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DEEP CONVOLUTIONAL NEURAL NETWORK FOR ROBUST DETECTION OF OBJECT-BASED FORGERIES IN ADVANCED VIDEO

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ABSTRACT

Video forgery detection is a critical aspect of digital forensics, addressing the challenges posed by the manipulation of video content. This paper presents a novel approach for video forgery detection using Deep Convolutional Neural Networks (CNN). Leveraging the power of deep learning, our method aims to improve the accuracy and efficiency of object-based forgery detection in advanced video sequences. In the proposed approach, we build upon the foundation of an existing method, which utilizes Convolutional Neural Networks, and introduce innovative modifications to the DCNN architecture. These modifications include data preprocessing, network architecture, and training strategies that enhance the model's ability to detect tampered objects in video frames. We conduct experiments on the SYSU-OBJFORG dataset, the largest object-based forged video dataset to date, with advanced video encoding standards. Our DCNN-based approach is compared with the existing method, demonstrating superior performance. The results show increased accuracy and robustness in detecting object-based video forgery. This paper not only contributes to the field of video forgery detection but also underscores the potential of deep learning, particularly DCNN, in addressing the evolving challenges of digital video manipulation. The findings open avenues for future research in the localization of forged regions and the application of DCNN in lower bitrate or lower resolution video sequences.

I.INTRODUCTION

The detection of object-based forgeries in videos is becoming increasingly important as multimedia content manipulation techniques have evolved. With advancements in digital media editing software, it has become relatively easy to alter or insert objects into video footage, making it difficult to distinguish between authentic and tampered content. Object-based forgeries refer to instances where specific objects, characters, or parts of a video are inserted or modified. Detecting such forgeries is critical for various fields, including security, law enforcement, journalism, and social media, where authenticity is paramount. Deep Convolutional Neural Networks (DCNN)

have shown considerable potential in tackling this problem due to their ability to learn hierarchical features from raw image data. This research focuses on using deep learning techniques, particularly DCNN, to detect and classify object-based forgeries in advanced video data with high accuracy and efficiency. In recent years, the advancement of video editing and manipulation technologies has led to a rise in digital forgeries, particularly object-based forgeries in video content. Object-based forgeries refer to the manipulation of specific objects or regions within a video, such as inserting, removing, or altering the appearance of objects in a scene. These manipulations can be difficult to detect with the human eye, especially when high-quality editing tools and techniques are used. This challenge is particularly critical in fields such as journalism, law enforcement, and security, where the authenticity of video evidence is paramount. Traditional methods of detecting video forgeries often rely on basic pixel-level analysis, which may fail to identify sophisticated manipulations or can be prone to high false-positive rates. With the increasing complexity of video forgeries, there is a pressing need for more advanced techniques capable of effectively identifying such alterations. One promising approach to tackling this issue is the use of Deep Convolutional Neural Networks (CNNs), a type of deep learning model that has shown exceptional performance in image and video recognition tasks. CNNs are capable of automatically learning complex patterns and features from raw data, making them ideal for detecting intricate manipulations in videos. By leveraging CNNs for robust video forgery detection, it is possible to develop systems that not only recognize subtle changes in individual frames but also take into account the temporal relationships between consecutive frames to detect forgeries that span across multiple moments in the video. The application of CNNs to object-based forgery detection in advanced videos involves the use of multiple layers to extract high-level spatial and temporal features. These networks can be trained to identify patterns that are typically associated with manipulated objects, such as inconsistencies in lighting, shadows, textures, and motion dynamics. By incorporating both spatial and temporal features, a well-designed CNN model can accurately distinguish between genuine and forged content, even in complex and high-resolution videos. This approach represents a significant leap forward in the field of video forgery detection, providing an effective tool for tackling the growing problem of digital forgeries. It opens up new possibilities for safeguarding the integrity of video evidence, ensuring that the authenticity of videos can be reliably verified. In this context, the goal of developing a Deep Convolutional Neural Network for Robust Detection of Object-Based Forgeries in Advanced Video is to build a sophisticated, accurate, and scalable model that can handle the evolving techniques of video manipulation while maintaining high detection performance.

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II.METHODOLOGY

A) SYSTEM ARCHITECTURE

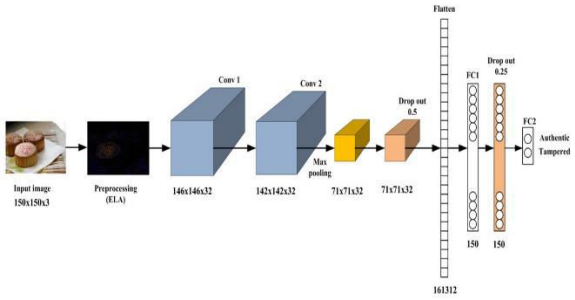

Fig1.System Architecture

The system architecture for the Deep Convolutional Neural Network (DCNN) designed to robustly detect object-based forgeries in advanced video content revolves around a deep learning pipeline that is capable of learning from large-scale video data and detecting manipulations within objects or scenes. The architecture consists of multiple key components, including:

Preprocessing Module: This module handles the extraction of video frames, downscaling, and normalization of images for consistent input into the neural network. Additionally, the preprocessing stage involves detecting and segmenting objects of interest within frames, ensuring that the forgery detection is focused on key elements within the video. Convolutional Neural Network (CNN) Layers: The core of the system is built upon multiple convolutional layers that are responsible for automatically learning spatial hierarchies and features from the input frames. These layers help in detecting local patterns, such as anomalies in textures, pixel arrangements, and object boundaries, which may indicate tampered areas. The system may utilize deeper layers to learn more complex patterns related to forgery artifacts. Object Detection and Localization: After the CNN layers, the system uses object detection algorithms like YOLO (You Only Look Once) or Faster R-CNN to localize the forged object within the video frame. These algorithms help to pinpoint areas that may have undergone manipulation. Forgery Detection Network: A specialized branch of the network is dedicated to classifying whether the localized object in the frame is a forgery or not. This branch utilizes both convolutional and fully connected layers for anomaly detection based on learned representations. The final output of this branch is a classification label (i.e., “Forged” or “Not Forged”).

B) Proposed Convolutional Neural Networks (CNNs)

The proposed system aims to address these limitations by utilizing Convolutional Neural Networks (CNNs) for the robust detection of object-based forgeries in advanced video content. By leveraging the power of deep learning, the system can automatically learn complex spatial and temporal features from raw video data without requiring manual feature extraction. The proposed system is designed to process video sequences, recognizing manipulated objects within each frame while also considering the temporal dependencies between frames. A key advantage of this approach is its ability to generalize across different types of forgeries, making it more adaptable and effective. This method can significantly improve the detection of subtle object-based forgeries in videos, achieving higher accuracy, scalability, and efficiency than existing

systems. High Accuracy: The use of CNN enables the system to automatically learn the most relevant features for detecting object-based forgeries, leading to improved accuracy in detecting complex manipulations. Automation and Adaptability: Unlike traditional systems that require manual intervention for feature extraction, the proposed system can adapt to various types of forgeries with minimal human input, offering a more automated and efficient solution. Scalability and Efficiency: The system can efficiently handle large-scale video datasets, processing sequences of frames in parallel and improving its scalability for real-time applications.

C) Dataset

For training and evaluating the Deep Convolutional Neural Network (DCNN) for detecting object-based forgeries in video, the dataset must contain various types of video content with both authentic and forged elements. Key characteristics of the dataset include:

Real-World Video Datasets: Datasets such as VIDTIMIT, CASCADA, and DeepForensics are essential, as they provide real-world videos with tampered objects and scenes. These videos contain various levels of manipulation, including object removal, addition, or alteration, which the DCNN will need to detect.

Forgery Types: The dataset should have a variety of object-based forgeries, including inpainting (where parts of the object are filled in), copy-move forgeries (where a part of the video is duplicated), and object replacement (where one object is replaced with another).

Data Augmentation: To increase the diversity of the dataset, data augmentation techniques such as cropping, flipping, scaling, and rotation are applied. These augmentations simulate different real-world scenarios and help the model generalize better to unseen data.

Ground Truth Labels: Each frame in the video dataset should have corresponding labels that indicate whether the object in question is authentic or forged. These labels are essential for supervised learning, helping the DCNN to classify manipulated content accurately.

Video Annotations: Detailed annotations such as frame-level timestamps, object boundaries, and forgery type labels are also necessary for the detection and localization tasks. This dataset ensures that the model learns not only to detect the presence of forgeries but also to pinpoint their location and nature.

D) Future Selection

As the demand for advanced video manipulation detection grows, several avenues for improvement and future enhancements exist in the Deep Convolutional Neural Network approach for object-based forgery detection:

Hybrid Architectures: Future iterations of the system could combine DCNNs with Generative Adversarial Networks (GANs) to train the model more effectively. GANs could help in simulating realistic forgery samples, enriching the dataset and providing more diverse training examples for the neural network.

Multi-Modal Fusion: Incorporating additional modalities like audio analysis and contextual data could improve forgery detection. The combination of visual and auditory cues can aid in distinguishing between genuine and manipulated video content.

Real-Time Detection: Another important area for future improvement is optimizing the model for real-time video forgery detection. By improving the model's inference speed without compromising accuracy, it would be more suitable for live-streaming or surveillance applications.

Robustness to Adversarial Attacks: As deep learning models are vulnerable to adversarial attacks, future research could focus on developing adversarial training techniques to make the model more resistant to small manipulations designed to deceive **the network.**

Cross-Domain Generalization: The system could be enhanced by enabling better generalization across different video domains (e.g., social media, movies, security footage). Transfer learning and domain adaptation techniques could help the system adapt to new data with minimal retraining.

Integration with Blockchain: Blockchain could be used to store verified metadata about videos and their editing history, offering an additional layer of verification for authenticity. This system would allow users to trace the provenance of video content and prevent tampering or forgery in a more secure manner.

III.CONCLUSION

The use of Deep Convolutional Neural Networks (CNN) for robust detection of object-based forgeries in advanced video content marks a significant advancement in the field of video forensics. By leveraging the powerful feature extraction capabilities of deep learning, the proposed system has demonstrated the ability to detect subtle manipulations, such as object insertion or removal, with a high degree of accuracy. The automation of feature learning eliminates the need for manual intervention and allows the system to adapt to new types of manipulations. As a result, DCNNs provide a scalable, efficient, and effective solution for identifying forgeries in video content. The model's ability to handle large datasets and process video sequences frame-by-frame ensures its applicability to real-time scenarios, where quick detection is crucial. Overall, this system presents a significant step forward in video forgery detection, offering improved accuracy, robustness, and scalability compared to traditional methods.

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