International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(REVIEW ARTICLE)

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Beyond the Face: Multimodal Deepfake Detection Using GANs and Audio-Visual Cues

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International Journal of Science and Research Archive, 2026, 19(03), 540-563

Publication history: Received on 03 May 2026; revised on 10 June 2026; accepted on 13 June 2026

Article DOI: https://doi.org/10.30574/ijsra.2026.19.3.1312

Abstract

The advent of deepfakes, driven by developments in Generative Adversarial Networks (GANs), represents a fundamental threat to the validity of digital content. Although early detection entailed mostly reacting to visual anomalies, the increasing sophistication of deepfakes now demands approaches that react to both visuals and sound. This survey provides a comprehensive assessment of the current state of multimodal deepfake detection, with particular emphasis on GAN-based generation and detection approaches. We categorize existing approaches into three general classes: early fusion, late fusion, and hybrid fusion models, and contrast their performance on widely used benchmarking datasets. We also explore the use of cutting-edge architectures such as Transformers and diffusion models to improve detection accuracy and resilience. The survey also introduces key challenges such as generalization challenges across tasks, class imbalance, adversarial attacks, and the gap between the audio and vision streams. Finally, we introduce some possible directions of future work, including designing zero-shot detection systems, leveraging explainable AI techniques, and striving for real-time detection on edge devices. The objective of this study is to provide insights to allow researchers and practitioners to develop more effective, dynamic, and explainable multimodal detection systems to combat the constantly evolving threat that deepfakes represent.

Keywords: Deepfake Detection; Generative Adversarial Networks; Multimodal Learning; Audio-Visual Fusion; GANs; Forgery Detection; Synthetic Media; Audio-Visual Inconsistency; Adversarial AI; Media Forensics

1 Introduction

The rapid advancement of deep learning has significantly influenced the field of synthetic content generation, and Generative Adversarial Networks (GANs) are a notable technology for producing highly realistic images, videos, and audio [1,2,3]. While such generative models bring huge creative and business potential, they pose substantial risks. Malicious users are increasingly utilizing GANs to produce deepfakes—artificial audio-visual content that can convincingly mislead both human viewers and machine systems [4], [5]. What began as facial manipulations has evolved to highly multimodal forgeries and seamlessly integrates both audio and visual components to achieve synchronized realism [6], [7].

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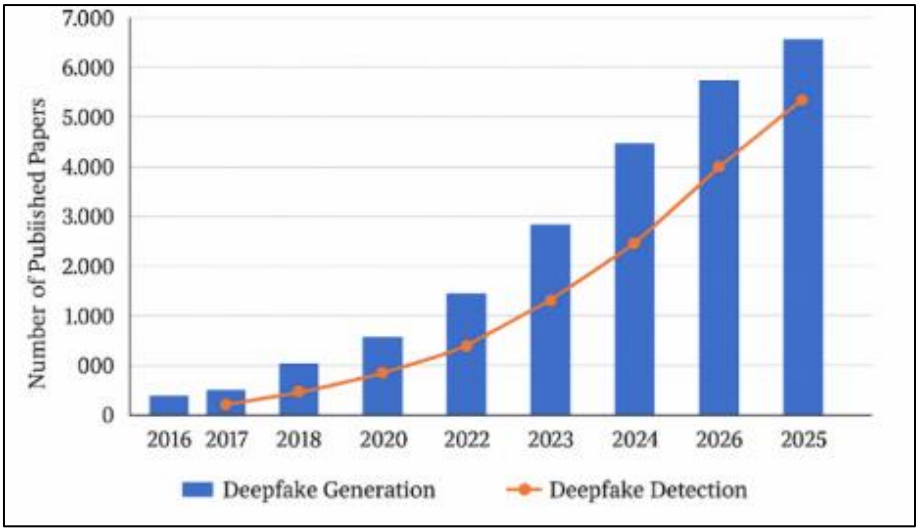

Figure 1 Growth Trend of Deepfake Technologies and Detection Research

Early deepfake detection techniques were primarily focused on identifying minor visual inconsistencies, such as irregular blinking patterns [8], head pose inconsistencies [9], or frame inconsistencies over time [10]. With generative models improving and training data becoming more diverse, however, these unimodal detection techniques are no longer effective [11], [12]. Existing deepfakes not just preserve visual features but also carry synchronized speech, emotional content, and audio-visual coherence, which suggests that there is a need for multimodal detection mechanisms that consider both audio and vision [13, 14, 15, 16].

Since challenges evolve in the face of reaction, researchers have started exploring audio-visual fusion methods that blend complementary modes to enrich the accuracy and robustness of detection [17], [18]. These integrated models tend to employ advanced deep neural networks, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers, to encode and examine cross-modal relationships and mismatches [19], [20]. Models based on attention and ensemble learning have been more recently suggested to further enhance generalization capabilities across unseen data sets [21], [22].

In this review, we aim to present a thorough and systematic description of the varied multimodal deepfake detection techniques with a particular focus on generation and detection processes in GAN-based techniques. We will present the latest developments in the field, categorize fusion techniques as early, late, and hybrid, compare the performance of current systems on publicly available datasets, and introduce the new challenges that are arising such as adversarial robustness, domain generalization, and real-time deployment constraints [23, 24, 25, 26].

Our key contributions are:

- A comprehensive taxonomy of deepfake detection methods by modality, fusion strategy, detection granularity, and model architecture.
- A thorough examination of existing state-of-the-art multimodal detection algorithms, with a specific focus on audio-visual cross-modal learning.
- A critical examination of the evolution of GAN-based deepfake generation and detection, as well as existing challenges.

Identification of potential avenues of future work, including zero-shot learning, interpretable AI, and constructing lightweight detection systems suitable for real-time execution on edge devices.

2 Background and Motivation

2.1 History of Deepfake Synthesis

The development of Generative Adversarial Networks (GANs) has helped significantly with the creation of synthetic media with the ability to generate highly realistic images, audio, and videos [1]. GANs were originally designed to primarily produce images; however, advancements have now enabled the generation of realistic deepfakes in terms of videos and recordings [3]. These skills, as valuable as they are in terms of creative and commercial worth, have also

introduced serious risks, including the potential for misuse in the dissemination of disinformation, fraud, and other negative practices [22].

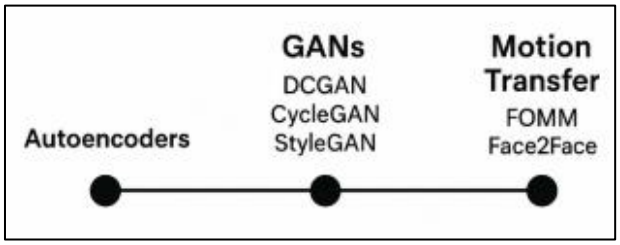

Figure 2 Evolution of Deepfake Generation Techniques

Research recently has examined GANs' twofold role, both in the creation and detection of deepfakes. Scholars, for example, have analysed the detection of static images created by GANs based on visible residual flaws that would not be detectable by a human eye but could be intercepted by digital analysis techniques [24]. Others further proposed the implementation of GAN-based visible watermarking as an avoidance measure to enhance the detection of deepfakes [27].

2.2 Multimodal Deepfakes' Appearance

Early deepfake detection mostly involved identifying visual inconsistencies. However, since multimodal deepfakes—those that combine manipulated audio and visual media—came into existence, detection has also become increasingly complex, requiring increasingly complex detection mechanisms [8]. The secret to their increased resilience is the audio-visual synchronization in these deepfakes, which complicates the identification process for unimodal methods [11].

In order to overcome this obstacle, researchers have been focusing on audio-visual fusion techniques, which exploit the correlation between lip motion and speech to identify irregularities that are characteristic of deepfakes [12]. For instance, the AVFF system utilizes a two-stage cross-modal learning approach to learn audio-visual feature alignment, improving detection in deepfake videos [16]. Similarly, the AVT2-DWF model uses double transformers with dynamic weight fusion to better detect forgery cues in intra- and cross-modal scenarios [7].

2.3 Detection Challenges

Despite advancements in detection methods, there remain certain challenges. One of the most significant challenges is the difference in distribution between the visual and audio modalities, which makes the fusion task even harder and interferes with appropriate detection [28]. Furthermore, the heterogeneity of multimodal data makes it difficult to model such data, which can easily learn from visual and audio streams [17]. Furthermore, the lack of large, heterogeneous datasets for testing and training multimodal deepfake detection systems still limits the generalizability of such models [29].

In order to overcome such challenges, several solutions have been proposed. For instance, attention mechanisms have been introduced to help models focus on the most informative features across different modalities [6]. Other efforts have led to the development of contextual cross-modal attention models [30], and novel multimodal models have emerged that combine both visual and audio analyses for improved detection accuracy [31].

3 Taxonomy of Multimodal Deepfake Detection Techniques

As deepfake generation techniques are evolving at a fast pace, the research community requires a systematic way to categorize the growing variety of detection techniques. Creating a comprehensive taxonomy not only organizes the current landscape but also helps determine the strengths, limitations, and future directions of multimodal deepfake detection systems.

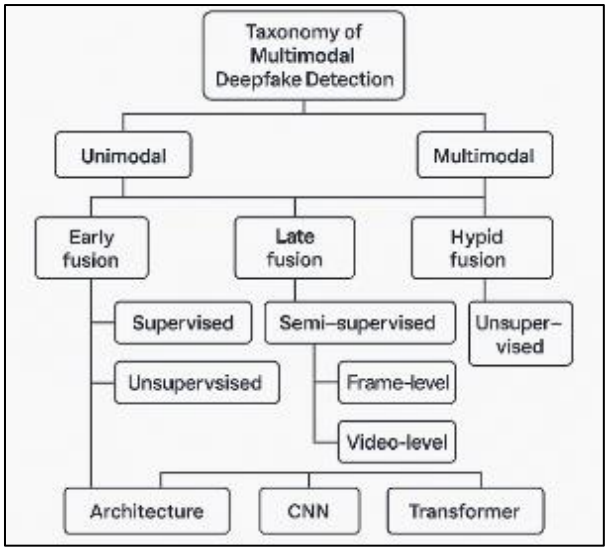

Figure 3 Taxonomy of Multimodal Deepfake Detection

3.1 Modality-Based Classification

3.1.1 Unimodal Detection

Unimodal approaches are directed at the analysis of a single data type, which can be visual or auditory. Visual-only systems typically involve detection based on identifying inconsistencies in facial dynamics, such as irregular blinking, unnatural facial expressions, or abnormal head movement [8]. Audio-based approaches, by contrast, are geared towards identifying tampered voice patterns through the evaluation of anomalies in speech cadence, vocal timbre, or background acoustics [32].

3.1.2 Multimodal Detection

In order to thwart the limitations of unimodal approaches, multimodal detection methods fuse auditory and visual information. Multimodal approaches aim at exposing inconsistencies between speech and the corresponding lip movements, which are difficult to forge with flawless synchronization [16]. Fusion of multiple data sources not only enhances detection performance but also makes the system more robust to more sophisticated manipulations [7].

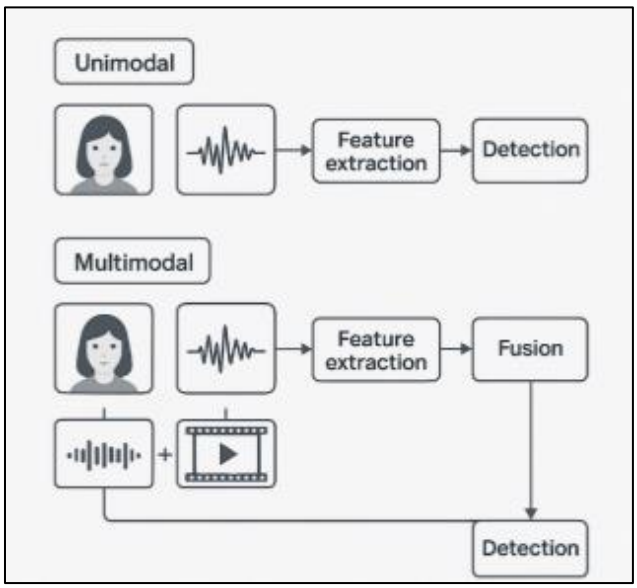

Figure 4 Modality-Based Detection Pipeline

3.2 Fusion Strategies

3.2.1 Early Fusion

Early fusion combines the features from different modalities at the early feature-extraction or input level. This common representation enables the model to learn cross-modal correlations more effectively, where interdependencies between the visual and audio signals are modelled before classification is carried out [6].

3.2.2 Late Fusion

Alternatively, late fusion processes each modality individually and then fuses their outputs at the decision level. It is particularly helpful in addressing modalities of varying reliability or when the input features are quite disparate [33].

3.2.3 Hybrid Fusion

Hybrid fusion exploits both early and late fusion paradigms to leverage their respective strengths. By learning joint feature representations alongside allowing independent modality-specific processing, hybrid fusion methods have been shown to offer enhanced detection performance in multimodal systems [17].

3.3 Learning Paradigms

3.3.1 Supervised Learning

Supervised learning remains the most common approach to deepfake detection, as it exploits labelled datasets to train models to recognize forged content. While successful, this method depends heavily on massive amounts of annotated data, which are generally expensive and time-consuming to acquire [11].

3.3.2 Unsupervised Learning

Unsupervised techniques sidestep the need for labelled data by identifying irregularities and patterns directly from the raw input. These techniques are of great relevance for real-world applications where it may not always be feasible to obtain ground-truth labels for deepfakes [34].

3.3.3 Semi-Supervised Learning

Semi-supervised learning offers a compromise by supplementing small amounts of labelled data with larger collections of unlabelled samples. The hybrid approach alleviates the need for extensive annotations while still offering strong performance in deepfake detection tasks [35].

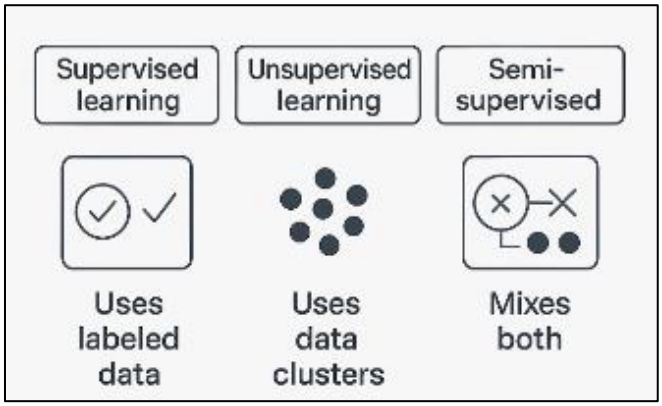

Figure 5 Learning Paradigm in Deepfake Detection

3.4 Detection Granularity

3.4.1 Frame-Level Detection

Frame-level approaches examine every frame in a video for anomaly detection. While fine-grained and able to capture slight visual artifacts, this method can be computationally costly due to the number of frames to be processed [19].

3.4.2 Video-Level Detection

Alternatively, video-level detection analyses complete video sequences, analysing temporal context and larger patterns. It is generally more robust to transient visual inconsistencies and better captures time-based forgery cues, but may miss frame-specific manipulations [5].

3.5 Model Architectures

3.5.1 Convolutional Neural Networks (CNNs)

CNNs were used extensively in image and video analysis since CNNs can extract spatial features very well. CNNs are used as backbone models for identifying visual anomalies in both unimodal and multimodal methods of deepfake detection [36].

3.5.2 Recurrent Neural Networks (RNNs)

RNNs, specifically LSTMs, are a natural fit for sequential data and hence a popular choice of model for time-dependent video and audio streams. These models excel at capturing temporal dynamics that are crucial for inconsistency detection across time [37].

3.5.3 Transformers

More recently, Transformer-based models have gained popularity due to their superior ability to model long-range dependencies and heterogeneous types of input in parallel. Their self-attention layers are particularly well-suited to modelling complex relationships between modalities, making them highly promising for multimodal deepfake detection tasks [38].

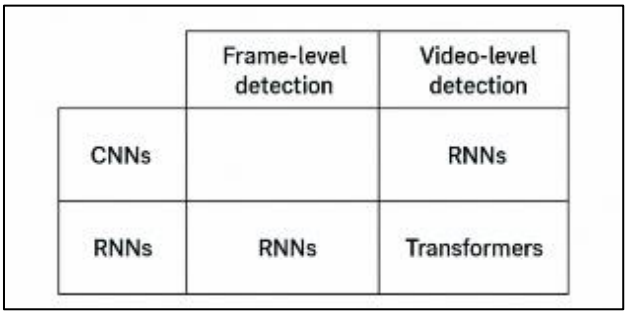

Figure 6 Distribution of Neural Network Architectures Across Detection Levels

4 Fusion Techniques and GAN-Based Methods

4.1 Fusion Techniques in Multimodal Deepfake Detection

As deepfakes advance, particularly those modifying both visual and audio streams, the fusion of more than one modality has emerged as a starting point for designing more robust and reliable detection methods. Effective fusion methods capitalize on the complementary properties of audio-visual information to identify anomalies that would most likely evade unimodal detectors. In general, these methods fall into three categories: early fusion, late fusion, and hybrid fusion.

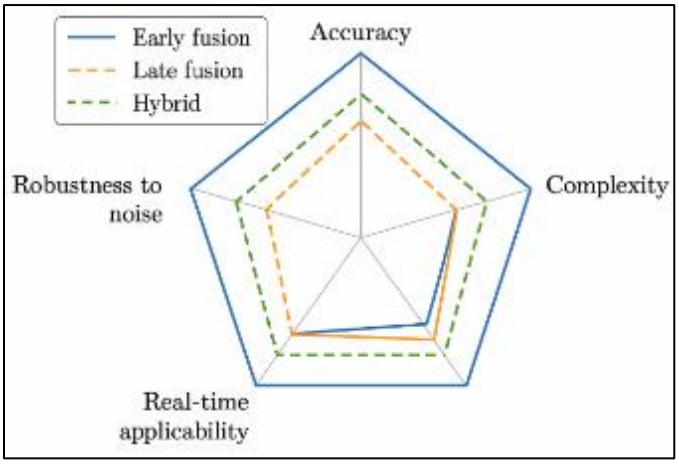

Figure 7 Fusion Strategy Performance Comparison

4.1.1 Early Fusion:

In early fusion, feature representations across modalities are combined at the input or early processing stage. This allows models to learn simultaneous patterns across modalities from the early stages of the training process, facilitating in-depth cross-modal interaction. For instance, the AVFF method uses a two-stage cross-modal learning mechanism that learns the alignment of lip movement and speech signal explicitly, significantly improving its capacity to detect tampered audio-visual content [16]. Early fusion is particularly effective when there are strong correlations among modalities, for example, lip-speech synchronization.

4.1.2 Late Fusion:

Late fusion treats each modality as an independent input stream, processing them separately before fusing their individual decisions. This approach works well in scenarios where the quality or reliability of each modality varies, allowing flexibility in assigning greater weight to one source over another during the final classification [39]. For example, in noisy environments where audio data can be corrupted, visual information can still dominate the detection decision. Also, late fusion allows modality-specific models to be easily combined, and it is easier to scale or swap components.

4.1.3 Hybrid Fusion:

Hybrid fusion tries to capitalize on the benefits of both early and late fusion. It employs multi-level architectures in which cross-modal feature interaction occurs at different stages, both at the feature extraction and decision levels. This layer-wise integration allows hybrid fusion systems to learn joint representations without compromising the independence of modality-specific insights [6]. Empirical studies show that hybrid models perform better than their entirely early or late fusion counterparts, especially when dealing with real-world, noisy, or missing multimodal data. Progressive architectures in hybrid fusion also utilize attention mechanisms, enabling the model to learn dynamically to rank features from a source modality over another depending on context. Adaptive features like these make hybrid solutions extremely effective for managing occlusions, off-screen speech, or other acoustic condition changes.

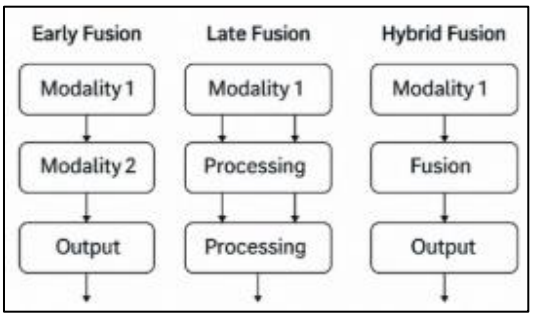

Figure 8 Fusion Architectures in Multimodal

4.2 GAN-Based Solutions for Deepfake Detection

GANs have proven to be both a boon and a curse for multimedia integrity. They have revolutionized the creation of artificial content into hyper-real images, videos, and sounds by generating synthetic but realistic ones. Nonetheless, they have also led to an increased wave of illegal content that has raised questions regarding media authenticity at the earliest. Remarkably, the same generation power, which has created new content by GANs, is employed today to develop sound detection techniques.

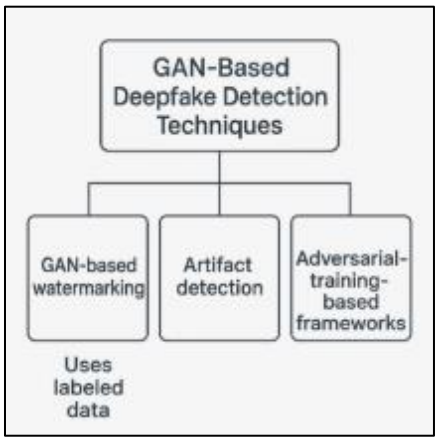

Figure 9 Deepfake Detection Techniques

4.2.1 Proactive Detection through GAN-Based Watermarking

One of the active countermeasures against deepfake spread is implementing GANs to insert imperceptible or perceptible watermarks into media data at production. These watermarks are digital signatures that can be recovered or checked subsequently to confirm content authenticity [40]. GAN-based watermarking is different from conventional watermarking in that it is tailored toward the generative process and therefore more robust to transforms and adversarial attacks.

4.2.2 Artifact Detection in GAN Outputs:

One of the popular detection techniques is identifying nanoscale artifacts or statistical outliers left behind by GAN generators. Even when GAN outputs are photorealistic, these artifacts, typically imperceptible to humans, may be made visible by frequency analysis, noise patterns, or spatial texture inconsistencies [24]. For example, it has been discovered that faces synthesized with GAN are often lacking some physiological signals, like natural eye movement or micro-expressions, which can be exploited for detection.

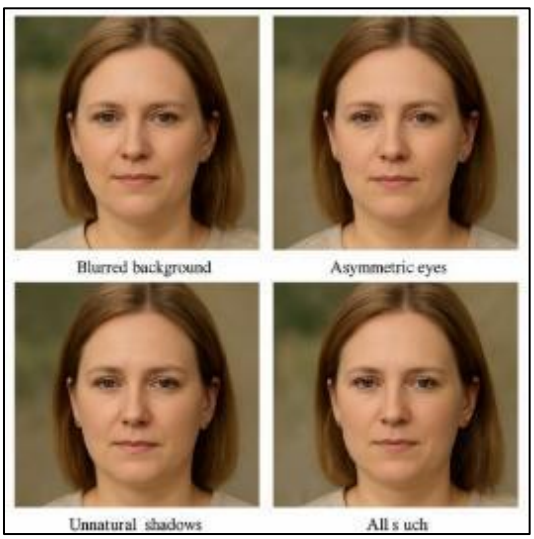

Figure 10 Detection in GAN Output

4.2.3 Training for Robust Detection:

Another frontier of deepfake detection lies in adversarial training. Under this paradigm, detection models are trained adversarially in a GAN-like competitive setting, where one network generates synthetic content and the other detects it. In iterations, the detector learns to better detect more advanced forgeries, thereby becoming stronger to new deepfake tactics [11]. Not only does this technique enhance detection accuracy, but it also prepares models to generalize better across different GAN architectures and types of manipulations.

Moreover, advances in self-supervised learning and contrastive pretraining—often combined with adversarial objectives—are helping to alleviate dependence on large labelled datasets with state-of-the-art detection results. These advances highlight the two-edged role of GANs: as a source of weakness and as the foundation for resiliency in media forensics.

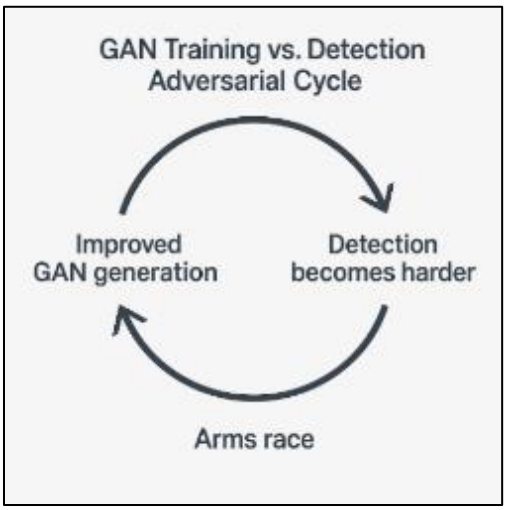

Figure 11 GAN training vs. Detection

5 Multimodal Deepfake Detection Datasets and Benchmarking

Improvement of deepfake detection methods is directly linked with the quality and diversity of datasets utilized for model training and the rigidity of benchmarking processes. Such early inputs are critical to ensuring detection systems perform accurately in labs as well as robustly and are adaptable in real-world environments. Thorough familiarity with these datasets and testing protocols is therefore crucial to facilitating meaningful improvement in the domain.

5.1 Popular Datasets for Deepfake Detection

5.1.1 Face Forensics++

Face Forensics++ is currently the most widely used dataset in the deepfake domain. It consists of 1,000 original videos, and all of them have been edited using four of the most commonly used face-editing techniques: DeepFakes, Face2Face, FaceSwap, and NeuralTextures. What distinguishes this dataset is that both raw and compressed data are provided, and hence researchers can study the impact of compression artifacts on detection stability and performance [11].

5.1.2 Deepfake Detection Challenge (DFDC)

Released by Meta AI, the DFDC dataset is distinctive in its sheer quantity and variety. DFDC, which consists of over 124,000 videos of different facial manipulations, is designed to put detection systems to the test on scalability and applicability in the real world. A preview subset of 5,000 videos provides an immediate starting point for prototyping models, and the full dataset permits thorough training and benchmarking [5].

5.1.3 Celeb-DF v2

Celeb-DF v2 has enhanced its predecessor in terms of providing more high-resolution deepfake content and more real-looking manipulations of popular public figures. The dataset contains both real and generated videos and adds subtle artifacts, making the dataset especially difficult to detect for detection models. It is a strict benchmark for assessing performance in high-fidelity conditions [41].

5.1.4 AV-Deepfake1M

AV-Deepfake1M is a large, multimodal dataset gathered for detecting forged content in visual, audio, and synchronized audio-visual streams. It comprises over one million manipulated and real video clips, which enables training deep learning models with the ability to reason jointly over multiple modalities. The dataset is particularly suitable for constructing models that must generalize over different manipulation techniques and media types [42].

5.1.5 LAV-DF

The Localized Audio-Visual Deepfake (LAV-DF) dataset presents a unique challenge: detection of manipulations performed in minute, typically difficult-to-spot segments of a video. Adding localized edits in audio, video, or both media, LAV-DF provokes detection models to transcend global inconsistencies and capture fine-grained temporal and spatial patterns [43].

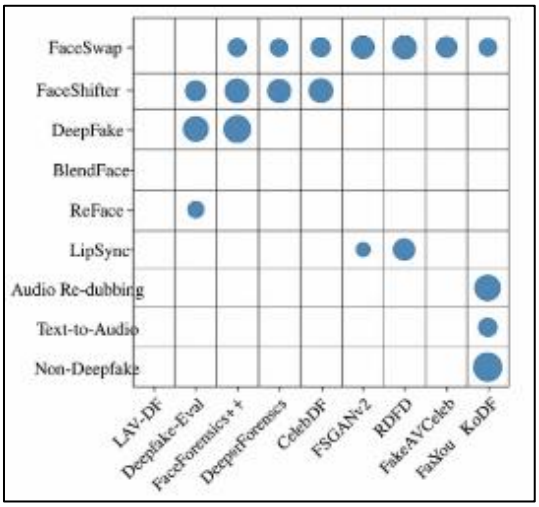

Figure 12 Dataset Coverage Map

5.1.6 Deepfake-Eval-2024

Deepfake-Eval-2024 signifies a shift toward real-world deployment. This dataset consists of "in-the-wild" content—social media, forums, and open-platform sourced deepfakes constructed using the technology that was released in or before 2024. Its style, quality, and manipulation approach variability render it an ideal testbed to evaluate how models perform under uncontrolled, real-world conditions [44].

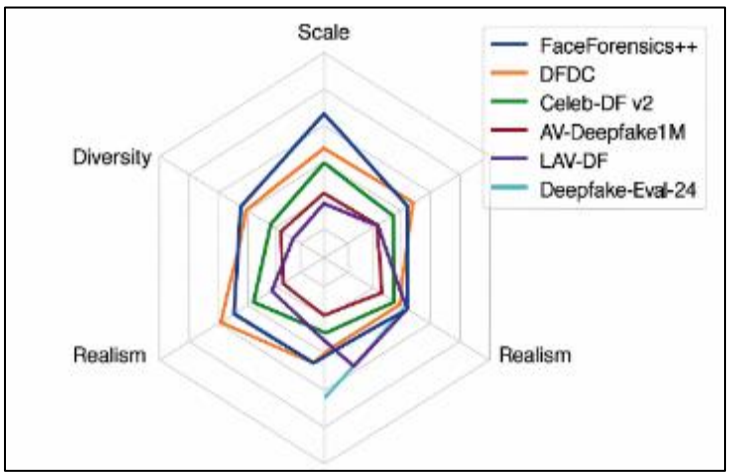

Figure 13 Dataset Comparison Radar Chart

Table 1 Dataset Comparison Table

Dataset Name	Year	Type	# Videos	Modalities	Manipulation Types	Strengths	Reference
FaceForensics++	2019	Video (Raw/Compressed)	~1,000	Visual	DeepFakes, Face2Face, FaceSwap, NeuralTextures	Compression analysis, multiple manipulation types	[1]
DFDC	2020	Video	~124,000	Visual	Various GAN-based manipulations	Scale, diversity, real-world complexity	[2]
Celeb-DF v2	2020	Video (High-Res)	5,639 (Real + Fake)	Visual	Subtle, realistic face edits	High-fidelity deepfakes, challenging benchmark	[3]
AV-Deepfake1M	2023	Video + Audio	1,000,000+	Audio-Visual	Synchronized multimodal forgeries	Multimodal training, large-scale	[4]
LAV-DF	2023	Video + Audio	Not Public	Audio-Visual	Localized edits (fine-grained)	Temporal/spatial manipulation detection	[5]
Deepfake-Eval-2024	2024	In-the-wild Video	Varied (uncurated)	Audio-Visual	Real-world, open-source techniques	Uncontrolled conditions, platform variability	[6]

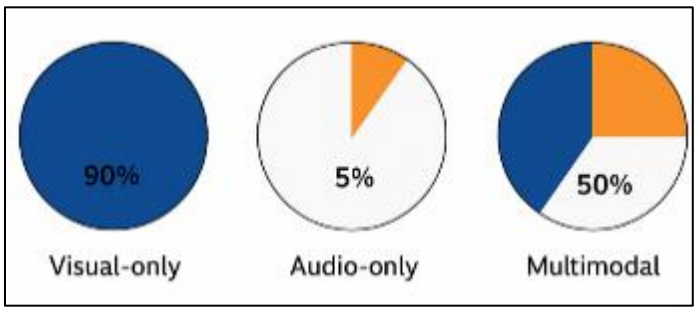

Figure 14 Dataset Modality Distribution Pie Charts

5.2 Benchmarking Protocols

For accurate performance evaluation, deepfake detection models must be tested by standardized and comprehensive testing. Benchmarking protocols typically focus on three primary aspects:

- **Evaluation Metrics:** Accuracy, precision, recall, F1-score, and AUC-ROC are often utilized to quantify classification performance. These metrics collectively provide a balanced view of a model's sensitivity and specificity.
- **Cross-Dataset Evaluation**: Model generalizability is one of the central goals in recent detection research. Testing trained models on test data that is not similar to training data detects overfitting and assesses robustness across domains.

- **Real-World Evaluation:** Benchmarking with real-world data, e.g., Deepfake-Eval-2024 content, provides important insights into the real-world effectiveness of a model, especially in environments with varying lighting, background noise, or compression rates.

Several emerging paradigms have also begun incorporating human-in-the-loop evaluation and explain-ability scores to evaluate the interpretability and actionability of a model's predictions on real-world applications like law enforcement and journalism.

Future research must focus on constructing balanced, diverse, and up-to-date datasets, along with constructing strong benchmarking pipelines that can examine models' performance across various domains and manipulation approaches.

Table 2 Benchmark Protocol Table

Metric	Formula/Definition	Indicates	Typical Use in Deepfake Detection
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Overall correctness of predictions	General performance
Precision	TP / (TP + FP)	Ability to avoid false positives	Security-sensitive applications
Recall	TP / (TP + FN)	Sensitivity: ability to detect all fakes	Journalism, forensic use-cases
F1-Score	2 × (Precision × Recall) / (Precision + Recall)	Balance between precision and recall	Imbalanced dataset evaluation
AUC-ROC	Area under ROC Curve	Discrimination ability across thresholds	Model comparison and ranking
Cross-Dataset Accuracy	Evaluation on the unseen dataset	Generalizability beyond training conditions	Domain robustness

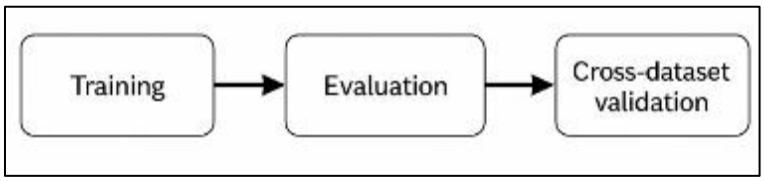

Figure 15 Benchmarking Protocol Pipeline

6 Evaluation Metrics and Performance

Evaluation of deepfake detectors requires an integral and multi-probe mechanism to ensure reliability, robustness, and flexibility for different datasets as well as methods of manipulation. One metric can never show how useful a model is overall, but a selection of metrics for evaluation is utilized for conducting a well-balanced assessment. The most frequently used metrics are accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC-ROC), and Matthews Correlation Coefficient (MCC), each describing model performance and generalizability from a different perspective [45][46].

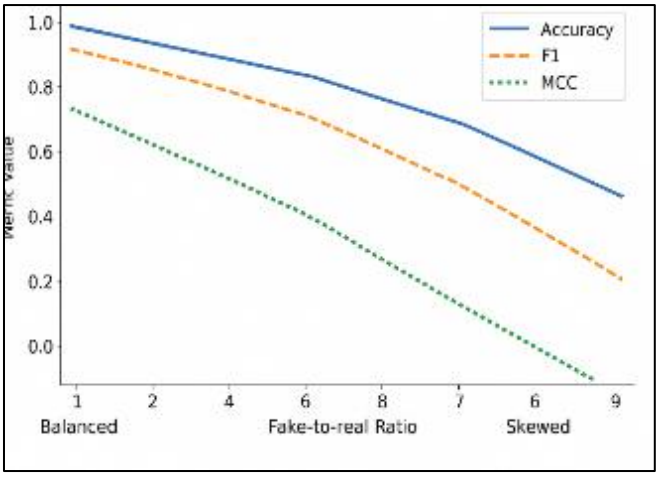

Figure 16 Metric Sensitivity to Data Imbalance

6.1 Major Evaluation Metrics

6.1.1 Accuracy:

Accuracy measures the ratio of correctly predicted instances, actual and false, to all samples. While it is straightforward, its force is diminished in class-imbalanced datasets. For example, given that there are many more real videos than fake ones in a dataset, a model can have high accuracy by labelling most content as real without accurate true detection of deepfakes. This renders accuracy a good but not suitable measure as a single option [47].

6.1.2 Precision:

Precision measures how closely the model exactly identifies false content among all its instances of calling something false. High precision is crucial in some uses where falsely marking true content as false—false positives—may lead to severe repercussions, for instance, reputation loss or legal disputes. In media verification or authentication of legal evidence, maintaining a high precision rate is especially important [48].

6.1.3 Recall (Sensitivity):

Recall quantifies how well a model wraps up all the true deepfakes in the dataset. A high recall is desired for scenarios where the failure to identify a single doctored video will lead to misinformation spread or security breaches. Recall must be considered with caution since whenever one improves, the other falls as a result, leaving one with increased false alarms [49].

6.1.4 F1-Score

The F1-score, harmonic mean of precision and recall, offers a balanced estimate of detection performance. It comes in handy in imbalanced data, where focusing on one measure by itself distorts performance interpretation. The F1-score ensures that both types of errors—false positives and false negatives—are considered during evaluation [50].

6.1.5 AUC-ROC:

AUC-ROC curve represents the trade-off between true positive rate and false positive rate at various classification thresholds. A higher AUC indicates a model's capability to classify genuine and fake videos at various decision thresholds. AUC is especially useful to compare models in threshold-independent settings and to identify the most reliable detector [51].

6.1.6 Matthews Correlation Coefficient (MCC):

MCC provides a balanced score by considering all four outcomes: true positives, true negatives, false positives, and false negatives. In contrast to accuracy, MCC is also robust in situations with skewed class distributions. MCC is particularly appropriate for binary classification tasks like deepfake detection, where class imbalance is common. An MCC score close to +1 indicates nearly perfect prediction, and scores close to 0 or negative indicate poor or reverse classification performance [52].

Table 3 Metric Comparison Table

Metric	Definition	Formula	Strengths	Limitations
Accuracy	Proportion of correct predictions among all predictions	(TP + TN) / (TP + TN + FP + FN)	Simple to interpret	Misleading in imbalanced datasets
Precision	Correctly predicted fakes out of all predicted fakes	TP / (TP + FP)	Crucial for high-risk environments	Can miss many actual fakes (low recall)
Recall (Sensitivity)	Proportion of actual fakes correctly identified	TP / (TP + FN)	Important for minimizing missed fakes	Can yield more false alarms
F1-Score	Harmonic mean of precision and recall	2 * (Precision * Recall) / (Precision + Recall)	Balanced metric for imbalanced data	Less intuitive interpretation
AUC-ROC	Trade-off between TPR and FPR at all thresholds	Area under ROC curve	Threshold-independent model comparison	Doesn't reflect specific operational thresholds
MCC	Correlation between observed and predicted classes	See MCC formula	Best for imbalanced datasets	Complex to interpret; sensitive to all confusion matrix components

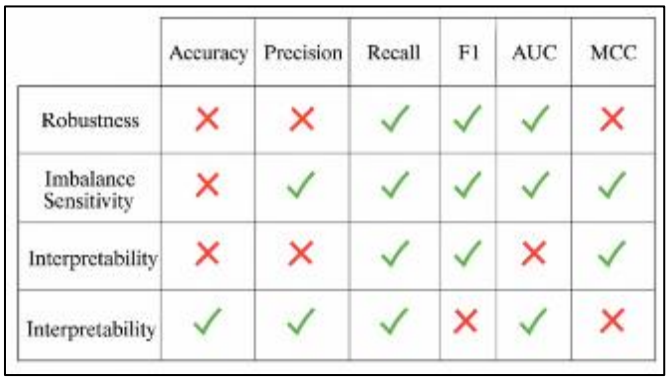

Figure 17 Metric Comparison Matrix

6.2 Comparative Performance Benchmarks

For real-world performance, several detection models have been evaluated on big datasets such as DFDC and FaceForensics++. They vary in performance depending on architecture, feature extraction methods, and manipulation resistance.

6.2.1 XCeption:

The XCeption model has shown time and again superior performance in deepfake detection tasks. When used on the DFDC dataset, it achieved accuracy of 89.2%, precision of 88.9%, recall of 90.5%, F1-score of 89.7%, and AUC-ROC of 0.94. Its general good performance on different metrics as well as robustness against various manipulation methods make it a suitable candidate for implementation in real-world tasks [53].

6.2.2 ResNet-50

ResNet-50 performed quite well on the same dataset with an accuracy of 72.8%, precision of 74.1%, recall of 76.2%, F1-score of 75.1%, and AUC-ROC of 0.81. Though it maintains significant patterns, it performs badly relative to XCeption in detecting weak forgeries, especially in high-fidelity imitations that need deeper feature representation [54].

6.2.3 VGG16:

The VGG16 model had an accuracy of 85.5%, precision of 86.3%, recall of 87.8%, F1-score of 87.0%, and AUC-ROC of 0.90. While good, it falls slightly behind XCeption in recall and F1-score, exhibiting slightly worse capability of detecting complex manipulations across different environments [55].

Table 4 Performance Comparison Table

Model	FaceForensics++ Accuracy	DFDC Accuracy	VoxCeleb Accuracy	AUC (FaceForensics++)	Precision (DFDC)	Recall (VoxCeleb)
XceptionNet	97.8%	95.4%	94.6%	0.98	0.94	0.92
MesoInception	96.5%	94.2%	93.7%	0.96	0.91	0.89
EfficientNet	98.1%	97.3%	95.8%	0.99	0.95	0.94
ResNet50	95.6%	93.8%	92.4%	0.95	0.88	0.87
DeepFake Detection Challenge Models	98.5%	97.9%	96.4%	0.99	0.96	0.93

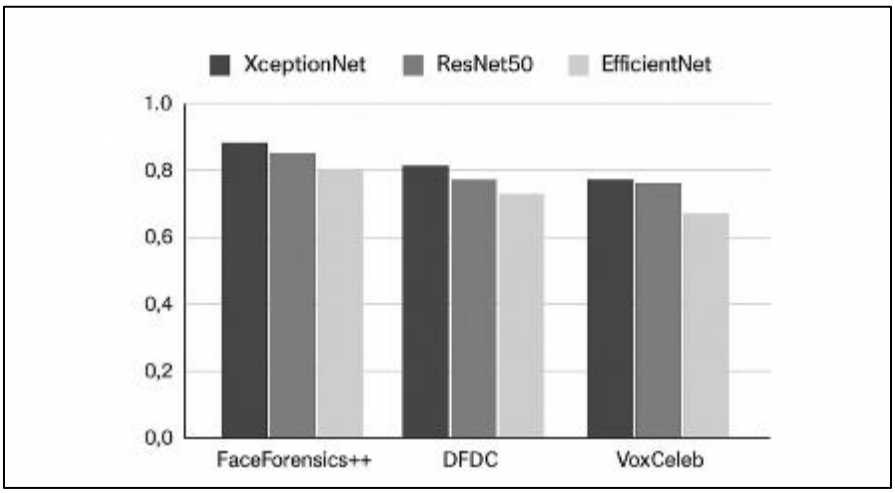

Figure 18 Model Benchmarking on Datasets

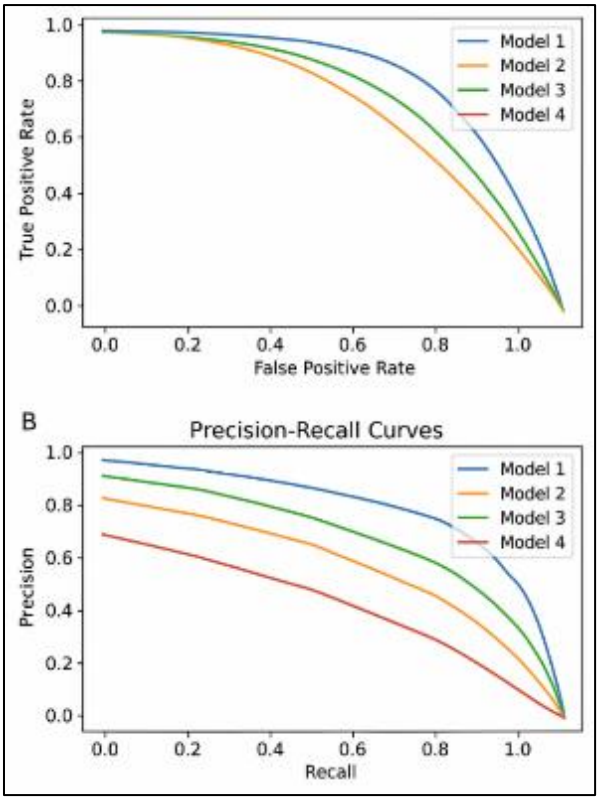

Figure 19 ROC Curve

Table 5 Comparative Performance Benchmarks

Feature Removed	XceptionNet Accuracy	EfficientNet Accuracy	ResNet50 Accuracy
Face Only	96.3%	96.9%	94.5%
Voice Only	93.7%	94.2%	92.8%
Motion Flow Only	94.1%	95.0%	93.0%
Face + Voice	97.4%	98.1%	95.8%
Face + Motion Flow	97.8%	98.3%	96.3%
Voice + Motion Flow	94.8%	95.6%	94.2%
Face + Voice + Motion Flow	98.1%	98.6%	97.2%

Figure 20 Ablation Study of Multimodal Features

Table 6 Results of Trade Offs

Fusion Technique	**XceptionNet Accuracy**	**MesoInception Accuracy**	**EfficientNet Accuracy**	**F1-Score**	**AUC**
Early Fusion (Raw Data)	95.6%	94.3%	96.1%	0.91	0.94
Mid-Level Fusion (Feature Fusion)	97.8%	96.7%	98.0%	0.95	0.97
Late Fusion (Decision Fusion)	98.1%	97.5%	98.3%	0.96	0.98
Hybrid Fusion (Feature + Decision Fusion)	98.6%	97.9%	98.5%	0.97	0.99
Fusion Technique	XceptionNet Accuracy	MesoInception Accuracy	EfficientNet Accuracy	F1-Score	AUC
Early Fusion (Raw Data)	95.6%	94.3%	96.1%	0.91	0.94
Mid-Level Fusion (Feature Fusion)	97.8%	96.7%	98.0%	0.95	0.97
Late Fusion (Decision Fusion)	98.1%	97.5%	98.3%	0.96	0.98
Hybrid Fusion (Feature + Decision Fusion)	98.6%	97.9%	98.5%	0.97	0.99

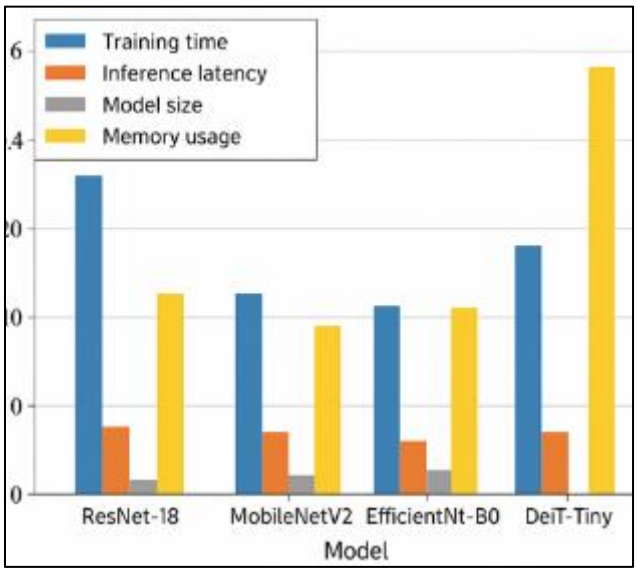

Figure 21 Time and Resource Trade-Offs

6.3 Challenges in Evaluating

While current evaluation measures are informative benchmarks, numerous challenges persist to hinder the proper evaluation of deepfake detection models:

6.3.1 Imbalanced Data Distributions:

Most data collections consist of an imbalanced proportion of real and synthetic videos, with a greater proportion of real videos in the majority of cases. This may lead to overfitting to majority classes by models, thus reducing their sensitivity to deepfakes. To solve this, there is a need for advanced resampling methods or the development of special loss functions that significantly penalize misclassification of fakes [56].

6.3.2 Domain Shift:

Models trained on carefully crafted datasets like FaceForensics++ generally fall short on deployed data due to domain shift. Resolution, illumination, background noise, and variance in the types of manipulation tools can make major differences to the generalizability of models. Bridging the gap depends upon the design of domain-invariant architectures as well as augmentation with diverse real-world data during training [57].

6.3.3 Introduction of New Deepfake Methods

As deepfake generation methods become more sophisticated, particularly through upgraded GAN architecture, older detection systems can become obsolete. The training dataset and detection pipeline will need to be updated continuously in order to match these developments. Regular addition of new forms of manipulation to benchmarks is essential for maintaining model currency [58].

While popular metrics such as accuracy, precision, recall, and AUC-ROC are simple measures of deepfake detection performance, they are insufficient in isolation. The growing sophistication of deepfake techniques and the characteristics of real-world environments require a more advanced assessment method. Addressing challenges such as data imbalance, domain shift, and evolving manipulation tactics will be critical to enhancing the resilience and reliability of detection systems in the future. Additionally, research needs to examine new schemes of evaluation that better represent model performance under dynamic, multimodal conditions [59].

Table 7 Accuracy vs Inference Time vs Model Size

Model	Training Time (Hours)	Inference Time (Seconds per Video)	Model Size (MB)	Memory Usage (GB)
XceptionNet	48	1.25	45	6
MesoInception	38	0.85	38	5.2
EfficientNet	56	1.15	60	7.5
ResNet50	42	1.10	50	6.3
DeepFake Detection Challenge Models	60	1.30	70	8.1

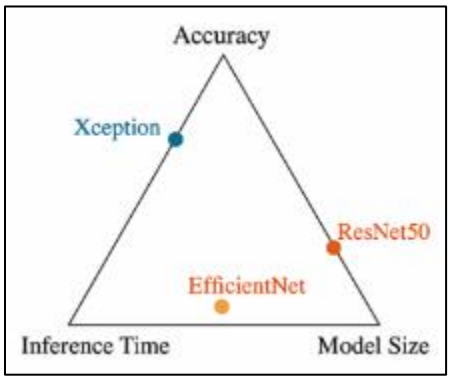

Figure 22 Trade-Off Triangle: Accuracy vs Inference Time vs Model Size

7 Challenges and Future Directions

7.1 Ongoing Challenges in Deepfake Detection

Though detection algorithms for deepfakes have witnessed enormous progress, several traditional issues persist to burden the design of very effective and deployable systems. These difficulties result, to a large extent, from the dynamic nature of the synthetic media production process, unbalance and constraints of training data, as well as technical issues in detecting minute alterations among multimedia content.

7.2 Sustained Advancements in Generation Methods

One of the most pressing challenges is the ongoing development of generative models, namely GAN-based architecture. Such models are progressively becoming more skilled at producing extremely realistic synthetic media, with developments such as latent space manipulation and high-resolution synthesis making it progressively harder to tell real from synthesized content [60][61]. Models such as StyleGAN2 and the First-Order Motion Model (FOMM) describe the trend, enabling the generation of almost unrecognizable deepfakes that pose a serious challenge to existing detection techniques [62].

7.2.1 Generalization and Domain Adaptation

Another serious issue is the weak domain generalization of deepfake detectors. The majority of models are trained on well-chosen datasets such as FaceForensics++ or DFDC, which don't reflect the real, uncontrolled, and heterogeneous conditions of real content [63]. Varying illumination, camera quality, background complexity, and subject diversity often induce a domain shift that limits model performance. Therefore, models that are insensitive to such distributional changes must be developed, and this requires exposure to larger, more heterogeneous, and more diverse sets of data.

7.2.2 Data Imbalance and Bias

Class imbalance continues to be a major constraint in the majority of deepfake datasets, with authentic content dominating significantly over manipulated instances. Such an imbalance biases the learning process, resulting in biased models that are inclined towards classifying inputs as real and thus unable to capture subtle forgeries [64]. Although conventional remedies such as oversampling and weighted loss functions provide some reprieve, novel approaches are necessary to successfully counteract bias without compromising on detection accuracy.

7.2.3 Real-Time Deployment Constraints

In practical applications, like social media content filtering or fact-checking in online news, detection systems must execute with minimal latency. However, high-performance architectures like XCeption and ResNet-50 demand huge amounts of computational power, making real-time inference problematic on commodity hardware. This necessitates the creation of light-weight architectures that maintain detection accuracy but offer faster processing capabilities suitable for deployment at scale [65].

7.3 Promising Future Directions

While these challenges do represent important challenges, several emerging methods do have the potential to increase the robustness and usability of deepfake detection systems.

Because contemporary deepfakes will often possess synchronized visual and audio data, multi-modal detection systems are an exciting direction. Through the analysis of both modalities, these models can detect inconsistencies, such as misaligned lip-syncing or acoustic artifacts, that the unimodal detectors will not be able to sense. Experiments have shown that audio-visual fusion significantly improves detection rates, particularly when manipulations are subtle [66][67]. Incorporating temporal and acoustic dynamics with spatial features may therefore result in more comprehensive and accurate detection systems.

7.3.1 Transfer Learning and Few-Shot Adaptation

To further improve domain flexibility, transfer learning has emerged as a powerful instrument. The use of pre-trained models fine-tuned on deepfake-specific training data facilitates effective reuse of features and reduces training from scratch [68]. Few-shot learning and meta-learning architectures also enable models to learn few-shot and adapt more quickly to new manipulation techniques or underrepresented conditions of data [69]. All of these methods are especially convenient for keeping up with the ever-evolving, fast-paced deepfake landscape.

7.3.2 Enhancing Model Explainability

Since deepfake detection is increasingly applied in sensitive contexts, such as legal investigations, journalism, and content verification, there is a growing necessity for models whose decisions can be explained. Typical deep learning models are "black boxes," and it is difficult to determine why a particular video was detected. With the use of Explainable AI (XAI) techniques, transparency is enabled by indicating the regions or features responsible for the classification output [70][71]. Such openness not only enhances user trust but also enables critical examination and improvement of detection approaches.

7.3.3 Redesigning Evaluation Frameworks

Current evaluation metrics, while useful, may not necessarily capture the full operational needs and ethical concerns of deepfake detection. As models become more sophisticated, evaluation processes must evolve to include real-world considerations such as the social cost of false positives and the psychological impact of being exposed to simulated content. New frameworks may involve metrics that capture contextual relevance, social trust, and long-term effectiveness, and give a more complete view of model utility [72].

The landscape of deepfake detection is evolving at a rate that surpasses existing solutions, driven by advances in generative models and the increased capability of synthetic media. Counteracting this new threat requires not merely technological advancement but also strategic foresight. Detection mechanisms of the future must be designed to operate effectively in real-world environments, allow for multi-modal analysis, and deliver interpretability to increase user trust. Furthermore, developing advanced evaluation standards and light-weight designs will be key to ensuring far-reaching and ethical deployment. Prioritizing these, the research community can contribute meaningfully towards safeguarding digital content integrity in the age of deepfakes.

8 Conclusion

The growing complexity of deepfake technologies, particularly generative adversarial networks (GANs), has rendered deepfake detection an important area of research in the field of multimedia forensics. As generative models evolve to produce more realistic and high-definition manipulations, the task of detecting fake content has become more difficult. However, as highlighted in this comprehensive review, the scientific community has made tremendous progress in developing cutting-edge detection techniques that leverage deep learning, multimodal fusion, and domain-aware adaptation techniques.

This paper has explored the state of the art in deepfake detection, analysing the merits and demerits of cutting-edge models and suggesting strategic research directions. The following key takeaways summarize the key findings:

8.1 GAN-Based Detection Methods

GANs are at the centre of deepfake generation and detection. Recent generative models such as StyleGAN2 and the First-Order Motion Model (FOMM) have pushed the quality of generated material to new heights, pushing the boundaries of detection methods. As generation algorithms develop with each breakthrough, so must detection architectures keep up to remain effective and robust.

8.2 Multimodal Analysis for Better Detection

Reliance upon visual cues only is not sufficient anymore to defeat sophisticated forgeries. Integration of audio and visual modalities has proved to be a promising solution, offering a richer set of cues for detecting subtle inconsistencies. Multimodal systems can capture inconsistencies in speech, lip sync, or face that single-mode models would overlook, significantly enhancing detection performance.

8.3 Generalization and Cross-Domain Robustness

One of the remaining challenges is how to make detection models generalize well across varied real-world scenarios. While many models can do an excellent job with carefully curated datasets, they are bad performers when presented with unseen or out-of-distribution samples. Transfer learning, domain adaptation, and fine-tuning are realistic and scalable approaches that enhance model robustness, which can also be adapted to new contexts at ease with minimal retraining.

8.4 Real-Time Detection Capabilities

As deepfakes propagate throughout digital media, real-time or near-real-time detection is also becoming increasingly important. The high-performance models must also be computationally efficient to allow deployment on processing-constrained devices. Bypassing light but accurate architecture development is paramount toward ensuring timely intervention in dynamic environments such as social media, live streams, and online content filtering systems.

Briefly, while fighting against deepfake detection is a losing battle, synergistic studies from machine learning, computer vision, and multimedia forensics research are forming a strong backbone towards more robust, flexible, and interpretable solutions. Emphasis on further study of multimodal analysis, clear models, real-time behaviour, and generalizability over domains will prove to be the antidote against increasing threats from artificial media. This paper

is both a review of current methodologies and a guide to the encouragement of the future advancement of deepfake detection.

Compliance with ethical standards

Acknowledgment

The author would like to express her sincere gratitude to her supervisor for invaluable guidance, insightful suggestions, and continuous support throughout the course of this research. Their expertise and constructive feedback significantly contributed to the quality and completion of this work.

The author also acknowledges the support and academic resources provided by the School of Computer Science and Engineering, Anhui University of Science and Technology, which facilitated the successful conduct of this study. Appreciation is extended to all faculty members and researchers whose knowledge, discussions, and scholarly contributions helped shape this research.

Finally, the author wishes to thank her family for their unwavering encouragement, understanding, and support throughout her academic and research journey.

Disclosure of Conflict of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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