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DETECTION OF IMAGE FORGERY FOR COPYRIGHT APPLICATIONS USING DEEP LEARNING

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ABSTRACT:

Technical evolution of the world is conquering; the trust on digital imaging technology is grinding down. Image forgery is the process of manipulating/ changing an original photo into different kinds. Now a day, people can easily tamper/forged image from tabloid magazines to the business industry due to the availability of powerful image processing & editing software i.e., Photoshop, ai etc. It could be done by the use of various techniques such as copy move, splicing of images, and image retouching. Image tampering can be a creative work. However, in some cases it is not good, since images appear to be proof for medical reports, crime scenes, etc. The result is death of patients and escape of criminals, respectively. Conventional methods in the literature for image forgery detection are based on traces developed while manipulations are performed on images. Most of such traces are confined to the scope of predefined assumptions about handcrafted features, size, and contrast. This paper proposes a fusion-based decision approach for the detection of forged images. So, the lightweight deep learning models employed in this fusion decision technique are Squeeze Net, MobileNetV2, and Shuffle Net. In this regard, the system of fusion decision will be implemented in two phases. First of all, the pre-trained weights of lightweight deep learning models were considered to evaluate the forgery of the images. Then, the results were compared with the fine-tuned weights of forgery of the images with pre-trained models. Experimental results prove that the proposed fusionbased decision approach ensures better accuracy than state-of-the-art approaches.

1.INTRODUCTION:

Image and video, in the current digital world, have become influential sources of evidence in trials, insurance fraud, and even social networking. The ease with which editing tools can be adapted for digital images without visible evidence of manipulation brings up questions of their authenticity. It is the job of image forensics authorities to develop technological innovations that would detect the forgeries of images. There are three primary classes of manipulation or forgery detectors studies until now: those supported features descriptors, those supported inconsistent shadows and eventually those supported double JPEG compression. With sophisticated software, it is easy to tamper the contents of an image to influence the opinions of others. Various Image forgery techniques are broadly classified into two categories, namely: Copy-move and splicing. In the case of copy-move forgery, elements of the image content area trace and smudge inside a similar image. While in splicing forgery parts of the image content smudge from alternative pictures. To rebuild trust in pictures, various image forgery detection techniques have been proposed over the past few years. So, most of the earlier works tried to extract completely different features from the image that may assist in finding the copy-paste or splicing of forged areas like lighting, shadows, sensing element noise, and camera reflections. The researchers determined credibility associated with the image and any place wherever it's known whether authentic or forged. Currently, various techniques exist that determines fake regions by exploiting the clues left by multiple JPEG compression and other image processing manipulations to view the forged region.

2.LITERATURE SURVEY:

A Machine Learning Based Approach for Detecting Image Tampering by M. Wu et al. (2018) - In this paper, the authors propose a machine learning based approach for detecting image tampering using local binary patterns (LBP) and support vector machines (SVM). The proposed method achieved an accuracy of 73.4% on a dataset.

Deep Learning-based Image Forgery Detection using Multi-Channel Convolutional Neural Networks by D. Kim et al. (2019) - In this paper, the authors propose a deep learning-based approach for detecting image forgeries using multi-channel CNNs. The proposed method achieved an accuracy of 81.1% on a dataset of real and forged images.

Image Forgery Detection using Machine Learning: A Comparative Study by N. Naik et al. (2020) - In this paper, the authors provide a comparative study of various machine learning-based approaches for detecting image forgeries, including SVM, k-nearest Neighbours (k-NN), decision tree, and random forest. The highest accuracy achieved in this study was 77.5% using a random forest classifier.

He et al. proposed a Markov based approach to detect this specific artifact. Firstly, the original Markov features generated from the transition probability matrices in DCT domain by Shi et al. is expanded to capture not only the intra-block but also the inter-block correlation between block DCT coefficients.

Change et al. proposed a novel forgery detection algorithm to recognize tampered inpainting images, which is one of the effective approaches for image manipulation. The proposed algorithm contains two major processes: suspicious region detection and forged region identification. Suspicious region detection searches the similarity blocks in an image to find the suspicious regions and uses a similarity vector field to remove the false positives caused by uniform area. Forged region identification applies a new method, multi region relation (MRR), to identify the forged regions from the suspicious regions. The proposed approach can effectively recognize if an image is a forged one and identify the forged regions, even for the images containing the uniform background. Moreover, this paper proposed a two-stage searching algorithm based on weight transformation to speed up the computation speed.

3.EXISTING SYSTEM:

In existing system the image forgery detection is done based on basic Machine Learning using SIFT(scale-invariant feature transform) with SVM(Support Vector Machine) extraction. In this model is trained by using original and forged images dataset.

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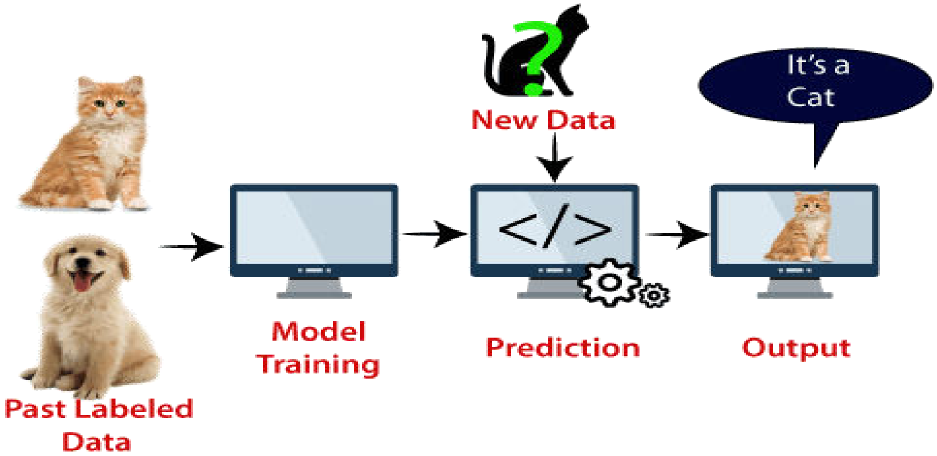
Support Vector Machine Algorithm:

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future.
This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane.



4.PROBLEM STATEMENT:

The challenge lies in developing a robust system that can accurately identify whether an image has been altered or forged, ensuring that copyright owners can validate the originality of their work. Traditional forensic techniques are often ineffective in detecting sophisticated manipulations such as copy-move, splicing, or deepfake alterations. Deep learning has shown potential in automating the process of forgery detection, but the problem remains complex due to the variety of manipulations and the quality of forged images that are increasingly indistinguishable from original content.

5.PROPOSED SYSTEM:

The architecture of the proposed decision fusion is based on the lightweight deep learning models as shown in Figure 4.1. The lightweight deep learning models chosen are SqueezeNet, MobileNetV2, and ShuffleNet. The proposed system is implemented in two phases i.e., with pre-trained and fine-tuned deep learning models. In the pre-trained model's implementation, regularization is not applied, and the pre-trained weights are used and for the fine-tuned implementation, regularization is applied to detect image forgery. Each phase consists of three stages namely, data pre-processing, classification, and fusion. In the data pre-processing stage, the image in the query is pre-processed based on the dimensions

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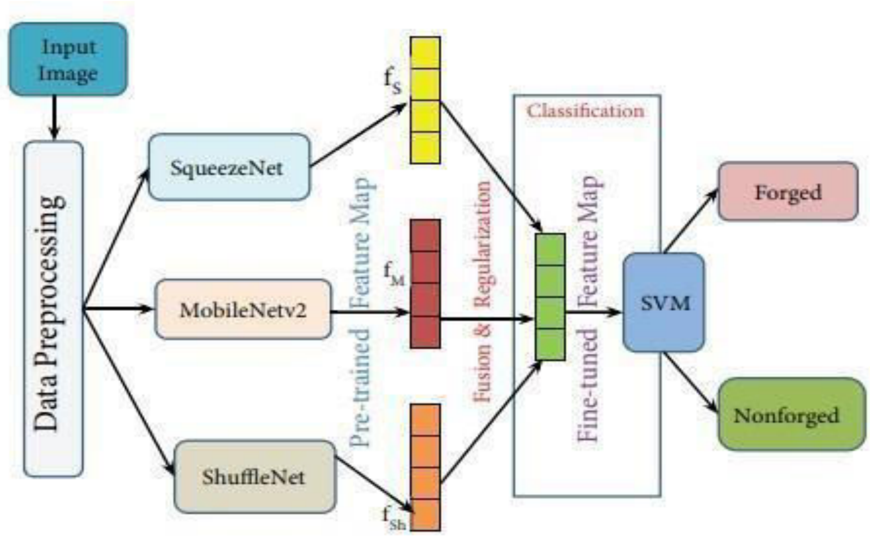
required by the deep learning models. SVM is used for the classification of the image as forged or non-forged. Initially, we discuss the lightweight deep learning models and then the strategy used for the regularization is discussed in the further sections.



1.Data preprocessing:

In this stage, the image in a query that needs to be identified whether it is forged or not is subjected to preprocessing. The height and width of the image required for SqueezeNet is 227×227. The height and width of the image required for MobileNetV2 is 224×224. The height and width of the image required for ShuffleNet is 224×224. The input image is pre-processe first based on the dimensions required for each of the models. Each model then takes the input image to produce feature vector in further stages.

2.Lightweight deep learning models:

The different lightweight deep learning models that are considered for fusion are SqueezeNet, MobileNetV2, and ShuffleNet. These models are used for the image classification problems numerously. In this section, these models are discussed briefly. The lightweight models1 considered are summarized as shown in the Table 1. It represents the depth, parameters and the image input size required for the lightweight models namely, SqueezeNet, MobileNetV2, and ShuffleNet.

3.Squeeze Net:

It is a CNN trained on the ImageNet dataset with 18 layers deep and can classify the images up to 1000 categories. The network has learned rich representations of the images with 1.24 million parameters. It requires only a few floating-point operations for the image classification.

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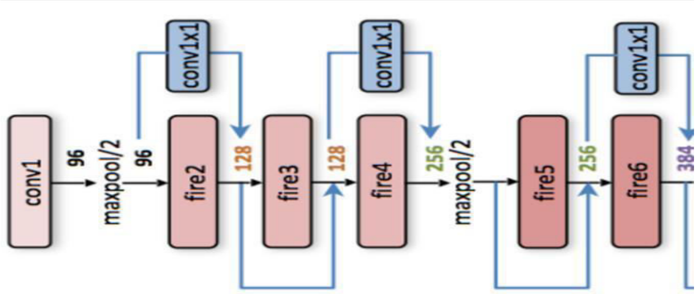
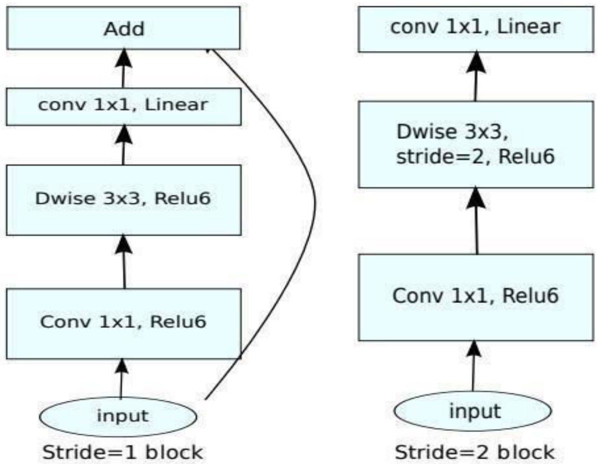


4. Mobile NetV2:

It is a CNN trained on the ImageNet dataset with 53 layers deep and can classify the images up to 1000 categories. The performance of the classification is improved based on the learning of the rich representations of the images.



5. Shuffle Net:

It is a CNN that is also trained on the ImageNet dataset with 50 layers deep and can classify the images up to 1000 categories. Table 1. Parameters of lightweight deep learning models. (Depth represents the largest number of sequential convolutional or fully connected layers on a path from the input layer to the output layer, parameter represents the total number of learnable parameters in each layer and image input size represents the required input image size)

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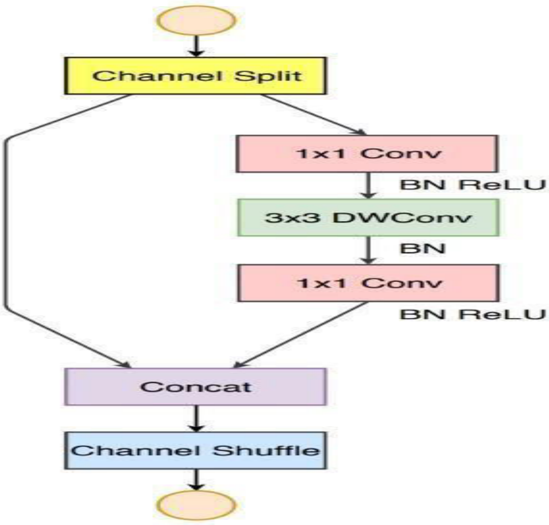
Models	Depth	Parameter (millions)	Image input size
SqueezeNet	18	1.24	227 × 227
MobileNetV2	53	3.5	224 × 224
ShuffleNet	50	1.4	224 × 224



6. IMPLEMENTATION:

There are five steps of implementations

Step 1: Dataset creation create a dataset that consists of forged and nonforged images

Step 2: Image pre-processing Image pre-processing involves various steps They are

-Image resizing

-Normalization

Step 3: light weight deep learning model

Apply Shuffle net, Mobile net, Squeeze net to the image dataset

Step 4: Support Vector Machine

Apply SVM algorithm to the image dataset

Step 5: Result

Based on the features extracted from light weight deep learning model, SVM classifies forged and non - forged images

7. CONCLUSION:

Image forgery detection helps to differentiate between the original and the manipulated or fake images. In this work, a decision fusion of lightweight deep learning-based models is implemented for image forgery detection. The idea was to use the lightweight deep learning models namely SqueezeNet, MobileNetV2, and ShuffleNet and then combine all these models to obtain the decision on the forgery of the image. Regularization of the weights of the pretrained models is implemented to arrive at a decision of the forgery. The experiments carried out indicate that the fusion-based approach gives more accuracy than the state-of-the-art approaches. In the future, the fusion decision can be improved with other weight initialization strategies for image forgery detection.

8. FUTURE SCOPE:

In future, light weight deep learning model for image forgery detection will be likely become more prevalent. These models will offers several benefits such as faster processing times, lower memory requirements and the ability to work on resource constrained devices.

Researchers will explore innovative technologies as architectures that can effectively detect a wide range of image manipulations, including but not limited to splicing, cloning, retouching and content-aware manipulation.

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