A

Major Project

On

UNDERWATER IMAGE COLOR CORRECTION AND CONTRAST ENHANCEMENT BASED ON HUE PRESERVATION

(Submitted in partial fulfillment of the requirements for the award of Degree)

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

By

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CMR TECHNICAL CAMPUS

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2019-2023

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the project entitled **”UNDERWATER IMAGE COLOR CORRECTION AND CONTRAST ENHANCEMENT BASED ON HUE PRESERVATION”** being submitted by **BHUPATHIRAJU GEETHA SUPRIYA(197R1A05J9), YOGITHA POTLAPALLY(197R1A05Q0), KATEPOGU STEPHEN KUMAR(177R1A05F1)** in the partial fulfillment of the requirements for the award of the degree of B.Tech in Computer Science and Engineering to the Jawaharlal Nehru Technological University Hyderabad, is a record of bonafide work carried out by them under our guidance and supervision during the year 2022-23.

The results embodied in this thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

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EXTERNAL EXAMINER

Submitted for viva voice Examination held on ____________________

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ABSTRACT

Underwater Image suffers from serious color distortion and low contrast problems because of complex light propagation in the ocean. In view of computing constraints of underwater vehicles, we propose a high-efficiency deep-learning based framework based on hue preservation. The framework contains three convolutional neural networks for underwater image color restoration. At first, we use the first CNN to convert the input underwater image into the grayscale image. Next, we enhanced the grayscale underwater image by the second CNN. And then, we perform the color correction to the input underwater image by the third CNN. At last, we can obtain the color-corrected image by integrating the outputs of three CNNs based on the hue preservation.

In our framework, that CNNs specialize on each work can be able to simplify each architecture of CNNs at most and improve the regression quality to achieve the low computing cost and high effeciency. However, the problem of the underwater CNNs is that the underwater training data is too few and without the corresponding ground truth. Thus, we use the unsupervised learning method CycleGAN to train the underwater CNNs. We design a training method as the combination of three CycleGANs that can train the three CNNs at the same time to share the regression status. This training method may let the three CNNs of our proposed framework support each other to avoid the training overfitting and without constraint. By the proposed framework and training method, our method can process the underwater images with high quality and low computing cost. The experimental results have demonstrated the correct colors and high image quality of the proposed method’s results, compared with other related approaches.

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1. INTRODUCTION

1.1 PROJECT SCOPE

This project has been developed to identify the Underwater image color correction and contrast enhancement based on hue preservation. The earth is associate aquatic planet and the maximum amount as eightieth of its surface is roofed by water.. Moreover, there is a strong interest in knowing what lies in underwater. Present days, an image of deep waters has a scope to large investigation to explore the underwater for sea floor expedition and navigation. Enthusiasm of underwater imaging includes the inspection of plants, seabed exploration, the search for wrecks up and to the exploration of natural resources.

1.2 PROJECT PURPOSE

This project has been developed to identify Underwater image color correction and contrast enhancement. Enthusiasm of underwater imaging includes the inspection of plants, seabed exploration, the search for wrecks up and to the exploration of natural resources. There were several issues faced by the human in the underwater, if he dives deep into the ocean and stay there for a long time to perform experimentation.so our project is usefull to the Hydrologists.

1.3 PROJECT FEATURES

In this project we mainly use some techniques such as Contrast Stretching and Adaptive Histogram Equalization, which are usefull for processing the image to improve the visual quality. There were several parameters which decreases the quality of an image in underground waters. So inorder to remove all these effects there are several techniques has been implemented and practiced.

2. SYSTEM ANALYSIS

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SYSTEM ANALYSIS

System Analysis is the important phase in the system development process. The System is studied to the minute details and analyzed. The system analyst plays an important role of an interrogator and dwells deep into the working of the present system. In analysis, a detailed study of these operations performed by the system and their relationships within and outside the system is done. A key question considered here is, "what must be done to solve the problem?" The system is viewed as a whole and the inputs to the system are identified. Once analysis is completed the analyst hasa firm understanding of what is to be done.

2.1 PROBLEM DEFINITION

A general statement of Underwater Image Color Correction and Contrast Enhancement is Underwater image quality improvement approaches present a path to magnify the object recognition in underwater surrounding.

2.2 EXISTING SYSTEM

Underwater optical imaging systems mainly include anoptical camera, or adopt techniques such as polarization, stereo/panoramic, and spectral imaging. However, each of techniques other than optical cameras has its limitations, such as a narrow field of view, limited depth, complex and professional operation, etc.There are several techniques which are used very frequently for processing the image to improve the visual quality. Some of them are Contrast Stretching and Adaptive Histogram Equalization.

2.2.1 DISADVANTAGES OF EXISTING SYSTEM

- In Contrast Stretching disadvantage is that the transformation function is not unique. Depending on the application the suitable transformation function is chosen.
- In Adaptive Histogram Equalization technique highlights the unwanted noise present in the background of an image and lead to loss in the information signal. It results in undesired effects in the resultant images.

2.3 PROPOSED SYSTEM

The proposed deep learning-based underwater image restoration framework consists of the four stages: (1) the underwater image grayscale stage relying on CNN to convert the underwater image to the best gray-channel image; (2) the grayscale underwater image details enhancement stage also relying on CNN to remove the noise and enhance the image quality; (3) the underwater image color restoration stage via end-to-end CNN; and (4) the generation stage of the final high image quality and correct color underwater image by integrating the outputs of the other three stages. The details of the four stage is in the following four subsection, respectively.

1. Underwater Image Grayscale Transformer:

Based on hue preservation enhancement method, the first stage is converting the input underwater image to the grayscale image. Different from the in-air image, the red channel and the green channel of underwater image is attenuated by light propagation. We have to analysis the degree of light attenuation to evaluate the best ratio among three channels. To accelerate the algorithm computing, we use the convolutional neural network to predict the ratios. The proposed underwater image grayscale transform CNN aims at transforming an inputunderwater RGB image to the three coefficients that are used to combine RGB three channel to the corresponding grayscale image.

2.Underwater Grayscale Image Detail Enhancement :

The end-to-end convolutional neural network method is a great way to solve the image processing problems with low computing cost and high quality. However, the deep learning methods still contain some problems. Because of slight deviation in image regression, the processed image may contains noise and blurry. Otherwise, the convolutional neural network with the light architecture cannot burden to do the underwater image color correction and the underwater image denoise at the same time. Thus, based on hue preservation, we proposed the underwater grayscale image detail enhancement CNN for the underwater image denoise and CNN processed image detail correction. Inspired by the Google Inception V3 Net, the architecture of underwater grayscale image detail enhancement CNN. This CNN aims at transforming an input underwater grayscale image to the enhancement transmission map. The architecture consists of seven convolutional layers.

3. Underwater Image Color Restoration:

The underwater image color restoration is the main stage of the framework. We use the end-to-end convolutional neural network to correct the color loss in underwater image. Underwater color correction is a complex problem. A high image quality in-air images have to contain high color saturation, right color balance and appropriate image contrast. Thus, we design a loss function which restricts many conditions for the underwater image color restoration CNN regression. The content details of the loss function present in Sec. III.

4. Hue Preservation Enhancement:

Hue preservation is necessary for color image enhancement. In this stage, we use the hue preservation enhancement method from Tian et al. Tian etal. proposed a global contrast adaptive enhancement method based on hue preservation enhancement. It is a great method to integrate the results of color correction and detail enhancement.

2.3.1 ADVANTAGES OF THE PROPOSED SYSTEM

- Remove the noise in underwater environment and reserve the detail that may affect by CNN, we propose a grayscale detail enhancement CNN.
- Our experimental results show that the proposed method achieve better underwater image restoration performance than other methods.
- Greater Efficiency.

2.4 FEASIBILITY STUDY

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensurethat the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are

- ECONOMICAL FEASIBILITY
- TECHNICAL FEASIBILITY
- SOCIAL FEASIBILITY

2.4.1 ECONOMIC FEASIBILITY

This study is carried out to check the economic impact that the system will have onthe organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

2.4.2 TECHNICAL FEASIBILITY

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on theavailable technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

2.4.3 SOCIAL FEASIBILITY

The aspect of study is to check the level of acceptance of the system by the user. Thisincludes the process of training the user to use the system efficiently. The user must notfeel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate theuser about the system and to make him familiar with it. His level of confidence must beraised so that he is also able to make some constructive criticism, which is welcomed, ashe is the final user of the system.

2.5 HARDWARE & SOFTWARE REQUIREMENTS

2.5.1 HARDWARE REQUIREMENTS:

Hardware interfaces specify the logical characteristics of each interface between the software product and the hardware components of the system. The following are some hardware requirements.

- Processor - Intel Core i5 and above
- Speed - 2.5 GHz RAM - 8 GB (min)
- Hard Disk - 50 GB

2.5.2 SOFTWARE REQUIREMENTS:

Software Requirements specifies the logical characteristics of each interface and software components of the system. The following are some software requirements.

- OS version - 5.0 and above
- Operating System - Windows 10 Programming
- MATLAB

3. ARCHITECTURE

3. ARCHITECTURE

3.1 PROJECT ARCHITECTURE

This project architecture shows the procedure followed for classification, starting from input to final prediction.

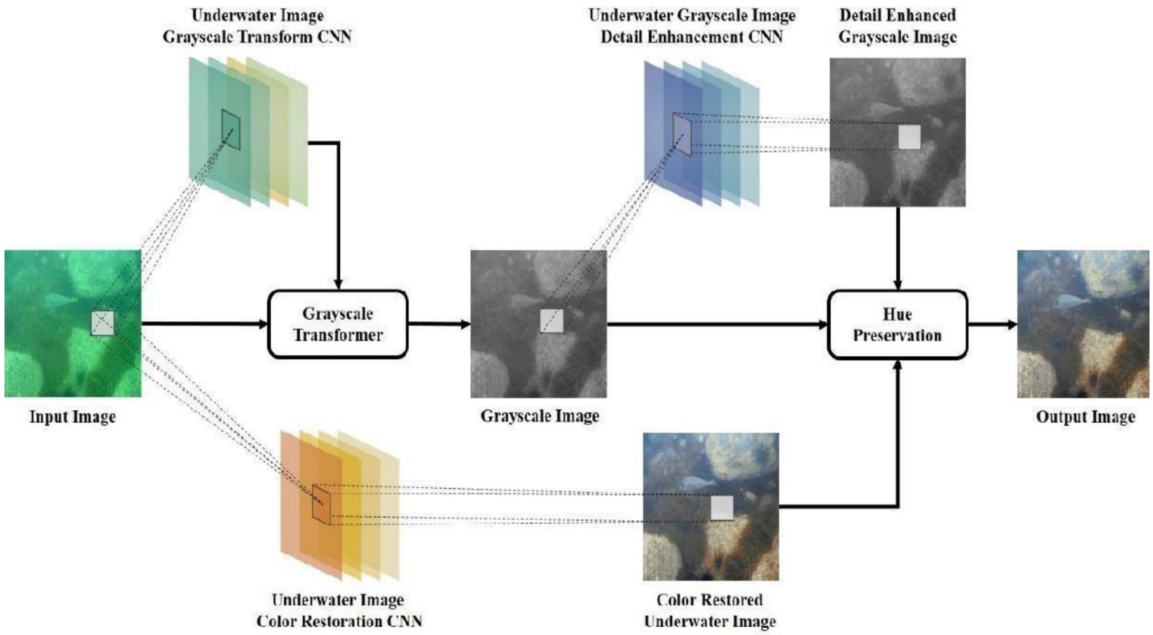


Figure 3.1: Project Architecture for Underwater Image Color Correction and Contrast Enhancement

3.2 DESCRIPTION

This project is totally based upon Underwater Image color correction and contrast enhancement based on hue preservation. The underwater image color restoration is the main stage of the framework. We use the end-to-end convolutional neural network to correct the color loss in the underwater image. Underwater color correction is a complex problem. A high image quality in-air images have to contain high color saturation, right color balance and appropriate image contrast. Thus we design a loss function which restricts many conditions for the underwater image color restoration CNN regression.

3.3 USE CASE DIAGRAM

In the use case diagram, we have basically one actor who is the user in the trained model. A use case diagram is a graphical depiction of a user's possible interactions with a system. A use case diagram shows various use cases and different types of usersthe system has. The use cases are represented by either circles or ellipses. The actors are often shown as stick figures.

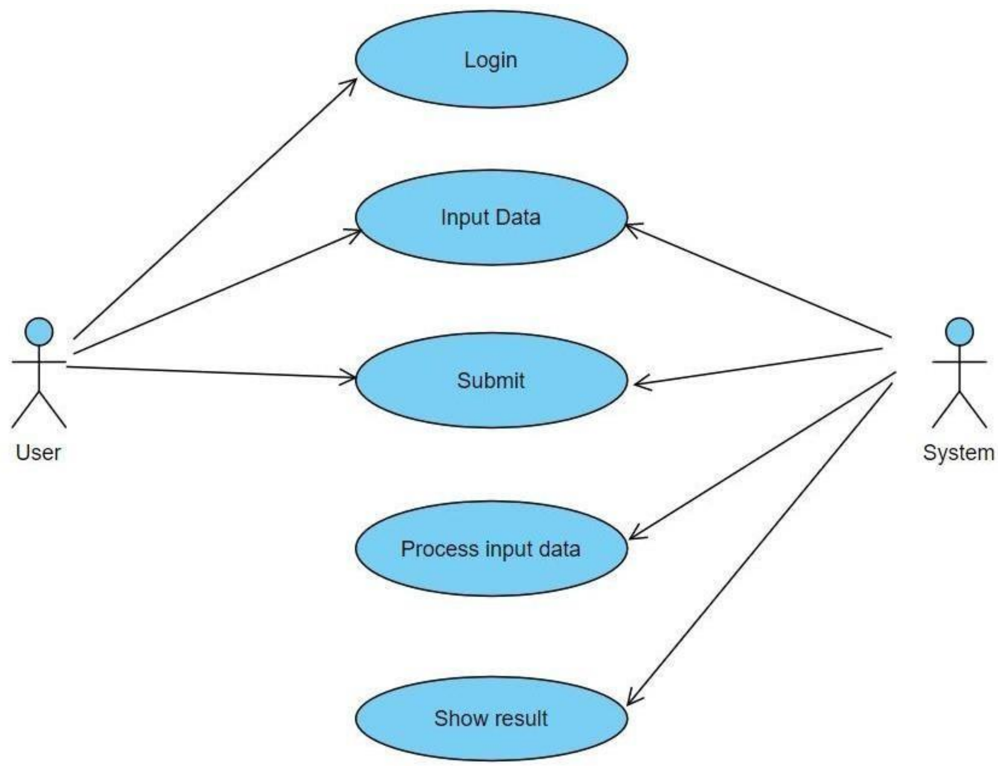


Figure 3.2: Use Case Diagram for Underwater Image Color Correction and Contrast Enhancement

3.4 CLASS DIAGRAM

Class diagram is a type of static structure diagram that describes the structureofa system by showing the system's classes, their attributes, operations(or methods), andthe relationships among objects.

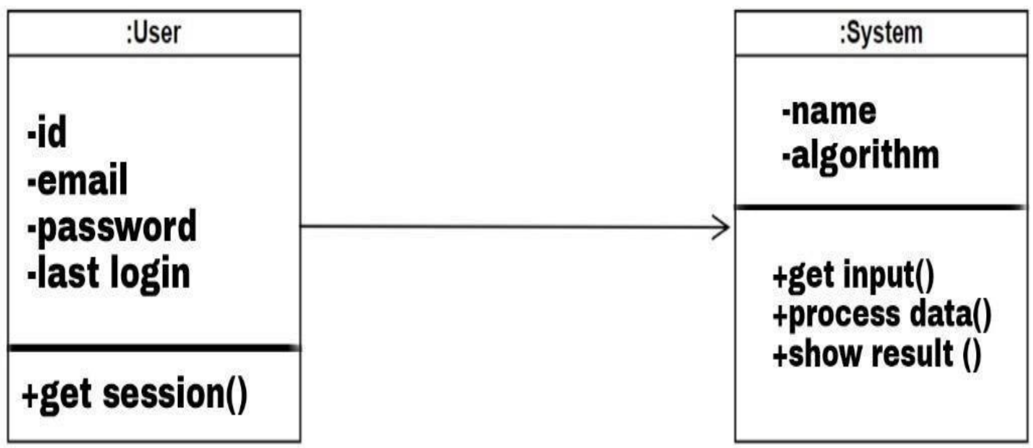


Figure 3.3: Class Diagram for Underwater Image Color Correction and Contrast Enhancement

3.5 SEQUENCE DIAGRAM

A sequence diagram shows object interactions arranged in time sequence. It depicts the objects involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the logical view of the system under development.

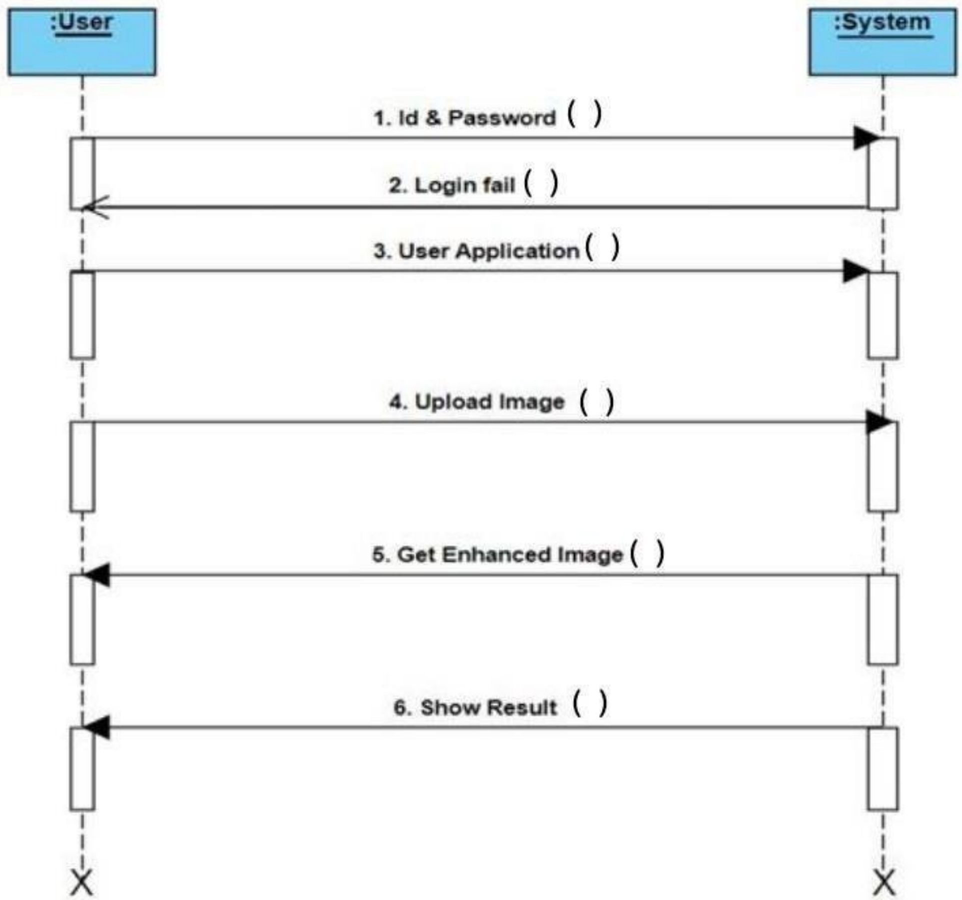


Figure 3.4: Sequence Diagram for Underwater Image Color Correction and Contrast Enhancement

3.6 ACTIVITY DIAGRAM

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. They can alsoinclude elements showing the flow of data between activities through one or more datastores.

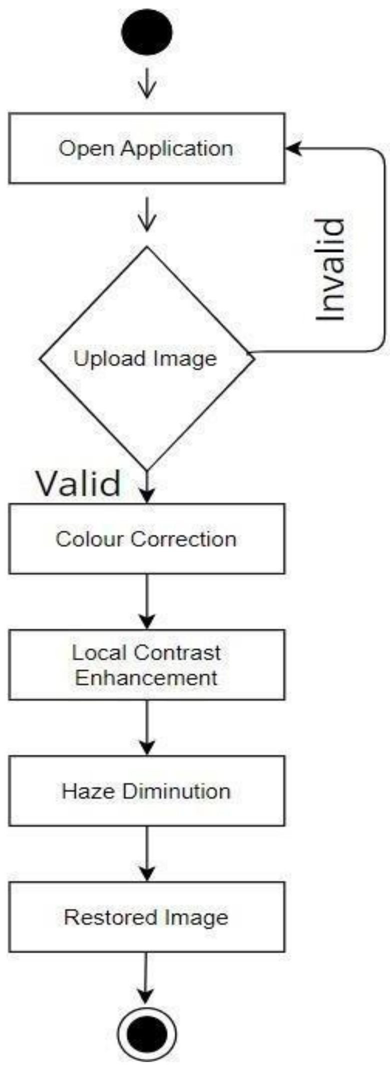


Figure 3.5: Activity Diagram for Underwater Image Color Correction and Contrast Enhancement

4. IMPLEMENTATION

4.1 SAMPLE CODE

```
clc;
close all;
clear all;
warning off
%%%%% under water image enhncement



%%%%%%%%%%%%%%%%      Image Aquisition
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[filename, pathname] = uigetfile({ ' * .jpg ' ; ' * .png '}, 'pick an image ' ) ;
if isequal(filename, 0) || isequal(pathname, 0)
   helpdlg( ' Image  input  canceled. ' ) ;

else
   X=imread(fullfile(pathname, filename));
End

figure,imshow(X);
title( ' original  image ' );
%%%%%%%%%%%%%%% devide color space images
   N = 256;       A = im2uint8(X);
                  a=rgb2hsv(X);
   fig = figure;
```

```
subplot( 2 , 2 , 1 );
imshow(A);
title( ' original image ' );
ColorList =  { ' Red '   ' Green '   ' Blue ' };
gr = 0:1/(N-1):1;


for k = 1: 3
    %  color  map:
    cMap = zeros ( N , 3 );
    cMap( : , k ) = gr ;
    subplot ( 2 , 2 , k+1 );
    imshow (ind2rgb(A ( : , : , k) , cMap ) );
    title (ColorList {k});
end


%%%  bidirectional  Empirical  Mode Decomposition (BEMD) analysis
normal_thr_limit = 0.5;
low_limt = 0.002;
up_limit = 0.999;
%________________________________________________
```

```
under_image = X;
[CONTRAST  saliency  chromatic]=size(X);

%____________________________________________



% apply CNN
[ nndata AlexNet ] = size (chromatic);
nn_data_image = 0 : 0.1 : nndata;
y=nn_data_image .^ 3;
net = newff (minmax (nn_data_image),[20 , AlexNet],{ ' logsig ' , ' purelin ' , '
 trainln ' } );
net.trainparam.epoches=4000;
net.trainparam.goal=1e-25;
net.trainparam.lr=0.01;
net=train(net,nn_data_image,y);



out_nn = y (11);
out_nn = net(nn_data_image (11) );
nn_data = (ceil (out_nn ) . / out_nn);
out_AlexNet = floor(nn_data);
G=[];
```

```
if chromatic==3
    inc_pixel_limit = 0.04;
    dec_pixel_limt = -0.04;
    max_chromatic = rgb2ntsc (under_image);
    mean_adjustment = inc_pixel_limit - mean(mean(max_chromatic(: , : , 2)));
    max_chromatic(:,:,2)   = max_chromatic(:,:,2)+mean_adjustment*(out_AlexNet-
max_chromatic(:,:,2));
    mean_adjustment = dec_pixel_limt-mean(mean(max_chromatic (:,:,3)));
    max_chromatic(:,:,3) = max_chromatic(:,:,3)+mean_adjustment*(out_AlexNet-
max_chromatic(:,:,3));


else
    max_chromatic = double(under_image)./255;
end
%________________________________________________


mean_adjustment = normal_thr_limit-mean(mean(max_chromatic(:,:,1)));
max_chromatic(:,:,1)    =    max_chromatic(:,:,1)+mean_adjustment*(out_AlexNet-
max_chromatic(:,:,1));
if chromatic == 3
    max_chromatic = ntsc2rgb(max_chromatic);
end
```

```
%________________________________________________________
under_image = max_chromatic.*255;
%_______________caliculate the min to max pixels__________________



for k =1:chromatic
   arr = sort(reshape(under_image(:,:,k),CONTRAST*saliency,1));
   saliency_min(k) = arr(ceil(low_limt*CONTRAST*saliency));
   luminance_max(k) = arr(ceil(up_limit*CONTRAST*saliency));
end
%________________________________________________________


if chromatic == 3
   saliency_min = rgb2ntsc(saliency_min);
   luminance_max = rgb2ntsc(luminance_max);
end
%________________________________________________________


under_image=(under_image-saliency_min(1))/(luminance_max(1)-
saliency_min(1));
figure,imshow(under_image);
title(' image enhancement');
```

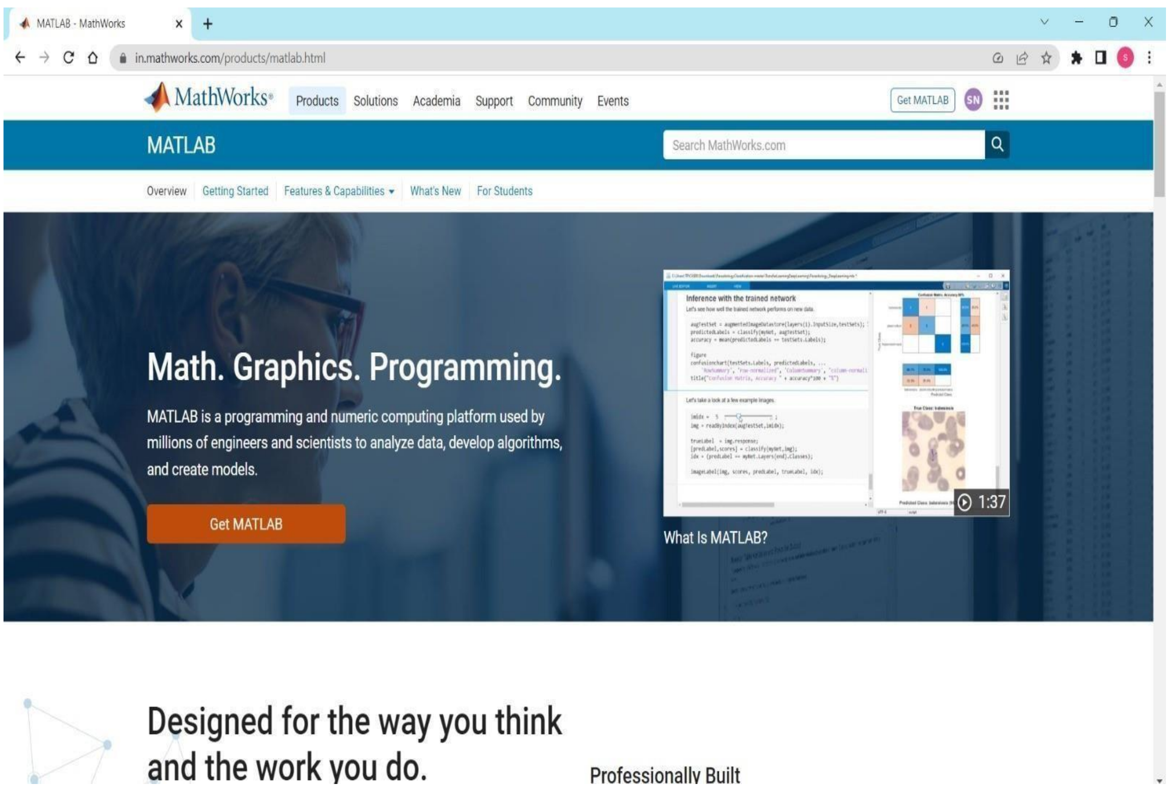
```
% % %%%%%%%%%%%%%%temporal correlation pixels separation

red_color_correlation = adapthisteq(under_image(:,:,1));
    green_adapthisteq_green = adapthisteq(under_image(:,:,2));
    blue_adapthisteq_blue = adapthisteq(under_image(:,:,3));

fusion_enhanced=cat(3,red_color_correlation,green_adapthisteq_green,blue_adapth
isteq_blue);
    figure,imshow(mat2gray(fusion_enhanced));title(' output image');


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
END %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

   %%%  singlr  part extrraction

   %  single_partr=imcrop(fusion_enhanced);
   %  figure,imshow(mat2gray(single_partr));title('particular part of image');
```

5. RESULTS

5. RESULT

Step - 1 : Open Matlab

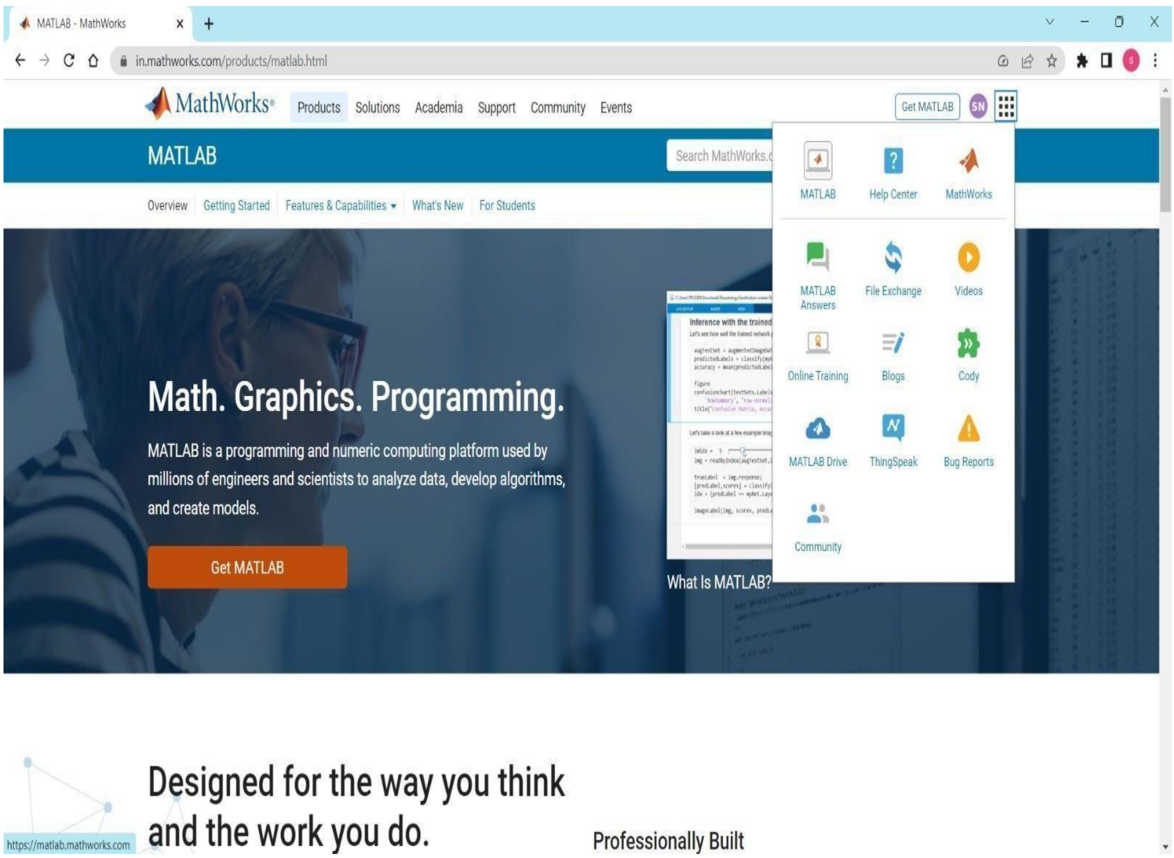
- On a Microsoft Windows platform, to start MATLAB, double-click the MATLAB shortcut icon on your Windows desktop.On a UNIX platform, to start MATLAB, type matlab at the operating system prompt. After starting MATLAB, the MATLAB desktop opens - see MATLAB Desktop. We can change the directory in which MATLAB starts, define startup options including running a script upon startup, and reduce startup time in some situations.



Screenshot 5.1 : Matlab Homepage

Step - 2 : Login to matlab page

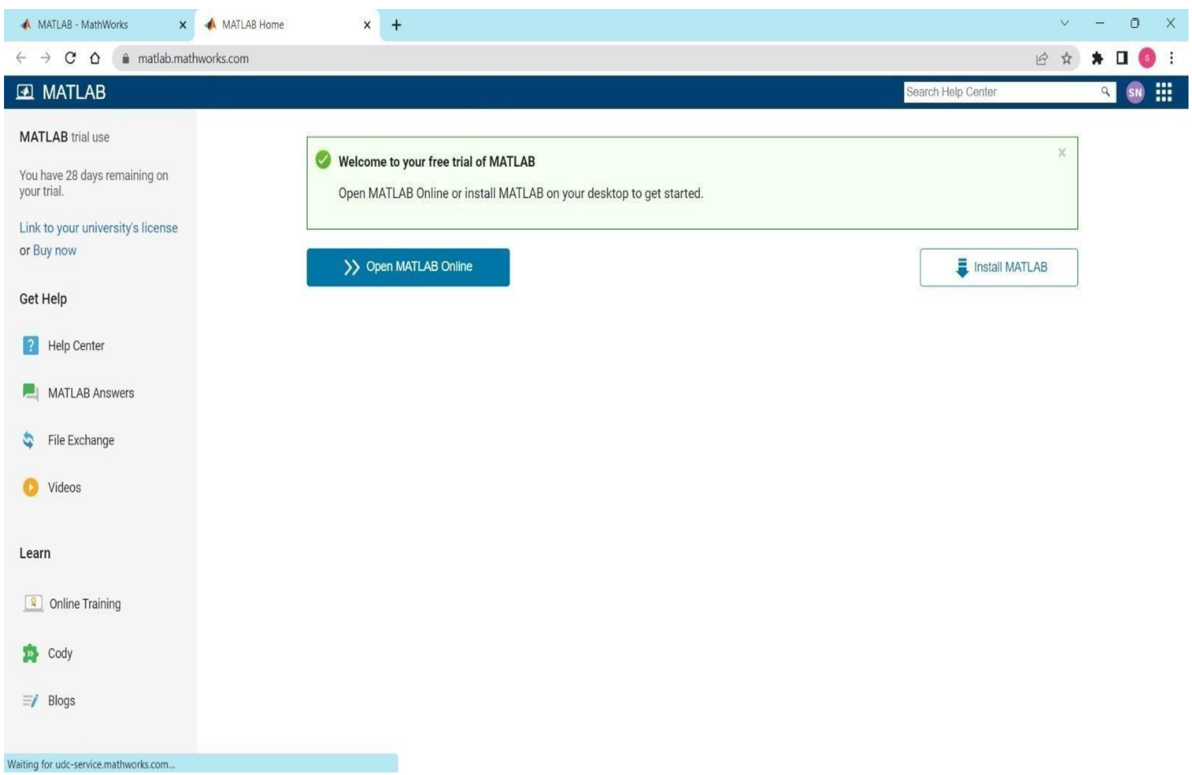
- After opening matlab a login page appears where the user has to enter the username and password to login. We can change the way our desktop looks by opening, closing, moving, and resizing the tools in it. We can also move tools outside of the desktop or return them back inside the desktop (docking). All the desktop tools provide common features such as context menus and keyboard shortcuts.



Screenshot 5.2 : Matlab login page

When the user account page is opened few options are appeared on the screen which are helps in proper usage of matlab. There are:

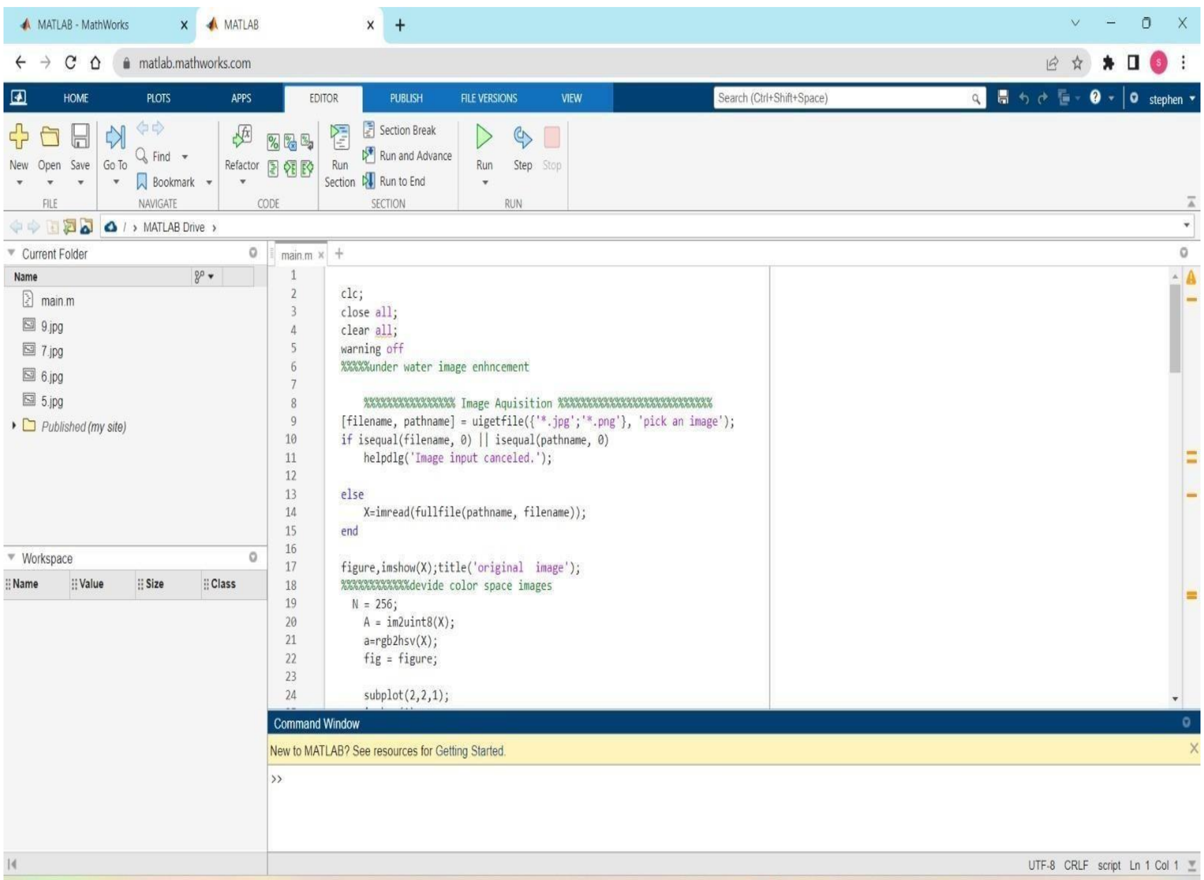
- Current Directory Browser
- Workspace Browser
- Array Editor
- Editor/Debugger
- Command Window
- Command History
- Launch Pad
- Help Browser



Screenshot 5.3 : Matlab user account page

Step - 3 : Upload the code

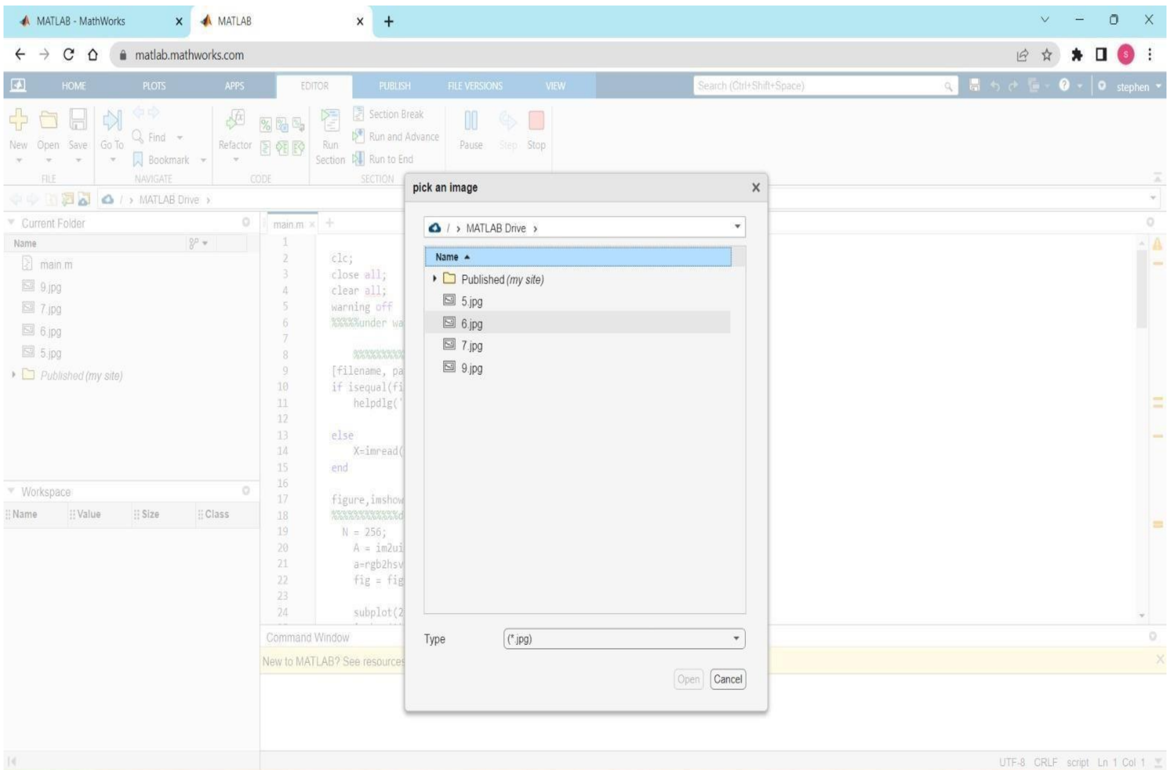
- To get the required results/output code is uploaded in the matlab and after uploading the code click on the run button to run the code. When we run external programs from the MATLAB Command Window. The exclamation point character! is a shell escape and indicates that the rest of the input line is a command to the operating system. This is useful for invoking utilities or running other programs without quitting MATLAB.



Screenshot 5.4 : Uploadation of code

Step - 4 : Select an image as an input

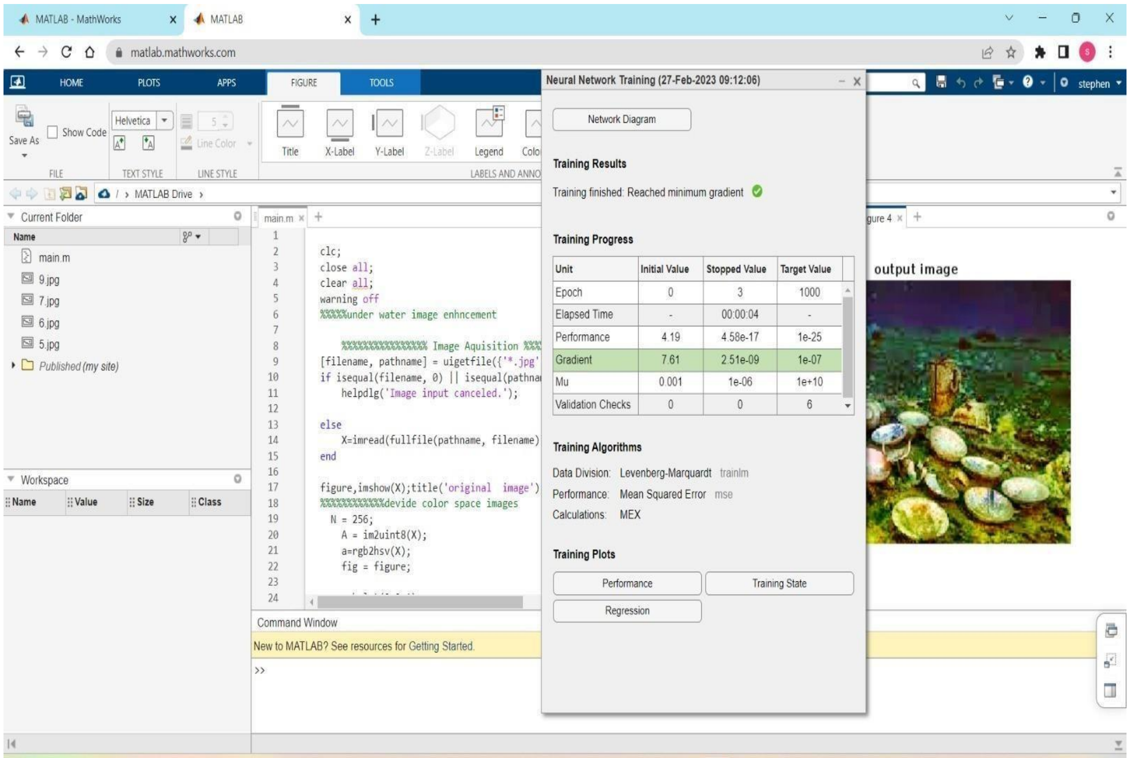
➢ After uploadation of the code an underwater image should be uploaded as an input to get the desired output image. The input image is considered as the raw image and the output image is in the enhanced form.



Screenshot 5.5 : Image uploadation

Step - 5 : Click on the option performance under the training plots when the dialog box appears

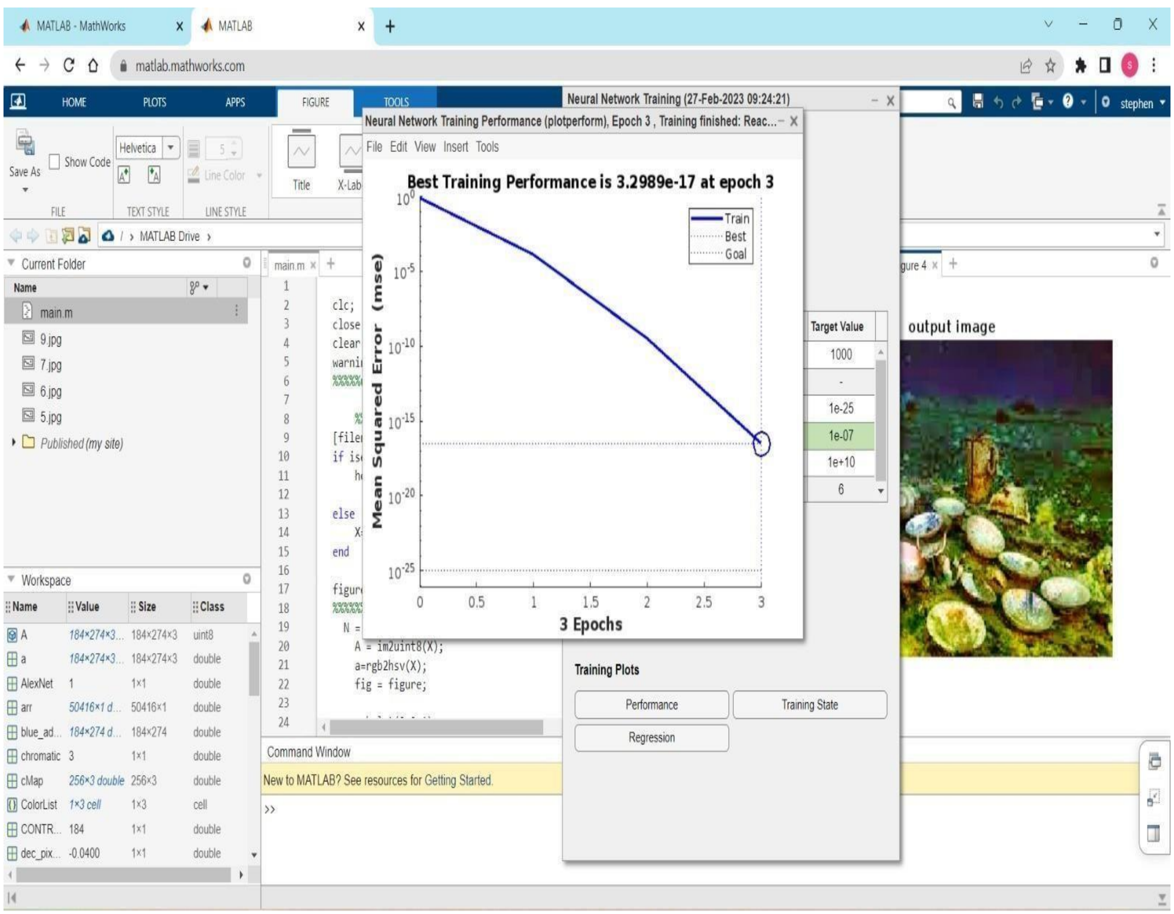
➢ In the neural network training dialogue box we get the training results, training progress, training algorithms and training plots information and in the training plots we get the performance, training state and regression graph outputs.



Screenshot 5.6 : Apperance of neural network training dialog box

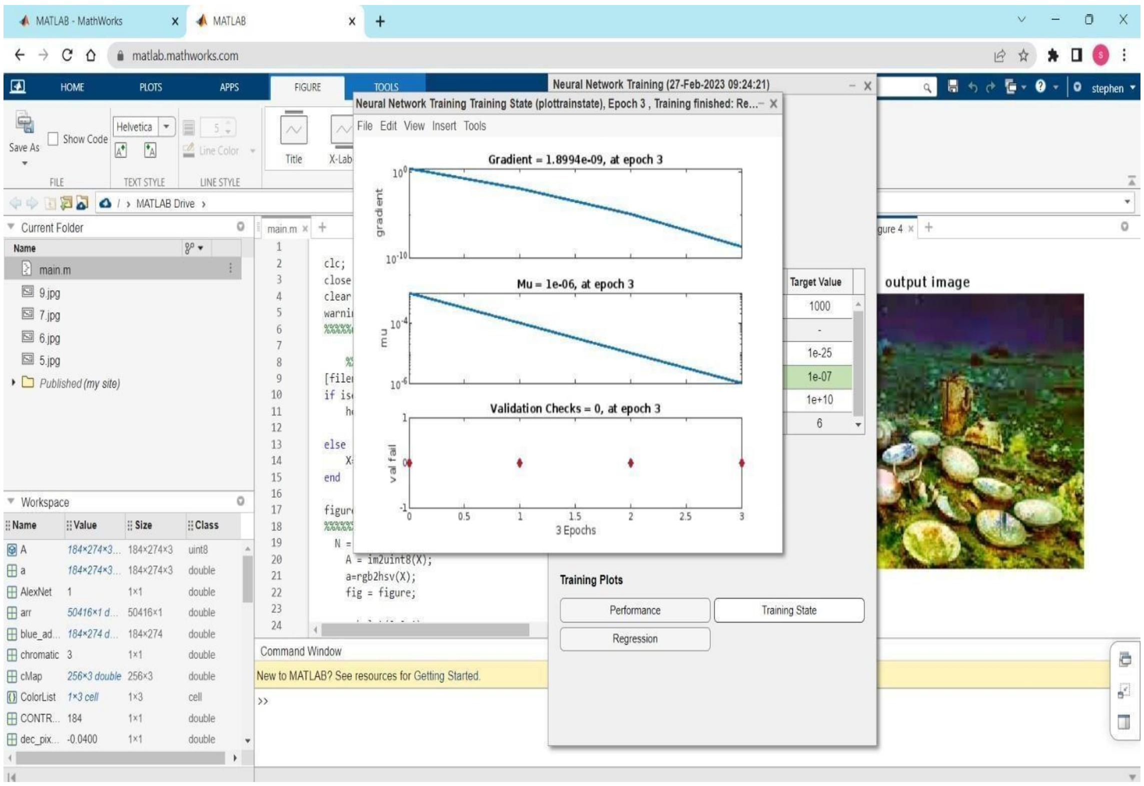
Step - 6 : After clicking on performance 3 output graphs are shown which shows the enhancement of the image

- As mentioned in the appearance of neural network training dialog box we get a performance graph as output. The graph is calculated between the mean squared error (msc) and 3 epoches. This graph represents the best training performance of the neural network and the best training performance is 3.2989e-17 at epoch 3. In this graph as the as the epochs value increases the mean squared error decreases.



Screenshot 5.7 : Performance graph output

- In the training state graph the gradient of the image, the Mu of the image and the validation check of the image are calculated with respect to the epochs where the gradient = 1.8994e-09 at epoch 3, mu=1e-06 at epoch 3 and validation checks = 0 at epoch 3. We observe that as the epoch value increases the gradient value decreases, mu decreases, and the validation check is constant



Screenshot 5.8 : Training state graph output

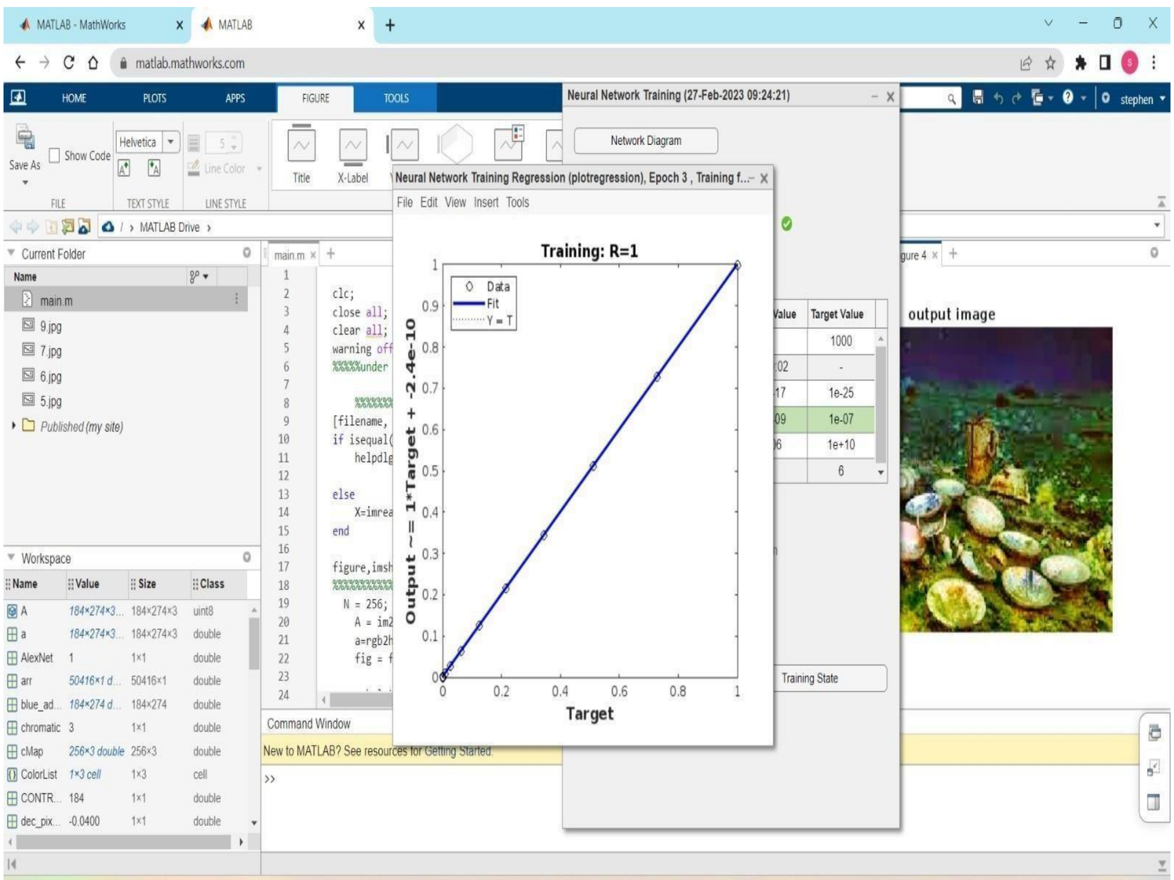
- In this graph regression is calculated between the target and the output. When the target value increases from 0 to 1 and the output value also increases from 0 to 1.

- The training regression:

  R=1

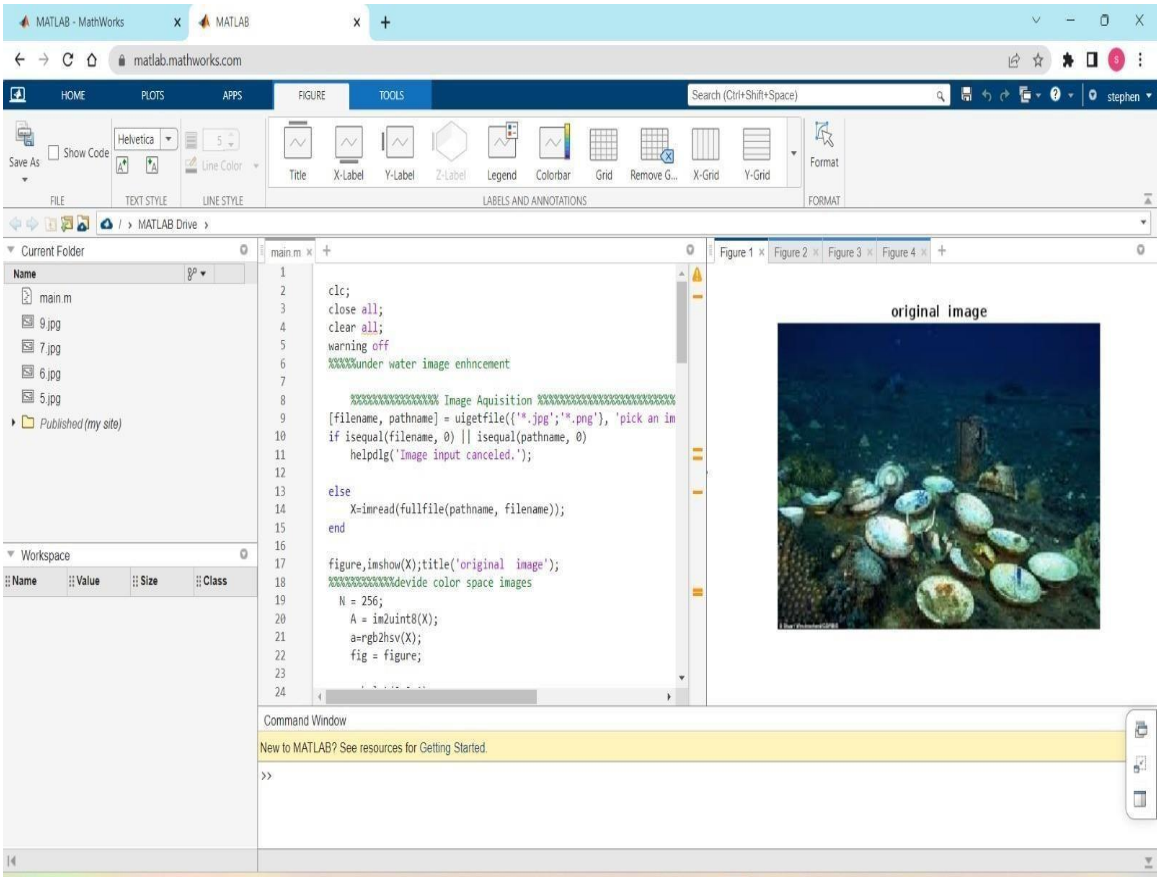
- Output:

  Output~= 1*Target+-2.4e-10



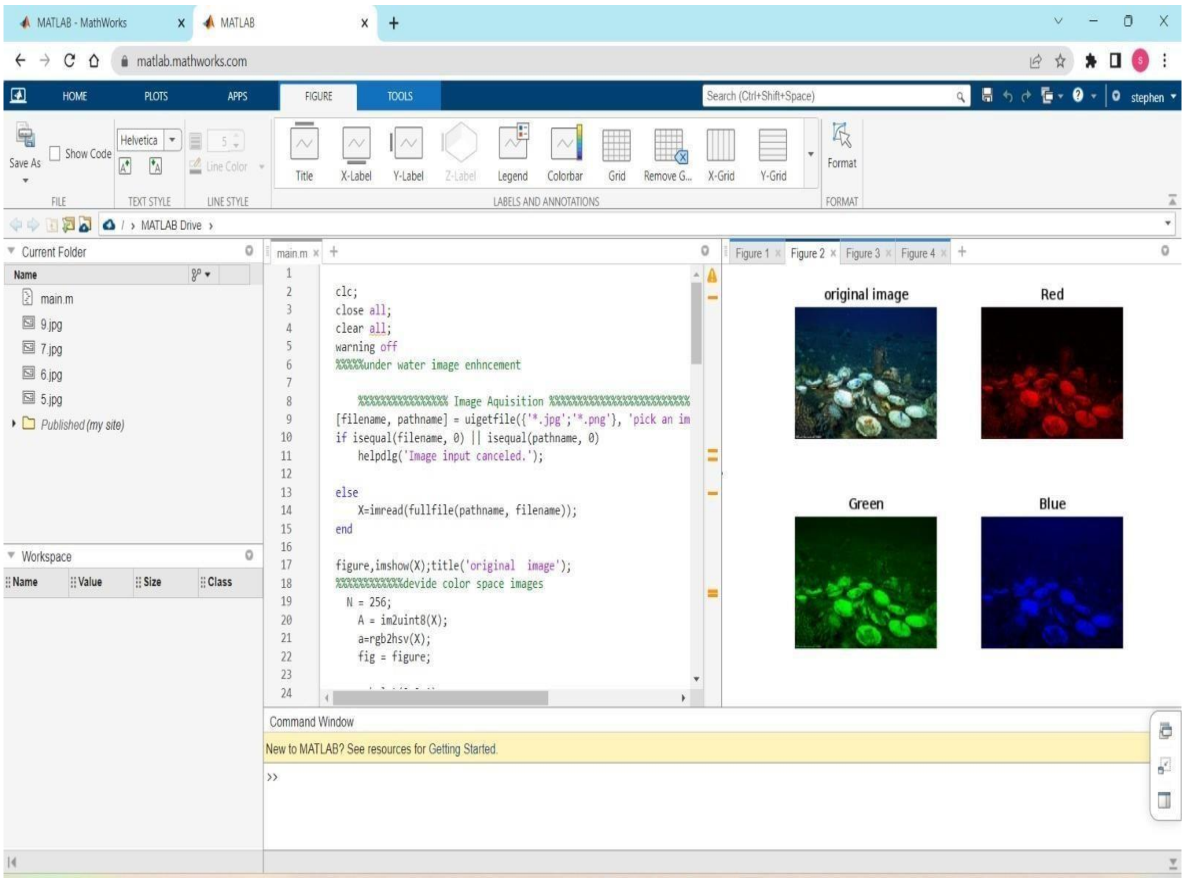
Screenshot 5.9 : Regression graph output

➢ In the below screenshot the original underwater image is shown which has to be enhanced to get an output image.



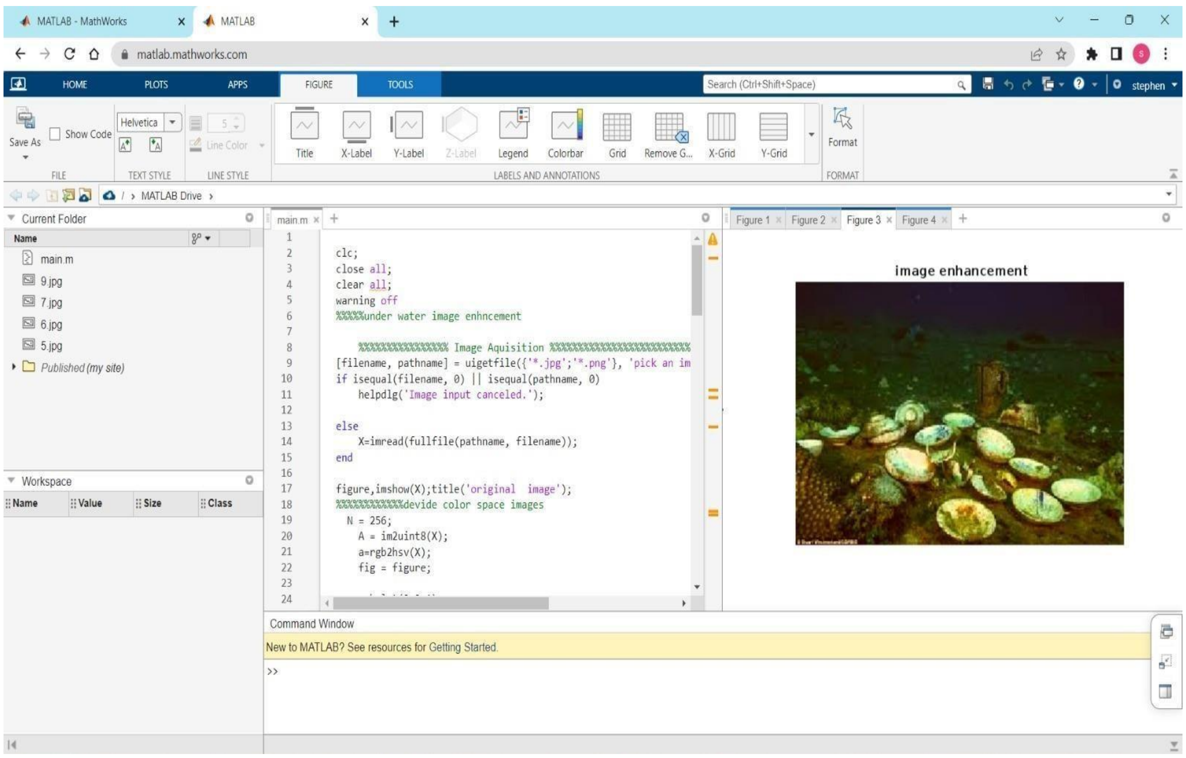
Screenshot 5.10 : Original Image

- In stages of enhancing the image, first the input image is converted into greyscale image and then by using the hue preservation method the input image is enhanced.



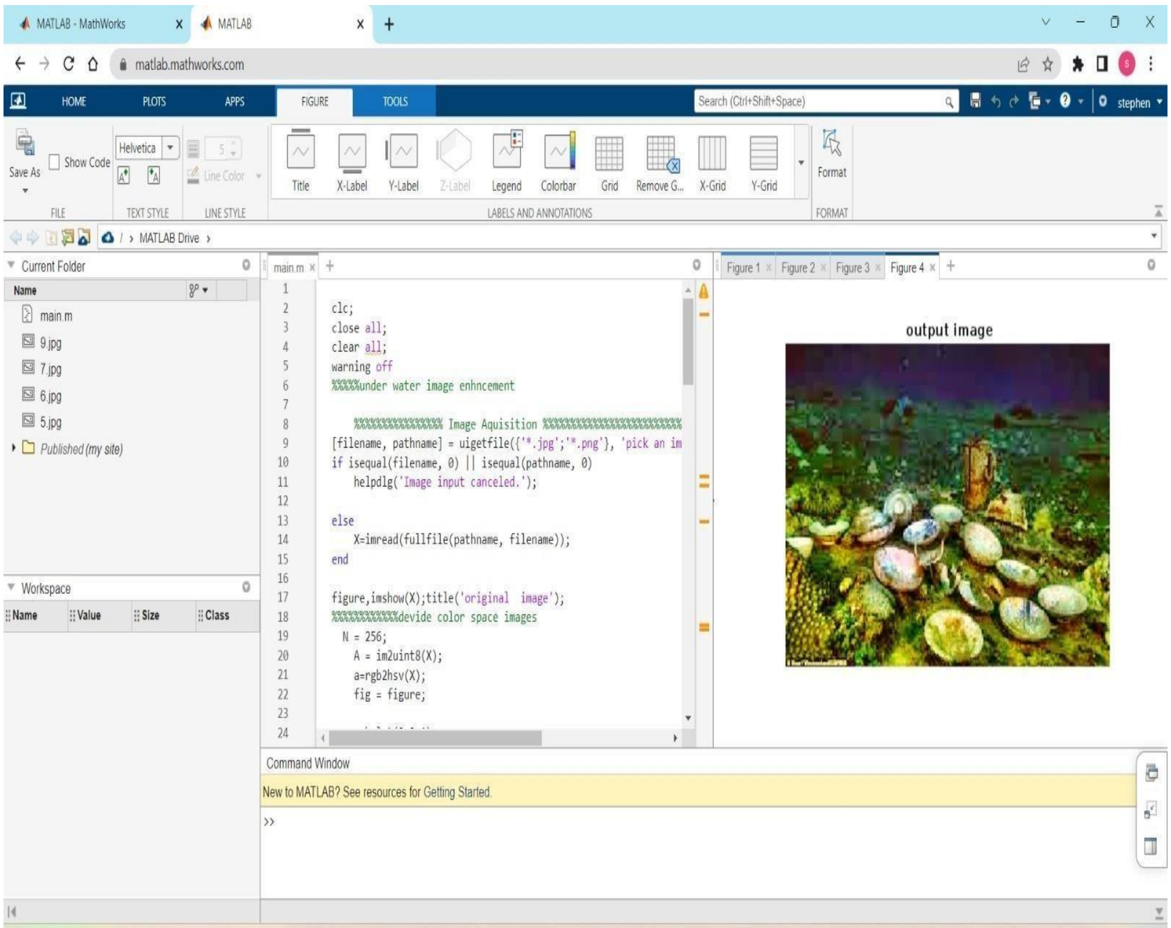
Screenshot 5.11 : Stages of enhancing the original image

- Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interesting an image. A familiar example of enhancement is when we increase the contrast of an image because "it looks better." It is important to keep in mind that enhancement is a very subjective area of image processing.



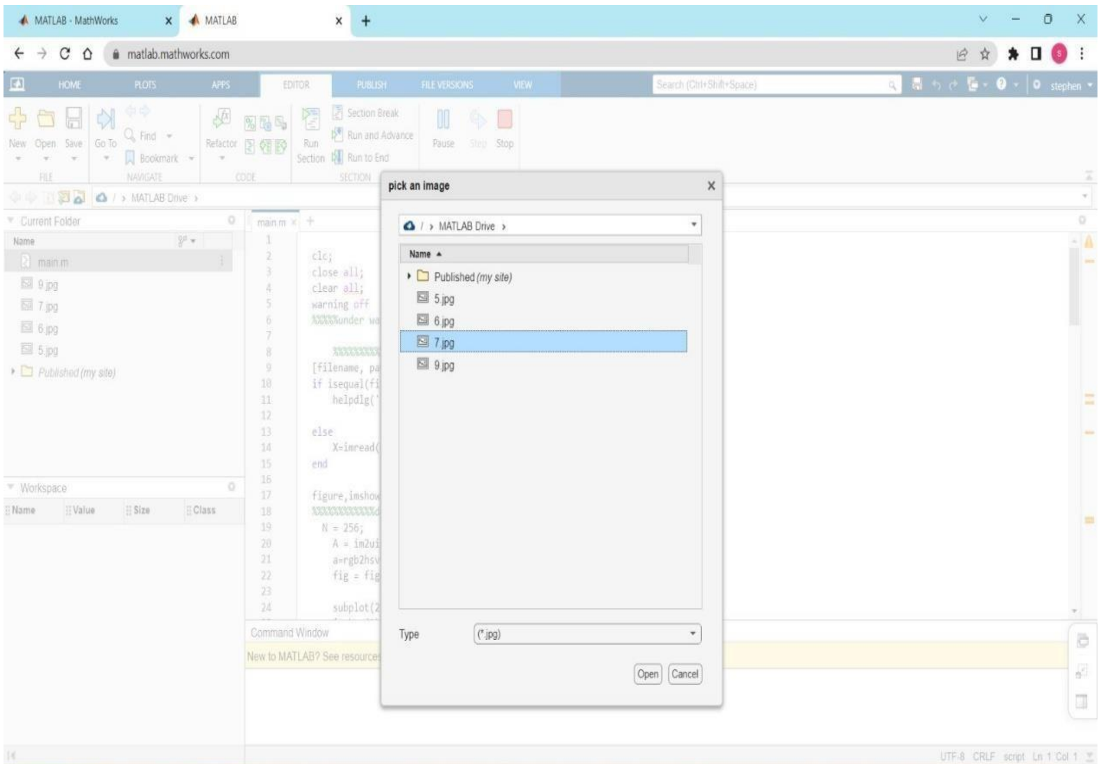
Screenshot 5.12 : Enhanced image

- After performing all the above steps to the original underwater input image we get the output image. The output image is in the form of an enhanced image. Finally we a enhanced color corrected image as an output.



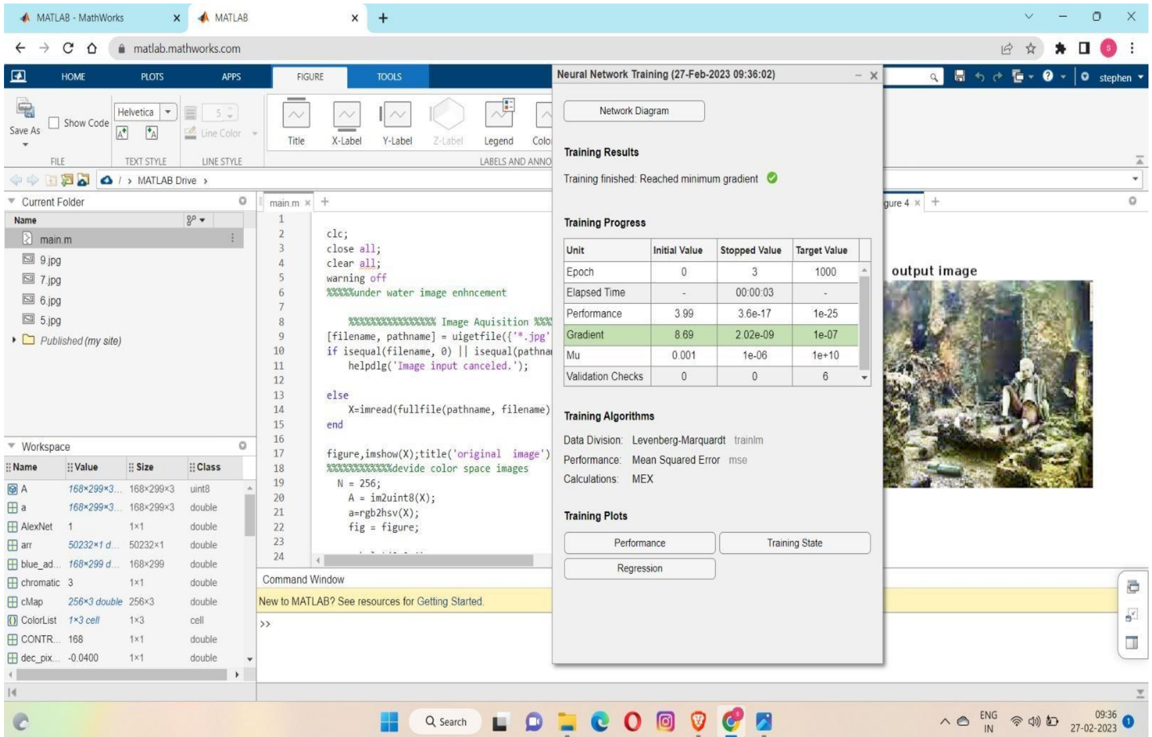
Screenshot 5.13 : Output image

➢ After uploadation of the code an underwater image should be uploaded as an input to get the desired output image. The input image is considered as the raw image and the output image is in the enhanced form.



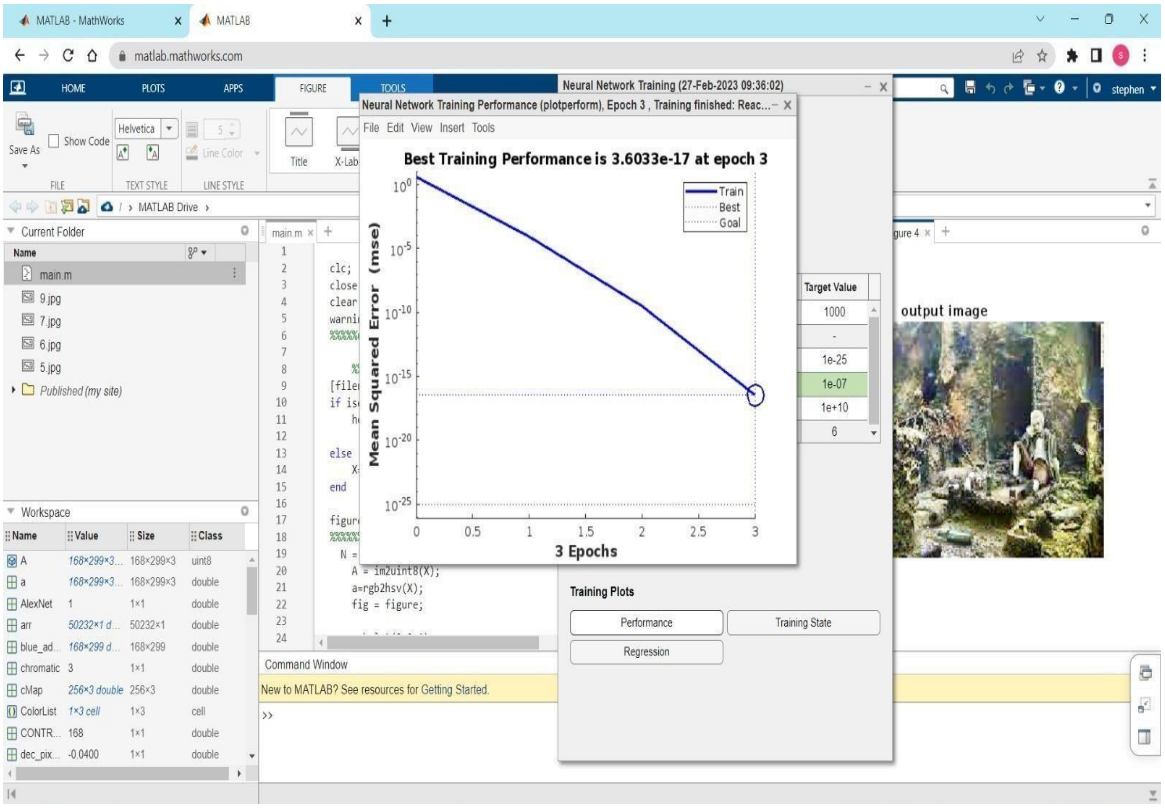
Screenshot 5.14 : Input image uploadation of example 2

- In the neural network training dialogue box we get the training results, training progress, training algorithms and training plots information and in the training plots we get the performance, training state and regression graph outputs.



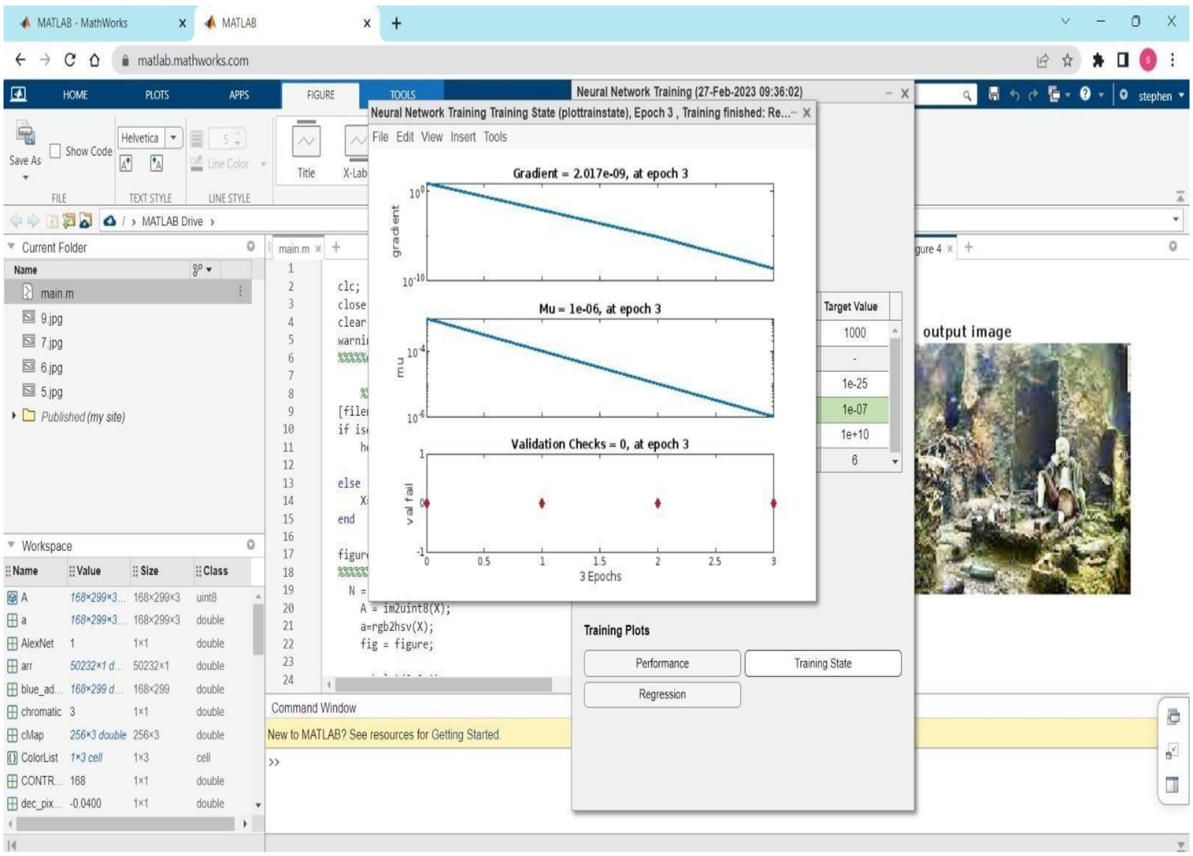
Screenshot 5.15 : Apperance of neural network training dialog box of example 2

- As mentioned in the appearance of neural network training dialog box we get a performance graph as output. The graph is calculated between the mean squared error (msc) and 3 epoches. This graph represents the best training performance of the neural network and the best training performance is 3.6033e-17 at epoch 3. In this graph as the as the epochs value increases the mean squared error decreases.



Screenshot 5.16 : Performance graph output of example 2

- In the training state graph the gradient of the image, the Mu of the image and the validation check of the image are calculated with respect to the epochs where the gradient = 2.017e-09 at epoch 3, mu=1e-06 at epoch 3 and validation checks = 0 at epoch 3. We observe that as the epoch value increases the gradient value decreases, mu decreases, and the validation check is constant



Screenshot 5.17 : Training state graph output of example 2

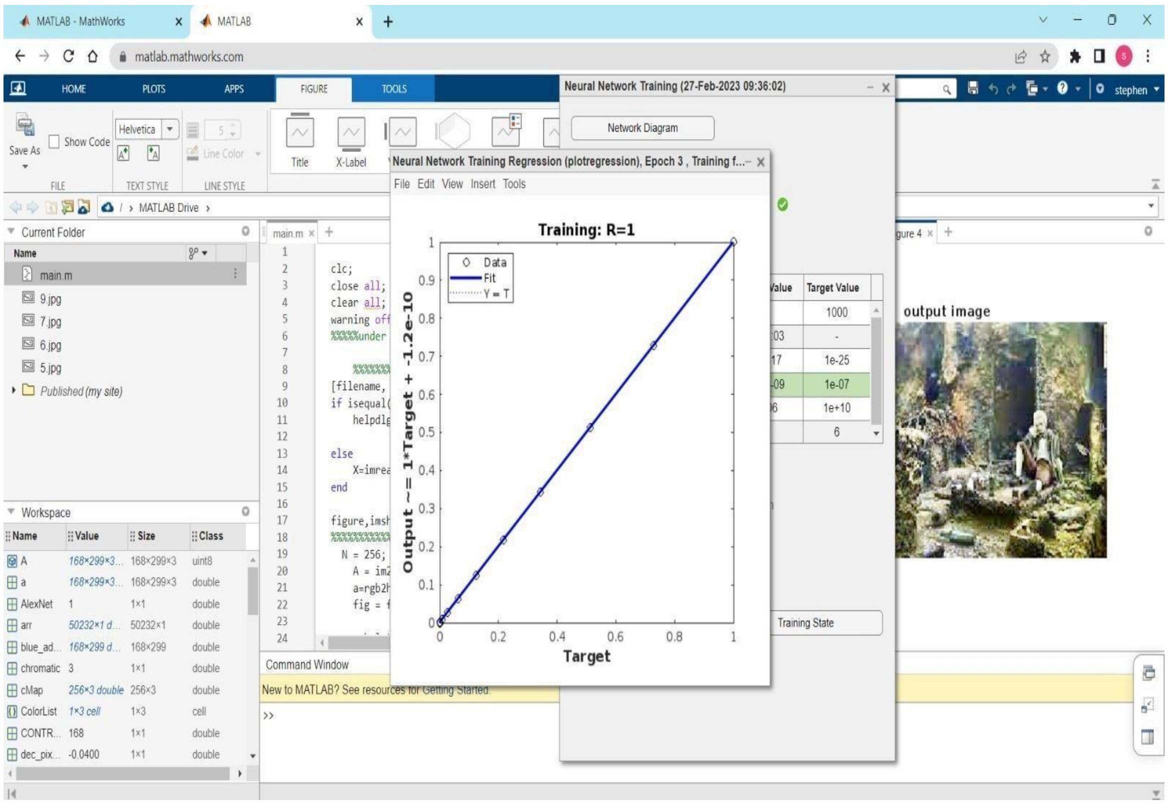
- In this graph regression is calculated between the target and the output. When the target value increases from 0 to 1 and the output value also increases from 0 to 1.

- The training regression:

  R=1

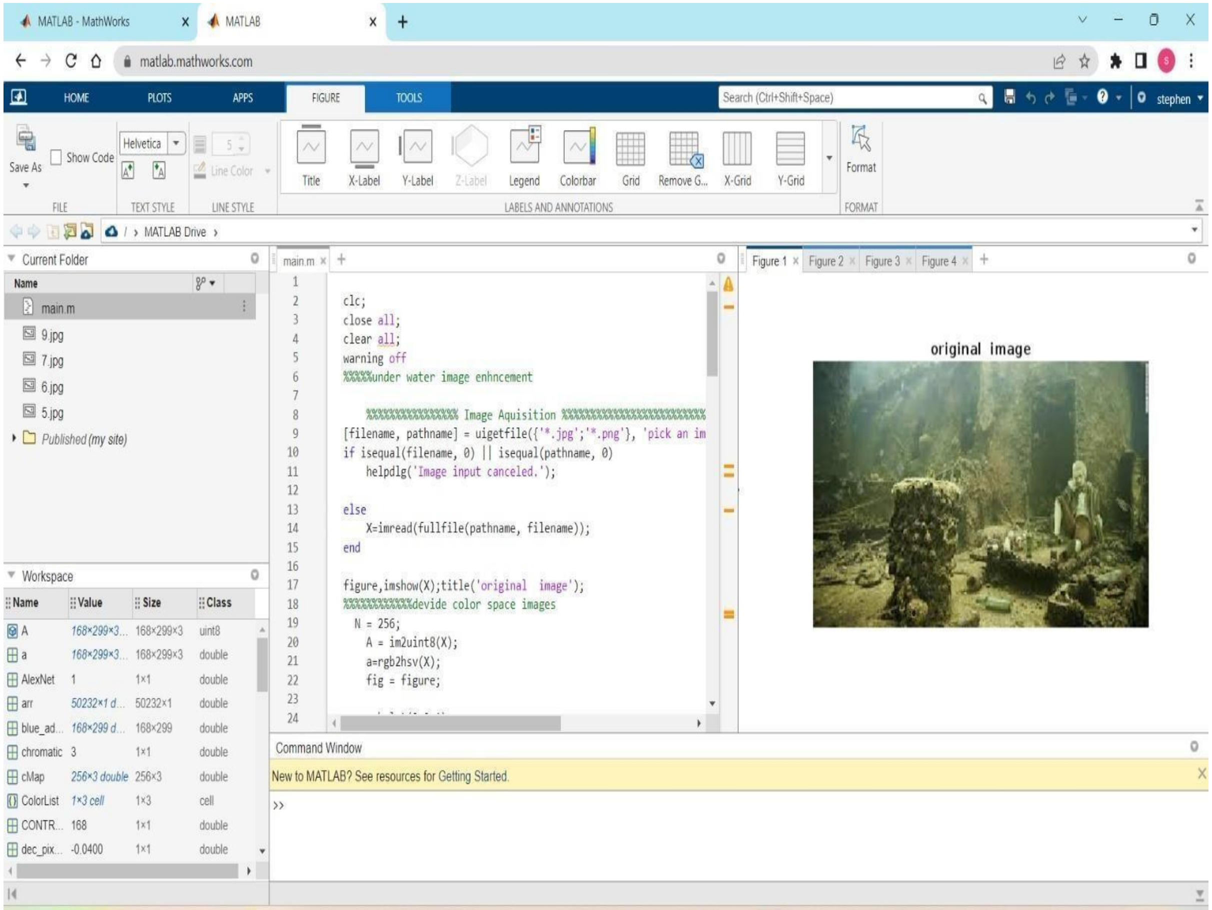
- Output:

  Output~= 1*Target+-1.2e-10



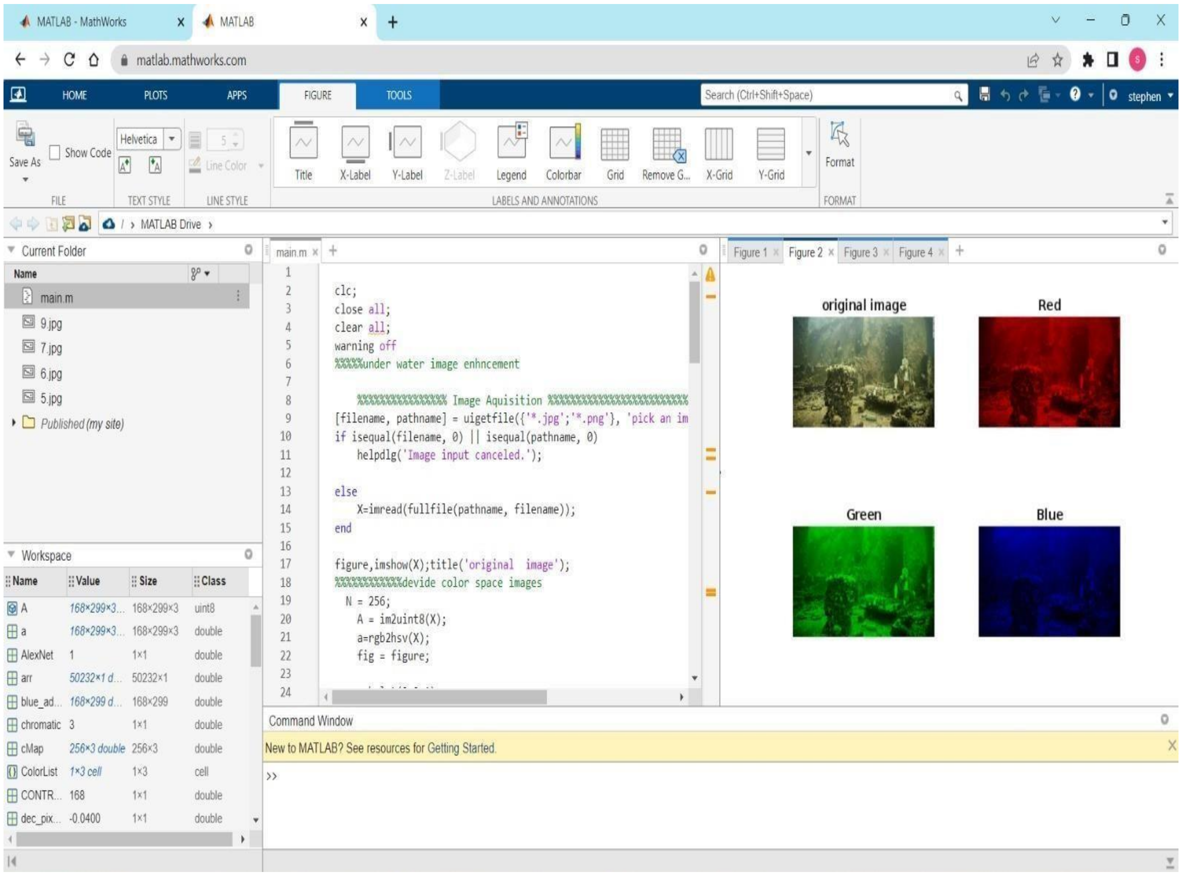
Screenshot 5.18 : Regression graph output of example 2

➢ In the above screenshot the original underwater image is shown which has to be enhanced to get an output image.



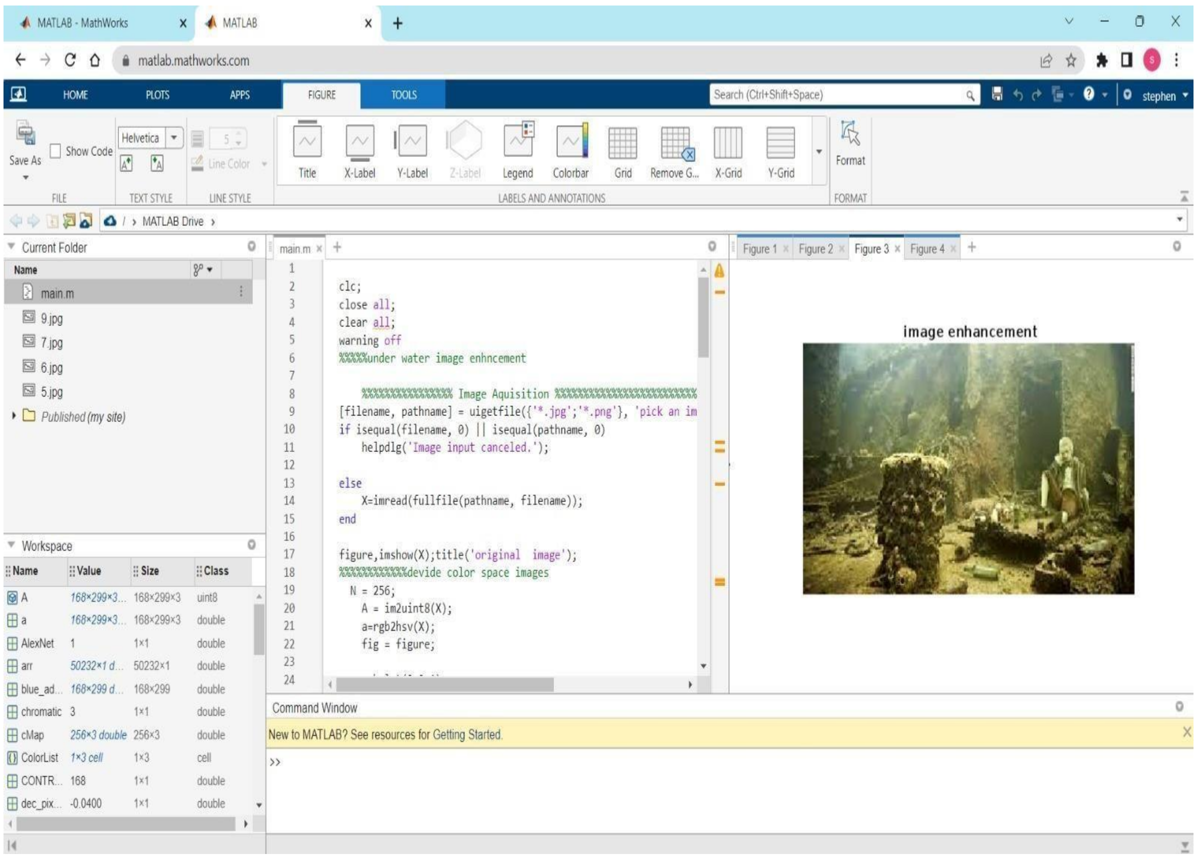
Screenshot 5.19 : Original Image of example 2

➢ In stages of enhancing the image, first the input image is converted into greyscale image and then by using the hue preservation method the input image is enhanced.



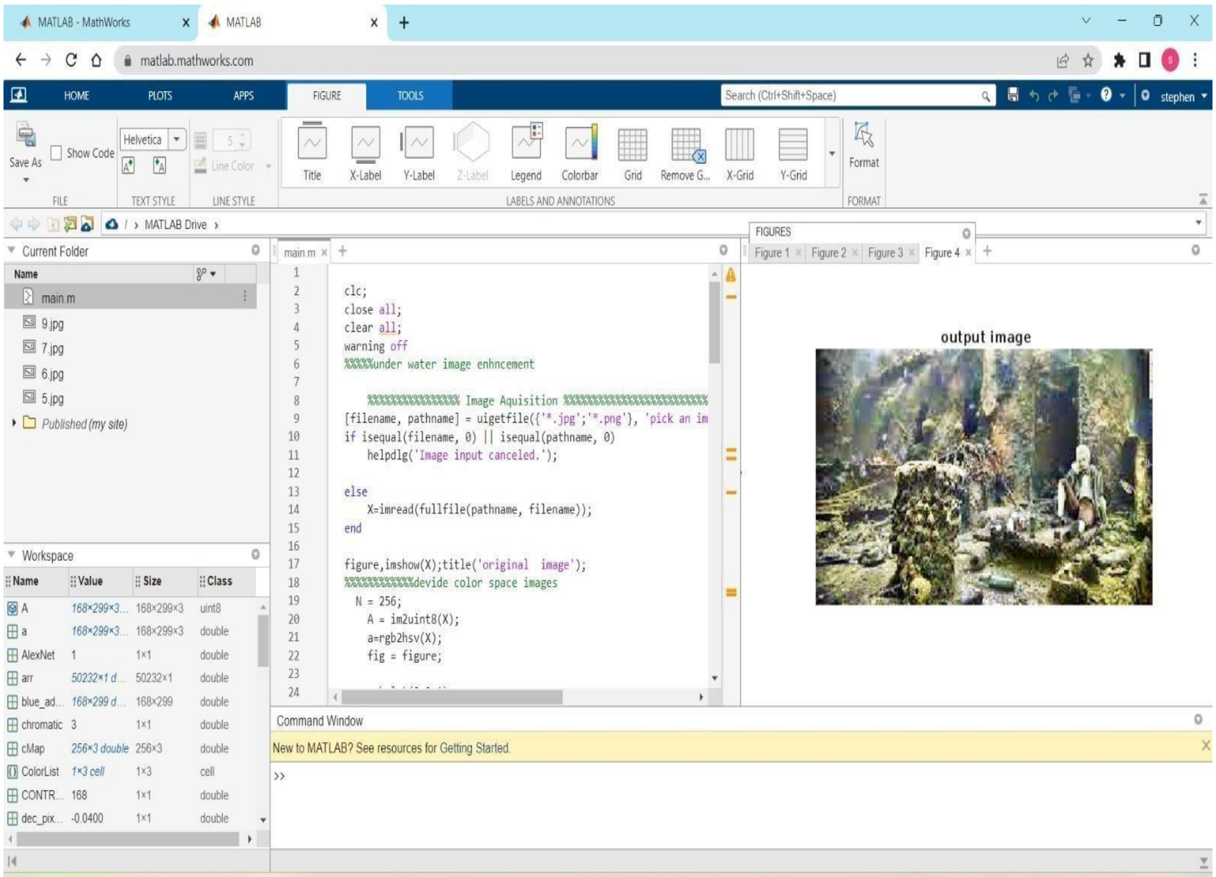
Screenshot 5.20 : Stages of enhancing the original image of example 2

- Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interesting an image. A familiar example of enhancement is when we increase the contrast of an image because “it looks better.” It is important to keep in mind that enhancement is a very subjective area of image processing.



Screenshot 5.21 : Enhanced image of example 2

- After performing all the above steps to the original underwater input image we get the output image. The output image is in the form of an enhanced image. Finally we a enhanced color corrected image as an output.



Screenshot 5.22 : Output image of example 2

6. TESTING

6. TESTING

6.1 INTRODUCTION TO TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, subassemblies, assemblies and/or a finished product. It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of tests. Each test type addresses a specific testing requirement.

6.2 TYPES OF TESTING

6.2.1 UNIT TESTING

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .It is done after the completion of an individual unit before integration. This is a structural testing that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component leveland test a specific business process, application and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

6.2.2 INTEGRATION TESTING

Integration tests are designed to test integrated software components to determine if they actually run as one program. Integration tests demonstrate that although the components were individually satisfactory, as shown by successfully unittesting, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

6.2.3 FUNCTIONAL TESTING

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input	: identified classes of valid input must be accepted.
Invalid Input	: identified classes of invalid input must be rejected.
Functions	: identified functions must be exercised.
Output	: identified classes of application outputs must be exercised.

Systems/Procedures: interfacing systems or procedures must be invoked. Organization and preparation of functional tests is focused on requirements, key functions, orspecial test cases.

6.3 TEST CASES

6.3.1 CLASSIFICATION

Test caseID	Test case name	Purpose	Input	Output	Test case result
1	Image Enhancement	To enhance the original underwater image by using CNN layers.	The user gives the input of an original underwater image.	An output is displayed in the form of an image by enhancing the original image.	Test case passed
2	Color contrast	Color Restoration of Underwater Image.	The user gives the input of an original underwater image.	An output is displayed in the form of an image by enhancing the original image.	Test case passed

7. CONCLUSION

7. CONCLUSION & FUTURE SCOPE

7.1 PROJECT CONCLUSION

In this project, we propose a CNN framework for underwater image color restoration. Our method converts an input underwater image to the grayscale image by using CNN to estimate the grayscale coefficients. We also use CNN to restore the color of the input underwater image. To remove the noise in underwater environment and reserve the detail that may affect by CNN, we propose a grayscale detail enhancement CNN. At last, we integrate all works by the hue preservation enhancement. Our experimental results show that the proposed method achieve better underwater image restoration performance than other methods.

7.2 FUTURE SCOPE

The potential idea behind the idea of the project is the additional feature, we aim to leverage the pre-trained convolutional neural networks on large image data for the appearance learning instead of training our convolutional appearance module from scratch. This would not only accelerate the training speed but also allows employing quite deeper architectures and abundant existing image data to improve the performance of the appearance learning.

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8.2 GITHUB LINK

https://github.com/Stephennani/Under-water-image-color-correction-and-contrast-enhancement-based-in-hue-preservation.git

9.PAPER PUBLICATION

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IJIEMR Transactions, online available on 21st Feb 2023. Link :http://www.ijiemr.org/downloads.php?vol=Volume-12&issue=Issue 03

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Title **HUE PRESERVATION BASED HIGH EFFICIENCY UNDER WATER IMAGE CORRELATION AND ENHANCEMENT USING DEEP LEARNING TECHNIQUE**

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Jonnadula Narasimharao

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HUE PRESERVATION BASED HIGH EFFICIENCY UNDER WATER IMAGE CORRELATION AND ENHANCEMENT USING DEEP LEARNING TECHNIQUE

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ABSTRACT: Underwater imaging is an emerging area of research. Underwater image processing has played an important role in various fields such as submarine terrain scanning, submarine communication cable laying, underwater vehicles, underwater search and rescue. However, there are many difficulties in the process of acquiring underwater images. Underwater Image suffers from serious color distortion and low contrast problems because of complex light propagation in the ocean. Underwater image capturing is a challenging task due to attenuation of light in water. Scattering and absorption are results of light attenuation which leads to faded colors and reduced contrast of images, respectively. To deal with these issues, to provide better visual quality image and in view of computing constraints of underwater vehicles, Hue preservation based high-efficiency under water image correlation and enhancement using deep-learning Technique is presented. The framework contains three convolutional neural networks for underwater image color restoration. At first, CNN is used to convert the input underwater image into the gray scale image. Next, grayscale underwater image is enhanced by the second CNN and then, the color correction is formed to the input underwater image by the third CNN. At last, color-corrected image is obtained by integrating the outputs of three CNNs based on the hue preservation.

KEYWORDS: Underwater image, Hue preservation, Convolutional Neural Network (CNN).

I. INTRODUCTION

Use of digital images has become inevitable in today’s world. This has areas related to image preprocessing and the environment of underwater is much more complex than that on land and as there is no source of light in underwater environment, underwater imaging systems have to rely on the artificial light to provide illumination. Underwater imaging is widely used in scientific research and technology such as marine biology and archaeology. Underwater scenario is attracting the scientists, biologists and researchers due to its wide variety of marine animals and fish species, incredible landscape, beautiful coral reefs and mysterious shipwrecks.

The ocean contains abundant resources both in Biology and energy, which is one of the core components for maintaining human’s sustainable development. Obtaining valuable information through images is a necessary means in the process of exploring the ocean. Autonomous underwater vehicles (AUV) are generally used for gathering images and videos from a wide variety of underwater environment like coral reefs, underwater mines, shipwrecks, telecommunication cables, oil and natural gas pipelines [5].

With recent advances in diversified technologies, high-end underwater remotely operated vehicles (ROVs), autonomous underwater vehicles (AUVs), and autonomous underwater robots have been extensively employed for navigation, exploration, and surveillance in underwater environments. These underwater vehicles and robots are typically equipped with optical sensors for acquiring underwater images. From the perspective of academia and industry, underwater imaging is critical to various applications such as archaeology, mine and wreckage detection, marine biology, water fauna identification and assessment, and offshore wind power turbine basis inspection [6].

Generally, captured underwater images are degraded by scattering and absorption. Scattering means a change of direction of light after collision with suspended particles, which causes the blurring and low contrast of images. Absorption means light absorbed by suspended particles which depends on the wavelength of each light beam. The light with shorter wavelength (i.e., green and blue light) travels longer in water. As a result, underwater images generally have predominantly green-blue hue. Contrast loss and color deviation are main consequences of underwater degradation processes, which bring difficulties to further processing [3].

The existing research shows that underwater images raise new challenges and impose significant problems due to light absorption, light reflection, bending and scattering of light, and poor visibility. Several factors such as selection of a colour model, characteristics of the human visual system, and colour contrast sensitivity must be considered for colour image enhancement. Contrast enhancement, colour correction, and nonuniform lighting improvement of underwater colour images are well-studied problems [4].

Image enhancement is to bring more visibility to the image and make it more appropriate to the required application. In today's scenario, the process of underwater image enhancement becomes an important area of study. Image enhancement intensifies the information content of the image by accentuates the deep underwater image edges and changes the visual influence of the observer. The sharpness and contrast of the images captured in underwater suffer from poor color contrast and poor visibility. Moreover, the quality of underwater images deteriorates due to the physical properties of the aquatic medium, light scattering, reflection, and becomes more and less visible as water depth increases.

Images captured under water are often characterized by low contrast, color distortion, and noise, hindering some visual tasks carried out on it. Despite remarkable breakthrough has been made in recent years, effective and robust enhancement of degraded image remains a challenging problem [2]. Therefore, it is expected to develop an effective method overcome these shortcomings.

To overcome this limitation, deep learning technology is used to estimate the unkown parameters. Recently, several Neural Networks (NNs) have been applied to estimate transmission. These deep learning models are trained with synthetic training set to regress transmission and obtain more refined restorations than conventional methods. Hence in this work, hue preservation based high efficiency under water image correlation and enhancement using deep learning technique. The rest of the work is organized as follows: The section II describes the Literature survey. The section III presents the hue preservation based high efficiency under water image correlation and enhancement using deep learning technique. The section IV evaluates the result analysis of presented approach. The section V provides the conclusion.

II. LITERATURE SURVEY

Zeba Patel, Chaitra Desai, Ramesh Ashok Tabib, Medha Bhat, Ujwala Patil, Uma Mudengudi et. al., [7] describes Framework for under water image enhancement. The main aim is to balance the color distribution of the underwater image in LAB color space, to remove the bluish green tin caused due to atmospheric light attenuation. Focus is on sharpening the underwater image to enhance the edges distorted during the process of color balance. We emphasize on fusion of outputs obtained after color balancing and edge sharpening. Authors demonstrated the performance of the proposed framework using qualitative evaluation metrics and show, the results obtained through this framework outperforms the state of the art enhancement methods.

Chonyi Li, Jichang Guo, and Chunle Guo et. al., [8] describes Emerging from Water: Underwater Image color correction based on weakly supervised color transfer inspired by Cycle-Consistent Adversarial Net- works, authors designed a multi-term loss function including adversarial loss, cycle consistency loss, and SSIM (Structural Similarity Index Measure) loss. In this way, they translate the color of underwater image as if it is taken in the air, and preserve the content and structure of original underwater image. Experiments on underwater images captured under diverse scenes show that the proposed method can produce visually pleasing results, even outperforms the art-of-the-state methods.

Krishnapriya T S, Dr. Nissan Kunju et. al., [9] presents Underwater Image Processing using Hybrid Techniques. Gray world technique is presented for white balance. From the corrected image, weight maps-based feature extraction would be done followed by multi fusion and image enhancement. Due to the wide application of wavelet transform in image processing, here using two- dimensional Discrete Wavelet Transform as fusion operator. Also, make the synaptic network to the new level of application. The result demonstrates that this enhancement algorithm can obtain a well visual result.

Jie Li, Katherine A. Skinner, Ryan M. Eustice, and Mathew Johnson-Roberson et. al., [10] describes WaterGAN: Unsupervised Generative Network to enable Real-Time color correction of Monocular Underwater Images WaterGAN. They describes a generative adversarial network (GAN) for generating realistic underwater images from in-air image and depth pairings in an unsupervised pipeline used for color correction of monocular underwater images. Using WaterGAN authors generated a large training dataset of corresponding depth, in-air color images, and realistic underwater images. These data serve as input to a two-stage network for color correction of monocular underwater images. Our proposed pipeline is validated with testing on real data collected from both a pure water test tank and from underwater surveys collected in the field. Source code, sample datasets, and pretrained models are made publicly available.

K. Panetta, Chen Gao, and Sos Again et. al., [11] describes Human-visual-system inspired Underwater Image Quality Measures. A new non-reference underwater image quality measure (UIQM) is presented in this analysis. The UIQM comprises three underwater image attribute measures: the underwater image colorfulness measure (UICM), the underwater image sharpness measure

(UISM), and the underwater image contrast measure (UIConM). Each attribute is selected for evaluating one aspect of the underwater image degradation, and each presented attribute measure is inspired by the properties of human visual systems (HVSs). The experimental results demonstrate that the measures effectively evaluate the underwater image quality in accordance with the human perceptions. These measures are also used on the AirAsia 8501 wreckage images to show their importance in practical applications.

III. HUE PRESERVATION BASED HIGH EFFICIENCY UNDER WATER IMAGE CORRELATION AND ENHANCEMENT

In this section, hue preservation based high efficiency under water image correlation and enhancement using deep learning technique is presented. The architecture of presented approach is shown in Fig. 1. This work is mainly based upon Underwater Image color correction and contrast enhancement based on hue preservation. The underwater image color restoration is the main stage of the framework. End-to-end convolutional neural network is used to correct the color loss in the underwater image. Underwater color correction is a complex problem. A high image quality in-air images have to contain high color saturation, right color balance and appropriate image contrast. Thus a loss function is designed which restricts many conditions for the underwater image color restoration CNN regression.

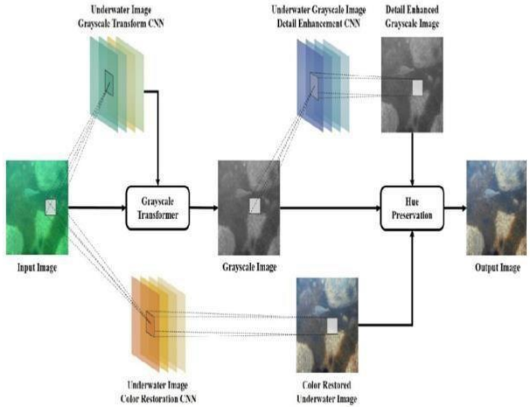

Fig. 1: The Architecture of hue preservation based high efficiency under water image correlation and enhancement

preservation based high efficiency under water image correlation and enhancement using deep learning technique consists of the four phases: (i) the underwater image grayscale stage relying onCNN to convert the underwater image to the best gray-channel image; (ii) the grayscale underwater image details enhancement stage also relying on CNN to remove the noise and enhance the image quality; (iii) the underwater image color restoration stage via end-to-end CNN; and (iv) the generation stage of the final high image quality and correct color underwater image by integrating the outputs of the other three stages.

A convolutional neural network (CNN) is a type of artificial neural network used primarily for image recognition and processing, due to its ability to recognize patterns in images. A CNN is a powerful tool but requires millions of labelled data points for training. A CNN is a neural network which has one or more convolutional layers and is used mainly for image processing, classification, segmentation and also for other auto correlated data. A convolution is essentially sliding a filter over the input.

Underwater Image Gray scale Transformer: Based on hue preservation

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enhancement method, the first stage is converting the input underwater image to the gray scale image. Different from the in-air image, the red channel and the green channel of underwater image is attenuated by light propagation. We have to analysis the degree of light attenuation to evaluate the best ratio among three channels. To accelerate the algorithm computing, we use the convolutional neural network to predict the ratios. The proposed underwater image gray scale transform CNN aims at transforming an input underwater RGB image to the three coefficients that are used to combine RGB three channel to the corresponding gray scale image.

Underwater Gray scale Image Detail Enhancement: The end-to-end convolutional neural network method is a great way to solve the image processing problems with low computing cost and high quality. However, the deep learning methods still contain some problems. Because of slight deviation in image regression, the processed image may contains noise and blurry. Otherwise, the convolutional neural network with the light architecture cannot burden to do the underwater image color correction and the underwater image denoise at the same time.

Thus, based on hue preservation, we proposed the underwater gray scale image detail enhancement CNN for the underwater image denoise and CNN processed image detail correction. Inspired by the Google Inception V3 Net, the architecture of underwater grayscale image details the enhancement using CNN. This CNN aims at transforming an input underwater gray scale image to the enhancement transmission map. The architecture consists of seven convolutional layers.

Underwater Image Color Restoration: The underwater image color restoration is the main stage of the framework. We use the end-to-end convolutional neural network to correct the color loss in underwater image. Underwater color correction is a complex problem. A high image qualityin-air images have to contain high color saturation, right color balance and appropriate image contrast. Thus, we design a loss function which restricts many conditions for the underwater image color restoration CNN regression. The content details of the loss function present in Sec.

Hue Preservation Enhancement: Hue preservation is necessary for color image enhancement. In this stage, the hue preservation enhancement method is used. The output image I_R is generated by integrating the outputs of other three stages as:

$$I_R(x) = \begin{cases} \dfrac{I_{GE}(x)}{I_G(x)} I_c(x), & if \dfrac{I_{GE}(x)}{I_G(x)} \leq 1 \\ \dfrac{255 - G_E(x)}{255 - G(x)} (I_c(x) + I_{GE}(x), & if \dfrac{I_{GE}(x)}{I_G(x)} > 1 \end{cases} \quad (1)$$

Where, $I_R(x)$ represents the hue preservation enhanced color image, $I_G(x)$ is the grayscale image of the input underwater image generated by the underwater image grayscale transformer stage, $I_{GE}(x)$ is the output of the grayscale image detail enhancement stage, $I_C(x)$ is the color restored underwater image from the underwater image color restoration stage and x denotes the positions of pixels on the image.

IV. RESULT ANALYSIS

In this section, hue preservation based high efficiency under water image correlation and enhancement using deep learning technique is implemented using Matlab. The implementation process is as follows: Step - 1: Open Matlab. The Fig. 2 shows the home page of Matlab.

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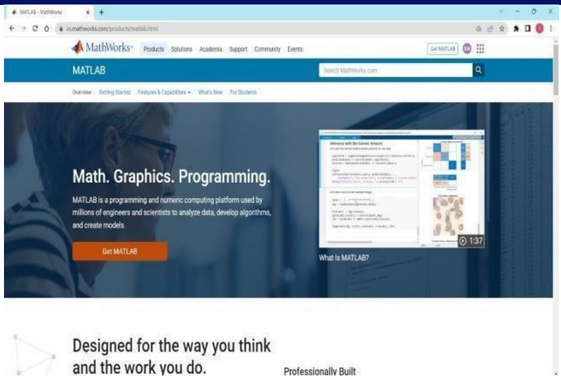

Fig. 2: Matlab Home page

Step - 2 : Login to matlab page. The Fig. 3 shows the user account page.

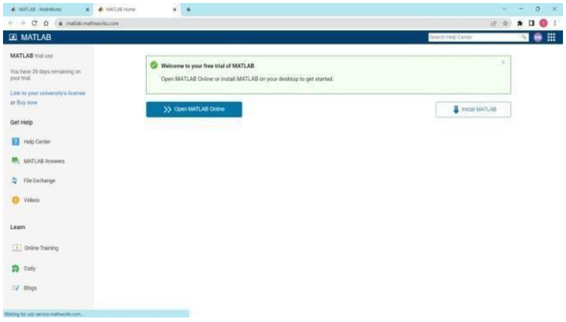

Fig. 3: MatLab User account page

Step -3: Upload the code. Step - 4: Select an image as an input. Step -5 : Click on the option performance under the training plots when the dialog box appears. Step -6 : After clicking on performance 3 output graphs are shown which shows the enhancement of the image. The fig. 4 shows the performance graph output.

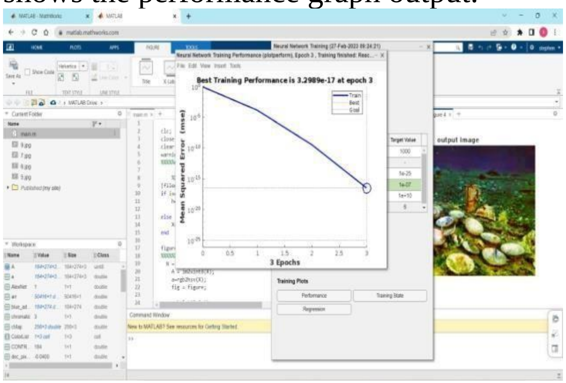

Fig. 4: Performance graph output

The Fig. 5 shows the original image.

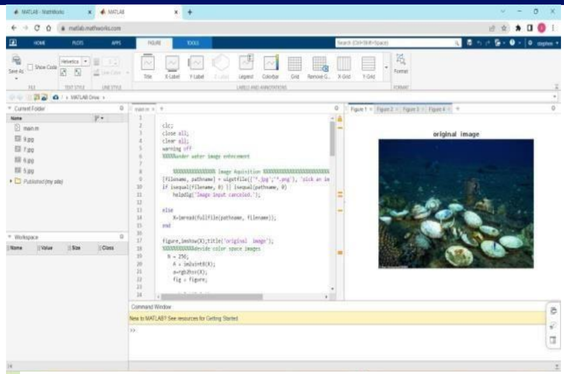

Fig. 5: Original Image

The Fig. 6 shows the Stages of enhancing the original image.

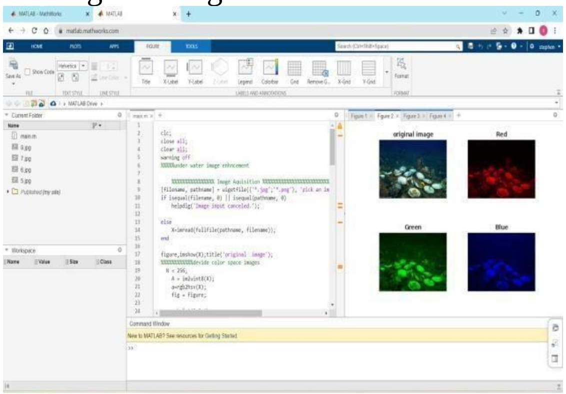

Fig. 6: Stages of original image Enhancement

The fig. 7 shows the enhanced image.

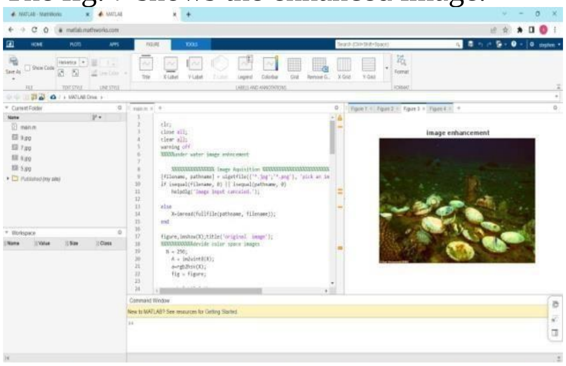

Fig. 7: Enhanced Image

The fig. 8 shows the output image.

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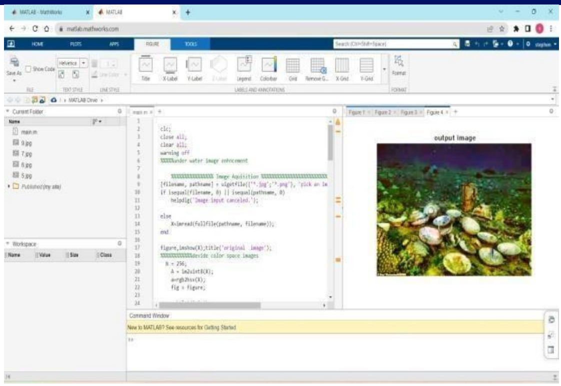

Fig. 8: Output Image

Hence this approach has effectively enhanced the underground image. In this manner one can enhance the underground image very effectively.

V. CONCLUSION

In this work, Hue preservation based high efficiency under water image correlation and enhancement using deep learning technique is presented. In this work, a CNN framework is used for underwater image color restoration. This method converts an input underwater image to the grayscale image by using CNN to estimate the grayscale coefficients. CNN is also used to restore the color of the input underwater image. To remove the noise in underwater environment and reserve the detail that may affect by CNN, a grayscale detail enhancement CNN is presented. At last, all phases are integrated by the hue preservation enhancement. The experimental results show that the proposed method achieved better underwater image restoration performance than other methods. In future, we aim to leverage the pre-trained convolutional neural networks on large image data for the appearance learning instead of training our convolutional appearance module from scratch. This would not only accelerate the training speed but also allows employing quite deeper architectures and abundant existing image data to improve the performance of the appearance learning.

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