ENHANCING DIGITAL IMAGE FORGERY DETECTION USING TRANSFER LEARNING

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Abstract: Nowadays, digital images are a main source of shared information in social media. Meanwhile, malicious software can forge such images for fake information. So, it's crucial to identify these forgeries. This problem was tackled in the literature by various digital image forgery detection techniques. But most of these techniques are tied to detecting only one type of forgery, such as image splicing or copy-move that is not applied in real life. This paper proposes an approach, to enhance digital image forgery detection using deep learning techniques via transfer learning to uncover two types of image forgery at the same time, The proposed technique relies on discovering the compressed quality of the forged area, which normally differs from the compressed quality of the rest of the image. A deep learning-based model is proposed to detect forgery in digital images, by calculating the difference between the original image and its compressed version, to produce a featured image as an input to the pre-trained model to train the model after removing its classifier and adding a new fine-tuned classifier. A comparison between eight different pre-trained models adapted for binary classification is done. The experimental results show that applying the technique using the adapted eight different pre-trained models outperforms the state-of-the-art methods after comparing it with the resulting evaluation metrics, charts, and graphs. Moreover, the results show that using the technique with the pre-trained model MobileNetV2 has the highest detection accuracy rate (around 95%) with fewer training parameters, leading to faster training time.

Keywords: Image forgery detection (IFD),Deep Neural Network (DNN), Pretrained Model, Image compression, Transfer learning.

I.INTRODUCTION

The tampering of a digital image is called digital image forgery, these forged images cannot be detected by the naked eye. Such images are the primary sources of spreading fake news and misleading information in the context of society with the aid of diverse social media platforms like Facebook, Twitter, etc. The editing software tools that can make these forgeries are available for free with some advanced features that are used for image tampering such as GNU, GIMP, and Adobe Photoshop. Such forgeries can be detected using digital image forgery algorithms and techniques, these algorithms are used in image security especially when the original content is not available. Digital image forgery means adding unusual patterns to the original images that create a heterogeneous variation in image properties and an unusual distribution of image features. Figure 1 shows the classification of digital image forgery. Active approaches require essential information about the image for the verification process. The inserted information within the picture is employed to observe the modification in that picture. The active approach consists of two types: digital signatures which insert some additional data obtained from an image by the end of the acquisition process, and digital watermarking which is inserted into images either during the acquisition phase or during the processing phase. The passive image forgery detection methods benefit from the features retained by the image allocation processes achieved in different stages of digital image acquisition and storage. Passive methodologies do not require past information about the image. These approaches exploit that the tampering actions modify the contents of information of the image that can facilitate tampering detection.

Copy move forgery involves duplicating a section or object within an image and pasting it again in a different location within the same image to replicate (or move) a specific scene in the image. Copy-move forgery is the most common technique used to manipulate images, it is also the most challenging type of forgery to detect due to the complexity of copying and replicating an object or section of the image with identical properties and feature distributions and pasting it within the same image. some post-processing techniques can be added after CMF processes such as rotation, scaling, JPEG compression, etc. which makes the detection further difficult and complex. Splicing forgery can be generated by adding or blending two images or set of images to produce an unprecedented image. The source images used to generate a spliced image may include dissimilar color temperatures, illumination conditions, and noise levels based on various factors. Average filtering or some other related image processing operation can be applied as post processing like resizing, cropping, rotating, and retouching each of the source images to match the visual attributes, shape, and size of the target image so that the forged image can look realistic. Retouching forgery involves modifying an image to hide or highlight particular features such as brightness, color, contrast, or other visual attributes and altering background coloring. It includes the visual quality enhancement of the image. Resampling Forgery is the act of altering the dimensionality of a particular object or section within an image to present a distorted or misleading view. Morphing forgery involves merging two scenes from different images to create an entirely new scene, this can be done through the use of graphic software to create a completely artificial image with no basis in reality.

The three major types of tampering are Copy Move, Image Splicing, and Image Retouching. Digital Image Forgery Detection is a binary classification task, to classify the image as either forged or authentic. Recently, deep learning has become a promising tool for enhancing digital image forgery detection. In any Deep learning model, feature extraction is an important phase that affects the performance of the algorithm, where the database size is considered a significant factor. Transfer learning presents a viable alternative solution when dealing with limited sample size problems that supports taking the knowledge acquired from a previously trained model including features, weights, and other relevant information that was trained on a large dataset such as the ImageNet database, that contains 1.2 million images grouped into 1000 classes to solve the problem of small size dataset in the new target domain. By utilizing a pre-trained model, significant amounts of time spent on training can be saved, and the model can be adapted to work with smaller datasets through retraining.

II.REALTED WORKS

The aim behind image forgery detection is to check the authenticity of digital images, especially when images are used as evidence in court and forensics, news, or historical data, or in the military, and medical diagnosis systems, it prevents the distribution of misinformation and fake news.
The objective of enhancing digital image forgery detection using transfer learning is to improve the accuracy and robustness of existing forgery detection models by leveraging knowledge gained from pre-trained models on related tasks. Transfer learning involves transferring knowledge learned from one domain to another, and in this context, it aims to apply insights gained from a source domain (such as general image recognition) to enhance the performance of a forgery detection model in the target domain (digital image forgery detection).

In image forgery detection field, various approaches were proposed. Traditional techniques mostly extract a set of handcrafted based features, followed by a classifying technique like feature matching to differentiate between the authentic and forged images. In the machine learning approach, a set of classifiers can be used in the classifying process like Support Vector Machine and Naïve Bayes classifier. While more recent techniques employ convolutional neural networks (CNNs) and deep neural networks (DNN) methods, others employ the network with the help of pre-trained models and the power of transfer learning. CNN and deep learning-based techniques will be discussed moving over the use of different pre-trained models

III. LITERATURE SURVEY

R. Agarwal, O. P. Verma, A. Saini, A. Shaw, and A. R. Patel, deep learning (DL), a branch of machine learning (ML) and artificial intelligence (AI) is nowadays considered as a core technology of today's Fourth Industrial Revolution (4IR or Industry 4.0). Due to its learning capabilities from data, DL technology originated from artificial neural network (ANN), has become a hot topic in the context of computing, and is widely applied in various application areas like healthcare, visual recognition, text analytics, cybersecurity, and many more. However, building an appropriate DL model is a challenging task, due to the dynamic nature and variations in real-world problems and data. Moreover, the lack of core understanding turns DL methods into black-box machines that hamper development at the standard level. This article presents a structured and comprehensive view on DL techniques including a taxonomy considering various types of real-world tasks like supervised or unsupervised.

C. D. P. Kumar and S. S. Sundaram, the extensive availability of advanced digital image technologies and image editing tools has simplified the way of manipulating the image content. An effective technique for tampering the identification is the copy-move forgery. Conventional image processing techniques generally search for the patterns linked to the fake content and restrict the usage in massive data classification. Contrastingly, deep learning (DL) models have demonstrated significant performance over the other statistical techniques. With this motivation, this paper presents an Optimal Deep Transfer Learning based Copy Move Forgery Detection (ODTL-CMFD) technique. The presented ODTL-CMFD technique aims to derive a DL model for the classification of target images into the original and the forged/tampered, and then localize the copy moved regions. To perform the feature extraction process, the political optimizer (PO) with Mobile Networks (MobileNet) model has been derived for generating a set of useful vectors. Finally, an enhanced bird swarm algorithm (EBSA) with least square support vector machine (LS-SVM) model has been employed for classifying the digital images into the original or the forged ones.

R. Indraswaria, R. Rokhanab, and W. Herulambang, melanoma is a fatal type of skin cancer; the fury spread results in a high fatality rate when the malignancy is not treated at an initial stage. The patients' lives can be saved by accurately detecting skin cancer at an initial stage. A quick and precise diagnosis might help increase the patient's survival rate. It necessitates the development of a computer-assisted diagnostic support system. This research proposes a novel deep transfer learning model for melanoma classification using MobileNetV2. The MobileNetV2 is a deep convolutional neural network that classifies the sample skin lesions as malignant or benign. The performance of the proposed deep learning model is evaluated using the ISIC 2020 dataset. The dataset contains less than 2% malignant samples, raising the class imbalance. Various data augmentation techniques were applied to tackle the class imbalance issue and add diversity to the dataset. The experimental results demonstrate that the proposed deep learning technique outperforms state-of-the-art deep learning techniques in terms of accuracy and computational cost.

S. Jabeen, U. G. Khan, R. Iqbal, M. Mukherjee, and J. Lloret**.** traditional multimedia forensics techniques inspect images to identify, localize forged regions and estimate forgery methods that have been applied. Provenance filtering is the research area that has been evolved recently to retrieve all the images that are involved in constructing a morphed image in order to analyze an image, completely forensically. This task can be performed in two stages: one is to detect and localize forgery in the query image, and the second integral part is to search potentially similar images from a large pool of images. We propose a multimodal system which covers both steps, forgery detection through deep neural networks(CNN) followed by part based image retrieval. Experimental results show that deep features outperform low-level features previously used to perform provenance filtering with achieved Recall@50 of 92.8%.

The proposed model is trained and tested using the MISD (Multiple Image Splicing dataset), and it is observed that the proposed model outperforms the variants of ResNet models (ResNet 51,101 and 151). The proposed model achieves an average precision of 82% on Multiple Image Splicing Dataset, 74% on CASIA 1.0, 81% on WildWeb, and 86% on Columbia Gray. The F1-Score of the proposed method on MISD was 67%, 64% on CASIA 1.0 68% on WildWeb, and 61% on Columbia Gray, outperforming ResNet variants.

IV.PROPOSED SYSTEM

Our proposed system leverages the synergy between deep learning through CNNs and the subtleties uncovered by ELA. This combination empowers the model to not only achieve high accuracy but also to provide insights into the specific regions of potential manipulation within an image. By harnessing the capabilities of Python and a well-structured CNN architecture, this project represents a significant stride towards robust digital image forgery detection, with potential applications in various domains where image authenticity is paramount.

The research titled "Enhancing Digital Image Forgery Detection Using Transfer Learning" aims to refine the current state of digital image forgery detection by incorporating advanced transfer learning techniques. Image forgery, involving manipulations to deceive or mislead, poses a significant challenge in various domains, necessitating robust detection methods. The emphasis on "enhancing" suggests a focus on improving existing detection methodologies, potentially addressing issues related to accuracy, false positives, or overall detection robustness. The integration of "transfer learning" indicates a strategic approach, leveraging knowledge acquired from pre-training on a different but related task or dataset. By applying transfer learning to the domain of image forgery detection, the research seeks to harness the power of previously acquired knowledge, potentially leading to more effective and efficient identification of manipulated digital images. This innovative approach holds promise for advancing the field and contributing to the development of more reliable forgery detection systems.

Dataset:

In the first module of Digital Image Forgery Detection, we developed the system to get the input dataset. Data collection process is the first real step towards the real development of a machine learning model, collecting data. This is a critical step that will cascade in how good the model will be, the more and better data that we get, the better our model will perform. There are several techniques to collect the data, like web scraping, manual interventions. Our dataset is placed in the project and it’s located in the model folder. The dataset is referred from the popular standard dataset repository kaggle where all the researchers refer it. The dataset consists of 12,615 Digital Image Forgery images. The following is the URL for the dataset referred from kaggle.

Retrieving the images:

In this module we will retrieve the images from the dataset and convert them into a format that can be used for training and testing the model. This involves reading the images, resizing them, and normalizing the pixel values. We will retrieve the images and their labels. Then resize the images to (200,200) as all images should have same size for recognition. Then convert the images into numpy array.

ELA image analysis:

Error level analysis is one technique for knowing images that have been manipulated by storing images at a certain quality level and then calculating the difference from the compression level. When JPEG was first saved, then it will compress the image the first time, most editing software like adobe photoshop, gimp, and adobe lightroom support JPEG compressing operation. If the image is rescheduled using image editing software, then compressed again.

CNN Convolutional Neural Networks

Padding

We have seen that convolving an input of 6 X 6 dimension with a 3 X 3 filter results in 4 X 4 output. We can generalize it and say that if the input is n X n and the filter size is f X f, then the output size will be (n-f+1) X (n-f+1):

Input: n X n

Filter size: f X f

Output: (n-f+1) X (n-f+1)

There are primarily two disadvantages here:

1. Every time we apply a convolutional operation, the size of the image shrinks
2. Pixels present in the corner of the image are used only a few number of times during convolution as compared to the central pixels. Hence, we do not focus too much on the corners since that can lead to information loss

To overcome these issues, we can pad the image with an additional border, i.e., we add one pixel all around the edges. This means that the input will be an 8 X 8 matrix (instead of a 6 X 6 matrix). Applying convolution of 3 X 3 on it will result in a 6 X 6 matrix which is the original shape of the image. This is where padding comes to the fore:

Input: n X n

Padding: p

Filter size: f X f

Output: (n+2p-f+1) X (n+2p-f+1)

There are two common choices for padding:

1. **Valid:** It means no padding. If we are using valid padding, the output will be (n-f+1) X (n-f+1)
2. **Same:** Here, we apply padding so that the output size is the same as the input size, i.e., n+2p-f+1 = n
   So, p = (f-1)/2

We now know how to use padded convolution. This way we don't lose a lot of information and the image does not shrink either. Next, we will look at how to implement strided convolutions.

So it shows that the original image when the first image is taken using a digital camera has been compressed twice, first use the camera and the second is editing software. When viewed with the naked eye the image looks the same, but by using this method it will look the difference between a forgery image with the original image. Calculation for the average difference of the quantization table Y (luminance) and CrCb (Chrominance). The digital camera does not optimize the image for a specified camera quality level (high, medium, low, etc.). Original images from digital cameras should have high ELA values. Each subsequent resave will decrease the potential error rate. Original images from photography have high ELA values shown through white on the ELA image. When the image is resaved, using ordinary human vision does not show a significant degree of difference, but ELA shows the dominant black and dark colors. If this image is resaved again it will decrease the image quality. If the original image is then modified, ELA will show the modified area has a color with a higher ELA level. The describes how the output of ELA on the condition of the image.

In the MaxPool2D layer we have kept pool size (2,2) which means it will select the maximum value of every 2 x 2 area of the image. By doing this dimensions of the image will reduce by factor of 2. In dropout layer we have kept dropout rate = 0.25 that means 25% of neurons are removed randomly.

We apply these 3 layers again with some change in parameters. Then we apply flatten layer to convert 2-D data to 1-D vector. This layer is followed by dense layer, dropout layer and dense layer again. The last dense layer outputs 2 nodes as the brain tumour or not. This layer uses the softmax activation function which gives probability value and predicts which of the 2 options has the highest probability.

Strided Convolutions

Suppose we choose a stride of 2. So, while convoluting through the image, we will take two steps – both in the horizontal and vertical directions separately. The dimensions for stride *s* will be:
Input: n X n
Padding: p
Stride: s
Filter size: f X f
Output: [(n+2p-f)/s+1] X [(n+2p-f)/s+1]
Stride helps to reduce the size of the image, a particularly useful feature.

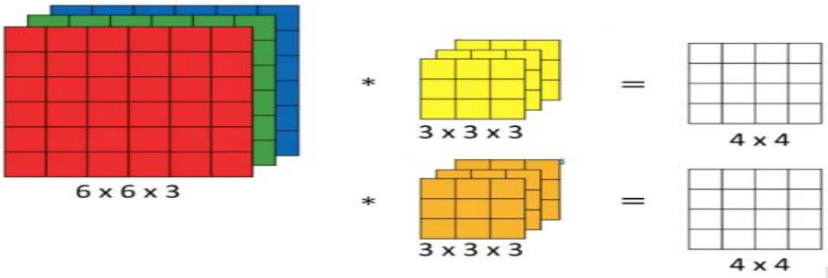
Convolutions Over Volume

Suppose, instead of a 2-D image, we have a 3-D input image of shape 6 X 6 X 3. How will we apply convolution on this image? We will use a 3 X 3 X 3 filter instead of a 3 X 3 filter. Let's look at an example:

- **Input:** 6 X 6 X 3
- **Filter:** 3 X 3 X 3

The dimensions above represent the height, width and channels in the input and filter. Keep in mind that the number of channels in the input and filter should be same**.** This will result in an output of 4 X 4. Let's understand it visually:

Since there are three channels in the input, the filter will consequently also have three channels. After convolution, the output shape is a 4 X 4 matrix. So, the first element of the output is the sum of the element-wise product of the first 27 values from the input (9 values from each channel) and the 27 values from the filter. After that we convolve over the entire image.



Instead of using just a single filter, we can use multiple filters as well. How do we do that? Let's say the first filter will detect vertical edges and the second filter will detect horizontal edges from the image. If we use multiple filters, the output dimension will change. So, instead of having a 4 X 4 output as in the above example, we would have a 4 X 4 X 2 output (if we have used 2 filters):
Generalized dimensions can be given as:

- **Input:** n X n X n_c
- **Filter:** f X f X n_c
- **Padding:** p
- **Stride:** s
- **Output:** [(n+2p-f)/s+1] X [(n+2p-f)/s+1] X n_c'

Here, n_c is the number of channels in the input and filter, while n_c' is the number of filters.

One Layer of a Convolutional Network

Once we get an output after convolving over the entire image using a filter, we add a bias term to those outputs and finally apply an activation function to generate activations. *This is one layer of a convolutional network*. Recall that the equation for one forward pass is given by:

$z^{[1]} = w^{[1]} * a^{[0]} + b^{[1]}$

$a^{[1]} = g(z^{[1]})$

In our case, input (6 X 6 X 3) is $a^{[0]}$and filters (3 X 3 X 3) are the weights $w^{[1]}$. These activations from layer 1 act as the input for layer 2, and so on. Clearly, the number of parameters in case of convolutional neural networks is independent of the size of the image. It essentially depends on the filter size. Suppose we have 10 filters, each of shape 3 X 3 X 3. What will be the number of parameters in that layer? Let's try to solve this:

- Number of parameters for each filter = 3*3*3 = 27
- There will be a bias term for each filter, so total parameters per filter = 28
- As there are 10 filters, the total parameters for that layer = 28*10 = 280

No matter how big the image is, the parameters only depend on the filter size. Awesome, isn't it? Let's have a look at the summary of notations for a convolution layer:

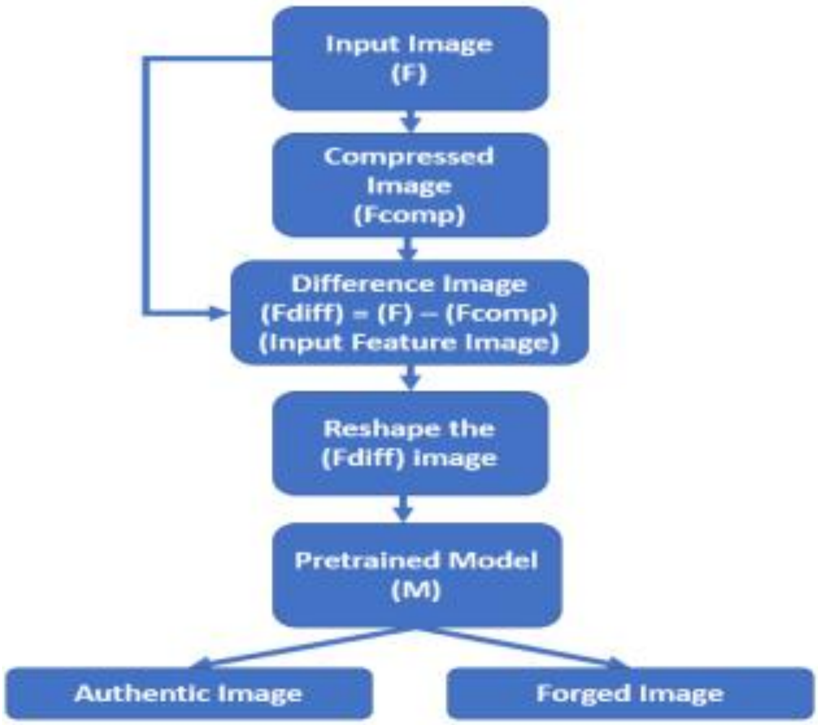
- $f^{[l]}$ = filter size
- $p^{[l]}$ = padding
- $s^{[l]}$ = stride
- $n_{[c]}^{[l]}$ = number of filters

Let's combine all the concepts we have learned so far and look at a convolutional network example.

V.PROPOSED TECHNIQUE USED OR ALGORITHM USED

CNN model

The advent of digital image manipulation tools has exacerbated the proliferation of image forgeries, necessitating robust solutions for their detection. This project presents a novel approach to address this challenge, utilizing Python and Convolutional Neural Network (CNN) model architecture. The CNN model, employed as the core of our forgery detection system, has exhibited remarkable performance.



With a training accuracy of 98% and a validation accuracy of 92%, it showcases its efficacy in distinguishing authentic from tampered images. The dataset utilized in this study comprises 12,615 images, consisting of 7,492 authentic (real) images and 5,123 tampered (fake) images, providing a diverse and extensive testbed for evaluation.To enhance the precision of our approach, we incorporate Error Level Analysis (ELA) as a preprocessing step. Each image is resized to a standardized 256x256 resolution, after which ELA is applied. ELA aids in the identification of regions within an image that exhibit varying compression levels. In an untampered image, all regions should exhibit uniform compression. Deviations from this uniformity may indicate digital manipulation. The processed images are stored as numpy arrays for subsequent analysis.

In the future, an enhancement to the proposed technique can be added to increase the detection accuracy rate, keeping in mind the minimization of the training time and computational cost. Additionally, image forgery type detection, splicing, or copy move, can be extended with localization. The combination of the proposed approach with other known image localization techniques will improve the accuracy, but it may increase the time complexity so it will need more improvement. The detection of forged videos that may be created by merging several videos is an incredibly challenging task.

VI. CONCLUSION

Image forgery detection techniques have become essential with the increased availability of image editing tools that can create forged. The paper presented an image forgery detection technique based on deep learning via a pre-trained model and transfer learning. The proposed technique considered the difference between an image and its compressed version to produce a featured image as an input to a pre-trained model that improved the detection accuracy rate. The technique with a given data set was applied to eight different pre-trained models adapted for binary classification. The recorded experimental results were compared with the state-of-the-art method. The results showed that using pre-trained models help achieve a higher detection accuracy rate than the state of the art which used CNN model.

Moreover, comparing the resulting evaluation metrics, charts, and graphs, for the eight pre-trained models, it was found that MobileNetV2 had the highest detection accuracy rate (around 95%) with a smaller number of training parameters which led to faster training, and lower computational costs, and lower system complexity and low memory consumption. So, it is highly recommended as a backbone with the image compression technique that effectively detects image splicing and copy-move at the same time with highly encouraging results.

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