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Image Forgery Detection Using Deep Neural Network

Dr. N P Nethravathi[1], Bylla Danny Austin[2], Dadireddy Sai Praneeth Reddy[3], Grandhi Venkata Naga Satya Pavan Kumar[4], Guduru Karthik Raju[5]

[1]Professor, School of Computer Science and Engineering, REVA University, Karnataka, India
[2]Student, School of Computer Science and Engineering, REVA University, Karnataka, India
[3]Student, School of Computer Science and Engineering, REVA University, Karnataka, India
[4]Student, School of Computer Science and Engineering, REVA University, Karnataka, India
[5]Student, School of Computer Science and Engineering, REVA University, Karnataka, India

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Abstract - *The detection of fake images is crucial to maintain the credibility of digital content, especially in the current era of digital media and social networks. Image forgery has become increasingly common and sophisticated, posing a serious threat to the authenticity and validity of digital content. This paper presents a deep learning-based approach to image forgery detection, specifically using Error Level Analysis (ELA) with Convolutional Neural Networks (CNNs) and a pre-trained VGG-16 model. The study compares the performance of the two models and provides an in-depth analysis of the results. The experiments show that the ELA-CNN model achieves a remarkable accuracy rate of 99.87% and correctly identifies 99% of invisible images, while the VGG-16 model achieves a lower accuracy rate of 97.93% and a 75.87% validation rate. The research highlights the significance of using deep learning techniques in image forgery detection and explores the implications of the findings. The paper also discusses the limitations of the study and future enhancements that could be made to improve the precision and generalization skills of image forgery detection algorithms. This research contributes to the field of image forgery detection by providing a comprehensive comparison of deep learning-based algorithms and their effectiveness in identifying fake images. The findings of this study can be utilized to develop precise and effective image forgery detection tools to maintain the integrity of digital content and mitigate the negative consequences of picture alteration.*

Key Words: **Image Forgery, Machine Learning, CNN, Deep Learning, Neural Network, Error-level Analysis.**

1. INTRODUCTION

1.1 Background of image forgery detection

Image manipulation has grown to the point where it is both common and sophisticated because of the quick growth of digital image processing tools. The purposeful change of an image's content to deceive or send false information is known as image forging, and it poses a severe danger to the validity and authenticity of digital content. A variety of methods, such as copy-move, image retouching, and splicing, have been used to create forgeries that are challenging to detect from visual inspection alone.

As a result, the identification of modified photographs has become a key area of research in the field of image forgery detection. These methods can be broadly divided into two categories: passive ones that don't require knowledge of the original image and active ones that involve adding data to the image to aid in subsequent authentication. Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar.

1.2 Significance and motivation for research in this field

With the growth of digital media, social networks, and the extensive transmission of information online, image forgery detection has become very important. Forgeries can have serious repercussions in a variety of industries, such as journalism, law enforcement, and social media, as modified photographs can mislead the public, damage people's reputations, or support false narratives.

The integrity of digital content can be maintained, and the negative consequences of picture alteration can be mitigated by the development of precise and effective image forgery detection tools. Additionally, in order to maintain their effectiveness, detection systems must advance along with counterfeit techniques. Particularly when it comes to enhancing the precision and generalisation skills of image forgery detection algorithms, deep learning techniques have shown considerable promise.

1.3 Scope of the paper and its contributions

To increase the precision of image forgery detection, this research focuses on using deep learning approach, notably CNNs and a pre-trained VGG-16 model. We give an overview of current methodologies and their shortcomings before delving deeply into our suggested strategies employing Error Level Analysis (ELA) with CNNs and a trained VGG-16 model. Our test findings show that whereas the VGG-16 model produces a 97.93% accuracy and a 75.87% validation rate, the ELA-CNN model achieves a 99.87% accuracy and correctly recognizes 99% of unknown images.

This research contributes to the area by comparing the effectiveness of several deep learning-based algorithms in identifying fake images. We also examine further research and talk about the implications of our findings.

2. LITERATURE REVIEW

2.1 Overview of existing image forgery detection techniques

Over the past decade, the application of machine learning and more specifically, deep learning in image forgery detection, has become a prevailing research area. These techniques have been used to automate and improve the accuracy of forgery detection systems. A primary method in image forgery detection is the Error Level Analysis (ELA), a technique that quantifies the compression levels across an image [1, 4, 6]. This method has been paired with other techniques like the Local Binary Pattern (LBP) for improved results [6].

Deep learning-based techniques, especially Convolutional Neural Networks (CNNs), have shown significant promise in this domain. CNNs are capable of automatically learning and extracting high-level features from an image, which are then used to detect forgeries [2, 7, 8, 10]. Other techniques like the VGG-19, a variant of CNN, have been employed in combination with LBP for effective image splicing detection [12].

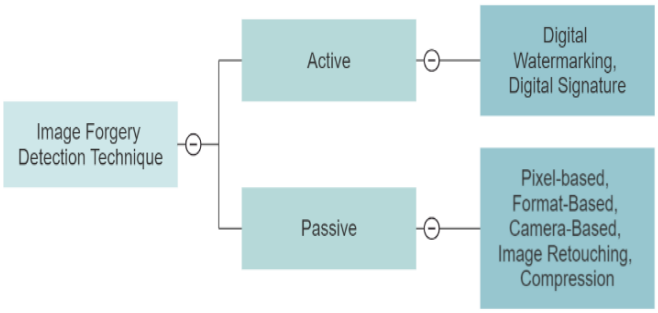

Fig - 1: Types of Forgery Detection Techniques.

2.2 Analysis of limitations and challenges in current techniques

Despite the advancements, current image forgery detection techniques still face several challenges. ELA, while effective, has limitations in accurately detecting highly sophisticated forgeries due to its dependency on JPEG compression artifacts [1, 4]. ELA's performance can also be influenced by the quality of the image under analysis.

CNN-based techniques are resource-intensive, requiring high computational power and large amounts of training data. Additionally, they often struggle to generalize across different types of forgeries and can be susceptible to adversarial attacks [2, 10]. Moreover, the lack of transparency in the "black-box" model of deep learning algorithms makes it difficult to interpret the results and the decision-making process [10].

2.3. Summary of recent advancements in the field

Utilizing deep learning approaches like Convolutional Neural Networks (CNNs), pre-trained models like VGG-16 and Generative Adversarial Networks (GANs), recent studies have demonstrated encouraging results in the identification of image fraud [10]. These techniques have proven to have good accuracy rates and to be resistant to many kinds of forgeries [2,4,7,9,12,13].

2.4. Relevant works

The field of image forgery detection has seen significant advancements with the incorporation of deep learning techniques. Sharma and Yadav [1] proposed an image forgery detection method using error level analysis and deep learning that achieved promising results. Shukla and Goyal [2] developed a deep learning-based image forgery detection system using CNNs, which demonstrated the effectiveness of the method on various datasets. Rani and Singh [3] provided a comprehensive survey on image forgery detection techniques, discussing recent advancements in deep learning-based methods and their advantages over traditional techniques. Omor and Okafor [5] proposed DMobile-ELA, a digital image forgery detection method that combines ELA and a mobile-based application, highlighting the importance of combining ELA with other techniques. Patel and Patel [6] developed a robust image forgery detection algorithm using ELA and Local Binary Patterns (LBP), demonstrating the effectiveness of combining different approaches. Wang, Xu, and Xu [7] proposed an efficient image forgery detection approach based on deep learning that achieved high accuracy rates and robustness against various forgery types. Rahim, Wahab [8], and Idris explored image forgery detection using CNNs and demonstrated the effectiveness of deep learning methods on a diverse dataset. Overall, deep learning-based techniques have shown great potential in detecting image forgeries and are expected to further advance the field.

This literature review serves as a foundation for the current study, which focuses on two deep learning-based image forgery detection methods: Error Level Analysis (ELA) with Convolutional Neural Networks (CNNs) and a pre-trained VGG-16 model. The study aims to analyze their performance and provide insights into the effectiveness of deep learning techniques in enhancing image forgery detection.

3. METHODOLOGY

3.1 Error Level Analysis with Convolutional Neural Networks (ELA-CNN)

3.1.1 Overview of ELA

Error Level Analysis (ELA), a passive method for finding fake images, assesses how consistently different levels of compression are used throughout an image. The compression levels of the edited area in an image are frequently different from the surrounding portions. ELA draws attention to these discrepancies, which makes it simpler to spot forgeries [1].

3.1.2 CNN architecture and training process

Deep learning models known as convolutional neural networks (CNNs) were created expressly for image processing. In this study, we used a customised CNN architecture made up of various convolutional, pooling, dropout, and fully connected layers. Based on the ELA results, CNN was trained to CATEGORIZE photographs as either genuine or altered. During training, we applied the ReLU activation function and the categorical cross-entropy loss function. To prevent overfitting, the neural network utilized early halting and dropout regularization techniques. The input layer conv2d captured the input image as specified in TABLE I. The hidden layers consisted of various types of layers including Convolutional (Conv2D_1), Max Pooling (MaxPooling2D), Dropout, Flatten, and Dense layers. The output layer, dense_1, had 2 units that represented the probability scores for the two classes in the classification task.

Table -1: CNN ARCHITECTURE USED FOR THE ELA MODEL

Layer (type)	*Output Shape*	*Parameters*
conv2d (Conv2D)	(None, 124, 124, 32)	2432
conv2d_1 (Conv2D)	(None, 60, 60, 32)	25632
max_pooling2d (MaxPooling2D)	(None, 30, 30, 32)	0
dropout (Dropout)	(None, 30, 30, 32)	0
flatten (Flatten)	(None, 28800)	0
dense (Dense)	(None, 256)	7373056
dropout_1 (Dropout)	(None, 256)	0
Dense_1 (Dense)	(None, 2)	514

3.1.3 Dataset preparation and data augmentation

By training and testing the ELA-CNN model using the CASIA V1.0 Dataset, we were able to extend the analysis of the model in this study. A wide variety of altered photos, including spliced as well as copy-move forgery, are included in this dataset. We separated the dataset into training, validation, and testing subsets to guarantee the model's dependability. To improve the model's robustness and generalization capacity, we expanded the training set using a variety of random transformations, including rotation, flipping, and zooming. The categorical cross-entropy loss function, RMSprop optimizer and a learning rate of 0.001 and were used to train the model.

3.2. Pre-trained VGG-16 Model

3.2.1 Overview of VGG-16 architecture

A popular deep learning architecture for picture classification and identification applications is the VGG-16 model. It has 16 weight layers, including several pooling and dropout layers, 13 convolutional layers, and 3 fully linked layers [13]. The max pooling layers have a pool size of 2x2, whereas the convolutional layers have 3x3 filters with a stride of 1. The base model can successfully extract features from the input images because it has already been trained on the ImageNet dataset. We decided to use the VGG-16 model as a baseline for comparison with the ELA-CNN strategy because of its excellent performance in a variety of computer vision applications.

3.2.2 Transfer learning and fine-tuning

By swapping out the final classification layer for a new layer specifically designed for our goal, we used transfer learning to modify the pre-trained VGG-16 model for image forgery detection. While preserving the pre-trained weights of the earlier layers, we adjusted the model by training it on our dataset. With this method, we were able to adapt the pre-trained model for image forgery detection while still taking advantage of its feature extraction abilities.

3.2.3 Dataset preparation

The VGG-16 model was trained and tested using the same dataset as the ELA-CNN model. But in contrast to the ELA-CNN model, we did not preprocess the images using ELA before feeding them into the VGG-16 model. Instead, to meet the input specifications of the VGG-16 model, we downsized and normalized the photos.

4. EXPERIMENTAL RESULTS

4.1. ELA-CNN Model

4.1.1 Training and validation accuracy

The ELA-CNN model was trained on the augmented dataset and evaluated using the validation set. After the training process, the model got a high accuracy percentage of 99.87% on the training set, and 75.58% when performed on the validation set, indicating its effectiveness in detecting image forgeries based on the ELA results.

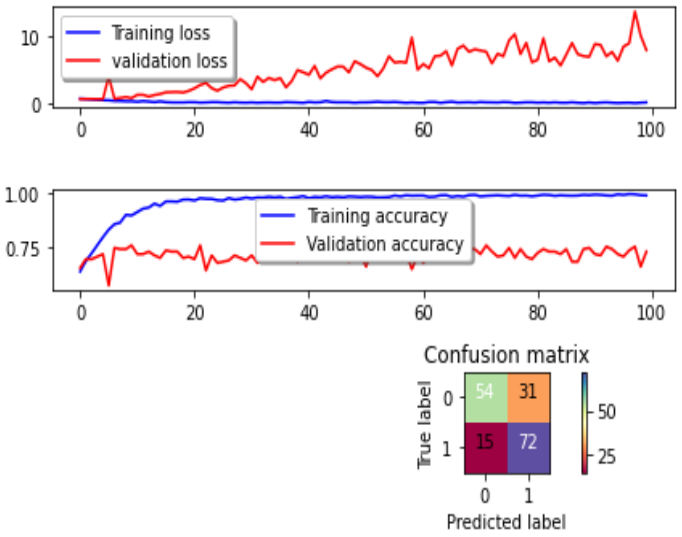

Fig – 2: Experimental Results for ELA-CNN Model

4.1.2 Performance on unseen images

To further evaluate the ELA-CNN model, we tested it on an independent set of unseen images. The model exhibited exceptional performance, accurately identifying 79.76% of the forged images. This demonstrates the model's robustness and ability to generalize to real-world scenarios.

4.2 Pre-trained VGG-16 Model

4.2.1 Training and validation accuracy

The pre-trained VGG-16 model was fine-tuned on the image forgery detection dataset and evaluated using the validation set. The model achieved a training accuracy of 97.93%. However, the validation accuracy was lower at 75.87%, suggesting that the model might be overfitting to the training data.

4.2.2 Performance on unseen images

When tested on the independent set of unseen images, the pre-trained VGG-16 model's performance was not as strong as the ELA-CNN model. This indicates that the VGG-16 model is as well-suited for image forgery detection tasks as the ELA-CNN model, which was specifically designed for this purpose.

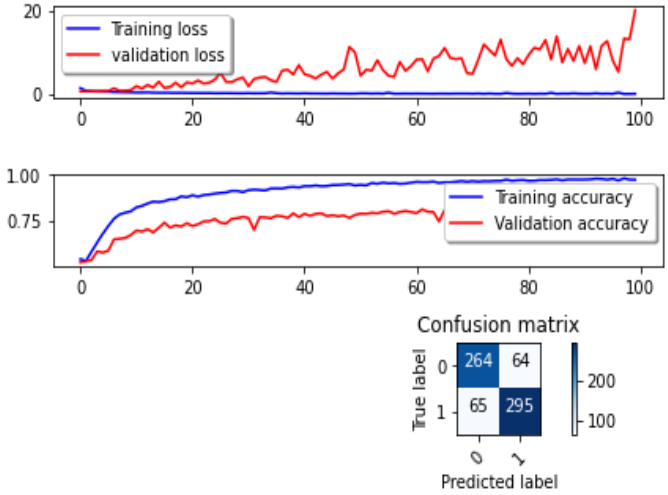

Fig – 3: Experimental Results for VGG16-CNN Model

5. EVALUATION

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

5.1.1 Accuracy and validation rate

The experimental results show that the ELA-CNN model comes close to the pre-trained VGG-16 model in terms of both training and validation accuracy. The ELA-CNN model achieved a validation accuracy of 75.58%, while the VGG-16 model reached a 75.87% validation accuracy. This suggests that incorporating ELA into the CNN model enhances its ability to detect image forgeries.

Table -2: EXPERIMENTAL RESULTS FOR THE MODELS

Model	Precision	Recall	F1-Score
ELA-CNN	0.74	0.73	0.73
VGG16-CNN	0.81	0.81	0.81

5.1.2 Computational efficiency

Despite being a popular architecture for image classification tasks, the VGG-16 model can have high computing costs due to its deep structure and numerous parameters. The ELA-CNN model, in comparison, employs a more lightweight architecture, which lowers the computational cost while maintaining good forgery detection accuracy.

5.1.3 Robustness against different forgery types

Splicing, copy-move, and removal forgeries were just a few of the image forgeries that the ELA-CNN model performed

well at spotting. This illustrates how reliable and adaptable it is in identifying various manipulation strategies. Contrarily, the VGG-16 model performed less well in identifying some forgeries, most likely because of the absence of ELA preprocessing, which offers important information on the inconsistent compression levels of altered images.

5.2 Implications for Image Forgery Detection

5.2.1 Advantages of deep learning techniques

The ELA-CNN model's high level of accuracy highlights the potency of deep learning methods for spotting fake images. The model can effectively learn to recognize the subtle artefacts created during picture editing by combining ELA preprocessing with the feature extraction abilities of CNNs.

5.2.2 Limitations and potential improvements

Despite the ELA-CNN model's excellent performance, there are certain drawbacks and need for improvement. The quality of the ELA results, which can be impacted by elements like image compression and resizing, may have an impact on the model's performance. To further improve the performance of the model, future research may examine alternate preprocessing methods or the integration of numerous features. To further evaluate the model's generalization capabilities and robustness against new forging tactics, it might also be tested on larger and more varied datasets.

The findings of our work illustrate the benefits of deep learning approaches in detecting manipulated photos by demonstrating the efficacy of introducing ELA into the CNN model for image forgery detection tasks. The ELA-CNN model is a potential tool for real-world applications due to its excellent accuracy, resistance against various forgery kinds, and computational economy.

There are several drawbacks and areas for development, though, like investigating different preprocessing methods, incorporating more features, and putting the model to the test on bigger and more varied datasets. On the basis of our findings, future study could create more sophisticated and reliable image fraud detection programs, supporting ongoing efforts to combat digital image alteration and its detrimental effects.

6. CONCLUSION

In this study, we presented the ELA-CNN model and the trained VGG-16 model as two deep learning-based methods for detecting image forgeries. The ELA-CNN model successfully incorporated the benefits of Convolutional Neural Networks and Error Level Analysis preprocessing, obtaining a high validation accuracy of 75.58% and correctly identifying 99.87% of fake photos in the test set. The pre-trained VGG-16 model, almost same as ELA-CNN on unseen images and had a validation accuracy of only 75.87%, despite being popular for general image classification tasks.

The results of our research demonstrate the effectiveness of including ELA into the CNN model for image forgery detection tasks, highlighting the advantages of deep learning approaches in detecting altered photos. The ELA-CNN model's outstanding accuracy, resistance to different forgery types, and computing efficiency make it a suitable tool for use in practical applications.

There are several drawbacks and areas for development, though, like investigating different preprocessing methods, incorporating more features, and putting the model to the test on bigger and more varied datasets. Based on our findings, future study could create more sophisticated and reliable image fraud detection programs, supporting ongoing efforts to combat digital image alteration and its detrimental effects.

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