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Revealing the Hidden Truth: Deep Convolutional Neural Networks for Image Forgery Detection and Analysis

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ABSTRACT: The advent of deep networks has facilitated significant Progress in the domain of visual perception technology. With the widespread dissemination of images and videos, Combined with the accessibility of powerful editing software, the ease of altering digital content has grown significantly."To identify such fraudulent activities, we have proposed novel techniques. Our paper presents two crucial facets of utilizing deep convolutional neural networks for detecting image forgery. Firstly, we investigate various pre-processing methods in conjunction with the CNN architecture. Subsequently, we assess the efficacy of several transfer learning techniques, such as pre-trained ImageNet (via fine-tuning), by implementing them on our dataset, CASIA V2.0. Our research involves investigating preprocessing methods using a simple convolutional neural network architecture and delving deeper into the powerful influence of transfer learning models.

Keywords: Visual perception, Forgery, Deep convolutional neural networks, ImageNet.

I. INTRODUCTION

In recent years, the research community has shown a keen interest in developing techniques for verifying the authenticity of documents. This is primarily due to the abundance of information that is readily available to the general public, such as images and videos, which can be effortlessly manipulated to produce false or deceptive information. Tampered, altered, or counterfeit content is frequently utilized and disseminated through various media platforms. Given the easy accessibility of modification tools, it has become increasingly arduous to reliably verify the authenticity of multimedia content. The focus of this study is on comparing the efficacy of CNN and its pre-processing stages, as well as contrasting the performance of transfer learning models. Multiple tables and figures have been utilized to present a comprehensive analysis of the statistics related to efficiency and performance.

The main objective of this study is to emphasize the improvements that can be achieved either by enhancing the pre-processing stage or utilizing superior algorithms. The Precision and cost function, specifically, the mean squared error (MSE) have been employed as evaluation metrics. The precision can be calculated by utilizing the confusion matrix[41], in which the sum of true positive and true negative is divided by the sum of true negative, true positive, false negative, and false positive. The term "true positive" indicates both the observed and predicted positive values, while "true negative" denotes both the observed and predicted negative values. On the other hand, "false negative" refers to the observed positive values that were predicted as negative, whereas "false positive" pertains to the observed negative values that were predicted as positive. In contrast, MSE is the square of the difference between the predicted output and the observed output.

The remaining parts of the article are organized as follows: Section II gives a synopsis of prior research on neural network-based image tampering. Section III provides an explanation of the methodology and approaches employed in this investigation. Section IV presents the experimental outcomes, along with visual representations and discussions. The conclusion is presented in Section V.

II. RELATED WORK

In their study, T. J. de Carvalho et al. [1] proposed a detection technique utilizing machine learning. The approach was designed to detect splicing forgery, which involves the composition of various regions from distinct images to create a new image. The method employed the concept of dissimilarity in color illumination, and feature extraction was accomplished using the SVM (Support Vector Machine) classifier, an in-demand machine learning technique. The experiment's findings revealed an accurate classification rate of 86% for web-based images when trained/tested on different databases."

In their research, J. Ouyang [2] introduced a method for detecting copy-move forgery utilizing deep CNNs. The approach was evaluated on three datasets: OXFORD flower [3] (as dataset1), UCID [4] (as dataset2), and CMFD [5] (as dataset3). The technique involved utilizing a pre-existing model for a large database such as ImageNet, which was modified to yield improved results. The obtained test errors for dataset1, dataset2, and dataset3 were 2.32%, 2.32%, and 42%, respectively.

Z. J. Barad and M. M. Goswami [6] conducted an analysis and reported their findings to assist other researchers in the field. They provided an overview of various research works along with details about the image forgery detection datasets. The paper focused on two popular approaches for forgery detection: (i) traditional and (ii) deep learning (DL). The study concluded that deep learning algorithms outperform traditional methods. This is because deep learning comprises of two stages - feature extraction and classification - which perform well even with complex datasets. Moreover, the article provided a concise overview of image tampering detection techniques and carried out a comparative evaluation of various deep learning models, such as Deep Neural Network (DNN), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN).

Sudiatmika, I.B.K. and Rahman [7] utilized a deep learning technique to differentiate authentic from manipulated images. They suggested an innovative system that integrated Error Level Analysis (ELA) with the transfer learning model Visual Geometry Group (VGG). Following the 100-epoch training of the model, the outcomes indicated 92.2% accuracy for training and 88.46% accuracy for validation". Y. Shah et al [8] utilized the CNN method and integrated the ELA into the pre-processing phase to address limitations in previous methods. They applied the Inception Residual Network architecture to detect deep fakes and a combination of deep fakes and fake images. The system achieved an accuracy of 91%. However, the ELA results were not satisfactory.

P. He, H. Li, and H. Wang et al [9] utilized the GAN (Generative Adversarial Network) approach to enhance previous performance. Their work focused on post-processing, variable extraction, and model learning. More specifically, they employed residual signals from the chrominance constituents of several multicolor spaces like YCbCr, HSV, and Lab to create strong deep representations using a well-crafted shallow convolutional neural network (CNN). Afterwards, the deep representations obtained from various color spaces were consolidated and fed into the Random Forest (RF) classifier, which is a widely used ensemble classifier, to obtain the final detection results."The experimental outcomes of this method show that it surpasses existing techniques and exhibits stronger detection accuracies (most notably above 99%) against post-processing attacks, particularly for operations that involve image blurring.

The present article discusses passive authentication techniques in the field of image forensics, which can be achieved through two main approaches. The first approach utilizes a basic and straightforward convolutional neural network model with two pre-processing techniques to generate results. The second approach involves evaluating the results obtained from various transfer learning models that have been fine-tuned. Finally, a comparison is made between all the models and a combination of techniques is selected to obtain the most accurate results using a specific dataset. The effectiveness of these approaches for image forgery detection is assessed, as well as potential avenues for further improvement.

III. METHODOLOGY

Our study involves two distinct stages: The first stage employs pre-processing techniques and a CNN architecture, as depicted in the flowchart figure 1, while the second stage utilizes a deep learning approach illustrated in the flowchart figure 4 to achieve superior outcomes. We trained our dataset utilizing two distinct transfer learning methodologies and identified the most efficient strategy.

3.1. Method 1

The primary neural network used for image recognition is the convolutional neural network (CNN) [10, 11, 39]. This network processes images as input and extracts important features from them.

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It is a multi-layered network, where each layer captures specific features. As the input progresses through the network, it can identify even more complex features. The architecture of the CNN, which is illustrated in Figure 2, is comprised of two distinct parts: Feature Extraction and Classification. It includes several layers[12,13]: "At the input layer, the images from the dataset are provided as input."

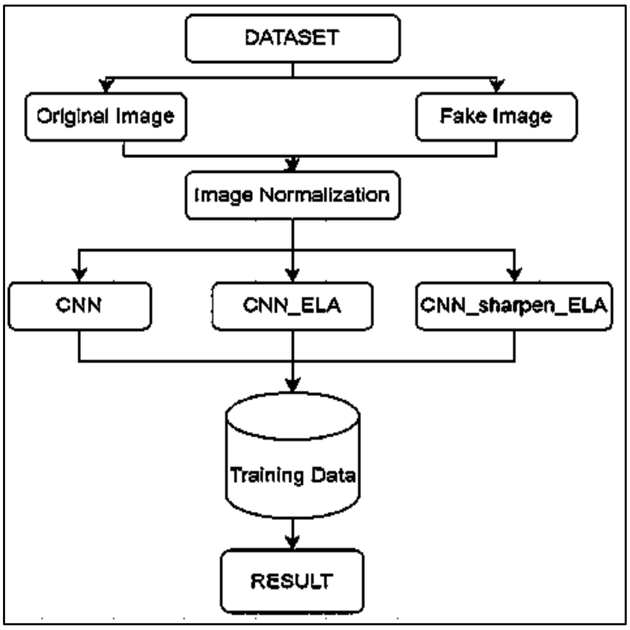

Figure 1: Flowchart for method-1

In the CNN architecture, illustrated in figure 2, the Feature-Extraction and Classification are divided into two parts, as mentioned in sources [12,13]. The following layers are employed:

- Input layer: The dataset images are fed here.
- Convolution layer: This layer identifies the features by extracting them from simple to complex, aiding further processing.
- Pooling layer: The content is reduced while retaining important features that are required. The convolution layer's spatial size is reduced, reducing computation power.
- Fully-connected layer: The image is flattened, forming a single column vector. After multiple epochs, the model utilizes the softmax classification technique [14,15,16] to differentiate between dominating and weak features in the images and classify them accordingly.

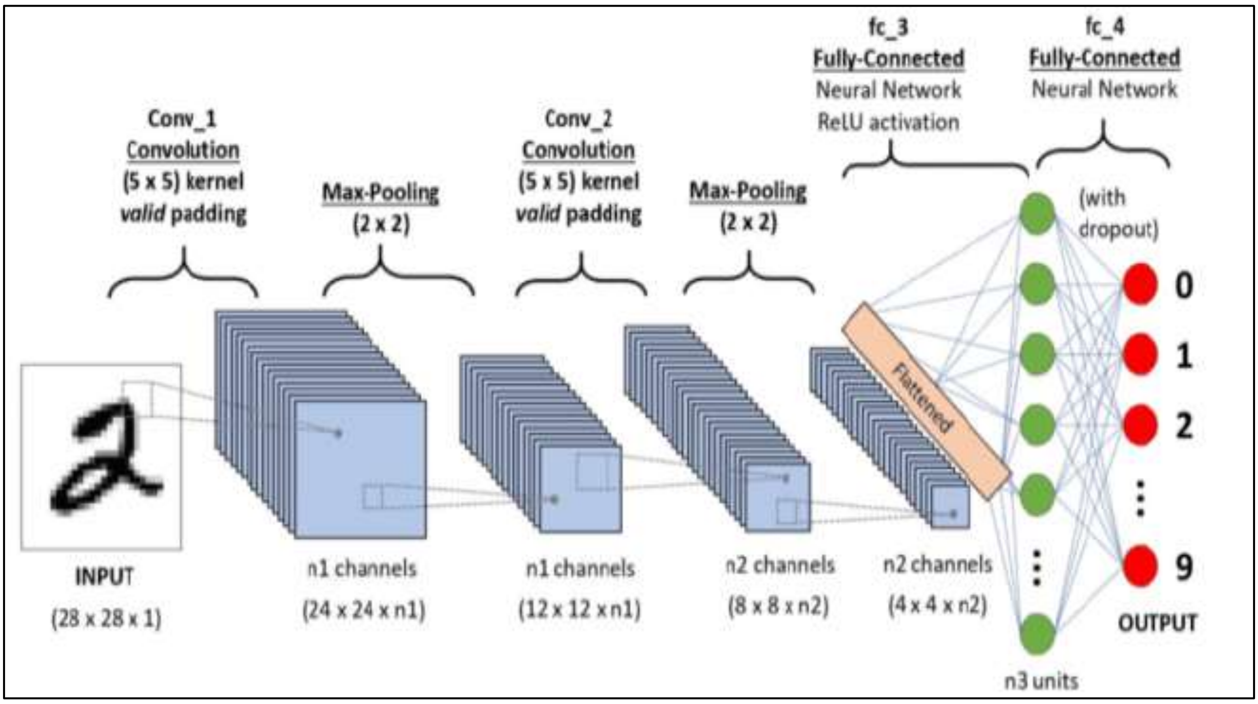

Figure 2: Architecture of convolution neural network

The collection of information is split into two categories, specifically the training and testing categories, with a proportion of 80:20. Next, the models known as CNN, CNN_ELA, and CNN_SHARPEN_ELA are instructed and assessed using their corresponding datasets, and afterwards, their outcomes are compared.In accordance with [17], ELA refers to a methodology utilized in image forensics, which entails preserving the tampered image at a specific level of quality and subsequently determining the contrast from the compression level. To carry out this task, a lossy and irreversible compression algorithm named JPEG [18] is employed. The ELA technique is established by means of a quantization process that approximates the JPEG quality. The image is partitioned into 8x8 segments and repressed at an error rate of 95%. If the image remains unmodified, then all the segments should possess an almost equal quality rate. Conversely, any inconsistencies in the quality level of the segments will indicate image tampering. Hence, the presence of such disparities in the segments can be used as a telltale sign of image manipulation. The ELA technique provides an error rate, which can be employed to identify any sort of manipulation in JPEG images [19,4].

To enhance the accuracy of detecting image forgery, we explored the combination of ELA and a sharpen filter. The sharpening process aims to increase the contrast between bright and dark regions, resulting in clearer features [20, 21, 22]. Our research employed the Pillow-Python image processing library [23] to implement this technique. The results indicate that the combination of these two pre-processing stages contributed to the improved performance of our model.

$$\begin{pmatrix} -2 & -2 & -2 \\ -2 & 32 & -2 \\ -2 & -2 & -2 \end{pmatrix}$$

Figure 3: Sharpening filter

The filter depicted in fig.3 is applied to produce a brightening effect, whereby the pixels are amplified relative to those around them. When applied to the altered image, this filter will perform an uneven contrast operation since the edges and lines of the tampered (fake) image have been blurred or distorted.

3.2. Method 2

For further investigation, the second method involves transfer learning, which is a form of active learning [24,25,26,27]. Transfer learning is a design methodology that involves applying knowledge gained from one task to improve the performance of another task. In this study, the CASIA V2.0 dataset was trained using the learned weights of the network. To streamline the neural network's execution cycle, the dataset was separated into training, validation, and testing sets, with the respective ratios of 40%, 30%, and 30%. This methodology is beneficial for minimizing the training time and is highly compatible with datasets of smaller proportions.

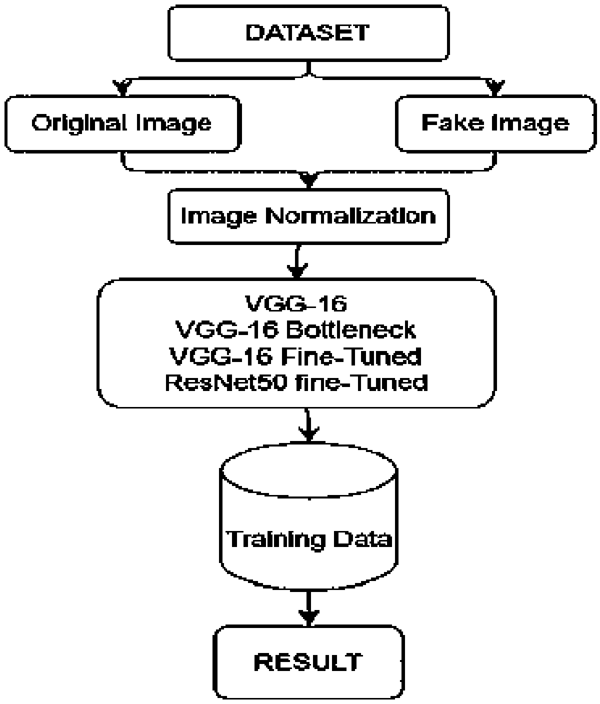

Figure 4: Flowchart for method-2

In our research, used two transfer learning models VGG-16 [37,38] and Resnet50 [32,33,34,35,36].

Table 1: Details of transfer learning models

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MODEL	Year	Top-1 Accuracy	Top-5 Accuracy	Depth	No of layers
ResNet50	2015	0.749	0.921	-	50
VGG16	2014	0.713	0.901	23	16

The VGG16 architecture, which is a variant of the VGGNet, comprises of 16 layers in total with 13 convolutional and 3 fully-connected layers. Its published parameter count is 138 million, which is higher than that of ResNet50. The latter, on the other hand, is another variant of the ResNet architecture, which consists of 50 layers including 48 convolutional, 1 max pool, and 1 average pool layer. ResNet50 has a lower parameter count of 26 million, and was published in 2015. Table I provides the detailed specifications of both algorithms. The accuracy and loss of our dataset were evaluated after training it using these two algorithms.

Following this, we utilized the ResNet50 model that was fine-tuned to progress our research and assess the evaluation metrics. During this procedure, we made adjustments to the last layer of the model to correspond with the classes in our dataset (namely, fake or real), which had been performed previously in the transfer learning process. However, during the fine-tuning phase [28,29,30,31], we opted to retrain specific layers of the network. This procedure involved not only retraining the classifier stage, but also the feature-extraction stage.

IV. EXPIERMENTAL RESULTS

This section provides details of the dataset utilized in our study and presents the results and visualizations of both methods. We have evaluated our models based on several metrics, such as train accuracy, training loss, validation accuracy, and validation loss, and drew inferences from these evaluations.

4.1. Dataset

The present study employed the CASIA V2.0 Image Tampering Detection Evaluation Database [40] as the dataset, which is listed in Table II. This publicly accessible dataset is designed for tampering detection techniques' comparison and evaluation. The dataset for forgery classification comprises two categories: tampered/fake and real/original, as depicted in Fig. 5. It is composed of 12,323 colored images, of which 7,200 are authentic and 5,123 are tampered.

Table 2: Details of CASIA V2.0 dataset

Dataset	Size	Components	Format
CASIA V2.0	7200 authentic 5123 tampered	From 320x240 to 800x600 color images	JPEG,BMP,TIFF

Figure 5: Images from the CASIA V2.0 dataset

4.2. Results and Visualization

The unaltered image retains identical ELA values, but as it is repeatedly saved, the quality level drops. In contrast, the tampered image exhibits increased ELA values, and the areas that have been altered display a color disparity.

Table 3 presents the results obtained from the original image depicted in fig.6, as well as the ELA-processed image in fig.8, which exhibits a uniform value. On the other hand, the tampered

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image shown in fig.7 presents inconsistencies that are difficult to detect by the human eye, and although there is no color variation in the ELA output, the entire image appears darker, as depicted in fig.9.

Table 3: Showing the original and tampered images with respective ela operation

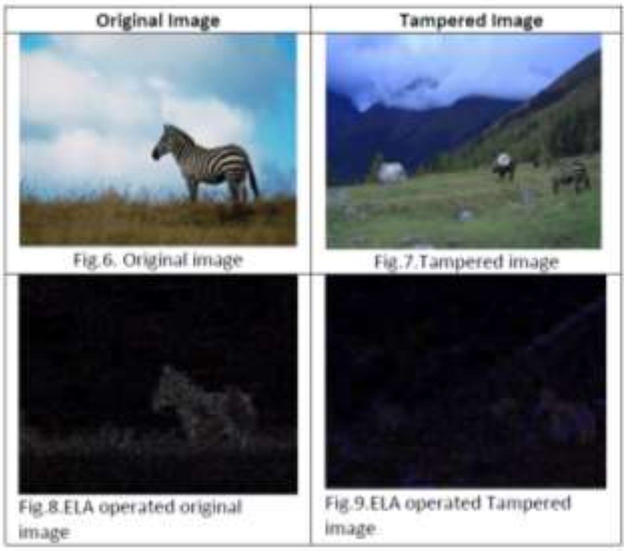

Fig.6. Original image
Fig.7.Tampered image
Fig.8.ELA operated original image
Fig.9.ELA operated Tampered image

Figures 12 and 13 demonstrate the outcomes of implementing the sharpen filter on the original image (Figure 10) and tampered image (Figure 11) respectively, as presented in Table IV. This technique enhances the contrast of the image uniformly. However, when the ELA is applied to this dataset, the results show a significant increase in numbers, as revealed in the table and its graphical representation.

Table 4: Showing original and tampered images with respective sharpen operation

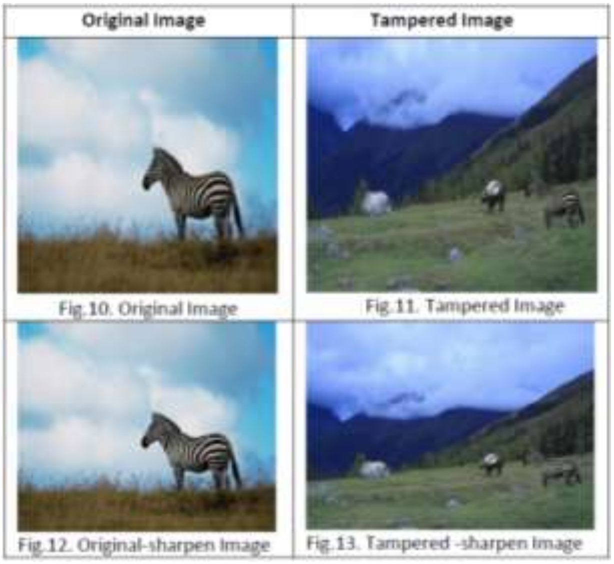

Fig.10. Original Image
Fig.11. Tampered Image
Fig.12. Original-sharpen Image
Fig.13. Tampered -sharpen Image

Table 5 compares various CNN models, with a clear numerical comparison presented. It demonstrates an improvement not only over the simple CNN model but also over the CNN_ELA model. The Sharpen_ELA model achieved a training accuracy of 97% and a loss of 0.1%, with an improvement margin of 19.87% and 0.36%, respectively. As the number of layers in an algorithm increased, so did its performance and efficiency, albeit at the cost of greater complexity. Therefore, we concluded that fine-tuning was the most effective approach for our research and tested it on ResNet50, a powerful transfer learning model.

V. CONCLUSION

Within this investigation, we carried out a comparative analysis of diverse deep learning methodologies utilized for identifying image forgery within the CASIA V2.0 dataset. Two techniques were employed to detect any instances of forgery: (i) the pre-processing stage and (ii) different models of deep learning. Our team was able to successfully implement detection techniques using various models and combinations. For instance, CNN_Sharpen_ELA gave us a training accuracy of 97% and a training loss of 0.1%, while ResNet50 yielded a test accuracy of 95% with a low test loss of approximately 0.4%. These approaches are straightforward and dataset-independent, meaning they can be utilized with any model and any dataset to study their effects and improvements in various cases. Future work will include conducting further research to identify tampered images and videos using other techniques.Based on the complexity of datasets, one can increase the number of convolution and pooling layers.

- The proposed approaches can be applied to different datasets or the current model can be modified with minor changes in training algorithms and/or preprocessing stage.
- To expand the scope, the proposed approaches can be extended to detect tampering in videos that are a collection of frames.

Table 5: Result different convolution neural network models

MODEL	Train Accuracy (%)	Validation Accuracy (%)	Train Loss (%)	Validation Loss (%)
CNN	77.13	75.68	0.4678	0.5121
CNN-ELA	94.00	90.02	0.2112	0.3022
CNN_Sharpen-ELA	97.00	94.52	0.1039	0.2932

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