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Survey on Detection of Generated Fake Images by using generative adversarial Networks

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ABSTRACT: Generative Adversarial Network(GAN) is a class of Machine Learning whose aim is to generate and detect images indistinguishable from the real images. People's ability to recognize the fake images through visual inspection proved to obtain less accuracies. Automatic algorithm achieved a much better detection performance than humans, so Machine Learning based approach with a properly trained classifier is used for image analysis which obtains high detection accuracies.

KEYWORDS: GAN, CNN, Image to Image Translation, Image Forensics

I. INTRODUCTION

Image forgery is an act of manipulating the images and making it to look different from the original image. Forgery art and photorealism has increased. It is essential to stop the spread of this act and therefore, use of computer automated algorithms like GAN and CNN are adapted.

1.1. Motivation

Increase in higher level of photorealism made it difficult for humans to distinguish between real and fake images this gave rise to machine generated algorithms.

II. LITERATURE REVIEW

[1] S.Fan,T-T.Ng,B.Koenig,J.Herberg, M.Jiang, Z.Shen and Q. Zhao, this paper proposed both empirically based and CNN based models for realism prediction and image type classification. It had a limitation that SVM using empirically based features over predicted and under predicted realism. In our proposed system, this limitation is solved by avoiding the use of SVM.

[2] J. Y. Zhu, T.Park, P. Isola and A.A.Efros proposed a system that translates an image from domain X to domain Y in the absence of paired images. It had a limitation that it was unable to identify paired images example-person riding on a horse.

[3] E.de.Rezende, G.Ruppert, and T.Carvalho proposed a system to classify images from the raw image data without any preprocessing. The limitation of this paper was that it didn't overcome all the fusiontechniques. In our proposed system, this limitation was overcome by using the concepts of fusion techniques.

[4] M.-Y.Liu, T.Breuel, and J.Kautz proposed a system that was able to translate an image from one domain to another domain without any corresponding images in two domains in the training dataset. The limitation of this system was one



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can infer nothing about the joint distribution from marginal distributions without additional assumptions. In our proposed system, this problem was solved as we do not need any additional assumptions

[5] N.Raahmouni, V.Nozick, J.Yamagishi, and I.Echizeny proposed system presented a deep learning method for distinguishing computer generated graphics from real photographic images from CNN. The limitation was that classifying smaller images was more challenging. In our proposed system, small images can be easily classified.

Sr. No.	NAME OF THE PAPER	PROPOSED SYSTEM	RESEARCH GAP
1	Image visual realism: From human perception to machine computation	Empirically based&CNN-based models for realism prediction & image type classification.	SVM over predicts & under predicts realism for images with specific content.
2	Unpaired image- to- image Translation using cycle-consistent adversarial networks	Translates an image from source domain X to target domain Y in the absence of paired images.	The system was trained on wild horse-zebra and thus was unable to identify the image of person riding horse or zebra.
3	Detecting computer generated images with deep convolutional neural networks	Able to classify images from raw image data without pre-processing	Doesn't overcome all fusion techniques.
4	Unsupervised image-to –image translation network	Translates an image from one domain to another without any corresponding images in two domains in the training dataset.	Can Infer nothing about the joint distribution from marginal distribution
5	Distinguishing computer graphics from Natural images using convolutional neural networks	Presents a deep learning method	Classifying smaller images is more challenging.

III. EQUATIONS

- $z \rightarrow$ Noise vector
- $G(z) \rightarrow$ Generator's output
- $x \rightarrow$ Training sample
- $D(x) \rightarrow Discriminator's output for real sample$
- $D(G(z)) \rightarrow Discriminator's output for fake sample$
- > At Discriminator D
- $D(x) \rightarrow$ should be maximized
- $D(G(z)) \rightarrow$ should be minimized
- $Dloss_{real} = log(D(x))$
- $Dloss_{fake} = log(1-D(G(z)))$



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- Total Loss
- a) $Dloss = Dloss_{real} + Dloss_{fake}$
- b) $\log(D(x)) + \log(1-D(G(z)))$
- > At Generator G
- $D(G(z)) \rightarrow$ should be maximized
- Gloss = -log(D(G(z)))

IV. PROPOSED ARCHITECTURE



Fig 1: Proposed System Architecture

In the proposed system's aim is to distinguish between the real and fake images. Generative Adversarial Networks are used. There are two main networks image to image network and support network. [1] The image to imagenetwork is the generator and the support network is the discriminator. One original image from the dataset is fed to the generator. The random noise vector is also fed to the generator. The generator generates the fake images. These fake images are then again fed to the discriminator along with the original image from the dataset. The discriminator compares the images and calculate the loss factor of the fake image. The discriminator then back propagates the loss to the generator. [1] The discriminator tells whether the image is fake or real along with its detection accuracy. The loss which is transported to the generator is analysed. It is used to train the generator to generate more realistic images. [1]

V. ALGORITHMS USED

To implement the GAN the CNN (Convolutional Neural Network) is used. It is a machine learning unit algorithm. It has various types of layers like input layer, convolution layer, activation function layer, pool layer and fully connected layer.



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VI. CONCLUSION

The proposed system is successful in distinguishing real and fake images with highest achievable accuracy. We plan to increase the efficiency of the algorithm. GAN's can be used as sub-supportive technology on What's app, Facebook, Twitter etc. or any other social networking site in future where image forgeries are quite high.

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