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Fake Colorized Images Detection Using CNN Classifier

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ABSTRACT: With the wide convenience of powerful media redaction tools, it becomes copious easier to regulate digital pictures. Image colorization achieves ton of realistic results with the increasing developments in deep learning techniques. Thus there is an increased concern regarding the trait of digital images. Effective forensic techniques desperately needed to verify the genuineness, originality, and integrity of digital pictures. It becomes more durable to identify the fake colorized images by human eyes. During this work, a unique theoretical methodology is planned to tell apart between natural images (NIs) and colorized images (CIs) supported convolutional neural network (CNN).

KEYWORDS: Colorization, Deep Learning, NI, CI, CNN.

I.INTRODUCTION

Current advanced colorization algorithms, more or less leveraging the powerful capacity of deep neural networks, can automatically colorize the grayscale images to get the high-quality color images. Fig. 1 shows a pair of images, the right one is the natural color image and the left one is a colorized image produced by a colorization algorithm that takes the grayscale version of the right one as input. Obviously, it's difficult to differentiate which one is colorized image by naked human eyes. Although this technique brings convenience to people's live, it may also be maliciously used and potentially lead to security issues, such as confounding object recognition or scene understanding [2]. Therefore, distinguishing between natural images (NIs) and colorized images (CIs) has become a crucial research problem in image forensics.

The paper describes following areas. A review of colorization, CNN and fake colorized image detection have presented in initial section. In second section, I tend to discuss block diagram and outline of every block. Third section presents experimental results. In fourth Section, I concluded the paper and references are provided.

Fig.1**:** The left one is a colorized image generated by the colorization method and the right one its natural image.

II. LITERATURE REVIEW

2.1 Review of Colorization

Colorization, a term describing the color adding method to gray scale pictures, was first introduced by Wilson Markle in 1970. However, this space began to develop chop-chop within the twenty-first century. Colorization types are:

Example-based ways sometimes need the users to supervise the system by providing reference color image(s) just like the gray scale image. The system then transfers the colors within the reference color image(s) to the target gray scale image by sorting out similar patterns/objects. The performances of those ways square measure passionate about the standard of the reference image(s). If the divergence between the gray scale image and therefore the reference image(s) is high, the colorized result is also disappointing.

Scribble-based ways square measure supervised techniques within which users begin assignment colors to pixels in the grayscale image. The milestone work, that assumes that the neighboring pixels with similar intensities ought to have similar colors, is planned initially. Various alternative approaches are planned in succession, such as, that constructs dictionaries for color and textures via thin illustration and colorizes the photographs consequently.

In distinction with the supervised approaches higher than, fully automatic ways need no superintendence while playacting the colorization task. It trains a neural network and predicts the chrominance values by considering the component patch, DAISY and semantic options. They colorize the images by conjointly utilizing the native and international priors with a finish-to end network.

2.2 Review of CNN

Initially, Chen et al. [8] projected to use CNN to find median filtering, and obtained important performance improvement compared with ancient strategies. Tuama et al. and Bondi et al. used CNN to accomplish the task of supply camera identification. This powerful tool was also used to tell apart between natural and special effect pictures [10], and to find image forgery. Additionally, Bayar et al. [11] developed alleged affected convolutional neural network to untravel general purpose image manipulation detection drawback. Most of previous CNN-based methods mentioned on top of use typical single stream networks to complete their tasks [8, 7, 10, 11]. Totally different from this conventional design, alternative style selections are thought about, for example injecting extra data to CNN and utilizing multi-stream inputs (i.e., multiple representations of the constant input image in numerous domains). Chen et al. introduced JPEG-phase data into the CNN design to detect trendy JPEG steganography. Another networks took three inputs: original images, noise residuals, and discrete cosine transform (DCT) histograms (with an extra sub-network to cypher DCT histograms), severally. They coalesced the output of DCT-based CNN and noise-based CNN as feature vector, and then trained a random forest to enhance the accuracy within the mixed case of aligned and misaligned compression. At last, to the simplest of information, there is no existing work that considers the “generalization” capability nevertheless for CNN-based image forensics. In fact, this is an extremely challenging situation because no coaching samples of the “unknown” colorization algorithms are obtainable. In alternative words, the trained network to be able to successfully find colorized images generated by new colorization strategies that remain unknown throughout the coaching of CNN.

2.3 Review of Fake Colorized Image Detection

Very recently, Guo *et al.* [2] first introduced two approaches to untravel this new forensic problem. On the idea of applied math distinction between NIs and CIs within the hue, saturation, dark, and bright channels, two methods, namely, histogram- based and Fisher-encoding-based, were designed to catch the distinction. When having obtained the discriminant feature vectors, they trained the support vector machine (SVM) classifiers to spot pretend colorized images. In fact, the classification performance of their methods still has some house for improvement. In FCID-HIST, four detection options, hue feature Fh, the saturation feature Fs, the dark channel feature Fdc and the bright channel feature Fbc, area unit planned to discover forgeries.

Although FCID-HIST offers an honest performance in the experiments, these options may not fully utilize the statistical variations between the natural and faux colorized images because the distributions are modeled channel by channel. Therefore, they propose another theme; Feature Encoding based Fake Colorized Image Detection (FCID-FE), to better exploit the statistical information by together modeling the info distribution and exploiting the divergences inside different moments of the distribution.

FCID-HIST exploits the foremost distinctive bins and total variations of the normalized histogram distributions and creates options for detection, whereas FCID-FE models the info samples with GMM and creates Fisher vectors for higher utilizing the statistical differences.

Both the above algorithms use SVM Classifier. There are many demerits for SVM. SVM algorithm is not suitable for giant data sets.SVM does not perform very alright, when the info set has more noise i.e. target classes are overlapping. In cases where number of features for every datum point exceeds the amount of training data sample, the SVM will underperform. For SVM, there's no probabilistic explanation for the classification.
In order to overcome these disadvantages, CNN Classifier is used in this work. CNN is a smart candidate for image classification and recognition because due to its high accuracy. The most advantage of CNN compared to its predecessors is that it mechanically detects the important options with none human supervision. As an example, given many pictures of cats and dogs it learns distinctive features for every category by itself. CNN is also computationally economical. The SVM does not perform well once the quantity of features is larger than the quantity of samples. Additional work in feature engineering is needed for an SVM than that needed for a multi-layer Neural Network. Convolution Neural Network is non-linear where as support vector machine is a linear classifier. Also error rate is less for CNN than SVM.

III. BLOCK DIAGRAM

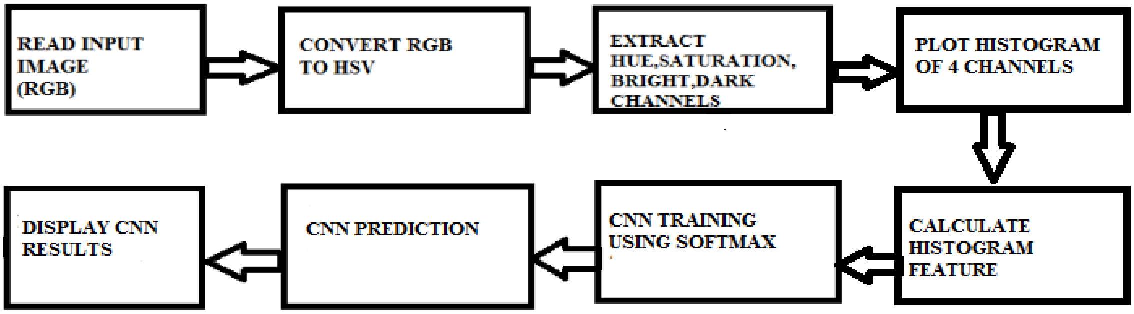

Fig.2**:** Block diagram

3.1 RGB and HSV Color Channel

RGB refers to a model for representing the colors to be used on a screen. RED, GREEN, and BLUE will be combined in numerous proportions to get any change color spectrum. **HSV** color space describes colors in terms of Hue, Saturation, and Value. Operating with HSV values is much easier to isolate colors. Hue determines the color required, saturation determines how intense the color is, and value determines the lightness of image. In RGB, it is difficult to predict how much color is present in an image. In HSV, it is easy to predict from hue value and can capture many details even in moderate lighting conditions.

3.2 Channel Extraction and Histogram Plotting

Extract out hue, saturation, bright and dark channel from the HSV model. Histograms of four channels are plotted. For the hue channel, the histogram of the fake images tends to be smoother and possesses lot of vital peaks compared to the natural images. For the saturation channel, the histogram of the fake images conjointly exhibits different peak values and variances compared to the histogram of the natural images. These statistics indicate that the fake images favour different colors and possess saturation variations compared to the natural images. Therefore, the natural and fake colorized images are statistically identifiable, though the fake colorized images appeared visually indistinguishable.

3.3 Histogram Feature Calculation

Four detection features, the hue feature, the saturation feature, the dark channel feature and the bright channel feature, are proposed to detect forgeries. Each feature calculates the most distinctive bin and the total variation of the normalized histogram distribution for hue, saturation, dark and bright channels, respectively. All these values are saved to a single variable known as histogram feature.

3.4 Convolutional Neural Network and Softmax

Calculated histogram feature is given to a trained CNN Classifier's Softmax Layer. Softmax assigns decimal probabilities to every category during a multi-class drawback. Those decimal probabilities should add up to 1.0. This extra constraint helps training converge additional quickly than it otherwise would. Softmax is enforced through a neural network layer simply before the output layer. The Softmax layer should have an equivalent number of nodes as the output layer. The explanation why softmax is beneficial is because it converts the output of the last layer in your neural network into what is primarily a probability distribution.

If the probability of real image is more, it informs the user with a message box that the image is real. If the probability of colorized image is more it informs the user that the image is colorized. Finally, it is able to predict whether the corresponding image is fake or not.

IV. EXPERIMENTAL RESULTS

Several datasets are widely reused for investigating and analysing different solutions in machine learning. For a thorough analysis of the proposed methods, different databases are constructed for different experiments. Dataset used here is SUN6. Fake colorized images and their corresponding natural images are taken from the SUN6 dataset.

The colorized images tend to possess less saturated colors, and the colorization technique favours some colors over others, though these variations are tough to be visually perceived. Since the Hue Saturation Value (HSV) color space individually represents the chrominance data in the hue and saturation channel, calculate the normalized histograms of the hue and saturation channel of natural images and their corresponding fake colorized images, separately.

4.1 Channel Extraction and Histogram Plotting

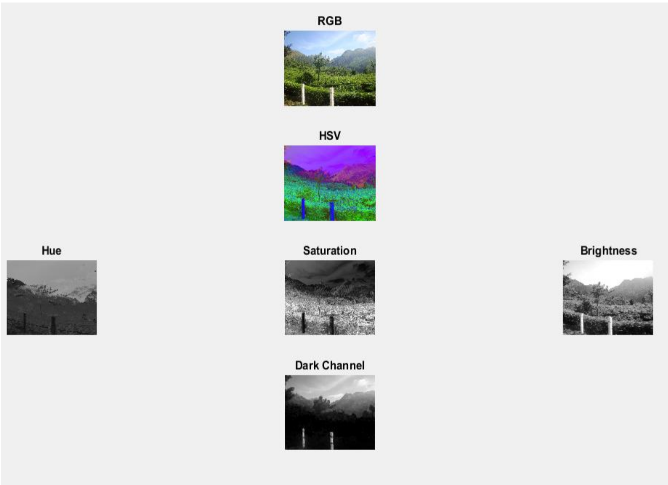

Fig.3**:** Channel extraction

RGB refers to a model for representing the colors to be used on a screen. RED, GREEN, and BLUE will be combined in numerous proportions to get any change color spectrum. **HSV** color space describes colors in terms of Hue, Saturation, and Value. Operating with HSV values is much easier to isolate colors. Hue determines the color required, saturation determines how intense the color is, and value determines the lightness of image. It is discovered that fake colorized images and their corresponding natural images exhibit mathematical variations, which might be further used as detection traces, in each color channels and image prior. The color channels concerned are the hue and saturation channels. Extract out hue, saturation, bright and dark channel from the HSV model.

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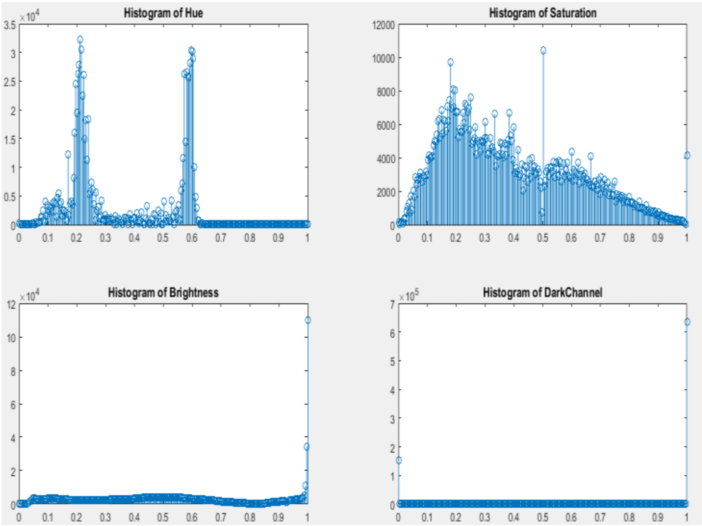

Fig.4: Histogram plot

Histograms of four channels are plotted. For the hue channel, the histogram of the fake images tends to be smoother and possesses lot of vital peaks compared to the natural images. For the saturation channel, the histogram of the fake images conjointly exhibits different peak values and variances compared to the histogram of the natural images. These statistics indicate that the fake images favor different colors and possess saturation variations compared to the natural images. Therefore, the natural and fake colorized images are statistically identifiable, though the fake colorized images appeared visually indistinguishable.

4.2 Neural Network Training and Message Box

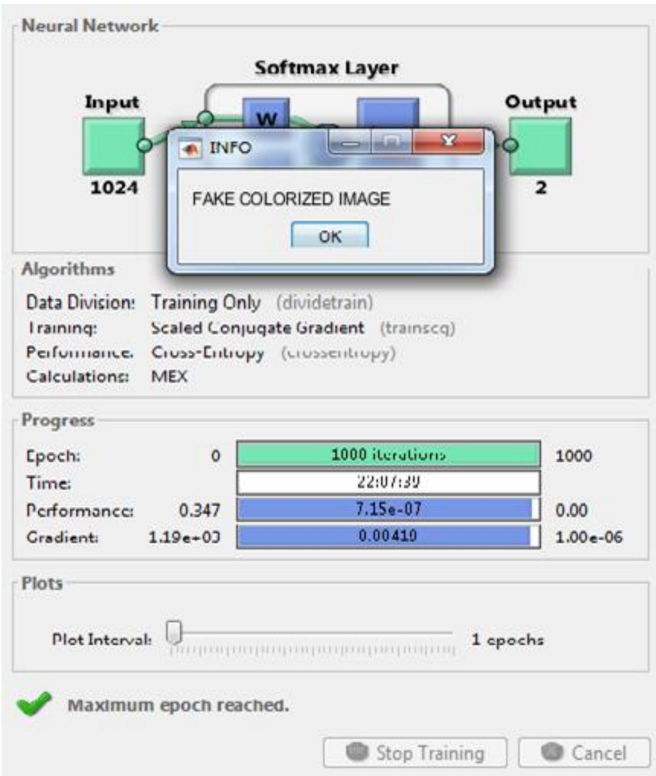

Fig. 5: Neural Network Training and message box

Softmax assigns decimal probabilities to every category during a multi-class drawback. Those decimal probabilities should add up to 1.0. This extra constraint helps training converge additional quickly than it otherwise would. Softmax is enforced through a neural network layer simply before the output layer. The Softmax layer should have an equivalent number of nodes as the output layer. The explanation why softmax is beneficial is because it converts the output of the last layer in your neural network into what is primarily a probability distribution.

The above message box shown is given as uiwait, message box. That means the user has to click the OK button for further processing. It informs the user whether the image is colorized or real. When the user clicks the OK button, the below graphs will be displayed.

4.3 HTER and ROC Curve

In this project, each the half total error rate (HTER) mensuration and the receiving operating characteristics (ROC) curve (area underneath AUC curve) measurements are used to gauge the performance of CNN over SVM. It is found that HTER of SVM is more compared with CNN. From the ROC Curve, it is clear that CNN is more accurate than SVM.

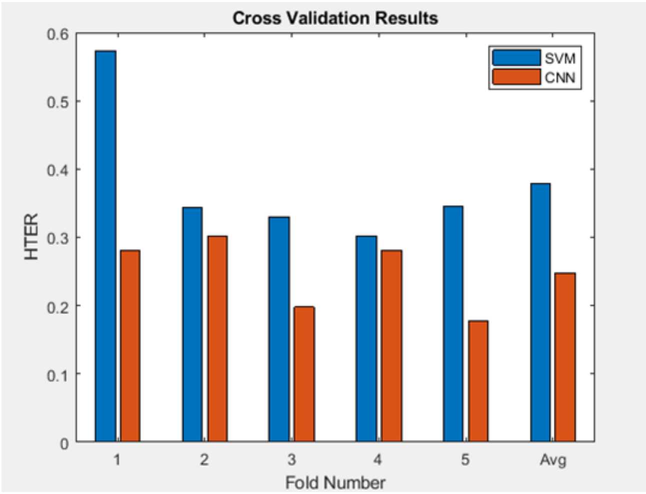

Chart 1: HTER characteristics of SVM and CNN

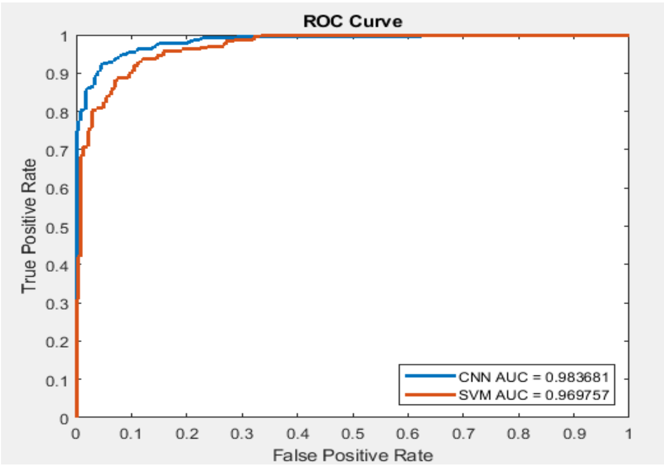

Chart 2**:** ROC Curve of CNN and SVM

CNN is a smart candidate for image classification and recognition because due to its high accuracy. The most advantage of CNN compared to its predecessors is that it mechanically detects the important options with none human supervision. As an example, given many pictures of cats and dogs it learns distinctive features for every category by itself. CNN is also computationally economical. The SVM does not perform well once the quantity of features is larger than the quantity of samples. Additional work in feature engineering is needed for an SVM than that needed for a multi-layer Neural Network. Convolution Neural Network is non-linear where as support vector machine is a linear classifier.

V. CONCLUSION

Through this project, it is aimed to handle a new problem in the field of artificial image detection. It is determined that fake colorized images and their corresponding natural pictures possess applied math variations in the hue, saturation, dark and bright channels. A straightforward however effective scheme, FCID using CNN Classifier is introduced to resolve this detection downside. It exploits the foremost distinctive bins and total variations of the normalized histogram distributions and creates options for detection.

CNNs have several applications in image and video recognition, recommender systems and natural language processing. CNN is a popular deep learning technique for current visual recognition tasks. Like all deep learning techniques, CNN is extremely captivated with the dimensions and quality of the training data. Given a well ready dataset, CNNs are capable of surpassing humans at visual recognition tasks. However, they are still not strong to visual artifacts like glare and noise, which humans are able to cope. The idea of CNN remains being developed and researchers are operating to endow it with properties like active attention and online memory, permitting CNNs to judge new items that are completely different from what they were trained on. This better emulates the mammalian sensory system, thus moving towards a better artificial visual recognition system.

This project is just a preliminary investigation, and there are several directions for future studies that require additional exploration. As results indicate, the performance of this current ways typically degrades clearly once when the training images and therefore the testing images are generated from different colorization methods or different datasets, thus blind fake colorized image detection features and methods could also be developed within the future by studying the common characteristics of various colorization methods. Moreover, better feature encoding approaches can be considered for improving performance, as well as the optimization of the detection features and parameters to improve the custom features constructed in this project.

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