**An Efficient Densely-Connected Pyramid Dehazing-Network**

A DISSERTATION

SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS
FOR THE AWARD OF DEGREE
OF
MASTER OF TECHNOLOGY
IN
**COMPUTER SCIENCE & ENGINEERING**

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## CANDIDATE'S DECLARATION

I, **Aditya Kunwar** , Roll No. 2K20/CSE/03 student of M. Tech (Computer Science andEngineering), hereby declare that the project Dissertation titled **"An Efficient Densely Connected Pyramid Dehazing Network based Image Dehazing Method"** which is submitted by me to the Department of Computer Science & Engineering, Delhi Technological University under the supervision of **Prof. Anil Singh Parihar**, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of and Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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## CERTIFICATE

I hereby certify that the Project Dissertation titled **"An Efficient Densely-Connected Pyramid Dehazing-Network based Image Dehazing Method"** which is submitted by Aditya Kunwar, 2K20/CSE/03 Department of Computer Science & Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carriedout by the students under my supervision. To the best of my knowledge, this workhas not been submitted in part or full for any Degree or Diploma to this Universityor elsewhere.

Place: Delhi

Date:31 May 2022

Dr. Anil Singh Parihar

Professor

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## ACKNOWLEDGMENT

The success of this project requires the assistance and input of numerous people and the organization. I am grateful to everyone who helped in shaping the result of the project.

I express my sincere thanks to **Dr. Anil Singh Parihar**, my project guide, for providing

me with the opportunity to undertake this project under his guidance. My mentor's consistent encouragement has helped me understand that In the end, the learning experience is more important than the product itself. I owe a debt of gratitude to the panel faculty members who guided and monitored my progress during each progress review and provided encouragement to see the project through to completion. All along, they suggested fresh ideas, helped me gather the facts I needed, and pushed me to finish the project.They helped me throughout with new ideas,provided information necessary and pushed me to complete the work.I also thank all my fellow students and my family for their continued support.



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## ABSTRACT

Imaze quality may degrade by scattering particles in atmospheric particles for ex. fog and smoke. Due to this image can have diminished contrast, altered colour, and blured effect .This makes it hard to be recognized by human eye and computer vision systems . Hence Image dehazing is necessary which is a growing technique for dealing with the deterioration of such photographs. This research proposes dehazing method based on densly connected pyramid structure, end-to-end single picture dehazing system. First we take the input image and combine it with dark channel to make new input which is then further put into generator made of densly connected pyramid structure. The output of this geberator is then given to discriminator along with dataset to find discriminator score. This way the dehazed image is achieved .All components are discussed in detail further in this report.

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# LIST OF ABBREVIATIONS

1. EDCPDN: Efficient Densely Connected Pyramid Dehazing Network
2. DCPDN: Densely Connected Pyramid Dehazing Network
3. GAN: Generative Adversarial Network
4. CNN: Convolutional neural Network
5. Q-A: Question Answering

# CHAPTER 1

# INTRODUCTION

## 1.1 OVERVIEW

The effect of particles in the environment reduces image quality significantly during adverse weather conditions such as fog and haze. Haze is made up of dust, aerosol, and smoke, among other things. Aerosol is basically a dispersed system of small particles floating in a gas. Substance disperses in normal light beam to line of vision and disperses out reflected light beam to different direction from line of vision.

Suspended particles scatter light, causing the reflected light from the scene to be diminished, and the dispersed ambient light will also combine with the light that camera receives, changing the picture contrast and colour. As a result, computer vision systems must increase the visual impacts of the image and emphasise image aspects. Image dehazing, also known as "haze reduction" or "defogging," is a technique that uses particular ways to decrease or entirely erase interference caused by haze in order to produce pleasing aesthetic effects and more relevant information. Image dehazing, often known as "defogging," is a technique for removing haze interference with unique procedures in order to get pleasing aesthetic effects and more usable results . Image dehazing eliminates undesired elements from images.visual effects and is frequently used to improve images technique. It does, however, differ from typical noise reduction methods.Various techniques for enhancing contrast because the decrease to.The existence of haze has an effect on picture pixels.depending on the object's distance from the capture device as well as the haze's geographical density. The influence of haze onThe dynamic range of colours is likewise suppressed by picture pixels.

## 1.2 IMAGE DEHAZING

Air has some particles that absorb and scatter light reaching our camera ,this can damage our outdoor photographs. The subsequent deterioration causes pixels to lose contrast, blur, and distort, resulting in reduced visibility. Due to these factors the effectiveness of computer vision systems is less and they have problems like in target tracking, surveillance, and pattern recognition .This reduces the colour accuracy of the photographed scene .The process to remove this haze from images is known as image dehazing. In terms of airlight and transmission, the picture created in an outside setting may be formalised as

$$I(x) = J(x)t(x) + A(x)(1 - t(x)), \qquad \ldots(1)$$

Where I (x) is the intensity of the acquired hazy picture at x, J(x) represents the genuine scene radiance at x, A represents atmospheric light present in nature, and x is the pixel location in the image which is hazy. Image dehazing has a wide range of uses. Researchers have proposed many approaches for removing haze from photos and producing images with higher image quality.

Figure 1.1: An example of imaze dehazing

### 1.3 DCPDN

The Densly-connected pyramid dehazing network(DCPDN) divided into four modules: First is Pyramid densely linked transmission map estimation net to find transmission map, second is Atmosphere light estimation net, third is Dehazing by Eq. 2, and at last a Joint discriminator.

$$\hat{J}(z) = \frac{I(z) - \hat{A}(z)(1 - \hat{t}(z))}{\hat{t}(z)}. \quad \ldots (2)$$

Learning from prior approaches that estimate the transmission map using multi-level features [11,12], a encoder-decoder structure that is densly connected is proposed which uses features from many levels of a CNN, with the dense block serving as the fundamental structure. The aim for using dense blocks is to optimise information flow along those features and provide superior convergence by linking all layers. Furthermore, a multiple -phase pyramidal pooling module is used to enhance the learnt characteristics by incorporating 'global' structure information into the optimized method. The first three Dense-Blocks along with the first Conv. layer and the with their accompanying down-sampling operators Transition-Blocks from a pre-trained dense-net 121 is used as our encoder structure to use the dense-pre-defined net's weights [13]. At the end of the encoding portion, the feature size is 1 by 32 of the input size. We stack five dense blocks using the enhanced up-sampling Transition-Blocks [17] as the decoding module to rebuild the transmission map into the original resolution. Furthermore, concatenations are used with features that have the same dimension. Even if the densely linked encoder-decoder structure incorporates multiple properties inside the network, the outcome will lacks structural information of objects of different sizes. One probable explanation is because characteristics from various scales are not directly used to find end transmission map. To handle this issue efficiently, a multi-level pyramid pooling block is used to ensure that characteristics from multiple scales are integrated in the final output.

This is motivated because of global context information for classification and segmentation tasks . Rather than using a high grouping size to collect more global context information across various different items, local information is required to define the global structure of each object. As a result, its a four-level process where pooling sizes are different ranging from 1/32, to 1/4 is used. Then, before the final estimation, All four level features are up-sampled and concatenated with the original feature .The suggested pyramid densely linked transmission map estimate network is seen in Figure 3. The overall optimization framework is immediately incorporated for bridging the relationship among the the ambient light, transmission map, and the dehazed image, and to ensure that the entire network is being simultaneously optimised for required goals.

### 1.3.1 Edge preserving Loss

The L2 loss also known as Euclidean loss is well accepted to distort the final output. As a result, estimating the transmission map using only the there may we less features due to l2 loss, resulting in halo artefacts in the dehazed image . To solve this problem effectively, a novel edge preserving loss was presented, which is driven by the two observations below. First being that Because of edges correspond to discontinuities in picture brightness, they may be distinguished by image gradients and second is it is well understood that low-level characteristics like as edges and contours may be caught in the CNN structure beginning layers. So, the initial few layers of a deep network serve as an edge detector.

# CHAPTER 2

# PRIOR WORK

There Are generally two types of approaches - Prior knowledge and learning-based strategies. In the part that follows, several algorithms were explored.. Existing work in this field are shown in fig 2.1 . Many of the study articles I've seen refer to and even cite the methodologies discussed here. Our primary focus would be on mathematical and statistical strategies for improving image quality. Current approaches may be grouped into three groups based on variations in dehazing principles: image restoration methods ,picture enhancement methods and image fusion methods.

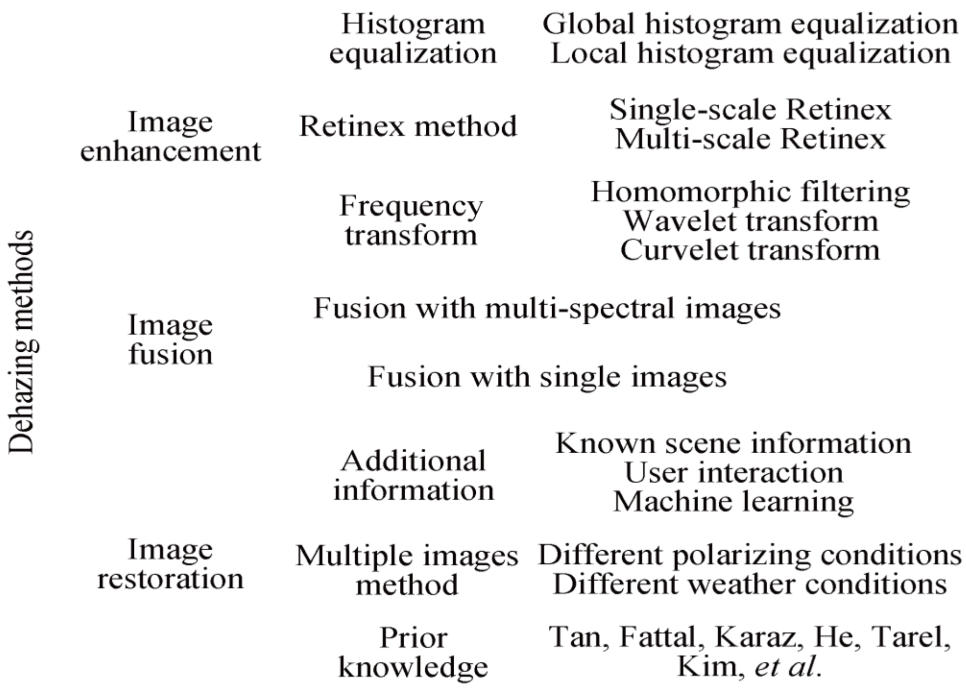



Figure 2.1: Different Types of Image Dehazing

Picture enhancement approaches do not consider the source of image deterioration, but instead rely on targeted image processing methods to increase contrast and details, as well as the aesthetic impact of the image. Image fusion approaches, which do not require a physical model, optimise the valuable information from numerous source channels to generate a high-quality image. To generate clear images, image restoration algorithms construct a foggy image degradation model by researching the physical principles of optical imaging, invert the degradation processes, and compensate for distortion induced by these degradation processes.

## 2.1 DARK CHANNEL PRIOR

The Dark Channel was introduced by Kaiming for Prior single picture dehazing. His discovery demonstrated that at least one colour channel of a rgb picture contains pixels with the lowest intensities, which tend to be zero. For example, an outside photograph of a landscape or cityscape may include trees, stones, grass, mountains, buildings, some brighter items, sky, and so on. Mountains, stones, and trees will have the lowest intensities in the image when contrasted to white automobiles and the sky region. The dark channel indicates that at least one colour channel in an RGB picture has the lowest intensities, which nearly always tend to be zero (When the pixels have lowest intensities or tendency to zero, the colour diverges towards dark or black-Thats why he named this phenomena as Dark Channel). Separating the RGB image into Red ,Green and Blue channels and choosing the pixels with the lowest brightness from all three channels will result in a black image. Again, the dark channel may be used to refer to the lowest intensity pixels in an RGB image's three channels. The technique of picking the least intense pixels from an RGB image is known as previous, and we call it dark channel prior (DCP). A minminimum operator is used to choose the smallest pixels from an RGB colour channel.

## 2.2 Single Image Dehazing by using Guided Filter

Following the idea of patchwise learning, the guided filter incorporates a reference image into its filtering process. You may use any image as the reference, including the input image. Better edge information management is possible with it. It betters the result from of the DCP approach. The image from is converted to the output image using the guiding picture.

Initially, the image is read from the line buffer and then transferred to the next step. Mean filter will filter The image from reference and the input image which has hazed to provide mI and mp, respectively. Using the input and input-guidance images as a starting point, we can next do a correlation analysis. The covariance and variance are then computed as, and the output picture is created using the mean values of the linear coefficients.

## 2.3 Color Attenuation Prior Method

Using supervised learning, we determine the scene depth in the CAP Method. Transmission and scene radiance may be simply determined using the depth map. The CAP approach generates the transmission map by utilising the depth of the scene. Transmission and scene depth are interconnected. It is correct. Assuming there is a relationship between scenedepth and The concentration in haze is stated as

$$d(y)\ \alpha\ c(y)\ \alpha\ v(y) - s(y) \quad \ldots(3)$$

where d is the depth of scene at that location . In HSV colour space, the value (brightness) component is represented by v and the saturation component by s. I(x1), I(x2), and I(x3) are photographs captured at distances x1, x2, and x3 such that x3 is the farthest and x1 is the closest to capturing scene locations. A linear model, which may be described as, can be used to associate these parameters from. Supervised learning may be used to determine the linear coefficients. To achieve the best results for 0, 1, 2, and, the training is performed on 500 hazefree photos obtained from web sources. The problem may then be solved to estimate the depth of scene and respective transmission. The same approach as in DCP was used to estimate the airlight. Finally, a haze-free image will be created. Because more noise in the surroundings affects the scene brightness.

## 2.4 DEHAZE NET

Dehaze Net [11] was presented as a [CNN] that could be taught to remember haze features and their transmission impacts. DehazeNet tries to learn from its mistakes. The transmission of diseases may be linked to the presence of fog. The features like Dark Channel, Maximum Contrast, and Colour Removed from a picture are Attenuation and Hue Disparity. It removes any haze from the picture. To increase the likelihood of convergence.This technique also includes a revolutionary non-linear approach.Bilateral-Rectified Linear Unit activation function(BReLU).

There are a lot of different components that go into building DehazeNet.Layers of convolution, pooling, and activation functions are piled on top of each other. In fig.(-) DehazeNet's key feature is the inclusion of haze-related content.A non-destructive method of extracting a certain feature from an image With BReLU as the basis for linear regression, the network learns to train itself Stochastic Gradient Descent (SGD) is used to estimate parameter values and Its loss function is the Mean-Squared Error (MSE). When everything is said and done,The most important feature of this network is its ability to calculate an accurate transmission map.Transmission near the sky was estimated throughout this process.DehazeNet, on the other hand, can estimate transmission rates with improved accuracy being the goal. Additionally, the CAP's performance has deteriorated dramatically.It is not noticed in the haze's concentration in the DehazeNet. A useful activation function is provided by BReLU as well for image restoration and conversion.

## 2.5 AOD-NET

AOD NET [16] is made using a model of how the atmosphere scatters light that has been changed. AOD-Net uses a light-weight CNN to construct the the uncluttered image as opposed to discovering the transmission map and the ambient light separately, as the majority of previous algorithms did before it.

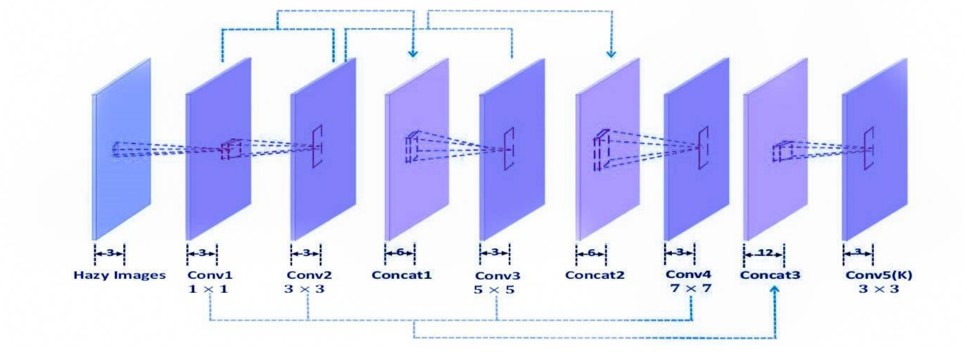



Figure 2.2: AOD-Net Architecture

When used in conjunction with other deep models like Faster R-CNN, such as the one described above, the new end-to-end design makes it simple to integrate AOD-Net. This model has outperformed the competition in terms of subjective visual quality in experiments using synthetic and natural hazy picture datasets. Performance for detecting object recognition on hazy pictures improves significantly when AOD-Net and Faster R-CNN are combined. AOD Net does not produce artefacts, halo effect, a drawback of certain other approaches. Faster results are possible when AOD Net is combined with other learning models.

# CHAPTER 3

# TECHNOLOGIES AND METHODS USED

## 3.1 Deep Learning

Deep learning is based on neural networks and feature learning. Instead of employing a set of pre-programmed commands, DL algorithms may learn from enormous volumes of data. A Variety of frameworks relying on deep learning have been implemented, with competitive results in areas like as Self Driving Cars, natural language processing, computer vision, and medical image processing, among others. Even while self-learning representations are a hallmark of deep learning algorithms, these algorithms are dependent on ANNs, which mimic how the human brain processes information. As the training phase progresses, algorithms use unknown input distribution components to extract features, organize objects, and find relevant data patterns. This is similar to teaching robots to learn on their own by applying algorithms to develop models. Several algorithms are used in deep learning models. Algorithms have different strengths and weaknesses when it comes to various jobs. Some of them are ConvolutionalNeuralNetworks (CNNs), Recurrent Neural Networks (RNNs), Radial Basis Function Networks (RBFNs) and Generative Adversarial Networks (GANs).

## 3.2 GANs

Unsupervised learning is facilitated by the use of Generative Adversarial Networks (GANs), which are strong family of neural networks. In 2014, Ian J. Goodfellow created and launched it. Basically in GANs there are basically two types of neural network that will compete to become better with each other to analyse, capture, and replicate data variations. These both competing neural network models that are able to analyse, capture, and replicate data variations. A discriminator and a generator are both present in GANs. Fake data samples (images, audio, etc.) are generated by the Generator, which attempts to mislead the Discriminator And Discriminator work is opposite to differentiate Samples that are either authentic or false . During the learning process, the GANs neural networks face off against one another . Both The Generator and Discriminator improves at their respective professions after each cycle of this process.

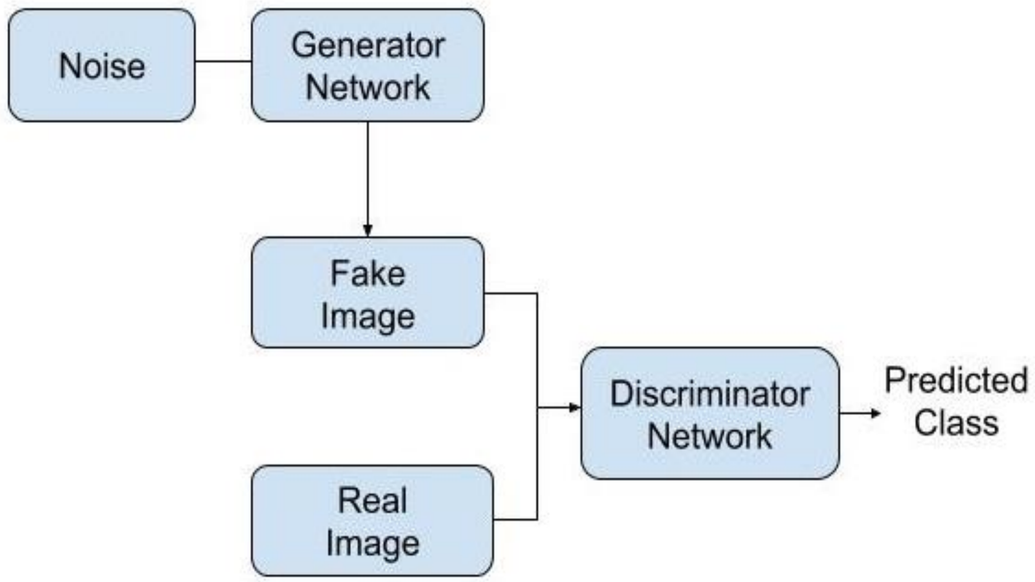



Figure 3.1 :Overview of a generative adversarial network

## 3.3 THE TEXT EDITOR

As an IDE, Visual Studio Code content management was employed. This Integrated Development Environment (IDE) is compatible with a wide range of programming languages. It comes with a connected code editorial management, compiler, CLI (command line interface), and breakpoint debugger that can debug both machine and source code. It has been flattened down for the goal of creating and investigating modern online and cloud App development.

## 3.4 LANGUAGE OF PROGRAMMING

We have used Python 2.7 and Python 3.6 as programming languages. Python allows for fast system integration and a basic working environment that even inexperienced users can learn and use quickly and effectively. Because it is an interpretative, general-purpose, and high-level programming language, it may be used to develop networks, servers, and a number of other applications. It is based on object-oriented programming. It has very straightforward syntax easy to use and allows developers to easily write accurate, logical code for both large and small projects.

## 3.5 PyTorch

Built on Python and Torch, the PyTorch deep learning tensor library is a powerful tool for the field of deep learning.The major market segment that this product is aimed at consists of applications that make use of GPU's and CPU’s. The firm focuses mostly on selling its products to software developers (CPUs).

PyTorch is recommended over other Deep Learning frameworks such as TensorFlow and Keras due to the fact that it employs dynamic computation networks and is entirely written in Python. It enables researchers, software developers, and neural network debuggers to test and run chunks of the code in real time, which is a significant advantage. Users do not need to wait until the whole of the code has been produced before assessing whether or not a section of the code works.PyTorch's two most notable characteristics are as follows: Tensor Computation, which is quite similar to NumPy, with significant support for GPU (Graphical Processing Unit) acceleration. Automated Differentiation for the Purposes of Developing and Training Deep Neural Networks.

# CHAPTER 4

# PROPOSED WORK

## 4.1 PROBLEM STATEMENT

Many different approaches of imaze dehazing have been given in past but many of them have problems like halo effect or distorted edges around image . To solve some of these problems a end to end dehazing method EDCPDN has been introduced which will together able to learn transmission map ,ambient lighting and dehazing working together in harmony.

## 4.2 PROPOSED METHOD

In our method we first take a input image (H × w × 3) and find its Dark Channel which is then combined with image itself(H × w × 1) to create a new image (H × w × 4) .This gives us more information about image and tells us how much dehazing is to be done . The generated image will be then used as input for our EDCPDN generator . Generator uses densely connected pyramid to dehaze the image . This generator gives us dehazed image .The output(dehazed image) from this generator will be further put in discriminator alongside with pretrained dataset to find the discriminator score of the model . On basis of this score our model learns to dehaze images and provide us better outputs .

The components method EDCPDN network architecture are in fig 4.1: image produced with dark channel , dehazing, the Pyramid densely linked generator is used to produce dehazed image and a joint discriminator.

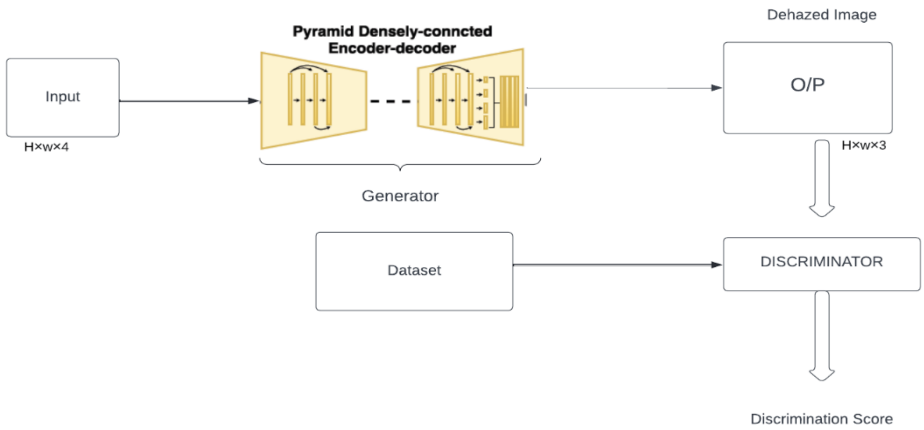



Figure 4.1: Proposed Model Architecture

Estimation Network of Pyramid-Densely Connected Transmission Maps Since prior approaches have employed multi-level features to estimate the dehazed image, an encoder-decode structure based on the dense block and using several layers of a CNN was used. Using dense blocks is the best way to enhance information flow along those features and provide superior convergence by linking all layers. Additional to that, a In order to improve learned features, a multi-level pyramid pooling approach is developed that takes into consideration their underlying structure.

We use the dehazed image produced by generator with images from our dataset as input for the discriminator .After this discriminator finds discrimination score which is further used to better our model.

# CHAPTER 5

# EXPERIMENTS AND RESULTS

The results were produced by running our model on a image dataset. As you can clearly see in results the output images are considerably dehazed and we can see objects clearly in images. This research has proven that the approach described in this study is very effective for Image Dehazing.

Input 1

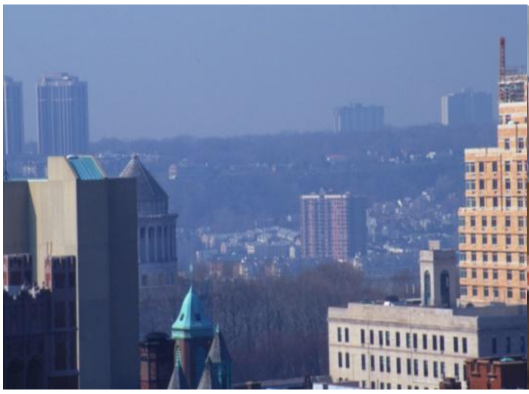
output 1

Input 2

Output 2

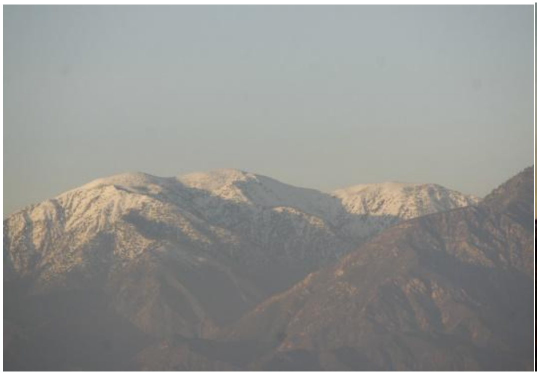
Input 3

Output 3



Input 4

Output 4



Input 5

Output 5

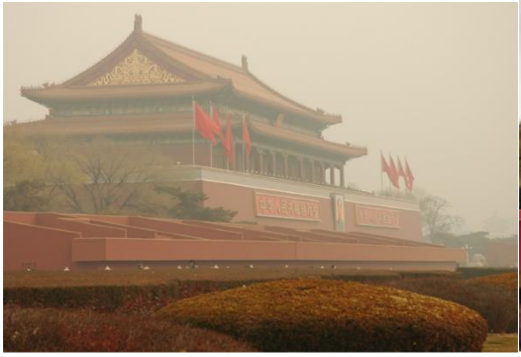
Input 6 Output 6

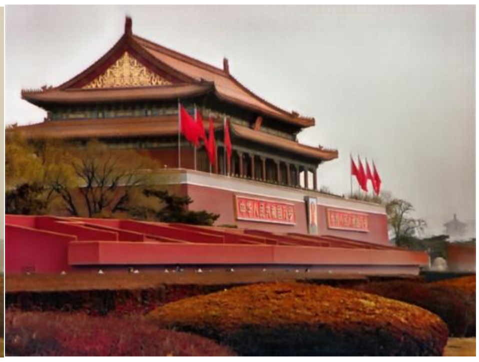
 

Input 7 Output 7

Input 8 Output 8





Input 9 Output 9

Input 10 Output 10

Figure 5.1: Dehazing results

# CHAPTER 6

# CONCLUSION

The Dehazing method been presented in this model can produce end to end result i.e., de-hazed image. Dark channel is included directly into input image and a GAN framework that is based on joint discriminator is used in the suggested technique to enhance a structural relationship and leverage the details the de-hazed picture. By using densely connected pyramid structure we were able to improve accuracy of our model as information loss between layers is less. The relevance of the suggested strategy was shown via a series of experiments and results were shown above. Hence this proves that our model works better than some of other state to art models.

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