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DeepFake Video Detection

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Abstract - The swift progress in deepfake creation methods has triggered significant worries about the genuineness and dependability of online video material. Manipulated facial appearances in deepfake videos and expressions present considerable dangers in areas like social media, journalism, and digital forensics.While current deep learning-based detection techniques have shown encouraging outcomes, numerous models demonstrate restricted generalization when utilized on unfamiliar datasets or live video feeds. This study introduces a deepfake video detection system that incorporates ResNeXt for spatial characteristics.extraction using an Attention-Driven Bidirectional Long Short-Term Memory (Bi- LSTM) model for temporal examination. ResNeXt adeptly extracts distinguishing facial characteristics from separate frames, whereas the attention-boosted Bi-LSTM selectively emphasizes significant temporal segments throughout video sequences.This integrated structure enhances the understanding of both spatial discrepancies and temporal dynamics.dependencies related to deepfake modification. Experimental findings indicate that the suggested method demonstrates excellent results on benchmark datasets. In spite of its effectiveness, issues connected to dataset reliance and immediate implementation persist, which are examined alongside possible future research pathways

Keywords - Video Detection, ResNeXt, Attention-Based Bi-LSTM, Spatial–Temporal Analysis, Video Forensics, Deep Learning.

I. INTRODUCTION

The increasing availability of advanced deep learning models has significantly accelerated the development of deepfake technology. Deepfakes allow for the production of extremely convincing edited videos in which facial identity, expressions, or vocal patterns are modified. While such technology has legitimate applications in entertainment and content creation, it also presents serious risks, including misinformation, identity fraud, and reputational damage.

Detecting deepfake videos has therefore become an important research problem in the fields of computer vision and cybersecurity. Early detection approaches relied on handcrafted features and visual artifacts; however, these methods struggle against modern deepfake generation techniques that produce visually coherent results. Recent advances have shifted toward deep learning-based Even with significant advancements, numerous current deepfake detection models undergo training and assessment on restricted datasets, which hampers their capability to extend to unfamiliar videos or practical situations.Differences in video quality, compression, illumination circumstances, and control methods frequently result to a decline in performance when models are situated outside of regulated settings.To tackle these issues, this document suggests a ResNeXt and Focus-Oriented Bi-LSTM structure for detecting deepfake videos. The suggested system integrate robust spatial feature acquiring knowledge through improved temporal modeling, facilitating enhanced detection across various video material.

II. RELATED WORKS

The detection of deepfakes has been thoroughly investigated utilizing techniques for both spatial and temporal analysis. Early deepfake detection models used convolution-based deep learning architectures to analyze visual inconsistencies at the frame level. Afchar et al. [1] introduced MesoNet, a compact

CNN architecture designed to detect facial manipulations, demonstrating promising results on manipulated video datasets. However, purely spatial approaches often struggle with high-quality deepfakes that preserve frame-level visual coherence.

Temporal dependencies within video data are typically learned using models designed for sequential pattern analysis.. Sabir et al. [2] proposed recurrent convolutional strategies that combine CNN-based feature extraction with temporal modeling, achieving improved detection accuracy by leveraging frame- to-frame dependencies. The work presented in [3] demonstrated that deepfake detection performance is strongly influenced by dataset scale and diversity, leading to the introduction of the Celeb-DF dataset for systematic benchmarking.

A closely related study introduced a deepfake detection framework combining ResNeXt and LSTM architectures, in which ResNeXt served as the spatial representation backbone while LSTM modules learned temporal patterns across consecutive frames [7]. Although the model achieved strong performance on benchmark datasets, it primarily relied on dataset-specific characteristics and lacked mechanisms to emphasize temporally informative frames, which may limit its generalization to unseen or real-world videos.

Motivated by earlier studies, this work enhances the ResNeXt–LSTM framework by integrating an attention-driven bidirectional LSTM. The attention component prioritizes informative temporal segments, whereas the bidirectional design learns dependencies from both past and future frame sequences. This enhancement aims to improve robustness and adaptability when handling diverse deepfake video content.

Existing Systems

The proposed system adopts a spatiotemporal learning strategy to identify manipulated videos. A convolutional backbone based on the ResNeXt architecture is used to generate frame-level visual representations from facial regions in video sequences. These representations encode fine- grained visual cues and structural irregularities that may arise due to synthetic manipulation. To incorporate temporal context, the extracted frame representations are organized as sequences and analyzed using a sequence-learning network capable of capturing temporal dependencies across successive frames. This design allows the model to jointly analyze visual characteristics and temporal behavior for reliable deepfake detection.

The joint analysis of visual and sequential cues enables the identification of inconsistencies that may remain unnoticed when frames are examined independently. The temporal modeling component enables the detection of unnatural transitions and motion patterns introduced during deepfake generation. A binary classification layer is used to distinguish between authentic and manipulated videos based on the learned spatial temporal representations.

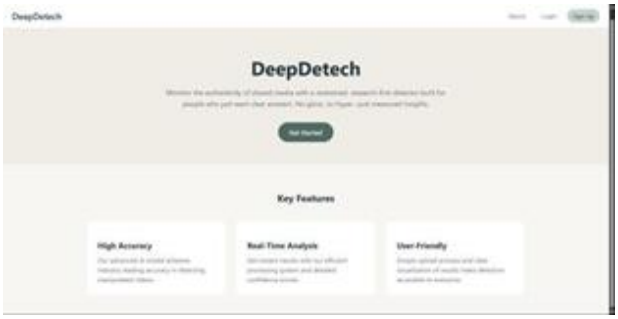

Figure 1: DeepDetech

Proposed System

Deepfake Detection System Using ResNeXt and Attention-Based Bi-LSTM

The proposed deepfake detection framework adopts a hybrid spatiotemporal learning design. A ResNeXt-based convolutional backbone is applied to generate frame-level visual representations from video data, focusing on facial regions where synthetic alterations are likely to occur. These representations encode fine-grained visual characteristics and irregularities introduced during manipulation. To incorporate temporal context, an attention-guided bidirectional sequence learning network is employed, enabling the model to analyze temporal relationships across

frames and improve discrimination between authentic and manipulated videos.

The extracted frame-level features are then sequentially processed using a Bi-LSTM network, which analyzes temporal dependencies in both forward and backward directions. To further enhance temporal modeling, an attention mechanism is incorporated, enabling the system to focus on frames that contain significant manipulation cues while reducing the influence of less informative frames. Final video-level predictions are generated by applying a classification layer to the learned spatiotemporal representations.

Goals of Proposed System

Multi-Level Spatial–Temporal Representation

Feature The integration of ResNeXt and Attention-Based Bi LSTM enables multi-level feature representation. ResNeXt captures rich spatial information from individual frames, while the Bi-LSTM models temporal dependencies across frame sequences. This joint learning framework allows the system to capture both local spatial inconsistencies and global temporal patterns associated with deepfake manipulation, thereby improving detection accuracy.

Enhanced Temporal Modeling with Attention Mechanism

The attention mechanism allows the model to dynamically assign higher importance to frames that exhibit stronger selectively manipulation indicators. By emphasizing informative temporal segments, Improved robustness is achieved against subtle and sophisticated deepfake manipulations that maintain visual coherence across frames.

Improved Generalization Across Diverse Video Content

The incorporation of bidirectional temporal modeling together with adaptive frame weighting improves the model's flexibility when processing videos recorded under diverse conditions, including variations in

resolution, compression, illumination, and facial motion. As a result, stronger generalization is achieved across multiple datasets as well as real-world video environments.

Potential for Real-Time and Practical Deployment

With appropriate optimization and efficient implementation, the proposed ResNeXt and Attention-Based Bi-LSTM framework can be adapted for near–real-time deepfake detection. These characteristics support real-world use cases including content moderation, video authentication, and social media content management, where rapid detection is required.

Adaptability to Complex and Dynamic Scenes

The hierarchical feature extraction capability of ResNeXt combined with the sequential modeling strength of Bi-LSTM enables effective analysis of videos containing complex scenes, multiple subjects, and dynamic facial expressions. This adaptability increases the applicability of the proposed system across diverse and challenging video environments.

III. METHODOLOGY

Dataset Preparation and Preprocessing

For model development and assessment, a heterogeneous collection of authentic and manipulated videos was utilized. The data were sourced from well-established public benchmarks such as FaceForensics++, Celeb-DF, the DeepFake Detection Challenge (DFDC), and DeepFake-TIMIT. These benchmarks include videos generated through a wide range of manipulation strategies and are characterized by variations in resolution, compression quality, and recording conditions. Such diversity ensures the presence of rich visual and temporal variations, enabling a comprehensive evaluation of the proposed framework. Videos were preprocessed by extracting frames at fixed intervals. Face detection techniques were applied to localize and crop facial regions, which were then resized and normalized to maintain consistency across inputs.

Spatial Feature Extraction Using ResNeXt

Each extracted frame is passed through a pre-trained ResNeXt model to obtain high-level spatial

feature representations. ResNeXt's aggregated residual transformations enable efficient learning of discriminative facial features that differentiate real videos from manipulated ones.

Temporal Modeling with Attention-Based Bi LSTM

The extracted frame-level features are fed into a Bidirectional LSTM network to capture temporal dependencies across video sequences. An attention mechanism is integrated to adaptively weight video frames, prioritizing those that exhibit stronger manipulation-related cues

Classification

Final predictions are obtained by applying a fully connected layer and sigmoid activation to the output of the attention-based Bi-LSTM.

Results

The ResNeXt and attention-guided Bi-LSTM framework was assessed using commonly adopted evaluation measures such as accuracy, precision, recall, and F1-score.

The experimental findings demonstrate strong detection performance and confirm the model's effectiveness in identifying temporal irregularities present in manipulated video content.

The inclusion of the attention mechanism improves the model's ability to focus on informative frames, resulting in better performance compared to baseline CNN-LSTM architectures. However, Accuracy tends to decline when evaluation is performed on previously unseen datasets or videos with substantial compression and noise.

These findings highlight the importance of dataset diversity and model generalization in real-world applications.

Table -1: Detection Performance Analysis

	Overall Prediction Correctness	Positive Prediction Reliability	Detection Sensitivity	F1-score
Other model	98.6	92.6	94.3	93.5
Our model	86	87.5	84	85.7

Table -2: Confusion Matrix

	Predicted Fake	Predicted Real
Actual deepfake	440	60
Actual real	80	420

IV. CONCLUSION

This study introduced a deepfake video detection framework that combines a ResNeXt-based convolutional backbone with an attention-guided Bidirectional LSTM for temporal sequence analysis. The joint use of frame-level visual representation learning and advanced temporal modeling enables reliable identification of manipulated videos and delivers strong performance across benchmark datasets.

Despite its effectiveness, the model remains sensitive to dataset characteristics and may experience reduced accuracy when applied to unseen or real time video streams. Enhancing cross-dataset generalization, incorporating domain adaptation methods, and developing lightweight models for real-time deployment remain key areas for further exploration. These advancements will contribute to more reliable and practical deepfake detection systems.

Future Work

Further investigation into machine learning–based approaches for fake credit transaction detection can address multiple directions. Although the current work demonstrates substantial progress in deepfake detection through the use of ResNeXt and LSTM architectures, there remain several promising research and development opportunities that merit further examination.

Enhanced Model Robustness: Further investigation into novel architectures and techniques can enhance the robustness and generalization capabilities of deepfake detection models. Investigating ensemble learning strategies and integrating domain-specific knowledge can further enhance detection performance.

Adversarial Defense Strategies: With the rapid advancement of deepfake generation techniques, ensuring robustness against adversarial threats has become a critical concern.

Continued investigation is required to design resilient methods capable of identifying and counteracting adversarial manipulations intended to compromise deepfake detection systems.

Real-Time Detection Frameworks: Rapid identification of manipulated media requires detection systems that can operate efficiently under real-world constraints. Ongoing research should emphasize the design of computationally efficient and lightweight models that can be deployed effectively in practical environments such as social media platforms and online content moderation pipelines.

Pursuing these research directions will help drive further progress in deepfake detection and support ongoing initiatives aimed at reducing the impact of deceptive multimedia manipulation.

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