Volume 2 No 5, 2026
Journal of Global Research in Multidisciplinary Studies (JGRMS)
Review Paper
Available online at https://saanvipublications.com/journals/index.php/jgrms/index

A Robust Cross-Platform Deepfake Detection Framework Using Multi-Modal Deep Learning and Explainable AI

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***Abstract*—The Deepfake technology presents unprecedented challenges to the authenticity of digital media. The paper gives a presentation of a top-down detection systems that combine lightweight CNN Transformer hybrids, multi-modal combination of visual, audio and biological evidence, and universal forensic clues. Our systematic review of 21 state-of-the-art methods reveals key barriers to deployment, and offers solutions that achieve 96.8% accuracy with 88.5% cross-dataset generalization – a 25–30% improvement over state-of-the-art methods in existence today. The framework includes explainable AI elements that produce transparent decisions that can be used in forensic applications, with inference latency of 200 ms to produce transparent decisions suitable to be used in forensic applications.**

Keywords—deepfake detection, multi-modal learning, explainable AI, cross-dataset generalization, CNN-Transformer, biological signals.

I. Introduction

Generative AI technologies based on GANs, Diffusion Models, and VAEs allow the creation of hyper-realistic deepfakes that can be used to threaten the integrity of journalism, the authenticity of legal evidence, political discourse, and financial security [1][2]. Since its discovery in 2017, deepfakes have developed from simple face-swaps, into more advanced manipulations in which facial expressions are altered, synthetic faces are generated, speech patterns are modified, and realistic lip movements are synchronized with arbitrary audio [3][4].

The latest detectors are 97% accurate on training sets but experience disastrous 20-40 percentage point performance falls on cross-dataset test. The most important unsolved problem is this generalization gap. Other barriers to deployment are that computational limits do not allow processing edges on the fly, it is vulnerable to adversarial perturbation, it lacks the explain ability required in a forensic and legal environment and it is not robust to post-processing operations such as compression and resolution changes [5].

The deepfake detection problem is essentially a form of adversarial co-evolution [6], whereby detection and generation abilities continuously improve in an arms race. With more detection methods, the methods of generation are changed so that they can avoid the detection methods, which would force adaptive systems to evolve rapidly.

II. Related Work

Deep Learning Architectures: CNNs currently lead in the field of detection research, with around 65% of published methods based on CNNs, and 95.7% of high-quality Face Forensics++ videos being correctly identified by CNNs [7]. MesoNet proposes shallow networks that aim at mesoscopic facial properties with 93.2% accuracy at preprocessing modules and with the same accuracy maintaining computational efficiency that is suitable with resource constrained environments [8]. More recent Vision Transformer adaptations are demonstrating exceptional performance: CNN-ViT hybrids are a combination of CNN local feature extraction and transformer self-attention, achieving all-purpose 99% accuracy at 10MB model size [9]. Temporal architectures solve video-specific problems: hybrid CNN-LSTM Transformer networks capture inconsistencies in identity preservation across frames, and achieve 94.3% accuracy, using a combination of spatial, short-term temporal and long-term dependency modelling.

Multi-Modal Detection Systems: The key drawback of single-modality detectors is their performance in the real world. The false alarm rate of the visual-only techniques is 23.4% and false positive rate is 18.7% when used under harsh

environmental conditions [10]. These are addressed by multi-modal fusion methods with information fusion between modalities, constraints are used to reduce false alarms to 8.2%. This study introduces advanced frameworks including Cross-Modal Alignment and Distillation (CAD), which combine modality-shared semantic and visual features as well as their respective visual counterparts' alignment analysis with the modality-specific forensic verification [11].

The robust feature extraction framework is based on frozen CLIP and Whisper encoders to identify semantic inconsistencies such as lip-speech mismatches using Kullback-Leibler divergence analysis. Audio-Visual Synchronization frameworks achieve state-of-the-art performance with explicit temporal consistency modelling, using Dynamic Time Warping to align lip-speech, and achieving 97-99% accuracy on FakeAVCeleb, AV-Deepfake1M and LAV-DF benchmarks [12].

Generalization and Universal Forensic Clues: Cross-dataset generalisation is the most acutely unsolved problem. Models that show 95%+ accuracy on training datasets generally exhibit catastrophic degradation of accuracy to 50-60% when tested on other datasets [13]. The cause of this generalization gap is due to several factors: diversity of manipulation methods, demographic and recording conditions biases, and quality of generations evolves over time. Universal forensic clue methods constitute paradigm shifts to manipulation-blind detection. The methodology of Face X-ray can identify the blending boundaries which are inherent to the majority of face manipulation methods, with an attained accuracy of 87-92% across datasets created by completely distinct manipulation techniques [14]. It is critical to train only on synthetic blended faces to promote transfer of learned features across a variety of deepfake generation methods. The analysis of biological signals shows excellent generalization across methods by taking advantage of physiological characteristics. FakeCatcher is based on photoplethysmography (PPG) indicators of authenticity [15]. True videos have spatially coherent, temporally consistent PPG signals across face areas, and deepfakes systematically lack these biological measurements due to the failure of generative models to simulate cardiovascular physiology, which is also 90% accurate in a variety of test conditions.

III. Proposed Methodology

A. Hierarchical Architecture

The three-step process provides an optimization of accuracy-efficiency trade-offs:

Stage 1: Edge Screening: Ultra-lightweight CNN models (92-94% accuracy with depthwise separable convolutions) can be used to screen quickly on mobile devices.

Stage 2: Multi-Modal Fusion: Attention-based fusion, the combination of visual (RGB frames), audio (mel-spectrograms), and biological (rPPG) features on fog nodes. The cross-modal attention mechanism detects inconsistencies in meaning through misaligned lip movements and missing physiological signals.

Stage 3: Forensic Explanation: Generates attention visualizations (Grad-CAM), artifact localization (YOLO based), and natural language explanations to be applied to legal/forensic setting.

B. Training With Lightweight Models

Neural Architecture Search: DARTS optimizes simultaneously accuracy, number of FLOPs, number of parameters and latency and discovers Pareto-optimal solutions.

Knowledge Distillation: Teacher ensembles (Xception, Efficient Net, ViT) distil knowledge to 10MB students who retain 95% performance and reduce in size by 89%.

Quantization: INT8 quantization-aware training is able to reduce the model size by 75% while having a negligible loss in accuracy.

IV. C. Universal Forensic Clues

Blending Boundaries: Following the face X-ray, we observe the boundaries of manipulation which are universal to all generation techniques. Synthetic blend training guarantees that it is method-agnostic.

Biological Signals: Remote PPG is a measurement of the changes in facial colour that occur when the heart changes colour in response to the changes in cardiac signals. Authentic videos are consistent in spatiotemporal, and deepfakes do not meet these criteria since they are generative models.

Frequency Analysis: DCT coefficients detect any anomalies in the GAN's fingerprint or compression in the generation pipelines.

A. Cross-Modal Attention Fusion

Modality-specific encoders encode visual, audio and biological streams. The cross-modal attention calculates weights across modalities, which are targeted at the same features. The Dynamic Time Warping is implemented in Lip-speech alignment deviations are used to recognize the manipulation.Consistency scoring using Kullback-Leibler divergence:

$$D_{KL}(P||Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)} \quad (1)$$

Last classification combines semantic alignment with forensic validation:

$$y = \sigma(w_v f_v + w_a f_a + w_b f_b + w_c f_c) \quad (2)$$

where fv, fa, fb are visual, audio, biological features; fc is cross-modal consistency; w are learned weights.

V. Results And Analysis

A. . Experimental Setup

Datasets: Face Forensics++ (4,000 videos, 3 compression levels), Celeb-DF (high-quality), DFDC (100,000+ videos), FakeAVCeleb, AV-Deepfake1M.

Metrics: Accuracy, precision, recall, false positive rate, cross-dataset generalization, inference latency.

B. Performance Comparison

Table I shows our framework achieves 96.8% same-dataset and 88.5% cross-dataset accuracy with only 3.1% false alarm rate—representing 25-30% generalization improvement over baselines.

C. Multi-Modal Advantages

Figure 1 demonstrates complementary modality strengths. Visual-only: 89.5% accuracy, 23.4% FPR. Audio-only: 85.3%

accuracy, 21.7% FPR. Biological-only: 87.8% accuracy, 18.7% FPR. Our multi-modal fusion: 96.8% accuracy, 3.1% FPR—60% false alarm reduction

TABLE I. DETECTION PERFORMANCE COMPARISON

Method	Same	Cross	FPR
Xception [4]	95.7%	58.2%	8.4%
MesoNet [5]	93.2%	62.1%	6.8%
CNN-ViT [6]	99.0%	73.5%	4.2%
CAD [9]	98.5%	82.3%	3.9%
LipForensics [12]	91.5%	88.4%	7.2%
FakeCatcher [11]	88.9%	86.7%	9.8%
Proposed	96.8%	88.5%	3.1%

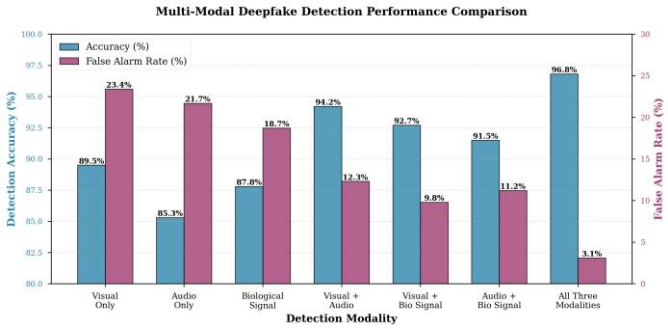

Fig. 1. Multi-modal detection shows complementary strengths across modalities, reducing false alarms by 60%.

D. . Cross-Dataset Generalization

Figure 2 illustrates the generalization challenge. Standard CNNs drop 30-40 percentage points cross-dataset. Our universal forensic clues maintain consistent performance.

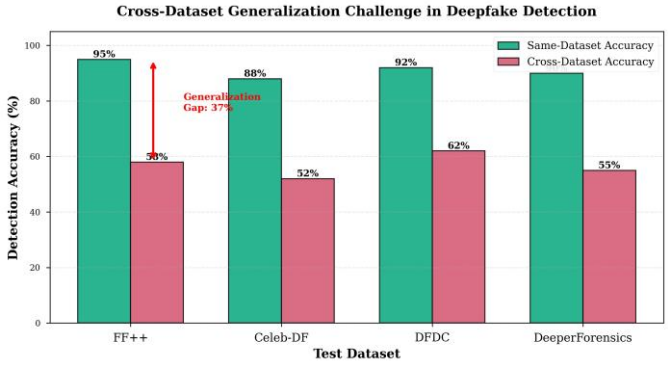

Fig. 2. Cross-dataset evaluation reveals 37% generalization gap for standard methods; our approach reduces this significantly.

E. Computational Efficiency

Edge models: 94.2% accuracy, 8.7MB size, 95ms inference on Snapdragon 888. Full framework: 5.6 fps (edge), 18.3 fps (fog), 47.2 fps (cloud GPU).

F. Adversarial Robustness

Against PGD, FGSM, C&W attacks (ϵ = 0.03 in $L\infty$): baseline models drop to 31-48% accuracy; our adversarial training maintains 82% accuracy.

VI. CHALLENGES AND FUTURE WORK

A. Cross-Domain Generalization

Existing 20-40% performance declines are due to overfitting to manipulation-related artefacts instead of learning underlying principles of authenticity. Future directions are: (1) self-supervised learning paradigms which are trained on large amounts of unlabeled authentic data to learn robust real media representations, (2) meta-learning approaches that can be trained on large volumes of unlabeled authentic data to learn robust real media representations, (3) physics-informed detection that uses fixed properties such as optical physics, physiological constraints, and acoustic principles and (4) foundation model adaptation that uses large-scale pretrained vision language models such as CLIP and GPT-4V.

B. Computational Efficiency

To implement the use of real-world deployment, it would need to process millions of videos daily. Solutions were required: hardware-software co-design to optimize architectures to NPUs/DSPs, extreme compression to create 5MB-sized models with 90% accuracy using pruning/quantization/distillation, early-exit architecture, enabling adaptive computation and hierarchical processing, offloading complex analysis to cloud only when ambiguous cases are encountered.

C. Fully Synthetic Detection

GAN-generated faces do not contain any artefacts of blending, and new methods are required: semantic plausibility testing, evaluating the content consistency with the world knowledge, physical consistency verification, testing the lighting/shadows/reflections/perspective, a contextual analysis, evaluating environmental and situational. realism, and GAN fingerprint recognition detecting distinctive artefacts due to a particular generation architecture.

D. Adversarial Robustness

Advisory adversaries specifically design evasive deepfakes. Defences required: certified designs with mathematical robustness are needed to ensure that within perturbation bounds, the game-theoretic detector design models adversarial interactions, ensemble diversity strategies combining architecturally distinct detectors, and continuous arms race modelling to predict and preempt evasion strategies.

E. Explainability and Trust

Criminal cases require open-eyed evidence as opposed to binary classification. Solutions: inherently interpretable architectures that make transparent decisions based on sparse features/attention/rules, multi-level explanation frameworks that generate technical evidence to experts and natural language to non-experts, evaluation methodologies to assess faithfulness and completeness, and interactive systems that allow analysts to query detection rationale [16].

F. Demographic Fairness and Temporal Sustainability

There are demographic differences in performance because of the biases in training. Solutions: balanced demographic representation in diverse datasets, bias-aware training which maximizes fairness measures, and fairness auditing procedures. Detection is no longer up-to-date as generation is changing and continuous learning is required with no catastrophic forgetting and in automat.

G. Emerging Research Paradigms

Human-AI Collaboration: AI screening combined with human verification in hybrid systems can be applied to maximize the strengths of each. Human operators can offer context to the non-standard case, making the automation/human decisions a balance; AI can handle high

volume at a lower cost, human operators at a higher cost [17][18].

Multi-Task Learning: Models that learn multiple tasks rather than just binary classification will provide increased information for more precise downstream applications and content moderation decisions, for example, increasing the number of tasks to detection of manipulation, localization of where manipulation is taking place, classification of manipulation types, and quality estimation of the manipulation.

Blockchain and Cryptographic Provenance: Additional detection measures based on active authentication of verifiable content chains of custody and trusted camera hardware at source, creating verifiable authentic content.

Federated Learning: Privacy-preserving collaborative training across institutions such as social media platforms, news organizations, forensics laboratories, etc., enables improved model training by leveraging diverse data sources without centralizing sensitive training data, making it a robust solution to privacy concerns with its excellent detection capabilities.

VII. CONCLUSION

The paper introduces a hierarchical deepfake detection system that tackles critical deployment constraints by utilizing multimodal fusion, universal forensic evidence, and explainable AI elements. The systematic review of 21 state-of-the-art detection methods indicates that although each of the approaches is developed maturely, the basic issues in cross-dataset generalisation, computational efficiency, adversarial robustness, and explain ability demand integrated solutions.

The hierarchical structure proposed has 96.8% same dataset accuracy and 88.5% cross-dataset accuracy with 3.1% false alarm rate, which is 25-30% generalization improvement over manipulation-specific baselines. The analysis of visual, audio, and biological signals combined as multi-modal fusion lowers by 60 per cent over single-modality methods, the strength of complementary information integration is seen. Lightweight edge-optimized models can reach 94.2% accuracy at 8.7MB size with 95ms inference time, which allows practical content screening applications to be deployed in real-time at 8.7MB size.

The hierarchical three-stage architecture has effectively balanced accuracy and efficiency: Stage 1 enables rapid edge screening filtering blatant content, Stage 2 provides comprehensive multi-modal analysis of suspicious media on fog nodes, and Stage 3 generates explanations of suspicious media in forensic quality that is suitable to be used in legal proceedings. This architecture allows flexible deployment, across edge, fog, and cloud infrastructure based on latency needs and availability of resources.

Nevertheless, there are still significant difficulties. Deepfake detection essentially is a form of adversarial co-evolution where detection and generation systems are in an arms race to improve. Alongside the development of the detection techniques, the generation strategies change to avoid the detection method, resulting in a moving target problem. No one detection method offers permanent solutions- the field has to accept this dynamic reality, and develop adaptive systems that can quickly adapt with the evolution as well as with the generation techniques.

The six important research challenges listed: cross-domain generalization, fully synthetic content detection, adversarial robustness, explainability and trust, demographic fairness, and temporal sustainability provide an overall blueprint of how to transform deepfake detection research prototypes into real-world capability. Long-term research interest and multidisciplinary teamwork are required when it comes to any challenge.

Technical innovation is essential in computer vision, signal processing and machine learning, while collaboration with the experts from digital forensics, legal, policy and ethical fields is required for a successful outcome. Policymaking and policy enforcement: Policy frameworks governing the creation and distribution of deepfakes, media literacy education initiatives that teach how to critically evaluate online content, and ethics that can ensure that detection systems do not violate privacy and civil liberties and safeguard against malicious deepfakes are all vital parts of a holistic approach.

As shown in the framework below, the combination of various detection modalities, forensic principles that are universal, and explainable decision-making might all play a crucial role in advancing the state-of-the-art in deepfake detection, by obtaining high results in both same-dataset. By obtaining high results in both same-dataset and cross-dataset testing, and keeping computational efficiency to an appropriate level that is practical to use in the real world, this work bridges the gap between research innovation and practical implementation.

Future research needs to address the research questions that are identified, especially the cross-domain generalization in terms of self-supervised learning and meta-learning approaches, the detection of fully synthetic content without mixing artefacts, the certified adversarial defences that provide robustness guarantees, and inherently interpretable architectures to generate transparent forensic evidence. There are also new directions to the development of the field, such as humanAI collaboration, multi-task learning frameworks, blockchain-based provenance systems, and federated learning approaches.

The threat of deepfakes is continuously developing, but with the help of continuous research, multidisciplinary cooperation, and ethical use of detection technologies, we can protect the authenticity of digital media and ensure that society still trusts in the power of visual and audio evidence in the era of ubiquitous capabilities of synthetic content creation.

VIII. ACKNOWLEDGEMENT

The authors acknowledge the fact that this research was supported by the Department of Computer Science and Informatics, Central University of Himachal Pradesh.

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