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I – Facial Image Denoising using CNN

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Abstract-- *In digital image processing, filtering noise to reconstruct a superior quality image is an important task. Noise makes tasks such as Classification, Recognition, and segmentation difficult. When used in any application, noisy images can generate faulty results that cannot be accepted in security-sensitive applications. The working and analysis of this project are done by adding Gaussian white noise [1] to the data images. Our project uses a Convolution Neural Network for facial image denoising to generate superior quality images and retain facial features. The advantage of using a Linear CNN is that it can be trained to become adaptive to different variations of noise.*

Keywords- *Convolution Neural Network, Image Denoising, Gaussian Noise.*

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I. INTRODUCTION

We know that nowadays, images are required in plenty of industries like space research, medicine, security, monitoring traffic, and a lot more. These images are given as input data to achieve the desired results. The main issue arises when the input images are polluted with external and unwanted noise. Noise can be defined as the unwanted information that gets added to the images, resulting in deterioration of the images' quality [1].

During the transmission of these data images through the transmission channels, the images get polluted with the external noise resulting in a poor-quality image. Because of the externally added noise, the system may not focus on the main features of images, and hence the perfection of results may not be achieved. Our objective in this project is to remove noise from the input images before giving them input to any system. We have mainly focused on restoring the images' essential features and eliminating the noise during the denoising process. For image denoising, we implement CNN and fine-tune the model to improve the output images' quality before its use. We consider input to our algorithm an image with Gaussian noise added to it, which is interpreted by a convolutional neural network (CNN) to produce a high-resolution image. Several traditional denoising methods have been used earlier, but the results were not satisfying as they produced blurry images losing important features in the process. Some of the traditional methods are

<u>Average/Mean Filtering:</u> In this method [2], a weighted, pre-defined filter is used, which sets each pixel value by taking the average of the pixel values of its neighbors, including itself.

<u>Median Filtering:</u> The method [2][3] performs denoising by replacing each pixel value with its neighbors' median value. It does so by considering the magnitudes of its neighbors within the mask.

<u>Wiener Filter</u>: This method [4][5] samples the image into various sub-images using a straight line of varying slopes. Each sub-image is then processed using the Wiener Filtering technique, which helps remove the blurriness produced due to moving pictures or slower camera shutter speed. The method tries to reduce the Mean Squared Error between the actual image and the blurred image.

With the study of some of these traditional denoising methods, it was observed that Mean filtering is extremely poor at maintaining edges. Median filtering, when having a larger kernel size, blurs the images. Reducing the kernel size does not remove the noise effectively. CNN requires a lot of pre-training on image inputs before achieving peak performance, thus requiring a larger dataset. CNN can make inaccurate predictions on noisy images, requires more iterations of training to work efficiently. Static algorithms are non-adaptive, i.e., highly dependent on noise distribution.

Traditional methods for image up-sampling use a static filter with pre-defined weights. The methods that do not adapt to the noise present in the original image. Even though they increase an image's quality, they produce a blurring effect on the image, forcing the output image to lose important features. They are also non-adaptive, meaning that they can work well only when the noise is uniform and follow a statistical distribution.

In most cases, they end up spreading the noise more or blurring the edges, effectively reducing the image quality. Convolutional Neural Networks (CNNs) can adapt [6][7][8] because of the adjustment in weights. The advantage of non-linear activations to encode general characteristics about photographs can add structure lost in the low-resolution input.

II. LITERATURE SURVEY

There are various traditional image denoising methods, such as mean filtering, median filtering, Wiener filtering, domain range filter, etc. We have studied mean, median, and average filters.

<u>Average/Mean Filter</u>

This method uses a mask over each pixel having pre-defined weights on the image. The pixels that fall under the mask show their values are averaged together, and a single pixel value is formed. This new pixel value is then used to replace the pixel value in the image under consideration [2]. The Mean Filter is unable to maintain the edges within the image as it smoothens it.

This method is simple, intuitive, and easy to implement to smooth out the images. It helps to reduce noise in images. Mean filtering is also considered a convolution filter. It is based around a kernel, which studies the pixel's neighborhood to be sampled when calculating the mean. Often a 3×3 square kernel is used. But larger kernels (e.g., 5×5 squares) can also be used for severe smoothing.

<u>Median filter</u>

It is a non-linear filter and is efficient in removing impulse noise. Median filter helps to preserve the sharpness of image edges while removing noise. The method of performing Median filtering is by taking the magnitude of all of the vectors within a mask and sorting the magnitudes. The pixel assigned with the median magnitude is then used to replace the pixel studied. The advantage of the Median Filter over the Mean filter is that it relies on the median of the pixel values' neighborhood instead of the mean [2][3]. The median of a set is more dominant concerning the presence of noise.

It works effectively with the noise-reduction capability for certain types of random noise with considerably less blurring than linear smoothing filters of similar size. It is effective for both bipolar and unipolar impulse noise.

<u>Wiener Filter</u>

It aims to reduce the amount of noise in a signal. It works by comparing the received signal with an estimation of a desired noiseless signal [4]. This is not an adaptive filter as it assumes input to be stationery. It works in a statistical approach to solve its goal. The filter's main aim is to remove the noise from a signal—spectral properties like the power functions for both the original signal and noise. And the resultant signal required is as close to the original signal. Signal and noise are both linear stochastic processes with known spectral properties. The process aims to have a minimum mean- square error. The difference between the original signal and the new signal should be as little as possible [5].

III. DATASET

Our dataset [9] consists of 630 images of 105 different people, which counts to 5 images per person.

Figure 1: Example of High-Resolution images

Figure 2: Example of Noisy image with σ = 0.07

We augmented our dataset using data augmentation techniques like left-right flip and up-down flip to increase the dataset size. From 630 actual images, using data augmentation, we obtained 1890 images which we split as 1350/270/270 as training/testing/validation dataset. To generate noisy input images, we added Gaussian noise to the images with σ = 0.07 having μ = 0.0

IV. PROPOSED SYSTEM

This project is notable for its security applications and many other fields, especially since image reconstruction offers a methodology for correcting the imperfections in the imaging system. For image denoising, we implement CNN and fine-tune the model [8] to improve the output images' quality before its use. Our model is given a low-resolution Gaussian noise added image with a particular standard deviation. The neural network generates a high-resolution noise-free output, overcoming the drawbacks of ubiquitous systems with the help of CNN, which is adaptive. This technology makes the system more accurate for further image processing tasks by eliminating noise. Also, we helped the ubiquitous system work better by increasing the value of the PSNR.

CNN's are widely used to solve Computer Vision Problem. One of the significant advantages of these neural networks is that they do not require feature extraction. The system learns to do feature extraction on its own and at the same time adapt to the data which is fed to it. This is an essential requirement of our project, as the noise is generally random and does not follow any statistical model. The next layer

Features are convoluted with different filters to generate more invariant and abstract features, and the process continues till one gets the final feature/output. The intensively trained machine is then used as a pre-trained model for the other applications where it trains itself in different environments.

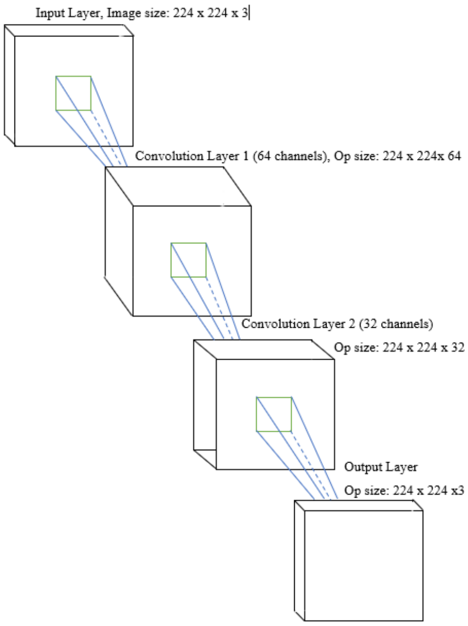

Figure 3: A pictorial representation of the image denoising model.

The figure above shows our 3-layer CNN model, which takes a 3-dimensional noisy image as input and generates a noise-free image with the same dimensions. The first Convolution layer, as shown, consists of 64 filters and a kernel size of 9. The second layer comprises 32 feature-map with a kernel size of 1. The third or the output layer has 3 filters corresponding to the RGB channels with a kernel size of 5. The ReLU activation layer follows each layer. We used Mean Squared Error (MSE) to evaluate the model loss and Peak Signal to Noise Ratio (PSNR) to evaluate the model's performance.

$$MSE\ (X, Y) = \frac{1}{N}\sum_{i=1}^{n}(X_i - Y_i)^2$$

Where X = input noisy image, Y = Output denoised image, and N is the number of examples considered.

V. METRICS

To evaluate the model's performance and test the quality of output images, we used Peak Signal to Noise Ratio (PSNR) as our metric [10]. Higher the

Value of PSNR for an image, better is its quality and vice-versa [11].

$$PSNR = 10\ \log_{10}(\frac{MAX_I{}^2}{MSE})$$

VI. RESULTS

To train the model in the proposed system, we used an Adam optimizer with hyper-parameters as learning rate = 0.001, $\beta_1 = 0.8$ *and* β_2 = 0.999 We used a batch size of 16 to train the neural network for 400 epochs.

Figure 4: Actual (left), Noisy (Middle), and Denoised (Right) Images when σ= 4%

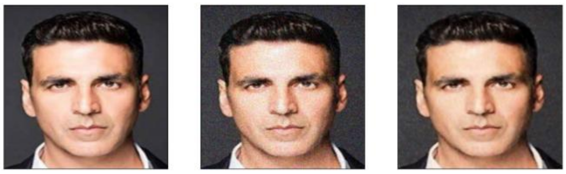

Figure 5: Actual (left), Noisy (Middle), and Denoised (Right) Images when σ= 8%

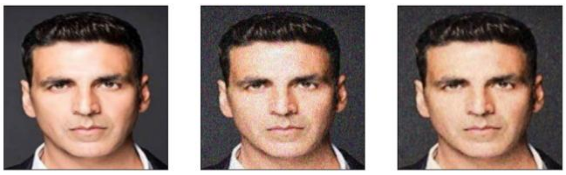

Figure 6: Actual (left), Noisy (Middle), and Denoised (Right) Images when σ= 12%

Table 1: PSNR values for noisy and denoised images

Image	Noisy Image PSNR	Median filtering PSNR	Model's output PSNR
Fig. 4	28.172	33.236	33.508
Fig. 5	22.296	30.781	31.874
Fig. 6	18.991	28.625	29.071

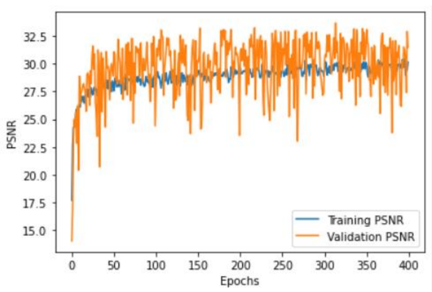

Figure 7: Training vs. Testing PSNR for our model

VII. CONCLUSION

In this project, we have explored various methods for denoising the images. But all of those methods ended up declining the quality of the image. So, we have used CNN (Convolution Neural Network) for the same. The results obtained in this research are applicable to resolve real-time problems like blurring out of images, pixelation of images, blurring of the edges resulting in a bad quality image. We have used a three-layer CNN model for the process of denoising. The three levels used helped in maintaining the original dimension of the image and better noise removal. Using the Image Denoising model, we then use these denoised images to make further predictions and classifications.

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