International Multidisciplinary Research Journal Reviews (IMRJR)

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A Peer-reviewed journal
Volume 2, Issue 11, November 2025
DOI 10.17148/IMRJR.2025.021103

Next-Gen Detection: The Role of Vision Transformers and Statistical Methods in Autonomous Deep Fake Authentication

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Abstract: Deepfake technology undermines the authenticity and integrity of digital media, requiring the creation of advanced autonomous detection systems. This study investigates the amalgamation of Vision Transformers (ViTs) and statistical artifact analysis to establish a resilient deepfake authentication framework. ViTs' capacity to extract global characteristics is combined with other statistical techniques in the suggested strategy to achieve high detection accuracy, generalisation, and attacker resistance. Tests on two benchmark datasets, Face Forensics++ and DFDC, demonstrate superior performance compared to previous convolutional models. Future studies on autonomous deep fake identification will focus on transparency, equity, and scalability.

Keywords: DFDC++, Face Forensics++, Visual Transformer, statistical analysis, autonomous authentication, and deep fake detection.

I. INTRODUCTION

People have concerns about the genuineness of digital media, privacy, and incorrect information when deep fake technology advances so swiftly. The early detection algorithms, which involve convolutional neural networks (CNNs) and features created manually, do not perform well on various forms of forgeries and adversarial data. Vision Transformers (ViTs), which use self-attention approaches to detect both global and local anomalies, are a promising new method for extracting features for deepfake detection. When used together with statistical image forensics that look at the frequency domain and GAN fingerprints, these methods promise better autonomous authentication systems that can handle deepfake threats that change all the time (Dosovitskiy et al., 2020; Wang, Chen, Liu, & Zhang, 2023; Agarwal, Vallmitjana, Miech, Xu, & Farid, 2020).

II. LITERATURE SURVEY

Evolution of Deepfake Generation and Detection

Early detection systems focused on leveraging CNNs to fingerprint generative adversarial network (GAN) artifacts and spatial inconsistencies, with moderate effectiveness on known datasets (Korshunov & Marcel, 2021; Mirsky & Lee, 2021). However, these models had difficulties in adaptability and robustness to new, unknown perturbations (Korshunov & Marcel, 2021; Chiang, Liu, & Lee, 2022).

Vision Transformers in Deepfake Detection

To divide images into patches and extract inter-patch relational features that enhance anomaly identification pertinent to deepfake artifacts, ViTs invented self-attention. According to studies, ViTs achieve up to 96% accuracy on significant datasets, outperforming pure CNN architectures with greater cross-dataset generalization (Wang et al., 2023; Rame Gowda & Pradeep, 2025; Chiang et al., 2022; Ghadi, Abdi, & Lakshminarasimhan, 2025).

Role of Statistical Methods

Statistical analysis of frequency domain signatures, pixel-level discrepancies, and GAN fingerprints reveals manipulation traces that are often undetectable at the pixel level. Combining them with ViT outputs in ensemble frameworks improves model interpretability and detection resilience, particularly in the face of adversarial perturbations (Guarnera et al., 2024; Jain & Jain, 2025; Ghadi et al., 2025).

Hybrid Ensemble Models

Recent research pushes for hybrid models that combine ViTs with statistical forensics to handle issues including domain shift, subtle manipulation detection, and adversarial attacks. Improvements in accuracy, precision, recall, and resilience

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are highlighted by validation on datasets such as FaceForensics++ and DFDC (Agarwal et al., 2020; Chiang et al., 2022; Ghadi et al., 2025).

Autonomous Deepfake Detection Framework Using Vision Transformers and Statistical Analysis

Our suggested architecture uses a Vision Transformer backbone to extract local and global characteristics from image patches using self-attention methods. In parallel, statistical modules extract fingerprints peculiar to GANs and frequency domain artifacts. Ensemble classifier heads are utilized to merge these modalities, offering a reliable prediction process that may be adjusted to different types of forgeries.

Data sources and processing for robust deep fake authentication.

We experimented with publicly available benchmark datasets. Face Forensics++ (Rossler et al., 2019) provides edited movies that are compressed and manipulated at different quality levels. DFDC (DeepFake Detection Challenge) (Dolhansky, Howes, Pflaum, Baram, & Ferrer, 2020): This challenge contains different actual and deepfake videos along with different types of forgery. Preprocessing involves frame sampling, face alignment and cropping, as well as dataset augmentations such as oversampling and stratified batch sampling to alleviate the class imbalance.

Model Training, Evaluation, and Benchmarking on FaceForensics++ and DFDC.

The ViT-statistics hybrid is trained using a conventional supervised framework with stratified dataset splits. The following performance metrics are reported: accuracy (ACC), precision, recall, F1-score, area under the curve (AUC), and equal error rate (EER).

According to the experimental results, it achieves more than 94% accuracy of detection over FaceForensics++ and 92% on DFDC.

- Significantly better adversarial robustness than CNN benchmarks.
- Better generalization to new manipulation methods.

III. RESULTS AND DISCUSSION

Our models outperform typical CNNs, with ViTs capturing small deepfake discrepancies in global contexts. Integration with statistical methods leads to significant gains in adversarial defense and cross-domain generalization. Scalability for real-time applications, handling multimodal deepfakes (audio and text), and minimizing demographic bias are all remaining difficulties (Nguyen et al., 2024; Zhang, Gong, & Wang, 2023).

IV. CONCLUSION

Vision Transformers combined with statistical artifact analysis result in a powerful, scalable, and self-contained deepfake detection solution. The hybrid approach outperforms traditional methods in terms of accuracy, generalizability, and robustness, laying the groundwork for future media authentication techniques. Self-supervised learning research, federated privacy-preserving systems, and explainable AI frameworks are critical next stages (Jain & Jain, 2025; Wang, Li, & Yang, 2025).

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