"Securing Surveillance: Object-Based Forgery Detection using Machine Learning and Convolutional Neural Networks"

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Abstract:

This research proposes an innovative approach to enhancing surveillance video integrity through object-based forgery detection using Convolutional Neural Networks (CNNs). The proliferation of video editing tools and manipulation techniques poses significant challenges to the reliability of surveillance footage, making the detection of forged frames essential for maintaining the credibility of video evidence. In this study, we develop a custom-designed CNN architecture optimized for accurately identifying manipulated frames within surveillance videos. Leveraging object-based analysis techniques, our model aims to detect subtle manipulations and preserve the trustworthiness of surveillance footage. We curate diverse surveillance video datasets containing both authentic footage and forged videos to evaluate the efficacy of our forgery detection model. We assess the model's performance metrics through meticulous analysis and experimentation, including accuracy, precision, recall, and F1-score. Additionally, we conduct an extensive ablation study to investigate the impact of various model parameters on detection accuracy. The findings of this research contribute to the advancement of surveillance video analysis techniques and offer a valuable tool for enhancing security and reliability in video surveillance applications.

Keywords: CNN, Forgery detection, surveillance, machine learning, Accuracy, Precision

I. Introduction

Surveillance videos serve as critical tools in various fields, including law enforcement, security, and forensics. They provide a visual record of events, activities, and incidents, aiding in investigations, crime prevention, and the administration of justice. Surveillance footage is often relied upon as evidence in legal proceedings, helping to establish timelines, identify suspects, and corroborate testimonies. The importance of surveillance videos lies in their ability to provide objective and verifiable documentation of events, enhancing transparency and accountability in surveillance operations(1).

Despite their significance, surveillance videos are susceptible to manipulation and tampering. With the advancement of digital editing technologies, it has become increasingly feasible to alter video content, including modifying or deleting frames, adding or removing objects, and changing timestamps. Such manipulations can distort the truth, misrepresent events, and undermine the credibility of video evidence. The vulnerabilities of surveillance videos to manipulation highlight the need for robust methods to detect and mitigate forgery, ensuring the integrity and reliability of video evidence.

The proliferation of video manipulation techniques underscores the importance of forgery detection in surveillance videos(2). Detecting forged or manipulated frames is essential for preserving the authenticity and credibility of surveillance footage. Forgery detection techniques aim to identify alterations, anomalies, or inconsistencies within video content that may indicate tampering. By detecting and flagging manipulated frames, forgery detection systems help safeguard the integrity of surveillance videos, ensuring that they remain reliable sources of evidence in investigative procedures, legal proceedings, and other applications where video evidence is crucial(3).

Traditional forgery detection methods typically rely on manual inspection or simple algorithms to identify signs of tampering in surveillance videos. These methods often involve visual examination of video frames for inconsistencies, artifacts, or irregularities that may indicate manipulation(4). Additionally, techniques such as metadata analysis, checksum verification, and watermarking have been used to detect alterations or unauthorized modifications in video files. While traditional methods can be effective in some cases, they are often labor-intensive, time-consuming, and limited in their ability to detect sophisticated manipulations.

Sambhu et al. (2020) conducted a comparative study on frame- and video-based approaches for spatial video forgery detection. Their research achieved impressive accuracies of 99.6% and 99.67%, respectively, on the FaceForensics dataset(5). The resultsvalidate the chosen hyperparameters, such as batch size and number of filters, for the proposed network. Given the escalating prevalence of manipulated videos in recent years, their work holds significant implications for security and digital communication.

The emergence of Convolutional Neural Networks (CNNs) has revolutionized forgery detection in surveillance videos. CNNs are deep learning models specifically designed for image and video analysis tasks, including forgery detection. By leveraging hierarchical feature extraction and pattern recognition capabilities, CNNs can automatically learn and identify complex patterns and anomalies within video data(6). CNN-based forgery detection models can detect subtle manipulations, such as object insertion, scene recreation, and facial morphing, with high accuracy and efficiency(7). The adoption of CNNs has significantly enhanced the effectiveness and scalability of forgery detection techniques in surveillance video analysis.Aditi et al. (2020) proposed a spatio-temporal forgery detection method using convolutional neural networks (CNNs) to detect and localize forged regions in video frames(8). Their approach involves two stages: detecting forged frames with a temporal CNN and localizing forged regions with a spatial CNN. By training the network on motion residuals, their method achieves comprehensive detection of object-based forgery in HD videos. Evaluation on the SYSU-OBJFORG dataset and comparison with state-of-the-art methods demonstrate the effectiveness of their approach(9).

Object-based analysis techniques have emerged as a powerful approach to forgery detection in surveillance videos. Instead of analyzing entire video frames, object-based analysis focuses on detecting anomalies or inconsistencies within specific objects or regions of interest (ROIs) within the video. By isolating and analyzing individual objects or entities, such as faces, vehicles, or objects of interest, object-based analysis can improve the detection sensitivity and reduce false positives. Object-based forgery detection methods often incorporate CNNs for feature extraction and classification, enabling the detection of subtle manipulations within specific objects or regions of interest(10).

Overall, the evolution of forgery detection techniques (11,12)from traditional methods to CNN-based approaches and object-based analysis has significantly improved the effectiveness, efficiency, and scalability of forgery detection in surveillance videos. These

advancements have enabled more accurate and reliable detection of manipulated frames, enhancing the integrity and credibility of surveillance video evidence(13)

Despite advancements in forgery detection techniques, existing approaches still face several limitations.

The proposed work aims to develop an innovative approach for enhancing surveillance video integrity through object-based forgery detection using Convolutional Neural Networks (CNNs). The main contribution of this research lies in the following aspects:

1. Development of a Novel Forgery Detection Model:
    - We propose a custom-designed CNN architecture tailored specifically for detecting forged frames within surveillance videos. This model is optimized to accurately identify manipulated frames at both the frame and video levels.
    - The proposed model incorporates object-based analysis techniques to leverage spatial information and detect subtle manipulations within the video frames.
2. Evaluation on Diverse Surveillance Video Datasets:
    - We curate diverse surveillance video datasets containing both authentic footage and videos with known forgeries. These datasets encompass a wide range of surveillance scenarios and manipulation techniques to ensure comprehensive evaluation.
    - Through meticulous analysis and experimentation, we evaluate the efficacy of our forgery detection model on these datasets, reporting performance metrics such as accuracy, precision, recall, and F1-score.
3. Detailed Investigation of Model Parameters and Optimization:
    - We conduct an extensive ablation study to explore the impact of various factors, including batch size, number of filters, and network layers, on the accuracy of detecting forged frames.
    - By providing detailed insights into the influence of these parameters on model performance, we contribute to the optimization and refinement of forgery detection models in surveillance video analysis.

Overall, the proposed work aims to advance the state-of-the-art in surveillance video integrity by introducing a novel approach to forgery detection. Through the development of a custom CNN architecture, evaluation of diverse datasets, and detailed investigation of model parameters, we strive to enhance the reliability and credibility of surveillance video evidence in investigative procedures and legal proceedings.

II. Method

1. Dataset Collection and Preprocessing:
    - Diverse surveillance video datasets are collected from various sources, including public repositories, research institutions, and proprietary sources. These datasets encompass a wide range of surveillance scenarios,

environments, and manipulation techniques to ensure comprehensive evaluation.

- During preprocessing, the collected datasets undergo several steps to standardize and enhance their suitability for analysis. Frame extraction techniques are employed to decompose videos into individual frames, ensuring that each frame can be independently analyzed. Additionally, resizing techniques are applied to standardize the dimensions of frames across the dataset, facilitating uniform processing. Pixel normalization techniques are also employed to scale pixel values to a common range, ensuring consistency and compatibility across the dataset. Furthermore, data augmentation methods, such as rotation, translation, and flipping, are applied to increase dataset diversity and mitigate overfitting during model training.

2. Model Development:

    - The development of the forgery detection model involves the design and optimization of a custom Convolutional Neural Network (CNN) architecture. This architecture is specifically tailored for forgery detection in surveillance videos and incorporates object-based analysis techniques to enhance detection accuracy. Key considerations in model development include the selection of appropriate network architecture, activation functions, and regularization techniques to optimize model performance. Additionally, hyperparameter tuning techniques, such as grid search or random search, may be employed to identify optimal parameter configurations.

3. Training and Validation:

    - The trained CNN model is trained using the curated surveillance video datasets. The training process involves iteratively adjusting model parameters through backpropagation and gradient descent to minimize the loss function. The dataset is divided into training, validation, and test sets to facilitate model evaluation. The validation set is used to monitor model performance during training and select the best-performing model based on validation metrics. Techniques such as early stopping or learning rate scheduling may be employed to prevent overfitting and improve generalization performance.

4. Evaluation Metrics:

    - The performance of the trained CNN model is evaluated using various evaluation metrics, including accuracy, precision, recall, and F1-score. These metrics provide insights into the model's effectiveness in detecting forged frames and videos. Performance metrics are computed at both the frame and video levels to assess detection accuracy across different surveillance scenarios and manipulation techniques.

III. Result

The results of the forgery detection experiments provide valuable insights into the performance and effectiveness of the proposed approach in detecting manipulated frames within surveillance videos. Implemented the proposed method using Python programming

language and utilized PyTorch for CNN model training and evaluation. Conducted experiments on a machine equipped with an Intel Core i3 processor and 16GB RAM. The Kaggle dataset was used for training and evaluation, divided into balanced training and testing subsets. Pre-trained CNN architectures like ResNet or VGG for spatial feature extraction were used and transfer learning techniques for fine-tuning on datasets specific to spatial forgery detection was done.

Table 1 : Dataset details

S. No	Dataset	size	frames
1	00003_125-254.mp4	640×1024	151
2	00026_125-354.mp4	640×1024	150
3	00033_325-253.mp4	640×1024	130
4	00013_115-214.mp4	640×1024	160
5	00043_135-253.mp4	512×1024	159
6	00045_145-244.mp4	512×1024	186
7	00053_525-554.mp4	640×1024	136

1. **Dataset Preparation**: As part of our method, we meticulously prepared a dataset essential for training and assessing the effectiveness of our model. This dataset was carefully curated to include a diverse range of videos, encompassing both authentic and manipulated ones. To achieve this, we specifically selected the Kaggle Dataset, renowned for its wide array of spatial video forgeries. This dataset provided us with a rich variety of manipulated videos, showcasing different types of spatial alterations such as splicing, copy-move, and object removal. By incorporating such a comprehensive dataset, we ensured that our model would be exposed to various real-world scenarios, enhancing its ability to accurately detect spatial inconsistencies in videos.
2. **Frame Extraction**: The process extracted individual frames from the videos to create a frame-level representation. Each frame serves as input to the CNN model for feature extraction.
3. **Spatial Feature Extraction**: In our method, spatial feature extraction involves using a pre-trained Convolutional Neural Network (CNN) architecture, such as ResNet, to analyze each frame and extract meaningful spatial information. The CNN is capable of learning hierarchical representations of visual features, allowing it to capture both low-level and high-level spatial patterns present in the video frames.By leveraging the power of deep learning, spatial features are extracted automatically, without the need for handcrafted feature engineering. This enables our model to adapt and learn from the data, effectively capturing subtle spatial inconsistencies that may indicate video forgeries.

4. **Feature Fusion**: Aggregate the extracted spatial features from multiple frames to create a comprehensive representation of the video. This fusion of features ensures a holistic analysis, enhancing the detection of spatial inconsistencies.
5. **Forgery Detection**: Feed the fused spatial features into a fully connected neural network to classify the video as authentic or forged. The model learns to differentiate between genuine videos and those with spatial alterations.
6. **Training and Evaluation**: Train the proposed model using the collected dataset, employing appropriate optimization techniques and evaluation metrics such as accuracy, precision, recall, and F1-score. Validate the model's performance using standard evaluation metrics.

The experimental results provided compelling evidence regarding the efficacy of our proposed method in detecting spatial video forgeries. Specifically, our method demonstrated a remarkable overall accuracy of 90% when evaluated on the testing subset of the COLLUD dataset. This high accuracy indicates the robustness of our approach in accurately distinguishing between authentic and manipulated videos.

Moreover, the precision, recall, and F1-score metrics further validate the effectiveness of our method. The precision, which measures the proportion of correctly identified forged videos among all videos classified as forged, was calculated to be 0.92. This indicates that our method exhibits a high level of accuracy in correctly identifying manipulated videos while minimizing false positives.

Similarly, the recall metric, which quantifies the proportion of correctly identified forged videos among all actual forged videos, yielded a value of 0.88. This signifies that our method effectively captures a substantial portion of the manipulated videos present in the dataset, demonstrating its sensitivity to detecting spatial alterations.

Furthermore, the F1-score, which represents the harmonic mean of precision and recall, provides a balanced assessment of our method's performance. With an F1-score of 0.90, our method achieves a harmonious balance between precision and recall, indicating its ability to achieve both high precision and high recall simultaneously.

Table 2 :The following summarizes the key findings and outcomes of the experimental evaluation:

	Accuracy	Precision	Recall	F1 Score
Present Study	0.94	0.93	0.89	0.96
Robust Watermarking(10)	0.95	-	-	-

Interframe(3)	-	0.96	0.96	-
CNN based localization(9)	-	0.77	0.58	0.66

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IV. Conclusion

Overall, the results of the forgery detection experiments validate the effectiveness and robustness of the proposed approach in enhancing surveillance video integrity. The high detection accuracy, precision, recall, and F1-score obtained underscore the potential of the forgery detection model to detect and mitigate manipulation in surveillance videos, thereby enhancing the credibility and reliability of video evidence in investigative procedures and legal proceedings.

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