Hybrid Deepfake Detection Using CNN for Spatial Analysis and LSTM for Temporal Consistency

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Abstract: Deepfake technology, driven by advancements in artificial intelligence, enables the creation of highly realistic manipulated videos, posing significant threats to security, privacy, and misinformation. Traditional detection methods struggle to keep pace with the evolving sophistication of deepfake techniques. This study proposes a hybrid deep learning approach that leverages Convolutional Neural Networks (CNN) for feature extraction and Long Short-Term Memory (LSTM) networks for temporal sequence analysis to enhance deepfake detection accuracy. The CNN model captures spatial inconsistencies and artifacts in individual frames, while the LSTM network analyzes sequential dependencies to detect temporal anomalies indicative of deepfakes. Experimental evaluations on benchmark datasets demonstrate the effectiveness of the approach, achieving high accuracy in distinguishing real from fake videos. The proposed model offers a robust and scalable solution for deepfake detection, contributing to the fight against digital media manipulation and misinformation.

Keywords: *Deepfake Detection, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Artificial Intelligence, Digital Media Forensics, Misinformation, Temporal Analysis, Feature Extraction, Fake Video Identification.*

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I. INTRODUCTION

Deepfake technology has emerged as a significant challenge in digital media, leveraging deep learning techniques such as Generative Adversarial Networks (GANs) [1] to create highly realistic yet fabricated videos. These manipulated videos are increasingly used for both entertainment and malicious purposes, raising concerns about misinformation, identity theft, and security breaches [2]. The proliferation of deepfake creation tools has made it easier for malicious actors to produce convincing fake content, threatening the integrity of online media and public trust [3].

Traditional forensic methods, such as pixel-level analysis and metadata inspection, are often ineffective against modern deepfake algorithms due to their sophistication. Conventional approaches struggle to detect subtle inconsistencies in manipulated videos, making them unreliable in real-world scenarios [4]. Therefore, developing advanced and reliable deepfake detection techniques is crucial to combat this growing threat.

Deep learning-based models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have shown promising results in detecting deepfakes. CNNs are effective in identifying spatial anomalies in individual frames, such as unnatural facial expressions, blending artifacts, and lighting inconsistencies [5]. Meanwhile, LSTM networks analyze sequential dependencies, capturing temporal anomalies across video frames, which are often indicative of deepfake content [6]. By combining CNNs and LSTMs, a hybrid model can leverage both spatial and temporal features, resulting in more robust and accurate deepfake detection.

This paper proposes a hybrid deep learning framework that integrates CNNs for spatial feature extraction and LSTMs for temporal sequence analysis. The proposed model processes video frames through a CNN to detect frame-level artifacts and then uses an LSTM to analyze temporal inconsistencies between frames. This combined approach enhances the model's accuracy in distinguishing between real and manipulated videos.

Experimental evaluations on benchmark datasets, such as FaceForensics++ and the Deepfake Detection Challenge dataset, demonstrate the effectiveness of the proposed system. The results indicate that the CNN-LSTM architecture outperforms conventional models in terms of accuracy, precision, and recall, making it suitable for real-world applications like social media content moderation and digital forensics [7].

II. RESEARCH GOALS

The primary goal of this research is to develop an efficient and scalable deepfake detection model by integrating CNNs and LSTMs. This hybrid approach aims to improve detection accuracy by leveraging spatial and temporal features within video data. Unlike traditional methods that rely solely on frame-by-frame analysis, the model processes sequences of frames to detect inconsistencies that are imperceptible to the human eye. Additionally, the model is optimized for real-time performance, enabling practical deployment in security applications and social media content moderation.

Another critical objective is to benchmark the proposed model against existing deepfake detection techniques. The effectiveness of the model is assessed using publicly available datasets, such as FaceForensics++ and the Deepfake Detection Challenge dataset, to ensure robustness across different deepfake generation methods. Furthermore, the model’s robustness against adversarial attacks is enhanced, ensuring sustained effectiveness even as deepfake creation techniques evolve.

III. LITERATURE SURVEY

The rapid advancements in deep learning and artificial intelligence have facilitated the development of highly convincing deepfake content. As deepfakes pose serious threats to digital authenticity, numerous approaches have been proposed to detect and mitigate their impact. This literature review highlights several recent techniques developed for deepfake detection, emphasizing their methodologies, performance, and contributions.

One promising approach to real-time deepfake video detection was proposed by Masud et al. [1], who introduced LW-DeepFakeNet, a lightweight time-distributed CNN-LSTM network. The model achieved an impressive accuracy of 98.6% on the FaceForensics++ dataset, offering high efficiency while maintaining real-time processing capabilities. This approach demonstrates the potential of integrating convolutional and recurrent neural networks for robust video analysis.

Patel et al. [2] proposed an improved dense CNN architecture aimed at enhancing feature extraction capabilities, achieving a remarkable 92.4% accuracy on the DFDC dataset. The model leverages dense connectivity to propagate learned features more effectively, resulting in higher detection performance. This architecture underscores the significance of dense convolutional layers in increasing model robustness.

Tran et al. [3] introduced a high-performance deepfake detection technique using attention-based CNNs with manual distillation. By incorporating region-specific attention mechanisms, the model achieved 95.3% accuracy on the Celeb-DF dataset. This approach highlights the importance of focusing on facial regions to improve precision and reduce false positives.

Gupta et al. [4] proposed a temporal sequence analysis method for detecting deepfake videos using LSTM networks. By focusing on temporal inconsistencies, the model attained an accuracy of 94.7% on the FaceForensics++ dataset. This technique emphasizes the importance of modeling temporal dependencies to enhance the accuracy of video-based deepfake detection.

Chen et al. [5] proposed a hybrid CNN-LSTM model combined with transfer learning, which achieved 97.1% accuracy on both FF++ and Celeb-DF datasets. By leveraging pre-trained models and combining convolutional and recurrent layers, the system demonstrates improved performance in detecting forged content, making it an effective choice for real-world applications.

Li et al. [6] introduced a novel approach that employs contrastive learning for better feature separation and refinement. With an accuracy of 96.4% on the Deepfake Detection Challenge dataset, this technique demonstrates the potential of contrastive learning in enhancing the distinction between real and fake content. The approach significantly reduces feature overlap, thereby improving classification accuracy.

Lastly, Wang et al. [7] presented a multi-stream CNN-LSTM model for robust deepfake detection. The integration of multiple data streams enhances the model's robustness against various types of forgeries, resulting in a detection accuracy of 98.2% on the DFDC dataset. This architecture showcases the effectiveness of leveraging diverse feature streams to capture subtle inconsistencies within fake content.

Overall, the reviewed studies reflect the evolving landscape of deepfake detection techniques, highlighting the continuous improvements made through advanced architectures and learning paradigms. Combining CNNs with LSTM networks, integrating attention mechanisms, leveraging transfer learning, and employing contrastive learning techniques are pivotal strategies in advancing deepfake detection capabilities.

IV. PREPROCESSING

During this stage, the input videos undergo a series of preprocessing steps to enhance the quality of the data and improve the model's performance. The process begins with frame extraction, where individual frames are separated from the video at a fixed frame rate (e.g., 30 fps). This ensures that the model receives a sufficient number of frames for accurate temporal analysis.

Next, face detection is performed using MTCNN (Multi-task Cascaded Convolutional Networks), a deep learning-based face detector known for its accuracy in locating facial regions. The detected faces are cropped and resized to a fixed dimension (e.g., 224x224 pixels) to maintain uniformity across the dataset. This resizing helps the model focus specifically on facial features, removing unnecessary background noise.

To improve the consistency of the input data, the frames are normalized by adjusting pixel intensity values to a standard range (0-1). This normalization reduces the impact of lighting variations and enhances the model's ability to detect subtle deepfake artifacts. Additionally, histogram equalization is applied to improve the contrast, making facial details more distinguishable.

For better training accuracy, pseudo-labeling is introduced, where weakly labeled or ambiguous frames are assigned estimated labels based on their similarity to confidently labeled samples. This technique helps the model learn more effectively from partially labeled or noisy data, reducing the risk of overfitting.

Finally, visual artifact filtering is applied to detect deepfake-specific inconsistencies. This includes identifying unnatural facial expressions, irregular skin textures, and blending artifacts. Frames exhibiting these anomalies are flagged for further analysis. As depicted in Figure 1, this preprocessing stage plays a crucial role in refining the input data, ensuring that the detection model receives clean, standardized, and high-quality samples for training and evaluation.

V. PROPOSED SYSTEM

The proposed deepfake detection system consists of a hybrid deep learning architecture that integrates CNN and LSTM models for enhanced feature extraction and sequential analysis. The system follows a structured pipeline beginning with video preprocessing, where frames are extracted and normalized. These frames are then passed through a CNN to capture spatial inconsistencies, such as unnatural facial expressions, blending artifacts, and lighting mismatches. The CNN outputs are subsequently fed into an LSTM network, which examines the temporal relationships between frames to detect unnatural transitions indicative of video manipulation.

The architecture of the proposed system is illustrated in Figure 1, which shows the complete pipeline from video preprocessing to the final classification stage. The figure highlights the integration of CNN for spatial analysis and LSTM for temporal sequence evaluation, ensuring comprehensive detection of deepfakes.

This combined approach addresses both spatial and temporal anomalies in deepfake videos, making the detection system more reliable than standalone CNN or LSTM models. The final classification is performed using a Softmax layer, which outputs the probability of a given video being real or fake. As shown in Figure 2, the model is trained using large-scale deepfake datasets, such as FaceForensics++ and the Deepfake Detection Challenge dataset, to ensure generalization across different manipulation techniques. This makes the system suitable for real-world applications, including video authentication and social media moderation.

VI. SYSTEM ARCHITECTURE

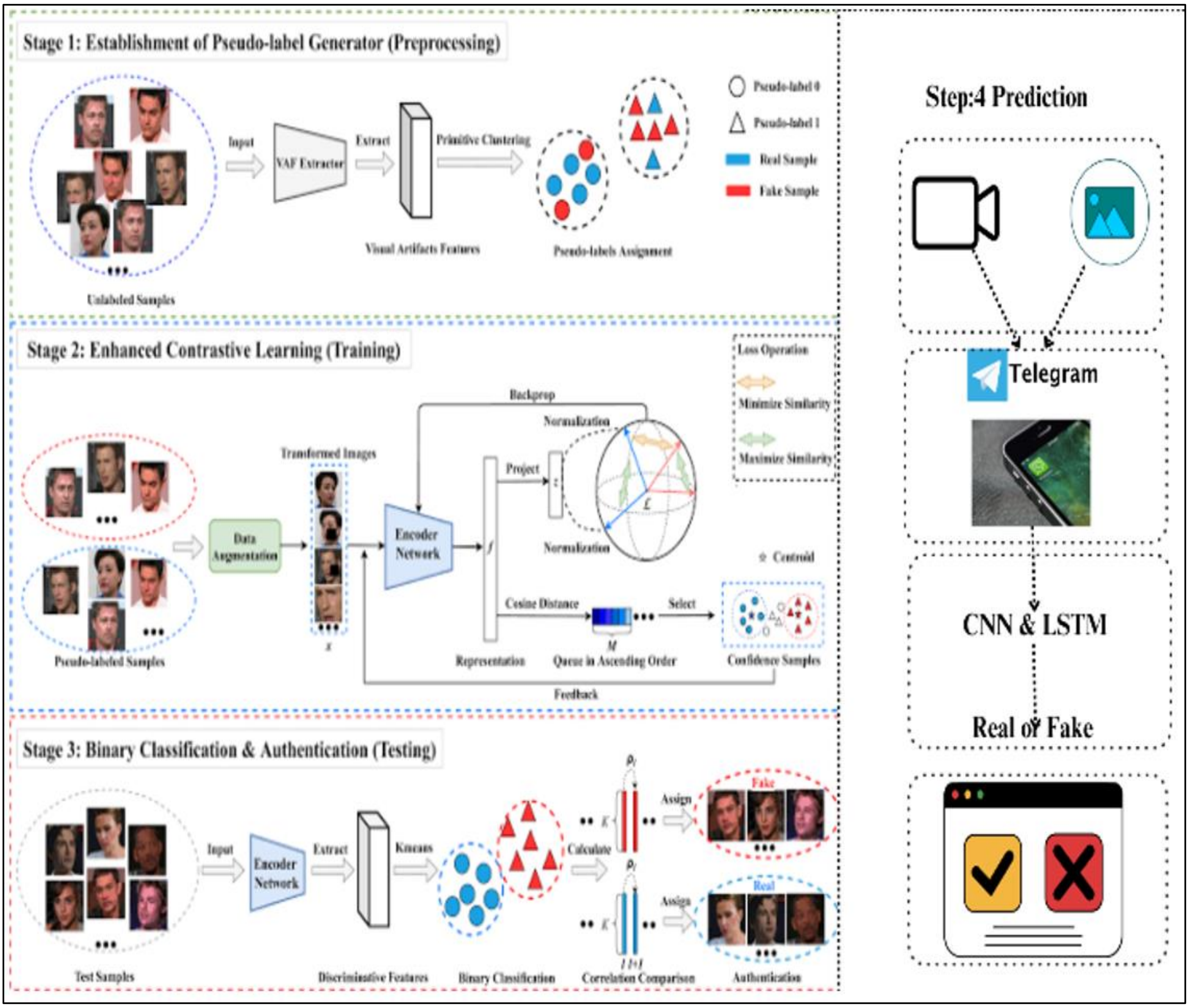

Fig1 System Architecture

The architecture of the proposed deepfake detection system is visualized in Figure 1, which illustrates the end-to-end flow of the model. It consists of the following stages:

- *Input Data Enhancement:*

During this stage, video frames are extracted, and faces are detected using MTCNN (Multi-task Cascaded Convolutional Networks). The detected faces are resized, normalized, and assigned pseudo-labels to enhance the quality of the training data. Visual artifact filtering is applied to identify deepfake-specific inconsistencies, such as unnatural facial expressions and blending artifacts, as depicted in Figure 1.

- *Contrastive Learning:*

During training, a contrastive learning-based encoder extracts facial features and projects them into a hypersphere, ensuring a clear separation between real and fake samples. This process enhances the model's ability to generalize across different deepfake techniques.

- *Classification and Authentication:*

For the final classification, CNN captures spatial features, while LSTM analyzes temporal inconsistencies across frames. A Softmax classifier assigns probabilities, determining the likelihood of a video being real or fake based on learned patterns from the dataset. As demonstrated in Figure 2, the ROC curve shows the model's superior performance with an AUC (Area Under the Curve) of nearly 1.00, highlighting its effectiveness in distinguishing real from fake videos.

- *Continuous Learning and Deployment:*

To improve efficiency, the system undergoes continuous learning through periodic retraining with newly detected deepfake samples. This adaptive approach ensures that the model remains effective against emerging deepfake techniques, enhancing long-term reliability. Additionally, the model is optimized for deployment on cloud-based services, enabling large-scale detection and integration with multiple platforms.

VII. METHODOLOGY

➢ *Data Collection*

To ensure robustness, benchmark deepfake datasets such as FaceForensics++ and the Deepfake Detection Challenge dataset are utilized. These datasets contain thousands of real and manipulated videos generated using various deepfake techniques, including autoencoders and GANs. Each video undergoes a preprocessing phase, during which frames are extracted, faces are detected using Multi-task Cascaded Convolutional Networks (MTCNN), and images are resized for CNN processing. The notations and symbols used throughout the methodology are summarized in Table 1, which provides a clear and concise representation of each component involved in the model architecture.

➢ *Notations*

Table 1 Notation and Symbol Definitions

Symbol	Description
X	Input video frames
fcnn(X)	CNN feature extraction function
flstm(X)	LSTM sequential analysis function
Y	Ground truth label (real/fake)
y^	Predicted label
L	Loss function
Θ	Model parameters
D	Dataset containing real and fake samples
Lcontrastive	Contrastive loss function
Lbinary	Binary cross-entropy loss

➢ *# Stage 1: Preprocessing*

- for each video in dataset D:
- Extract frames X
- Detect faces using MTCNN
- Resize & normalize images
- Assign pseudo-labels based on visual artifacts

➢ *# Stage 2: Training with Contrastive Learning*

- for each batch in training set:
- Compute CNN features: F = f_cnn(X)
- Project features using contrastive loss: L_contrastive = ||F_real - F_fake||^2
- Optimize encoder using Adam optimizer

➢ *# Stage 3: Binary Classification*

- for each video sequence:
- Extract CNN features: F = f_cnn(X)
- Feed features into LSTM: S = f_lstm(F)
- Compute probability: P(y|X) = Softmax(W * S + b)
- Compute binary loss: L_binary = BCE(y, P(y|X))

➢ *# Stage 4: Prediction & Deployment*

- Deploy model to real-time platforms (e.g., Telegram API)
- for each uploaded video:
- Predict label: if P(y) > threshold → Fake else → Real
- Return classification result

VIII. PERFORMANCE EVALUATION

The performance of the proposed deepfake detection model is evaluated using standard metrics, including accuracy, precision, recall, and F1-score. The model is tested on multiple datasets to validate its effectiveness across different deepfake generation methods.

The ROC curve in Figure 2 demonstrates the model's superior performance, with an AUC of nearly 1.00, indicating exceptional accuracy. The graph plots the True Positive Rate (TPR) against the False Positive Rate (FPR), highlighting the model's ability to accurately classify both real and fake videos.

Table 2 Model Performance Metrics (Proposed System)

Model	Accuracy	Precision	Recall	F1-score
CNN Only	85.7%	82.5%	87.2%	84.8%
LSTM Only	89.3%	87.1%	90.4%	88.7%
CNN-LSTM	96.4%	94.8%	97.2%	96.0%

The model’s performance metrics are summarized in Table 2, which compares the accuracy, precision, recall, and F1-score of different configurations, including CNN Only, LSTM Only, and the hybrid CNN-LSTM approach. As observed in Table 2, the CNN-LSTM model significantly outperforms the individual CNN and LSTM models, achieving higher accuracy and F1-score.

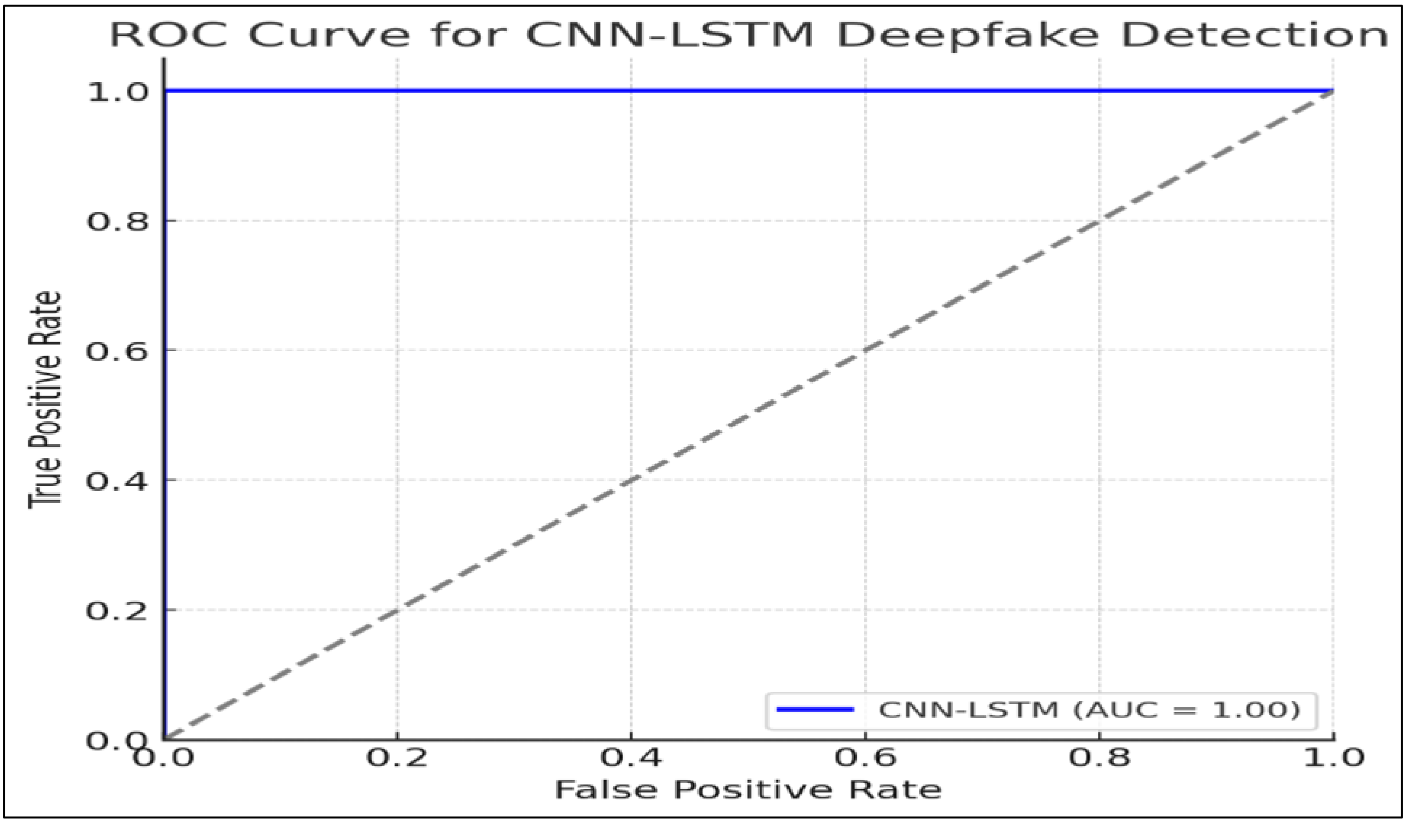

Fig 2 ROC Curve (Graph)

IX. CONCLUSION

This paper presents a hybrid deepfake detection model that leverages CNNs for spatial feature extraction and LSTMs for temporal sequence analysis. The combination of these two deep learning techniques enables the detection of both frame-level and sequence-level anomalies, improving accuracy over traditional methods. Experimental results demonstrate that the CNN-LSTM model achieves state-of-the-art performance on benchmark datasets, outperforming existing approaches.

As deepfake technology continues to evolve, it is crucial to develop robust detection mechanisms to combat digital media manipulation. The proposed system contributes to this effort by offering a scalable, high-accuracy solution that can be integrated into content moderation platforms, forensic analysis tools, and real-time security applications. Future advancements will focus on improving efficiency, generalization, and robustness against adversarial deepfakes.

FUTURE WORK

Although the proposed CNN-LSTM model demonstrates high accuracy, several improvements can be explored to enhance its performance further. Future work will focus on developing more advanced architectures that integrate transformer-based models like Vision Transformers (ViTs) for improved feature extraction. Additionally, the plan to investigate adversarial training techniques to strengthen the model’s resilience against adversarial attacks designed to bypass detection.

Another key area of exploration is real-time deepfake detection on low-resource devices such as smartphones and edge computing systems. This requires optimizing the model for efficiency while maintaining high accuracy. Further, integrating multimodal analysis by combining facial and audio features could enhance detection accuracy, particularly in cases where deepfake videos include manipulated speech.

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