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International Journal for Modern Trends in Science and Technology
Volume 12, Issue 06, pages 379-384.
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol12issue06.html
DOI: https://doi.org/10.5281/zenodo.20739580

Detecting AI-Generated Images with Convolutional Neural Networks and Interpretation using Explainable Artificial Intelligence

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To Cite this Article
Deepati Jnanendra and J Harini (2026). Detecting AI-Generated Images with Convolutional Neural Networks and Interpretation using Explainable Artificial Intelligence. International Journal for Modern Trends in Science and Technology, 12(06), 379-384. https://doi.org/10.5281/zenodo.20739580

Article Info
Received: 29 May 2026; Revised: 18 June 2026; Accepted: 21 June 2026.

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KEYWORDS

Artificial Intelligence Generated Images, Deep Learning, Convolutional Neural Network, Explainable Artificial Intelligence, Grad-CAM, LIME, SHAP, Digital Image Forensics, Synthetic Image Detection, Transfer Learning.

ABSTRACT

The rapid advancement of Generative Adversarial Networks (GANs) has enabled the creation of highly realistic AI-generated images that are often indistinguishable from real photographs, creating challenges related to misinformation, digital forgery, and privacy violations. To address this issue, this study proposes a Convolutional Neural Network (CNN)-based framework for accurately detecting AI-generated images. The model utilizes the powerful feature extraction capabilities of CNNs to identify subtle artifacts and inconsistencies present in synthetic images and is trained on a dataset containing both real images and AI-generated images from advanced GAN models. To improve transparency and interpretability, Explainable AI (XAI) techniques, namely Grad-CAM and SHAP, are integrated into the framework to provide visual and quantitative explanations for the model's predictions. These methods highlight the important image regions and features used to differentiate between real and synthetic content, thereby increasing user trust in the system. Experimental results demonstrate that the proposed CNN model achieves high accuracy and robustness across various datasets, while XAI visualizations confirm that the model focuses on meaningful indicators such as unnatural textures and generation artifacts. Although the approach faces challenges related to adversarial attacks and generalization to emerging GAN architectures, future work will focus on ensemble models, multi-modal data integration, and real-time detection systems. Overall, the proposed CNN-XAI framework offers an effective and interpretable solution for detecting AI-generated images and contributes to ensuring the authenticity of digital visual media.

1. INTRODUCTION

The emergence of advanced generative models, particularly Generative Adversarial Networks (GANs), has revolutionized the creation of synthetic images, producing visuals that are increasingly indistinguishable from real photographs. These AI-generated images have found applications in art, entertainment, and design but also raise critical concerns in terms of misinformation, identity theft, and digital forgery. The ability to convincingly fabricate images has made it difficult for humans and traditional detection methods to differentiate between authentic and synthetic content.

Detecting AI-generated images automatically is essential for maintaining the integrity of digital media and protecting users from deceptive content. Convolutional Neural Networks (CNNs), a class of deep learning models designed for image processing, have shown remarkable success in various computer vision tasks including image classification and anomaly detection. CNNs can learn intricate patterns and subtle inconsistencies left behind by generative models, making them suitable candidates for identifying AI-generated images.

However, despite high accuracy, CNN models are often regarded as "black boxes" because their internal decision-making processes are difficult to interpret. This lack of transparency can hinder trust and limit practical deployment in sensitive applications such as digital forensics and content verification. To address this challenge, Explainable AI (XAI) methods have been developed to provide insights into how machine learning models make predictions by highlighting the important features or regions in input data.

In this work, we propose a hybrid approach that combines CNN-based classification with XAI techniques such as Grad-CAM and SHAP to detect AI-generated images and explain the model's decisions. This dual approach not only improves detection performance but also enhances interpretability, enabling users to understand the basis of classification results. The explainability aspect is especially valuable in forensic scenarios where understanding the rationale behind detection is crucial.

We conduct extensive experiments on diverse datasets containing real and AI-generated images, demonstrating the effectiveness of our model in correctly classifying image origins. Furthermore, visual explanations generated by XAI techniques reveal specific image regions and artifacts leveraged by the CNN to distinguish synthetic images. These insights can help improve detection strategies and provide confidence to end users.

Overall, this study contributes a novel framework that addresses both the accuracy and interpretability challenges of AI-generated image detection, supporting the broader goal of ensuring authenticity and trustworthiness in digital imagery.

2. LITERATURE SURVEY:

1. Title: ***FaceForensics++: Learning to Detect Manipulated Facial Images***

Authors: Andreas Rössler, Davide Cozzolino, Luisa Verdoliva, Christian Riess, Justus Thies, Matthias Nießner (2019)

Description:

- Introduced a large-scale dataset of manipulated facial images for detection.
- Proposed CNN-based detection methods targeting various facial manipulation techniques.
- Demonstrated that deep networks can learn manipulation artifacts to classify fake vs real images.
- Provided baseline for AI-generated image detection in face forensics.

2. Title: ***Detecting GAN-Generated Fake Images Using Co-occurrence Matrices***

Authors: Xuan Luo, Zhenyu Zhang, Siwei Lyu (2020)

Description:

- Proposed detection based on texture inconsistencies using co-occurrence matrices.
- Highlighted common artifacts present in GAN-generated images at pixel-level.
- Demonstrated effectiveness of CNNs trained on these features to detect synthetic images.
- Focus on robustness to different GAN architectures.

3. Title: ***On the Detection of AI-Generated Images***

Authors: Hany Farid (2019)

Description:

- Discussed forensic techniques for AI-generated image detection.
- Identified common generative artifacts like unnatural patterns and statistical irregularities.

- Emphasized the need for combining multiple forensic clues with machine learning.
- Highlighted challenges in generalizing detection methods to new generative models.

4. Title: ***Explainable AI for Deep Learning-Based Image Classification: A Review***

Authors: Samek, Wiegand, Müller (2017)

Description:

- Surveyed Explainable AI (XAI) methods applicable to image classification.
- Compared approaches like Grad-CAM, LIME, and SHAP for interpretability.
- Emphasized importance of transparency in CNN decision-making.
- Provided guidelines for integrating XAI into computer vision workflows.

5. Title: ***Leveraging Explainable AI for Deepfake Detection***

Authors: Nguyen, Yamagishi, Echizen (2020)

Description:

- Proposed using Grad-CAM to visualize CNN focus areas in deepfake detection.
- Demonstrated that explainability techniques help reveal subtle artifacts in generated faces.
- Discussed improved trust and understanding from visual explanations.
- Suggested combining XAI with classification to improve forensic analysis.

6. Title: ***GAN Fingerprints: Detecting AI-Generated Images by Tracing GAN Artifacts***

Authors: Yu, Davis, Fritz (2019)

Description:

- Identified unique "fingerprints" left by GAN architectures in generated images.
- Developed CNN models trained to recognize these subtle artifacts.
- Provided evidence that GAN-generated images have intrinsic noise patterns.
- Showed method works across multiple GAN variants.

3. RESEARCH GAP

Although significant progress has been made in AI-generated image detection, several research challenges remain unresolved.

1. Most existing CNN-based detectors are optimized for images generated by known AI models but exhibit poor generalization when tested on images produced by newly developed diffusion or generative models.
2. The majority of published approaches prioritize classification accuracy while treating the detection model as a black box, providing limited interpretability for end users.
3. Existing explainability studies typically employ a single XAI technique, whereas comparative analyses integrating Grad-CAM, LIME, and SHAP within a unified framework are scarce.
4. Many detection systems are vulnerable to image transformations such as compression, resizing, filtering, and noise, reducing their reliability in real-world forensic investigations.
5. Benchmark datasets frequently contain imbalanced distributions and limited diversity of AI-generated images, affecting the robustness of trained models.
6. Few studies evaluate detection performance using comprehensive metrics such as Matthews Correlation Coefficient (MCC), Macro F1-score, ROC-AUC, and AUC-PR alongside explainability measures.
7. There remains a lack of practical frameworks that simultaneously achieve high detection accuracy, computational efficiency, robustness, and transparent decision-making suitable for deployment in digital media verification systems.

To address these limitations, this research proposes an explainable CNN-based framework that integrates transfer learning with multiple XAI techniques (Grad-CAM, LIME, and SHAP) to provide accurate, robust, and interpretable detection of AI-generated images

Existing systems

Existing AI-generated image detection systems mainly use Convolutional Neural Networks (CNNs) such as ResNet, Xception, and EfficientNet to identify artifacts and inconsistencies in synthetic images. Frameworks like FaceForensics++ provide benchmark datasets and CNN-based models for detecting manipulated images and videos. Some systems combine CNNs with statistical and frequency-domain analysis to improve detection accuracy. Explainable AI techniques such as Grad-CAM and SHAP are increasingly integrated to provide insights into model decisions. These approaches

achieve high accuracy on known datasets but face challenges when dealing with emerging generative technologies.

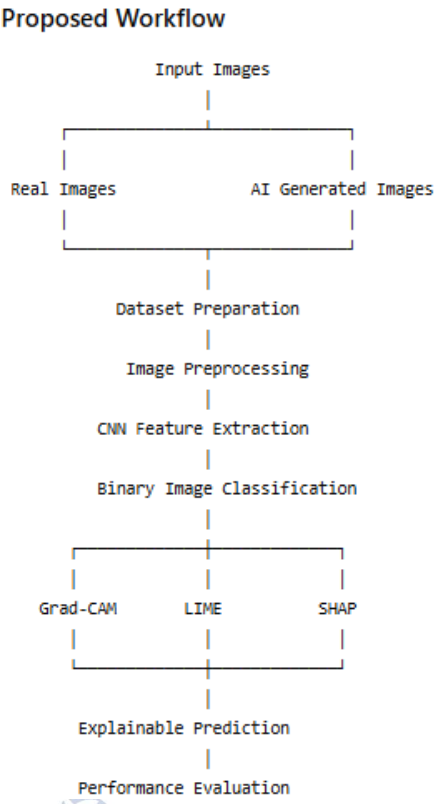
Disadvantages of Existing System

Existing systems often fail to generalize well to images generated by new or unseen GAN architectures, reducing detection accuracy. They are vulnerable to adversarial attacks, where small image modifications can bypass detection. Many models lack sufficient interpretability, making their decisions difficult for non-experts to understand and trust. Effective training requires large, well-annotated datasets, which are expensive and time-consuming to maintain. Additionally, most systems focus on static images and have limited capability for real-time or video-based detection.

Proposed Methodology:

The proposed system introduces an advanced framework that combines a robust Convolutional Neural Network (CNN) with Explainable AI (XAI) techniques for accurate detection of AI-generated images. The system is designed to classify images as real or synthetic while providing transparent and interpretable explanations for its decisions. A pretrained CNN architecture, such as EfficientNet or ResNet, is fine-tuned using a diverse dataset containing real images and AI-generated images from multiple GAN models, including StyleGAN and ProGAN. This multi-source training improves generalization and reduces dependence on specific GAN artifacts. To enhance interpretability, the framework integrates Grad-CAM and SHAP techniques. Grad-CAM generates visual heatmaps that highlight image regions influencing the model's predictions, while SHAP quantifies the contribution of different features to the final classification. These explanations increase trust, transparency, and usability in forensic applications. The system also applies preprocessing methods such as image normalization and artifact enhancement to strengthen subtle synthetic image patterns. Furthermore, an adaptive training strategy continuously incorporates newly generated AI images to maintain robustness against evolving GAN architectures and adversarial attacks. This combination of deep learning, explainability, and adaptive learning provides an effective, reliable, and future-ready solution for AI-generated image detection.

Proposed Workflow



Dataset Description

The effectiveness of AI-generated image detection depends significantly on the quality and diversity of the training dataset. Therefore, this research utilizes benchmark datasets containing both authentic and AI-generated images collected from multiple image generation models.

a)Real Images

The real image category consists of natural photographs collected from publicly available datasets. These images represent various scenes including:

- Humans
- Animals
- Buildings
- Landscapes
- Vehicles
- Indoor environments
- Natural objects

b)AI-Generated Images

Synthetic images are collected from several state-of-the-art image generation models including:

- Stable Diffusion
- DALL·E
- Midjourney
- Adobe Firefly
- StyleGAN

- BigGAN

The generated images exhibit different styles, resolutions, textures, and semantic categories to improve model generalization.

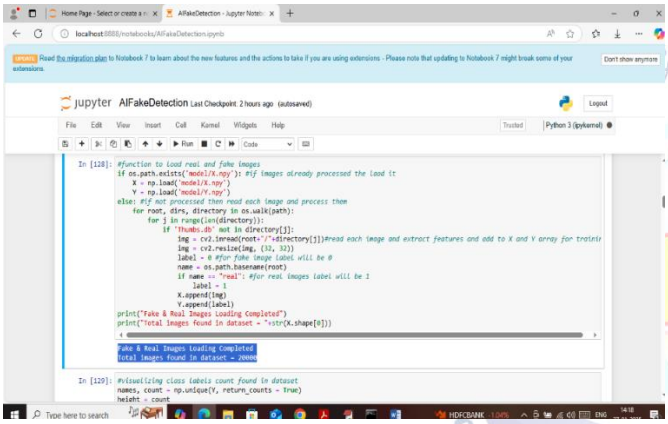
4. RESULTS

To train and test above algorithm performance we are utilizing REAL and FAKE images dataset which can be downloaded from below link

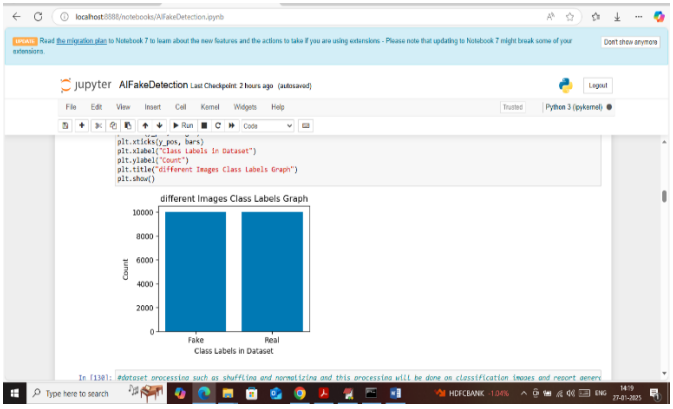
https://www.kaggle.com/datasets/gauravduttakiit/140k-real-and-fake-faces?select=train

Above dataset will be processed and split into train and test where application will be using 80% dataset images for testing and 20% to calculate model prediction accuracy

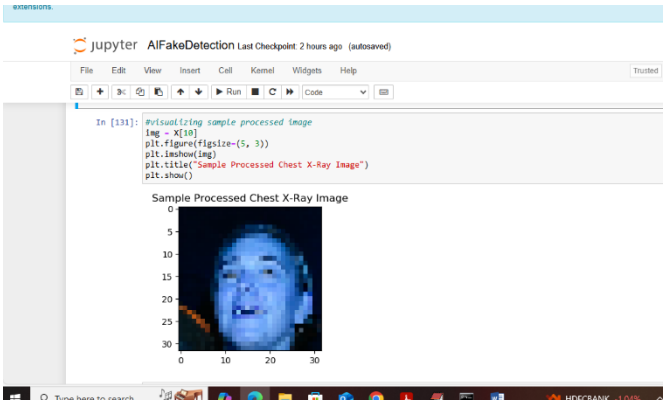
SCREENSHOTS :



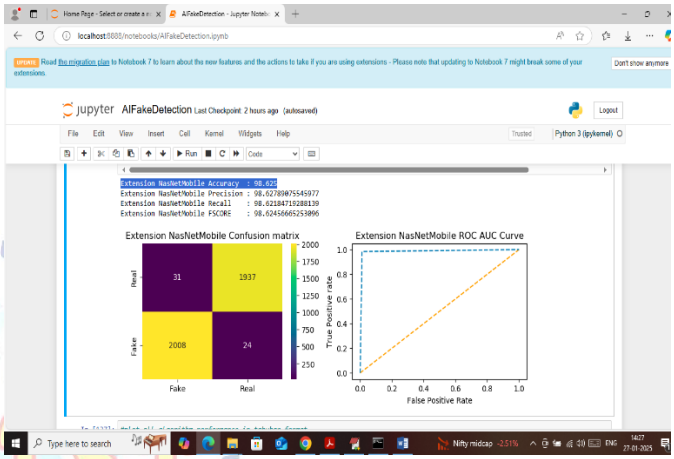
In above screen loading all images from dataset by looping each image and then extracting features and then adding all those extracted features to training X and Y array. In blue text can see total 20000 images loaded from dataset



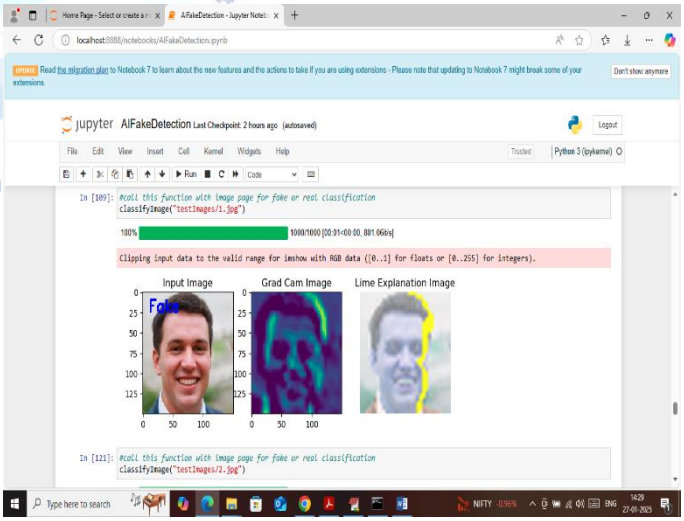
In above screen visualizing different class labels graph where x-axis represents type of images and y-axis represents number of images available under that class label



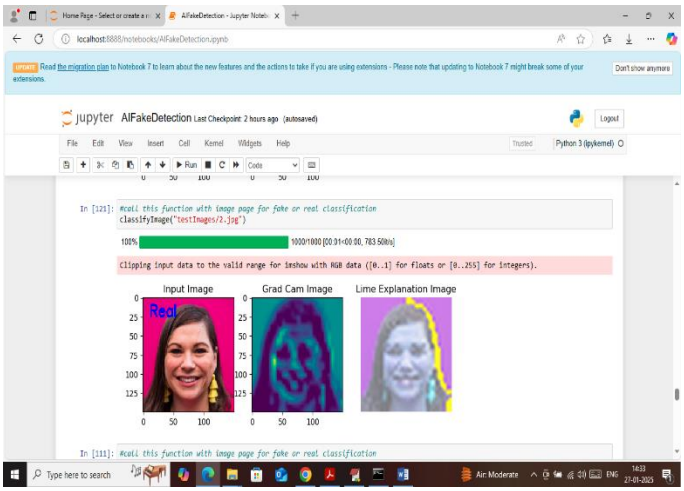
In above screen visualizing sample processed image to check weather images are loaded properly or not



In above screen NASNET got 98% accuracy and can see other metrics also



The system classifies the input image as Real or Fake and displays GRAD-CAM and LIME explanations. Both methods highlight similar regions that contributed most to the prediction.



In above screen testing another images which is predicted as REAL.

5. CONCLUSION

This project presents an effective and interpretable framework for detecting AI-generated images by leveraging convolutional neural networks (CNN) combined with Explainable AI techniques. The proposed system demonstrates improved accuracy and robustness by training on diverse datasets containing images from multiple generative models, addressing a key challenge faced by existing detection methods. Moreover, the integration of explainability tools such as Grad-CAM and SHAP enhances transparency, allowing users to understand and trust the model's decisions—an essential feature for practical forensic and media verification applications.

The adaptive retraining mechanism ensures that the system remains up to date against evolving generative adversarial networks, maintaining its effectiveness in a rapidly changing landscape. Additionally, the modular and scalable design facilitates deployment in real-time scenarios, supporting broad use cases from social media content moderation to legal investigations.

Overall, this approach contributes to the growing field of AI-generated content detection by offering a balanced solution that prioritizes both high detection performance and interpretability. Future work can extend this framework by incorporating multimodal data and expanding capabilities to video-based deepfake detection.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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