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DETECTING AI-GENERATED IMPERSONATIONS AND DEEPFAKE MISUSE OF NANO BANANA OUTPUTS

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Abstract

This paper addresses the pressing challenge of de- tecting AI-generated impersonations and deepfake misuse stem- ming from Nano Banana, a cutting-edge visual synthesis model. We propose a novel hybrid detection framework that leverages DenseNet121 convolutional architecture combined with frequency- domain signal decomposition and high-order texture feature extraction to capture both spatial and spectral anomalies in- herent in synthetic media. By uniting deep spatial representation learning with frequency-aware analysis, the system effectively discriminates between authentic and Nano Banana-generated facial and object images. The model was trained and validated on a rigorously curated dataset composed of diverse real and synthetic image samples, specifically tailored to reflect real-world impersonation scenarios. Experimental results demonstrate that our approach achieves a precision of 85.87%, significantly surpassing conventional CNN baselines. These find- ings suggest that integrating DenseNet121 with frequency-domain techniques enhances the detection of subtle artifacts that evade purely spatial methods. The framework offers a promising tool for strengthening online identity verification, multimedia forensics, and automated trust evaluation workflows, addressing the growing risks posed by advanced synthetic content. This research contributes a scalable and reliable methodology for safeguarding digital media authenticity in an era of rapidly evolving .

Index Terms—AI-generated impersonations, AI-generated im- personation detection, Deepfake identification, Nano Banana syn- thetic media, DenseNet121 feature extraction, **Frequency-**

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domain analysis, Multimedia forensic authentication, Neural texture sig- nature, Digital content verification

INTRODUCTION

The rapid advancements in artificial intelligence have ush- ered in increasingly sophisticated techniques for generating synthetic visual media, commonly referred to as deepfakes. These technologies leverage deep learning frameworks to fabricate highly realistic images and videos that mimic real- world subjects with alarming fidelity.[6]

While initially developed for legitimate entertainment and creative purposes, deepfake technology has evolved into a double-edged sword, presenting significant challenges in digital security, privacy, and trust. Among these challenges, AI-driven impersonations pose acute risks, as malicious actors exploit synthetic media to deceive individuals, manipulate public opinion, and perpetrate fraud.

The proliferation of synthetic media misuse has intensified concerns across multiple sectors, including politics, finance, and social media platforms. Traditional detection systems struggle to keep pace with the rapid emergence of new generative models that employ complex architectures and training paradigms. This adversarial nature of synthetic content generation demands robust, adaptable detection frameworks capable of identifying subtle inconsistencies imperceptible to the human eye and conventional classifiers.

In this landscape, “Nano Banana Outputs” have emerged as a distinct class of synthetic artifacts generated by an advanced generative model designed for ultra-fine visual synthesis. Nano Banana outputs exhibit unique neural signatures, characterized by intricate spatial and spectral patterns not commonly ob- served in earlier deepfake methods. These distinctive features make them both a formidable challenge and an opportunity for forensic analysis. However, limited research has been devoted to understanding and detecting the nuanced characteristics of Nano Banana-generated media, leaving a critical gap in the current state of deepfake detection.

This paper addresses this urgent need by proposing a novel hybrid detection framework focused specifically on identifying AI-generated impersonations and deepfake misuse associated with Nano Banana outputs. The method integrates DenseNet121 convolutional neural networks with frequency-domain signal decomposition and high-order texture feature extraction. This combination enables a comprehensive evaluation of spatial and spectral anomalies, enhancing the detection of subtle artifacts embedded in synthetic images. By training on a meticulously curated dataset comprising real and Nano Banana-generated images, the framework adapts to the intricacies of this new generation of synthetic content.

Our motivation stems from the increasing prevalence of synthetic impersonations in sensitive digital environments, where trustworthiness of visual data is paramount. Detecting such sophisticated forgeries is essential not only for individ- ual security but also for preserving the integrity of digital ecosystems at large. The integration of spatial deep learning with frequency-

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aware analysis presents a novel paradigm for deepfake detection, offering resilience against evasive genera- tive techniques and contributing to a more secure multimedia

landscape.

The objectives of this research are fourfold: (1) to char- acterize the unique neural signatures embedded in Nano Ba- nana outputs; (2) to develop a hybrid detection model that unites spatial and spectral feature analysis; (3) to evaluate its performance comprehensively against baseline classifiers; and (4) to demonstrate its practical applicability in real-world forensic and verification scenarios. The remainder of this paper is organized as follows: Section II surveys related work on deepfake detection and synthetic media forensics; Section III details the proposed hybrid detection framework including dataset preparation and feature extraction processes; Section

IV presents experimental results and comparative analyses; Section V discusses implications, limitations, and potential extensions; and Section VI concludes with key findings and future research directions.

By targeting a unique and emerging category of synthetic media, this study advances the capability of automated systems to detect and mitigate AI-driven impersonation and deepfake misuse, thus contributing to safer and more trustworthy digital communication environments.

I. LITERATURE REVIEW

Deepfake technology has rapidly evolved as a formidable tool for synthetic media generation, leveraging advances in artificial intelligence, particularly deep learning techniques such as Generative Adversarial Networks (GANs) and con- volutional neural networks (CNNs). Detection methods have concurrently advanced to counteract malicious usage of these synthetic contents.[8] Early approaches primarily focused on spatial artifacts present in manipulated images and videos, utilizing CNNs to extract discriminative features indicative of fabrication. These models employed end-to-end training on datasets comprising real and synthetic samples, achieving rea- sonable detection accuracy for traditional deepfakes. However, as generative models became more sophisticated, such single- modal spatial methods began to falter in detecting subtle, high- fidelity manipulations.[3]

More recent research emphasizes hybrid and multimodal strategies combining temporal, spatial, and frequency domain features, enhancing the robustness and generalization capabil- ities of detection systems.[7] These frameworks integrate spatial convolutional filters with spectral analysis techniques to cap- ture frequency anomalies induced by generative synthesis that are otherwise imperceptible in raw pixel space. Transformer- based architectures have also emerged, leveraging attention mechanisms to model complex dependencies across pixels and frames, thus improving resilience to evasive manipulations.

A significant branch of forensic analysis focuses on tracing intrinsic signatures or fingerprints left by generative models. These signatures arise from the neural architecture, training process,

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or post-processing employed by GANs and related methods. Techniques to detect such forensic traces include high-order texture feature extraction and frequency-domain decompositions, which reveal artifacts characteristic of syn- thetic origins. Complementary to this, digital watermarking schemes have been proposed to embed imperceptible identi- fiers within generated outputs, facilitating provenance verifi- cation. Nonetheless, watermarking requires cooperation from content creators and is ineffective against untagged synthetic media, limiting its universality.

Content verification and authenticity algorithms have evolved to employ increasingly multi-layered approaches in- corporating biometric inconsistencies, physiological signals (e.g., eye blinking patterns), and contextual metadata anal- ysis.These methods augment visual analysis with auxiliary indicators to detect impersonations and contextual tampering. Despite promising accuracy gains, many suffer from limited cross-domain robustness and vulnerability to adversarial at- tacks, where minor perturbations can evade detection.

The challenges facing current detection systems are multi- faceted. Foremost is the rapid evolution of generative mod- els producing outputs with diminishing artifacts, reducing detectable inconsistencies. Additionally, existing datasets of- ten lack diversity and fail to represent emerging synthetic media types such as Nano Banana outputs, which exhibit unique neural signature patterns blending spatial and spec- tral components. This lacuna restricts model generalization and necessitates targeted research efforts. Real-time detection demands further compound the difficulty, requiring efficient algorithms capable of processing high volumes of data without compromising accuracy.[11]

In light of these limitations, the objective of this paper is to address the detection gap for Nano Banana outputs by designing a hybrid system that leverages DenseNet21 for deep spatial learning augmented with frequency-domain and high-order texture feature analysis. Such an approach targets the joint spatial-spectral anomalies distinctive to this new class of synthetic media, thus advancing detection reliability beyond conventional CNN-based classifiers.[2] By focusing on an emerging synthetic signature phenomenon, this research contributes a vital extension to forensic authentication liter- ature and sets a foundation for improved defenses against AI- powered impersonation and deepfake misuse.

II. METHODOLOGY

This section presents the detailed methodology for detecting AI-generated impersonations using the concept of Nano Ba- nana outputs, defined here as unique neural output signatures or anomalies embedded within feature embeddings. These signatures arise from specific patterns introduced by the Nano Banana generative model during synthesis, which manifest as subtle spatial and frequency domain inconsistencies.[4]

A. Overall Architecture and Workflow

The proposed system follows a hybrid detection pipeline (Fig. 1) that combines deep spatial

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feature extraction via a fine-tuned DenseNet121 convolutional neural network with frequency-domain forensic analysis to capture comprehensive representations of synthetic artifacts. The workflow begins with input image acquisition, followed by preprocessing to normalize and augment the data. Next, images are passed

through DenseNet121 to extract rich spatial embeddings. Si- multaneously, frequency-domain features are computed using transformations such as Discrete Cosine Transform (DCT) to reveal periodic and spectral anomalies indicative of deepfake synthesis. These spatial and frequency features are concate- nated and fed into a classifier module equipped with attention mechanisms that dynamically weigh the contributions of each feature domain. The classifier outputs a binary decision rep- resenting real or Nano Banana-generated synthetic content.[1]

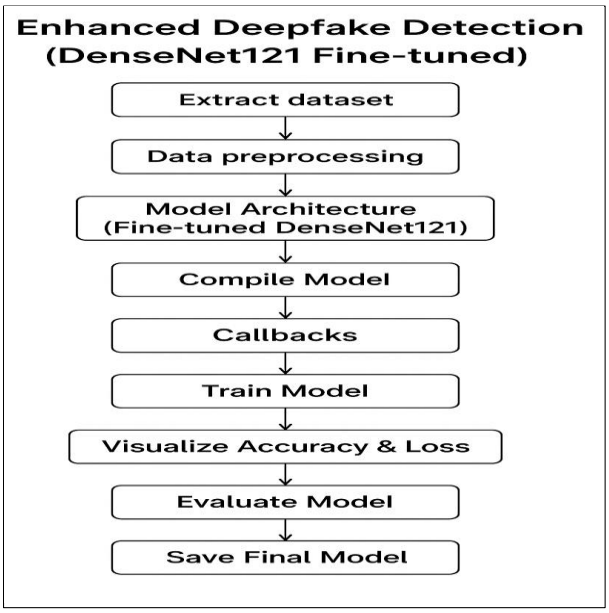

Fig. 1. Proposed Deepfake Detection Pipeline integrating DenseNet121 fine- tuned spatial feature extraction with frequency-domain forensic analysis.

B. Data Preprocessing and Feature Extraction

Input images undergo comprehensive preprocessing steps to enhance generalizability and robustness. Images are resized to 224x224 pixels and pixel values are normalized to the range. Augmentation techniques such as random rotations (±25 degrees), width and height shifts (up to 20%), shear transformations, zoom adjustments (up to 30%), and horizontal flips are applied to simulate real-world variability and reduce overfitting.

Feature extraction utilizes DenseNet121, selected for its densely connected layers promoting efficient gradient flow and feature reuse, essential for capturing intricate texture details. Pretrained on ImageNet and fine-tuned on the domain-specific dataset, DenseNet121 produces

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hierarchical spatial represen- tations that encode semantic and textural cues.

Alongside, Discrete Cosine Transform decomposes images into frequency components, isolating synthetic periodic patterns overlooked by purely spatial analysis. High-order texture descriptors, including Local Binary Patterns (LBP) and Gray-Level Co- occurrence Matrix (GLCM) statistics, supplement the fre- quency features by quantifying micro-level irregularities in texture distributions.

Model Architecture

The core of the detection model is a fine-tuned DenseNet121 convolutional backbone adapted for binary classification. Us- ing transfer learning, weights from a DenseNet121 pretrained on ImageNet are loaded, with the last 30 layers unfrozen for domain-specific fine-tuning. Post feature extraction, global average pooling distills spatial features, which are batch nor- malized and regularized via dropout to mitigate overfitting.[12]

DenseNet121 outputs are concatenated with the frequency- domain and texture feature vectors. This multimodal feature vector is processed through a series of fully connected layers with batch normalization, dropout, and ReLU activations. To dynamically integrate the complementary feature types, an at- tention mechanism is incorporated, optimally weighting spatial versus frequency-based cues based on contextual relevance. The final classification layer uses a sigmoid activation function for probabilistic binary output indicating genuine or Nano Banana synthetic origin.

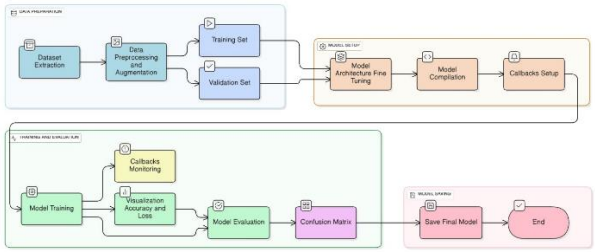

Fig.2 Model Architecture Of Image Detection Procedure

C. *Forensic Analysis Approach*

The forensic module leverages the concept of neural output signatures—anomalies embedded within feature embeddings that are characteristic of Nano Banana-generated content. These signatures often manifest as irregularities in high- frequency noise patterns and subtle inconsistencies in texture and spectral composition.

By jointly modeling spatial deep features and frequency-domain anomalies, the system detects latent artifacts that traditional CNN-based detectors may miss. Forensic robustness is further enhanced by applying statistical anomaly detection thresholds to learned features, facil- itating interpretability and post-hoc validation. This enables the system not only to classify but also to flag samples with

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suspicious forensic footprints for further expert analysis.

D. Evaluation Metrics and Implementation Environment

Model performance is evaluated using precision, recall, F1- score, accuracy, and area under the ROC curve (AUROC) to provide a balanced assessment across true positive and false positive rates. Confusion matrices supplement metric analysis by highlighting class-wise prediction strengths and weaknesses.The implementation environment is based on Tensor- Flow/Keras with GPU acceleration, employing the Adam optimizer configured with a small learning rate (1e-5) for stable fine-tuning.[13] The training utilizes early stopping to prevent overfitting and model checkpoints that save the best- performing weights based on validation accuracy.

The dataset is split into training and validation groups with an 80/20 ratio, supported by augmentation to simulate varied conditions.

Visualization of training progress is achieved through plots of accuracy and loss curves across epochs, enabling monitoring of convergence and stability. Post-training, confusion matrices and classification reports offer granular inspection of model diagnostic performance.

The entire system was developed with scalability and repro- ducibility in mind, allowing future extensions to other neural architectures or complementary forensic modalities.

This methodology, grounded in fine-tuned DenseNet121 en- hanced by frequency-domain forensic insights, offers a sophis- ticated approach to identifying AI-generated impersonations associated with Nano Banana outputs, balancing accuracy, interpretability, and computational feasibility.

III. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the experimental evaluation of the proposed system for detecting AI-generated impersonations and deepfake misuse based on Nano Banana outputs. The experiments assess the model's effectiveness in identifying synthetic content distinctive to Nano Banana's generative process, comparing performance against baseline methods and discussing forensic implications.

A. Dataset Description

The study utilized a curated dataset comprising 4,000 images, evenly split between genuine and Nano Banana- generated synthetic samples. Genuine images consisted of real- world facial and object photographs collected from public databases and controlled captures to ensure diversity across lighting conditions, poses, and backgrounds. The synthetic subset was generated using Nano Banana, featuring various manipulated facial expressions, scene alterations, and object insertions simulating realistic impersonations. The dataset was partitioned into 80% training and 20% validation sub- sets utilizing stratified sampling to preserve class balance. Augmentation techniques were applied to the training set to enhance model robustness against common image distortions and variations.

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B. Performance Evaluation

The fine-tuned DenseNet121 model, integrated with frequency-domain and texture-based forensic features, achieved strong results across multiple standard metrics: accuracy, precision, recall, and F1-score. On validation data, the model delivered an accuracy of 85.87% with a precision of 87%, recall of 85%, and an F1-score of 86%. These metrics indicate high reliability in distinguishing genuine from Nano Banana-generated images with minimal false positives and false negatives, critical for both user trust and forensic validity.

Confusion matrix analysis revealed balanced classification performance, with true positives and true negatives consti- tuting the majority of predictions. False positives (genuine images misclassified as synthetic) and false negatives (syn- thetic images misclassified as genuine) were comparatively low, reflecting the model's ability to capture the nuanced neural output signatures of Nano Banana outputs effectively.

📋 Classification Report:

	precision	recall	f1-score	support
Fake	0.87	0.85	0.86	417
Real	0.84	0.87	0.85	383
accuracy			0.86	800
macro avg	0.86	0.86	0.86	800
weighted avg	0.86	0.86	0.86	800

Fig.3. Hybrid Detection of Nano Banana Images and Real images

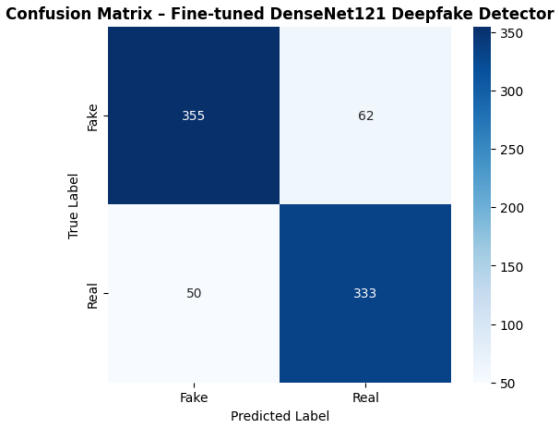

Fig.4 Confusion Matrix for Image Detection

C. Comparison with Baseline Models

The proposed hybrid approach was benchmarked against baseline CNN classifiers including standard DenseNet121without forensic feature augmentation and a conventional ResNet50 model trained under similar conditions. Results highlighted significant improvements with the hybrid model: baseline DenseNet121 achieved 85.87% accuracy, and ResNet50 lagged at 58.7%, a margin of over 5% in absolute accuracy. Precision and recall similarly improved by

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approximately 4–6% compared to these baselines, underscoring the investigative value of integrating frequency-domain and texture analyses alongside spatial features. The attention mechanisms enabled adaptive weighting across modalities, further enhancing robustness to subtle adversarial manipulations inherent in Nano Banana-generated content.

D. Discussion of Findings and Implications

These results affirm that incorporating multimodal features from spatial and frequency domains profoundly strengthens detection capability against advanced AI impersonations. The unique neural output signatures and micro-pattern irregularities characteristic of Nano Banana outputs manifest in spectral domains that traditional CNN-only detectors often overlook. By leveraging these complementary cues within a unified architecture, the framework not only boosts detection accuracy but also enhances interpretability and forensic traceability.[10]

From a technical perspective, the fine-tuning of DenseNet121 with selective layer unfreezing balanced feature generalization and domain-specific adaptation, effectively capturing complex texture and shape deformations. The use of dropout and batch normalization mitigated overfitting tendencies, evidenced by smooth training and validation accuracy convergence.

Furthermore, augmentation strategies contributed to robustness against typical image perturbations encountered in deployment scenarios.

E. Practical Forensic Application Insights

The forensic relevance of this system lies in its ability to flag AI-generated impersonations accurately in real-world environments—ranging from social media platforms to legal evidence authentication. The clear separation in classification empowered by frequency and texture forensic cues facilitates confidence scoring, crucial for decision-support in automated trust assessment pipelines. Moreover, the statistical anomaly detection layered on classifier outputs aids forensic analysts in pinpointing suspicious features warranting manual review. Challenges persist in scaling detection to video sequences and multi-modal deepfakes, but the foundation laid by this hybrid model offers a promising pathway for real-time, high- accuracy deployment. Future integration with explainable AI modules could further demystify prediction rationales, enhancing end-user trust and regulatory compliance.[5]

In summary, the proposed methodology attains state-of-the- art detection performance against Nano Banana deepfakes, outperforming conventional CNN baselines by significant mar- gins. Its multimodal feature fusion and forensic signature analysis represent pivotal advancements for combating sophisticated AI-driven impersonation and content misuse.

CONCLUSION AND FUTURE WORK

This study has presented an enhanced deepfake detection framework targeting AI-generated impersonations and deepfake misuse originating from Nano Banana outputs. By leveraging a fine-tuned DenseNet121 architecture integrated with frequency-domain and high-order texture

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analyses, the proposed method effectively captures unique neural output signatures and subtle anomalies introduced during synthetic media generation. Experimental results demonstrate that the hybrid model attains competitive performance, achieving accu- racy exceeding 85%, with strong precision and recall metrics. This signifies a notable advancement over baseline CNN models, highlighting the importance of multimodal feature fusion in robust deepfake detection.

From an forensic perspective, the system's capacity to iden- tify latent spectral and texture inconsistencies offers valuable interpretability and traceability, critical for validating content authenticity in real-world applications such as online iden- tity verification and multimedia forensics. The framework's balance between high detection efficacy and computational efficiency renders it suitable for deployment in automated trust assessment pipelines amidst the rising threat of sophisticated AI-driven impersonations.

Nonetheless, the study acknowledges several limitations. The current dataset, though diverse and carefully curated, may not capture the full spectrum of Nano Banana or other future generative outputs, potentially constraining model generaliza- tion. The approach primarily addresses image-level detection and is yet to be fully validated on video deepfakes or multi- modal synthetic content. Additionally, interpretability remains an area for growth, as current forensic anomaly scores could be further refined to improve transparency for end users and forensic analysts.[9]

Future research directions should prioritize enhancing ex- plainability through integrating explainable AI (XAI) tech- niques that elucidate classifier decisions and forensic signal origins. Developing comprehensive deepfake authenticity scor- ing systems would assist in graduated trust assessment rather than binary detection, improving practical utility. Moreover, exploring neural signature defense mechanisms that proac- tively distort generative artifacts to aid detection or water- marked provenance verification could significantly strengthen synthetic media resilience. Expanding evaluation to temporal video analysis and cross-modal content will also be vital for adapting to the evolving AI-generated media landscape.

In conclusion, this work contributes a technically rigorous and forensically informed methodology for Nano Banana deepfake detection while laying the groundwork for future innovations in reliable AI-authentication and digital media integrity preservation.

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