Deepfake Video Detection with Explainable AI

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Abstract - The increasing complexity of deepfake technology poses a serious threat to digital media integrity and strong detection and explanation mechanisms are needed. This project presents a complete system that detects not only deepfake videos but also gives detailed, interpretable explanations to support user understanding and trust. The detection pipeline integrates an InceptionV3-based Convolutional Neural Network (CNN) for spatial feature extraction and a Gated Recurrent Unit (GRU) for modeling temporal sequences, enabling accurate classification of video content as real or fake. Facial feature segmentation is performed using the CelebAMask-HQ model to highlight specific facial regions, while Grad-CAM is applied to visualize areas of high influence in the model's decision-making. Another new addition to the system is the integration of Gemini AI, which generates natural language explanations based on technical metrics such as confidence scores, face consistency, and temporal anomalies. The complete system is deployed via a Streamlit interface, offering an intuitive platform for users to upload videos and receive both technical and AI-powered insights. This work advances the field of explainable deepfake detection by combining deep learning, visual interpretation, and natural language explanation in a unified, user-friendly framework.

Key Words: Deepfake detection, Explainable AI , InceptionV3, GRU, CelebAMask-HQ, Grad-CAM, Gemini analysis, Streamlit interface.

1.INTRODUCTION

The rapid advancement of generative adversarial networks (GANs) and related AI techniques has led to the widespread proliferation of deepfake content—realistic-looking videos in which faces or speech are artificially manipulated. Although these technologies hold promise for artistic and entertainment applications, they also present serious threats to individuals' privacy, political stability, and public trust in digital media. It is thus essential to detect deepfakes.

Conventional deepfake detection tools usually depend on binary classification alone, determining whether a video is authentic or synthetic. This is inadequate when users need transparency or justification for their decisions. In critical areas such as journalism, law enforcement investigations, or social media moderation, knowing why a video is detected is as critical as detecting it.

The current project offers an end-to-end solution that not only predicts the video content to be real or manipulated but also provides the reason behind the prediction. Our model integrates a deep learning-based classifier for videos along with state-of-the-art explainable AI (XAI) methods. Specifically, it leverages an InceptionV3-based Convolutional Neural Network (CNN) for spatial feature extraction, a Gated Recurrent Unit (GRU) network for temporal sequence modeling, and Grad-CAM heatmaps for visual explanation. In addition to this, integrating Gemini AI also provides the capabilities of generating understandable, natural language explanations based on technical measures including facial feature homogeneity, confidence scores, and temporal irregularities.

To improve usability, the system is deployed via a Streamlit web interface, which allows users to upload videos and obtain both visual and textual insights. This method not only enhances detection accuracy but also enhances transparency and user trust, representing a major advancement in the area of explainable deepfake detection.

2. LITERATURE SURVEY

2.1. Deep Learning Methods in Deepfake Detection

Recent technological developments in the detection of deepfakes have largely been facilitated by deep learning methods, using mainly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), and specifically Long Short-Term Memory (LSTM) networks. CNNs have been extensively employed due to the capability to harvest spatial features out of individual images, detecting objects like unnatural texture and inconsistencies with lighting. RNNs are used to extract temporal dynamics, processing patterns of facial motion over sequences of videos. The use of hybrid models that employ CNNs for spatial processing and RNNs for temporal processing has yielded encouraging results in improving detection accuracy.

For example, Guera and Delp [1] introduced a hybrid CNN-LSTM model that successfully extracts both the spatial and temporal features and obtained an accuracy of 97% on the FaceForensics++ dataset. In a similar vein, Saikia et al. [2] proposed a system that utilizes optical flow features along with a CNN-LSTM architecture, achieving accuracies of 91.21% on the FaceForensics++

dataset and 79.49% on the Celeb-DF dataset. These works highlight the effectiveness of combining spatial and temporal analyses to enable deepfake detection.

2.2. Explainable AI in Deepfake Detection

The incorporation of Explainable AI (XAI) methods into deepfake detection has become a highly important field of study, responding to the demand for transparency within automated systems. XAI improves user trust as well as informed decision-making by offering insights into the decision-making process. Chen et al. [3] presented an explainable deepfake detection model that employs attention mechanisms to identify the most significant features impacting the model's predictions. Their method reached 89% accuracy while providing interpretable visualizations of the decision-making process, enabling users to see the reasoning behind the classification.

In our project, we utilize a novel explanation module based on the Gemini API, which examines important frames and produces human-understandable explanations in terms of facial features, lighting coherence, and artifact detection. This novel combination not only enhances detection accuracy but also equips users with information about the fine-grained cues that distinguish real and fake videos.

2.3. Other Detection Techniques

Outside of deep learning, different other approaches have been investigated for the detection of deepfakes. For instance, Younus and Hasan [4] used Haar wavelet transforms to detect inconsistency in blur between the synthesized face and the background and reported 90.5% accuracy on the UADFV dataset. The approach shows the capability of conventional image processing methods to extend the range of deep learning solutions.

Further, Ciftci et al. [5] emphasized the investigation of residual analysis with biological signals to determine generator-specific signatures of manipulated videos. Their approach demonstrated 93.39% accuracy on the FaceForensness++ dataset as a stepping stone for the next generation of holistic detection systems fusing real and fake video signature analysis.

2.4. Challenges and Future Directions

In spite of the advancement achieved in detecting deepfakes, there are various challenges. The fast-paced advancement of deepfake generation algorithms means that detection models need to be constantly adapted to keep up with the times. In addition, interpretability of detection systems continues to be critical, with users needing straightforward explanations for suspicious content. Our work tackles these issues by merging a deep learning-based detection pipeline with an explainable AI module. Although our system's competitive accuracy is 81%, its most valuable strength is to produce rich, human-readable explanations in the form of Grad-CAM visualizations and Gemini-facilitated natural language descriptions. This combined strategy not only enhances user trust but also facilitates informed decision-making in critical real-world applications.

3. METHODOLOGY

The proposed deepfake detection and explanation system is designed as a multi-stage pipeline that integrates spatial and temporal analysis with explainable AI components. The methodology consists of the following key components:

3.1 Preprocessing and Frame Extraction

Videos uploaded by users are first processed to extract frames using OpenCV. To optimize computational efficiency while preserving temporal information, one frame is extracted every two frames (skip_frames=2). MTCNN (Multi-task Cascaded Convolutional Neural Network) is employed to detect and align facial regions within each frame. These cropped face regions are resized to 224×224 pixels to match the input requirement of the feature extraction model.

3.2 Feature Extraction Using InceptionV3

Each selected frame is passed through a pre-trained InceptionV3 Convolutional Neural Network (CNN), which extracts high-level spatial features. InceptionV3 is chosen for its robust performance in identifying subtle image-level artifacts such as unnatural skin textures, edge distortions, and lighting inconsistencies commonly present in manipulated content.

3.3 Temporal Analysis with GRU

The spatial features from a sequence of 20 frames are fed into a Gated Recurrent Unit (GRU) network to capture temporal dependencies and facial movement patterns across time. The GRU outputs a classification prediction indicating whether the video is real or fake, along with a confidence score.

3.4 Facial Feature Segmentation

To enhance visual explainability, each face frame is processed using the CelebAMask-HQ model. This model segments facial regions into 19 labeled components, such as eyes, lips, skin, and hair. The segmentation output is later used to overlay masks on the original frame for region-specific analysis.

3.5 Attention Visualization with Grad-CAM

Grad-CAM (Gradient-weighted Class Activation Mapping) is applied to generate attention heatmaps, which highlight the most influential regions that contributed to the model's prediction. These heatmaps are overlaid on the facial frames to visually indicate model attention areas, improving interpretability for end users.

3.6 Natural Language Explanation with Gemini

To complement the visual explanations, our system integrates the Gemini API to generate natural language justifications for the prediction. It analyzes model outputs, attention maps, facial masks, confidence levels, and temporal anomalies to create human-readable summaries explaining why the content was classified as real or fake.

3.7 User Interface with Streamlit

The entire system is wrapped in a Streamlit-based web interface. Users can upload videos and receive comprehensive analysis results, including:

a) Classification outcome (real/fake) with confidence score
b) Attention-based heatmaps
c) Facial segmentation overlays
d) Gemini-generated textual explanations
e) Technical metrics such as face detection consistency and temporal variation scores

This combination of advanced deep learning techniques and explainable AI tools results in a robust, interpretable, and user-friendly deepfake detection system.

4. PROPOSED SYSTEM

The proposed system is a user-friendly deepfake detection framework that classifies videos as real or fake and offers interpretable visual and textual explanations to enhance user trust and understanding, addressing the limitations of traditional detectors through advanced technology integration.

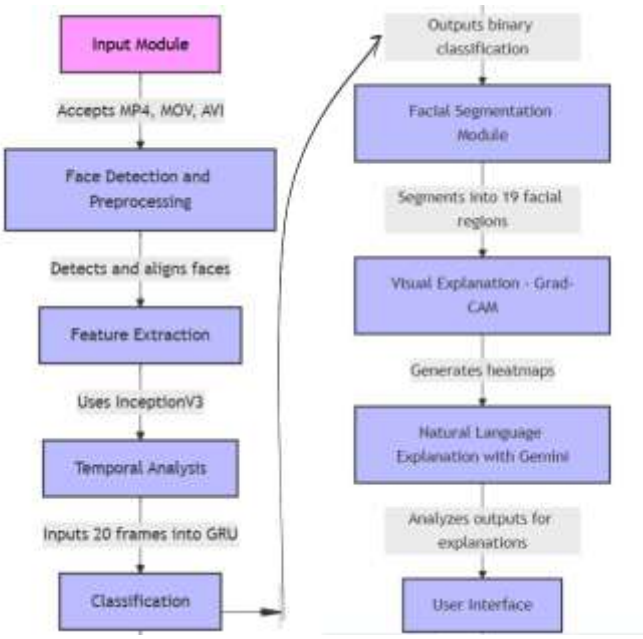

Fig -1: System Architecture

The integration of deep learning models, facial segmentation, Grad-CAM visualization, and AI-driven explanation makes this system well-suited for addressing both detection accuracy and explainability, which are critical in combating the rise of deepfake content.

5. EXPERIMENTAL SETUP

To evaluate the performance and effectiveness of the proposed deepfake detection and explanation system, a structured experimental environment was set up. The setup includes hardware specifications, software frameworks, dataset details, preprocessing steps, and training configurations.

5.1 Software Tools and Libraries

The software tools and libraries used include Python 3.8 as the programming language. Deep learning frameworks consist of TensorFlow and Keras for the CNN-GRU model, and PyTorch for the CelebAMask-HQ segmentation model. Face detection is implemented with MTCNN via facenet-pytorch. Video processing utilizes OpenCV. Visualization is achieved through Matplotlib and Grad-CAM. The web interface is developed using Streamlit, and AI explanations are generated with the Gemini API for natural language understanding.

5.2 Dataset

For model training and evaluation, benchmark deepfake datasets were used:

a) *FaceForensics++*: A widely used dataset containing real and manipulated videos with various compression levels.

b) *Celeb-DF v2*: (for generalization testing): Includes more realistic deepfakes for model evaluation.

Each dataset was split into training (70%), validation (15%), and testing (15%) sets. Videos were preprocessed to extract 20-frame sequences with a frame size of 224×224 pixels.

5.3 Preprocessing Steps

a) *Face Detection and Alignment:* Applied MTCNN to extract faces from video frames.
b) *Resizing:* All frames resized to 224×224 for model compatibility.
c) *Normalization:* Pixel values normalized to the [0, 1] range.
d) *Sequence Framing:* Consecutive 20-frame sequences were grouped for temporal modeling.

5.4 Training Details

a) *CNN Architecture:* InceptionV3 (pre-trained on ImageNet)
b) *Temporal Module:* GRU with 128 units
c) *Loss Function:* Binary Crossentropy
d) *Optimizer:* Adam (learning rate = 0.0001)
e) *Batch Size*: 16
f) *Epochs:* 20 (early stopping used)
g) *Validation Strategy*: K-Fold Cross Validation (k=5)

6 . EXPERIMENTAL RESULS AND EVALUATION

This section presents the performance outcomes of our proposed deepfake detection system

6.1. Model Accuracy and Loss:

The model's training and validation accuracy and loss were monitored over multiple epochs. The trends are shown in the plots below :

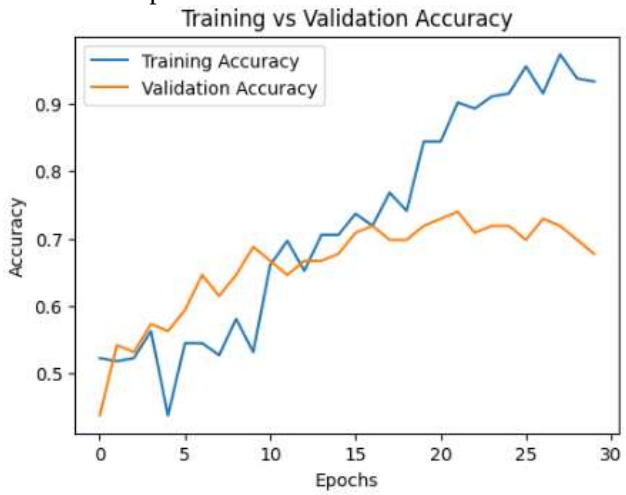

Fig -2: The ratio between training accuracy and validation accuracy

6.2 Loss:

The loss graph demonstrates the model's error trends during training. As training progresses, the training loss decreases consistently, which indicates the model is refining its predictions based on the training data. On the other hand, the validation loss remains steady, reflecting stable performance on unseen data throughout the training process. This pattern suggests that the model is adapting well to the training data while maintaining consistent results on the validation set.

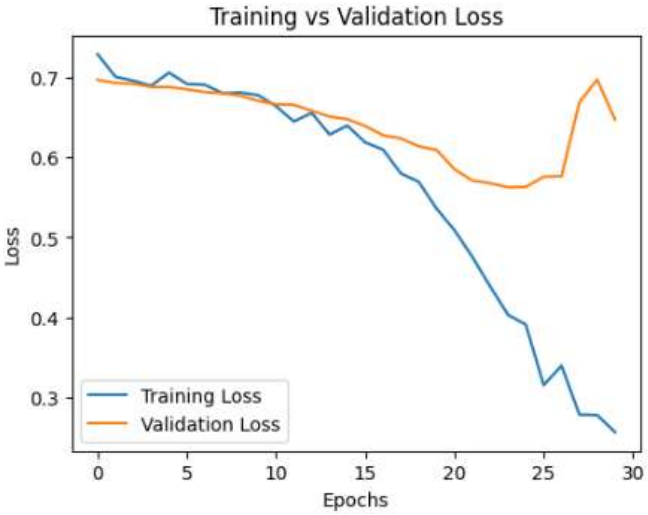

Fig -3: The ratio between training loss and validation loss

6.3 Visual Explanation Evaluation

Using Grad-CAM and facial segmentation, the system generates intuitive visualizations that highlight manipulated facial regions. These heatmaps often focus on key regions like the mouth, eyes, and jawline—areas typically prone to artifacts in deepfake videos.

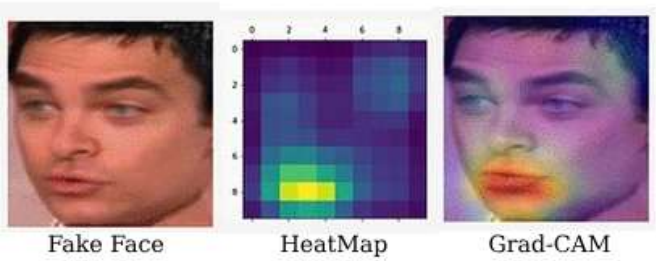

Fig 4:Fake face , Heat Map , Grad-CAM

6.4 Prediction Result (System Output):

Below is the typical output generated our model :

Fig 5 – Streamlit Interface video Upload

Fig 6 – Technical and AI analysis To know Why the video is fake or real

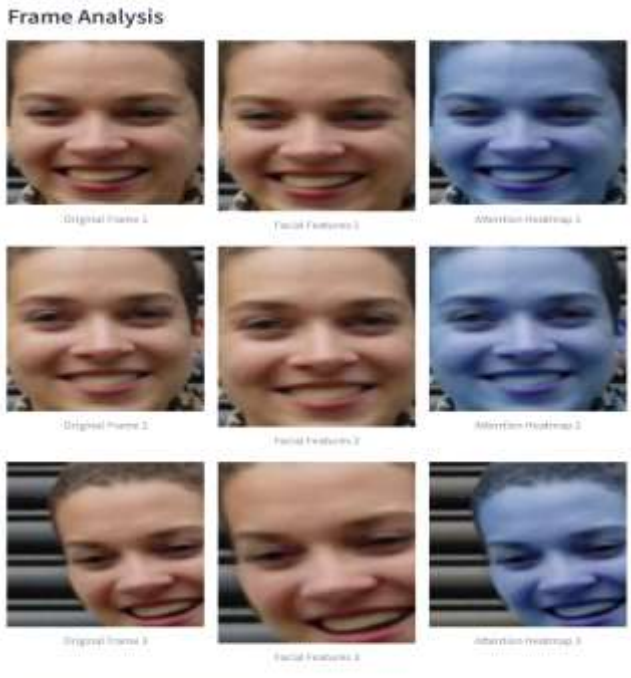

Fig 7 – Original Frame , Facial Feature , Attention HeatMap

3. CONCLUSIONS

In this project, we developed a comprehensive deepfake detection and explanation system that not only classifies videos as real or fake but also provides interpretable insights to support human understanding and trust. By integrating an InceptionV3-based Convolutional Neural Network for spatial analysis and a Gated Recurrent Unit (GRU) for temporal sequence modeling, the system achieves reliable detection accuracy.

To add to transparency, we also integrated facial feature segmentation with the CelebAMask-HQ model and visual attention maps through Grad-CAM, which emphasize the areas impacting each frame. An added innovation is the inclusion of Gemini AI, which provides human-readable explanations from model outputs and temporal discontinuities.

Although the final detection accuracy of 81% may not exceed state-of-the-art benchmarks, the strength of this system lies in its explainability, ease of use, and real-time visualization capabilities through a user-friendly Streamlit interface. This work contributes to the ongoing need for transparent and accountable AI tools in the fight against deepfake content.

Future enhancements may include real-time webcam detection, support for multilingual explanations, and integration of advanced XAI techniques such as LIME and SHAP for deeper interpretability.

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