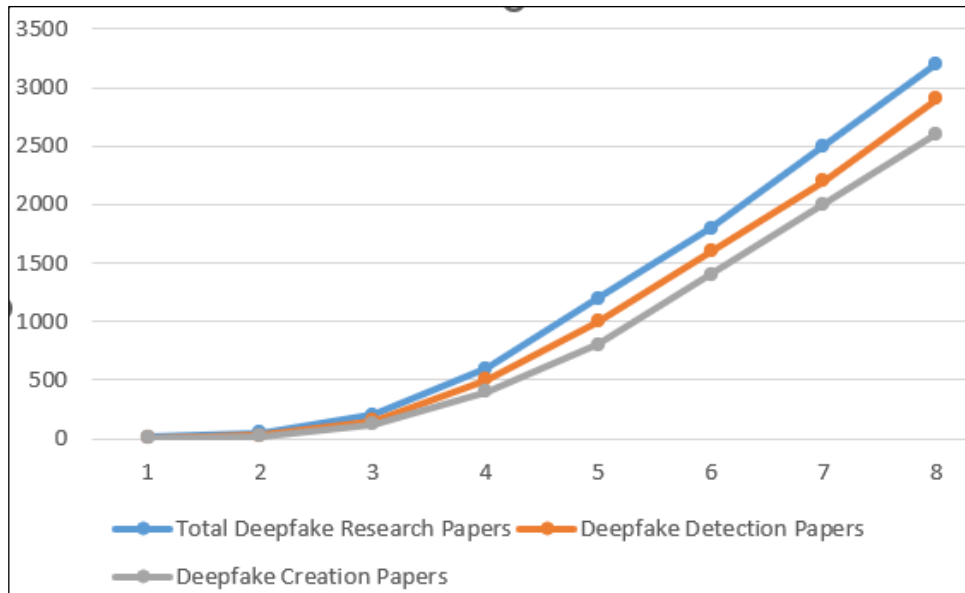


Figure 1: Growth of Deep-fake Research creation and Detection research publications Over Time

Source: Authors, (2026).

II. RELATED WORK

Deep-fake technology has evolved considerably, creating concerns over privacy, misinformation, and security threats. Additional detection methods have been introduced to tackle these issues. Deep-fake detection has been researched for different modalities, including visual, audio and textual perceptible content. The demand for a readily accessible and rapid detection system that can be adapted to the digital propagation of fake content, regardless of the modality, is of significant interest [1]. The role of artificial intelligence in deep-fake production has also been highlighted in a study, most notably by using generative adversarial networks (GANs), which have allowed to create very realistic media [1]. The task of finding deep-fakes has been fundamentally obfuscated yet further by far-qarning face masks, hiding facial structures and offering up additional complications in forensic studies. A dataset was proposed to detect these kind of masked face fake videos and achieved a detection result of 99.81% using different deep learning architectures [2].

Model detection benchmarking, however, is still a challenge as variations in evaluation approaches prevent direct comparative analysis of systems. To better evaluate deep-fake detection methods, a benchmark was constructed for 13 deep-fake detection schemes through extensive datasets and evaluation criteria, providing a standard way to assess performance [3]. Another recent work proposed masked relation learning for detecting deep-fake videos which reframes the task to a graph classification problem. This effectively reduces redundancy of relational information and improves the false positive rates of manipulated facial regions, leading to better performance in terms of cross-dataset evaluation [4]. Deep-fake detection systems are constantly being improved; however, one challenge is mislabeled data and noisy label attacks. Some suggested solutions included use of contrastive learning techniques with negative sample capture that improved model performance against adversarial attacks [5].

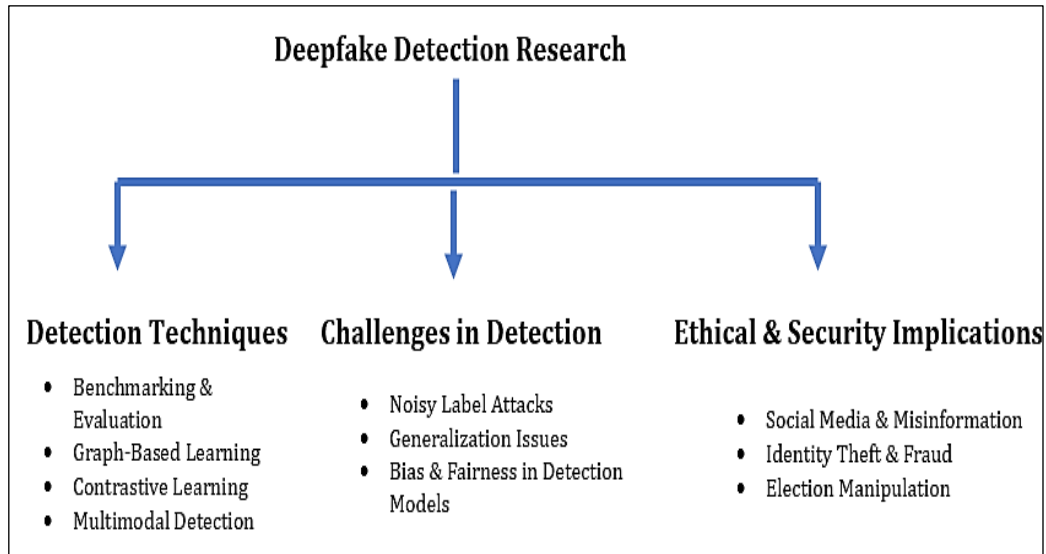


Figure 2: Key Aspects of Deep-fake Detection Research.

Source: Authors, (2026).

Some other approaches used multimodal methods with audio and video components to overcome the gaps between the modalities. A new strategy was proposed for enhancing forgery detection in cross-modal which was shown to improve generalization and accuracy in addition to many diverse datasets [6]. There has been extensive research on the techniques of generating deep-fakes, especially in regard to disinformation, identity fraud, and the impacts of social manipulation during elections or issues of morality revolving around deep fake technology [7]. In attempts to achieve higher generalization on various deep-fake datasets, a new detection framework based on meta-learning was developed. This enables deeper neural networks to perform well for cross-domain detection of deep-fakes without being retrained for new methods of generation. a deep-fake video detection approach that leverages complementary dynamic inconsistencies present in manipulated videos.

Their method analyzes temporal incoherence across frames to effectively distinguish forged content from authentic video sequences [8]. Bias in machine learning models for deep-fake detection remains a concern, as demographic factors including age, gender, and ethnicity have been shown to influence the accuracy of detection. Research has found the current datasets used are often under diverse and do not perform well on different population subgroups [9].

This paper proposed a novel method of deep-fake videos detection by exploiting complementary dynamic interaction to improve the analysis of facial dynamics. This of it improves the recognition of altered mouth motions and overall face inconsistencies, eventually attaining improved generalization against unknown deep-fake methods [10]. One such purpose of this existing literature draws attention towards the rapidly evolving nature of deep-fake creation methods, and the struggles to design potentially robust, fair and generalizable detection systems. We advocate for the development of adaptive, multimodal methods that can improve detection performance while also mitigating bias and adversarial energy. As seen in Figure 2, research on deep-fake detection spans multiple domains. The area of study can be delineated more generally into three areas:

- **Detection Techniques** – Discusses various technical methods covering a range of techniques including benchmarking, graph-based learning, contrastive learning, multi-modal detection.
- **Challenges in Deep-fake Detection** – explores significant challenges like noisy label attack, generalization, and bias in the detection model.
- **Ethical & Security Implications** – Addresses real world issues like misinformation, identity fraud and election manipulation resulting from deep-fakes.

III. DEEP-FAKE DETECTION METHODOLOGIES

As deep-fake technology has evolved, researchers have come up with numerous methods for detecting manipulated media. These methods employ various machine learning and deep learning models with their own strengths in detecting forged content. Some of the most widely used approaches are Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Autoencoders, Bayesian Inference Models, and Transformer-based models.

CNN-based methods, such as YOLO and Efficient-Net, are commonly used in medical deep-fake detection and image-based classification [11]. GANs, which are also commonly used to produce deep-fakes, have been used to enhance detection models by creating training data and boosting generalization [12-13]. Bayesian inference models, meanwhile, detect deep-fakes in videos, providing lightweight and real-time detection for Internet of Things (IoT) applications [14].

In recent times, Transformer-based models have been in the limelight because they generalize more across datasets than CNN-based architectures [15]. Deep-fake detection is still difficult because of adversarial attacks, which try to mislead detection systems. Researchers are now integrating hybrid methods that use several detection approaches together to improve robustness [16]. To understand deep-fake detection techniques in more detail, the following subsections explore specific methodologies, including CNN-LSTM-based detection and Autoencoder-based detection, which are widely used for analysing deep-fake content.

III.1 CNN-LSTM BASED DEEP-FAKE DETECTION

One strong method of detecting deep-fakes uses Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. CNNs capture significant features in single frames of a video, while LSTMs inspect frames in sequences to identify inconsistencies over time in doctored videos. This CNN-LSTM architecture enhances detection by identifying both image-based and time-based patterns in edited media [16].

Figure 3 depicts the deep-fake detection process of CNN-LSTM, in which CNNs scan every frame to extract the spatial features, which in turn are used as an input for the LSTM network to examine time-based relationships. It enables detection of slight frame-to-frame variations that commonly occur in deep-fakes.

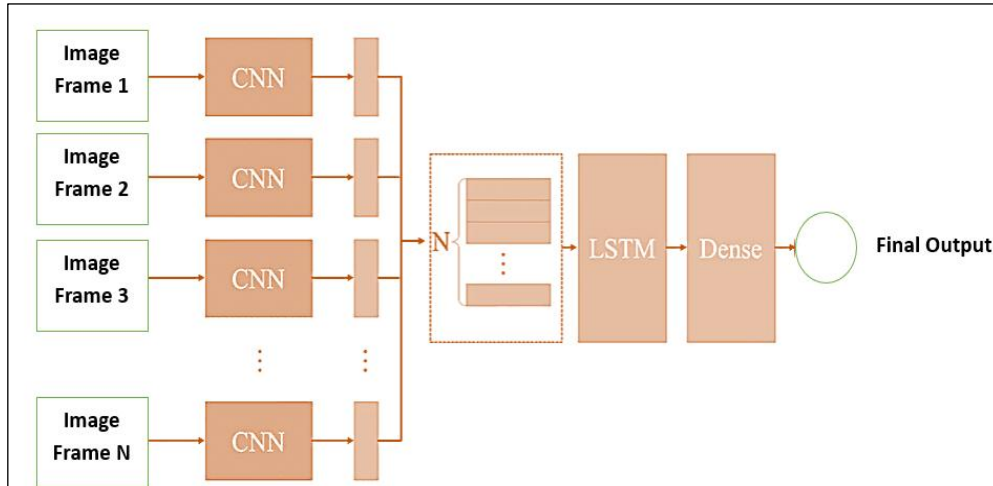


Figure 3: CNN-LSTM based Deep-fake Detection
Source: Authors, (2026).

III.2. AUTOENCODER BASED DEEP-FAKE DETECTION

Autoencoders are another effective method for detecting deep-fakes. These models learn to reconstruct input images and identify inconsistencies in fake content. In this approach, encoder-decoder networks process real images, while fake images result in noticeable reconstruction errors. Additionally, a discriminator network is used to refine detection by introducing an adversarial loss, making it harder for fake content to bypass detection.

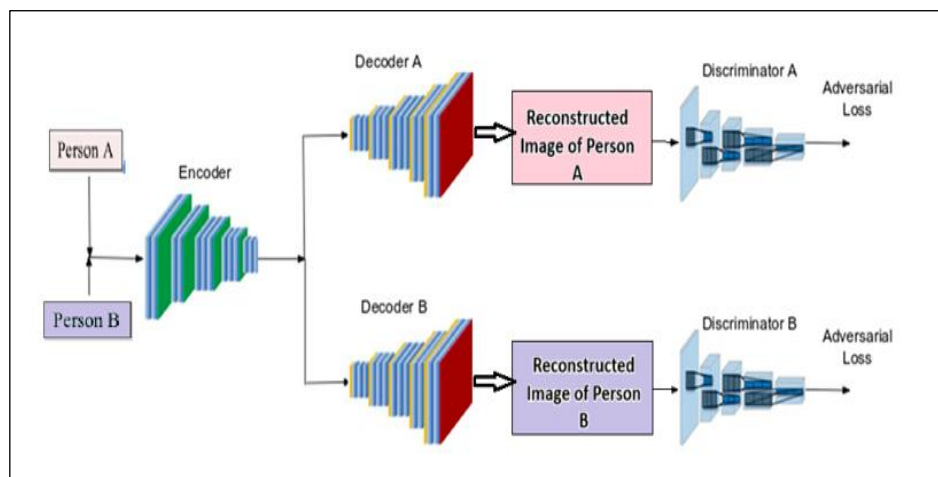


Figure 4: Auto-encoder based deep-fake detection technique
Source: Authors, (2026).

Figure 4 presents an Autoencoder-based deep-fake detection method that separates real and fake images by the accuracy of reconstruction. The encoder maps the input image to a compressed version, while the decoder tries to reconstruct the original image. In case of a fake image, the reconstructed image will be distorted, and it can be identified using a discriminator network.

III.3 EMERGING DEEP-FAKE DETECTION TECHNIQUES

Recent progress in deep-fake detection targets multimodal learning, contrastive learning, and graph-based models for enhanced accuracy. These approaches exploit multiple sources of information, including facial expressions, voice patterns, and video consistency, to support detection reliability. Researchers are also developing improved evaluation methods to examine the efficacy of these detection techniques on various datasets.

These enhancements intend to make detection of deep-fakes stronger, faster, and flexible to meet emerging deep-fake production methods.

IV. COMPARISON OF DEEP-FAKE DETECTION METHODS

The table 1 provides a comparative overview of ten new deep-fake detection studies published recently, indicating their methodologies, performance on benchmark datasets, advantages, and limitations. All these methods adopt distinct strategies, varying from unsupervised learning, spatial-temporal analysis, multimodal fusion, and transformer-based architectures to proactive defence approaches like watermarking. The table groups these methods in terms of their fundamental methodologies, experimental performance, and utilized datasets, making it easy to grasp their real-world applications and efficiency.

The table 1 also contains a systematic comparison of these detection methods, showcasing the trade-off between accuracy, generalization, and computational requirements. Transformer-based models have better cross-dataset performance but are computationally expensive, whereas contrastive learning-based methods have high performance but tend to introduce artifacts through pseudo-labelling.

Table 1: Comparison of Recent Deep-fake Detection Methodologies.

Source	Methodology	Performance & Dataset Used	Limitations
Yang et al. [17]	Diffusion Probabilistic Mask (DPMask)	High accuracy on RFFD, Seq-Deep-Fake, and HiFi-IFDL datasets	Limited generalization across diverse datasets
Qiao et al. [18]	Unsupervised contrastive learning with pseudo-labels	Comparable to supervised methods, tested on FF++, Celeb-DF, DFD, DFDC, UADFV	Relies on pseudo-labelling, which may introduce errors
Zhao et al. [19]	Spatial-temporal video transformer with interpretability	Strong intra-dataset & cross-dataset performance on FF++, Face-Shifter, Celeb-DF, DFDC	High computational cost due to transformer architecture
Tan et al. [20]	Transformer-based feature compensation and aggregation	AUC 99.85% on Face Forensics++, 78.57% on Celeb-DF	Potential overfitting to specific training datasets
Huang et al. [21]	Implicit spatial-domain notch filtering to evade deep-fake detection	Reduces detection accuracy of three methods by 36.79% on average, up to 97.02%	Enhances evasion rather than improving detection
Xie et al. [22]	Feature space aggregation and separation for domain-generalized audio deep-fake detection	Improves generalization, reduces EER by 39.24% in cross-domain audio deep-fake detection	Focused only on audio deep-fake detection
Yuan et al. [23]	Multiclass forgery-domain classification with non-negative constrained learning	Competitive performance on deep-fake benchmarks, forgery domain classification approach	Complexity increases due to additional classification layers
Wang et al. [24]	Proactive deep-fake detection with dual-task mutual learning and watermarking	Excels in proactive detection, robust watermarking technique improves accuracy	Limited to applications where watermarking is feasible
Liu et al. [25]	Self-blending images and residual-based analysis for robust deep-fake detection	Superior cross-dataset adaptability, tested on FF++ and Wild Deep-fake datasets	May struggle with high-resolution deep-fake content

Source: Authors, (2026).

Certain methods, like DPMask, perform well on particular data sets but generalize poorly, while others concentrate on evading adversarial attacks instead of enhancing detection accuracy. Deep-fake detection methodologies based on audio improve cross-domain transferability but are restricted to exposing manipulations in speech data.

V. KEY CHALLENGES AND FUTURE DIRECTIONS IN DEEP-FAKE DETECTION

The fast development of deep-fake technology brings forth various challenges for detection systems, such as dataset generalization, adversarial robustness, real-time deployment, and ethics. Solutions to these challenges necessitate novel research to further boost detection accuracy, efficiency, and flexibility.

1) Improving Generalization Across Datasets

Most detection models are poor at handling unknown deep-fakes because they overfit to individual datasets. Transfer learning, contrastive learning, and domain adaptation should be the areas of research in the future to enhance cross-dataset performance and flexibility.

2) Enhancing Robustness Against Adversarial Attacks

Deep-fake developers keep innovating to stay one step ahead of detection. Improving models with adversarial training, self-supervised learning, and perturbation-robust architectures will counter emerging threats.

3) Developing Lightweight and Scalable Detection Systems

Deep-fake manipulations are now expanding into audio and text-based fakes. The combination of lip-sync checking, voice analysis, and sentiment analysis will enhance detection accuracy for cross-modal deep-fakes.

4) Advancing Multimodal Detection Techniques

Deep-fake manipulations now extend beyond visuals to include audio and text-based forgeries. Integrating lip-sync verification, voice analysis, and sentiment detection will improve detection accuracy for cross-modal deep-fakes.

5) Establishing Ethical and Legal Safeguards

The abuse of deep-fakes for misinformation, fraud, and identity theft requires more stringent regulatory controls. Future research must investigate AI-driven watermarking, blockchain-based authentication, and uniform legal frameworks to hold entities accountable.

VI. CONCLUSION

Deep-fake detection research has to advance to address issues in generalization, adversarial robustness, real-time scalability, and multimodal analysis. Future research should be directed towards cross-domain learning, resilient AI architectures, and low-latency detection models for mass-scale applications. Improvements in Explainable AI, blockchain-based verification, and AI-based watermarking can facilitate transparency and accountability. Lightweight, high-performance model development for edge AI and IoT will allow for real-time deployment. By combining deep learning, multimodal analysis, and ethical AI paradigms, scientists are able to design more robust and flexible deep-fake detection systems for the sake of digital security and public trust.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Navnee Babar, Shilpa Metkar, Rashmi Gaikwad, and Shweta Patil

Methodology: Navnee Babar, Shilpa Metkar, Rashmi Gaikwad, and Shweta Patil

Investigation: Navnee Babar, Shilpa Metkar, Rashmi Gaikwad, and Shweta Patil

Discussion of results: Navnee Babar, Shilpa Metkar, Rashmi Gaikwad, and Shweta Patil

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Writing – Review and Editing: Navnee Babar, Shilpa Metkar, Rashmi Gaikwad, and Shweta Patil

Resources: Navnee Babar, Shilpa Metkar, Rashmi Gaikwad, and Shweta Patil

Supervision: Navnee Babar, Shilpa Metkar, Rashmi Gaikwad, and Shweta Patil

Approval of the final text: Navnee Babar, Shilpa Metkar, Rashmi Gaikwad, and Shweta Patil

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