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DETECTING ARTIFICIAL IMAGES THROUGH LOCAL BINARY PATTERNS

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ABSTRACT

Now-a-days biometric systems are useful in recognizing person's identity, but criminals change their appearance in behaviour and psychological to deceive recognition system. To overcome from this problem, we are using new technique called Deep Texture Features extraction from images and then building train machine learning model using CNN (Convolution Neural Networks) algorithm. This technique refers as LBPNet or NLBPNet as this technique heavily dependent on features extraction using LBP (Local Binary Pattern) algorithm. In this project we are designing LBP Based machine learning Convolution Neural Network called LBPNET to detect fake face images. Here first we will extract LBP from images and then train LBP descriptor images with Convolution Neural Network to generate training model. Whenever we upload new test image then that test image will be applied on training model to detect whether test image contains fake image or non-fake image. Below we can see some details on LBP. LBPs are a type of visual descriptor used for classification in computer vision and is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings.

Keywords: Forgery detection, image forgery, artificial images, local binary patterns, machine learning.

1. INTRODUCTION

Recently, the generative model based on deep learning such as the generative adversarial net (GAN) is widely used to synthesize the photo-realistic partial or whole content of the image and video. Furthermore, recent research of GANs such as progressive growth of GANs (PGGAN)[1] and BigGAN could be used to synthesize a highly photo-realistic image or video so that the human cannot 20 recognize whether the image is fake or not in the limited time. In general, the generative applications can be used to perform the image translation tasks [3]. However, it may lead to a serious problem once the fake or synthesized image is improperly used on social network or platform. For instance, cycleGAN is used to synthesize the fake face image in a pornography video [4]. Furthermore, GANs may be used to create a speech video with the synthesized facial content of any famous politician, causing severe problems on the society, political, and commercial activities. Therefore, an effective fake face image detection technique is desired. In this paper, we have extended our previous study associated with paper ID #1062 to effectively and efficiently address these issues.

In traditional image forgery detection approach, two types of forensics scheme are widely used: active schemes and passive schemes. With the active schemes, the externally additive signal (i.e., watermark) will be embedded in the source image without visual artifacts. In order to identify whether the image has tampered or not, the watermark extraction process will be performed on the target image to restore the watermark [6]. The extracted watermark image can be used to localize or detect the tampered regions in the target image. However, there is no "source image" for the generated images by GANs such that the active image forgery detector cannot be used to extract the watermark image. The second one-passive image forgery detector–uses the statistical information in the source image that will be highly consistency between different images. With this property, the intrinsic statistical information can be used to detect the fake region in the image [7], [8]. However, the passive image forgery detector cannot be used to identify the fake image generated by GANs since they are synthesized from the low-dimensional random vector. Nothing change in the generated image by GANs because the fake image is not modified from its original image.

Intuitively, we can adopt the deep neural network to detect the fake image generated by GAN. Recently, there are some studies that investigate a deep learning-based approach for fake image detection in a supervised way. In other words, fake image detection can be treated as a binary classification problem (i.e., fake or real image). For example, the convolution neural network (CNN) network is used to learn the fake image detector [9]. In [10], the performance of the fake face image detection can be further improved by adopting the most advanced CNN–Xception network [11]. However, there are many GANs proposed year by year. For example, recently proposed GANs such as [1][12][13][14][15][16][3][2] can be used to produce the photo-realistic images. It is hard and very time-consuming to collect all training samples of all GANs. In addition, such a supervised learning strategy will tend to learn the discriminative features for a fake image generated by each GANs. In this situation, the learned detector may not be effective for the fake image generated by another new GAN excluded in the training phase.

In order to meet the massive requirement of the fake image detection for GANs-based generator, we propose novel network architecture with a pairwise learning approach, called common fake feature network (CFFN). Based on our previous approach [5], it is clear that the pairwise learning approach can overcome the shortcomings of the supervised learning-based CNN such as methods in [9][10]. In this paper, we further introduce a novel network architecture combining with pairwise learning to improve the performance of the fake image detection. To verify the effectiveness of the proposed method, we apply the proposed deep fake detector (DeepFD) to identify both fake face and generic image. The primary contributions of the proposed method are two-fold:

- We propose a fake face image detector based on the novel CFFN consisting of several dense blocks to improve the representative power of the fake image.
- The pairwise learning approach is first introduced to improve the generalization property of the proposed DeepFD.

2. LITERATURE SURVEY

2.1. TITLE: Remote Sensing and Image Interpretation.

Author: Lillesand, T.M. and Kiefer, R.W. and Chipman, J.W.,

Remote Sensing and Image Interpretation, 7th Edition is designed to be primarily used in two ways: as a textbook in the introductory courses in remote sensing and image interpretation, and as a reference for the burgeoning number of practitioners who use geospatial information and analysis in their work. Because of the wide range of academic and professional settings in which this book might be used, we have made the discussion "discipline neutral." In short, anyone involved in geospatial data acquisition and analysis should find this book to be a valuable text and reference.

2.2 Title: Deep Learning: methods and applications.

Author: Li Deng and Dong Yu.

This monograph provides an over view of general deep learning methodology and its applications to a variety of signal and information processing tasks. The application areas are chosen with the following three criteria in mind: (1) expertise or knowledge of the authors; (2) the application areas that have already been transformed by the successful use of deep learning technology, such as speech recognition and computer vision; and (3) the application areas that have the potential to be impacted significantly by deep learning and that have been experiencing research growth, including natural language and text processing, information retrieval, and multimodal information processing empowered by multi-task deep learning.

2.3 Title: A Logical Calculus of Ideas Immanent in Nervous Activity.

Author: McCulloch, Warren; Walter Pitts.

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

2.4 Title: An introduction to convolutional neural networks.

A Convolutional neural network (CNN) is a neural network that has one or more convolutional layers and is used mainly for image processing, classification, segmentation and also for other auto correlated data. A convolution is essentially sliding a filter over the input. One helpful way to think about convolutions is this quote from Dr Prasad Samarakoon: "A convolution can be thought as "looking at a function's surroundings to make better/accurate predictions of its outcome."Rather than looking at an entire image at once to find certain features it can be more effective to look at smaller portions of the image.

2.5 Title: Receptive fields and functional architecture of monkey striate cortex.

Author: Hubel, D. and Wiesel, T.

The striate cortex was studied in lightly anaesthetized macaque and spider monkeys by recording extracellularly from single units and stimulating the retinas with spots or patterns of light. Most cells can be categorized as simple, complex, or hypercomplex, with response properties very similar to those previously described in the cat. On the average, however, receptive fields are smaller, and there is a greater sensitivity to changes in stimulus orientation. A small proportion of the cells are colour coded.2. Evidence is presented for at least two independent systems of columns extending vertically from surface to white matter. Columns of the first type contain cells with common receptive-field orientations. They are similar to the orientation columns described in the cat, but are probably smaller in cross-sectional area. In the second system cells are aggregated into columns according to eye preference. The ocular dominance columns are larger than the orientation columns, and the two sets of boundaries seem to be independent.3. There is a tendency for cells to be grouped according to symmetry of responses to movement; in some regions the cells respond equally well to the two opposite directions of movement of a line, but other regions contain a mixture of cells favouring one direction and cells favouring the other.4. A horizontal organization corresponding to the cortical layering can also be discerned. The upper layers (II and the upper two-thirds of III) contain complex and hypercomplex cells, but simple cells are virtually absent. The cells are mostly binocularly driven. Simple cells are found deep in layer III, and in IV A and IV B. In layer IV B they form a large proportion of the population, whereas complex cells are rare. In layers IV A and IV B one finds units lacking orientation specificity; it is not clear whether these are cell bodies or axons of geniculate cells. In layer IV most cells are driven by one eye only; this layer consists of a mosaic with cells of some regions responding to one eye only, those of other regions responding to the other eye. Layers V and VI contain mostly complex and hypercomplex cells, binocularly driven.5. The cortex is seen as a system organized vertically and horizontally in entirely different ways. In the vertical system (in which cells lying along a vertical line in the cortex have common features) stimulus dimensions such as retinal position, line orientation, ocular dominance, and perhaps directionality of movement, are mapped in sets of superimposed but independent mosaics. The horizontal system segregates cells in layers by hierarchical orders, the lowest orders (simple cells monocularly driven) located in and near layer IV, the higher orders in the upper and lower layers.

3 PROPOSED SYSTEM

We propose a strategy for consolidating highlights from different layers in given CNN models. In addition, effectively learned CNN models with preparing pictures are reused to separate highlights from numerous layers. The proposed combination strategy is assessed by picture classification benchmark informational indexes, CIFAR-10, NORB, and SVHN. In all cases, we show that the proposed strategy improves the detailed exhibitions of the current models by 0.38%, 3.22% and 0.13%, separately.

4. RESULTS

This work utilized python KERAS and Google TENSORFLOW CNN algorithm to classify images, CNN algorithm can predict images correctly up to 90% which is better prediction accuracy compared to all other algorithms such as SVM, KNN etc. To classify images using CNN we need to train CNN network with all possible images and when new images uploaded then CNN train model will be applied on this new image to predict or identify image.

To demonstrate how to build a convolutional neural network-based image classifier, we shall build a 6 layer neural network that will identify and separate one image from other. This network that we shall build is a very small network that we can run on a CPU as well. Traditional neural networks that are very good at doing image classification have many more parameters and take a lot of time if trained on normal CPU. However, our objective is to show how to build a real-world convolutional neural network using TENSORFLOW.

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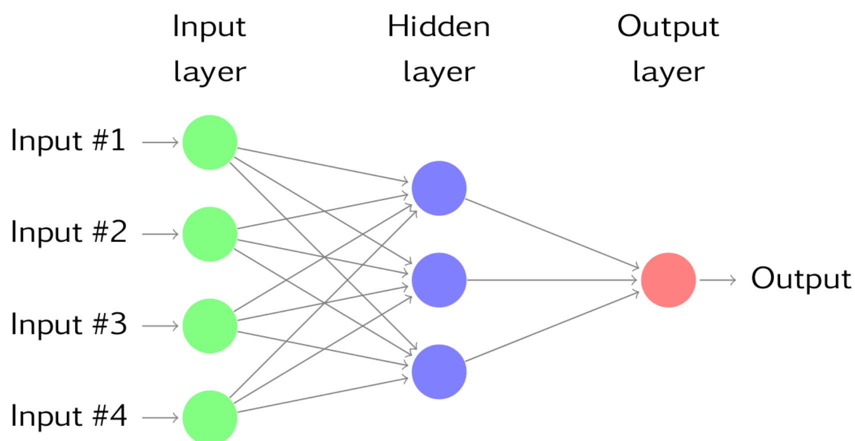
Neural Networks are essentially mathematical models to solve an optimization problem. They are made of neurons, the basic computation unit of neural networks. A neuron takes an input (say x), do some computation on it (say: multiply it with a variable w and adds another variable b) to produce a value (say; z= wx+b). This value is passed to a non-linear function called activation function (f) to produce the final output(activation) of a neuron. There are many kinds of activation functions. One of the popular activation function is Sigmoid. The neuron which uses sigmoid function as an activation function will be called sigmoid neuron. Depending on the activation functions, neurons are named and there are many kinds of them like RELU, TanH.

If you stack neurons in a single line, it's called a layer; which is the next building block of neural networks. See below image with layers



To predict image class multiple layers operate on each other to get best match layer and this process continues till no more improvement left.

This work consists of following modules:

1. Generate NLBPNet Train & Test Model: in this module we will read all LBP images from LBP folder and then train CNN model with all those images.
2. Upload Test Image: In this module we will upload test image from 'testimages' folder. Application will read this image and then extract Deep Textures Features from this image using LBP algorithm.
3. Classify Picture In Image: This module apply test image on CNN train model to predict whether test image contains spoof or non-spoof face.

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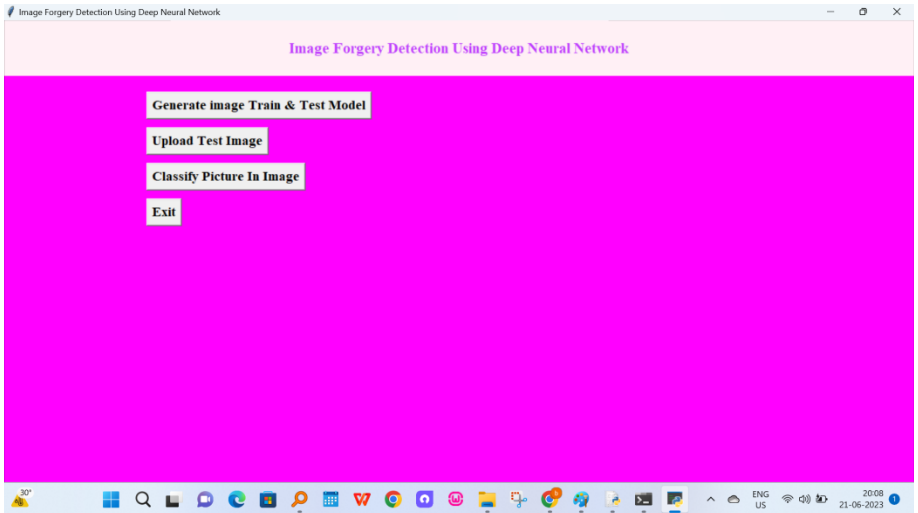
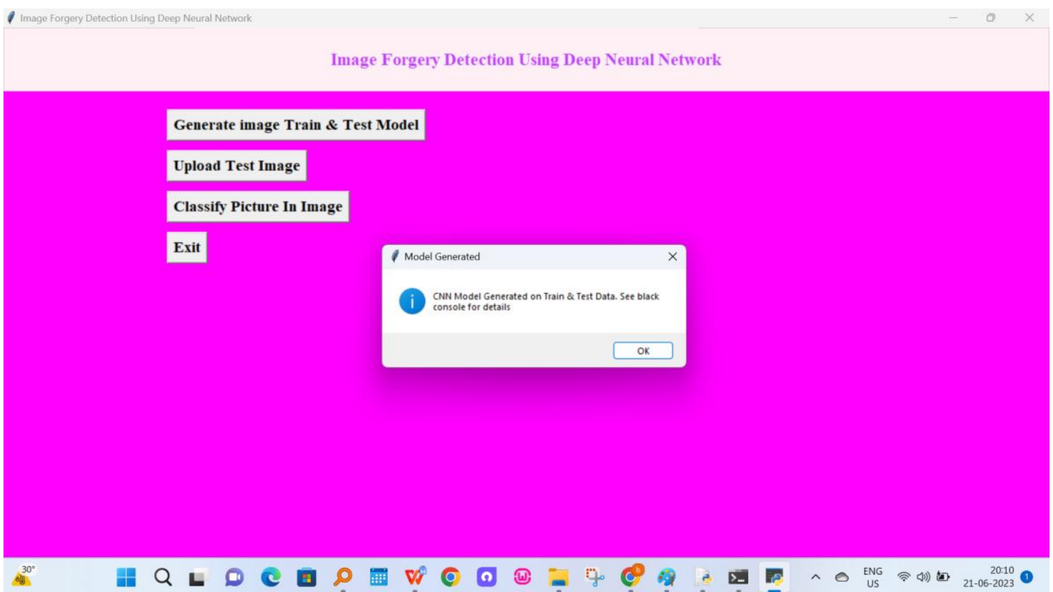


In above screen click on ‘Generate Image Train & Test Model’ button to generate CNN model using LBP images contains inside LBP folder.



In above screen we can see CNN LBPNET model generated. Now click on ‘Upload Test Image’ button to upload test image

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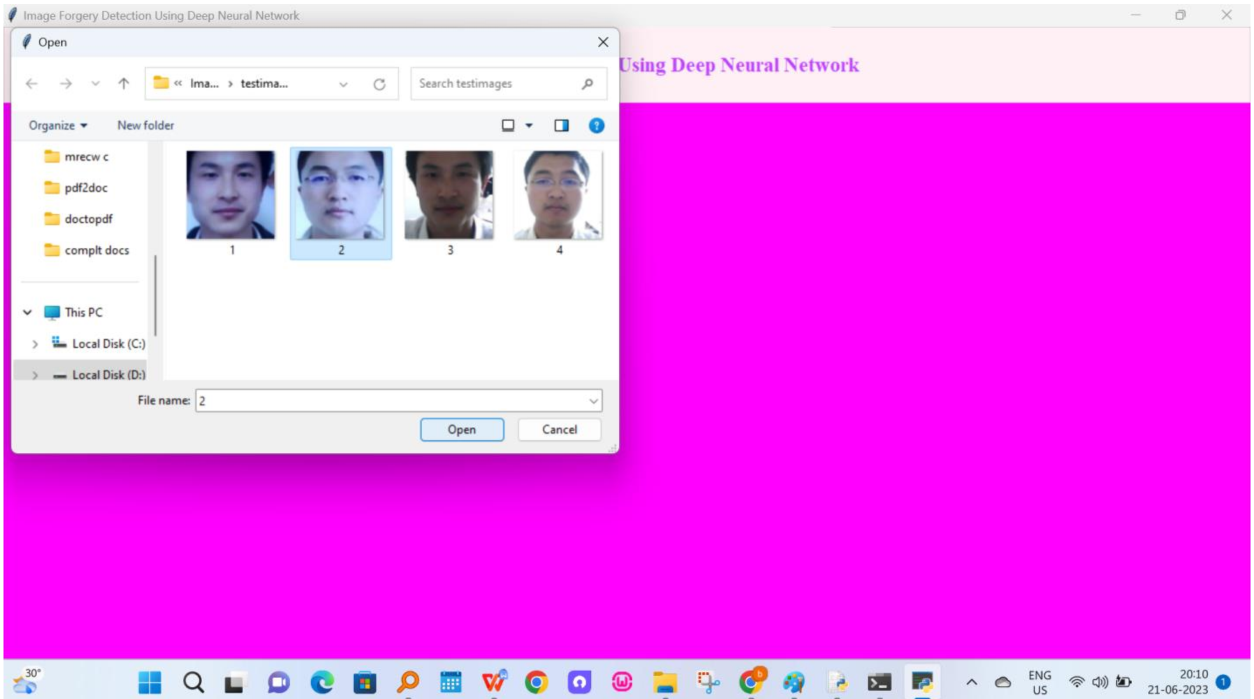
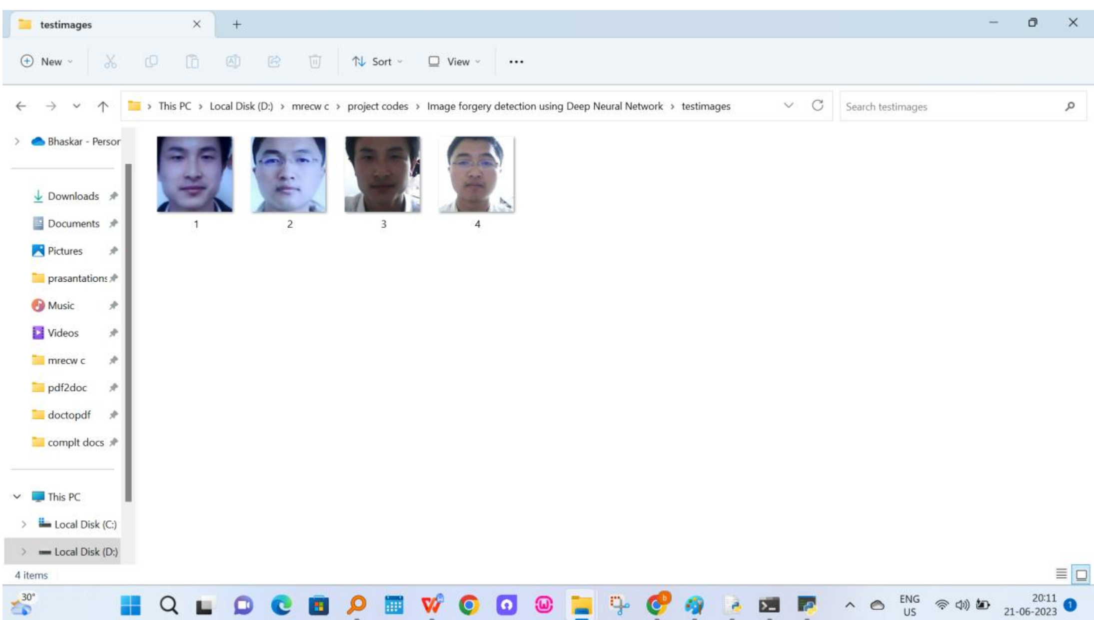


In above screen we can see two faces are there from same person but in different appearances. For simplicity I gave image name as fake and real to test whether application can detect it or not. In above screen I am uploading fake image and then click on ‘Classify Picture In Image’ button to get below result.



In above screen we can see all real face will have normal light and in fake faces peoples will try some editing to avoid detection but this application will detect whether face is real or fake

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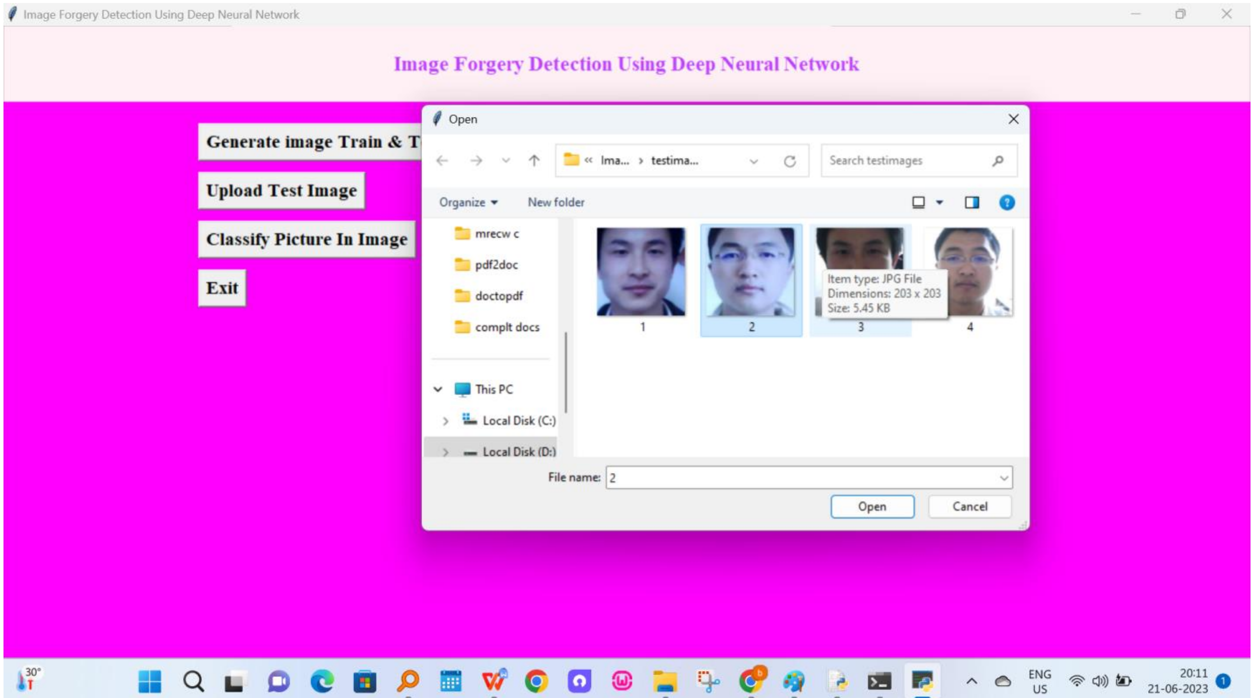
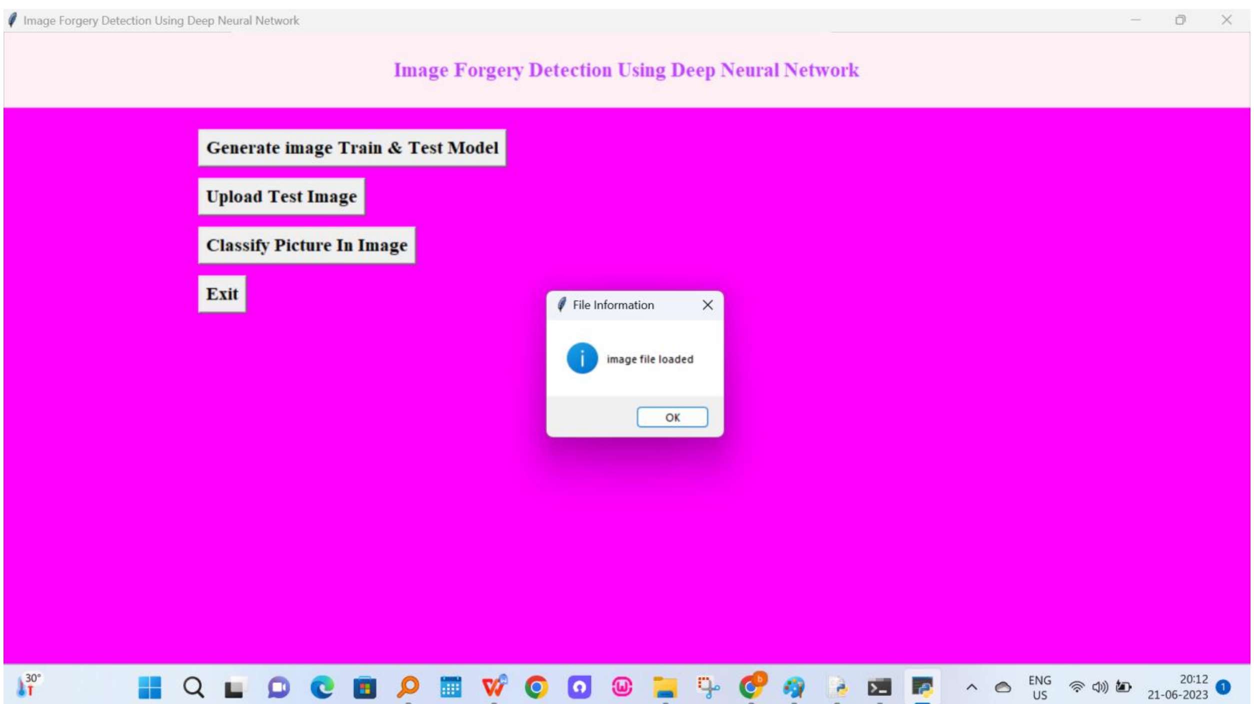


In above screen I am uploading 1.jpg and after upload click on open button to get below screen



And now click on ‘classify Picture in Image’ to get below details

In above screen we are getting result as image contains Fake face. Similarly u can try other images also. If u want to try new images then u need to send those new images to us so we will make CNN model to familiar with new images so it can detect those images also.

5. CONCLUSION

In this paper, we have proposed a novel common fake feature network based the pairwise learning, to detect the fake face/general images generated by state-of-the-art GANs successfully. The proposed CFFN can be used to learn the middle- and high-level and discriminative fake feature by aggregating the cross-layer feature representations into the last fully connected layers. The proposed pairwise learning can be used to improve the performance of fake image detection further. With the proposed pairwise learning, the proposed fake image detector should be able to have the ability to identify the fake image generated by a new GAN. Our experimental results demonstrated that the proposed method outperforms other state-of-the-art schemes in terms of precision and recall rate

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