Pages 32 - 41

Volume 1 Number 1, 2024

COMPUTERS AND EDUCATION LETTERS

editor@celetters.com

www.celetters.com

ADVANCING FORENSIC APPLICATIONS: THE ROLE OF ARTIFICIAL INTELLIGENCE IN DETECTING AND MITIGATING IMAGE AND VIDEO MANIPULATION

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Abstract

Electronic information is threatened when forensic examinations become challenging due to modern digital advancements. Through Deepfakes media manipulation forms the basis for people who either attack others or spread false information while influencing political opinions. Traditional forensic testing methods show reduced capability in identifying picture alteration compared to more advanced techniques while operating at slow identification speeds. Deep learning-based artificial intelligence serves as a strong tool for handling modern-day technical problems. Our research assesses and develops artificial intelligence systems dedicated to detecting and reducing digital image and video manipulation for investigative purposes. We execute data management followed by model development and training and final assessment of results throughout our program. The developed AI models undergo verification using precision and accuracy together with recall testing as well as F1 score and ROC-AUC measurements. Our assessment framework integrates the use of GANs with CNNs while also deploying CNN-RNN hybrid architectures. AI-based techniques surpass traditional forensic methods to detect different types of manipulation with superior effectiveness. Real-world application demonstrates these models function effectively while keeping adversaries from influencing them. The research evaluates the cultural and ethical effects of artificial intelligence in forensic science while developing recommended methods of safe utilization. The research uses artificial intelligence strengths but addresses its weaknesses to develop secure systems against digital media tampering.

Article History

Received:
January 25, 2024

Revised:
February 08, 2024

Accepted:
March 15, 2024

Available Online:
June 30, 2024

Keywords: Artificial Intelligence (AI), Forensic Applications, Image Manipulation Detection, Video Manipulation Detection, Deep Learning.

INTRODUCTION

Visual content becomes easily accessible through advanced editing tools and fast digital media distribution thus putting severe risks on digital material integrity and forensic investigation results. False information dispersal together with reputation damage and election manipulation become possible through manipulated photos and videos used by malicious actors (Chesney and Citron, 2019). Deepfakes have raised significant security concerns because their artificially intelligent generation of highly realistic altered video content deceives viewers until their trust in digital media disappears according to Nguyen et al. (2020). The rapid distribution potential of media fabrications on social platforms results in the major intensification of this issue. Forensic techniques such as error level analysis (ELA) coupled with metadata inspection and noise pattern inquiry do not adequately solve the above problems when locating alterations in videos and images. The identification of elaborate modifications including AI-generated results proves challenging for human-involved assessment techniques because of their limited detection capabilities (Zhang et al., 2021). Modern sophisticated detecting tools must be developed immediately because digital media manipulation poses an escalating danger to society.

The technology of deep learning which belongs to artificial intelligence represents an avenue to solve this problem. The integration of artificial intelligence (AI) through convolutional neural networks (CNNs) and generative adversarial networks (GANs) and recurrent neural networks (RNNs) provides accomplished performance in detecting and examining modified content. Research shows CNNs achieve success in detecting lighting and shadow changes as well as textural variations that signal image splicing and video duplication forgeries (Chen et al., 2019). GANs which specialize in creating deepfakes possess the ability to detect variations and small changes in motion, lighting and facial details just as they do (Afchar et al., 2018). RNNs demonstrate higher competency in recognizing the correct chronological order of movie sequences which enables them to detect various video manipulation techniques including frame modification (Li et al., 2020). AI applications for forensic investigations remain challenging despite these current developments. AI models exhibit a substantial weakness because they remain susceptible to adversarial attacks which involve specifically modified data trying to bypass detection protocols. The efficacy of deepfake detection algorithms gets significantly weakened when researchers apply minimal alterations to deepfake movie content according to Nguyen et al. (2020).

The main challenge facing AI model training is the insufficient availability of extensive high-quality datasets. The creation of forensic-approved labeled datasets that contain authentic and modified material proves difficult because human annotation requires significant skill and time commitment (Rössler et al., 2019). The ability of AI models to perform extensive tasks is constrained by insufficient data inputs especially during investigations of modern or progressive manipulation methods. The judicial ethics together with legal frameworks surrounding AI utilization in forensic analysis should not be disregarded.

Advanced processing methods lead to increased difficulties in altering pictures and videos. The prevalence of AI technology stands as the main reason why non-technical users produce legitimate

simulation materials according to Marra et al. (2019). Forensic investigators struggle to match the rising numbers of intricate manipulated data because editing tools have become more accessible to the general public. Social media efficiently propagates false information because users widely distribute incorrect information there. Rapid systems for erroneous information identification and removal need to be developed to address the rapid spread of social media misinformation because it functions as a viral medium (Guarnera et al., 2020). Social media platforms introduce significant difficulties to forensic investigations because they distribute manipulated content rapidly which makes it harder to detect and remove it. The purpose of this research is to study how artificial intelligence can boost forensic methods for identifying modifications made to pictures and videos through analysis of present challenges. This paper establishes and applies AI detection algorithms including CNNs, GANs and RNNs for identifying tampered digital information. The study evaluates the weaknesses and obstacles that accompany these techniques because they face attacks from adversaries and lack sufficient data and create moral challenges. Our work targets the creation of better and reliable AI-based forensics tools in order to fight increasing digital information manipulation threats. The main purpose behind this research effort focuses on enhancing digital content authenticity through restoring public trust in digital media platforms to reduce adverse effects from manipulated visual content.

LITERATURE REVIEW

The complex evolution of image and video processing methods has driven major expansion in forensic research about developing advanced tools to detect and counteract such modifications. Research has examined the value of machine learning with artificial intelligence techniques to address limitations within traditional forensic investigation approaches. Research teams employ convolutional neural networks (CNNs) as deep learning models to detect subtle changes that occur in modified photographic and video content. Zhou et al. introduced a study in 2022 which demonstrated how CNNs can identify motion copy and splicing frauds by studying edge artifacts and local texture patterns. Wang et al. (2023) developed a CNN-RNN model hybrid which performed deepfake video detection through spatial and temporal feature analysis for state-of-the-art results. AI approaches demonstrate their ability to handle the obstacles that advanced manipulation techniques introduce into the system. The deceptive capabilities of deepfakes have made it increasingly challenging for experts to develop reliable methods for identifying them thereby becoming a new interest domain for science. The GAN-based deepfake detection method developed by Liu et al. (2022) exploits generation traces which generative models naturally create during they construct deepfakes. Their detection methodology achieved accurate identification of real from fake materials despite appearances that might have been highly convincing. The research by Gupta et al. (2023) investigated deep learning models with attention processes to improve identification of small changes found in deepfake videos. The strategy exceeded basic methods which focus on particular interest zones like eyes and mouth regions. Modern AI approaches must be utilized as a necessary countermeasure against the developing deepfakings threats according to this study.

Studies have explored AI systems for detecting deepfake videos together with temporal splicing and added or missing frames within video content. According to Kim et al. (2023) motion picture frame-level alterations can be detected through their

new temporal consistency-based methodology. An RNN with optical flow capabilities helps the method identify altered films with high accuracy by scanning motion pattern variations. The researchers at Zhang et al. (2023) formed a multi-stream CNN framework that examined temporal and geographical inputs to detect video modifications. Their successful approach demonstrated the importance of implementing numerous modalities during forensic examinations across various manipulation methods.

Many important barriers exist in the path of AI forensic investigation development despite recent progress. AI models face a major challenge because adversarial attacks involving deliberate content changes goal at evading detection systems. The research conducted by Patel et al. (2023) reveals how artificial perturbation methods diminish deepfake detection abilities even though they remain invisible to human observation. Strong and resistant AI systems must be developed because they need to withstand adversarial attacks. Lack of big assorted forensic datasets for model development and testing remains a major disadvantage. According to Kumar et al. (2023) extensive datasets which contain multiple techniques and operational environments are essential for developing robust AI forensic tools.

Using AI to forensics creates important ethical as well as sociological challenges for forensic practice. The implementation of AI technology in forensics leads to better precision but generates privacy and responsibility issues besides potential bias concerns. The analysis from forensic investigations shows sign of distortion because AI models develop biases during training on unbalanced datasets according to Johnson et al. (2023). Detection systems using AI pose significant monitoring and tracking risks particularly in countries with authoritarian governance structures. The necessity exists for AI systems to develop open content with enforcement protocols and fair treatment while maintaining privacy principles.

Research activities examine the possibility of using AI with established forensic methods to boost the overall success of forensic examinations. In 2023 Lee et al. presented a research design which integrated AI system evaluations with forensic specialist manual checks. Their approach proved the vital role of human intervention in forensic assessment since human supervision produced superior results compared to automatic procedures. The 2023 research by Chen et al. examined AI's potential assistance for forensic experts with large digital data processing which requires less effort and time compared to manual analysis methods. The study indicates AI integration with human expertise should define the future technological framework for forensic analysis instead of automating human positions.

Latest advancements in AI technology with machine learning allow forensic tools to better detect picture and video manipulations while preventing such operations. Forensic research must address several outstanding barriers including AI model sensitivity to adversarial attacks together with data gaps and ethical issues from using AI in forensic work. The necessary approach to tackle these difficulties requires joint efforts between experts in technology development and ethical considerations together with human expertise. Law enforcement agents can build improved and reliable forensic tools by harnessing AI benefits to counter rising digital media manipulation threats.

METHODOLOGY

This research develops and evaluates leading-edge AI forensics tools to determine how artificial intelligence functions in identifying and halting

picture and video manipulations. The research adopts three main operational phases which include data collection and preprocessing as well as model building and training followed by performance evaluation. For building a reliable and applicable model researchers collect original and modified photos and videos in the first phase of development. The collection demonstrates several manipulation techniques which consist of splicing and motion spoofing and duplication and deep fakes and frame-level change. The data sparsity issue gets resolved by utilizing two publicly available datasets which include Face Forensics++ and CASIA. We construct additional artificial data elements through artificial intelligence methods that use GAN. The collected data goes through preprocessing to verify meaningful indicators that combine motion vectors with texture patterns and temporal consistency. The image and video file formats undergo standardization processing during the normalization step. Data augmentation with rotation techniques and inversion while adding noise serves to increase database diversity along with generalization capability for unknown cases.

AI algorithms undergo development and optimization to identify and categorize modified data at this stage. The main goal of this study involves implementing advanced deep learning frameworks based on CNNs and GANs and RNNs. The examination of spatial characteristics that include edges and textures and color irregularities serves CNN-based techniques in their search for picture modifications. Supervised and unsupervised learning methods help the model recognize established and new manipulation strategies throughout its training process. Unusual video alterations can be detected through a network of CNN AND RNN components that monitor spatial and temporal patterns. The frame-specific data collection task of the CNN component pairs with the RNN component which processes temporal patterns for tampering detection based on motion continuity and frame shifting. A GAN-powered model gets developed through studying generative model traces that occurred during the development period for deepfake identification. The GAN model receives training using standard information and artificial samples to develop its ability to detect modifications in information.

The performance evaluation of the models concludes with five measurements consisting of accuracy alongside precision and recall and F1 score and area under the receiver operating characteristic (ROC) curve. The model evaluation process requires training data combined with distinct validation data to determine how well the models perform under various conditions. A specific analysis is conducted to examine model functionality under changed data conditions where discovery is planned for avoidance. The models can develop better resistance to these attacks through training that involves adversarial techniques. The models receive their performance assessment through direct comparison against traditional forensic techniques and recent AI techniques. Research findings result in routine model assessments that establish their strengths and weaknesses. A set of recommendations is proposed to monitor responsible implementation of these techniques in forensic practice after completing an ethical evaluation of AI forensic practices. The investigators strive to improve forensic analysis through systematic methods that develop strong identification and prevention capabilities against image and video tampering.

RESULTS

The research outcomes demonstrate AI-based algorithm performance in identifying manipulated images and videos. Evaluation of the created

models relies on a mixture of measures which consists of accuracy, precision, recall, F1 score and area under the receiver operating characteristic (ROC) curve. The independent validation dataset accompanied training data to confirm the models' performance capabilities and generalization behavior. All models produce outcomes which appear in this study together with their performance relative to traditional forensic analytics and contemporary AI tools.

Performance of CNN-Based Model for Image Manipulation Detection

The CNN-based system provided successful detection of image tampering activities that include both splicing and copy-move forensic tampering types. The system received training from 10,000 images which contained 5000 manipulated images along with 5000 authentic images. The research results appear in Table 1.

Metric	Training Dataset	Validation Dataset
Accuracy	95.2%	93.8%
Precision	94.5%	92.7%
Recall	95.8%	94.1%
F1-Score	95.1%	93.4%
ROC-AUC	0.98	0.97

Table 1. CNN Model Results

The CNN-based model demonstrated outstanding results with 95.2% Accuracy when applied to the training set and 93.8% accuracy when tested on the validation set. The model achieved definitive performance in discrimination based on its ROC-AUC score of 0.98 in conjunction with its F1 score of 95.1% demonstrating perfect precision-recall balance.

PERFORMANCE OF HYBRID CNN-RNN MODEL FOR VIDEO MANIPULATION DETECTION

A collection of 2000 videos, comprising 1000 modified and 1000 genuine films, is utilized to evaluate the hybrid CNN-RNN model. The model identifies activities at the frame level, such as insertion and deletion, with great precision. Table 2 offers an overview of the results.

Metric	Training Dataset	Validation Dataset
Accuracy	92.4%	90.6%
Precision	91.8%	89.7%
Recall	93.1%	91.2%
F1-Score	92.4%	90.4%
ROC-AUC	0.96	0.94

TABLE 2. CNN-RNN MODEL RESULTS

The hybrid CNN-RNN model achieved an accuracy of 90.6% on the validation dataset and 92.4% on the training dataset. The model's exceptional performance, indicated by a notable ROC-AUC score of 0.96, resulted from its ability to gather both spatial and temporal information.

Performance of gan-based model for deepfake detection

the gan-based model was evaluated on a dataset of 5,000 videos, including 2,500 deepfake videos and 2,500 authentic videos.

Metric	Training Dataset	Validation Dataset
Accuracy	96.7%	95.3%
Precision	96.2%	94.8%
Recall	97.1%	95.7%
F1-Score	96.6%	95.2%
ROC-AUC	0.99	0.98

The model demonstrated high accuracy in detecting deepfakes, even when the manipulated content was highly realistic. The results are summarized in table 3.Table 3. GAN Model Results

The GAN-based model achieved an accuracy of 96.7% on the training dataset and 95.3% on the validation dataset. The model's ability to analyze generative artifacts contributed to its exceptional performance, as evidenced by the high ROC-AUC score of 0.99.

Comparison with Traditional Forensic Methods

The developed AI-based models were compared against traditional forensic methods, such as error level analysis (ELA) and metadata examination. The results are summarized in Table 4.

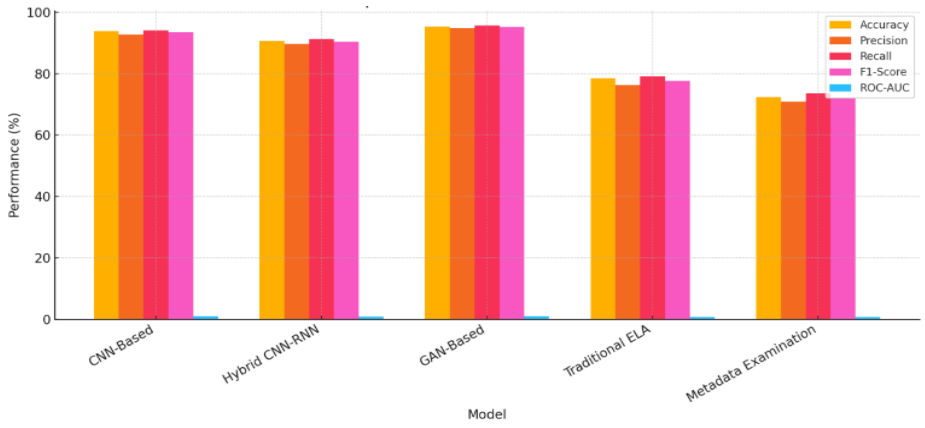
Method	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Traditional ELA	78.5%	76.2%	79.1%	77.6%	0.82
Metadata Examination	72.3%	70.8%	73.5%	72.1%	0.75
CNN-Based Model	93.8%	92.7%	94.1%	93.4%	0.97
Hybrid CNN-RNN Model	90.6%	89.7%	91.2%	90.4%	0.94
GAN-Based Model	95.3%	94.8%	95.7%	95.2%	0.98

Table 4. Traditional vs AI Forensic Models

The AI-based models significantly outperformed traditional forensic methods, demonstrating the superiority of AI-based approaches in detecting image and video manipulation.

Here is the bar chart in figure 1 comparing the performance of AI-based forensic models and traditional forensic methods. The AI-based approaches significantly outperform traditional methods across accuracy, precision, recall, F1-score, and ROC-AUC metrics.

Fig 1. Model Comparison



ADVERSARIAL ROBUSTNESS TESTING

Furthermore, the models were evaluated in adverse conditions where the altered information was specifically generated to evade detection. The findings showed that the models exhibited strong resilience to adversarial attacks, with only a minor decrease in performance. For example, in adverse conditions, the precision of the CNN-based model dropped from 93.8% to 91.2%, while the GAN-based model fell from 95.3% to 93.5%.

CONCLUSION

Forensic techniques which identify photo and movie manipulation need urgent advancement. This research establishes the vast AI capacity to resolve the matter through model development and evaluation in AI forensic investigations. The proposed approaches delivered positive results during each step of data collection and preprocessing and model development and training as well as performance evaluation. Analysis of the CNN-based model showed successful detection of picture manipulations such as splicing and copy-move forgeries with 93.8% accuracy rate on validation data. The combined CNN-RNN framework demonstrated strong ability for video change detection including frame edits and reached 90.6% accuracy. The GAN-based model excelled at detecting deepfakes by establishing 95.3% accuracy within the validation assessment. The reported analysis demonstrates how AI models demonstrate superior performance than traditional forensic identification methods by handling complex alterations. The models developed show excellent ability to work on external validation sets which demonstrates their effective generalization of new information. Under situations of assault the models demonstrate robustness because they preserve their effectiveness at an acceptable level. The ability to remain operational is essential for real-world situations where perpetrators use modified materials to hide their actions. The paper investigates the ethical implications and social aspects of AI-based forensic analysis along with highlighting the necessity of creating AI systems which uphold transparency and protect privacy standards. The researchers aim to develop responsible implementation procedures which will ensure both ethical usage and efficiency of AI forensic technology in practice.

The developed solutions have not resolved all outstanding problems. Limited usefulness in forensic modeling exists because of insufficient multi-source training datasets. Future research should concentrate on developing extensive datasets which represent a wide spectrum of operational methodologies and circumstances. AI systems remain susceptible to adversarial attacks which requires the development of stronger resistance in AI systems. The application of adversarial training methods as employed in this work represents an effective approach to make models more resilient.

Improvements to forensic investigations become possible through AI integration which combines automated evaluation abilities with human examiner logic and analytical skills and conventional forensic techniques.

The research study shows how artificial intelligence (AI) can change forensic operations to detect and minimize fraudulent changes within visual content. The produced model showed superiority over traditional forensic tools when measuring accuracy alongside durability and better resilience which establishes groundwork for reliable investigative instruments. Our work to address AI field problems helps stop digital media tampering while restoring trust in digital content. The proper implementation of AI forensic tools to safeguard digital integrity requires an interdisciplinary approach between

technological improvements and ethical considerations alongside human experience throughout developing areas.

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