

# **AI and Normal Image Detection.**

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**Abstract:** *This project focuses on identifying whether an image is real or created by AI. As AI image-generation tools become more common, it is difficult for people to tell the difference between real photos and computer-made images. To solve this problem, we built a system that uses a Convolutional Neural Network (CNN) to learn the features of both AI-generated and normal images. The system is trained using a dataset that contains both types of images. When a user uploads an image, the system processes it and then predicts if the image is AI-generated or real. The goal of this project is to provide a simple and accurate way to check image authenticity*

**Keywords:** AI-generated images, Image authenticity, Convolutional Neural Network (CNN), Deep learning, Image classification, Fake image detection, Computer vision, Machine learning, Digital forensics

## **I. INTRODUCTION**

- Today, many tools can create images using AI, and sometimes these images look very real.
- Because of this, it is hard to know if an image is real or made by AI.
- Our project aims to solve this problem by building a system that can check any image and tell whether it is AI-generated or a normal real image.
- We use a deep learning model (CNN) that learns the differences between AI images and real photos.
- After training, the system can look at a new image and give a clear result.
- In the modern digital era, artificial intelligence has enabled the development of advanced image generation tools capable of producing highly realistic images. These images often closely resemble real photographs, making visual differentiation increasingly difficult. As a consequence, determining whether an image is authentic or artificially generated has become a significant challenge.
- This project addresses the issue by proposing an automated system designed to analyse images and accurately identify whether they are AI-generated or real. The system employs a deep learning approach based on a Convolutional Neural Network (CNN), which is trained to recognize and learn distinguishing features between synthetic images and genuine photographs.
- Once the model has been trained on a diverse dataset, it is capable of evaluating new, unseen images and providing a clear and reliable classification result. The proposed solution aims to offer an efficient and dependable method for verifying image authenticity in an era of rapidly advancing AI technologies.

### **1.1 Background**

- These technologies are capable of producing highly realistic images that are often indistinguishable from real photographs. As mentioned in the project introduction and abstract, AI-generated images are now widely used in creative industries, media, and social platforms, making visual content creation easier and faster.
- However, this progress has introduced serious challenges related to image authenticity. The increasing presence of synthetic images has made it difficult for humans to reliably identify whether an image is genuine or artificially generated. This creates risks such as misinformation, fake news, identity misuse, and digital



fraud. Traditional image verification methods are no longer sufficient because AI-generated images contain subtle patterns that are not easily detectable by the human eye.

- To address this challenge, the project proposes a deep learning-based approach using Convolutional Neural Networks (CNNs). CNNs are well-suited for image analysis because they can automatically learn spatial features, textures, and visual inconsistencies. By training the CNN model on a dataset containing both real and AI-generated images, the system can effectively classify new images and determine their authenticity with high accuracy.

### **1.2 Additional Technical Approaches:**

#### **• Lightweight CNN Models:**

The project references research that uses lightweight CNN architectures with fewer layers to reduce computational cost while maintaining high accuracy. These models are efficient and suitable for real-time image detection systems.

#### **• Transfer Learning:**

Pre-trained models can be fine-tuned on AI-generated and real image datasets. Transfer learning helps improve performance, especially when the available dataset is limited, by leveraging knowledge from large-scale image datasets.

#### **• Attention Mechanisms:**

Some referenced studies integrate attention mechanisms like Squeeze-and-Excitation (SE) blocks to focus on important image regions and channel-wise features. This helps the model detect subtle artifacts present in AI-generated images.

#### **• Texture and Frequency Analysis:**

Additional approaches include analyzing image textures and frequency-domain features. AI-generated images often exhibit unnatural frequency patterns, which can be captured using preprocessing techniques combined with deep learning models.

#### **• Hybrid Models:**

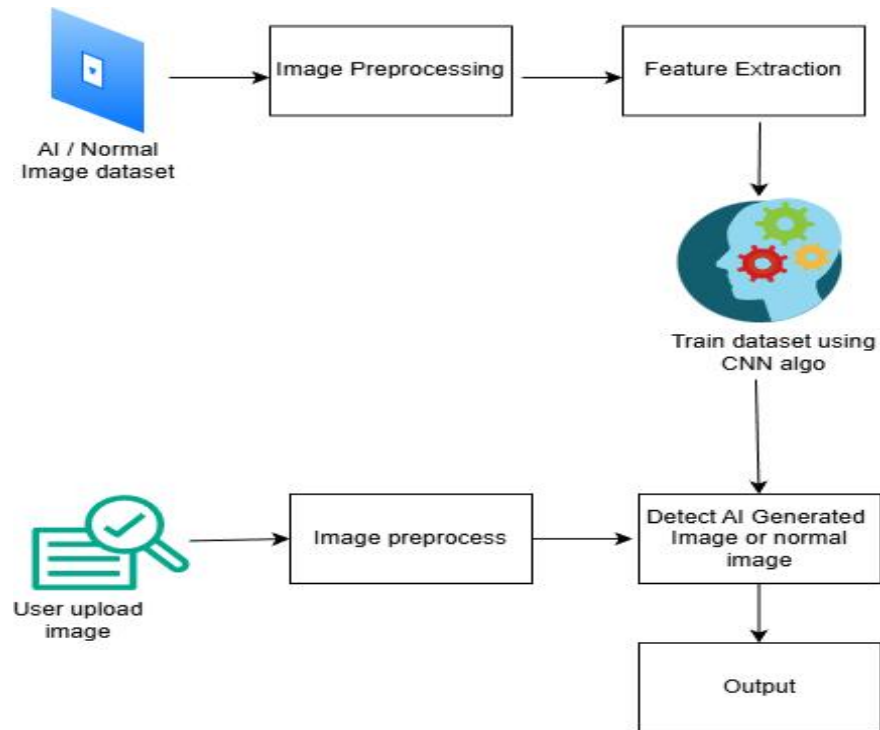
Combining CNNs with transformer-based architectures or multi-head attention networks can improve robustness and generalization, especially when detecting images generated by unseen AI models.

## **II. REASON FOR DEVELOPING THIS SYSTEM**

- The primary reason for developing the AI and Normal Image Detection system is the growing difficulty in distinguishing real images from AI-generated ones in today's digital environment. people often trust visual content without verification, which can lead to serious consequences such as misinformation, fake news propagation, and misuse of synthetic media.
- Images play a crucial role in journalism, social media, security, education, and research. The misuse of AI-generated images can damage public trust and credibility. Human judgment alone is no longer reliable for identifying synthetic content due to the high realism of modern AI-generated images.
- Therefore, this project was developed to:
  - Provide an automated and reliable solution for image authenticity verification
  - Reduce the spread of fake or misleading visual content
  - Support media professionals, researchers, students, and security agencies
  - Demonstrate the effectiveness of CNN-based deep learning models in real-world applications
- By developing this system, the project aims to enhance digital safety, promote trust in online media, and contribute to responsible use of AI technologies



## 2.1 System Architecture



### 1) AI And Normal Image Dataset.

- The system first uses a dataset containing AI-generated images and normal (real) images.
- This dataset is used to teach the system how to identify differences.

### 2) Image Pre-processing

- Images are prepared before training.
- This includes:  
Resizing  
Normalization  
Noise removal

### 3) Feature Extraction

- Important features like textures, edges, and pixel patterns are extracted.
- These features help differentiate AI images from real images.

### 4) Training Using CNN Algorithm

- A Convolutional Neural Network (CNN) is trained using the extracted features.
- The CNN learns patterns specific to AI-generated and normal images.
- The trained model is saved for later use.

## 2.2 Algorithms

### CNN (Convolutional Neural Network) :

- A CNN is a special type of neural network made for images.
- It looks for small patterns (like edges, textures) and combines them to recognize bigger features (like eyes or objects).



- Main parts: Convolution layers, Activation (ReLU), Pooling layers, Fully Connected layers, and Softmax.
- During training the CNN learns the best filters (small patterns) by comparing predictions with correct labels and adjusting weights.

**CNN Layers :**

- Input Layer

The image goes in (e.g.,  $224 \times 224 \times 3$ ).

- Convolution Layer

Small filters (kernels) slide over the image and create feature maps. Each filter finds a specific pattern (edge, texture).

- Activation (ReLU)

Adds non-linearity so the network can learn complex patterns. Changes negative values to zero (keeps positives).

- Pooling Layer

Reduces size (downsamples) while keeping important info. Commonly max-pooling (keeps the maximum value in each window).

- Repeat Conv + ReLU + Pool

Stacks of these layers extract higher-level features (from lines  $\rightarrow$  shapes  $\rightarrow$  object parts).

- Fully Connected (Dense) Layers

Flatten the features and learn combinations to make final decisions.

- Output Layer (Softmax)

Produces probabilities for each class (e.g., AI-generated vs. Real). Highest probability = predicted class.

**III. LITERATURE SURVEY**

Sr. no	Title	Author	Abstract
1	Advanced Detection of AI-Generated Images Through Vision Transformers	Darshan Lamichhane	The rapid advancement of Artificial Intelligence (AI) models such as Generative Adversarial Networks (GANs) has been a great success in the field of image synthesis and creation.
2	Detection of AI-Generated Synthetic Images with a Lightweight CNN	Adrian Lokner Ladevi	The rapid development of generative adversarial networks has significantly advanced the generation of synthetic images, presenting valuable opportunities and ethical dilemmas in their potential misuse across various industries.
3	Detecting AI-Generated Images Using a Hybrid Res Net-SE Attention Model	Abhilash Reddy Gunukula	The rapid advancements in generative artificial intelligence (AI), particularly through models like Generative Adversarial Networks (GANs) and diffusion-based architectures, have made it increasingly difficult to distinguish between real and synthetically generated images.
4	Detection of AI-Generated Images from Various Generators Using Gated Expert Convolutional Neural Network	R. AHMADFATTAH SASKORO	The rapid advancement of artificial intelligence (AI), particularly in text-to-image generative models, has led to a proliferation of synthetic images. This progress, while remarkable, raises concerns about misuse in fraudulent activities.
5	Detecting AI Generated Images Through Texture and Frequency Analysis of Patches	Maryam Yashtini	The significant improvement in AI image generation in recent years poses serious threats to social security, as AI generated misinformation may infringe upon political stability, personal privacy, and digital copy rights of artists.



#### **IV. FUTURE DIRECTIONS:**

- Can be improved with a larger and more diverse image dataset.
- Can be upgraded to detect edited or partially AI-generated images
- Can be turned into a mobile app or browser extension
- Can be used by news agencies, social media platforms, and security teams
- Can be expanded to detect deep fakes and AI-generated videos
- Accuracy can be increased by using more advanced AI models.

#### **V. OBJECTIVES**

- To create a system that can identify whether an image is AI-generated or real.
- To collect and prepare a dataset of both AI and normal images for training.
- To train a Convolutional Neural Network (CNN) to learn the differences between the two types of images.
- To allow users to upload any image and get a clear result.
- To provide fast and accurate image classification.
- To help reduce confusion and misinformation caused by AI-generated images.

#### **VI. ADVANTAGES**

- Helps tell whether an image is real or AI-generated
- Reduces misinformation and fake content
- Useful for media, security, and verification
- Easy to use — just upload an image to check
- Provides quick and reliable results
- Improves trust in digital images

#### **VII. CONCLUSION**

This project successfully identifies whether an image is real or AI-generated. By training the model on both types of images, the system learns clear differences and provides accurate results. Users can easily upload any image and get a quick and reliable prediction. This project helps reduce fake content and supports trust in digital images. With more data and improvements, the system can become even more accurate and useful in real-world applications.

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