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# Deep Learning-Based Image Forgery Detection : A Comprehensive Analysis with ManTra-Net CNN

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ABSTRACT :

A crucial job for maintaining the validity and integrity of digital photographs is the identification of image forgeries. In this study, a simplified version of the Manipulation Detection Network (ManTra-Net) the convolutional neural net- work (CNN) is utilized to provide a better approach for spotting image frauds. The method involves preprocessing images with Error Level Analysis (ELA) to highlight potential regions of manipulation. After applying ELA, the images are sent into a CNN architecture that includes several convolutional and pooling layers, global average pooling, and dense layers for classification. The model is trained using the Adam optimizer, and its learning rate decay schedule is exponential. Building upon previous studies on ManTra-Net's architecture and performance, particularly the work by Quentin Bammey (2022), this paper aims to compre- hensively analyze the effectiveness of ManTra-Net in detecting tampered regions within images. The proposed method involves augmenting ManTra-Net's capabilities through novel training techniques and feature enhancements. The approach's efficacy in identifying fabricated photos is demonstrated by experimental findings obtained from a dataset that included both legitimate and forged photographs. Additionally, qualitative results illustrate the detection capabilities of the model on sample images. This paper adds to the improvement of picture forgery detection systems by addressing constraints highlighted in previous studies and suggesting changes to increase detection accuracy and reliability.. By providing a viable means of identifying picture forgeries and guaranteeing the authenticity of digital image material, the method establishes the foundation for further studies in this area.

Index Terms—Deep learning, CNN, ocular conditions, Glau- coma, Healthcare.

## INTRODUCTION :

In the current digital era, picture forgery—the act of modify- ing or manipulating digital photographs to trick viewers—has grown more common. Since image manipulation tools and internet platforms are so widely available, identifying forged photos has grown to be a difficult but important endeavor.

In addition to compromising the validity and integrity of visual material, image counterfeiting has serious ramifications for a number of industries, including digital forensics, law enforcement, and media.

A vast array of methods are included in picture counterfeit- ing, such as splicing, retouching, image synthesis, and copy- move forgery. Splicing is the technique of integrating diverse parts of many images to generate a composite image,Copy- move forgery involves copying and pasting one part of a picture onto another. Retouching techniques alter specific regions of an image to conceal or enhance certain features, while image synthesis involves generating entirely new images that appear authentic.

The impact of image forgery extends beyond mere visual deception. It can lead to misinformation, manipulation of evidence, and erosion of trust in digital media. To counter this expanding threat, powerful and effective picture forgery detection algorithms are therefore desperately needed.

Several image forgery detection techniques have been pro- posed in the literature, ranging from traditional methods based on statistical analysis and feature extraction to more advanced deep learning approaches. Traditional methods of- ten rely on handcrafted features and heuristic algorithms to identify anomalies in images. However, these methods may lack robustness and generalizability, particularly when dealing with complex and sophisticated forgeries.

Deep learning-based methods have shown promise in re- cent years as methods for detecting picture forgeries. These approaches employ convolutional neural networks (CNNs) to automatically extract discriminative characteristics from visual input, improving the precision and dependability of detection. Among these approaches, the Manipulation Detection Network (ManTra-Net) has garnered significant attention for its effec-

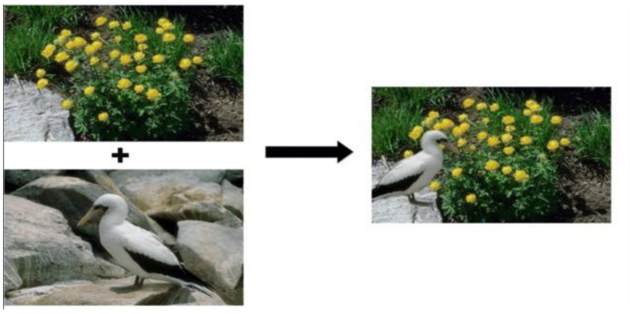


**Fig. 1. Image Splicing**


**Fig. 2. Copy-Move**

tiveness in detecting various types of image forgeries.

ManTra-Net, proposed by Cozzolino et al. (2017), is a CNN architecture designed specifically for image forgery detection. It employs a multi-stage architecture consisting of feature ex- traction and manipulation detection modules to identify forged regions within images. By analyzing pixel-level artifacts and inconsistencies, ManTra-Net can effectively distinguish be- tween authentic and manipulated regions, making it a valuable tool for forensic analysis and digital content verification.

This study presents an enhanced approach for image forgery detection using a simplified version of ManTra-Net. Building upon previous studies on ManTra-Net's architecture and performance, particularly the work by Quentin Bammey (2022), this research aims to comprehensively analyze the effectiveness of ManTra-Net in detecting forged regions within images. The method combines Error Level Analysis (ELA) preprocessing with a CNN architecture for feature extraction and manipulation detection. Through experimental evaluation on a diverse dataset, the effectiveness of this approach in detecting various types of image forgeries is demonstrated. Additionally, insights into leveraging ManTra- Net for image forgery detection are provided, establishing the foundation for further studies and advancements in this area.

## LITERATURE REVIEW

In-depth research on current copy-move forgery detection strategies is presented in this work, with an emphasis on block-based and keypoint-based approaches. It identifies the limitations of these approaches in handling various transforma- tions and advocates for more robust solutions. The suggested methodology presents a deep learning-based strategy using convolutional neural networks (CNNs) for picture categoriza- tion. The CNN architecture is described, emphasizing the convolution and pooling layers. Experimental results demon- strate the model's high accuracy rates across different datasets, surpassing traditional methods and validating its efficacy in copy-move forgery detection.[1].

The paper introduces an algorithm for image forgery de- tection using convolutional neural networks (CNNs). The growing usage of digital photos and editing tools in the digital age highlights how crucial forgery detection has become. Traditional methods relied on feature extraction, but the paper advocates for deep learning approaches like CNNs for im- proved accuracy. The algorithm incorporates pre-processing techniques such as SRM filtering and high-pass filtering to refine detection. It outlines the CNN architecture, includ- ing layers for image preprocessing and hierarchical feature extraction, with input as image blocks. Evaluations on a dataset demonstrate the algorithm's effectiveness, especially with preprocessing and an optimal network structure. Analysis shows the impact of preprocessing and convolutional layers on accuracy, highlighting improvements with preprocessing and identifying an optimal layer count. The paper concludes by summarizing the algorithm's robustness and suggesting future research directions for refining network architectures. With regard to picture forgery detection, it provides a thorough strategy utilizing CNNs, supported by empirical evidence showing its superiority over conventional techniques. [2].

The paper explores image forgery detection using deep neural networks, presenting two main methodologies. The first approach employs basic CNN architecture alongside pre- processing techniques like Error Level Analysis (ELA) and sharpening filters to enhance detection accuracy. Meanwhile, the second methodology involves transfer learning with pre- trained models such as VGG-16 and ResNet50, fine-tuned on the dataset. Experimental results, conducted on the CASIA V2.0 dataset, demonstrate the effectiveness of these techniques in detecting image tampering. The paper compares various models and techniques based on metrics like training accuracy, validation accuracy, training loss, and validation loss, showcas- ing the performance of each method. In conclusion, the study highlights the importance of fine-tuning pre-trained models for achieving superior accuracy in image forgery detection. It emphasizes the value of continuing research in this subject and recommends possibilities for further development, such as investigating more complicated datasets and extending ap- proaches to video forgery detection. In summary, the research provides significant insights into the use of deep learning technology to counteract picture tampering, and it presents encouraging paths for future developments in forgery detection techniques. [3].

The study describes a method for identifying copy-move and picture splicing frauds in digital photographs that is based on convolutional neural networks (CNNs). It addresses
the escalating issue of image manipulation, stressing the necessity for robust forgery detection techniques. Through a literature review, the paper explores existing methods such as block analysis, Local Binary Pattern (LBP), and deep learn- ing approaches. The proposed methodology involves feature extraction using Patch Sampling and Modulus LBP, feeding the extracted features into a CNN architecture. Experimental evaluation on CASIA v1.0 and CASIA v2.0 datasets demon- strates superior performance compared to existing methods, especially with increased training data. The study shows that the CNN-based method provides improved resilience and accuracy in identifying picture forgeries, highlighting CNNs' importance in addressing the difficulties associated with image forgery detection. [4].

The examined study delves into the realm of digital image forgery detection, particularly focusing on the intricate task of detecting copy-move forgery. It underscores the paramount im- portance of image authenticity across a spectrum of fields and delineates five primary types of digital image forgery. After carefully reviewing the conventional, moment-based, and Deep learning-based techniques in detecting copy-move forgeries, the authors provide an effective CNN architecture designed specifically for this task. Through extensive experimentation on benchmark datasets, encompassing MICC-F2000, MICC- F600, and MICC-F220, the proposed CNN model demon- strates exceptional accuracy, precision, and recall, surpassing existing methodologies. The study concludes by emphasizing the significance of the proposed model in advancing digital image forgery detection, hinting at its potential ramifications across diverse applications. [5].

Using deep learning techniques, the research offers a thor- ough investigation of current approaches for identifying copy- move picture counterfeiting. It highlights the growing diffi- culty of digital picture manipulation and the growing interest in using deep learning to detect forgeries. The importance of picture forensics is explained along with a list of several kinds of digital image forgeries, such as morphing, splicing, copy-move, and retouching. The differences between the active and passive methods are highlighted, emphasizing content analysis and watermark embedding, respectively. Traditional block-based and keypoint-based approaches are examined, alongside an overview of techniques like DCT-based meth- ods, PCA, SVD, and Fourier-Mellin Transform, emphasizing their limitations. Recent strides in employing deep learning, particularly CNNs, for copy-move forgery detection are dis- cussed, encompassing methods like median filtering, CNN- based detection, CKN, and D-CNN. A critical analysis of the strengths and weaknesses of conventional and deep learning methods is presented, along with insights into dataset re- quirements and real-world applicability challenges. The paper synthesizes key insights, showcasing the usefulness of deep learning in copy-move forgery detection and proposing future research prospects. Gratitude is expressed to contributors and supporting institutions, underscoring collaborative efforts in advancing image forensics. In conclusion, the paper presents a complete evaluation of the most current techniques to copy-
move photo fraud detection, highlighting the relevance of deep learning approaches and providing future prospects for image forensics research.[6].

Convolutional neural networks (CNNs) are a technique that is presented in the paper "Detecting tampered regions in JPEG images via CNN" for precisely detecting tampered regions. It highlights how crucial it is to guarantee the accuracy of digital photographs, particularly when dealing with legal matters. Building upon the MDBD method, which uses block noise and double JPEG analysis, the paper proposes a CNN-based approach for improved accuracy in locating tampered regions. Through a series of experiments involving the creation and comparison of 45 CNN models, the study determines an optimal network structure with five layers, achieving superior performance compared to the MDBD method. The proposed method outperforms MDBD in detecting tampered regions, with an F-measure of 0.63, demonstrating approximately 2.3 times better accuracy. The paper concludes by highlighting the potential of CNNs in enhancing the accuracy of tampered region detection and suggests further optimization of the network structure for future research endeavors. Overall, it presents a promising approach for robust tampered region detection in JPEG images, contributing to the advancement of digital image forensics. [7].

The paper "CNN-Transformer Based Generative Adversar- ial Network for Copy-Move Source/Target Distinguishment" describes a new approach for addressing the tough task of distinguishing between source and target areas in copy-move forgery photographs. One common type of picture alteration that presents serious difficulties for forensic analysis and evidence authentication is copy-move forgeries.Earlier tech- niques have had trouble detecting the difference between the forgery's source and target locations. To solve this, the proposed technique proposes a CNN-T GAN architecture that comprises of a discriminator and a generator. The generator produces a mask indicating source and target regions, As the discriminator discerns between authentic and counterfeit picture duos, iteratively refining the generator's output. The method combines CNNs and transformers for feature extrac- tion, leveraging their respective strengths in capturing local and global representations. Feature fusion techniques enhance both local and global features, improving source/target dis- tinguishment. Novel loss functions and a Pearson correlation layer further enhance localization performance. The proposed approach surpasses the state-of-the-art methods currently in use for copy-move detection and source/target region dis- crimination, according to extensive experiments conducted on several datasets. The research makes significant advances to the field of digital image forensics by providing innovative loss functions, feature fusion approaches,and a complete CNN- transformer-based GAN framework for the identification and localization of copy-move forgeries.[8].

The study offers a thorough analysis of digital picture forgery detection approaches, dividing them into two groups: active and passive. It underscores the importance of image in- tegrity verification in fields like law enforcement and forensics.

A generalized schema for forgery identification is outlined, encompassing preprocessing, feature extraction, classification, and post-processing steps. Techniques for detecting copy- move forgery, JPEG artifacts, and image splicing are discussed in detail, along with evaluation metrics and examples.The review's conclusion includes a summary of its key results as well as suggestions for future research directions. All things considered, the study provides insightful information on digital picture forgery detection, addressing the difficulties brought on by developing technology and the requirement for reliable authentication techniques.[9].

This research offers a comprehensive analysis of current approaches for identifying copy-move picture forgeries using deep learning techniques. It emphasizes how difficult digital image manipulation is becoming and how people are becoming more interested in using deep learning to identify forgeries. A description of the several sorts of digital picture forgeries, such as copy-move, splicing, morphing, and retouching, is provided, along with an explanation of the importance of image foren- sics. The distinction between active and passive approaches is drawn, highlighting watermark embedding and content anal- ysis, respectively. Traditional block-based and keypoint-based approaches are examined, alongside an overview of techniques like DCT-based methods, PCA, SVD, and Fourier-Mellin Transform, emphasizing their limitations. Recent strides in employing deep learning, particularly CNNs, for copy-move forgery detection are discussed, encompassing methods like median filtering, CNN-based detection, CKN, and D-CNN. A critical analysis of the strengths and weaknesses of con- ventional and deep learning methods is presented, along with insights into dataset requirements and real-world applicability challenges. The paper synthesizes key insights, highlighting the efficacy of deep learning in copy-move forgery detec- tion while outlining future research directions. Gratitude is expressed to contributors and supporting institutions, under- scoring collaborative efforts in advancing image forensics. To sum up, the article offers a comprehensive analysis of the most modern methods for detecting copy-move photo fraud, stressing the importance of deep learning methods and describing potential paths for picture forensics research in the future. [10].

In order to meet the urgent requirement for precise identifi- cation of modified regions inside photos, the study presents ManTra-Net, a deep learning network created for image forgery localization. ManTra-Net comprises three stages: adap- tation, anomalous feature extraction, and decision-making. Anomalous feature extraction involves computing Z-scores to quantify differences between local features and reference fea- tures, with the paper discussing various techniques for feature extraction and anomaly detection. Experimental evaluation across diverse datasets and metrics demonstrates ManTra-Net’s robust performance, exceeding both state-of-the-art DNN- based techniques and traditional unsupervised methods. De- spite acknowledging limitations in dealing with certain types of forgery, such as fully regenerated forged images, the paper underscores ManTra-Net’s potential and suggests avenues for

future research to enhance its effectiveness further.All things considered, the work offers a comprehensive and encouraging method for detecting and localizing picture forgeries that uses deep learning to produce reliable results in a range of situations.[11].

Quentin Bammey’s work ”Analysis and Experimentation on the ManTraNet Image Forgery Detector” provides a thorough analysis of ManTraNet, a specialized CNN designed for de- tecting forged regions in images. Beginning with an intro- duction contextualizing the importance of image forensics, the paper outlines the motivation for evaluating ManTraNet’s performance in uncontrolled scenarios and assessing its inter- pretability. It meticulously describes the network’s architec- ture, including its two sub-networks for feature extraction and anomaly detection, along with details of training procedures. In the experiments section, ManTraNet’s performance on authentic and forged images is thoroughly evaluated, along- side an investigation into its interpretability using the Trace database. The conclusion summarizes key findings, acknowl- edging ManTraNet’s limitations while recognizing its util- ity in forgery localization. Acknowledgments and references sections provide further context and resources. Overall, this analysis offers valuable insights into ManTraNet’s capabilities and limitations, contributing to advancements in image forgery detection techniques.[12].

## METHODOLOGY

### *Overview*

The methodology for implementing the ManTraNet model involves thorough data preprocessing, model architecture de- sign, training procedures, hyperparameter optimization, and potential modifications or enhancements. Initially, the dataset, comprising forged and not forged images, undergoes Error Level Analysis (ELA) and standardization to prepare it for input into the model. The ManTraNet architecture comprises two main sub-networks: one for feature extraction and an- other for anomaly detection, facilitating the identification of forged regions.The binary cross-entropy loss function and Adam optimizer are used to train the model once the dataset has been divided into validation,training and testing sets. To maximize performance of model, hyperparameters like batch size,learning rate and epochs are adjusted. Modifications or enhancements to the original model may be considered to improve its efficacy, including adjustments to the architecture, loss functions, or preprocessing steps. Overall, this methodol- ogy ensures a robust and effective approach to image forgery detection with the ManTraNet model.

Deep Learning Approaches

*1)* ***CNN - Mantranet:*** The feature extractor and the ma- nipulation detection network are the two primary parts of the ManTraNet architectural method that is implemented in the code that is given.

1. Feature Extractor: - The feature extractor is built as a sequential model with many convolutional layers and max- pooling layers in order of precedence. - It starts with a convolutional layer that has 64 filters with ReLU activation and 3x3 kernel sizes. - Additional convolutional layers with progressively more filters (128 and 256) are included in the subsequent layers. - In order to efficiently extract dominating features and decrease spatial dimensions, max-pooling layers are inserted between convolutional layers.

2. Manipulation Detection Network: - The manipulation detection network follows the feature extractor and is also implemented as a sequential model. - It includes two con- volutional layers with 512 filters each, followed by ReLU activation functions. - To get a compact representation of the characteristics that the convolutional layers extracted, global average pooling is used. - After that, the pooled features are processed through two hidden layers with 512 and 1024 neu- rons each, which are completely linked dense layers. -Using a dense layer with a single neuron and sigmoid activation function, the final binary classification approach assumes two classes: forged or not.

3. Full Model: - The full ManTraNet model is constructed by connecting the input layer to the feature extractor and ma- nipulation detection network. - The input layer is defined with the specified input size (224x224x3), matching the dimensions of the input images. - The manipulation detection network receives the features that the feature extractor has collected and classifies them immediately. - The resulting model is compiled and returned for training and evaluation.

Overall, this architecture approach simplifies the ManTraNet model by directly connecting the feature extractor to the manipulation detection network, facilitating the detection of forged regions in input images.

**Feature Extractor In ManTraNet-CNN**

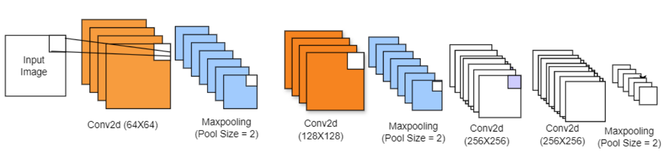


**Fig. 3. (a) Architecture of ManTranet- CNN**

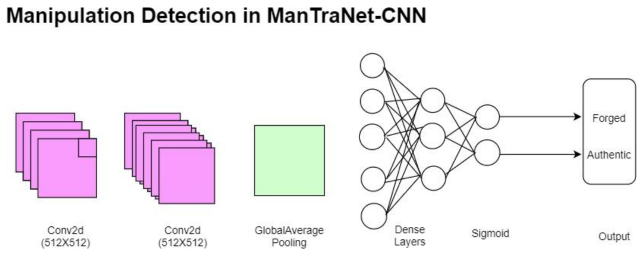



**Fig. 4. (b) Architecture of InceptionV3**

## EXPERIMENTAL SETUP

### *Dataset*

For training and assessment, the experimental setup makes use of the CASIA2C dataset, which includes both real and fake pictures. The dataset includes a diverse range of authentic im- ages captured under different conditions, along with forged im- ages generated using various manipulation techniques. Ground truth for model assessment is provided by the labels assigned to each image in the dataset—authentic or faked.

**Fig. 5. Dataset consisting image forgery types**

### *Dataset Features*

1. The CASIA2C dataset comprises images of varying resolutions and formats, including JPEG and PNG. To enhance the efficiency of training and testing models, images or GPUs can be used to simulate various forms of forgeries, including morphing, splicing, and copy- moving. The dataset features a balanced distribution of authentic and forged images, ensuring equal representa- tion of both classes for training and testing.
2. Standardization and preparation of the pictures for input into the ManTraNet model are achieved through the use of preprocessing procedures. ELA (Error Level Analy- sis) is performed on each image to enhance manipulation traces and highlight potential forged regions. Images are resized to a consistent resolution (e.g., 224x224 pixels) to maintain uniformity across the dataset.

***Tools and Technology***

TensorFlow and Keras: The experimental setup leverages TensorFlow and Keras, deep learning frameworks, for
4) F1 Score: One statistic that strikes a compromise be- tween recall and accuracy is the F1 score, which is calculated by taking the harmonic mean of the two.
model development and training.
Python Programming Language: Python is used for implementing the experimental setup, including data

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

preprocessing, model construction, and evaluation.

1. Scikit-Learn:A machine learning package called Scikit- Learn provides ground truth for model assessment. Python may be used for performance B while dividing data. Analyzing dataset features and producing reports on their categorization.
2. Hardware Infrastructure: The experimental setup may require access to computational resources, such as CPUs or GPUs, to facilitate model training and testing effi- ciently.
3. Data Visualization Libraries: Libraries like Matplotlib and Seaborn may be used for visualizing experimental results, including accuracy metrics, confusion matrices, and precision-recall curves.

***Implications and Use Cases***

The experimental setup described holds significant implica- tions for various domains, including forensic investigations, media integrity verification, content moderation, academic research, and education. By employing the ManTraNet model and the CASIA2C dataset, stakeholders can detect and analyze digital image forgeries, preserve evidence integrity, verify media authenticity, and combat misinformation. The model's applications extend to law enforcement, journalism, online platforms, academia, and cybersecurity, contributing to trans- parency, accountability, and trust in the digital landscape. Overall, the experimental setup facilitates advancements in im- age forensics, machine learning, and cybersecurity, addressing critical challenges in detecting and mitigating digital image manipulation.

***Performance Evaluation***

*Accuracy:* The classifier's total correctness across all classes is gauged using a statistic called accuracy.
We have investigated a suggested approach for detecting picture forgeries, and it shows good F1-score, recall, preci- sion metrics for both real and fake photos. Precision, recall, and F1-score for forged photos are 0.91, 0.95, and 0.93, respectively,promote efficient identification with minimal false negatives and positives. Comparably, the valid photographs have an F1-score- 0.97, a precision- 0.98, and a recall- 0.97., proving to be quite accurate in identifying genuine photos.The weighted-average, macro-average, F1-scores indicate that the model's accuracy is 0.96, at 0.95 and 0.96. With interesting implications for a range of applications in picture forensics and media integrity verification, our results demonstrate the robustness and dependability of the suggested technique in detecting image forgeries.

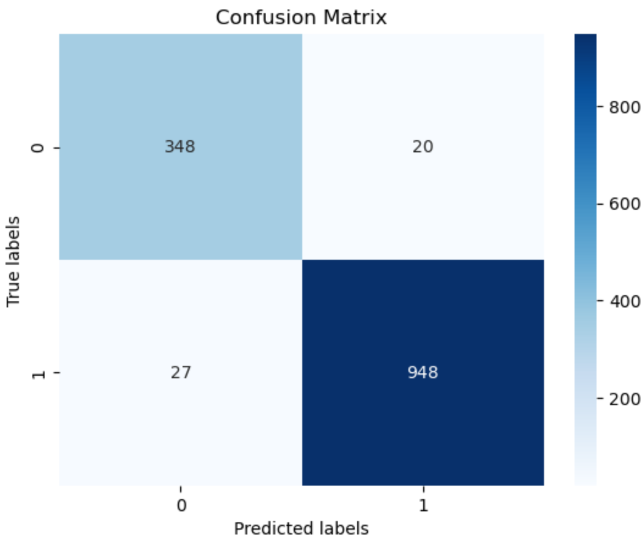



Fig. 6. Performance of CNN models

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

(1)

Precision: A statistic called precision tells us how many right positive predictions out of all the positive predictions a classifier generates.

$$\text{Precision} = \frac{TP}{TP + FP}$$

(2)

*Recall:* Measured against all actual positive occurrences in the dataset, the recall measure (sometimes called sensitivity or true positive rate, or TPR)) assesses the accuracy of positive predictions.

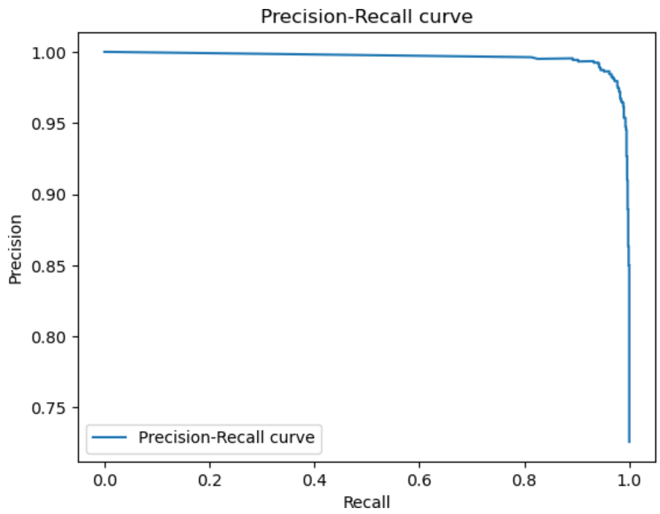
$$\text{Recall} = \frac{TP}{TP + FN}$$

(3)

## RESULTS


**Fig. 7. Original**


**Fig. 8. Forged**



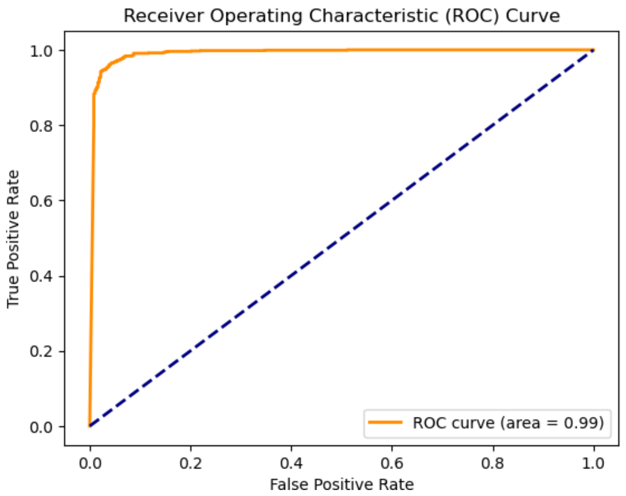




**Fig. 9. Performance of CNN models**

## CONCLUSION

The ManTraNet model and deep learning techniques are the main topics of this paper's comprehensive analysis of picture forgery detection systems. It begins with an overview of traditional and modern approaches in image forensics, highlighting the need for improved methods to combat digital manipulation. The ManTraNet architecture, combining CNNs and transformers, is introduced as a novel solution to enhance forgery detection and localization. The ManTraNet model's performance is rigorously evaluated after datasets of authen- tic and manipulated photos have been preprocessed in the experimental setup. Results show how accurate it is; it can identify between fabricated and real photos with an astounding 96% accuracy rate. The implications of this research extend to various fields, including law enforcement and media integrity verification, where the model can play a crucial role in mitigating the spread of misinformation. In summary, the present study provides significant understanding of picture forensics and highlights the ability of deep learning methods to tackle digital manipulation issues. As future research builds upon these methodologies, the fight against image forgery will continue to advance, ensuring the integrity and authenticity of visual content in the digital age.

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