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Image Depixelizer

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Abstract- The main aim of Image depixelizer is to convert the given low-resolution image into respective high and super resolution image. Image depixelizer works based on CNN algorithm, which takes the low-resolution as an input and apply various functions(like enlarge, c) to enhance the image without changing its original data and convert it into respective super and high-resolution image. Experimental results shows that the embedded Image depixelizer is quite robust in face of various low-resolution images and provides good results in terms of resolution.

Keywords – Image depixelizer, CNN,ResNET, EDSR

I. INTRODUCTION

In many areas (such as medicine, astronomy), sharp, high-resolution images are difficult to obtain due to issues of cost, hardware restriction, or memory limitations. This leads to the capture of blurry, low-resolution images. In other cases, images could be old and therefore blurry, or even in a modern context, an image could be out of focus. In addition, recently demand for sharp images and video has increased. This leads to the creation of realistic high-resolution images for a given low-resolution input image.

The rest of the paper is organized as follows. Proposed algorithm is explained in section II. Experimental results are presented in section III. Concluding remarks are given in section IV.

II. LITERATURE SURVEY

A. *Existing system*

Existing resolution system uses DRCN model. As, increasing the depth of the network will add more parameters, which will lead to two problems. One problem is that it is easy to overfit, and the other issue is that the model is too large to be stored and reproduced. Hence a recurrent neural network is used. It is similar to the proposed model but it is easy to cause network degradation.

B. Proposed System

By considering the above existing system, a new model is being proposed called, Enhanced Deep Residual Network (EDSR). As we know, most of the information contained in an LR image must be preserved in the HR image. Image resolution model therefore mainly learns the residuals between low-resolution and high-resolution images. This model uses Relu activation function.

II. PROPOSED ALGORITHM

A. Working

The network structure directly convolves the original low-resolution small image, reconstructs it with a deconvolution layer, and adds a patch extraction, non-linear mapping and expanding layer to achieve high operating speed without loss of recovery. The working of an image depixelizer is explained in the following steps:

Step1: Upload a low-resolution image.

Step2: Convert the input image into a vector notation.

Step3: Extract the features from the vector.

Step4: Map the pixels in the input image to the images in dataset.

Step5: Reconstruct the image vector after non-linear mapping of pixels in the image.

Step6: Obtained vector result is converted into image format.

Step7: Generation of a high-resolution image.

B. Edsr model –

In image-resolution, most of the information contained in an LR image must be preserved in the HR image. Image resolution models therefore mainly learn the residuals between LR and HR images. Therefore, Residual network designs are preferred. EDSR is developed using ResNet architecture. Identity information is conveyed via skip connections whereas reconstruction of high frequency content is done on the main path of the network.

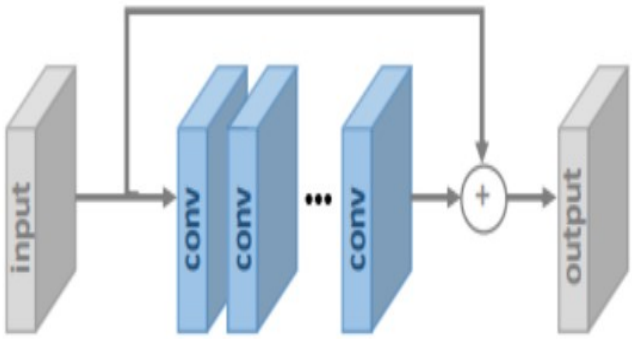

Figure 1. EDSR model

C. Dataset

The dataset used for training the model is DIV2K which contains 1000 images with different scenes and is splitted into 800 for training, 100 for validation, 100 for testing.

III. EXPERIMENT AND RESULT

The test set for this evaluation experiment image is randomly selected from the demo folder in the system. Jupyter Notebook software platform is use to perform the experiment. The PC for experiment is equipped with an Intel i3 2.2GHz Personal laptop and 4GB RAM.

The proposed scheme is tested using ordinarily image processing. From the simulation of the experiment results, we can draw to the conclusion that this method is robust to many kinds of testing images.

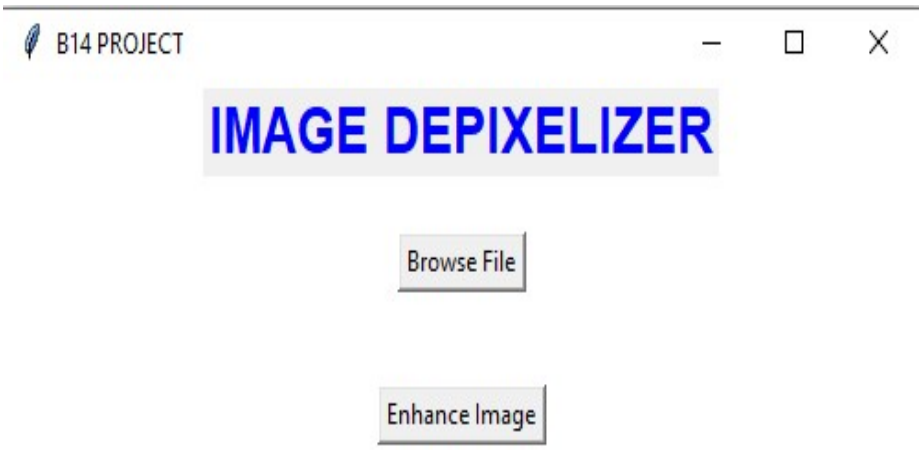

Figure 2. Interface

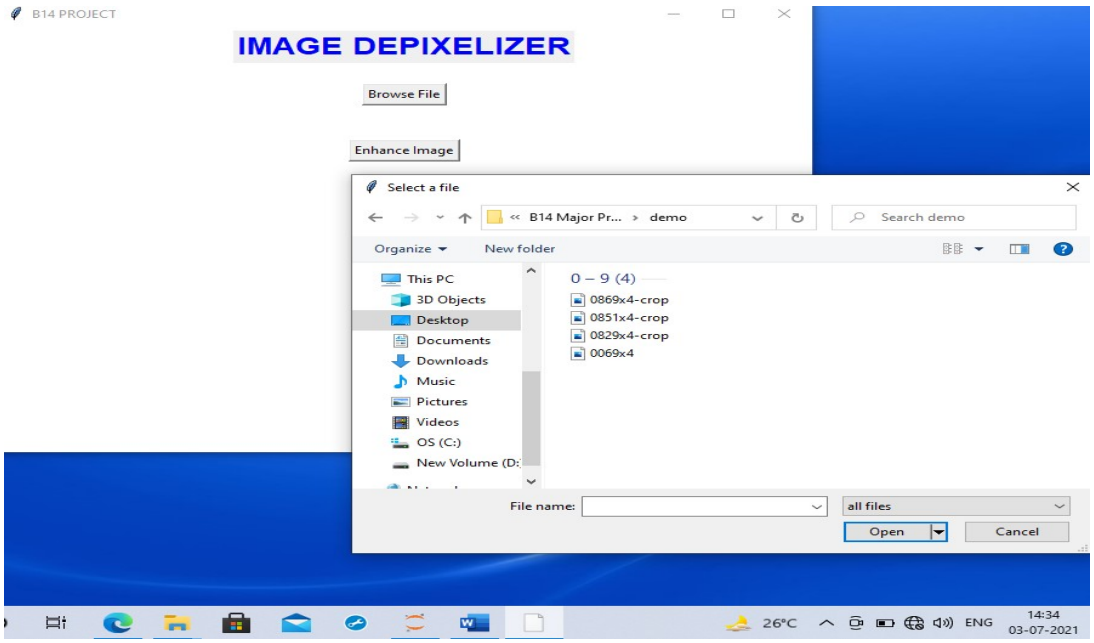

Figure 3. Select a File

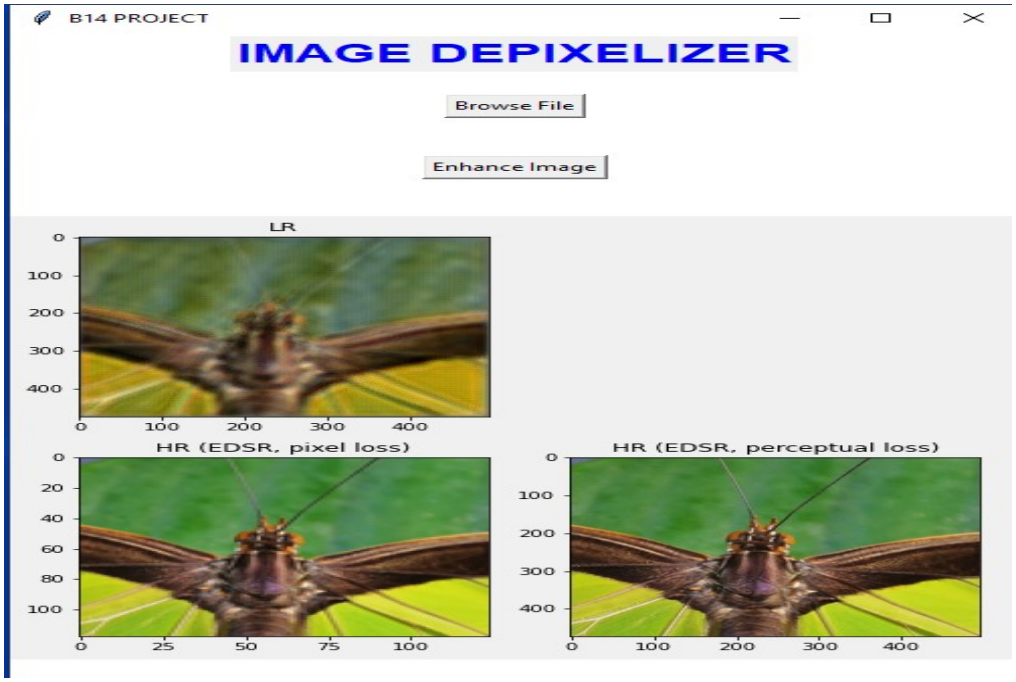

Figure 4. Output1

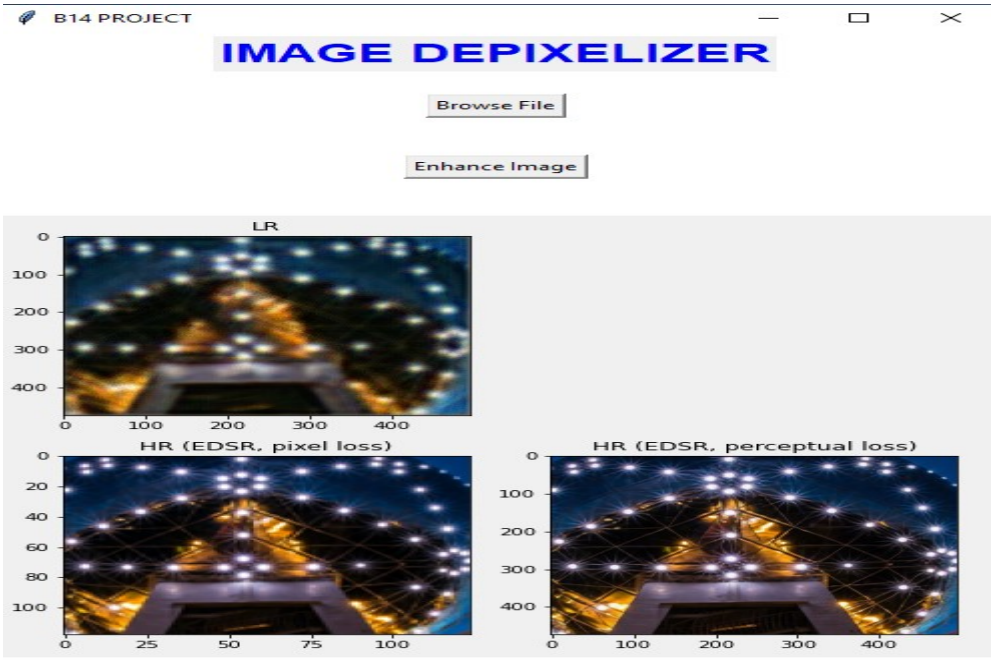

Figure 5. Output1

IV.CONCLUSION

The proposed approach for image resolution attains a remarkable success than the traditional-learning based models. Image depixelizer may be used for many image processing applications, which includes natural image enhancement, surveillance so that automatic recognition systems to improves their performance on low resolution images. Image

depixelizer performance can be further increased by exploring more filters while upscaling and different training strategies includes changing the model .

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