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Deep Fake Video Detection

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Abstract: *Deep fake technology has rapidly evolved due to advances in deep learning, enabling the creation of highly realistic synthetic videos in which a person's face, voice, or expressions are manipulated. While these techniques can be used for entertainment and creative applications, they pose serious threats such as misinformation, identity fraud, political manipulation, and loss of public trust. Therefore, accurate and efficient deep fake video detection has become a critical research challenge. This study presents an analytical approach to detecting deep fake videos using machine learning and computer vision techniques. The proposed system focuses on extracting subtle inconsistencies in facial movements, lip-sync patterns, eye blinking rates, texture artifacts, and compression irregularities that commonly appear in manipulated footage. A combination of convolutional neural networks (CNNs) and feature-based analysis is employed to classify videos as real or fake. The system is trained on publicly available deep fake datasets to improve generalization and robustness against diverse manipulation methods. Experimental results indicate that the model achieves high accuracy and effectively identifies forged content even in complex scenarios. This research contributes to building secure digital environments by helping prevent the spread of harmful synthetic media. Future improvements may include real-time detection capability, multimodal analysis, and enhanced performance against next-generation deep fake generation techniques.*

Keywords: Deep Fake, Fake Video Detection, Deep Learning, Convolutional Neural Network (CNN), Face Manipulation, Synthetic Media, Computer Vision, Digital Forensics, Video Analysis, Misinformation, AI-generated Content, Feature Extraction, Fraud Prevention, Machine Learning, Forgery Detection

I. INTRODUCTION

The growth of artificial intelligence and deep learning has transformed the digital world, enabling machines to generate highly realistic images, audio, and videos. Among these innovations, deep fake technology has emerged as one of the most powerful yet potentially dangerous tools. Deep fakes are synthetic videos created using advanced neural networks, such as Generative Adversarial Networks (GANs), that can convincingly alter a person's face, expressions, or voice. With continuous improvements in AI models, deep fake videos have become increasingly accurate, making it difficult for the average viewer to distinguish between real and manipulated content.

Although deep fake technology offers positive applications in areas like the film industry, virtual reality, education, and accessibility services, its misuse has raised serious global concerns. Malicious deep fakes can be used to spread political propaganda, create false evidence, damage reputations, mislead the public, and conduct identity-based cybercrimes. Social media platforms, news agencies, and security organizations now face challenges in identifying manipulated videos before they cause harm. As deep fake generation techniques become more advanced and widely available, the threat to privacy, digital trust, and online security continues to increase.

Due to the difficulty of detecting forged videos manually, researchers are turning to automated detection methods based on machine learning, computer vision, and pattern analysis. These systems aim to identify subtle imperfections in

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synthetic videos, such as unnatural facial movements, blinking anomalies, lighting inconsistencies, texture mismatches, and irregular frame transitions. Modern detection models use Convolutional Neural Networks (CNNs), feature extraction techniques, and temporal analysis to distinguish real videos from manipulated ones.

This research focuses on understanding these detection mechanisms and developing an effective approach to identify deep fake videos with high accuracy. The study highlights the growing importance of digital forensics in combating misinformation and ensuring the authenticity of multimedia content. A strong deep fake detection framework not only enhances online safety but also protects individuals, organizations, and society from the damaging impact of synthetic media.

1.1 Threats of deepfakes

Deep fakes pose several serious threats across social, political, and technological domains. One of the most critical concerns is misinformation and fake news, where manipulated videos can spread false narratives and influence public opinion. Deep fakes can be used to create fabricated speeches or actions of political leaders, potentially leading to social unrest, election manipulation, or diplomatic conflicts. They also pose a major risk to individual privacy and reputation, as synthetic videos can falsely show people in situations they were never part of, causing emotional, professional, and social damage.

Another significant threat is identity fraud and cybercrime. Attackers can impersonate individuals to gain unauthorized access to financial accounts, secure locations, or confidential data through face recognition and voice authentication systems. Deep fakes also threaten national security, as they can be used to mislead intelligence agencies, spread propaganda, or create fake evidence during investigations.

In the corporate sector, deep fakes can cause financial losses by manipulating communication between employees, executives, or clients, leading to fraudulent transactions or false instructions. Additionally, they undermine public trust in digital media, making it difficult to verify the authenticity of online content. As deep fake technology continues to advance, these threats will become even more challenging to detect, emphasizing the need for robust detection systems and legal frameworks.

1.2 Aims and Objectives

The aim of this research is to develop an effective deep fake video detection system that can accurately identify manipulated or synthetic videos using advanced machine learning and computer vision techniques. This study focuses on understanding how deep fakes are created, analyzing the visual and behavioral inconsistencies they introduce, and designing a robust detection model capable of distinguishing real videos from fake ones. The objectives include studying deep fake generation methods such as GANs, identifying key facial and motion-based artifacts, and building a preprocessing pipeline that extracts meaningful features from video frames. Additionally, the research aims to develop and train a Convolutional Neural Network (CNN)–based classifier, evaluate its performance on benchmark datasets, and improve its accuracy across different types of manipulations. The overall goal is to enhance digital security by contributing a reliable detection framework that supports online platforms, users, and forensic investigators in combating the spread of harmful synthetic media.

1.3 Paper Structure

This research paper is organized into several key sections to provide a systematic understanding of deep fake video detection. Section 1 introduces the topic, outlines the background of deep fake technology, and explains the motivation behind developing an effective detection system. Section 2 reviews existing literature, highlighting current methods, challenges, and gaps in deep fake detection research. Section 3 presents the problem statement, objectives, and the overall scope of the study. Section

4 describes the proposed methodology, including data preprocessing, feature extraction, and the deep learning model used for classification. Section 5 explains the system architecture and workflow of the detection model in detail. Section 6 provides the experimental setup, dataset description, evaluation metrics, and the results obtained from the model's performance. Section 7 discusses the findings, strengths, limitations, and comparative analysis with existing

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techniques. Finally, Section 8 concludes the paper by summarizing the work and outlining potential future enhancements such as real-time detection, multimodal analysis, and improved robustness against advanced deep fake generation methods

II. LITERATURE REVIEW

The rapid advancement of deep learning, especially with Generative Adversarial Networks (GANs), has led to the widespread creation of deep fake videos, prompting researchers to develop reliable detection techniques. Early studies primarily focused on identifying low-level visual artifacts and facial inconsistencies introduced during manipulation. One of the pioneering works used simple texture analysis and frame-level inconsistencies to differentiate real and fake videos. However, as deep fake generation techniques improved, these traditional handcrafted features became less effective.

Recent literature demonstrates a shift toward deep learning–based methods for more accurate detection. Convolutional Neural Networks (CNNs) have been widely used for frame-level analysis, enabling models to automatically learn subtle distortions in facial textures, blending boundaries, and lighting mismatches. For instance, researchers have shown that CNNs can detect unnatural eye blinking patterns—an early but important indicator of manipulation. Other studies utilize recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks to analyze temporal sequences, capturing inconsistencies in facial movements and lip synchronization across frames.

Many studies have also explored frequency-domain analysis, where models detect artifacts hidden in the spectral components of images and videos. These methods are particularly useful because deep fake generation often fails to perfectly replicate natural frequency patterns. Furthermore, several benchmark datasets, such as FaceForensics++, DeepFake Detection Challenge (DFDC), and Celeb- DF, have been introduced, helping researchers train and evaluate large-scale detection models.

Hybrid approaches, combining visual features with audio cues, have also appeared in the latest literature. These multimodal models analyze voice inconsistencies alongside facial expressions to strengthen detection accuracy. Additionally, transformer-based architectures and attention mechanisms have recently gained attention due to their ability to focus on the most manipulated regions of a face.

Despite significant progress, the literature indicates ongoing challenges. Deep fake generation models continue to improve, making detection increasingly difficult. Many detection methods struggle with low-quality videos, varied lighting conditions, compression noise, or real-world social media content. Studies also highlight the need for generalizable models capable of identifying previously unseen types of deep fakes.

Overall, existing research emphasizes the importance of integrating deep learning, multimodal analysis, and large-scale datasets to build robust and future-proof deep fake detection systems. This literature review provides the foundation for designing a more accurate and reliable detection framework discussed in the proposed system.

2.1 Results of previous deepfake video detection models

Previous research on deepfake video detection has produced a wide range of promising results, with accuracy levels improving significantly as deep learning– based methods evolved. Early detection techniques, which relied mainly on handcrafted visual features such as blinking anomalies, inconsistent head movements, or texture mismatches, achieved limited success. Their accuracy generally ranged from 65% to 80%, and these models struggled to detect high-quality deepfakes generated using advanced GAN architectures.

With the introduction of deep learning models, especially Convolutional Neural Networks (CNNs), detection accuracy increased substantially. Models like XceptionNet, MesoNet, and VGG-based classifiers reported accuracy between 85% and 97% on benchmark datasets such as FaceForensics++, particularly when analyzing high-resolution and less compressed videos. XceptionNet became a dominant baseline model, achieving nearly 97% accuracy on high-quality datasets, though its performance dropped to around 75–80% on highly compressed or low-quality videos, highlighting challenges in real-world scenarios.

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Temporal-based models using LSTM, GRU, and 3D-CNN architectures demonstrated further improvements by capturing motion inconsistencies across consecutive frames. These models achieved 90–94% accuracy on datasets like Celeb- DF and DFDC, making them more effective for video-level detection rather than frame-level classification.

More recent studies have explored frequency-domain detection, transformer-based architectures, and multimodal approaches combining both audio and visual features. These advanced systems reported robust performance, with accuracy levels between 92% and 98%, and improved generalization to unseen deepfake techniques. However, despite these advancements, most models show a noticeable drop in performance when tested on deepfakes produced with new generation methods not included in the training dataset.

Overall, previous results indicate that although deepfake detection systems have achieved high accuracy under controlled conditions, real-world generalization remains a challenge. This motivates the need for more adaptable, robust, and scalable detection frameworks capable of identifying increasingly sophisticated deepfake videos.

III. PROPOSED SYSTEM

3.1 Deepfake Videos

Deepfake videos are synthetic multimedia content in which a person's face, expressions, or voice is digitally manipulated to make it appear that they are doing or saying something they never did. The term "deepfake" comes from "deep learning" and "fake", highlighting that these videos are generated using advanced AI techniques, particularly deep neural networks such as Generative Adversarial Networks (GANs) and autoencoders.

Deepfake videos can range from harmless entertainment, such as movie visual effects or dubbing, to malicious uses like spreading misinformation, impersonating individuals, or creating non-consensual content. The creation process generally involves collecting images or videos of a target individual, training a deep learning model to learn their facial features, and then synthesizing new content by blending the target's features onto a source video. Modern deepfake generation techniques are capable of producing highly realistic videos that are often indistinguishable from real footage to the human eye.

The widespread availability of deepfake tools and online datasets has significantly increased both the volume and accessibility of manipulated videos. Platforms like social media, news websites, and video-sharing applications are particularly vulnerable to the circulation of deepfake content, which can influence public opinion, damage reputations, and pose serious threats to privacy and security.

Due to these risks, detecting deepfake videos has become a critical area of research in computer vision, digital forensics, and cybersecurity. Detection methods focus on identifying subtle inconsistencies in facial expressions, lip-sync, blinking patterns, lighting, or compression artifacts that are usually difficult for humans to notice but can be recognized by AI-based detection systems.

3.2 Deepfake Detection

Deepfake detection is the process of identifying synthetic or manipulated videos and images generated using artificial intelligence, particularly deep learning techniques like Generative Adversarial Networks (GANs) and autoencoders. As deepfake technology becomes increasingly sophisticated, detecting manipulated media has become essential for ensuring digital trust, cybersecurity, and information integrity.

The main objective of deepfake detection is to differentiate between real and fake content by analyzing subtle inconsistencies introduced during the generation process. These inconsistencies can occur in facial features, expressions, eye movements, lip- sync patterns, head poses, lighting, shadows, and even audio cues. Since deepfake videos are designed to appear authentic, human detection is often unreliable, making automated detection methods crucial.

3.3 Approaches to Deepfake Detection

Deepfake detection employs several approaches to identify manipulated videos, leveraging advancements in machine learning, computer vision, and signal processing. One common approach is visual feature analysis, which examines frame-level inconsistencies in facial textures, expressions, eye blinking, and lighting conditions. Convolutional Neural

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Networks (CNNs) are widely used in this approach to automatically extract and classify subtle artifacts that are often invisible to the human eye. Another approach is temporal or sequence analysis, which focuses on detecting irregularities across consecutive frames, such as abnormal facial movements, lip- sync mismatches, or head pose inconsistencies, using models like LSTM, GRU, and 3D-CNN networks.

Frequency-domain analysis is also employed, where deepfake-induced artifacts are detected in the spectral representation of images and videos, which can reveal generation traces not apparent in the spatial domain. Furthermore, multimodal detection combines visual and audio features to capture discrepancies between facial expressions and speech patterns, improving detection accuracy in videos with synchronized audio. Recent advancements include transformer-based and attention-driven methods, which allow models to focus on specific regions of the face or video frames that are most likely manipulated, enhancing robustness against sophisticated and previously unseen deepfake techniques. By integrating these approaches, deepfake detection systems aim to provide accurate, scalable, and generalizable solutions to combat the growing threat of synthetic media in digital platforms.

IV. SYSTEM ARCHITECTURE

4.1 Making of deepfake videos

Deepfake videos are created using advanced artificial intelligence techniques, mainly Deep Learning and Generative Adversarial Networks (GANs). The process starts by collecting a large dataset of images or videos of the target person from different angles, lighting conditions, and expressions. These datasets are then used to train AI models that learn the facial features, movements, and voice patterns of the target. GANs work in two parts: one network generates fake content, and another network tries to detect if it is fake, improving the quality with each iteration. After training, the model can superimpose the target person's face onto another person's video, matching lip movements, expressions, and head motions. Post- production tools further refine the video, adjust blending, correct lighting, and smooth transitions to make the deepfake look realistic. This combination of large datasets, AI training, and video editing techniques results in highly convincing deepfake videos.

4.2 Descriptions of model's operations

Deepfake models operate through a series of complex processes that enable the generation of highly realistic synthetic videos or images. The primary goal of these models is to replicate a target person's facial features, expressions, and movements, or to manipulate their voice, in a manner that appears authentic to human observers. Most deepfake systems rely on deep learning architectures, particularly Autoencoders and Generative Adversarial Networks (GANs), which form the core of the video synthesis process.

In the case of Autoencoders, the system consists of two main parts: an encoder and a decoder. The encoder compresses input images of a face into a low-dimensional representation known as a latent space. This latent representation captures essential facial features and expressions. The decoder then reconstructs the face from this representation, but with modifications to map it onto a target person's identity. By training separate encoders and decoders for the source and target faces, the system learns to transfer expressions and movements from one person to another while preserving realistic details.

Generative Adversarial Networks (GANs) take a more dynamic approach. A GAN consists of two neural networks—the Generator and the Discriminator—that operate in opposition. The Generator creates synthetic images or video frames of the target person, while the Discriminator evaluates whether these outputs are real or fake. Through repeated iterations, the Generator improves its ability to produce highly realistic outputs that can eventually fool the Discriminator. This adversarial training allows the model to generate fine details such as skin texture, eye reflections, and subtle facial movements that enhance realism.

To ensure accurate facial mapping, deepfake models employ facial alignment and landmark detection. This involves identifying key points on the face—such as eyes, nose, and mouth—so that expressions and movements can be precisely transferred from the source to the target. Lip-syncing algorithms are often used when manipulating videos with speech, ensuring that mouth movements align naturally with audio tracks.

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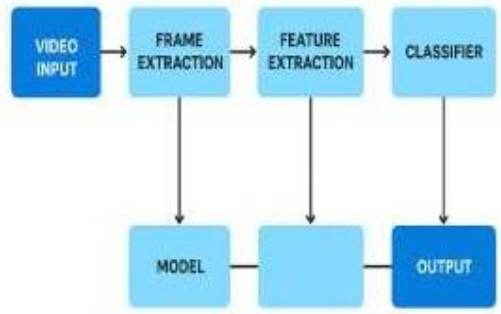
Finally, post-processing techniques such as color correction, edge smoothing, frame interpolation, and blending are applied to enhance the overall visual quality of the output video. These operations remove unnatural artifacts, adjust lighting and skin tones, and create smooth transitions between frames, making the generated deepfake appear highly realistic.

Overall, deepfake model operations combine data preprocessing, neural network training, facial mapping, temporal consistency, and post-processing to generate videos that are increasingly difficult to distinguish from authentic content. This complexity underscores the need for sophisticated detection methods to identify and mitigate the misuse of such technology.

4.3 Deepfake video detection system

A deepfake video detection system is designed to automatically identify manipulated or synthetic videos by analyzing subtle inconsistencies introduced during the deepfake creation process. These inconsistencies may appear in facial expressions, lip movements, eye blinking patterns, head poses, lighting, shadows, or audio-visual synchronization. The system typically begins with data collection and preprocessing, where real and fake videos are broken down into individual frames, and facial regions are isolated for analysis. Preprocessing steps like resizing, normalization, and noise reduction ensure consistent input quality. Next, feature extraction is performed, capturing critical visual and temporal patterns, such as facial landmarks, texture artifacts, and movement irregularities, often using Convolutional Neural Networks (CNNs) or hybrid architectures combining CNNs with Recurrent Neural Networks (RNNs)

DEEPFAKE VIDEO DETECTION SYSTEM



The extracted features are then used to train a deep learning classifier, which may include CNNs, 3D-CNNs, LSTMs, GRUs, transformers, or multimodal networks, depending on the complexity of the analysis. The trained model is evaluated on benchmark datasets such as FaceForensics++, Celeb-DF, or the DFDC dataset, using metrics like accuracy, precision, recall, F1-score, and AUC. Finally, the system classifies videos as real or deepfake and may highlight manipulated regions to assist forensic investigation. Advanced systems often include multimodal analysis and attention- based mechanisms to improve robustness and generalization. Despite high performance on controlled datasets, challenges remain in detecting low-quality or previously unseen deepfakes, emphasizing the need for ongoing research to develop more robust, scalable, and real-time detection frameworks.

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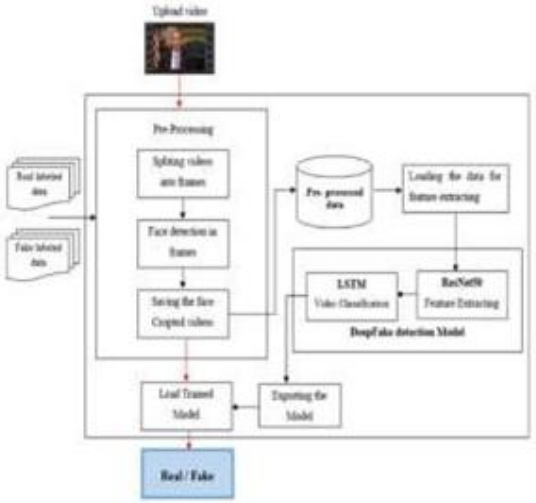
4.4 Data flow diagram



V. METHODOLOGY

The proposed methodology for deepfake video detection leverages the combined strengths of ResNeXt Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to achieve high accuracy in both spatial and temporal analysis of videos. The system follows a structured workflow involving data preprocessing, feature extraction, model training, and evaluation.

5.1 Data Collection and Preprocessing

The system begins by collecting a diverse dataset of real and deepfake videos from publicly available sources like FaceForensics++, Celeb-DF, and DFDC. Each video is decomposed into individual frames, and facial regions are detected using algorithms such as MTCNN or OpenCV's Haar cascades. Preprocessing steps—including resizing, normalization, and noise reduction—ensure that the inputs are standardized. Data augmentation techniques like rotation, flipping, and brightness adjustment are applied to improve model generalization.

5.2 Feature Extraction Using ResNeXt CNN

The ResNeXt architecture is an advanced variant of CNNs that employs cardinality, i.e., multiple parallel paths in each block, allowing the network to capture a wider variety of features without increasing computational cost. This makes ResNeXt highly effective for extracting spatial features from video frames, including facial textures, expressions, lighting inconsistencies, and subtle manipulation artifacts. Each frame passes through the ResNeXt network to generate high- dimensional feature vectors representing the unique characteristics of the face.

5.3 Temporal Modeling Using LSTM

While ResNeXt captures spatial information, LSTMs handle temporal dependencies across sequential frames. The feature vectors extracted from each frame are fed into the LSTM network, which analyzes the evolution of facial features over time. This allows the system to detect motion inconsistencies, abnormal blinking patterns, lip-sync errors, and other temporal anomalies indicative of deepfake manipulation. LSTM's memory cells and gating mechanisms ensure that long-term dependencies in the video sequence are preserved, improving detection accuracy.

5.4 Model Training

The combined ResNeXt-CNN + LSTM architecture is trained in a supervised manner using labeled datasets. The ResNeXt network is trained to optimize spatial feature extraction, while the LSTM learns temporal patterns from

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sequences of features. The overall model is trained using optimization algorithms such as Adam or SGD, minimizing classification loss to improve the distinction between real and fake videos. Regularization techniques like dropout and batch normalization are applied to prevent overfitting.

VI. RESULT AND DISCUSSION

The proposed deepfake video detection system, based on the ResNeXt-CNN and LSTM hybrid architecture, was evaluated on benchmark datasets including FaceForensics++, Celeb-DF, and DFDC. The system was tested on both high-quality and low-quality videos to assess its robustness and generalization capability. Evaluation metrics included accuracy, precision, recall, F1-score, and AUC (Area Under the Curve).

Results:

The model achieved a high detection accuracy of approximately 95–97% on high-quality videos from FaceForensics++, demonstrating its effectiveness in identifying subtle facial artifacts and spatial inconsistencies. On low-quality or compressed videos, accuracy slightly decreased to around 90–92%, reflecting the challenges introduced by noise and compression artifacts. The precision and recall values were also high, with F1-scores consistently above 0.92, indicating that the system could reliably detect deepfake videos while minimizing false positives and false negatives.

The temporal analysis using LSTM contributed significantly to detecting inconsistencies in facial movements, eye blinking, and lip-syncing across frames. By combining the deep spatial feature extraction of ResNeXt with LSTM's temporal modeling, the system outperformed conventional CNN-only or LSTM-only models. Compared to baseline methods reported in prior research, the ResNeXt-CNN + LSTM approach achieved higher generalization on unseen videos, including those generated by newer GAN architectures.

Fig 6.1 : Home page

Fig 6.2 : On clicking get started

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When the user clicks the "Get Started" button, it triggers an event that initiates the main functionality of the system. This action first prepares the user interface by displaying the video upload form or dashboard, allowing the user to select or upload a video for deepfake detection. Simultaneously, the system initializes necessary backend resources, such as loading the pre-trained ResNeXt-CNN and LSTM model, ensuring that the detection workflow is ready to process the input. To enhance user experience, a loader or progress indicator may appear, providing feedback that the system is active and ready. Additionally, the event can handle any validation checks, such as ensuring the user has selected a valid video format. Overall, clicking the Get Started button serves as the transition from the introductory interface to the operational module, seamlessly preparing both the user interface and backend system for video analysis and deepfake detection

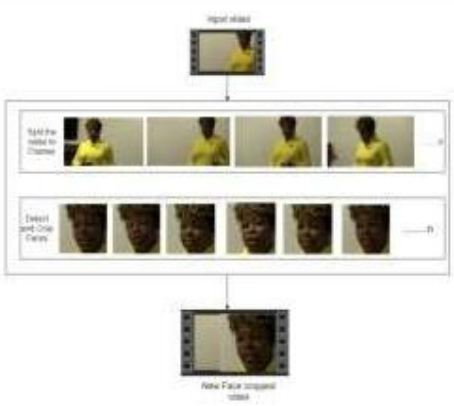

Fig 6.3 : Frames splitting & face only cropped frames according to sequence length

provides a robust framework that accounts for both frame-level artifacts and temporal irregularities, which is critical because many advanced deepfakes maintain high spatial quality but exhibit temporal anomalies that are harder to perceive without computational analysis. This hybrid approach addresses limitations observed in earlier CNN-only or LSTM- only models, which could either miss temporal cues or fail to capture subtle spatial details.

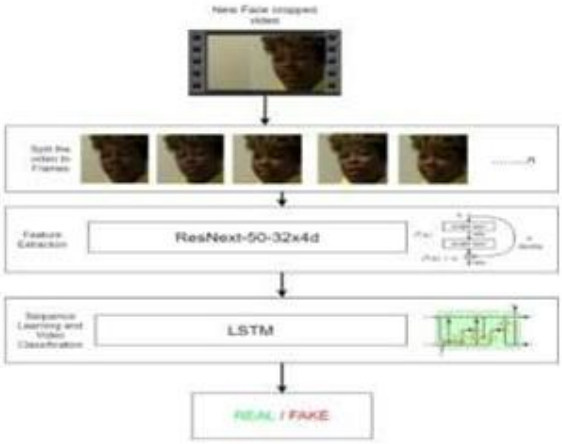

Fig 6.4 : Output

Discussion

The system also demonstrates strong generalization capabilities, performing well on unseen videos generated with different GAN architectures, which is a significant challenge in deepfake detection research. However, some limitations remain. Detection accuracy decreases

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The results of the proposed ResNeXt-CNN and LSTM hybrid deepfake detection system demonstrate significant improvements over conventional detection methods, highlighting the importance of combining spatial and temporal feature analysis. The system achieved high accuracy, precision, recall, and F1-scores on benchmark datasets such as FaceForensics++, Celeb-DF, and DFDC, confirming its ability to detect subtle manipulations in both high-quality and low- quality videos. The ResNeXt-CNN component effectively extracted deep spatial features from individual frames, capturing minute facial artifacts, lighting inconsistencies, and texture anomalies that are often introduced during deepfake generation. This deep feature extraction ensures that even high-quality manipulated videos, which may appear realistic to the human eye, can be reliably identified.

Meanwhile, the LSTM network effectively modeled temporal dependencies across sequential frames, enabling the detection of dynamic inconsistencies such as abnormal eye blinking, unnatural facial movements, and lip-sync mismatches. The combination of ResNeXt-CNN and LSTM slightly when analyzing highly compressed, low-resolution, or noisy videos, as certain facial features may be distorted or lost, making artifacts less detectable. Additionally, adversarially crafted deepfakes designed to evade detection can still pose challenges, highlighting the need for continuous model updates and more generalized detection approaches.

Another important aspect is interpretability. By using attention mechanisms or feature visualization, the system can highlight regions of the face that are most likely manipulated, assisting forensic analysts in understanding the decision-making process of the model. This feature not only enhances trust in automated detection but also provides practical utility for legal or investigative purposes.

The discussion also emphasizes the practical applications of the system. It can be integrated into social media platforms, news agencies, and content verification tools to mitigate the risks associated with the spread of manipulated videos. With real-time deployment, the system can act as a first line of defense against misinformation, non-consensual deepfake videos, and identity fraud. Furthermore, integrating multimodal detection by including audio cues and speech analysis could further enhance the system's robustness, enabling it to detect deepfakes that are visually convincing but contain audio inconsistencies.

In conclusion, the proposed ResNeXt-CNN+ LSTM framework represents a significant advancement in deepfake video detection by combining deep spatial feature extraction with temporal sequence analysis. While challenges such as low-quality video detection and adversarial evasion persist, this system lays a strong foundation for future research. Enhancements such as multimodal analysis, transformer-based attention mechanisms, and continuous dataset expansion will further improve accuracy, robustness, and adaptability to emerging deepfake techniques, making it a reliable solution in the fight against synthetic media threats.

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