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Enhancement of Image Quality via Pre-processing for Improved Image Classification in Low-quality Images

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***Abstract*—The image classification rate of a bad quality image can be improved by performing pre- processing techniques on it. Pre-processing techniques like Mean filter, Image normalization, DeCarrstrech, luminizer, linear-contrast Adjustment, Blur removal can help in removing noise, unevencolor intensity distribution, improving the luminance of low light images, unintentional blur detection, and removal, etc. While implementing pre-processing techniques it is necessary to identify which techniques are to be used and also the order of using them to get an optimized result. While the existingsystem was developed to handle a singular problem, our proposed system is an ensembled system to handle multiple image defects. To automate this pipeline, we use Neural Image Assessment (NIMA) which will identify the defects in the image and the designed system will choose the appropriate image preprocessing channel which would yield the best results for image manipulations like feature extraction, image classification, object detection, facial recognition, and identification, etc. [5].**

***Index Terms*— Image pre-processing, NIMA, Image Enhancement, Low-Quality Image, Aesthetic value.**

I. INTRODUCTION

As the days pass by the importance of automation increases immensely. One of the fastest-growing elements of automation is computer vision because of its wide field of application, right from space research to sports. There aremany advanced and highly complex algorithms for computer vision. The bottleneck in this domain is the availabilityof good-quality images. It is evident that image manipulation is poor in low-quality images and it can be improved by using different image pre-processing techniques. With the rise of image pre-processing techniques, the defects in the low-quality images were certainly curable to a certain degree. Owing to these pre-existing image pre-processing techniques we aim to create an ensembled pre-processing strategy that would decrease the defect in the image to a greater extent than any individual pre-processing technique.

II. LITERATURE SURVEY

Neural image assessment helped us to assess an image based on its aesthetic value. We got to know how NIMA scores an image based on user classified data i.e., Good or Bad [4]. Poor illumination conditions of an image greatlylimit the performance of computer vision algorithms. We got to know various algorithms for low light image enhancement like grey transformation methods, histogram equalization methods, frequency-domain methods, imagefusion methods, defogging model methods, and machine learning methods [15], and we found the

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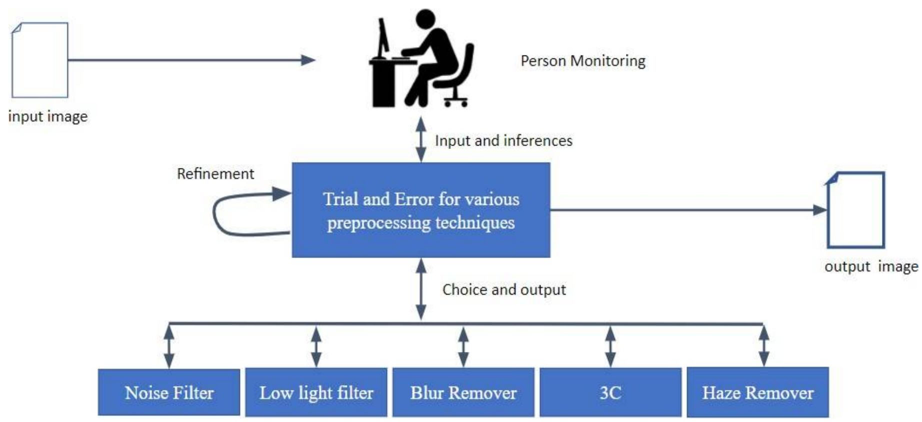
Gray Transformation method to be the most suitable algorithm to enhance low light images. A good quality image gives a better recognition rate than a noisy image which hinders the performance while trying to extract features from an image [8]. Blur image limits the efficiency of computer vision algorithms and blur images possess a unique threat i.e., determining the blur if it is intentional or unintentional. The basic idea of identifying the blur of a pixel being intentional or unintentional is whether the blur occurs on a salient and semantic meaningful object [13]. The region with unintentional blur is passed through a Gaussian filter for deblurring.

III. EXISTING SYSTEM

The systems that exist now are intended to solve singular defects in an image like wiener filter removes noise, imagenormalization improves pixel range, Linear contrast adjustment enhances the difference between objects, etc. which leaves other issues unaddressed. To avoid these users manually use multiple pre-processing techniques one after another until the user is satisfied, which is hard to do in an optimized way since the optimization of one pre- processing technique could impact via worsening another pre-processors output.



IV. THE PROPOSED SYSTEM

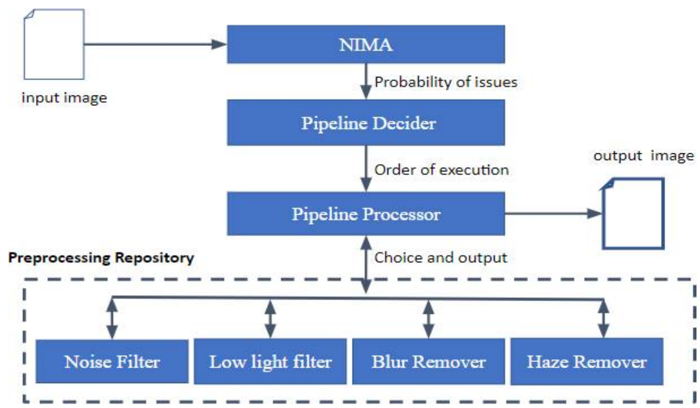
We propose an intelligent system capable of finding the defects in a given image like noise, low-light, blur, haze, etc., and find the optimal order of execution which would decrease the necessity of human involvement. By following this order of execution, the quality of the image is improved greater than the existing singular techniques.
Using modified Neural Image Assessment (NIMA) we have designed an algorithm that classifies images based on thedefects that are predominantly present in the image. Using the experimental results which we found out during our experimentation the system will choose the order of execution to achieve higher image quality.

V. WORKING OF PROPOSED SYSTEM

Before performing any of the different computer vision algorithms on an image, one can give that image to our ensembled pre-processor. The image that is given as input for the system will be first evaluated using the "NIMA module" which provides a probability of defects that could be present in that image which would decrease the efficiency of computer vision algorithms. Based on the probability values the "Pipeline Decider module" will find the defects that are needed to be treated According to this inference the Pipeline Decider module finds the optimal series of execution of various pre-processing techniques from the experimental result.
The optimal series is fed to the "Pipeline Processor module" which is responsible for the execution of the series in correct order and finally the enhanced image is provided to the computer vision algorithm that was originally intended.

A. Neural Image Assessment module

NIMA is a quality and aesthetic predictor [3] which often scores an image from 1 to 10. Whereas we have customizedour NIMA module to provide probability value for each class of defect, which helps the system in finding the exact defect(s) in an image.



The input image is given to the Deep Neural Network model such as VGG16[5] or MobileNet which has been trainedusing a custom dataset. VGG16[5] is a heavy Deep Neural Network model which is suited for server-based applications and MobileNet[3] is a light weight Deep Neural Network model which is suited for portable applications.

The Deep Neural Network model provides a probability distribution for various classes of defects.

Training NIMA:- We collected images that were of similar kind of specification to that of the images that would be faced by the system.The collected images were categorised based on the defects in them into separate classes. An image count of at least 100 per class was required to achieve an acceptable result. Initially we used all layers of MobileNet to train the modeland on the basis of the validation and accuracy scores we fine-tuned the model into using 6 layers for optimal resultsusing our dataset.

To further improve the efficiency of the images used to train the model can be amped up to 100*Number of classes, for each category.

B. Pipeline Decider

Using the probability scores produced by the NIMA module the Pipeline Decider initially finds the defects that are needed to be addressed by the system. With the above inference and the lookup table (Table 1) developed during ourresearch the Pipeline Decider finds the optimal series of execution for that image.

TABLE I

Problem / Order	First	Second	Third
Low Light	Brighten	NA	NA
Haze	Dehaze	NA	NA
Blur	Deblur	NA	NA
Low Light and Haze	Brighten	Dehaze	NA
Low Light and Blur	Brighten	Deblur If Blur is Higher than threshold	NA
Haze and Blur	Dehaze	Deblur	NA
Low Light, Haze and Blur	Brighten	Dehaze	Deblur If Blur is Higher than threshold

C. Pipeline Processor

Using the order of execution given by Pipeline Decider and the input image the Pipeline Processor regulates the inputand output flow of each pre-processing module. It is the responsibility of this module to maintain the correct order ofexecution and provide output image.

Advantages

- The need for human involvement in pre-processing of images is reduced by the automation in the PipelineDecider and Pipeline Processor.
- Adding pre-processing techniques to the system in future requires less effort due to the flexible design of thesystem.
- Due to enhancement of quality of the images efficiency of computer vision algorithm improves.
- The need for high-cost equipment for high quality images is reduced.

VI. Experimental Results

For our research implementation we took the most frequently used computer vision algorithm which is used in a wide range of real-world applications which is object recognition. For implementing object recognition, we used YOLO object recognition API which is a Unified, Real-Time Object Detection [14].

In order to quantify the effect of our system we used a low-quality image as input for YOLO [14]. The low-quality image was initially passed to the object detection directly and once after passing the image to our system we passed itto the object detection. The results were recorded

Picture1 and Picture 2 is the shows comparison between the two results

Picture1

Picture 2

Table shows the improvement in the likelihood of the persons detected.

Table II

	Probability of person 1	Probability of person 2	Probability of person 3
Directly	64.00	54.81	NA
After applying to the system	89.34	72.11	54.66

From the graph we infer that although the computed pre-processing time is only increased marginally while using oursystem the NIMA score is increased significantly and accounting for the removal of human intervention to solve the defects in the image the actual time required to perform pre-processing is reduced greatly.

Thus, using our system can reduce the effort in pre-processing an image and thereby reducing effort of the entire process of any computer vision project.

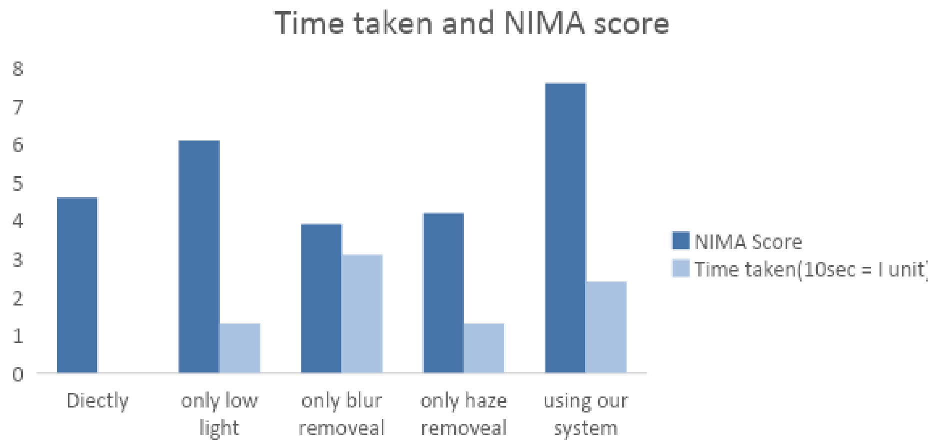


Figure 3

Table 3 shows the time taken for the YOLO algorithm to run directly versus using our system.

TABLE III

	Time
Directly	2.3
After Using our module	9.2

VII. CONCLUSION

The system that we have designed has the ability to automate the task of pre-processing images in order to avail betterresults in computer vision algorithms. We trained a Deep Neural Network model to find the probability of defects in an image and classify them. Based on which we prescribe an order of execution of pre-processing techniques to get optimal results and execute them to produce an enhanced image.
As part of our future work, we will upgrade the system to accompany more pre-processing techniques and we aim toprocess videos where the outputs can be improved greatly.

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