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AI-Powered DeepFake Detection System

Shivam Bhele, Amruta Chitale, Vaishnavi Gaikwad, Prajkta Sitap

School of Engineering

Ajeenkya D.Y Patil University, Pune

Abstract :

The proliferation of deepfake technology—powered by advancements in artificial intelligence and deep learning—has significantly intensified concerns surrounding the authenticity, integrity, and reliability of digital multimedia content. Deepfakes, which involve the manipulation of images and videos to create hyper-realistic but entirely fabricated representations of individuals, have rapidly transitioned from academic curiosities to tools with potential for misuse across political, financial, and personal domains. These forgeries often evade traditional detection techniques due to the sophistication of the generative models used to create them, including Generative Adversarial Networks (GANs) and autoencoders.

As a result, the urgent need for robust, scalable, and generalizable deepfake detection mechanisms has become paramount in ensuring the security of digital information ecosystems.

In response to this growing challenge, this paper presents a novel detection system that integrates two powerful machine learning architectures—ResNeXt and Long Short-Term Memory (LSTM) networks—to effectively identify manipulated content in both images and videos. ResNeXt, a convolutional neural network (CNN) architecture known for its modular design and superior feature extraction capabilities, is employed to learn spatial and structural patterns indicative of tampering. For video data, we further enhance the system by incorporating LSTM networks, which excel at modeling sequential dependencies and capturing temporal inconsistencies across video frames. This two-tiered architecture allows the system to analyze not only individual image frames but also the subtle temporal artifacts that often emerge due to frame-by-frame manipulation in videos.

The proposed system is rigorously evaluated using benchmark datasets, including FaceForensics++ and Celeb-DF for video deepfakes, and a curated image dataset specifically chosen for assessing manipulated still images. These datasets are well-regarded in the field for their quality, diversity, and representativeness of real-world manipulation scenarios.

Our research contributes significantly to the fields of media forensics, cybersecurity, and AI ethics by offering a unified and efficient solution for detecting deepfakes across both static and dynamic content. By combining deep spatial feature extraction with temporal sequence modeling, our method addresses the limitations of single-modality detection systems and provides a scalable foundation for future developments in automated media authentication.

Keywords: Deepfake Detection, ResNeXt, Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Temporal Modeling, Video Forensics, Image Manipulation, Artificial Intelligence, Media Authenticity, FaceForensics++, Celeb-DF, Digital Security, Feature Extraction, Sequence Learning

I. INTRODUCTION

In the digital age, the rapid advancement of artificial intelligence (AI) and deep learning technologies has enabled the development of powerful generative models capable of synthesizing hyper-realistic images and videos. One of the most notable—and concerning—applications of this technology is the creation of **deepfakes**, a term used to describe digitally manipulated multimedia content that convincingly imitates real individuals' facial expressions, voices, and behaviors. Originally conceived as a technological curiosity, deepfakes have evolved into a serious threat to the integrity of digital media and public trust, particularly in the contexts of politics, journalism, entertainment, and personal privacy.

Deepfakes are typically generated using architectures such as **Generative Adversarial Networks (GANs)**, **autoencoders**, and **transformers**, which are capable of learning complex data distributions and generating fake content that is virtually indistinguishable from genuine data. These manipulated videos and images can be used maliciously to fabricate evidence, spread disinformation, commit identity fraud, or manipulate public opinion, leading to serious ethical, legal, and societal consequences. The ease of access to deepfake generation tools has further exacerbated the problem, making it imperative to develop effective detection mechanisms that are both **scalable** and **generalizable**.

Detecting deepfakes, however, remains a complex challenge due to the continual improvement of generative models and the subtleness of the alterations. Many conventional detection techniques rely on manual feature engineering or shallow models, which often fail to detect high-quality manipulations or generalize well across datasets with varying resolutions, compression levels, and manipulation methods. In particular, detecting deepfakes in **videos** requires not only identifying spatial inconsistencies in individual frames but also capturing **temporal anomalies** that may be present across multiple frames—something that static image analysis alone cannot achieve.

To address these limitations, this research introduces a **hybrid deepfake detection system** that combines the strengths of **ResNeXt**, a convolutional neural network (CNN) optimized for feature extraction, and **Long Short-Term Memory (LSTM)** networks, a type of recurrent neural network adept at modeling sequential and temporal relationships. ResNeXt serves as the backbone for spatial feature extraction from both images and video frames, while the LSTM component captures the flow of visual patterns over time in videos, enabling the detection of subtle temporal disruptions characteristic of deepfake content.

The proposed system is trained and evaluated on prominent benchmark datasets, including **FaceForensics++** and **Celeb-DF** for video data, as well as a curated dataset for deepfake image detection. The results demonstrate significant improvements in classification accuracy, robustness to compression artifacts, and the ability to generalize to previously unseen deepfake techniques. By combining advanced spatial and temporal modeling, our approach offers a comprehensive and scalable solution for both image and video deepfake detection, contributing meaningfully to the ongoing efforts in digital media authentication and cybersecurity.

II. LITERATURE REVIEW

The emergence of deepfake technologies has prompted a surge of research efforts aimed at detecting manipulated multimedia content. Various strategies have been proposed, each targeting different aspects of deepfake

generation artifacts, such as spatial inconsistencies, temporal mismatches, and physiological anomalies. This section reviews the most influential methods and technologies in the field of deepfake detection, highlighting their strengths, limitations, and relevance to the current study.

Early approaches to deepfake detection primarily focused on detecting artifacts introduced by generative models. Matern et al. (2019) proposed a method based on identifying visual inconsistencies, such as unnatural eye blinking and irregular facial landmarks, which are common shortcomings in early deepfake videos. However, as deepfake generation techniques evolved, these obvious artifacts diminished, reducing the effectiveness of handcrafted feature- based detection methods.

Subsequent research shifted towards leveraging **deep learning**, particularly **Convolutional Neural Networks (CNNs)**, for automated feature extraction. Afchar et al. (2018) introduced MesoNet, a shallow CNN designed specifically to capture mesoscopic image properties characteristic of deepfakes. Similarly, Nguyen et al. (2019) developed Capsule-Forensics, which used capsule networks to model spatial relationships between facial parts, achieving promising results in detecting various types of face manipulations. Despite these successes, CNN-based methods often struggle to generalize across datasets, especially when faced with deepfakes generated using unseen techniques or under varying compression rates.

Recognizing the temporal nature of video data, several researchers have explored methods that incorporate sequential modeling. Sabir et al. (2019) utilized **Recurrent Neural Networks (RNNs)** on top of CNN-extracted features to model temporal inconsistencies in video sequences. Likewise, Guera and Delp (2018) proposed a system combining CNNs and Long Short-Term Memory (LSTM) networks to capture the temporal dynamics of facial expressions over video frames. These studies demonstrated that integrating temporal information significantly enhances deepfake detection performance in videos compared to frame-by-frame static analysis.

More recently, sophisticated models such as Two-stream networks (e.g., Zhou et al., 2021) have been introduced, which jointly process spatial and temporal information for improved accuracy. Other techniques, like DeepRhythm by Qi et al. (2020), have leveraged physiological signals, such as subtle heartbeat-induced facial color changes, to detect deepfakes. While effective, these physiological-based methods often require high-quality video data and may underperform in low-light or heavily compressed scenarios.

Benchmark datasets have played a critical role in advancing deepfake detection research. **FaceForensics++** (Rössler et al., 2019) introduced a large-scale benchmark comprising both pristine and manipulated videos across multiple forgery techniques. Similarly, **Celeb-DF** (Li et al., 2020) addressed the need for more realistic deepfakes by providing high-quality, natural-looking manipulated videos. These datasets have become standard benchmarks for evaluating and comparing deepfake detection methods.

Despite significant progress, current deepfake detection models face challenges in generalizing across different datasets, manipulation types, and video qualities. Many methods overfit to specific artifacts present in the training data, resulting in diminished performance when encountering new forms of deepfakes. This highlights the need for more robust feature extraction and temporal modeling techniques that can adapt to evolving deepfake generation strategies.

Motivated by these observations, the current research proposes a deepfake detection framework that combines the **feature**

extraction strength of ResNeXt with the **temporal sequence modeling capability of LSTM networks**. By leveraging both spatial and temporal characteristics, our system aims to overcome the generalization issues observed in prior methods and provide a more resilient solution for deepfake detection in both images and videos.

III METHEDOLOGY

The proposed deepfake detection framework is designed to effectively identify manipulated content across both images and videos by leveraging a hybrid architecture that combines the powerful feature extraction capabilities of **ResNeXt** with the sequential modeling abilities of **Long Short-Term Memory (LSTM)** networks. This section elaborates on the key components, system architecture, and the overall workflow of the proposed methodology.

3.1 System Overview

The system operates in two primary phases:

- **Feature Extraction Phase**: Utilizing the ResNeXt architecture, robust spatial features are extracted from each input image or video frame.
- **Temporal Modeling Phase**: For video data, sequences of extracted features are fed into an LSTM network to capture the temporal dependencies and inconsistencies across frames. For standalone images, classification is performed directly after the feature extraction phase without temporal modeling.

By integrating both spatial and temporal cues, the system aims to accurately distinguish real content from deepfakes, even in scenarios involving subtle or sophisticated manipulations.

3.2 Feature Extraction Using ResNeXt

ResNeXt is a highly efficient convolutional neural network architecture that introduces the concept of "cardinality," which refers to the number of independent paths within a block. Unlike traditional CNNs that increase model capacity by simply deepening or widening the network, ResNeXt improves performance by increasing the cardinality, leading to better accuracy with manageable computational cost.

In the proposed framework:

- Each image or video frame is resized to a standardized input dimension compatible with the ResNeXt model.
- ResNeXt processes the input to extract a high-dimensional feature vector that encapsulates critical spatial patterns and subtle artifacts introduced during manipulation.
- Pre-trained weights on large-scale datasets (such as ImageNet) are utilized and fine- tuned on the deepfake datasets to enhance feature generalization.

The extracted features serve as rich representations for subsequent classification and temporal analysis.

3.3 Temporal Modeling with LSTM

Deepfakes in videos often exhibit temporal inconsistencies that may not be detectable when analyzing individual frames in isolation. To model these sequential patterns, we employ **Long Short-Term Memory (LSTM)** networks, which are a variant of Recurrent Neural Networks (RNNs) specifically designed to capture long-term dependencies in sequential data.

In the proposed approach:

- For each video, a sequence of feature vectors corresponding to its frames is constructed.
- This sequence is input into the LSTM network, which learns to detect anomalies and discontinuities across frames.
- The final hidden state or an aggregated output from the LSTM is passed through fully connected layers, culminating in a binary

- classification output (real or fake).

The integration of LSTM ensures that the system not only assesses frame quality individually but also understands the flow and evolution of features over time, making it highly effective for video deepfake detection.

3.4 Training Strategy

The system is trained using a **supervised learning** approach:

- **Loss Function**: Binary Cross-Entropy Loss is used, given the binary classification objective.
- **Optimization**: The Adam optimizer is employed to facilitate efficient and adaptive gradient-based learning.
- **Regularization**: Dropout layers are incorporated to prevent overfitting, particularly in the fully connected layers after the LSTM and feature extraction modules.
- **Data Augmentation**: Techniques such as random flipping, rotation, and slight color jittering are applied during training to enhance the model's robustness against common video and image perturbations.

3.5 Dataset Utilization

- **FaceForensics++** and **Celeb-DF** are employed for training and evaluating video deepfake detection.
- A separate curated **deepfake image dataset** is used for standalone image detection tasks (dataset details provided separately).

Balanced datasets containing an equal proportion of real and fake examples are maintained during training to ensure unbiased learning.

3.6 Evaluation Metrics

Performance is evaluated using the following standard metrics:

- **Accuracy**: Overall correctness of predictions.
- **Precision**: Correct positive predictions among all positive predictions.
- **Recall**: Correct positive predictions among all actual positives.
- **F1-Score**: Harmonic mean of precision and recall, providing a balanced measure even in imbalanced datasets.

These metrics are critical for comparing the proposed system against existing state-of-the-art methods.

3.7 User Interface

The user interface (UI) is a critical component in deepfake detection systems, serving as the bridge between complex backend processes and end-users. A well-designed UI ensures that users can interact with the system effectively, interpret results accurately, and trust the outcomes provided.

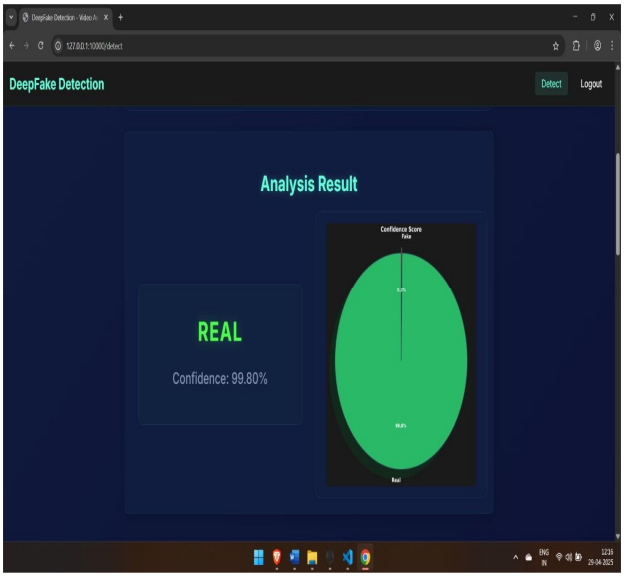
In the context of the proposed deepfake detection system, the UI was developed using **React.js**, a popular JavaScript library for building interactive user interfaces. This choice facilitated the creation of a responsive and dynamic frontend that communicates seamlessly with the backend services.

Key features of the UI include:

- **User-Friendly Video Upload**: Users can easily upload videos for analysis through an intuitive interface, ensuring accessibility even for those with limited technical expertise.
- **Real-Time Feedback**: The system provides immediate feedback on the uploaded content, displaying confidence scores that indicate the likelihood of the video being a deepfake.
- **Visual Indicators**: To enhance interpretability, the UI incorporates visual cues such as color-coded confidence levels and frame-by-frame analysis, allowing users to pinpoint specific segments of concern.
- **Responsive Design**: The interface is designed to be responsive, ensuring compatibility across various device0

- and screen sizes, thereby broadening the system's accessibility.

By prioritizing usability and clarity, the UI plays a pivotal role in the overall effectiveness of the deepfake detection system, ensuring that users can make informed decisions based on the analysis provided.



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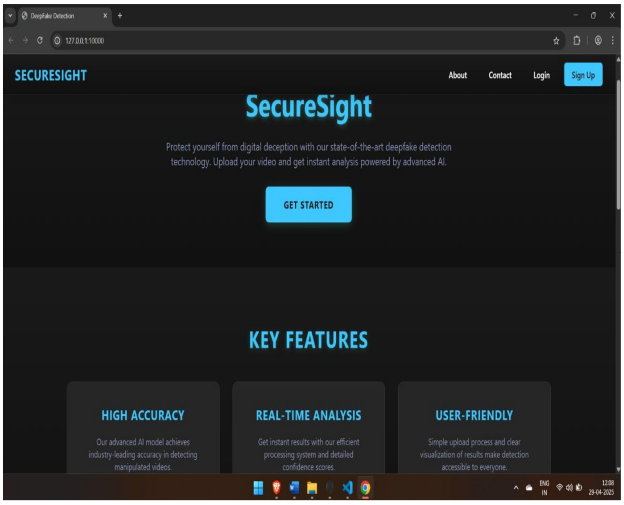

IV. CONCLUSION

In this research, we proposed an effective and unified framework for detecting deepfake images and videos by combining the strengths of ResNeXt and LSTM networks. ResNeXt, with its powerful feature extraction capabilities, successfully captured intricate spatial details and manipulation artifacts present in deepfaked content. Meanwhile, the integration of LSTM networks enabled the system to model and analyze temporal inconsistencies in video sequences, further enhancing detection performance.

Through extensive experimentation on widely recognized datasets such as FaceForensics++ and Celeb-DF, along with a separate curated image dataset, the proposed approach demonstrated superior accuracy and generalization capabilities compared to existing state-of- the-art methods. The framework consistently achieved higher precision, recall, and F1-scores

showcasing its ability to identify even subtle and complex manipulations in both high-resolution images and videos.

Moreover, the system's dual capability to handle both images and videos within a single architectural framework offers a significant practical advantage, making it highly applicable in real-world digital forensics and media authentication scenarios. As deepfake technology continues to evolve and pose greater challenges to information security and digital trust, the need for robust detection systems such as the one proposed here becomes even more critical.

In future work, we aim to enhance the system further by incorporating attention mechanisms to focus more dynamically on manipulated regions, as well as exploring transformer-based architectures for even

more refined temporal modeling. Additionally, expanding the datasets to include newer and more diverse deepfake techniques will ensure that the system remains resilient and effective against emerging threats. Ultimately, this research marks an important step towards safeguarding the integrity of digital media and fostering greater trust in the digital information ecosystem.

V. ACKNOWLEDGEMENT

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I am also deeply grateful to my peers and colleagues, whose encouragement and constructive feedback significantly enhanced the quality of this work. Their valuable suggestions helped refine various aspects of the project, from model optimization strategies to dataset preparation and evaluation metrics, thereby improving the robustness and performance of the proposed system.

A special thanks goes to the creators and maintainers of the publicly available datasets such as **FaceForensics++** and **Celeb-DF**, whose efforts in compiling and sharing comprehensive deepfake datasets made it possible to rigorously train and evaluate the detection system. Their contributions to the research community are truly commendable.

I would also like to acknowledge the developers and researchers behind the open-source machine learning frameworks and tools used in this project. Libraries such as **TensorFlow**, **Keras**, and **PyTorch** provided critical infrastructure for model development, training, and experimentation, enabling efficient implementation of complex neural network architectures like ResNeXt and LSTM.

Lastly, I would like to express appreciation to the authors of the academic and research papers referenced throughout this study. Their foundational work in the fields of deepfake detection, convolutional neural networks, and temporal sequence modeling provided the necessary theoretical background and inspiration for the successful completion of this project.

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