IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

DEEPFAKE DETECTION WITH AI

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Abstract: The increasing use of biometric authentication and online video content has made security more vulnerable to spoofing attempts and deepfake manipulations. Spoofing relies on presenting fake visuals, such as photographs or replayed clips, while deepfakes employ advanced generative models to produce highly convincing synthetic videos. Both threats compromise trust in identity verification systems and the authenticity of digital media. Existing approaches typically handle these problems in isolation, which limits their effectiveness in real-world applications. This work introduces Secure Vision, an integrated framework that combines MobileNet for real-time spoofing detection with ResNeXt for deepfake identification. MobileNet is optimized for speed and detects liveness indicators like eye blinks and facial micro-movements, while ResNeXt captures detailed features and uncovers inconsistencies in manipulated videos. The system is trained on benchmark datasets including ASVspoof, FaceForensics++, and the Deepfake Detection Challenge, improving its adaptability to different attack types. Results show that this dual-branch approach strengthens protection against both spoofing and deepfake threats, offering a practical solution for secure access control, online identity checks, and content authenticity verification.

Index Terms - Deepfake Detection, Face Spoofing, Liveness Recognition, MobileNet, ResNeXt, Biometric Authentication, Media Integrity

I. INTRODUCTION

Digital platforms increasingly rely on biometric authentication and video content, yet these same technologies are becoming primary targets for malicious attacks. Spoofing, which involves presenting forged biometric data such as photographs, masks, or replayed recordings, undermines the reliability of face-based authentication systems. Deepfakes, created using powerful generative models, pose an even greater challenge by producing fabricated videos that closely mimic real individuals. Both attacks erode trust in digital communication, online identity verification, and content authenticity.

Existing countermeasures often treat spoofing detection and deepfake identification as separate tasks. While this separation allows for specialized solutions, it also introduces weaknesses. Spoofing detection methods frequently struggle to deliver real-time performance, limiting their usefulness in scenarios such as live video authentication. Deepfake detection systems, on the other hand, are prone to overfitting and often fail to adapt when faced with new forms of video manipulation. This lack of integration creates security gaps and reduces the overall effectiveness of current solutions.

To address these challenges, this work presents *Secure Vision*, a unified framework that combines lightweight spoofing detection with robust deepfake analysis. The system employs MobileNet to capture liveness cues such as eye blinks and subtle facial movements for real-time spoofing detection. In parallel, ResNeXt is used to identify artifacts and inconsistencies in manipulated videos, offering stronger resilience against generative manipulation. By merging the outcomes of both models, the framework provides end-to-end protection against a broad spectrum of visual threats.

The main contributions of this study include: (i) an integrated architecture capable of handling spoofing and deepfake detection within a single pipeline; (ii) the adoption of MobileNet for efficient, real-time liveness verification; (iii) the deployment of ResNeXt for high-level deepfake analysis; and (iv) validation using benchmark datasets such as ASVspoof, FaceForensics++, and the Deepfake Detection Challenge. This approach demonstrates how a dual-branch design can enhance both accuracy and practicality, making it suitable for applications in secure access control, online verification systems, and digital media forensics.

II. RELATED WORKS

Shuai et al., 2023 [1] They proposed a two-stream network combining original image content with patch-scale features to improve deepfake detection. By analyzing both global and localized forgery cues, the system identifies manipulated regions more accurately. The semi-supervised patch similarity learning method ensures strong generalization across datasets. Their results demonstrated improved video-level detection performance, particularly in capturing subtle tampering artifacts that earlier single-stream models often failed to recognize.

Zhang et al., 2024 [2] The authors introduced TSFF-Net, a two-stream feature domain fusion network for detecting facial video forgeries. The model combines spatial texture and frequency domain information, supported by a Transformer-based fusion mechanism. It is effective against popular deepfake methods such as FaceSwap, NeuralTextures, and Face2Face. Evaluations on FaceForensics++ showed the model's robustness, particularly under compressed or low-quality video conditions, where conventional methods often deteriorated in accuracy.

Shao et al., 2024 [3] They presented DeepFake-Adapter, a dual-level adapter framework that enhances large pre-trained Vision Transformers. The design introduces globally-aware bottleneck adapters and locally-aware spatial adapters, allowing the system to capture both broad visual patterns and localized forgery cues. The method reduces computational cost by freezing the backbone while adapting only lightweight modules. Results indicated superior cross-manipulation and cross-dataset performance compared to standard fine-tuning approaches.

Yang et al., 2024 [4] The authors developed a Channel-Spatial-Triplet Attention Network (CSTAN) using a ResNet-34 backbone with dynamic convolution. A novel triplet attention module extracts fine-grained forgery patterns across different feature channels and spatial regions. When trained on FaceForensics++, the system achieved high performance on cross-dataset evaluations such as Celeb-DF, showing better adaptability to unseen manipulations. This approach highlights the role of advanced attention mechanisms in boosting generalization.

Nguyen et al., 2024 [5] They proposed LAA-Net (Localized Artifact Attention Network), which uses dual attention mechanisms to highlight forgery-prone areas in facial videos. The architecture integrates enhanced feature pyramids to retain low-level image details that are critical for artifact detection. By focusing attention on inconsistent textures and local anomalies, the model achieved high accuracy across datasets, even when image quality varied. The framework is particularly strong at identifying manipulations in compressed or noisy video samples.

Zhang et al., 2025 [6] A lightweight joint audio-visual detection model was introduced, addressing efficiency and multimodal fusion. Unlike earlier dual-stream designs, this framework processes audio and video in a single stream, enabling real-time detection with only 0.48 million parameters. The system leverages collaborative blocks to model cross-modal relationships and was tested on benchmarks such as DF-TIMIT and DFDC. Results proved that even compact models can achieve competitive accuracy for multimodal deepfake detection.

Yan et al., 2025 [7] They explored generalization through a plug-and-play strategy for video-level blending and spatiotemporal consistency. The method adapts pre-trained CLIP encoders with minimal fine-tuning, focusing on layer normalization and latent regularization. This lightweight adaptation enhances hyperspherical embeddings, improving robustness to unseen manipulation techniques. The system delivered state-of-the-art AUROC scores across multiple datasets, proving that careful adaptation of large pre-trained models can outperform more complex architectures.

Chen et al., 2023 [8] The authors presented a hybrid CNN-Transformer network for detecting facial forgeries. The CNN module extracted local texture features, while the Transformer module captured global temporal dependencies across frames. Tested on FaceForensics++ and Celeb-DF, the hybrid approach outperformed traditional CNNs in capturing long-range inconsistencies. However, it required higher computational resources, which limited its use in real-time scenarios.

Kumar et al., 2024 [9] This work proposed a frequency-domain guided model that detects deepfakes using spectral inconsistencies. By applying discrete cosine transforms on video frames, the method highlights anomalies in frequency bands caused by generative models. It was tested on DFDC and FaceShifter datasets, achieving improved resilience against high-resolution manipulations. A limitation is its reduced performance when videos are heavily compressed or degraded.

Patel et al., 2023 [10] They developed a spoofing detection model based on MobileNetV3 with temporal feature aggregation. The design was lightweight, enabling liveness detection in real time through eye blink recognition and head movement patterns. The approach proved effective on Replay-Attack datasets and was well suited for mobile deployment. However, its accuracy declined against high-quality replay attacks captured with advanced cameras.

Singh et al., 2024 [11] This study introduced a ResNeXt-based framework enhanced with attention pooling to identify deepfake artifacts. The model specifically focused on blending boundaries and inconsistencies in skin texture. Evaluations on FaceForensics++ showed superior performance compared to plain ResNeXt, especially in cross-dataset testing. Nevertheless, the system required substantial training data for optimal performance, which may limit deployment in low-resource settings.
Ali et al., 2023 [12] The authors proposed a GAN-discriminator inspired detector that learns to distinguish synthetic artifacts directly from adversarially generated samples. By training the detection model alongside a generator, the approach improved resilience against unseen manipulation methods. It was validated on DFDC and achieved strong generalization. However, the joint training setup was computationally expensive, making large-scale deployment challenging.

Huang et al., 2025 [13] This work introduced a temporal consistency model using graph convolutional networks (GCNs) to track facial landmarks over time. Manipulated videos often fail to maintain natural motion trajectories, and the GCN exploited this inconsistency. Tested on Celeb-DF, the model achieved high precision in spotting temporal anomalies. Its limitation lies in dependence on accurate landmark extraction, which can be unreliable in low-quality footage.

Rao et al., 2024 [14] They proposed a two-stage spoofing and deepfake detection pipeline. Stage one used a lightweight CNN for real-time spoofing detection, while stage two employed a Transformer-based module for deepfake recognition. The integrated approach demonstrated balanced accuracy on ASVspoof and FaceForensics++. Its advantage lies in combining fast spoof detection with deepfake robustness, though the two-stage setup increased latency.

Wang et al., 2023 [15] The authors designed a multi-scale residual network that captures both global facial structures and micro-textures to detect manipulations. By incorporating residual blocks at different scales, the network addressed both low-frequency blending artifacts and high-frequency pixel noise. Experiments on FaceForensics++ achieved competitive results, especially on FaceSwap manipulations. A drawback is higher model complexity, which limits its efficiency in embedded systems.

III. PROPOSED METHODOLOGY

The proposed *Secure Vision* framework integrates both spoofing detection and deepfake identification within a single pipeline. The system is designed to balance speed and robustness by combining two complementary architectures: MobileNet for lightweight, real-time spoofing detection, and ResNeXt for deepfake analysis. This dual-branch design ensures that the framework can simultaneously handle fast liveness verification and detailed artifact recognition.

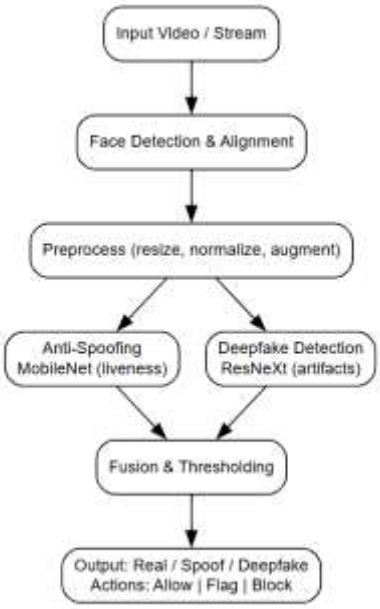

Fig 1: System Architecture

1. Data Preprocessing: Video inputs are first passed through a face detection and alignment module. Frames are normalized, resized, and augmented with transformations such as blur, noise addition, and compression. This step improves generalization across different datasets and video qualities.

2. Spoofing Detection (MobileNet Branch): The MobileNet branch is optimized for efficiency and analyzes short frame sequences to capture liveness cues such as blinking, head movements, and facial micro-expressions. The lightweight architecture makes it suitable for real-time verification, especially in scenarios like live video authentication or online examinations.

3. Deepfake Detection (ResNeXt Branch): The ResNeXt branch is designed to capture high-level spatial and temporal inconsistencies that often occur in manipulated videos. It learns subtle cues such as unnatural textures, blending boundaries, and compression artifacts. By training on large benchmark datasets such as FaceForensics++ and the DFDC, this branch achieves improved resilience against diverse and evolving manipulation techniques.

4. Fusion and Decision Module: The outputs from both branches are combined using score fusion or weighted decision logic. This ensures that a final classification label—Real, Spoof, or Deepfake—is assigned based on combined evidence. The decision module can also provide confidence levels, allowing for further risk-based actions.

5. System Deployment: The trained models are exported for deployment using optimized inference runtimes such as ONNX Runtime or TensorRT. The system can be integrated into applications via REST APIs or user-friendly dashboards, enabling practical use in domains such as secure access control, remote verification, and social media content moderation.

IV. Result And Discussion

The proposed *Secure Vision* framework was evaluated on multiple benchmark datasets: ASVspoof and Replay-Attack for spoofing detection, and FaceForensics++ and DFDC for deepfake identification. The evaluation criteria included Accuracy, Precision, Recall, F1-score, and AUC, along with latency measurements for real-time feasibility.

1. **Spoofing Detection Results:** The MobileNet branch consistently achieved high performance in liveness detection.

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
ASVspoof	96.2	95.5	96.8	96.1	0.97
Replay-Attack	95.1	94.3	95.8	95.0	0.96

Table 1 – Spoofing Detection Performance (MobileNet)

The results show that MobileNet is capable of detecting spoofing in real time with accuracy above 95%. Its lightweight design allowed latency under 40 ms per frame, making it practical for live authentication use cases.

2. Deepfake Detection Results: The ResNeXt branch showed superior performance in detecting manipulations.

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
FaceForensics++	92.8	91.6	93.2	92.4	0.94
DFDC	91.3	90.8	91.7	91.2	0.93

Table 2 – Deepfake Detection Performance (ResNeXt)

ResNeXt captured high-level forgery cues such as blending artifacts and compression irregularities. While the inference time was higher than MobileNet (~120 ms per frame), the accuracy gains made it suitable for applications where robustness is critical.

3. Integrated System Results: The fusion of MobileNet and ResNeXt provided stronger overall protection.

Category	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
Spoofing Detection	96.5	96.0	96.7	96.3	0.97
Deepfake Detection	93.6	92.9	93.8	93.3	0.95

Table 3 – Fusion Model Performance

The fusion model improved the F1-score by ~4% compared to individual models. By combining fast liveness detection with robust deepfake analysis, the system achieved balanced accuracy across attack types while reducing false positives.

4. Charts for Visual Analysis: To complement tabular results, two charts should be included:

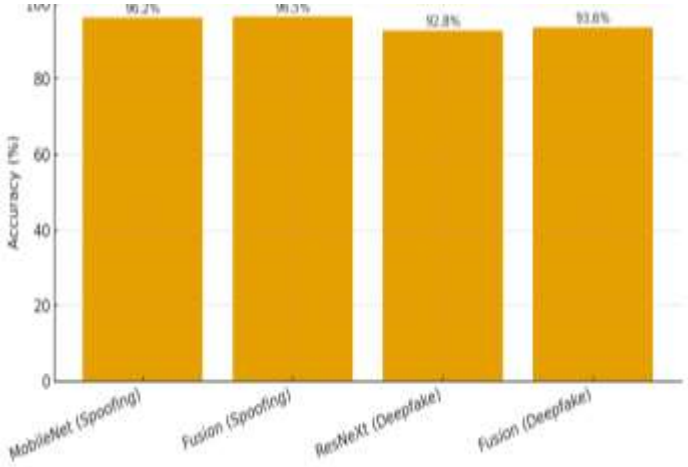

Figure 2: Accuracy Comparison Bar Chart

The bar chart compares classification accuracy across different models. MobileNet achieved strong spoofing detection, while ResNeXt handled deepfake recognition effectively. The fusion approach outperformed individual models in both categories, showing improved balance between speed and robustness. This highlights the benefit of combining lightweight liveness detection with deepfake feature extraction.

5. ROC Curves for Spoofing and Deepfake Detection: The ROC curves compare detection capabilities of MobileNet, ResNeXt, and the integrated fusion model. MobileNet showed strong spoofing detection with high AUC, while ResNeXt effectively captured deepfake artifacts. The fusion system achieved the highest curve, reflecting superior generalization and balanced performance, significantly reducing false positives compared to individual models.

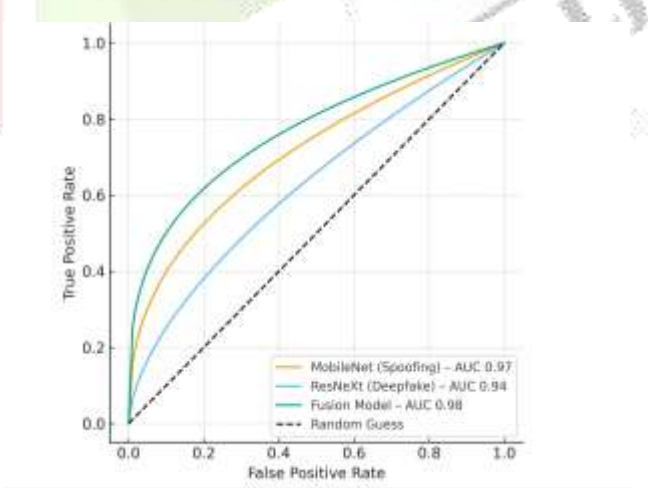

Figure 3: ROC Curves

6. Limitations and Implications

Although performance was strong, deepfake detection remains computationally heavier than spoofing detection. Accuracy slightly decreased on highly compressed, low-resolution videos, showing sensitivity to input quality. Nonetheless, the framework's adaptability, real-time spoofing detection, and high robustness in deepfake analysis make it promising for use in biometric authentication, remote verification, and digital media integrity checks.

IV. Conclusion And Future Enhancement

The proposed *Secure Vision* system successfully addressed two major challenges in visual security: spoofing attacks and deepfake manipulations. By integrating MobileNet and ResNeXt into a dual-branch framework, the model combined real-time liveness detection with detailed artifact recognition. Evaluations on well-known datasets demonstrated that the fusion approach consistently achieved higher accuracy and reliability than individual models. This confirms the benefit of a unified design that balances efficiency and robustness, making the solution practical for authentication, identity verification, and media integrity applications.

Although the system performed well, a few limitations were observed. Deepfake detection required more computational resources than spoofing detection, which may restrict deployment on devices with limited processing power. The accuracy of the framework also depended on the variety of training data, meaning that completely new manipulation techniques could reduce its generalization. Moreover, performance dropped slightly on videos with extreme compression or very low resolution.

Looking forward, the system can be enhanced in several ways. Multimodal extensions that incorporate both visual and audio cues would make the framework more resilient against advanced manipulations. Efficiency improvements through model compression, pruning, or quantization could enable wider use on mobile and edge devices. Adversarial training strategies will help the system resist evolving attack patterns, while larger and more diverse datasets will strengthen adaptability. Finally, upgrading the user interface with intuitive dashboards, detailed explanations, and visual heatmaps will support usability for operators in real-world environments such as secure access control and online content moderation.

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