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Synthetic Image Detection Using Convolutional Neural Networks

A.Prasmitha, Kakuturi Gayathri, Sanagari Vaishnavi, Bathuru Hemala, Bontha Sushmanth, Kanuparthi Manoja

Department of CSE-Artificial Intelligence, PBR Visvodaya Institute of Technology and Science, Kavali, Andhra Pradesh, India.

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KEYWORDS

Synthetic Image Detection, AI-Generated Images, Deep Learning, MobileNetV2, Transfer Learning, Image Classification, Digital Media Authentication

ABSTRACT

In recent years, the rapid growth of generative artificial intelligence has made it possible to produce images that closely resemble real photographs. Technologies such as GANs and diffusion models can now generate highly convincing visuals of faces, objects, and natural scenes, making it increasingly difficult to differentiate between authentic and synthetic content. This development has raised serious concerns across digital platforms, particularly in areas like social media, journalism, identity verification, and cybersecurity, where manipulated or fabricated images can lead to misinformation, fraud, and loss of public trust. To tackle this issue, this project presents a synthetic image detection system built using the MobileNetV2 architecture. The model is trained to classify images as either real or AI-generated by learning subtle visual patterns and structural inconsistencies present in synthetic media. Implemented using Python, TensorFlow, and Flask, the system allows users to upload images through a web interface and receive instant predictions along with confidence scores. By providing an efficient and scalable solution for image authenticity verification, the proposed system contributes to improving digital content reliability and security.

INTRODUCTION

CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network (CNN) is a specialized deep learning model designed to process and analyze visual data such as images. Unlike traditional machine learning algorithms that require manual feature extraction, CNNs automatically learn important features directly from raw pixel values. They achieve this through convolutional layers that apply filters across the image to detect patterns like edges, textures, shapes, and color variations. As the network goes deeper, it captures more complex and abstract features, enabling accurate image classification and recognition.

CNNs typically consist of convolutional layers, activation functions, pooling layers, and fully connected layers.

TRANSFER LEARNING

Transfer learning using MobileNetV2 involves using a pre-trained MobileNetV2 model and adapting it for synthetic image detection instead of training a network from scratch. Since MobileNetV2 is already trained on a large dataset like ImageNet, it has learned general visual features such as edges, textures, and shapes. In this project, the base layers of MobileNetV2 are reused as a feature extractor, and the final layers are modified for binary classification to identify real and AI-generated images. This approach reduces training time, requires less data, improves accuracy, and enhances the model's ability to generalize across different image types.

LITERATURE SURVEY

1FaceNet: A unified embedding for face recognition and clustering

https://ieeexplore.ieee.org/document/7298682

ABSTRACT: FaceNet is a deep learning-based system developed for efficient face recognition and verification. It transforms facial images into a compact Euclidean feature space where the distance between two points represents the similarity between faces. This approach eliminates the need for traditional classification methods and instead focuses on learning meaningful embeddings directly from image data. The model uses a convolutional neural network trained to optimize these embeddings for better accuracy.

The training process involves a triplet loss function, where the network learns to differentiate between matching and non-matching face images. By using triplets of images, the model ensures that similar faces are closer in the feature space while dissimilar ones are farther apart. FaceNet achieves high accuracy on benchmark datasets such as LFW and YouTube Faces, demonstrating its effectiveness in large-scale face recognition tasks with improved efficiency and reduced storage requirements.

2. MMGANGuard: A Robust Approach for Detecting Fake Images Generated by GANs Using Multi-Model Techniques

https://ieeexplore.ieee.org/document/10508385

ABSRACT: Recent developments in Generative Adversarial Networks (GANs) have enabled the creation of synthetic images with very high visual quality, making them almost indistinguishable from real images created by humans. These images, commonly known as deepfakes, have become a significant source of misinformation, especially through social media platforms. As technology continues to evolve rapidly, there is a growing need for reliable techniques to differentiate between real and fake images. Existing detection methods rely on image forensics tools such as error level analysis (ELA) and clone detection for identifying manipulated content. However, these methods have limitations as they require expert knowledge, involve manual processes, and lack scalability, creating the need for an efficient framework that can be used by both experts and non-experts to prevent the spread of manipulated content and ensure digital image authenticity.

To address this challenge, a multi-model ensemble framework based on transfer learning is proposed for effective fake image detection. The method, known as Multi-Model GAN Guard (MMGANGuard), combines multiple deep learning models within a single framework to capture GAN-generated image features and improve detection accuracy. It incorporates architectures such as Gram-Net, ResNet50V2, and DenseNet201 along with co- occurrence matrices using transfer learning. Experimental results show that the model performs effectively on the StyleGAN dataset, achieving high accuracy in deepfake detection. The system records over 97% accuracy, 98.5% true positive rate, 98.4% true positive rate, and 95.6% true positive rate, removing the need for manual verification and demonstrating strong potential for future research in this field.

3. GANprintR: Improved Fakes and Evaluation of the State of the Art in Face Manipulation Detection

https://ieeexplore.ieee.org/document/9133490

ABSTRACT: The availability of large-scale facial datasets, along with rapid advancements in deep

learning technologies, especially Generative Adversarial Networks (GANs), has enabled the creation of highly realistic synthetic facial images, raising serious concerns about their potential misuse. These concerns have encouraged the development of manipulation detection techniques that often outperform human capabilities in various scenarios. This study specifically focuses on the generation of complete facial images, which represents a particular form of facial manipulation. The contributions of this work are four-fold: i) it introduces a novel method to remove GAN "fingerprints" from synthetic images using autoencoders, aiming to deceive detection systems while preserving visual quality; ii) it provides a detailed review of recent advancements in facial manipulation detection;
iii) it conducts a comprehensive experimental evaluation of this manipulation type using state-of-the-art detection methods, including deep networks, steganalysis, and local artifact analysis, highlighting the challenges in real-world conditions; and iv) it presents a new public dataset called iFakeFaceDB, created using the proposed GAN fingerprint removal technique (GANprintR) applied to highly realistic synthetic images.
The experimental results demonstrate that further improvements are necessary to develop more robust and reliable facial manipulation detection systems that can handle unseen scenarios and advanced spoofing techniques, such as those introduced in this work.

4. Deepfake Image Verification using DCNN with MobileNetV2

https://ieeexplore.ieee.org/document/10866044

ABSTRACT: In today's modern era, numerous activities occur around us that we often accept without questioning their origin or authenticity. Many of these are driven by communication platforms that utilize Artificial Intelligence to generate content that appears to be created by humans, but is actually produced through algorithms, commonly known as deepfakes. While this technology has provided benefits in areas such as entertainment, storytelling, and digital art, it also raises serious concerns regarding misuse. Through our study, we observed that several research works have proposed systems capable of detecting deepfake images by identifying modifications within visual content. These advancements have contributed valuable insights toward improving the authenticity and reliability of digital media. To achieve this goal, techniques from Deep Learning and Computer Vision are widely applied. Models such as DCNNs and MobileNetV2 are highly effective in feature extraction, object detection, and classification, making them suitable for deepfake detection tasks. As technology continues to evolve, it introduces new challenges that require adaptive and intelligent solutions. Therefore, the proposed system is designed with self-learning capabilities to effectively handle various deepfake techniques. It aims to serve as a foundation for developing more advanced detection systems that ensure the security of visual media. The objective is to build a flexible and user-friendly system that operates efficiently across different environments and integrates well with other applications, ultimately contributing to data protection and a safer digital ecosystem.

5. Detecting the Undetectable: Deep Learning Model for Identification of Fake Images

https://ieeexplore.ieee.org/document/11039386

ABSTRACT: Deep learning (DL) has significantly transformed the field of image processing by enabling the creation of synthetic images, commonly referred to as deepfakes. Due to rapid progress in generative models, distinguishing between real and fake images has become increasingly challenging. This study investigates the effectiveness of deep learning-based Convolutional Neural Networks (CNNs) in detecting deepfake images. In this work, three CNN architectures—VGG16, VGG19, and InceptionV3— are utilized to evaluate their performance in identifying fake images. The main objective is to improve detection accuracy by leveraging the strong feature extraction capabilities of these models and enhancing their performance through fine-tuning techniques. Experimental results show that VGG16 achieves the highest accuracy of 94% in detecting fake images.
Furthermore, this research compares the performance of VGG16, VGG19, and InceptionV3 to analyze their effectiveness in deepfake detection. The primary goal is to enhance classification accuracy by utilizing advanced feature extraction methods and optimizing model parameters. The results indicate that among the evaluated models, VGG16 performs the best with an accuracy of 94%, demonstrating its effectiveness in identifying synthetic images.

OBJECTIVE

The main objective of this project is to develop a deep learning-based system capable of identifying whether an image is real or AI- generated. The system focuses on providing an efficient and practical solution for digital media authentication using the MobileNetV2 architecture. The main objectives are:

- Designing a robust binary classification model for real and synthetic images.
- Implementing transfer learning using MobileNetV2 for enhancing better detection accuracy.
- Developing a web-based interface for real-time image upload and prediction.
- Ensuring strong generalization across multiple image categories.

NEED FOR STUDY

The rapid advancement of generative AI technologies has made it possible to create highly realistic synthetic images that are often indistinguishable from real photographs. These AI-generated images are increasingly being used across social media platforms, online marketplaces, digital journalism, and identity verification systems. While such technology has positive applications, it also poses significant risks when misused for creating fake profiles, spreading misinformation, or committing identity fraud. As synthetic media becomes more accessible, the challenge of verifying digital content authenticity continues to grow.

Traditional methods of image verification rely heavily on manual inspection, which is time-consuming, subjective, and often unreliable. Human observers may fail to detect subtle artifacts introduced by advanced generative models. Therefore, there is a strong need for an automated and scalable detection system that can accurately differentiate between real and AI-generated images. Developing a deep learning-based solution helps address this challenge by providing fast, consistent, and reliable authenticity verification, ultimately strengthening digital trust and security.

EXISTING SYSTEM

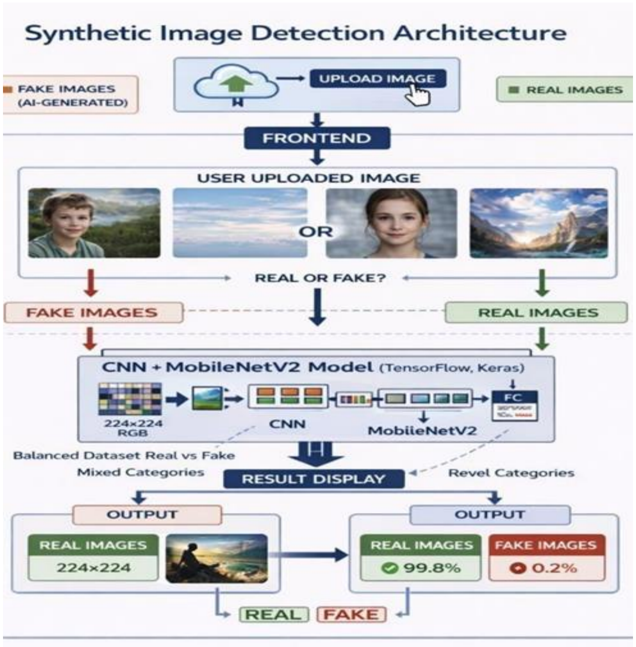
Existing synthetic image detection approaches, as discussed in the base paper, primarily focused on detecting GAN-generated face images by analyzing statistical inconsistencies in image data. The proposed method in that work utilized spatial and cross-band co-occurrence matrices extracted from color channels (R, G, B) and fed them into a Convolutional Neural Network for classification. The key idea was that although GANs can generate visually realistic images, maintaining consistent relationships among color channels is more challenging. By capturing these spectral inconsistencies, the system was able to distinguish real images from GAN-generated ones with high accuracy.

The model architecture in the base paper consisted of multiple convolutional layers trained specifically on co-occurrence features rather than raw image pixels. Experimental results demonstrated strong detection performance and improved robustness against post-processing operations such as resizing, filtering, rotation, and JPEG compression. However, the approach mainly concentrated on synthetic face images generated by specific GAN architectures, making it more specialized rather than fully generalized across diverse image categories.

Disadvantages:

- Limited to specific GAN face datasets
- Depends on complex feature extraction methods
- Performance drops under heavy compression
- Requires retraining for new AI models
- Not easily scalable to multiple image categories
- Sensitive to image transformations
- Less suitable for lightweight real-time deployment

SYSTEM ARCHITECTURE



MODULES

- Image Acquisition Module
- Image Preprocessing Module
- Data Augmentation Module
- Dataset Splitting Module
- Feature Learning Module
- Classification Module
- Output Module

1. Image Acquisition Module

The Image Acquisition Module is responsible for collecting and organizing the dataset used for training and evaluation. The system uses multiple datasets to ensure diversity and better generalization. Real images are taken from FFHQ and CIFAR-10, while synthetic images are collected from SFHQ, StyleGAN-generated datasets, SuSy dataset and Synthetic Image datasets. These datasets include various images like:

- Human Faces
- Animals
- Objects
- Places

2. Image Preprocessing Module

The Image Preprocessing Module prepares the collected images before they are passed to the deep learning model. All images are resized to 224×224 pixels to match the input requirement of MobileNetV2. Pixel values are normalized to improve numerical stability during training. Since the dataset contains images from multiple sources with varying resolutions and lighting conditions, preprocessing ensures uniformity and consistency. This step reduces noise and enhances feature learning efficiency, enabling the model to focus on meaningful visual patterns rather than irrelevant variations.

3. Dataset Augmentation Module

The Data Augmentation Module increases the variability of the training dataset by applying transformations such as rotation, horizontal flipping, zooming, and shifting. Even though the dataset size is already large, augmentation helps simulate real-world variations and prevents overfitting. Because the system is designed to detect synthetic images from different categories and environments, augmentation improves the model's ability to generalize to unseen images captured under different lighting conditions, backgrounds, or resolutions.

4. Dataset Splitting Module

The Dataset Splitting Module divides the collected dataset into training, validation, and testing subsets. The training set contains 60K images, which are used to train the MobileNetV2 model. The validation set consists of 10K images and is used to monitor model performance during training and tune hyperparameters. The testing set also contains 10K images and is used to evaluate final model performance on unseen data. Maintaining a balanced distribution of real and fake images across all splits ensures unbiased learning and accurate performance measurement. Proper dataset splitting helps prevent data leakage and ensures reliable evaluation of the system

5. Feature Learning Module

The Feature Learning Module forms the core of the system and utilizes the MobileNetV2 architecture for deep feature extraction. The model automatically learns hierarchical representations from input images, including texture inconsistencies, structural irregularities, and subtle artifacts introduced by generative models. Because the dataset includes diverse image categories and synthetic sources, the model learns generalized discriminative features rather than dataset-specific patterns. Transfer learning further enhances feature extraction by leveraging pretrained weights from large-scale datasets.

6. Classification Module

The Classification Module takes the features extracted by MobileNetV2 and passes them through fully connected layers to perform binary classification. A sigmoid activation function produces a probability score indicating whether the image is real or fake. Since the model is trained on a balanced dataset with equal representation of both classes, it minimizes bias and improves classification reliability across different image types.

7. Output Module

The Output Module presents the final prediction result to the user through the web interface. After classification, the system displays whether the uploaded image is Real or Fake along with the corresponding confidence score. The prediction is based on the model's analysis of visual characteristics such as texture consistency, edge artifacts, structural irregularities, and lighting variations that are commonly observed in AI-generated images. By highlighting these learned feature patterns internally and providing a clear confidence percentage, the system ensures transparent and reliable real-time image authenticity verification.

PROPOSED SYSTEM

The proposed system introduces a deep learning–based framework for detecting synthetic images using the MobileNetV2 architecture. Unlike traditional methods that depend on manually extracted statistical features, this system leverages transfer learning to automatically learn meaningful visual representations directly from image data. The model is trained on a large and balanced dataset consisting of real images from FFHQ and CIFAR-10, and AI-generated images from SFHQ, StyleGAN, and CIFAKE10. By incorporating diverse datasets, the system improves its ability to generalize across multiple image categories such as faces, objects, animals, and natural scenes. The system follows a structured pipeline that includes image acquisition, preprocessing, feature extraction, and binary classification. During training, the model learns to identify subtle patterns such as texture inconsistencies, edge artifacts, lighting variations, and structural distortions that are commonly introduced by generative models. The trained model is integrated into a Flask-based web application, allowing users to upload images and receive real-time predictions along with confidence scores. The proposed approach provides a scalable, efficient, and practical solution for digital media authentication and synthetic content detection.

Advantages:

• High detection accuracy due to deep learning- based feature extraction.

• Efficient and lightweight architecture using MobileNetV2.

• Balanced and diverse datasets improves generalization across various categories.

• Suitable for real-time detection through web deployment.

• Scalable system that can adapt to new synthetic image sources.

• Reduced computational complexity when compared to traditional forensics.

Hardware Requirements

• Processor : Intel Core i5 or higher

• RAM : 8 GB minimum

• Storage : Minimum 20 GB free disk space

• Input Device : Image dataset / Web image upload

• Output Device:Monitor/Display Software Requirements:

• Operating System : Windows / Linux

• Programming Language: Python

• IDE : VS Code / Jupyter Notebook

• Deep Learning Frameworks:TensorFlow, Keras

• Model Used : MobileNetV2(Transfer Learning)

• Backend Framework : Flask

• Datasets Used : FFHQ, SFHQ , StyleGAN , CIFAKE -10, SuSy

TECHNIQUES USED IN THE PROJECT

The proposed system is implemented using deep learning techniques based on transfer learning with MobileNetV2. The model training pipeline follows a structured approach that includes dataset loading, Preprocessing, feature extraction and Optimization techniques.

1. Transfer Learning using MobileNetV2:

The system utilizes a pre-trained MobileNetV2 model with ImageNet weights as the feature extraction backbone. The top classification layer of MobileNetV2 is removed and the based model is frozen to remain previously learned visual features. This approach reduces training time and improves generalization by leveraging large-scale pre- trained knowledge.

2. Global Average Pooling:

Instead of flattening feature maps, the model uses a GlobalAveragePooling2D layer. This reduces the number of trainable parameters, prevents overfitting, and maintains spatial feature importance

3. Regularization using Dropout:

A Dropout layer with a rate of 0.4 is added before the final classification layer. This randomly deactivates neurons during training, reducing overfitting and improving model robustness.

4. Binary Classification with Sigmoid Activation:

The final layer uses a single neuron with a sigmoid activation function to perform binary classification. The model outputs a probability score indicating whether the image is real or AI-generated.

5. Optimized Training Strategy:

The model is compiled using the Adam optimizer with a low learning rate (1e-4) to ensure stable fine-tuning.

Binary Crossentropy loss with label smoothing (0.05) is used to reduce overconfidence and improve generalization. Accuracy is used as the evaluation metric.

6. Early Stopping and Model Checkpointing:

EarlyStopping is implemented to monitor validation loss and prevent overfitting by restoring the best weights. ModelCheckpoint saves the best-performing model based on validation accuracy, ensuring optimal performance during deployment.

7. Grad-CAM (Explainable AI Technique):

Grad-CAM (Gradient-weighted Class Activation Mapping) is an explainable AI technique used to visualize how a convolutional neural network (CNN) makes its predictions. It helps identify which regions of an input image are most important for the model's decision.

EVALUATION METRICS OVERVIEW

1. Confusion Matrix

A confusion matrix summarizes prediction results by comparing actual vs predicted classes.

TP → correctly predicted positive TN → correctly predicted negative

FP → predicted positive but actually negative FN → predicted negative but actually positive

2. Precision

Measures how many predicted positives are truly positive.

Precision = TP/(TP+FP)

High precision → fewer false positives

3. Recall (Sensitivity / True Positive Rate) Measures how many actual positives are correctly detected.

Recall =TP/(TP+FN)

F1 Score

Harmonic mean of precision and recall (balances both).

F1 Score = 2 x (Precision x Recall)/ (Precision +Recall)

ROC Curve :

ROC Curve is a graphical representation that shows the performance of a classification model by plotting True Positive Rate (TPR) against False Positive Rate (FPR) at different thresholds.

TPR = TP / (TP +FN)(Y-AXIS) FPR = FP / (FP + TN)(X-AXIS)

AUC (Area Under ROC Curve)

Measures the area under the ROC curve.

$$AUC = \int_{0}^{1} \boldsymbol{TPR}(\boldsymbol{FPR})\, \boldsymbol{d}(\boldsymbol{FPR})$$

Interpretation

- 1.0 → perfect classifier
- 0.5 → random guessing
- <0.5 → poor model

CONCLUSION

In this project, a deep learning-based Synthetic Image Detection system was developed using transfer learning with the MobileNetV2 architecture. The model was trained on a large and balanced dataset containing real and AI-generated images from multiple sources, enabling it to generalize across different image categories. By leveraging pretrained weights and fine-tuning a lightweight classification head, the system effectively learned to identify subtle visual artifacts such as texture inconsistencies, edge irregularities, and lighting variations commonly introduced by generative models.

The integration of preprocessing, data augmentation, regularization techniques, and optimized training strategies resulted in stable and reliable model performance. The system was successfully deployed using a web-based interface, allowing real-time image upload and authenticity verification with confidence scores. Overall, the proposed approach demonstrates that transfer learning with MobileNetV2 provides an efficient, scalable, and practical solution for detecting AI-generated images and enhancing digital media authenticity.

FUTURE ENHANCEMENT

Although the proposed system demonstrates effective performance in detecting AI-generated images, there is scope for further improvement and expansion. As generative models continue to evolve rapidly, detection systems must also adapt to High recall → fewer false negatives remain reliable and robust. Enhancing the model's capability to handle more complex scenarios and integrating advanced deployment strategies can significantly improve its real-world applicability and scalability. Future enhancements include:

- Extending the model to multi-class classification to identify specific generative sources.
- Expanding the dataset with additional real- world and emerging synthetic image sources.
- Improving robustness against adversarial attacks and heavy image compression.
- Developing a mobile application for real- time image authentication.

Conflict of interest statement

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

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