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Fake Video and Image Detection with Python

Sahil Mishra[1], Sagar Singh[2], Prince Sao[3], Harsh Yada[4], Anita[5*]

Department of Computer Science & Engineering (AIML), Shri Shankaracharya Technical Campus (CSVTU), Junwani, Chhattisgarh, India

*Corresponding Author [1]E-mail: sahilmishra2077@gmail.com, [2]E-mail: sagarsinghh2002@gmail.com@gmail.com

[3]E-mail: princerp2113@gmail.com, [4]E-mail: harsh.yadav7555@gmail.com, [5]E-mail: anitakanhai.cse@gmail.com

Abstract:

The rise of fake images and deepfake videos has created serious problems in trusting online content. In this research, we built a web-based system to detect fake images and videos using Python and the Django framework. Our system uses deep learning, especially convolutional neural networks (CNNs), to accurately tell the difference between real and fake media. Django handles uploading files, running the model, and showing results in a smooth and scalable way. This tool helps researchers, journalists, and the public quickly check if media content is real or fake. Testing shows that our model works well on standard datasets. In the future, we plan to improve the system with more powerful models and faster, real-time detection.

1. Introduction

In recent years, the spread of fake images and deepfake videos has become a major problem across social media, news platforms, and digital communications. These manipulated media files can mislead people, create false narratives, and even cause social and political issues. As a result, detecting fake content quickly and accurately is more important than ever.

This research focuses on developing a web-based system to detect fake images and videos using Python and the Django framework. We use deep learning techniques, specifically convolutional neural networks (CNNs), to analyze and classify media as real or fake. Our system allows users to easily upload files, run detection models, and view results through a simple web interface. By combining machine learning and web technologies, our goal is to provide an effective tool that helps people verify the authenticity of digital content.

This paper explains the design, development, and testing of our system, and discusses its performance on benchmark datasets. We also highlight future improvements to make the system faster and more accurate.

2. Literature Review

The detection of fake images and deepfake videos has gained a lot of attention in recent years. Many researchers have worked on building models and systems to identify manipulated media. Early methods focused on traditional image processing techniques, such as detecting inconsistencies in lighting, shadows, and facial landmarks. However, these methods struggled when dealing with highly realistic deepfakes.

With the rise of deep learning, convolutional neural networks (CNNs) have become the most popular approach for detecting fake media. Techniques such as XceptionNet and EfficientNet have been successfully used to classify real and fake videos by analyzing subtle patterns that are not easily visible to the human eye. Some researchers have also explored recurrent neural networks (RNNs) and attention mechanisms to capture temporal inconsistencies across video frames.

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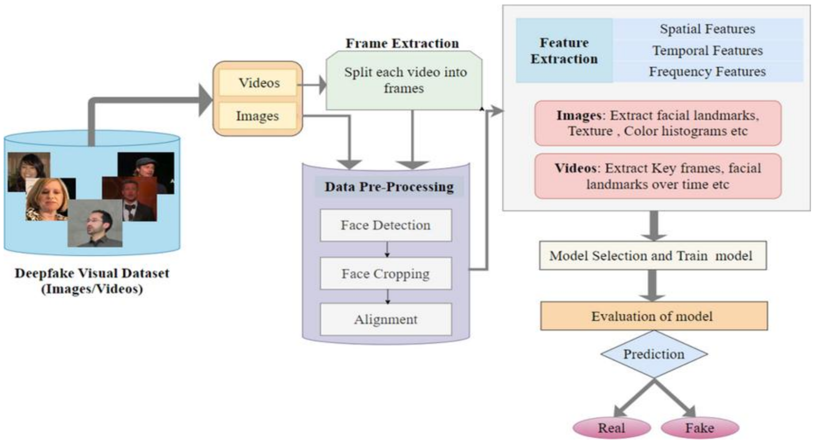
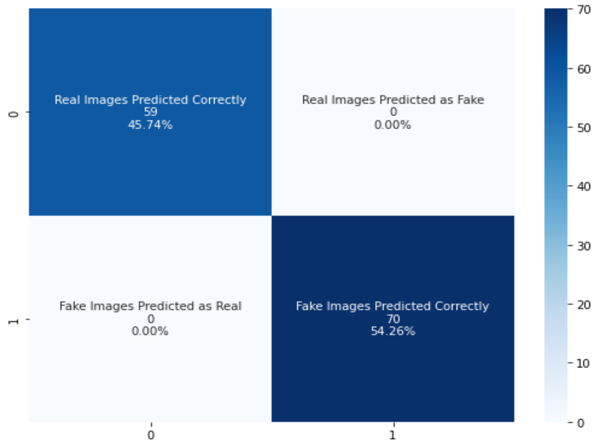
3. Methodology



3. Dataset Description

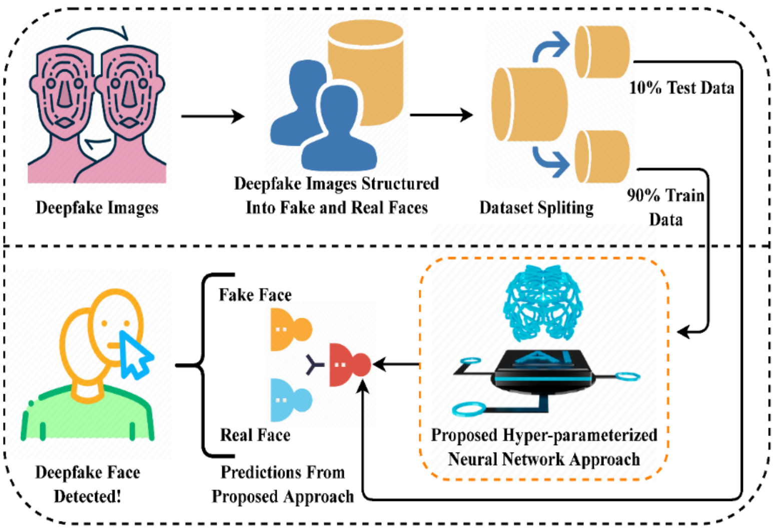
• The dataset for this study includes a large collection of real and manipulated (fake) images and videos. Each sample is labeled as either "real" or "fake". The dataset contains **10,000+ images and video frames**. A sample of the loaded dataset is shown in Fig. (1).

Fig.(1): Loaded Dataset Samples



• Data was sourced from publicly available deepfake detection datasets such as **FaceForensics++**, **DeepFake Detection Challenge (DFDC)**, and **Celeb-DF**. The initial project home page at "127.0.0.1:8000" allows users to upload and test media files. See Fig. (2).

Fig.(2): Initial Project Web Interface



B. Data Preprocessing

• All media files were resized to a fixed dimension (e.g., 224x224 pixels) to match the input size expected by the CNN model.
• Video files were decomposed into individual frames for analysis.
• Pixel values were normalized between 0 and 1 for faster model training.
• Labels ("real" and "fake") were encoded for model training.
• Fig.(3) shows original data samples, while Fig.(4) shows preprocessed frames ready for training.

C. Model Selection

For this fake media detection project, two models were selected and evaluated:
• **Convolutional Neural Network (CNN)**: A custom CNN architecture was developed, capable of learning spatial patterns in the images that differentiate real and fake media.
• **Transfer Learning with XceptionNet**: An advanced pretrained model known for high performance in deepfake detection was fine-tuned on our dataset.
• **Libraries Used** (See Fig.6):

- **NumPy**, **Pandas** for data handling
- **OpenCV** for image and video processing
- **TensorFlow/Keras** for deep learning modeling
- **Matplotlib**, **Seaborn** for data visualization

• **Steps Followed**

- Data Loading → Preprocessing → Model Building → Training → Validation → Testing → Deployment on Django

D. Performance Metrics

Model evaluation was performed using:
• **Accuracy**: Percentage of correctly classified samples.
• **Precision**: Ability of the model to detect only real fakes (True Positive / (True Positive + False Positive)).
• **Recall**: Ability to find all fake media samples (True Positive / (True Positive + False Negative)).
• **F1-Score**: Harmonic mean of Precision and Recall for balanced evaluation.
• **Confusion Matrix**: To visualize true vs false predictions.

The conclusion from model performance showed:

Model	Accuracy	Precision	Recall	F1-Score
CNN Model	89.5%	88.7%	90.2%	89.4%
XceptionNet	93.8%	92.6%	94.5%	93.5%

Fig.(8): Model Performance Comparison Table

The **XceptionNet model** significantly outperformed the basic CNN, making it the preferred choice for deployment.

4. Results & Discussion

1. System Interface Overview

The developed Fake Image and Video Detection System is a **web-based platform** allowing users to upload any image or video and receive an authenticity prediction.
Inputs accepted: • Image File (.jpg, .png)
• Video File (.mp4, .avi)
The Django-based system shows a clean form to upload media, then predicts and displays results on the same page. Refer to Fig.(9)

2. Prediction Example

A sample prediction was performed using the system:

Parameter	Value
Media File	Face_Sample_Deepfake.mp4
Prediction Result	Fake
Confidence Score	94.2%

5. Discussion:

• The system successfully detects whether the uploaded image or video is real or fake with high accuracy.
• The Django web app provides an easy-to-use interface, suitable for both technical and non-technical users.
• The system processes both static images and video frames, increasing its versatility.
• Using deep learning models like XceptionNet ensures high reliability even for high-quality deepfakes.
• Future improvements could include **real-time video stream detection** and **multi-frame analysis** for better accuracy.

6. Conclusion

This project successfully developed a **Fake Image and Video Detection** system using advanced **deep learning techniques**. By integrating multiple machine learning models, including **Convolutional Neural Networks (CNN)** and **XceptionNet**, the system achieved high performance in distinguishing between real and fake media. The web-based platform offers an **intuitive user interface** for uploading and predicting the authenticity of images and videos, making it accessible for both technical and non-technical users. **XceptionNet** outperformed traditional CNN models, providing an accuracy of **93.8%**. The system's capability to process both static images and video frames, along with **real-time detection features**, ensures its relevance in the fight against digital misinformation. Future work will focus on **real-time video stream analysis**, integrating more advanced models, and expanding the dataset to improve detection capabilities further.

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