RECOLORED IMAGE DETECTION VIA A DEEP DISCRIMINATIVE MODEL

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ABSTRACT

Near duplicate image detection needs the matching of a bit altered images to the original image. This will help in the detection of forged images. A great deal of effort has been dedicated to visual applications that need efficient image similarity metrics and signature. Digital images can be easily edited and manipulated owing to the great functionality of image processing software. This leads to the challenge of matching somewhat altered images to their originals, which is termed as near duplicate image detection. This paper discusses the literature reviewed on the development of several image matching algorithms. Image recoloring is a technique that can transfer image color or theme and result in an imperceptible change in human eyes. Although image recoloring is one of the most important image manipulation techniques, there is no special method designed for detecting this kind of forgery. In this paper, we propose a trainable end-to-end system for distinguishing recolored images from natural images. The proposed network takes the original image and two derived inputs based on illumination consistency and inter-channel correlation of the original input into consideration and outputs the probability that it is recolored. Our algorithm adopts a CNN-based deep
architecture, which consists of three feature extraction blocks and a feature fusion module. To train the deep neural network, we synthesize a dataset comprised of recolored images and corresponding ground truth using different recoloring methods. Extensive experimental results on the recolored images generated by various methods show that our proposed network is well generalized and much robust.

Keyword: ***.python,Django,GUI,windows OS,OPENCV,Tensorflow,HTML,CSS,Javascript etc***

EXISTING SYSTEM:

Forgery detection methods intend to verify the authenticity of images and can be broadly classified into two classes: active authentication and passive authentication. In active authentication techniques, data hiding techniques are employed where some codes are embedded into the images
during generation. These codes are used for further verifying to authenticate the originality of image. Active authentication methods can be further classified into two types: digital signatures and digital watermarking. Watermarking embeds watermarks into images at the time of image acquisition while digital signatures embed some secondary information extracted from images at the acquisition end into the images. Lots of work has been proposed in both digital watermarking and digital signatures. For example, two image authentication algorithms are proposed in to embed an image digest based on error diffusion half toning technique, into the image in the Integer Wavelet Transform domain and

the Discrete Cosine Transform domain, respectively. Lu et al. construct a structural digital signature using image content information in the wavelet transform domain for image authentication. The main drawback of these approaches remains that they must be inserted at the time of recording, which limits these approaches to specially equipped digital cameras. In addition, the prior information is necessary for an authentication process.

DISADVANTAGE:

We are the first attempt to distinguish recolored images from natural images.We analyze the inter-channel correlation and illumination consistency for natural images which may not hold after the color transfer operation. Based on these two properties, we propose a deep discriminative model for recoloring detection.We generate a large-scale and high-quality training dataset for training the proposed network and create a benchmark dataset consisting of 100 skillfully recolored images and the corresponding 100 original photographs for testing.

Proposed Method:

Existing forgery detection methods adopt some description techniques to combine the information attained by evidence estimators. However, every description technique has its own limitations and drawbacks. Recently, CNNs have shown an explosive popularity in image classification and
other computer vision tasks. Traditional neural networks employ the original image in RGB channels as the input since it contains information about the picture such as color and structural features. In this paper, we use three feature extractors and a feature fusion module to learn forgery-relevant features. The flowchart of our proposed approach is We adopt the
original image as one of the input branches like traditional neural networks. Additionally, we derive DIs and IM as two pieces of evidence of image recolored detection based on the observations that images may not maintain the inter-channel correlation or illuminant consistency after the recoloring process. These two pieces of evidence are employed as two
additional input branches together with the original image. The network architecture can be found in. Since the learned features are based on a data-driven approach, they are able to describe the intrinsic properties of forgery formation and help distinguishing the authenticity of an image. After extracting forgery-relevant features, we use a feature fusion network to refine these features and output the probability of authenticity. Based on this premise, we evaluate the proposed algorithm on forged images generated by various color transfer methods and the images collected through the Internet.

ARCHITECTURE:

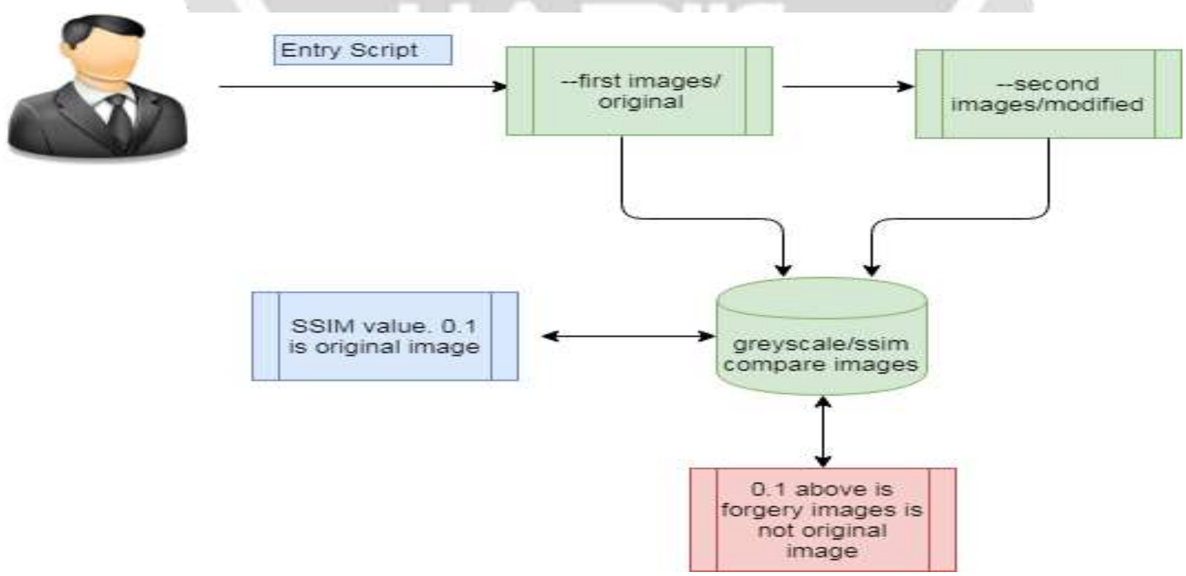


Figure1:Architecture of proposed method

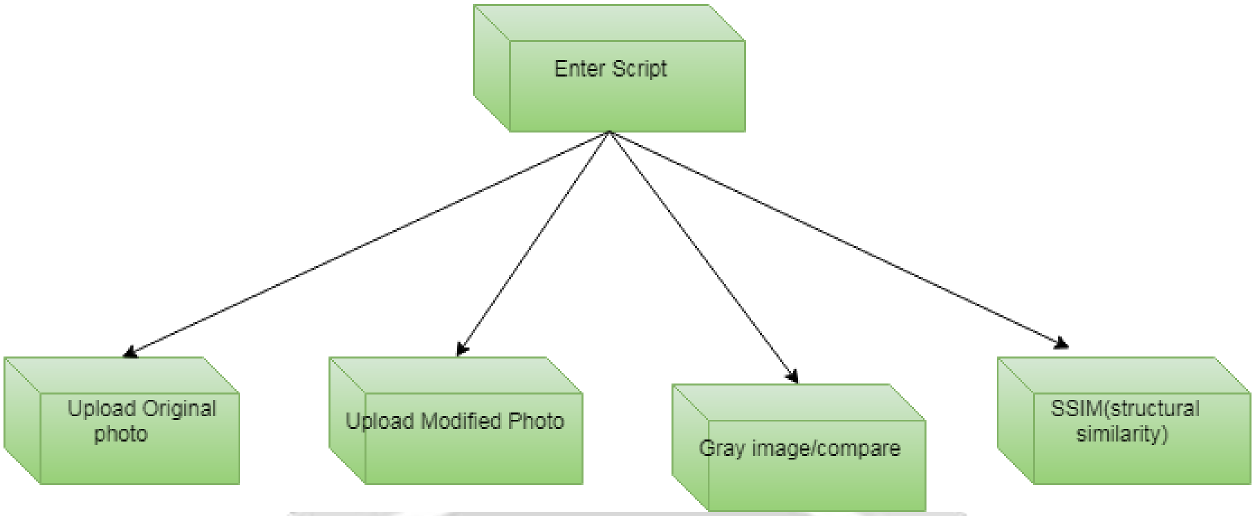


Figure2.Component diagram

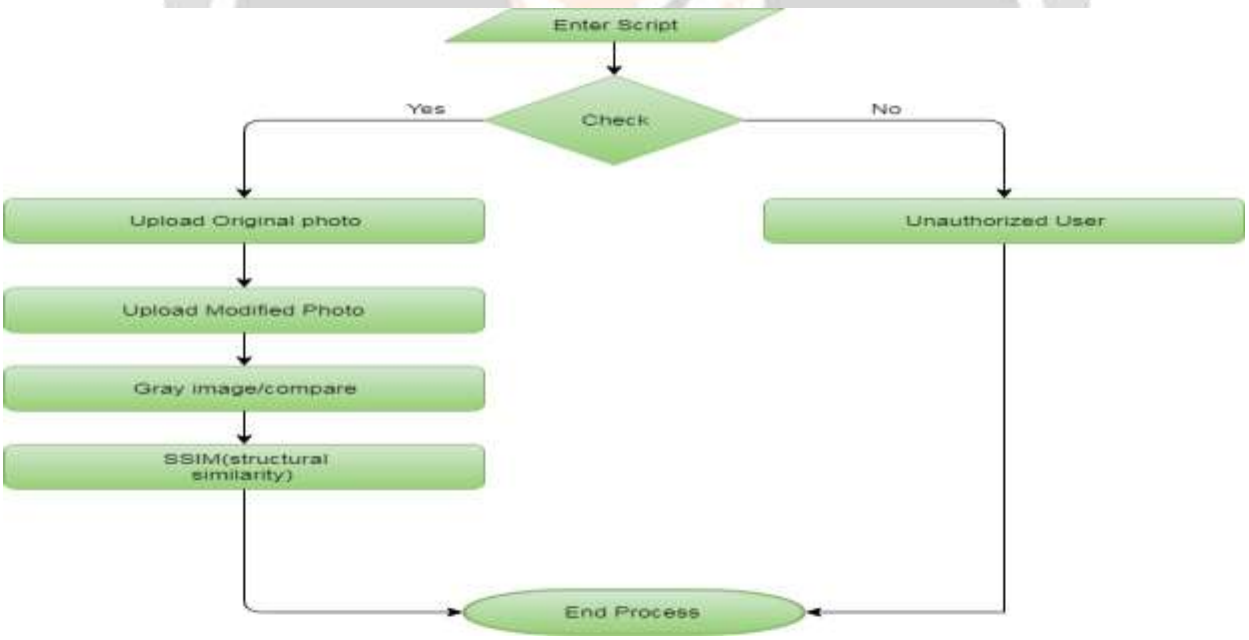


Figure3:Pipeline flow

MODULES:

VISUAL INFORMATION DESCRIPTION:

Visual descriptors give statistics about an image. A good descriptor permits to discriminate between similar and dissimilar images. Note that the notion of similarity highly depends on the application. For instance, similarity means “visually consistent images” in the framework of image retrieval while it signifies “visually nearly identical” in duplicate detection. There exist many published surveys on image description, the reader can refer for surveys centered around image description for content-based image retrieval applications. In the following, four types of low-level image descriptors are presented.

DUPLICATE DETECTION:

Duplicate detection is a task that aims at detecting the duplicates of an original image. Consequently, it is first necessary to define what a duplicate is. In short, a duplicate is a transformed version of an original artwork that keeps a similar visual value. In other words, ‘being a duplicate’ is a pairwise equivalence relationship that links the original to any of its variations through a transformation operation, for example, compression, brightness changes or cropping. By extension, if an image A is a duplicate of another image B and yet another image C is duplicate of image B, then image C is in turn a duplicate of image A. Finally, the task of duplicate detection can be expressed as follows. Duplicate detection aims at detecting all the duplicates of a particular image among a collection of images. Or in a simplified form, duplicate detection’s goal is to determine whether two given images are duplicates of each other or unrelated to each other

VISUAL ATTENTION SIMILARITY MEASURE:

human visual attention is enhanced through a process of competing interactions among neurons representing all of the stimuli present in the visual field. The competition results in the selection of a few points of attention and the suppression of irrelevant material. In this context of visual attention, we argue that humans are able to spot anomalies in a single image or similarity between two images through a competitive comparison mechanism, where dissimilar and similar regions are identified and scored by means of a new similarity measure. The comparison is a flexible and dynamic procedure, which does not depend on a particular feature space which may be thought to exist in a general image database

GRAYSCALE IN IMAGE PROCESSING:

Grayscale is the collection or the range of monochromic (gray) shades, ranging from pure white on the lightest end to pure black on the opposite end. Grayscale only contains luminance (brightness) information and no color information; that is why maximum luminance is white and zero luminance is black; everything in between is a shade of gray. That is why grayscale images contain only shades of gray and no color.

Grayscale is also known as achromatic.

ALGORITHM:

Structural similarity:

Differences with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate *absolute errors*; on the other hand, SSIM is a perception-based model that considers image degradation as *perceived change in structural information*, while also incorporating important perceptual phenomena, including both luminance masking and contrast masking terms. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene. Luminance masking is a phenomenon whereby image distortions (in this context) tend to be less visible in bright regions, while contrast masking is a phenomenon whereby distortions become less visible where there is significant activity or "texture" in the image.

The SSIM index is calculated on various windows of an image. The measure between two windows x and y of common size $N \times N$ is:[4]

where μ_x, μ_y, σ_x,σ_y, and σ_{xy} are the local means, standard deviations, and cross-covariance for images *x, y*. If $\alpha = \beta = \gamma = 1$ (the default for Exponents), and $C_3 = C_2/2$ (default selection of C_3) the index simplifies to:

$$SSIM^{(x,y)=}(2\mu^{x}\mu^{y}+C^{1})(2\sigma^{xy}+C^{2})(\mu^{2x}+\mu^{2y}+C^{1})(\sigma^{2x}+\sigma^{2y}+C^{2})$$

REQUIREMENT ANALYSIS:

The project involved analyzing the design of few applications so as to make the application more users friendly. To do so, it was really important to keep the navigations from one screen to the other well ordered and at the same time reducing the amount of typing the user needs to do. In order to make the application more accessible, the browser version had to be chosen so that it is compatible with most of the Browsers.

Hardware Requirements:

For developing the application, the following are the Hardware Requirements:

- Processor: Pentium IV or higher
- RAM: 256 MB
- **Space on Hard Disk: minimum 512MB**

ADVANTAGES:

- Free space is ignored.
- The layout of the files on the disk is ignored.

OutCome:

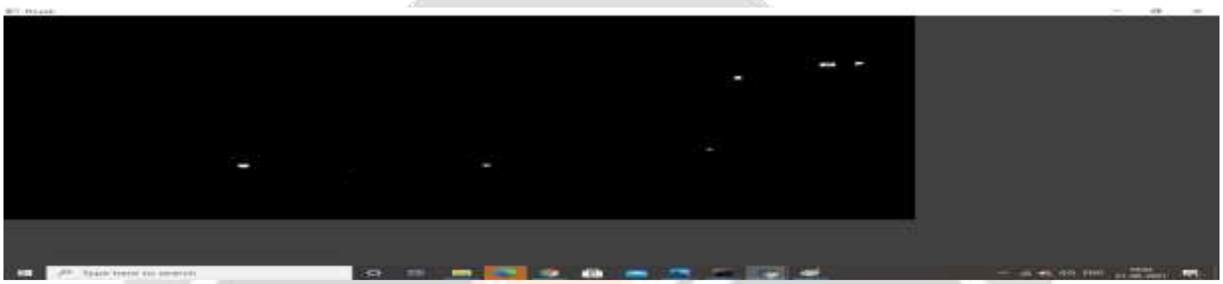
Recoloured output:

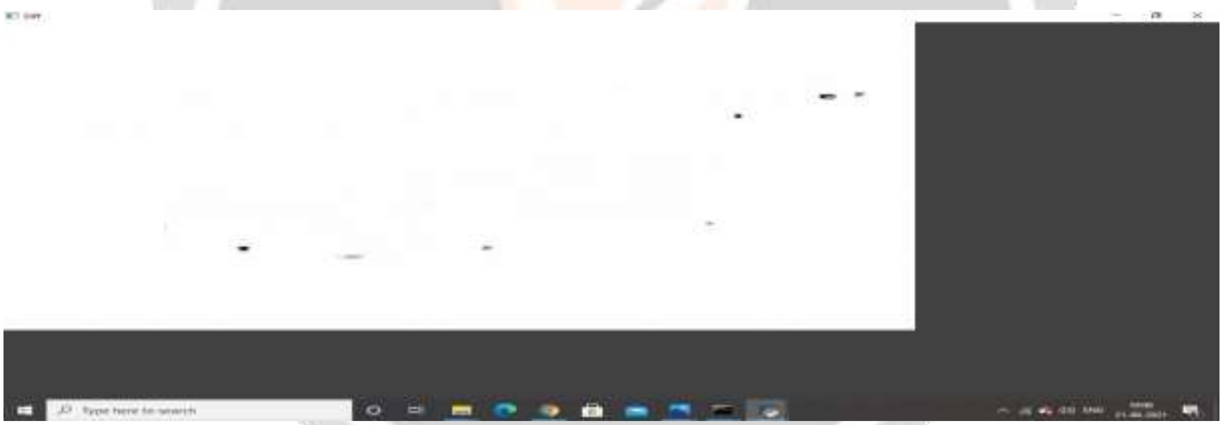
Figure a :input image

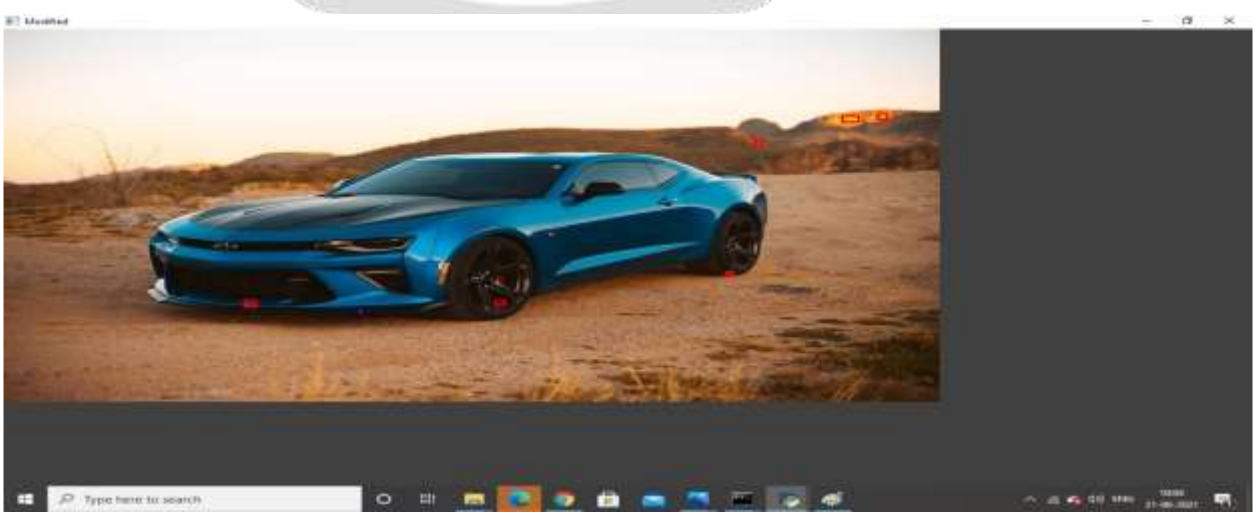
figure b.Grayscale image

figure c:black and white thresholded image

figure d:Modified output image







Conclusion:

In this work, we present a novel deep learning approach for recolored image detection. Both the inter-channel correlation and the illumination consistency are employed to help the feature extraction. We elaborate the design principle of our Recent and systematically validate the rationality by running a number of experiments. Furthermore, two recolored datasets with different sources are created and the high performance of our Recent demonstrates the effectiveness of the model. We hope our simple yet effective Recent will serve as a solid baseline and help future research in recolored images detection. Our future work will focus on designing a more effective network architecture and searching for some high-level cues for better distinguishing.

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