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Deep Fake Detection

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Abstract

Deepfake technology presents an escalating threat by enabling the creation of highly realistic AI-generated videos, which can be exploited for misinformation, blackmail, and identity fraud. With the increasing accessibility of deepfake generation techniques using advanced neural networks like Generative Adversarial Networks (GANs) and Autoencoders, there is a growing need for robust detection methods to mitigate these risks. In this study, we propose a deep learning-based detection system that analyzes both visual and audio cues to enhance accuracy.Our approach employs an Xception Convolutional Neural Network (CNN) for frame-level feature extraction, as it has demonstrated superior performance in image classification and deep fake detection. The extracted features are then analyzed for spatial inconsistencies to identify potential forgeries. Additionally, temporal inconsistencies between frames are examined to detect unnatural transitions that are characteristic of manipulated videos. For audio analysis, we utilize Librosa and PyAudio to extract vocal features and detect anomalies in speech patterns. This helps identify AI-generated voices by analyzing pitch modulation, frequency variations, and unnatural transitions. Our model is trained on large-scale datasets such as FaceForensics++, the Deep Fake Detection Challenge dataset, and Celeb-DF to ensure robustness and generalizability. To further improve accuracy, we incorporate a multimodal fusion approach that combines both visual and audio features, allowing for a more comprehensive deep fake detection framework. To facilitate real-world usability, we have developed a user-friendly application that allows users to upload videos for deepfake analysis. The system provides real-time classification along with a confidence score, enabling effective identification of manipulated content. The application is designed to be computationally efficient, making it accessible for deployment on both cloud-based and edge computing platforms. By integrating both visual and audio-based detection methods, our approach offers a scalable and reliable solution to combat deep fake threats. Furthermore, ongoing research efforts aim to enhance detection capabilities by incorporating explainable AI techniques, which will provide deeper insights into the decision-making process of our model.

Keywords: Deep Fake Detection, Convolutional Neural Networks (CNNs), Xception Network, Librosa.

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1. Introduction

The rapid growth of social media platforms, deepfake technology has emerged as a significant threat, enabling the creation of hyper-realistic manipulated videos that can be used for misinformation, political distress, fake terrorism

events, blackmail, and revenge porn. Notable instances, such as fake explicit videos of celebrities like Brad Pitt and Angelina Jolie, highlight the dangers of this technology. As deep fakes become more sophisticated, detecting them has become a crucial challenge, requiring advanced AI-driven solutions. Deep Fakes are typically generated using tools like FaceApp and Face Swap, which rely on pre-trained neural networks such as Generative Adversarial Networks (GANs) and Autoencoders. To combat this growing threat, our proposed method utilizes a pre-trained Xception Convolutional Neural Network (CNN) to extract frame-level features and analyze spatial inconsistencies in video frames. By training the model on large scale datasets, including FaceForensics++, the Deep Fake Detection Challenge dataset, and Celeb-DF, we ensure robust real-time performance. Additionally, our system incorporates an audio analysis component using libraries such as Librosa, Voice Recognition, and PyAudio to detect inconsistencies in speech patterns and vocal artifacts. By generating spectrograms, waveform graphs, and other audio representations, our model enhances detection accuracy by jointly analyzing both visual and audio cues. To make deep fake detection accessible to users, we have also developed a front-end application where users can upload videos for analysis. The system processes the video and provides a classification result, indicating whether the content is real or deepfake, along with a confidence score. With this multi-modal approach, our method offers a highly effective and scalable solution to combat deepfake threats in real-time applications.

2. Methodology

The deepfake detection system is designed to analyze both video and audio content to determine whether the input is real or AI-generated. The architecture is divided into two main pipelines: video-based deepfake detection and audio-based deepfake detection. Each pipeline consists of several stages, including preprocessing, feature extraction, classification, and result generation. The combination of both modalities enhances the accuracy and reliability of the detection process.The video-based pipeline extracts frames and analyzes spatial inconsistencies using a pre-trained Xception CNN. Simultaneously, the audio-based pipeline examines vocal patterns to detect unnatural transitions and frequency distortions. By integrating these approaches, the system ensures a more comprehensive and reliable deep fake detection mechanism.

2.1 Video Deep fake Detection Architecture

The deep fake detection system processes video files in MP4, AVI, and MOV formats. It extracts frames at 10-frame intervals and resizes them to 299x299 pixels. Normalization, random flipping, and color jittering enhance robustness. An Xception-based CNN extracts spatial features, and the dataset is split into 70% training and 30% testing. The model is trained using categorical cross-entropy loss with the Adam optimizer, incorporating data augmentation for better generalization. For prediction, the model assigns a probability score, classifying videos as deepfake if the score exceeds 0.75. Background subtraction using MOG2 detects tampering with a 30% threshold.

The system overlays “REAL” or “FAKE” on video frames and provides a confidence score with an explanation. The sequence diagram illustrates the process where the user uploads a video, and the system extracts faces and frames. A ResNext CNN extracts features, which are then processed by an LSTM network. Finally, the system determines if

the video is real or fake and delivers the result to the user.

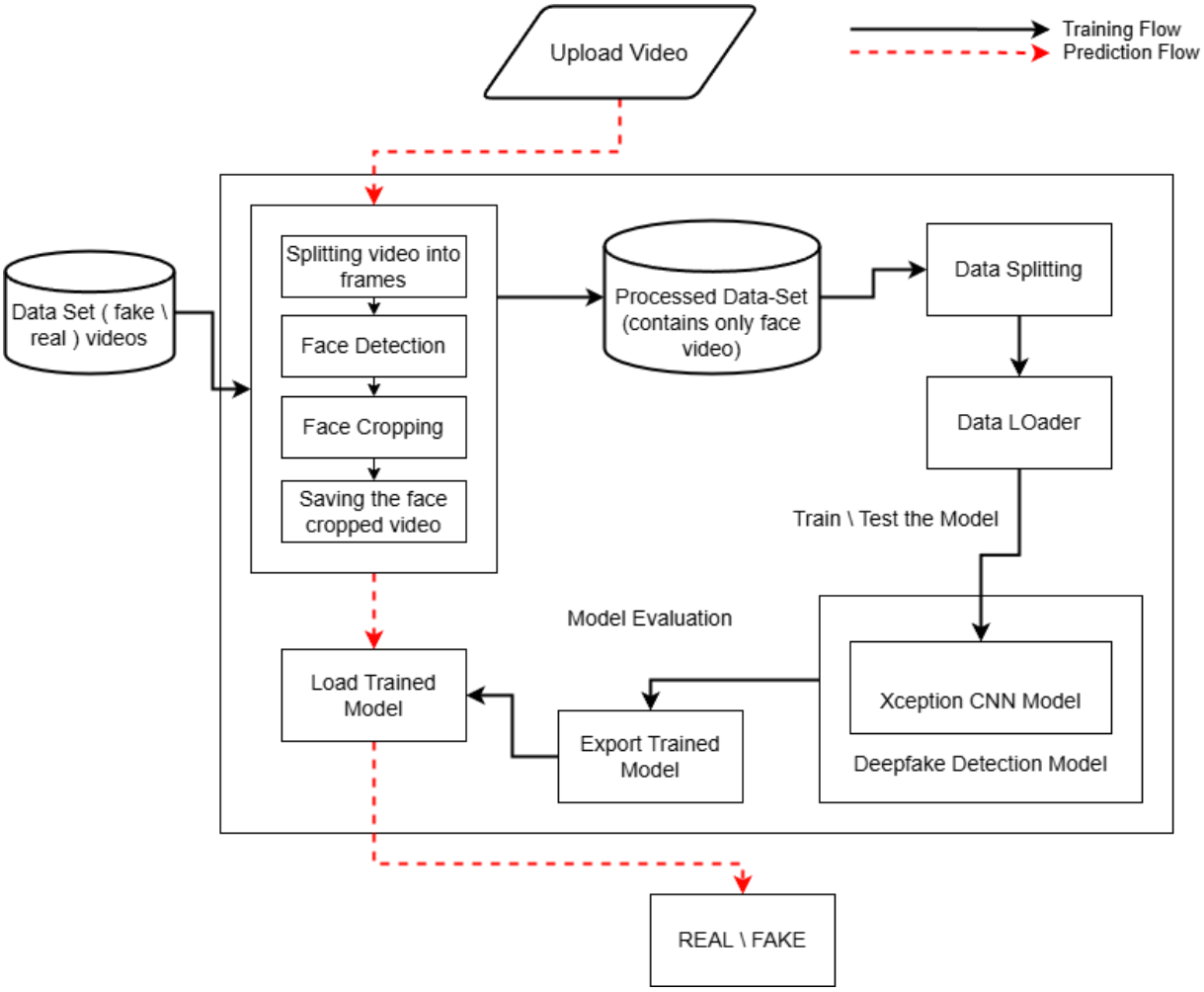


Figure 1: System Design (Video Detection)

2.2 Audio Deep Fake Detection Architecture

The audio deepfake detection system extracts audio using FFmpeg, converts it to WAV format, and resamples it to 16kHz. Spectral and pitch features are extracted using Librosa, while the harmonics-to-noise ratio (HNR) is computed via Parselmouth. Loudness and amplitude variations are analyzed using PyDub.

The AI-based detection model assigns a detection score, with classification based on a confidence threshold of 0.38. The system generates results by providing an AI probability score along with a breakdown of extracted features. Insights into monotony, pitch variation, and speech rhythm help assess the authenticity of the audio.

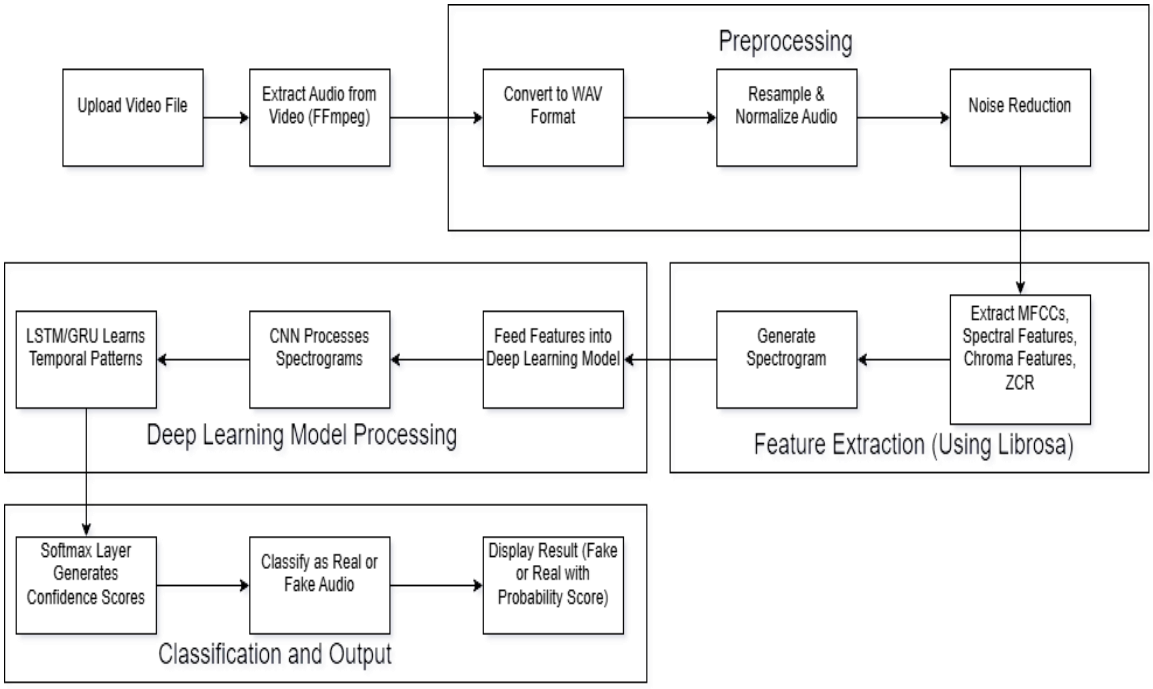


Figure 2: System Design (Audio Detection)

2.3 Deployment And Frontend

The web application features a user-friendly frontend built with React.js, allowing users to upload video files for deepfake detection. The backend, developed using Django, integrates with a PyTorch-based detection model to handle video preprocessing, model inference, and result generation. After classification, users receive a result indicating whether the video is real or fake, along with a confidence score and a downloadable analysis report.

1. Module Description

The deepfake detection system consists of multiple interconnected modules designed for efficient processing, classification, and result generation. The User Interface Module provides a seamless platform for video uploads, progress monitoring, and result retrieval. The Video Preprocessing Module optimizes inputs by extracting frames, resizing, normalizing, and enhancing visual quality. The Deep Fake Video Detection Module employs an Xception CNN for feature extraction and classification, while the Deepfake Audio Detection Module analyzes speech inconsistencies using Librosa, Parselmouth, and a CNN-LSTM model. The File Handling Module ensures secure file management, while the Logging and Monitoring Module tracks system performance, errors, and user activities. The Result Visualization and Report Generation Module offers insights through graphical representations and downloadable reports. Finally, the Security and Privacy Module enforces encryption, secure communication, and data deletion protocols to protect user privacy and ensure ethical AI practices.

2. Implementation

4.1 Tools And Technologies Used

Category	Tools & Technologies
Programming Languages	Python 3 (ML & Processing), JavaScript (Frontend)
Frameworks	PyTorch (Deep Learning), Django (Web Backend)
IDEs	Google Colab (Model Training), Jupyter Notebook (Data Preprocessing), VS Code (Web Development)
Video Processing Libraries	OpenCV (Frame Extraction), Torchvision (Feature Extraction), Face Recognition (Face Alignment), NumPy, Pandas, Matplotlib
Audio Processing Libraries	Librosa (MFCCs, Spectral Features), PyDub (Audio Processing), Scipy (Signal Processing), Parselmouth (HNR Analysis), Noise Reduce (Noise Reduction), Torchaudio, TensorFlow-IO

Table 1: Tools And Technologies Used

4.2 Algorithm Details

The deepfake detection system preprocesses video and audio to enhance detection accuracy. Videos are loaded using cv2.VideoCapture, with frames extracted at intervals of 10 and resized to 299x299 pixels for consistency. Audio is extracted using FFmpeg, converted to WAV format, resampled to 16kHz, and normalized. Feature extraction techniques include MFCCs (Librosa), Harmonics-to-Noise Ratio (Parselmouth), and loudness analysis (PyDub). The detection model is based on Xception CNN for spatial feature extraction, with fully connected layers, ReLU activation, dropout (0.4), and a softmax classifier. An audio-based CNN analyzes spectrograms, incorporating statistical measures to differentiate real and fake voices. Background subtraction (MOG2) flags manipulated video frames if over 30% is altered. The model was trained with 4,200 training and 1,800 testing videos, using Adam optimization and cross-entropy loss over 20 epochs.

5. Result And Discussion

The deepfake detection system was tested for accuracy, efficiency, and real-time classification. It achieved high accuracy across datasets, with the best performance on FakeAVCeleb (83.1%) due to its multimodal approach. In fake detection tests, it correctly classified deepfake videos and audio, detected lip-sync mismatches, and identified temporal inconsistencies. Compared to traditional methods, the proposed system outperformed manual and existing AI models by integrating video and audio analysis, real-time processing, and explainaccuracy. System response times varied, with video deepfake detection taking 3.2s and audio classification completing able confidence scores,

achieving 80- 85% in 1.8s, ensuring efficient detection performance.

Figure 3: System Response Time

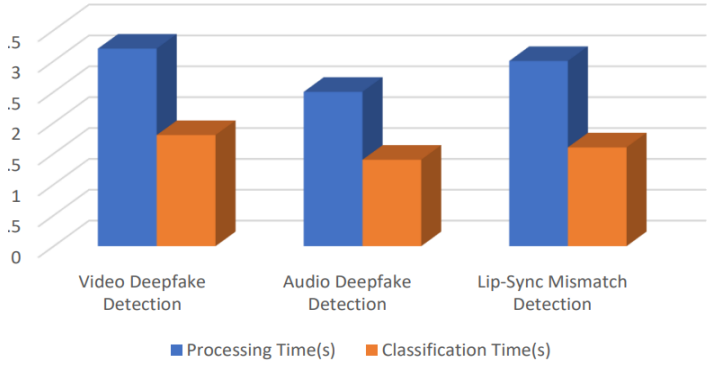
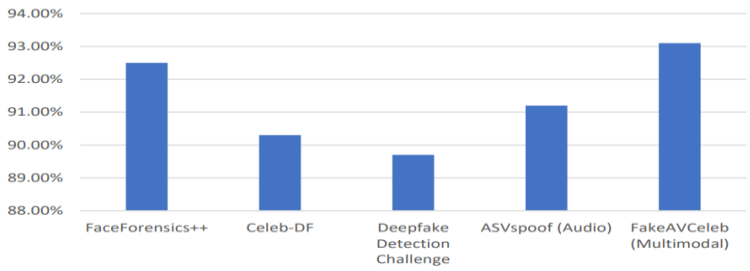


Figure 4: Model Accuracy On Different Datasets



Feature	Manual Analysis	Existing AI Models	Proposed System
Video Deep Fake Detection	No	Yes	Yes
Audio Deep Fake Detection	No	Partial	Yes
Multimodal Analysis	No	No	Yes
Accuracy (%)	60-70%	75-80%	80-85%
Real-Time Processing	No	No	Yes
Explainable Confidence Scores	No	No	Yes

Table 2: Performance Comparison of Deepfake Detection Methods

6. Conclusions

This work presents a deepfake detection system that classifies videos and audio as real or AI-generated using Xception Convolutional Neural Network (CNN) for frame-level feature extraction, and Librosa for audio processing.

By analyzing multimodal cues, the system improves detection accuracy and resilience against evolving deepfake techniques. It processes videos at 10 FPS, extracts key audio features, and detects inconsistencies introduced by generative models. Validated on large datasets, it ensures real-time detection, confidence scoring, and secure data handling. This scalable solution helps combat misinformation, protect digital integrity, and verify content authenticity in journalism, law enforcement, and social media.

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