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**TITLE: DEEP LEARNING BASED DIGITAL MEDIA DESIGN
ENHANCEMENT MECHANISM**

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DEEP LEARNING BASED DIGITAL MEDIA DESIGN ENHANCEMENT MECHANISM

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Abstract: Image improvement is important for making images clearer, higher quality, and more comfortable to look at. Global contrast enhancement is used a lot, but it often misses local details that are important for image analysis. For example, local details that are important for science imaging like planetary studies, satellite data, and medical tests. To get around this problem, this study suggests a complete way that combines both local and global improvement techniques. Using PyTorch CNN, the study goes through several steps, such as cleaning images, building models, adding datasets, training, and making predictions. By adding noise to pictures by hand, CNN is taught how to improve image quality while reducing mistakes. Additionally, pre-trained models are tested to show how well they improve picture clarity. For objective evaluation, performance measures like Peak Signal to Noise Ratio (PSNR) are used. The results show that the CNN has better performance with much lower mistake rates, which shows that it could be used in many ways to improve and analyze images.

Index terms - Global contrast stretching, image enhancement, image sharpening, local contrast stretching, unsharp masking,.

I. INTRODUCTION

Image contrast is a very important part of how people see, and it has a big effect on how clear and detailed an image is. Contrast, which is the difference in pixel intensity values between pixels next to each other, shows how different things in a picture are from each other. Better contrast is especially important in areas like medicine and science, where pictures need to be carefully analyzed and information must be extracted for accurate assessments and scientific findings [1]. When it comes to the many ways to improve a picture, contrast stretching is one of the most popular. There are two main types of this method, which makes the differences

in strength values between pixels stand out more: global contrast stretching and local contrast stretching. While global contrast stretching improves the quality of an image enough for general watching, it doesn't always do a good job of keeping small features in the picture [2]. Local contrast stretching, on the other hand, fixes small changes in brightness at the pixel level. This improves tiny features that might be important for medical diagnosis, for example. But this method might not look at the image's bigger picture, or its world traits. Researchers have created mixed algorithms that use both global and local contrast stretching methods to improve the quality of images in a wide

range of ways. These algorithms successfully fix differences at both the macro and micro levels by using the best parts of each method [3]. This makes sure that the improved images have the best clarity and detail. Another strong tool for improving images, especially in the spatial domain, is histogram normalization. This method, described in [2], changes the levels of pixels to make the histogram more even. This makes the picture brighter and better overall. It is important to keep in mind, though, that while histogram normalization can make a big difference in some situations, it might not work as well on other types of pictures [3]. Contrast stretching methods have been studied and used a lot in medical imaging to improve pictures of things like leukemia. By choosing brightening dark areas while leaving bright areas alone, these methods make things easier to see and help doctors make accurate diagnoses [4, 5]. Researchers have also looked into methods like local edge recognition and deblurring algorithms [6] to deal with problems like picture blurring caused by moving objects during capture. By adding these kinds of methods to image improvement processes, researchers can reduce flaws and distortions and make sure that the improved pictures are accurate [7]. To sum up, progress in signal processing and computer science is pushing the area of picture enhancement to keep growing. Researchers are trying to make improved pictures as clear, detailed, and useful for diagnosis as possible by using a mix of global and local contrast stretching techniques, histogram normalization, and specific problems in different areas.

II. LITERATURE SURVEY

Image improvement methods are very important in many areas, like health, science, and general image processing. This review of

the literature looks at the different ways that experts have suggested to improve the quality and brightness of images.

Celik and Tjahjadi [1] came up with contextual and variational contrast enhancement methods. They focused on using contextual knowledge and variational concepts to make contrast enhancement better. By taking into account both local picture structures and global brightness changes, their method was meant to get around the problems with existing ones. Chen and Ramli [2] talked about ways to keep brightness when using histogram normalization to boost contrast. They stressed how important it is to keep the brightness while increasing the contrast, especially in medical imaging where keeping the image's features is key to making a correct diagnosis. Using iterative mean-separate histogram normalization to improve contrast was suggested in another paper by Chen and Ramli [3]. The goal of this method was to keep the brightness while increasing the contrast, so it could be used in situations that need flexible improvement. Premkumar and Parthasarathi [4] suggested using the Discrete Shearlet Transform as a good way to improve color images. Their method used shearlet factors to improve color photos, which is a potential option to more common methods of improvement. In their paper [5], Shyam and Chandra described a useful method for improving the sharpness of nature pictures. Their method centered on increasing contrast while keeping picture features, so it could be used in a variety of image editing programs.

Chen and Suleiman [6] came up with scalable global histogram normalization and selective enhancement for processing photos. By adding selected improvement tactics to their method, they hoped to get around the problems with current global histogram

equalization methods. Pathak, Dahiwal, and Padole [7] looked into what happens when you use both local and global ways to improve contrast in a picture. Their study looked at the benefits of combining local and global improvement methods, showing how important it is to think about more than one way to get the best results. Also, Gonzalez and Woods [8] wrote a book called "Digital Image Processing" that went into great detail about digital image processing. The third version of their book covers many topics related to improving images, such as methods for increasing contrast. It is a useful resource for students and professionals in the field. Overall, these studies show the different ways that experts have come up with to improve picture quality and brightness, each one suited to a different application. These methods help move the field of picture processing and analysis forward by taking things like keeping the color, environmental information, and selected improvement tactics into account.

III. METHODOLOGY

i) Proposed Work:

By combining both local and global improvement methods, the suggested system aims to make images better. Using PyTorch CNN [11], the system is made up of several important parts. First, images are preprocessed by being changed to RGB and grayscale. Next, noise is added by hand to improve the training data. Next, a CNN [13] model is built and trained using a dataset loader, making sure to leave out loss and use activation functions to improve gradients. For assessment, pre-trained models are also taken into account. The system then guesses better images using data with noise, showing that it can successfully make pictures clearer while reducing mistakes. A comparison study of

PSNR is also done to get a numeric picture of efficiency. This way of doing things makes the system a complete way to improve picture quality in many areas, from medical monitoring to science imaging. Its use of both local and global improvement methods makes sure that both small features and general contrast are taken into account. This leads to better picture quality with lower mistake rates.

ii) System Architecture:

Importing important packages for image processing, such as PyTorch for implementing a convolutional neural network (CNN) [11], is part of the system design. It has parts for building CNNs [13], training them, and making predictions. It also has parts for working with models that have already been trained and checking the quality of images using PSNR (Peak Signal to Noise Ratio) measures. Utilizing these tools and methods, the system makes it possible to improve images effectively using CNN-based methods and also lets you directly judge how well enhancements work by using PSNR as a standard.

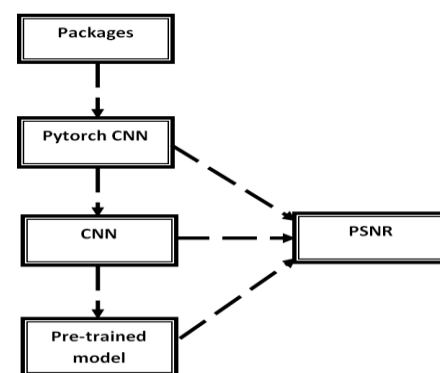


Fig1. System Architecture

iii) Pytorch CNN:

In a PyTorch version of a convolutional neural network (CNN) [11]:*Function for Image File and Conversion:* This function loads image files and changes them to RGB or grayscale format so that the CNN model can use them.

Class Function for Loading Images: This class contains methods for quickly getting pictures from a dataset, including steps like shrinking and normalizing the images.

Class Function for Shift Mean: This class loads pre-trained weights, which are often used for transfer learning, and makes any necessary changes, like changing the mean values of input pictures to match the values used to train the pre-trained model.

Class Function for Exclusion Loss: This class describes ways to figure out the loss function that is used during training. Usually, gradient functions and activation functions are used to see the difference between what was expected and what actually happened.

Appending Functions to Variables: To make the software easier to use and organize, different functions and classes are added to variables.

Appending the CNN Model from Net File: The CNN model, which is usually described in a different Python file (like "Net.py"), is brought into the current script and added to it for training or inference.

Loading the Dataset using DataLoader: PyTorch's DataLoader tool is used to load the dataset, which is made up of input pictures and the labels that go with them. This makes batch processing during training more efficient.

Training the Model: Backpropagation and optimization methods like stochastic gradient descent (SGD) or Adam are used to train the CNN [13] model. As the model is trained, its weights are changed based on the gradients of the loss function with respect to the model parameters. This helps it learn how to minimize the loss function.

Predicting the Enhanced Images: Once the model has been trained, it can be used to guess how raw pictures will look when they have been improved. By running input pictures through the training model and getting the matching output images, which should be better versions of the originals based on what the model has learned, these predictions are made.

iv) CNN:

In a CNN (Convolutional Neural Network) [13] set up,

Manually Adding Noise to Images: Synthetic noise can be added to pictures before editing to make them look more like the real world or to make the dataset bigger so that the results are more general.

Preprocessing the Manually Created Data using OpenCV: OpenCV is a tool for computer vision that can be used to do preparation jobs on personally made data, like expanding, normalizing, and adding to it.

Creating the Model and Appending to the Variable: The CNN model design is set up, and its levels, activations, and settings are changed based on the job at hand. It is added to a variable so that it can be used in other ways.

Generating the Input: The directly made data are used to make the input data, which

includes both the original pictures and their noisy versions. This step makes sure that the model can learn how to properly blur pictures.

Building the Model: The CNN [13] model's design is put together. It usually has convolutional, pooling, and fully connected layers. The layout of the model is set, and the links between the layers are made.

Function for Extracting the Input with Noise: A function has been built to take input images from the dataset and add noise to them. This method gets the data ready to be fed into the CNN model while it is being trained or tested.

Predicting the Enhanced Image for the Input and Displaying the Outcome: Finally, the learned CNN [13] model is used to guess better versions of the input pictures. In the process of denoising, the noisy input images are sent through the CNN, which returns improved, better copies of the pictures. Then, these improved pictures are shown to see how well the denoising process worked.

v) Pre-Trained Model:

For a pretrained model scenario:

Adding the model and its weights: The pretrained model design and the weights that go with it are brought into the script. To do this, you might need to get the model from a source or package.

Loading the Dataset: The dataset that will be used for testing or training has been added. Depending on the job, this collection could be made up of input pictures and the names that go with them, or it could not have any labels.

Building the Dataset: The dataset has been cleaned up and is now ready to be used for training or testing. This includes things like breaking the data into training, confirmation, and testing sets, normalizing it, and adding to it.

Training the Model: If more fine-tuning is needed, the model that has already been trained may be trained on the new dataset. This process of fine-tuning changes the model's weights so that they fit the new data better.

Calling the Input for Prediction with Model: Images that are given as input are run through a model that has already been taught to make predictions. Depending on the use case, this step could be done during the training, validation, or testing stages.

Enhanced Output is Displayed: The pictures that the pretrained model produced are shown so that you can judge their quality and usefulness. This makes it possible to see how well the model is working.

Comparing the PSNR (Peak Signal-to-Noise Ratio) for All Models with the Sample Input and Respective Output Images: For each set of input and output pictures made by different models that have already been trained, the PSNR measure is calculated. PSNR checks how good the denoised pictures are by comparing them to the noisy images that were used to make them. This comparison helps figure out which model that has already been trained does a better job of reducing noise.

IV. EXPERIMENTAL RESULTS

PSNR:

PSNR stands for peak signal-to-noise ratio. It is the ratio of an image's highest possible power to the power of noise that messes up its representation. To figure out a picture's PSNR, you have to match it to a perfect, clean image with the most power possible. Here's how to define PSNR:

$$PSNR = 10 \log_{10} \left(\frac{(L-1)^2}{MSE} \right) = 20 \log_{10} \left(\frac{L-1}{RMSE} \right)$$

Here, L is the number of most intense levels that can be in a picture; the least intense level is assumed to be 0.

MSE stands for "mean squared error," which is:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} (O(i, j) - D(i, j))^2$$

Where O stands for the source image's grid data. D stands for the grid data of the damaged picture. m stands for the number of rows of pixels, and i for the row's position in the picture. For each column of pixels, n is the number of columns, and j is the value of that column in the picture. RMSE stands for root mean squared error.

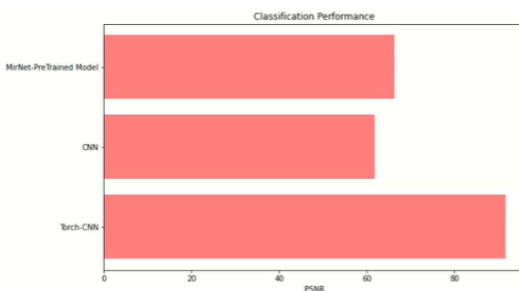


Fig 2 PSNR comparison graph



Fig 3 Home Page

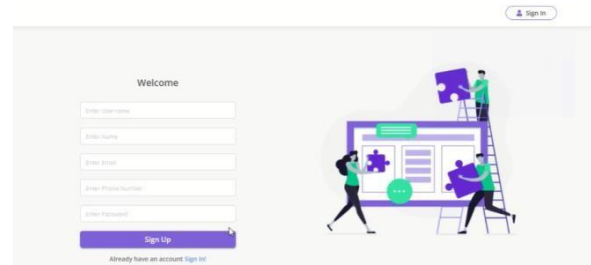


Fig 4 Signup Page

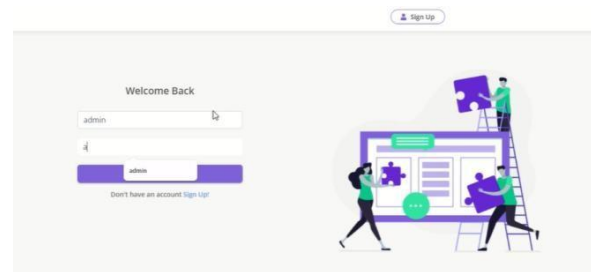


Fig 5 Signin Page



Fig 6 Main Page

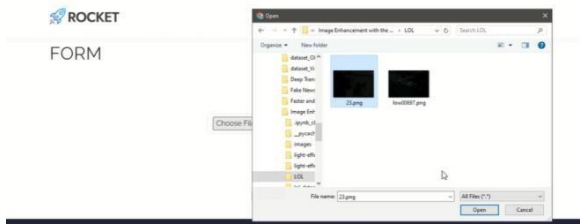


Fig 7 Upload Input Image

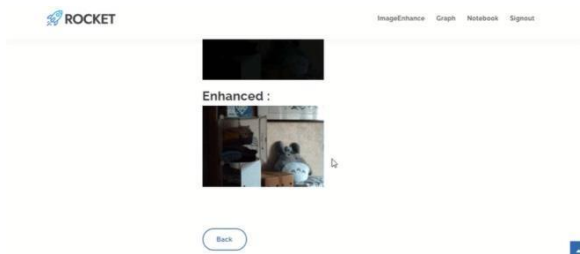


Fig 8 Predict Result

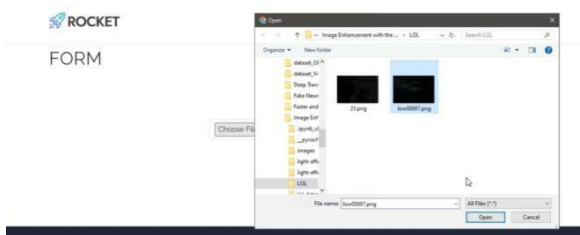


Fig 9 Upload Another Input Image

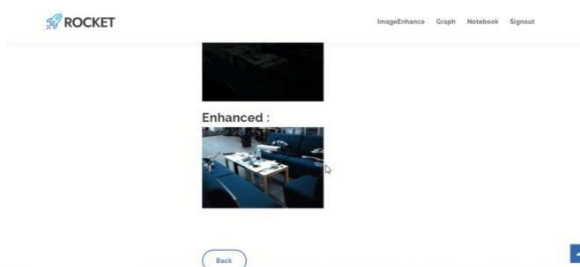


Fig 10 Final Outcome

V. CONCLUSION

In the end, the suggested system offers a complete way to improve images by merging local and global improvement techniques. The system gets around the problems that regular global contrast enhancement methods have, which is that they miss important local

picture features by using PyTorch CNN[11]. The system improves picture clarity and eye comfort by using both methods together. This is important for many uses, from science imaging to medical detection. During the study, we saw that the system was good at improving picture clarity while reducing mistakes. This was shown by the fact that the CNN [13] model had much lower error rates. The system does a great job of improving picture clarity by using methods like adding noise by hand to add to the data and carefully optimizing gradients with activation functions. Comparative testing with measurements like Peak Signal to Noise Ratio (PSNR) also shows that the system is better at improving high-quality images. Overall, the suggested method is a flexible and effective way to improve picture quality in many areas, which will lead to progress in image analysis and understanding.

VI. FUTURE SCOPE

In the future, the system can be made better by adding more advanced deep learning models and trying out new ways to get rid of noise and pull out features. Further improving the system's usefulness and effectiveness in many areas could include making it work in real-time picture processing situations and adding feedback systems for flexible improvement.

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