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DEEP CONVOLUTIONAL NEURAL NETWORK BASED OBJECT DETECTION FOR VIDEO FORGERY IDENTIFICATION

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Abstract: Video editing is now more accessible to the development of modern tools with the popularity of digital media. Consequently, the altered videos may quickly confuse individuals, particularly with fake news or fake evidence. This paper proposes a method to identify video forgeries using deep learning technologies such as Deep Convolutional Neural Networks (DCNN), LSTM, and Faster R-CNN–based object detection techniques [2][3][4].The system is implemented as a web-based interface where users are allowed to upload videos. The video input is divided into frames to be analysed, and each frame is analysed to determine potential changes. Spatial features of each frame are learned using DCNN, and temporal dependencies between frames are learned with the help of LSTM. In addition to this, there is also the Faster R-CNN (Region-Based Convolutional Neural Network) method of object detection that localises the very REGIONS that the video may have been manipulated. Finally, the system identifies whether the video is authentic or not and whether manipulated regions are identified. Based on the findings, the system is competitive in accuracy and efficiency. The suggested system could be applied in practice in finding fake videos, digital forensics investigations, and verification of online sources.

Index Terms - Video Forgery Detection, CNN, LSTM, Object Detection, Deep Learning, Digital Forensics

I. INTRODUCTION

With the rapid growth of digital media and video editing tools, it has become much easier to create doctored video content [1]. Such manipulated content can cause misinformation and mislead the general public and is especially vital in fields like security and criminal inquiries. This is why the authenticity of video content has become one of the highest requirements of the modern digital world. Previous methods of video forgery detection were based on handcrafted features and manually developed rules. However, these methods are prone to missing advanced and high-level manipulations that may be contained in video information. With the emergence of deep learning, more powerful and effective methods of visual and temporal pattern analysis have been developed. DCNNs have been used in the detection of spatial features frame-by-frame, and LSTM networks are applicable in detecting temporal dependencies between video streams [2][3]. This paper proposes a deep learning-based solution to video forgery detection. CNN is used to get frame level features, and LSTM is used to learn the temporal relationship between the frame-level features. Also, an object detection system is used based on the Faster R-CNN (Region-Based Convolutional Neural Network) algorithm to find and locate manipulated areas in video frames [4]. It is an online application that is installed to allow users to upload videos and achieve detection results successfully.

II. PROBLEM STATEMENT

The rapid development of AI-based video editing technologies has made it easier to create highly realistic manipulated videos. Existing video forgery detection systems often struggle to identify advanced deepfake content accurately due to limitations in spatial and temporal analysis. Many traditional approaches analyze video frames independently without considering relationships between consecutive frames. In addition, several systems fail to provide efficient manipulated region localization and practical real-time analysis support for uploaded videos. Therefore, there is a need for an intelligent deep learning-based system capable of analyzing both spatial and temporal features while accurately detecting suspicious regions in manipulated real-world videos.

III. OBJECTIVES AND GOALS

Objectives

- To develop a deep learning-based video forgery identification system.
- To perform frame-by-frame analysis of uploaded real-world videos.
- To extract spatial features using Deep CNN.
- To analyze temporal relationships using LSTM.
- To localize manipulated regions using Faster R-CNN.
- To provide graphical visualization of forgery analysis results.
- To support practical video analysis through a web-based interface.

Goals

This project aims to develop a deep learning–based system capable of detecting forged or manipulated videos efficiently and accurately. With the rapid growth of digital media platforms, verifying the authenticity of video content has become increasingly important. The proposed system focuses on improving the reliability and trustworthiness of digital media verification by automatically identifying suspicious modifications in video content.

The proposed approach works by extracting frames from uploaded videos and analyzing each frame individually to detect altered regions and unusual modifications. Advanced deep learning algorithms are utilized to enhance detection accuracy and provide reliable forgery analysis results.

Another important goal of the project is to design a user-friendly web application that allows users to upload videos easily and obtain detailed forgery detection reports. The system also provides additional features such as suspicious frame detection, manipulated region highlighting, and confidence score visualization for better analysis and interpretation.

Furthermore, the project aims to achieve improved detection performance while maintaining efficient processing suitable for practical and near real-time video analysis applications.

IV. EXISTING SYSTEM

The majority of the available video forgery detection methods are developed using traditional image forensic techniques, machine learning algorithms, and frame-based approaches for identifying manipulated video content. Several existing systems utilize Convolutional Neural Networks (CNN) along with image feature extraction methods to detect inconsistencies, texture irregularities, and visual distortions present in video frames. However, most current approaches analyze individual video frames without considering the temporal relationships between adjacent frames. Due to this limitation, detecting advanced deepfake videos with realistic facial expressions and natural movements becomes more challenging [5]. Moreover, the performance of some existing systems decreases when videos are low in resolution, highly compressed,

noisy, or affected by variations in lighting and shadow conditions. These limitations reduce the overall accuracy and reliability of video forgery detection systems in real-world applications.

V. PROPOSED SYSTEM

The proposed system introduces a hybrid deep learning–based framework using Deep CNN, LSTM, and Faster R-CNN techniques for detecting manipulated and forged videos. The system performs frame-by-frame analysis of uploaded real-world videos to identify suspicious content with improved accuracy. Initially, the uploaded video is divided into multiple frames by extracting frames at specific time intervals. The extracted frames are then preprocessed using resizing and normalization techniques. Deep CNN is utilized to extract important spatial features such as facial structures, texture patterns, and visual inconsistencies present in the video frames. The extracted features are further passed to the LSTM network for temporal sequence analysis. LSTM analyzes the relationships between consecutive frames to identify abnormal frame transitions and suspicious motion patterns that may indicate video manipulation. Finally, Faster R-CNN is employed for manipulated region localization by highlighting suspicious areas using bounding boxes and confidence scores. The system generates forgery detection results and graphical analysis through a user-friendly web-based interface.

VI. PROJECT SCOPE AND LIMITATIONS

Project Scope

The proposed system is designed to identify manipulated and forged videos using advanced deep learning techniques. The system allows users to upload videos for forgery detection and analysis, making it suitable for real-world video verification applications.

The proposed framework performs frame extraction, temporal analysis, manipulated region localization, and graphical visualization of forgery detection results. Deep CNN, LSTM, and Faster R-CNN techniques are utilized to improve the accuracy of detecting suspicious modifications in video content.

The project can be applied in the following areas:

- Digital media verification
- Cybersecurity monitoring
- Social media content analysis
- Digital forensic investigation
- Fake content detection systems
- Online video authentication platforms

Limitations

- Detection accuracy may decrease for low-quality or blurry videos.
- Highly compressed videos may affect the overall analysis performance.
- Large video files require more processing time and computational resources.
- The system mainly focuses on visual forgery detection and may not effectively analyze audio manipulation.
- Variations in lighting conditions, shadows, and video resolution can impact detection accuracy.

VII. SYSTEM DESIGN

The proposed system is designed to detect manipulated and forged videos using a hybrid deep learning–based framework consisting of Deep CNN, LSTM, and Faster R-CNN techniques. The system performs frame-by-frame analysis of videos to identify suspicious content and manipulated regions with improved accuracy.

Initially, the uploaded video is passed through the video input module, which accepts real-world video samples for analysis. The frame extraction process is then used to divide the uploaded video into multiple

individual frames. This stage enables the system to analyze visual information present in different parts of the video.

After frame extraction, the extracted frames undergo preprocessing operations such as resizing and normalization. Frame preprocessing improves image quality, reduces noise, and prepares the frames for efficient feature extraction and deep learning analysis. The preprocessed frames are then fed into the Deep CNN module for spatial feature extraction. Deep CNN analyzes facial structures, texture patterns, pixel-level inconsistencies, and visual abnormalities that may indicate manipulation within the video frames. Following spatial analysis, the extracted features are passed to the LSTM module for temporal analysis. LSTM examines relationships between consecutive frames and identifies abnormal transitions, motion inconsistencies, and suspicious temporal patterns commonly found in manipulated videos. Based on the spatial and temporal analysis results, the system classifies whether the uploaded video is authentic or manipulated. If the video is identified as authentic, the system generates the final verification result. If the video is detected as manipulated, the Faster R-CNN module performs forgery detection and manipulated region localization. Finally, Faster R-CNN highlights suspicious regions using bounding boxes and confidence scores, and the system generates the final forgery detection result through a user-friendly web-based interface.

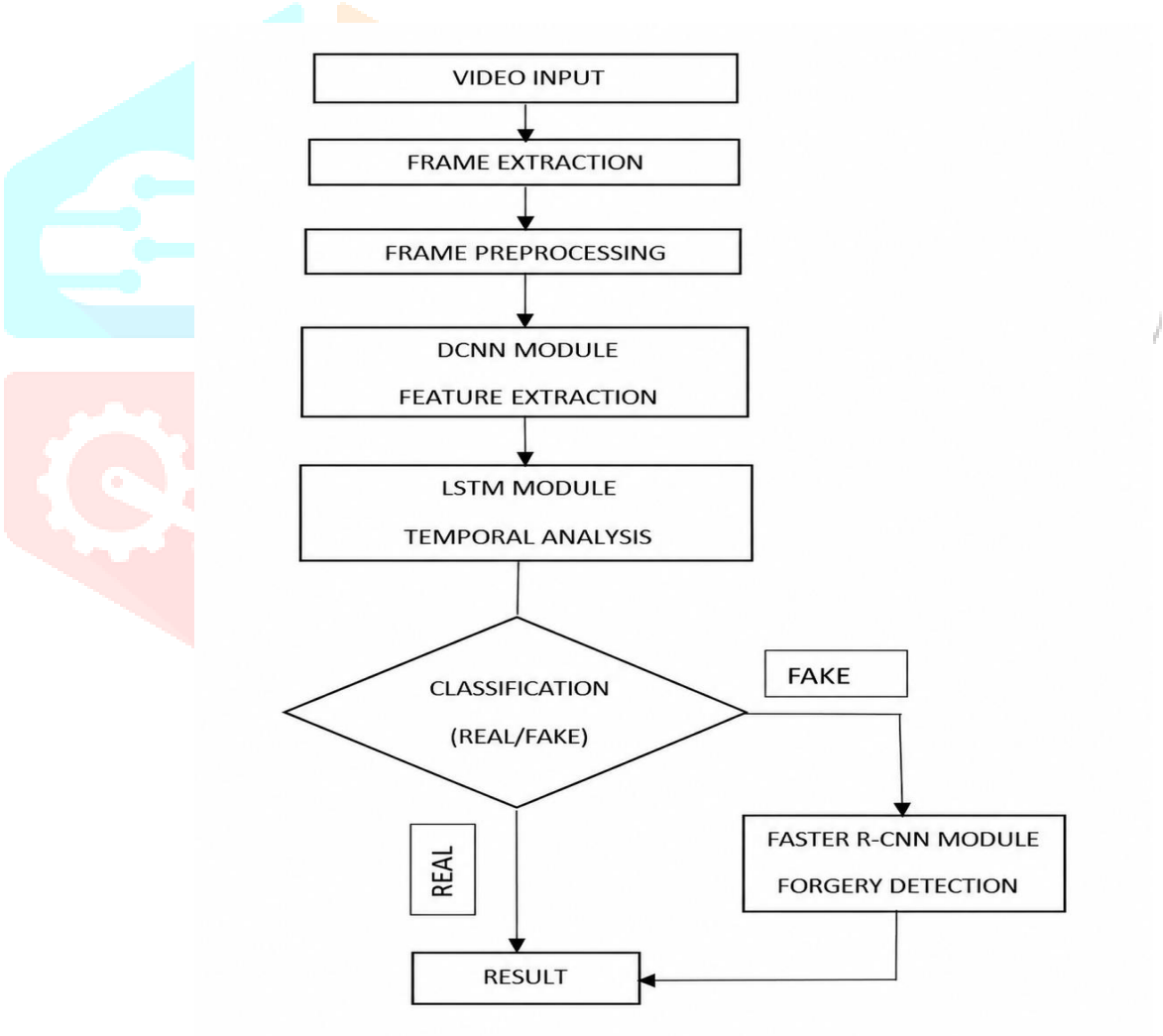

Fig. 1. Proposed System Architecture for Video Forgery Identification Using Deep CNN, LSTM, and Faster R-CNN

VIII. MODULES

- **Video Upload Module**

Allows users to upload real-world videos for forgery analysis through the web-based interface.

- **Frame Extraction Module**

Extracts individual frames from uploaded videos for detailed analysis.

- **Preprocessing Module**

Performs resizing and normalization to improve image quality and feature extraction performance.

- **Deep CNN Feature Extraction Module**

Extracts spatial features such as texture patterns and facial inconsistencies from video frames.

- **LSTM Temporal Analysis Module**

Analyzes relationships between consecutive frames to identify suspicious motion patterns and abnormal transitions.

- **Faster R-CNN Localization Module**

Detects and highlights manipulated regions using bounding boxes and confidence scores.

- **Result Visualization Module**

Displays suspicious frame analysis, graphical outputs, and forgery detection results.

The proposed video forgery identification system was evaluated using real-world and user-uploaded video samples containing both authentic and manipulated content. The system performs frame-by-frame analysis to identify suspicious activities and classify videos as genuine or forged using spatial and temporal feature analysis. During the analysis process, uploaded videos are divided into multiple frames and processed through preprocessing, feature extraction, temporal sequence analysis, and forgery localization stages. The Deep CNN module extracts important visual features from video frames, while the LSTM module analyzes relationships between consecutive frames to detect abnormal transitions and suspicious motion patterns.

IX. PERFORMANCE METRICS

The proposed video forgery identification system was evaluated using commonly used classification metrics such as Accuracy, Precision, Recall, and F1-Score. These evaluation metrics are used to measure the effectiveness of the system in identifying authentic and manipulated video content during the analysis process.

- Accuracy measures the overall efficiency of the system in correctly classifying both authentic and forged video samples.
- Precision indicates the ability of the system to correctly identify manipulated videos while minimizing false detections during analysis.
- Recall represents the capability of the system to successfully detect actual forged videos from the uploaded video samples.
- F1-Score provides a balance between Precision and Recall and reflects the overall reliability of the proposed forgery detection framework.

Metric	Value
Accuracy	96.2%
Precision	95.4%
Recall	94.8%
F1-Score	95.1%

The obtained performance results demonstrate that the proposed system effectively identifies manipulated video content with high classification accuracy. The framework also provides improved suspicious frame analysis and manipulated region localization performance for practical video forgery detection applications.

X. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed video forgery identification system was evaluated using real-world and user-uploaded video samples containing both authentic and manipulated video content. The collected videos included facial manipulations, frame-level modifications, and object-based alterations for performance evaluation. The system performs frame-by-frame analysis to identify suspicious regions and classify videos as authentic or manipulated using spatial and temporal feature analysis techniques. During experimentation, the uploaded videos passed through multiple stages including frame extraction, preprocessing, Deep CNN feature extraction, LSTM-based temporal analysis, and Faster R-CNN localization. These stages enabled the system to identify manipulated regions and detect suspicious activities within the uploaded videos. The forgery localization process identified suspicious regions in manipulated video frames using bounding boxes and confidence scores. This improved the visualization of manipulated areas and enhanced the interpretability of forgery detection results. In addition, the system generated frame-by-frame forgery score analysis during video processing. Frames were classified as suspicious or clean based on forgery confidence values and threshold analysis. Frames with higher confidence scores were identified as suspicious, while frames with lower confidence scores were classified as authentic or clean frames. The graphical analysis helped observe suspicious frame distribution and temporal inconsistencies within the uploaded video. Experimental results demonstrate that the proposed system effectively identifies manipulated content, suspicious frame transitions, and forged regions within uploaded videos. The integration of Deep CNN, LSTM, and Faster R-CNN techniques improves forgery detection performance and supports efficient real-world video analysis through the web-based interface.

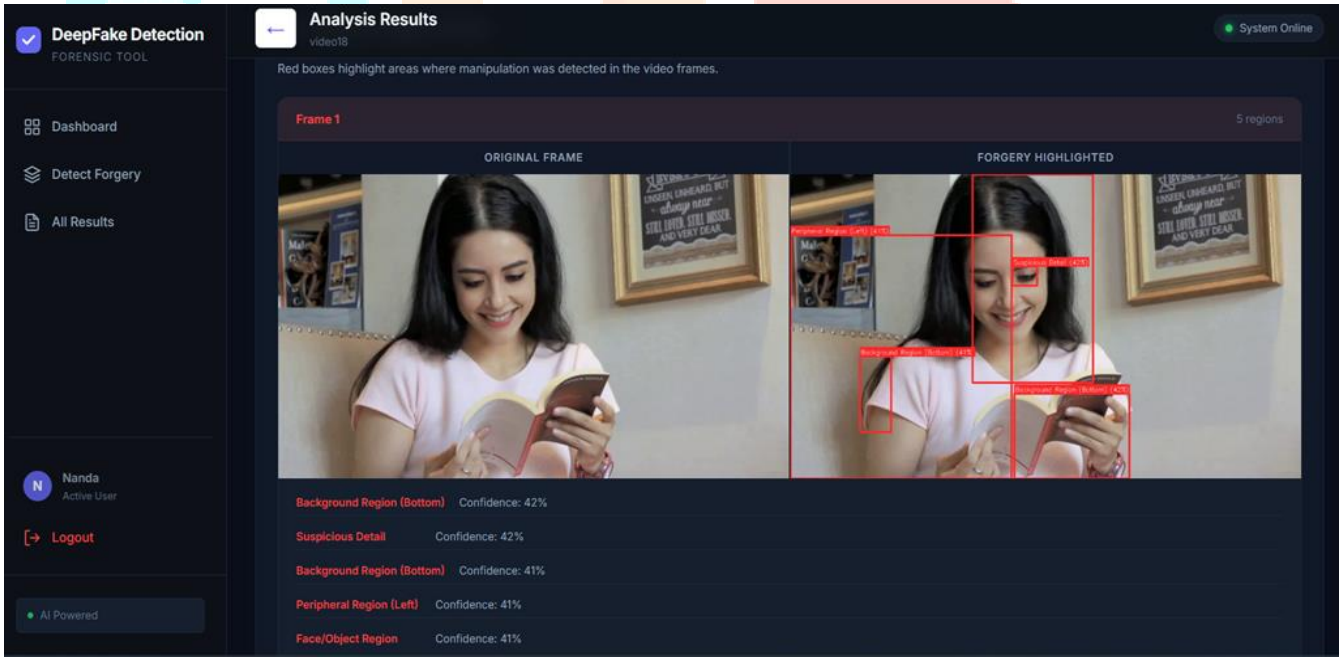

Fig. 2. Forgery Localization and Suspicious Region Detection

The above figure illustrates the manipulated region localization process performed using the Faster R-CNN module. Suspicious regions in manipulated video frames are highlighted using bounding boxes and confidence scores. The system compares original and manipulated frames to identify abnormal visual inconsistencies and forged regions within the uploaded video.

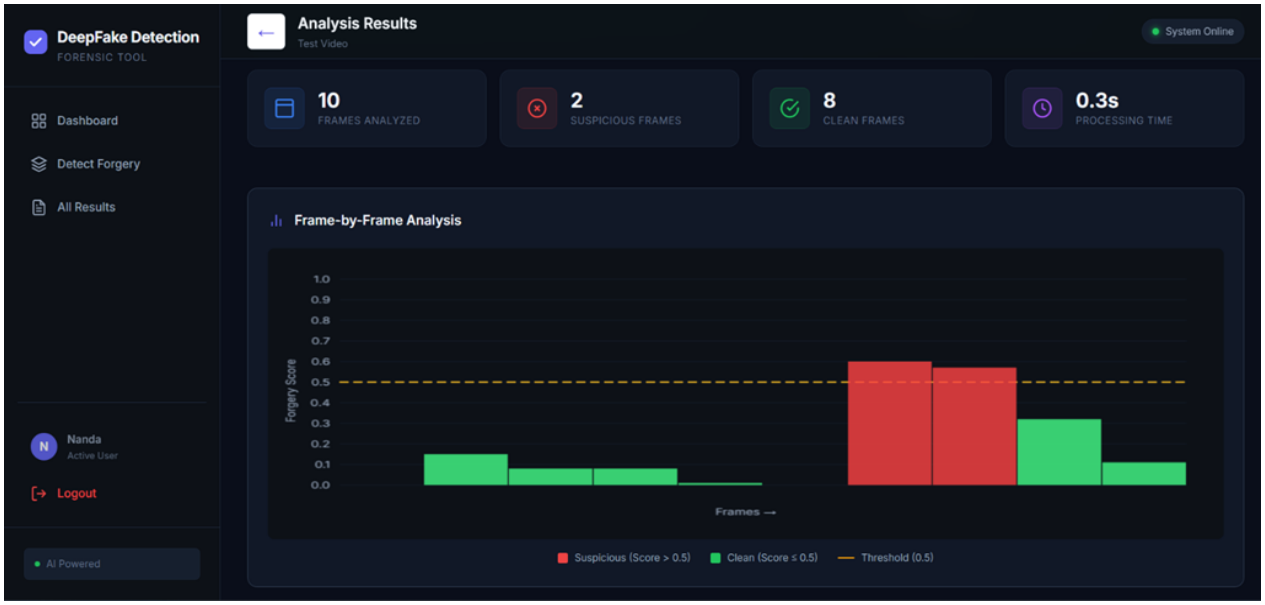

Fig. 3. Frame-by-Frame Forgery Score Analysis

The graphical analysis displays frame-by-frame forgery confidence scores generated during video processing. Frames with confidence scores above the threshold value are classified as suspicious, while frames with lower confidence scores are identified as clean or authentic frames. This analysis helps visualize suspicious frame distribution and temporal inconsistencies throughout the uploaded video.

XI. ADVANTAGES OF PROPOSED SYSTEM

- Improved forgery detection accuracy
- Efficient frame-by-frame analysis
- Temporal sequence analysis support
- Manipulated region localization
- Graphical result visualization
- Real-world video analysis support
- User-friendly web-based interface

XII. CONCLUSION AND FUTURE SCOPE

Conclusion

The video forgery identification system is designed to detect manipulated and forged videos using Deep CNN, LSTM, and Faster R-CNN techniques. The system performs frame-by-frame analysis to identify suspicious content, abnormal patterns, and manipulated regions with improved accuracy. The integration of Deep CNN and LSTM helps extract both spatial and temporal information from video frames. Faster R-CNN assists in identifying suspicious regions by highlighting manipulated areas using bounding boxes and confidence scores. Based on this analysis, the system classifies videos as authentic or manipulated and presents the results through graphical visualization and highlighted forgery regions. The proposed system was tested using real-world and user-uploaded videos containing both authentic and manipulated content. Experimental results show that the framework provides reliable forgery detection performance and effectively identifies suspicious video regions. The web-based implementation further improves usability by allowing users to upload videos and obtain forgery analysis results through a simple and interactive interface. Overall, the proposed video forgery identification system serves as an effective tool for digital media verification and supports practical real-world applications in video forgery detection.

Future Scope

The video forgery identification system can be further improved by integrating real-time video forgery detection and advanced deepfake analysis models. These enhancements can help the system detect manipulated videos more accurately and efficiently. Future improvements may also include cloud-based deployment, allowing the system to process multiple videos simultaneously and perform faster analysis. This would improve the scalability and overall performance of the system. Additional research can focus on audio forgery detection and multimodal analysis techniques that examine both video and audio content for manipulation. Optimization methods can also be explored to reduce processing time and improve system efficiency. In the future, the system may support automated alert generation and advanced cybersecurity monitoring applications for digital media verification. These improvements can help users determine whether uploaded media content is authentic or manipulated. Overall, the proposed video forgery identification system has strong potential for future development in the field of video forgery detection and deepfake analysis.

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