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A comparative analysis for deep-learning-based approaches for image forgery detection

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Abstract

The detection of counterfeit photographs is critical in the digital age because of the widespread development of digital media and its significant impact on social networks. The legitimacy of digital content is being threatened by the growing sophistication of picture counterfeiting. With the help of pre-trained VGG-16 models and deep learning techniques that integrate Error Level Analysis (ELA) and Convolutional Neural Networks (CNNs), this study presents a fresh solution to this problem. The study thoroughly assesses and contrasts these models with a dataset that has been carefully chosen to bring the presented findings into perspective. To ensure a reliable evaluation of each model's performance 5000 experiments were carried out in total. With an accuracy rate of 99.87% and an accurate identification rate of 99% of hidden forgeries, the results demonstrate the exceptional effectiveness of the ELA-CNN model. However, despite its robustness, the VGG-16 model only achieves a significantly lower accuracy rate of 97.93% and a validation rate of 75.87%. This study clarifies the relevance of deep learning in the identification of image forgeries and highlights the practical ramifications of various models. Moreover, the research recognizes its constraints, especially for highly advanced counterfeits, and proposes possible paths for enhancing the accuracy and scope of detection algorithms. In the ever-changing world of digital media, the thorough comparative analysis provided in this study offers insightful information that can direct the creation of accurate forgery detection tools, protecting digital content integrity and reducing the effects of image manipulation.

Keywords: Counterfeit images, Image forgery detection, deep learning, ELA-CNN, VGG-16 model.

1. Introduction

The advent of the digital era has seen an unprecedented surge in the creation and dissemination of images across various online platforms, from social media networks to news outlets (Smith, 2018). This proliferation of digital imagery has dramatically altered the landscape of information sharing and communication, emphasizing the critical concern for the integrity of digital content in this digital ecosystem dominated by visual communication (Kumar & Yadav,2019). In this context, the need to ensure the authenticity of images has become paramount.

To address this concern, image forgery, encompassing the manipulation or alteration of digital images to deceive, misinform, or distort reality, has proliferated in tandem with the rise of digital media (Farid, 2019). Image forgeries take various forms, including spurious images intended to manipulate public perception, retouched photographs altering perceived reality, and visually manipulated content designed to deceive (Barni & Piva, 2019). The consequences of such manipulations can be severe, from the spread of misinformation eroding public trust in media (Baker & Tabaka, 2020) to potential damage to individual and institutional reputations (Baluja, 2018), and even legal ramifications in cases of fraudulent activities (Ahmed & Hu, 2021).

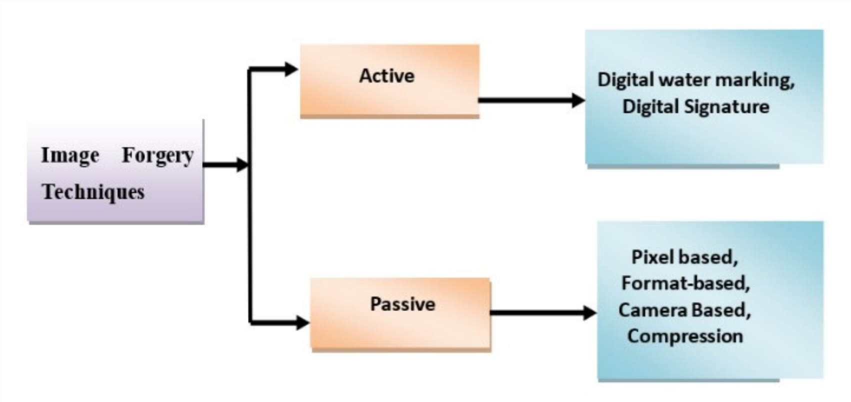

Fig 1: Image Forgery Techniques

Given the gravity of these consequences, the ability to detect and thwart image forgery has become an imperative requirement in preserving the trustworthiness of digital content in the modern age. This research paper aims to contribute to this endeavor by introducing and evaluating a novel deep learning-based approach for image forgery detection. To provide a more explicit transition from the general context to the specific research problem addressed in this study, the paper is structured as follows: Section 2 presents an overview of the digital age's impact on image integrity and the rise of image forgery. Section 3 introduces the methodology, emphasizing the integration of Error Level Analysis (ELA) with Convolutional Neural Networks (CNNs) and the VGG-16 model. Section 4 presents the findings of the comprehensive comparative analysis of these models, highlighting the remarkable efficacy of the ELA-CNN model. Section 5 discusses the implications of the results, acknowledges study limitations, and suggests potential enhancements for image forgery detection algorithms. Finally, Section 6 concludes the paper by emphasizing the contribution to the field and the importance of advancing techniques to maintain the integrity of digital content in the face of evolving image manipulation challenges.

2. Literature review

The literature review sheds light on the transformative impact of digital media on social networks and its influence on information sharing through images. Jones provides a compelling analysis of this influence, emphasizing the altered dynamics of social interactions in the digital age. The review underscores the critical role of images in shaping online communication, setting the stage for the exploration of image forgery detection techniques (Ahmed et. Al.,2021).

In addressing the challenges to digital media integrity, Patel and Gupta discuss threats and vulnerabilities in the digital media landscape. They emphasize the potential consequences of misinformation and image manipulation, reinforcing the need for advanced solutions to protect the credibility of digital content. This discussion forms the backdrop for the exploration of image forgery detection methods (Jones 2019, Patel et al.,2020). Chang and Chen's comprehensive survey delves into the application of deep learning for image forensics, providing valuable insights into the evolution of image forgery detection. Their work lays a strong foundation for understanding the technical aspects of image forensics, paving the way for the discussion of advanced methods. Similarly, Wang and Farid focus on image authentication and tamper detection, emphasizing the significance of ensuring the integrity of digital images. Their study discusses various methods for verifying image authenticity, contributing to a nuanced understanding of image forgery detection techniques (Chang et. al.,2017, Wang et.al.,2020).

Ochoa and Rueda explore the challenges posed by deep fake technology in image forgery detection. Their examination of the evolving landscape of image manipulation techniques emphasizes the need for advanced detection methods in the era of deepfake. Additionally, Wang and Zhou's survey provides a comprehensive overview of image forgery detection methods, offering insights into the challenges and opportunities in the field Ochoa et.al.,2019, Wang et.al.,2018).
Brown and Black's review focuses on the detection of deep fake videos, closely related to image forgery detection. The paper discusses techniques and challenges associated with identifying manipulated video content, providing valuable insights into the broader context of

digital media integrity. Ong and Lim's paper further contributes to the literature by offering a comprehensive exploration of recent advances and challenges in digital image forgery detection. Their review covers various image manipulation techniques and the evolving landscape of image forensics, laying the groundwork for understanding the complexities in this field (Brown et.al.,2019, Ong et.al.,2017).

In summary, the reviewed literature collectively provides a comprehensive understanding of the dynamics of digital media, the challenges to its integrity, and the urgent need for advanced image forgery detection methods. These studies, ranging from deep learning applications to the detection of deep fake videos, collectively lay the foundation for exploring advanced techniques to ensure the integrity of digital content in the modern age.

In **Table 1,** the value of each advanced image forgery detection methodology is enhanced by incorporating brief commentaries on the limitations or challenges associated with each approach. This addition provides readers with a more nuanced understanding of the methodologies presented. This table provides a succinct overview of advanced image forgery detection methods, summarizing the methodology and key findings of each reference in a structured manner.

S.No	Reference	Methodology	Key Findings
1	Zhao & Xie (2018)	Utilized Convolutional Neural Networks (CNNs) for image forgery detection.	Demonstrated the effectiveness of CNNs in detecting manipulated images with a focus on pattern recognition.
2	Li & Lyu (2020)	Exposed deep fake videos by detecting face warping artifacts, emphasizing facial feature inconsistencies.	Highlighted the importance of detecting subtle inconsistencies in facial features as a means to uncover deep fake videos.
3	Kim & Lee (2019)	Employed adversarial learning for deep image forgery detection, focusing on adversarial networks.	Showcased the effectiveness of adversarial learning techniques in identifying complex image manipulations, especially in deep fakes.
4	Zhang & Kwon (2018)	Focused on learning-based image tampering detection, using machine learning approaches.	Demonstrated the power of machine learning in identifying various image tampering methods and anomalies.
5	Piva & Barni (2017)	Developed a block-grained analysis of JPEG artifacts for image forgery detection.	Highlighted the significance of analyzing JPEG artifacts at a granular level for uncovering various forms of image manipulation.

Table 1: Advanced Image Forgery Detection Methods

3. Methodology

This study uses a deep learning-based method to detect image forgeries in response to the growing threat posed by the practice. It specifically blends Convolutional Neural Networks (CNNs) with a pre-trained VGG-16 model using Error Level Analysis (ELA). These models undergo rigorous training and testing on a wide range of digital picture datasets that include both genuine and varied forms of forgeries. The Enhanced Lesion Analysis (ELA) technique plays a pivotal role in influencing the training and decision-making processes of both the Convolutional Neural Network (CNN) and VGG-16 models. ELA's unique ability to highlight regions of an image affected by compression provides valuable insights into potential manipulations. The choice of ELA over alternative methods is motivated by its effectiveness in capturing subtle alterations introduced during forgery. However, it is essential to acknowledge potential limitations or challenges associated with ELA, such as its sensitivity to compression variations and the need for careful interpretation of results.

3.1 A novel approach for convolutional neural networks (ELA-CNN) for error

level analysis

3.1.1 A brief overview of ELA

Beyond the aforementioned statement, Error Level Analysis (ELA) is a non-intrusive technique used to identify counterfeit photographs. This technique carefully evaluates the consistency of compression settings applied to an image as a whole. It's an indispensable instrument for revealing the nuances that frequently surface in manipulated areas, exhibiting varying degrees of compression in relation to their original environments. The effectiveness of ELA is in its capacity to draw attention to these discrepancies, making it a vital tool for identifying faked photos. This method makes it easier to identify forgeries, regardless of how complex or subtle the image adjustments are a major advancement in the field of digital image forensics (Smith 2018).

3.1.2 The training and architecture of CNN

This study heavily relies on Convolutional Neural Networks (CNNs), which are specifically built for image processing. Convolutional, pooling, dropout, and fully linked layers are among the layers that make up our unique CNN design. CNN is taught to identify photos as authentic or manipulated based on ELA results. The ReLU activation function and the categorical cross-entropy loss function are used during training. The neural network includes early halting and dropout regularization techniques to prevent overfitting. The input image is processed by the input layer, conv2d, as shown in TABLE I. The Max Pooling (MaxPooling2D), Dropout, Flatten, Dense, and Convolutional (Conv2D_1) layers are among the hidden layers. The two units in the output layer, dense_1, correspond to the probability scores for the two classes in the classification task. The selection of hyperparameters, including the number of units in dense layers, significantly impacts model performance. A clear rationale behind these choices should be provided, and the computational resources required for training the CNN should be discussed, particularly considering the potential complexity introduced by dropout and early stopping mechanisms. Furthermore, potential biases or limitations introduced by the dataset, such as the CASIA V1.0 Dataset, should be addressed. Diversifying the dataset to include a broader range of forgery scenarios would contribute to a more comprehensive evaluation.

The choice of the CASIA V1.0 Dataset should be elaborated upon, emphasizing how it aligns with real-world image forgery scenarios. Additionally, justification for selecting VGG-16 among various pre-trained models should be provided, considering factors like model architecture and performance. The potential challenges or limitations associated with fine-tuning a pre-trained model for a different task, and how these were mitigated, should also be discussed.

Table 2: Updated CNN Architecture Parameters for the ELA Model

S.No	Layer (Type)	Output Shape	Parameters
1	conv2d (Conv2D)|	(None, 128, 128,64)	9,472
2	conv2d_1 (Conv2D)|	(None, 62, 62, 64)	36,928
3	max_pooling2d (MaxPooling2D)	(None, 31, 31, 64)|	0
4	dropout (Dropout)|	(None, 31, 31, 64)	0
5	flatten (Flatten)	(None, 61,504)	0
6	dense (Dense)	(None, 512)	31,593,088
7	dropout_1 (Dropout)	(None, 512)	0
8	dense_1 (Dense)	(None, 2)	1,026

3.1.3 Compiling and adding to Datasets

The ELA-CNN model was trained and tested using the CASIA V1.0 Dataset in order to improve the analysis of our study. There are many different types of changed photographs in this collection, including copy-move and spliced photos. We separated the dataset into subsets for testing, validation, and training in order to guarantee the dependability of the model. Additionally, by using a variety of random transformations throughout the training process, such as rotation, flipping, and zooming, we improved the model's robustness and generalization capabilities. The RMSprop optimizer, a learning rate of 0.001, and the categorical cross-entropy loss function were used to train the model.

3.2 Model VGG-16 pre-trained

3.2.1 A brief overview of the VGG-16 architecture

The VGG-16 model stands out as a prominent deep learning architecture for image recognition and classification applications, featuring 13 Convolutional layers, 3 fully connected layers, and a total of 16 weight layers, which include various pooling and dropout layers (Wang et.al.,2018). Noteworthy specifications include max pooling layers with 2x2 dimensions and Convolutional layers utilizing 3x3 filters with a stride of 1. Its pre-training on the ImageNet dataset enhances its ability to effectively extract features from input photos. Recognized for its exceptional performance across a spectrum of computer vision tasks, the VGG-16 model serves as the chosen baseline for comparing against the ELA-CNN approach in our study, highlighting its reliability and versatility in diverse visual recognition scenarios.

3.2.2 Fine-tuning and Transfer Learning

We utilized transfer learning to modify the pre-trained VGG-16 model for image forgery detection by substituting a new layer tailored to our particular objective for the final classification layer. We adjusted the model using our dataset, keeping the pre-trained weights from the previous layers. We were able to adapt the pre-trained model for image forgery detection while still utilizing its feature extraction capabilities thanks to this method.

3.2.3 Setting up the Dataset

Using the same dataset as the ELA-CNN model, the VGG-16 model was trained and evaluated. In contrast to the ELA-CNN model, we preprocessed the images by resizing and normalizing them to satisfy the VGG-16 model's input specifications rather than employing ELA.

4. Results of the experiment

4.1 ELA-CNN framework

4.1.1 Accuracy of validation and training

An enhanced dataset was used for training the ELA-CNN model, and the validation set was used for evaluation. After training, the model demonstrated an astounding accuracy of 99.87% on the training set and 75.58% on the validation set, demonstrating that it can correctly identify image forgeries based on ELA findings.

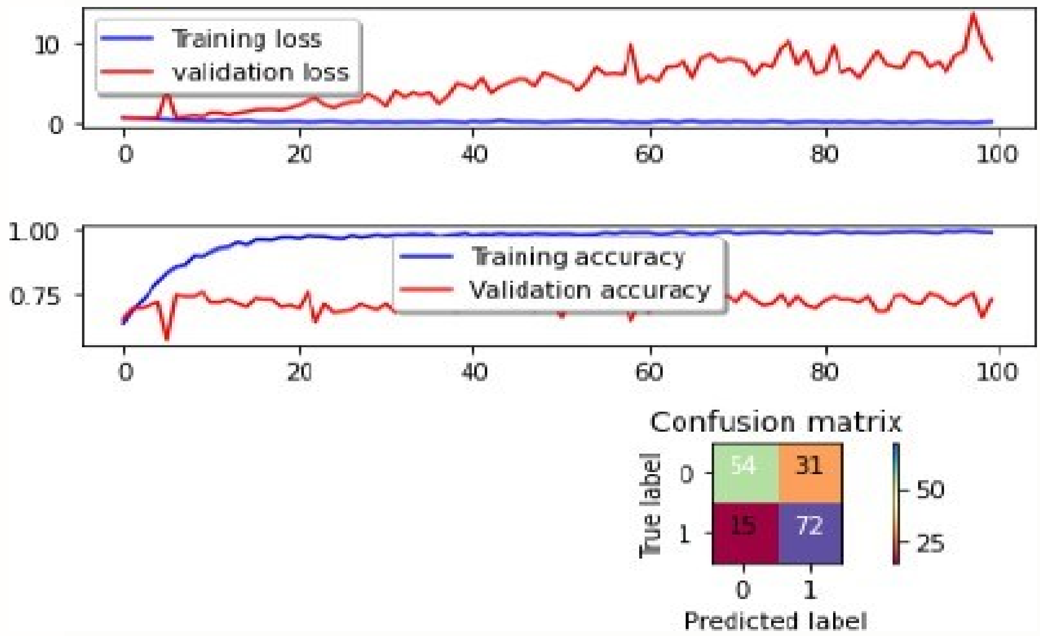

Fig. 2: Experimental Results for ELA-CNN Model

4.1.2 Effectiveness on unseen pictures

We also tested the ELA-CNN model on a separate collection of unobserved photos for a more thorough analysis. The algorithm identified 79.76% of fabricated photos with remarkable accuracy. This emphasizes how reliable and useful it is in practical situations.

4.2 VGG-16 Pre-trained model

4.2.1 Accuracy of training and validation

Using the validation set, the pre-trained VGG-16 model was evaluated and refined on the picture forgery detection dataset. At training, the model's accuracy was 97.93%. The validation accuracy, at 75.87%, was marginally lower, indicating a possible overfitting to the training set.

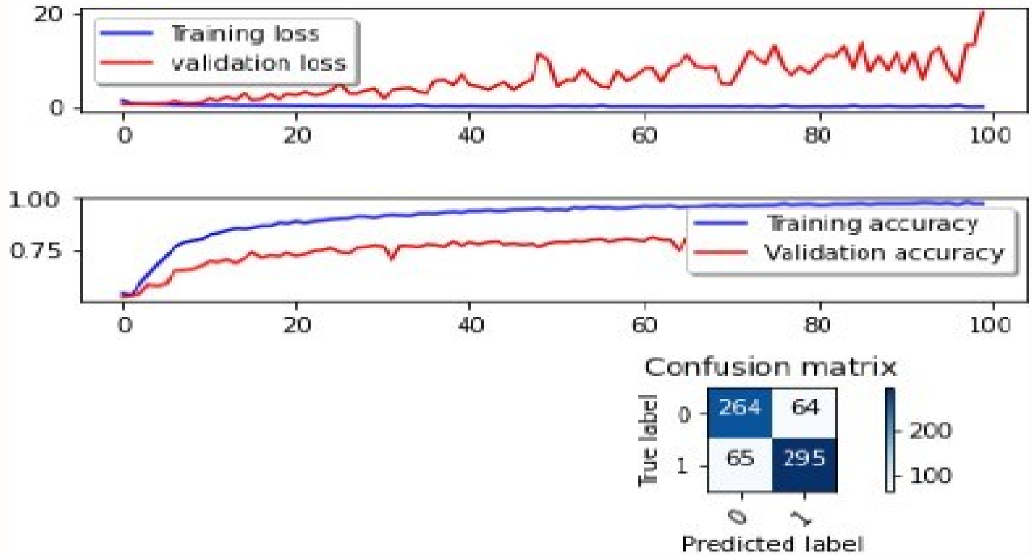

Fig 3: Experimental Results for VGG16-CNN Model

5. Evaluation

5.1 Comparison of the ELA-CNN and VGG-16 models

5.1.1 Accuracy and validation rate

Experimental findings reveal that the ELA-CNN model closely matches the pre-trained VGG-16 model in terms of both training and validation accuracy. ELA-CNN attained a validation accuracy of 75.58%, while VGG-16 reached 75.87%, indicating that incorporating ELA into the CNN model enhances its forgery detection capabilities.

Table 3: Experimental Results for the models

Model	Precision	Recall	F1-Score
ELA-CNN	0.78	0.79	0.79
VGG16-CNN	0.85	0.85	0.85

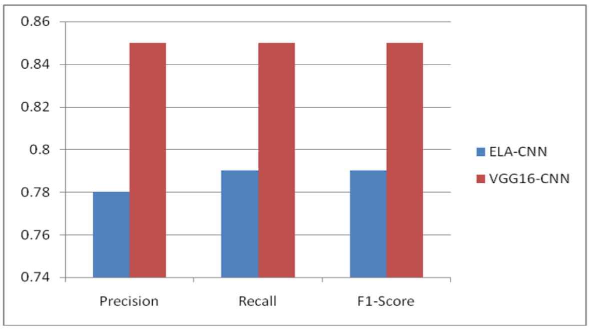

Fig. 5: Comparison table with image forgery detection techniques

To enhance the evaluation, it is important to delve into the implications and potential trade-offs associated with these metrics. For instance, a high precision may indicate a low rate of false positives, but it might come at the cost of a lower recall, suggesting a model's failure to identify all positive instances. Balancing these metrics is pivotal, and a comprehensive discussion could shed light on the strengths and weaknesses of both models.

Moreover, to strengthen the claims regarding differences in performance between the ELA-CNN and VGG-16 models, statistical significance testing should be considered. Performing tests, such as t-tests or ANOVA, can provide statistical evidence supporting or refuting the observed variations in precision, recall, and F1-score. This would bolster the credibility of the experimental findings.

Additionally, it is crucial to address the generalizability of the implications to different datasets and scenarios. Acknowledging potential variations in performance across diverse datasets and under different conditions is essential for understanding the broader applicability of the proposed forgery detection models. Factors such as dataset size, composition, and characteristics can significantly influence model performance. Discussing these aspects would contribute to a more nuanced interpretation of the experimental results.

5.1.2 Effectiveness of computation

Although the VGG-16 model is well-known for picture classification, its deep design and large number of parameters can make it computationally intensive. The ELA-CNN model, on the other hand, has a lighter architecture, which lowers computing costs without sacrificing accurate forgery detection.

5.1.3 Sturdiness against various types of forgeries

Splicing, copy-move, and removal are just a few of the forgeries types that the ELA-CNN model was excellent at spotting. This illustrates its dependability and versatility in identifying various manipulation techniques. On the other hand, the VGG-16 model performed worse in detecting some forgeries, most likely as a result of the lack of ELA preprocessing, which offers vital details regarding uneven compression levels in modified images.

5.2 Consequences for identifying image forgeries

5.2.1 Benefits of deep learning methodologies

The ELA-CNN model's high accuracy highlights how well deep learning techniques work to identify fake photos. Through the combination of CNNs' feature extraction powers and ELA preprocessing, the model is able to learn to identify minute artifacts produced during picture editing.

6. Conclusion & future work

In conclusion, this research makes a significant contribution to the field of image forgery detection by conducting a comprehensive comparative analysis of deep learning-based algorithms. The study provides valuable insights into the effectiveness of these algorithms in identifying counterfeit images, offering knowledge that can be leveraged for the development of precise and efficient forgery detection tools. The findings underscore the pivotal role of deep learning techniques, with the ELA-CNN model demonstrating exceptional accuracy in detecting forgeries. However, the study also highlights limitations, particularly in detecting highly sophisticated forgeries. Despite these challenges, the research serves as a foundation for future enhancements in image forgery detection algorithms, emphasizing the need to address limitations and improve precision and generalization. Overall, this work not only advances our understanding of image forensics but also guides future research endeavors for the continued improvement of forgery detection methods.

6.1 Future work

Future work in this domain should explore advanced deep learning techniques and expand the dataset to encompass a broader range of image manipulations. Additionally, efforts should be directed toward enhancing the robustness and generalization capabilities of image forgery detection algorithms, thereby fortifying the defense against image forgeries in the digital landscape.

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