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IMAGE FORGERY DETECTION BASED ON FUSION OF LIGHT WEIGHT DEEP LEARNING MODELS

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Abstract- Image forgery detection is one of the key challenges in various real time applications, social media, and online information platforms. The conventional methods of detection based on the traces of image manipulations are limited to the scope of predefined assumptions like hand-crafted features, size, and contrast. In this paper, we propose a fusion based decision approach for image forgery detection. The fusion of decision is based on the lightweight deep learning models namely Squeeze Net, MobileNetV2 and Shuffle Net. The fusion decision system is implemented in two phases. First, the pretrained weights of the lightweight deep learning models are used to evaluate the forgery of the images. Secondly, the fine-tuned weights are used to compare the results of the forgery of the images with the pre-trained models. The experimental results suggest that the fusion-based decision approach achieves better accuracy as compared to the state-of-the-art approaches.

KEYWORDS: Image forgery, Decision Approach, Deep Learning, Squeeze Net, MobileNetV2.

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1. INTRODUCTION

In this digital era, images and videos are being used as influential sources of evidence in a variety of contexts like evidence during trials, insurance fraud, social networking, etc. The easy adaptability of editing tools for digital images, especially without any visual proof of manipulation, give rise to questions about 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 the image to influence the opinions of others. Image forgery techniques are broadly classified into two categories namely copy-move and splicing. For copy-move forgery, elements of the image content area are traced and smudge inside a similar image, whereas for splicing forgery, parts of the image content smudge from alternative pictures. To reconstruct the trust in pictures, various image forgery detection techniques have been proposed over the past few years. Many previous studies have tried to extract totally different properties from the image to spot the copy-paste or splicing of forged areas, such as the lighting, shadows, sensing element noise, and camera reflections.

Researchers determined the credibility of the image wherever it is known either as authentic or forged. Currently, there are many techniques to spot forged regions that exploits the artefacts left by multiple JPEG compression and other techniques of image manipulation to sight the forged regions. Camera primarily based ways have additionally analyzed where the detection relies on demosaicing regularity or sensing element pattern noise wherever the irregularities of the sensing element pattern area unit extracted and compared for anomalies.

An approach of decision fusion-based system is proposed using the lightweight for the image forgery detection. The lightweight models used for the fusion decision are Squeeze Net, MobileNetV2, and Shuffle Net.

2. LITERATURE SURVEY

Detection of Copy-Move Forgery in Digital Images

Digital images are easy to manipulate and edit due to availability of powerful image processing and editing software. Nowadays, it is possible to add or remove important features from an image without leaving any obvious traces of tampering. As digital cameras and video cameras replace their analog counterparts, the need for authenticating digital images, validating their content, and detecting forgeries will only increase. Detection of malicious manipulation with digital images (digital forgeries) is the topic of this paper. We focus on detection of a special type of digital forgery – the copy-move attack in which a part of the image is copied and pasted somewhere else in the image with the intent to cover an important image feature. In this paper, we investigate the problem of detecting the copy-move forgery and describe an efficient and reliable detection method. The method may successfully detect the forged part even when the copied area is enhanced/retouched to merge it with the background and when the forged image is saved in a lossy format, such as JPEG. The performance of the proposed method is demonstrated on several forged images.

Digital Image Forgery Detection Based on Lens and Sensor

A new approach to detecting forgery in digital photographs is suggested. The method does not necessitate adding data to the image (such as a Digital Watermark) nor require other images for comparison or training. The fundamental assumption in the presented approach is the notion that image features arising from the image acquisition process itself or due to the physical structure and characteristics of digital cameras, are inherent proof of authenticity and they are sensitive to image manipulation as well as being difficult to forge synthetically. Typically, such features do not affect image content nor quality and are often invisible to the inexperienced eye. The approach presented in this work is based on the effects introduced in the acquired image by the optical and sensing systems of the camera. Specifically, it exploits image artifacts that are due to chromatic aberrations as indicators for evaluating image authenticity.

3. EXISTING SYSTEM:

The development of deep learning has led to improving methodologies where state-of-the-art methods, such as CNN, Mobile Net, and ResNet50v2, automatically extract the potential features, having been trained on large datasets. Some of the examples of CNN-based feature extractions are deep features utilized for image quality assessment, skin lesion classification, or person re-identification. These extracted features are adapted into the inherent structural patterns of the data. This is the main reason behind their non-discriminative and robust architecture compared to the hand-engineered features. In this project, motivated by the deep learning technique, we propose a transfer learning-based approach.

DISADVANTAGES OF EXISTING SYSTEM:

1) Less accuracy

2)low Efficiency

4. PROPOSED SYSTEM:

The architecture of the proposed decision fusion is based on the lightweight deep learning models as shown in Figure. The lightweight deep learning models chosen are Squeeze Net, MobileNetV2, and Shuffle Net. 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 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 section.

ADVANTAGES OF PROPOSED

SYSTEM:

1) High accuracy

2)High efficiency

5. MODULES:

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.

MobileNetV2

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.

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.

5. RESULTS

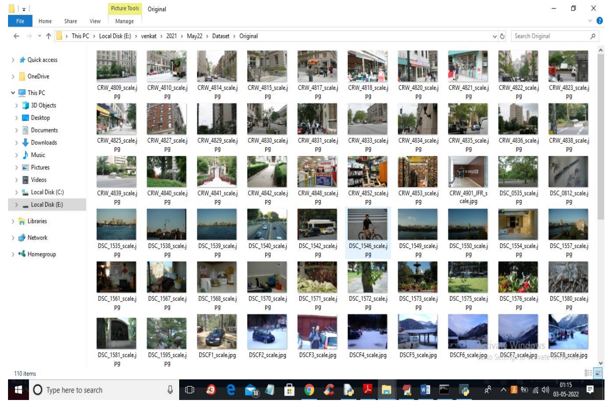


Fig1. So, by using above images we will train all algorithms and calculate their performances**.**

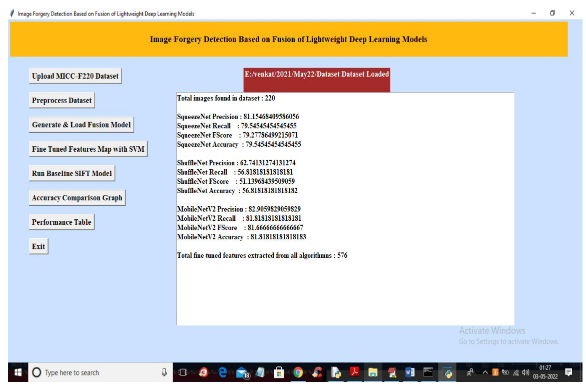


Fig 2.In above screen we can see accuracy of all 3 algorithms and then in last line we can see from all 3 algorithms application extracted 576 features and now click on 'Fine Tuned Features Map with SVM' to train SVM with extracted features and get its accuracy as fusion model.

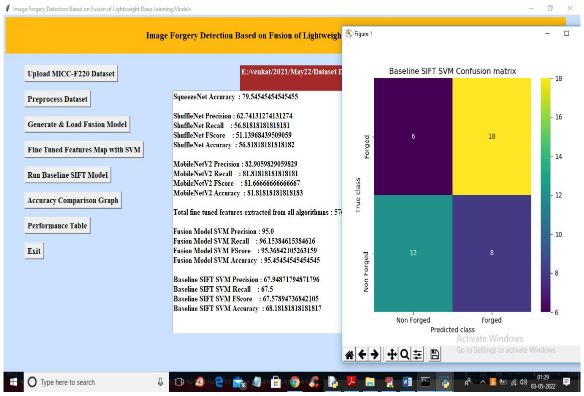


Fig 3.In above screen with existing SIFT SVM features we got 68% accuracy and in confusion matrix graph we can see existing SIFT predicted 6 and 8 instances incorrectly. So we can say existing SIFT features are not good in prediction and now close above graph and then click on ‘Accuracy Comparison Graph’ button to get below graph.

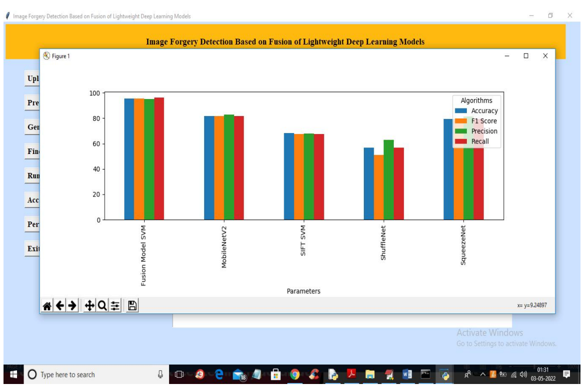
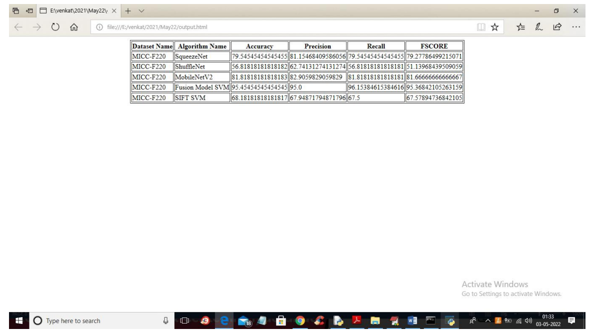


Fig 4.where each different color bar represents different metrics like precision, recall etc. Now close above graph and then click on ‘Performance Table’ button to get result in below tabular format.



Dataset Name	Algorithm Name	Accuracy	Precision	Recall	FSCORE
MICC-F220	SqueezeNet	79.54545454545455	81.15468409586056	79.54545454545455	79.27786499215071
MICC-F220	ShuffleNet	56.81818181818182	62.74131274131274	56.81818181818181	51.13968439509059
MICC-F220	MobileNetV2	81.81818181818183	82.9059829059829	81.81818181818181	81.66666666666667
MICC-F220	Fusion Model SVM	95.45454545454545	95.0	96.15384615384616	95.36842105263159
MICC-F220	SIFT SVM	68.18181818181817	67.94871794871796	67.5	67.57894736842105

Fig 5.In above screen we can see propose fusion model SVM with fine tune features has got 95% accuracy which is better than all other algorithms.

7. CONCLUSION

Image forgery detection helps to differentiate between the original and the manipulated or fake images. In this paper, 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 Squeeze Net, MobileNetV2, and Shuffle Net 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. REFERENCES

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