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An Enhanced Explainable AI Framework for Detecting the Computational Authenticity of Videos Using Spatio-Temporal Analysis

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Abstract:*The rapid advancement of generative artificial intelligence has enabled the creation of highly realistic synthetic media such as deepfake and AI-generated videos, which pose serious threats to digital trust, media authenticity, and cybersecurity. Traditional detection approaches mainly rely on spatial artifacts or handcrafted rules that are increasingly ineffective against modern generative models. This research proposes an Explainable Artificial Intelligence (XAI) based spatio-temporal framework for detecting both AI-generated and AI-manipulated videos. The proposed system analyzes spatial artifacts and temporal motion inconsistencies in video sequences. Spatial features are extracted using Vision Transformer (ViT) models, while temporal relationships between frames are captured using Long Short-Term Memory (LSTM) networks. Frame-level predictions are aggregated using a Mean Probability Aggregation algorithm to generate a reliable video-level authenticity score. To improve interpretability, explainable AI techniques such as Grad-CAM and SHAP are integrated to highlight suspicious regions and quantify feature contributions responsible for the model's decision. Experimental evaluation demonstrates that the proposed framework effectively distinguishes authentic videos from manipulated and AI-generated content while providing interpretable explanations for predictions.*

Keywords: *Deepfake Detection, AI-Generated Video Detection, Explainable AI, Spatio-Temporal Analysis, Vision Transformer, LSTM, Grad-CAM, SHA*

I.Introduction

The rapid development of generative artificial intelligence has significantly improved the creation of realistic synthetic media, including manipulated videos known as deepfakes. Deepfake technology allows the alteration of facial expressions, speech patterns, and identities using deep learning techniques such as Generative Adversarial Networks (GANs). Although these technologies offer benefits in entertainment and digital media production, they also introduce serious risks such as misinformation, identity theft, and financial fraud.

Traditional deepfake detection approaches focus on identifying pixel-level artifacts or handcrafted features within images. However, modern generative models have significantly reduced these artifacts, making manipulation increasingly difficult to detect using conventional methods.

Another major challenge is the lack of interpretability in deep learning models. Most detection systems operate as black-box models that provide only classification outputs without explaining the reasoning behind their predictions.To address these challenges, this research proposes a spatio-temporal deep learning framework integrated with Explainable Artificial Intelligence techniques. The system analyzes spatial inconsistencies within frames and temporal anomalies across frame sequences to detect manipulated videos. In addition, explainability methods such as Grad-CAM and SHAP provide visual explanations highlighting manipulated regions responsible for the prediction.

II.Related Work

Reference [1], the authors proposed a deepfake detection method using recurrent neural

networks to analyze temporal inconsistencies across video frames. The model extracts frame-level features and processes them sequentially to detect abnormal motion patterns such as irregular blinking and unnatural facial movements. Although the method improves detection accuracy compared to frame-based approaches, it primarily focuses on temporal features and does not fully analyze spatial artifacts.

Reference [2] presents a deepfake detection technique based on identifying face warping artifacts generated during face swapping. The approach analyzes inconsistencies in facial regions caused by resizing operations during manipulation. While the method performs well for early deepfake techniques, it becomes less effective when advanced generative models produce higher-quality synthetic faces.

Reference [3] introduces the DeepFake Detection Challenge (DFDC) dataset, which provides a large-scale dataset containing thousands of manipulated videos for training and evaluating deepfake detection models. Several deep learning architectures such as XceptionNet and EfficientNet were evaluated using this dataset. However, most of these methods operate at the frame level and do not consider temporal relationships between frames.

Reference [4] proposes the use of capsule networks for detecting manipulated images and videos. Capsule networks preserve spatial relationships between facial features, which helps identify structural inconsistencies caused by manipulation. Although this method improves detection performance, it requires higher computational resources.

Reference [5] introduces the FaceForensics++ dataset, which contains manipulated videos generated using different face manipulation techniques. The study demonstrates that convolutional neural networks can detect manipulation artifacts when trained on large datasets. However, CNN-based models mainly focus on spatial information and may overlook temporal inconsistencies.

Reference [6] discusses the use of Vision Transformer (ViT) models for image analysis. Transformers capture global spatial relationships between image patches using self-attention mechanisms, improving feature representation compared to traditional convolutional networks.

Reference [7] introduces ensemble learning approaches combining multiple neural network models to improve classification accuracy. Although ensemble techniques increase prediction performance, they also increase computational complexity and may reduce model interpretability.

Reference [8] presents Grad-CAM, an explainable artificial intelligence technique that generates heatmaps highlighting important regions responsible for model predictions. This method improves transparency in deep learning models.

Reference [9] introduces SHAP, a feature attribution method based on cooperative game theory that explains the contribution of each feature to the model's prediction. SHAP helps interpret deep learning models by quantifying feature importance.

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III.Proposed System and Metodologies

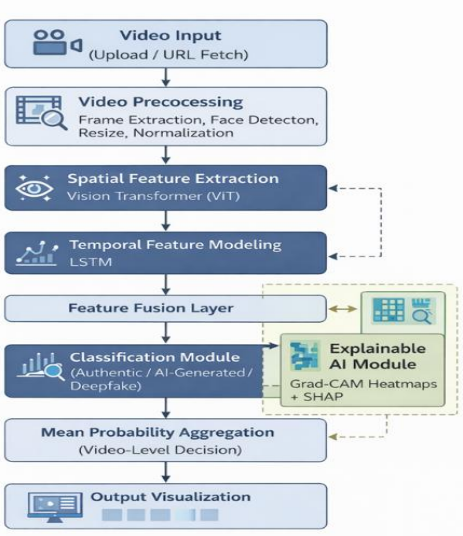

Figure1: Architecture of the proposed system

The proposed system detects both AI-generated videos and AI-manipulated (deepfake) videos using a spatio-temporal deep learning framework integrated with Explainable Artificial Intelligence (XAI). The methodology consists of several stages including dataset preparation, video preprocessing, spatial feature extraction, temporal modeling, classification, and explainable AI analysis. The overall workflow enables the system to analyze both visual artifacts within frames and temporal inconsistencies across video sequences.

3.1 Dataset Preparation

To train and evaluate the proposed model, two publicly available datasets were used: the DeepFake Detection Challenge (DFDC) dataset and the Real-AI Video Dataset.

The DFDC dataset was released by Facebook AI and contains over 120,000 video clips including both authentic and manipulated videos generated

using different face-swapping techniques. The dataset includes recordings from thousands of actors under varying lighting conditions, facial expressions, and camera angles. This diversity helps the model learn robust spatial patterns associated with deepfake manipulation.

Dataset Source:

https://www.kaggle.com/c/deepfake-detection-challenge

For detecting AI-generated videos, the Real-AI Video Dataset from Kaggle is used. This dataset contains both real videos and synthetic videos created using generative AI techniques. The dataset helps the model identify synthetic patterns that are commonly present in AI-generated content.

Dataset Source:

https://www.kaggle.com/datasets/kanzeus/realai-video-dataset

The combined datasets are divided into three subsets:

- Training set – used to train the deep learning model
- Validation set – used for parameter tuning
- Testing set – used to evaluate model performance

This dataset combination enables the system to learn both deepfake manipulation artifacts and AI-generated video patterns.

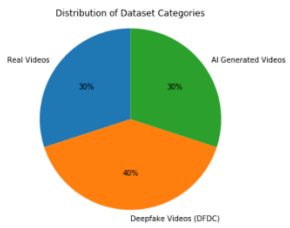

Figure 2: Overview of the dataset

3.2 Video Preprocessing

The preprocessing stage converts input videos into a format suitable for deep learning analysis. The following steps are performed:

Frame Extraction

Videos are decomposed into individual frames using the OpenCV library. If a video contains TT frames, it can be represented as:

$$V = \{F_1, F_2, F_3, \ldots, F_T\}$$

where $F_i F_i$ represents the $i^{th} i^{th}$ frame extracted from the video.

Face Detection and Alignment

Since most deepfake manipulations occur in the facial region, face detection is applied to identify and crop the face area in each frame. The FaceNet-PyTorch model is used for detecting facial landmarks and aligning faces.

Frame Resizing and Normalization

Each frame is resized to 224 × 224 pixels to match the input size required by the deep learning model. Pixel values are normalized from 0–255 to 0–1 to improve training stability.

3.3 Spatial Feature Extraction

Spatial feature extraction identifies visual artifacts present in individual frames. The proposed system uses a Vision Transformer (ViT) architecture to capture spatial patterns.

Instead of traditional convolutional filters, ViT divides an image into smaller patches and converts them into embedding vectors. These patches are processed using a self-attention mechanism that learns relationships between different regions of the image.

The attention mechanism is defined as:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where

QQ = query matrix

KK = key matrix

VV = value matrix

This mechanism allows the model to detect spatial artifacts such as:

- facial boundary mismatches
- unnatural skin textures
- lighting inconsistencies
- GAN-generated visual artifacts

The output of this stage is a high-dimensional spatial feature vector for each frame.

3.4 Temporal Feature Modeling

While spatial features capture frame-level artifacts, manipulated videos often exhibit temporal inconsistencies across frames. To model these patterns, the proposed system uses Long Short-Term Memory (LSTM) networks.

LSTM networks process sequential data and maintain memory of previous frames, allowing the system to learn temporal relationships between frames.

The LSTM architecture contains several gates:

Forget Gate

$$f_t = \sigma(W_f [h_{t-1}, x_t] + b_f)$$

This gate determines which information from the previous frame should be discarded.

Input Gate

$$i_t = \sigma(W_i [h_{t-1}, x_t] + b_i)$$

This gate controls how much new information should be stored.

Cell State Update

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t$$

The LSTM captures temporal anomalies such as:

- abnormal blinking patterns
- lip-sync mismatches
- unnatural head movements
- inconsistent facial expressions

3.5 Classification Module

After extracting spatial and temporal features, the features are combined and passed through fully connected layers for classification.

The classifier predicts three classes:

- Authentic Video
- AI-Generated Video
- Deepfake Manipulated Video

The final prediction probability is computed using the Softmax activation function:

$$P(y = i \mid x) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

where $z_i z_i$ represents the output score for class ii.

3.6 Mean Probability Aggregation

Since predictions are generated at the frame level, a video-level decision must be obtained. The proposed system uses a Mean Probability Aggregation algorithm to combine frame predictions.

$$V = \frac{1}{N} \sum_{i=1}^{N} P_i$$

where

VV = final video authenticity score

$P_i P_i$ = prediction probability of frame ii

NN = total number of frames

Decision rule:

- If $V > 0.5 V > 0.5$ → Authentic Video
- If $V \leq 0.5 V \leq 0.5$ → Manipulated Video

This method improves reliability by considering predictions from multiple frames rather than a single frame.

3.7 Explainable AI Techniques

To improve transparency and interpretability, the proposed framework integrates two explainable AI techniques: Grad-CAM and SHAP.

I.Grad-CAM (Gradient-weighted Class Activation Mapping)

Grad-CAM is an explainable artificial intelligence technique that generates visual heatmaps highlighting important regions in the input image that influence the model's prediction. It improves the transparency of deep learning models by indicating which parts of the input frame contribute most to the classification result.

Grad-CAM works by computing the gradient of the predicted class score with respect to the feature maps of the final convolutional layer. These gradients represent how strongly each feature map influences the target class. The gradients are then globally averaged to obtain importance weights for each feature map.

The Grad-CAM localization map is computed as:

$$L^{GradCAM} = ReLU\left(\sum_k \alpha_k A_k\right)$$

where

$A_k A_k$ = activation map of the $k^{th} k^{th}$ feature map

$\alpha_k \alpha_k$ = gradient weight obtained from global average pooling

The ReLU function is applied to focus only on features that positively influence the target class.

In the proposed framework, Grad-CAM is applied to the spatial feature extraction stage to generate visual explanations for manipulated regions in video frames. The resulting heatmaps highlight suspicious areas such as:

- face boundary inconsistencies
- unnatural skin textures
- lighting mismatches
- blending artifacts caused by face swapping

By overlaying the Grad-CAM heatmap on the original video frame, the system provides a visual interpretation of the model's decision, helping users understand why a particular video was classified as authentic or manipulated. This significantly improves the trustworthiness and interpretability of the deep learning model.

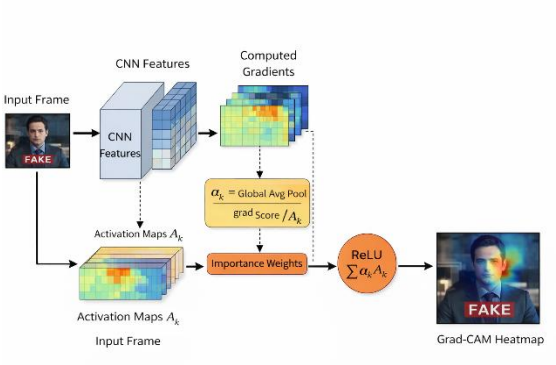

Figure 3: Working of Gradcam in the system

II.SHAP (SHapley Additive Explanations)

SHAP is a feature attribution method based on Shapley values from cooperative game theory. It explains the contribution of each feature to the final prediction of a machine learning model.

The SHAP model explanation can be represented as:

$$f(x) = \phi_0 + \sum_{i=1}^{n} \phi_i x_i$$

where

$\phi_0 \phi_0$= base value representing the average model prediction

$\phi_i \phi_i$= contribution of feature ii

$x_i x_i$= input feature value

Each SHAP value represents the marginal contribution of a feature toward the prediction outcome. Positive SHAP values indicate that a feature increases the probability of a class, while negative values decrease the probability.

In the proposed framework, SHAP is applied to analyze the importance of spatial and temporal features extracted from the video frames. The method evaluates how different features such as facial texture patterns, motion consistency, and frame-level artifacts influence the classification result.

SHAP provides several advantages for explainability:

- Quantifies the importance of each feature contributing to the prediction
- Provides global and local interpretability of the model
- Helps identify which spatial or temporal features most strongly indicate manipulation

By combining SHAP with Grad-CAM, the proposed system provides both visual explanations (heatmaps) and feature-level importance analysis, enabling a more comprehensive interpretation of the deep learning model's predictions.

IV.Result and Discussions

The proposed framework was evaluated using real and manipulated video samples from the datasets. The system extracts frames and predicts authenticity probabilities for each frame.

Example results:

Video Type	Score	Prediction
Real video	0.81	Authentic
AI generated video	0.35	Fake
Deepfake video	0.32	Fake

Table 1: Demonstration of the output

The results demonstrate that the system successfully identifies manipulated videos.

V. Conclusion

This research presented an explainable spatio-temporal deep learning framework for detecting AI-generated and AI-manipulated videos. The proposed system integrates Vision Transformer (ViT) for spatial feature extraction and Long Short-Term Memory (LSTM) networks to model temporal dependencies across video frames. By combining spatial and temporal analysis, the system effectively identifies subtle visual artifacts and motion inconsistencies present in manipulated videos.

To improve model transparency, explainable artificial intelligence techniques such as Grad-CAM and SHAP were incorporated to highlight suspicious regions and identify important features influencing the prediction. The Mean Probability Aggregation algorithm was used to combine frame-level predictions and produce a reliable video-level authenticity score. Experimental

evaluation using publicly available datasets demonstrates that the proposed framework can effectively distinguish authentic videos from AI-generated and manipulated content while also providing interpretable explanations for its decisions.

VI. Future Enhancements

Although the proposed framework shows promising results, further improvements can be achieved through multimodal analysis. In many deepfake videos, inconsistencies occur not only in visual features but also in the synchronization between audio and lip movements.

Future work will focus on integrating audio-visual consistency analysis using Mel-Frequency Cepstral Coefficients (MFCC) to extract speech features from video audio tracks. By comparing MFCC-based audio features with lip movement patterns detected in video frames, the system can identify lip-sync mismatches that frequently occur in manipulated videos. Additionally, future research may explore larger multimodal datasets, advanced transformer architectures for joint audio-visual learning, and real-time detection systems capable of identifying manipulated content on social media platforms.

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