Deepfake Detection Using ML

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***Abstract*—The rapid development in generative artificial intelligence has dramatically improved the realism and availability of synthetic media, raising serious concerns about misinformation, identity theft, and the authenticity of digital content. Traditional deep learning-based detection methods mainly rely on spatial features extracted from images, and often neglect artifacts in the frequency domain [3], [4].**

In this work, we propose a hybrid deepfake detection framework by combining the convolutional neural network (CNN)-based spatial feature extraction with the frequency domain using the Fast Fourier Transform (FFT). The proposed system is based on an EfficientNet-B0 architecture pre-trained on ImageNet and fine-tuned for the binary classification of real and AI-generated images [5]. In parallel, frequency-domain features are analyzed in order to catch high-frequency inconsistencies often seen in synthetic media [6].

The system incorporates Grad-CAM based visualization to provide better interpretability by identifying the regions of an image that influence the model's prediction [7]. We also evaluate robustness under real-world distortions such as compression, noise, and blur.

The system is deployed on a FastAPI-based backend, enabling inference on images and video frames in real-time. Experimental results show that the hybrid approach can improve the detection reliability and generalization ability in comparison with the individual CNN models, and provide explainable information for the model decision.

Keywords— Deepfake Detection, EfficientNet, Frequency Domain Analysis, FFT, Explainable AI, Computer Vision, Image Forensics

I.INTRODUCTION

The proliferation of deepfake technology, driven by advances in generative models such as Generative Adversarial Networks (GANs) and diffusion-based architectures, has enabled the creation of highly realistic synthetic media [2], [4]. These developments pose significant challenges to the integrity of digital information, particularly in domains such as journalism, social media, and digital forensics.

Deepfake images can manipulate facial features, generate entirely synthetic identities, or alter contextual information in a visually convincing manner. As these techniques evolve, traditional detection approaches based solely on visual inspection or handcrafted features become insufficient [3].

Recent studies have concentrated on deep learning methodologies, especially convolutional neural networks (CNNs), which can autonomously acquire discriminative spatial features from image datasets. EfficientNet and other architectures have shown that they can do a great job at classifying images because they are optimized for scaling and computational efficiency [5]. But CNN-based methods often act like black boxes and might not be able to pick up on small artifacts that are added during image synthesis.

One thing to remember about media forensics is that synthetic images often have strange patterns in the frequency domain, like high-frequency patterns that aren't normal and spectral distributions that aren't normal [6]. Frequency-domain analysis, employing methods such as Fast Fourier Transform (FFT), yields supplementary information that may not be fully represented in the spatial domain.

Because of these problems, this paper suggests a hybrid deepfake detection system that combines frequency-domain analysis with CNNs for learning spatial features. Combining these two areas makes detection more accurate and more resistant to changes in image quality.

To fix the problem of deep learning models not being clear, an explainability module based on Gradient-weighted Class Activation Mapping (Grad-CAM) is also added [7]. This lets you see the areas that affect classification decisions, which is especially useful for journalism and forensic analysis.

This work's main contributions are:
• A hybrid deepfake detection framework that uses CNN-based spatial analysis and FFT-based frequency-domain features • Combining Grad-CAM with explainable AI for deepfake detection
• Testing how well it works with real-world image problems like noise, blur, and compression
• Use of FastAPI to set up a real-time detection system for real-world uses

II. METHODOLOGY

The next section explains the design and implementation of the proposed deepfake detection system hybrid. It uses a curated dataset of real images, tagged as "Real", and AI-generated images, tagged as "Fake". The system is a binary classifier and is developed to support real-time image and video-based detection.

2.1 Dataset Description

In this work we used a dataset of more than 18,000 labeled images classified into two classes:

- Real images
- Fake (ai-generated) images

For a proper evaluation of the model the dataset is split into 3 subsets:

- Training set (80%)
- Validation set (10%)
- Test set (10%)

There are two operation workflows defined: •:

- Training Pipeline: The model is trained on labeled data to learn patterns that distinguish real images from synthetic ones..
- Inference Workflow: Users upload images or videos and the model that has been trained predicts in real time.

This two-pronged workflow allows for both good model development and practical deployment.

2.2 Preprocessing

Preprocessing is an important step to guarantee consistency and improve model performance.

2.2.1 Image Resize and Normalize

The input images are all resized to 224 × 224 pixels to satisfy the input requirements of the EfficientNet-B0 model. Then we normalize by ImageNet mean and std for training stability.

2.2.2 Data Cleaning Process

The dataset is clean from invalid/corrupted image files that can not be read to ensure smooth training processes.

2.2.3 Splitting the dataset

To avoid bias in performance evaluation, the dataset is partitioned into training, validation, and testing sets with a ratio of 80:10:10.

2.2.4 Data Augmentation

To improve the generalization ability and reduce the overfitting, the following augmentation techniques are used:

- Flip horizontally
- Rotation - random
- Brightness and contrast control
- Cropping at random

2.2.5 Feature Representation

The proposed method is data driven and does not require manual feature engineering. During training the convolutional neural network automatically performs feature extraction. So the model learns complex spatial patterns from raw pixel data.

2.3 Deep Learning Model

The main model used is EfficientNet-B0, a convolutional neural network architecture that is well known for its balance between accuracy and computational efficiency. The model is initialized with the ImageNet pre-trained weights and fine-tuned for binary classification.

2.3.1 Model Training

The model is trained to classify images as real or AI-generated by learning discriminative spatial features.
The customized classification head includes:

- Fully connected layers
- Batch normalisation
- Dropout layers for regularization

2.3.2 Prediction of the Model

The model, after being trained, assigns a probability score to each input image, which represents the likelihood of that image being generated by AI. The final class label is determined by a threshold.

2.3.3 Performance Measures

The model performance is evaluated in terms of the following metrics:
Accuracy: The overall correctness of predictions

Precision: ability to minimize false positives
Recall (Sensitivity): Ability to correctly identify fake images
F1-Score: F1-Score balances the precision and recall

2.3.4 Analysis of the confusion matrix

To analyze the classification results, a confusion matrix is used to find out how the misclassification occurs between the real and the fake classes.

2.4 Hybrid Frequency-Domain Analysis

Besides spatial feature extraction, frequency domain analysis is also applied to increase the robustness of detection.

2.4.1 FFT-Based Analysis

Each image is transformed to the frequency domain using Fast Fourier Transform (FFT). The analysis is based on the detection of irregular high frequency patterns that are typically present in AI generated images.

How it functions::
- Convert image to black and white
- FFT transformation
- Center the frequency components
- Magnitude spectrum extraction

2.4.2 Statistical Analysis of Features

Natural images can be distinguished from synthetic images by statistical measures such as pixel variance, intensity distribution, etc. These features provide additional cues to complement the CNN-based predictions.

2.4.3 Hybrid Decision Strategy
The final prediction is a combination of:
- Probability score based on CNN
- Frequency domain anomaly indicators

Such hybrid approach improves detection accuracy and reduces false predictions.

2.5 Explainability with Grad-CAM

Incorporating Grad-CAM into the system improves transparency. It generates heatmaps that indicate important regions that influence the model's decisions for better interpretability of the classification results.

2.6 Video Detection Using the System

For video inputs , frames are extracted at fixed intervals and processed individually with the trained model . The final classification result of the entire video is obtained by a majority voting mechanism.

2.7 System Implementation and Interface

The system is implemented using FastAPI as the backend framework providing the following functionalities:
- Image prediction API
- Video Analysis API
- Detection based on snapshot
- History logging

There is a web interface where users can upload files and see results in real-time.

2.7.1 Usability of the System
The system is configured as follows::
- Scalable and lightweight architecture
- User friendly interface for both technical and non-technical users
- Real time processing ability (efficient)

The system has applications in journalism, digital forensics and content verification.

III.RESULT AND ANALYSIS

In this section, we present the evaluation of the proposed hybrid deepfake detection system that integrates spatial analysis based on EfficientNet-B0 with features in the frequency domain. The model

performance is tested on unseen data by quantitative metrics and qualitative observations.

3.1 Model Performance

The model is trained on approximately 80% of the dataset, and the remaining data is used for validation and testing. The evaluation relies on measuring the ability of the system to distinguish between real and AI-generated images.

We use the following metrics to judge performance:

- Accuracy: This is the percentage of images that were correctly classified. A high accuracy means that the program can tell the difference between real and fake images well.
- Precision: This tells you how many of the AI-generated images that were predicted to be fake were actually fake. It shows how well the model can cut down on false positives.
- Recall (Sensitivity): This tells you how many of the real fake images were correctly identified as AI-generated. This metric is very important for making sure that synthetic content isn't missed.
- F1-Score: The harmonic mean of precision and recall, which gives a balanced evaluation. This is especially useful when classes are not evenly distributed.
- Loss: During training, binary cross-entropy loss is used. A trend of loss going down shows that the model is learning well and getting closer to its best performance.

A lot of people use these metrics to test deep learning-based classification systems for deepfake detection tasks [6].

3.2 Analyzing the Confusion Matrix

A confusion matrix is created with validation data to look at how well both classes are doing at classification. The confusion matrix shows us things like::

- Putting real and fake images in the right category
- False positives (real images that are wrongly labeled as fake)
- False negatives (real images that are thought to be fake)

The confusion matrix shows that the hybrid model does a good job of classifying things, with fewer mistakes than CNN-based models that work on their own. Adding frequency-domain features makes it easier to find small artifacts.

3.3 Sample Predictions and Qualitative Analysis

A set of validation images is used to further test how well the model works by comparing the predicted labels to the ground truth values.

Before going through the hybrid detection pipeline, each image is preprocessed (resized and normalized). The system gives both the predicted label and a score of how sure it is.

Qualitative analysis shows that misclassifications are usually linked to:

- Pictures with low resolution or heavy compression
- Pictures with hard-to-see light or shadows
- Patterns that look like real-world textures but are hard to see

Adding frequency-domain analysis helps with some of these problems by finding hidden artifacts that can't be seen in the spatial domain.

3.4 Robustness assessment

The model is evaluated on a variety of image distortions to assess its practical applicability:

- Compression: Mimicking social media image quality loss
- Noise Injection: Testing robustness against random pixel differences
- Blur Effects: Performance evaluation on degraded images

The hybrid approach shows better robustness than traditional CNN models with stable performance under adverse conditions. This illustrates the benefit of joint spatial and frequency domain features.

3.5 Video Detection Performance

The system extends the detection from still images to video by extracting frames at fixed intervals. The trained model classifies each frame independently.

The final classification for the video is obtained by a majority voting scheme.

This ensures that occasional classification errors at the frame-level do not heavily influence the overall result. Experiments show that it is able to consistently and reliably detect deepfake content in videos.

3.6 Real-World Applicability

The model is deployed through a FastAPI based application which provides real-time inference for images and videos.

Key features include:

- Upload image (JPG, PNG formats)
- Automatic pre-processing (resize and normalize)
- Classification in real time (real vs fake)
- Visualizing results with confidence scores
- Export results for further analysis

The system is practically usable for applications like digital media verification, journalism and content moderation.

3.7 Conclusion of Findings

Improved detection accuracy through hybrid feature integration:

- Higher detection accuracy with hybrid feature fusion
- Good balance of precision and recall performance
- Improved robustness to real world image distortions
- Uniform performance on image and video inputs
- Ability to practically deploy with real time processing

Overall, the results validate the developed hybrid system to be effective, scalable and applicable to real-world deepfake detection tasks.

IV.CONCLUSION

In this paper, a hybrid deepfake detection system that combines spatial feature extraction with convolutional neural network and frequency domain analysis was proposed. We propose an EfficientNet-B0 model combined with Fast Fourier Transform (FFT) to capture both visual and spectral inconsistencies of AI-generated images [5], [6].

The experimental results show that the fusion of spatial and frequency domain features improves the overall detection performance compared to CNN-based methods alone, as reported in recent deepfake detection research [4]. The hybrid framework obtains a balanced performance in terms of accuracy, precision, recall and F1-score. It also shows an increased robustness under real-world distortions such as compression, noise and blur.

Moreover, the Grad-CAM is used to enhance the interpretability of the model by providing visual explanations for the classification decisions [7]. This is especially beneficial for applications where transparency and trust are critical, such as journalism and digital forensics.

The system deployment with FastAPI-based architecture further demonstrates the practical applicability of the system enabling the real-time detection of both images and video content. The results show that the proposed approach is effective, scalable and suitable for real-world implementation.

In summary, the combination of deep learning with frequency domain analysis and explainability methods provides a robust and efficient solution for AI-generated media detection, addressing important issues raised in previous studies [3], [4].

V. FUTURE WORK

The proposed hybrid deepfake detection system has been demonstrated to be effective in detecting AI-generated images, yet there are many improvements that can be investigated to further enhance its efficiency, robustness, and practical implications.

One important direction is the extension of the system towards real-time deepfake detection. Future implementations can evolve from static images to live video streams for real time detection in applications such as social media monitoring and content moderation platforms. Another way of improving the detection accuracy for video-based deepfakes is to incorporate temporal modeling techniques in addition to the frame-level analysis.

Another major area for improvement is model explainability. In this work, Grad-CAM has been used, but other explainability methods like SHAP and LIME can be incorporated for more thorough insights into the

model's decision-making [4]. This would make the system more transparent and trustworthy, especially in sensitive use cases like journalism and digital forensics.

The system can also be expanded to support more media formats including GIFs and live streaming. Modeling with various data types and compression levels will enhance the generalization capability to real world scenarios.

Dataset challenges such as class imbalance and the lack of diversity are still important in deepfake detection. Future work may explore more advanced data augmentation strategies, balanced sampling methods, and adaptive loss functions to improve model performance under imbalanced conditions [6].

Another important consideration is scalability. The system can be implemented with cloud-based or distributed computing architectures that enable efficient processing of large scale data and support real-time applications. This would be particularly useful for large-scale deployment.

From the usability perspective, improving visualization and user interface design can increase system accessibility. Features such as ROC curves, precision recall graphs, feature activation maps can give deeper insights on the model performance.

Finally, future research can address security and automation aspects such as secure data handling, compliance with data protection standards and automated alerts/reporting upon detection of deepfake content. Model updating and retraining on an ongoing basis will be required to keep pace with the evolving deepfake generation techniques [6].

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