Underwater Photography Noise cancellation Using Artificial Intelligence And Deep Learning.

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1 Abstract

Cameras submerged underwater are widely used to see the ocean floor. Unmanned underwater vehicles, autonomous underwater vehicles, and in situ ocean sensor networks are common places to find them (AUVs). While being an essential sensor for keeping track of underwater landscapes, recent underwater camera sensors have a number of issues. Because of how light moves through water and the biological activity at the seafloor, underwater photographs are typically cluttered with scatters and noise. Over the past five years, a variety of tactics have been developed to Important facets of oceanographic study include image processing and underwater sensing. One of the related challenges is light absorption and scattering, which reduces the image quality in underwater conditions.

2 Introduction

The method of image denoising involves taking the noise out of an image. Information will be lost if there is an increase in noise. The noise may be caused by a variety of factors, including taking pictures in low-light conditions, damaging electrical circuits from heat, a digital camera's sensor illumination levels, incorrect memory locations in the hardware, or bit mistakes in long-distance data transfer. Technically speaking, noise here refers to the growth of undesired pixels. Impulse noise (IN) is one sort of picture noise in which the pixel values are vastly different from those of the surrounding pixels. There are two varieties of impulse nose: random valued impulse noise and salt-and-pepper impulse noise (RVIN). Additive White Gaussian Noise (AWGN), which will slightly alter the value of each pixel in the picture.

3 Problem faced in the domain:

To view the ocean floor, underwater cameras are frequently employed. They are typically found in insitu ocean sensor networks, unmanned underwater vehicles, and autonomous underwater vehicles (AUVs). Recent underwater camera sensors have a lot of problems, despite being a crucial sensor for monitoring underwater landscapes. The quality of the imaging is diminished in underwater environments due to light absorption and scattering, which is one of the linked difficulties. Underwater imaging has a number of problems, including colour distortion, poor contrast, and detail loss (especially edge information).

4 Existing Solutions:

DxO PureRaw 2, Adobe Lightroom, Adobe Photoshop, Noiseware, and Luminar NEO are a some of the solutions that are now available for the domain. Modern sonar systems have significant hurdles in the detection, feature extraction, and recognition of underwater acoustic signals because of the complexity of the marine environment and the ongoing invention of underwater target noise reduction technique. Reducing image noise can significantly improve the final image or print because it can compromise the level of detail in your digital or film photographs. The issue is that most noise reduction or removal procedures always result in softening the image as well.

5 Ground Truth

Ground truth of a satellite image means the collection of information at a particular location. It allows satellite image data to be related to real features and materials on the ground. This information is frequently used for calibration of remote sensing data and compares the result with ground truth.

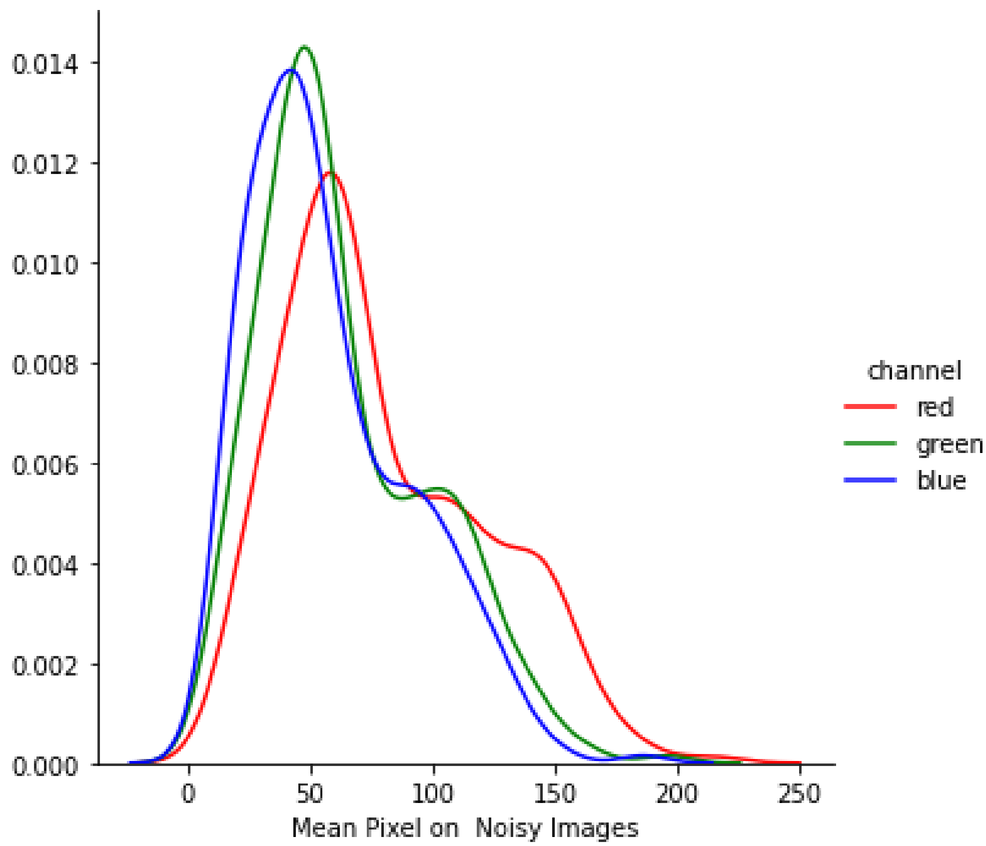


Figure 1: Data collection workflow

6 Literature Survey

[1]one of the important deep learning architecture is DnCNN here given noisy image Y as input which will predict the Residual image 'R' We can get output as clear image 'X'.DnCNN is trained in an end-to-end fashion.[2]. Finally, the denoised high pass filtered image is the resultant dust removed image. CLAHE is applied to remove partial noises, thus improving the contrast of the image.[3]The quality of an image is measured using the parameters namely, the signal noise ratio (SNR), mean squared error (MSE), underwater image quality measure (UIQM), and structural similarity index (SSIM).[4]The performance of deep convolutional neural networks is limited on real-noisy images and necessitates multi-stage network modelling. Deep convolutional neural networks perform better on images including spatially invariant noise (manufactured noise). This research offers a unique single-stage blind real image denoising network (RIDNet) using a modular architecture to increase the applicability of denoising techniques. To facilitate the flow of low-frequency information, we employ a residual on

the residual structure, and we employ feature attention to take advantage of the channel dependencies. Additionally, the comparison of our RIDNet's performance to 19 cutting-edge algorithms using quantitative parameters and visual quality on three synthetic and four actual noisy datasets shows its supremacy.

7 Data Architecture

We focus on two key problems with underwater images: noise in the image brought on by light dispersion and poor contrast brought on by low lighting. There are various methods for removing noise from an image. The filtering approach, anisotropic diffusion, based on nonlocal pixel averaging, wavelet transforms, block matching algorithms, deep learning, etc. are the most popular techniques for removing noise. Convoluting the image with filters is the most efficient approach to remove noise. The Gaussian filter has the advantage that the Fourier transform of its Fourier transform is also a Gaussian distribution centred on zero frequency. This increases O(Ncomputational)'s complexity, which is more effective than modern bilateral filtering techniques. Convolutional neural networks (CNN)are used to process underwater image data to eliminate noise brought on by dust, silt, haze. The application of CLAHE improves the contrast of image by removing partial noises. To clear haze and noise from underwater photos, this CLAHE(Contrast Limited Adaptive Histogram) and OpenCV approach use deep learning. According to the suggested approach's run-time complexity and higher reconstruction image resolution, it performs better than the current method The size of convolutional filters are set to be 3×3 and all pooling layers are removed.

Therefore, the receptive field of DnCNN with depth of d should be (2d+1)(2d+1).

For Gaussian denoising with a certain noise level, the receptive field size of DnCNN is set to 35×35 with the corresponding depth of 17. For other general image denoising tasks, a larger receptive field is adopted by setting the depth to be 20.

The residual learning formulation is adopted to train a residual mapping: x = y-R(y). Thus, R(y) is learnt.

To be specific, there are 3 types of layers.

(i) Conv+ReLU: For the first layer, 64 filters of size 3×3×c are used to generate 64 feature maps. c = 1 for gray image and c = 3 for color image.

(ii) Conv+BN+ReLU: for layers 2 to (D-1), 64 filters of size 3×3×64 are used, and batch normalization is added between convolution and ReLU.

(iii) Conv: for the last layer, c filters of size 3×3×64 are used to reconstruct the output. Simple zero padding strategy is used before convolution which does not result in any boundary artifacts.

By incorporating convolution with ReLU, DnCNN can gradually separate image structure from the noisy observation through the hidden layers. DnCNN is trained in an end-to-end fashion.

7.1 Data collection

Conventionally, the data and the image is pre-processed using the camera and the image is captured . But however, we would implement it based on the selenium web scrapping and beautiful soup wherein the data is generally scrapped and then it is pre-trained.

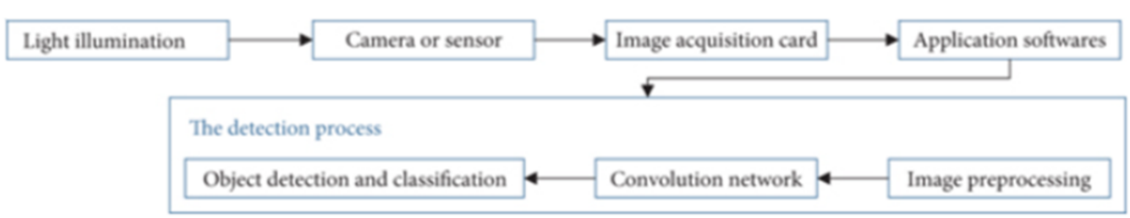


Figure 2: Data collection workflow

The scrapped image is fed in the UI created in streamlit for testcase input images to predict the outcomes.There by the collected perfect trained model will fit the data into the raw file

7.2 Data Preparation

The prepared and trained model was then given the obtained data. The algorithm used fixed data to forecast legitimate outcomes without using the MSE value.

7.3 Inference from the Data

We may classify the acquired data into several categories and conduct various analyses to determine the individual components' ground truth values, which can then be used to fulfil the accuracy requirements for the model.

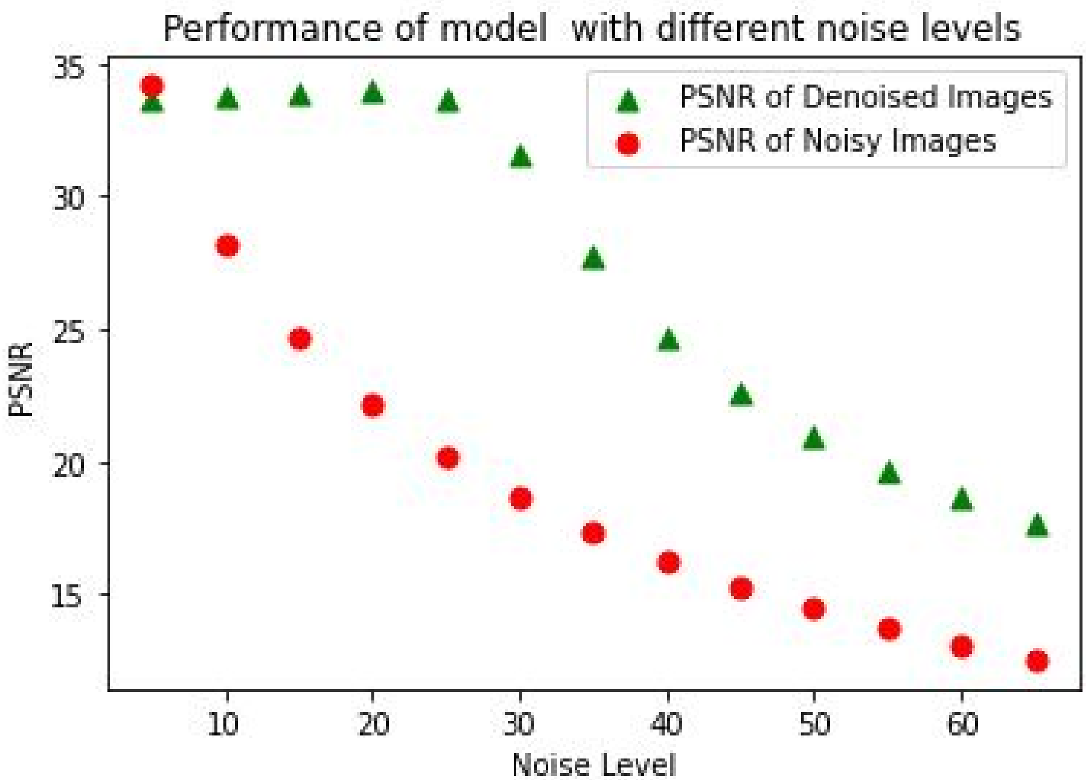


Figure 3: Classes from dataset

8 Workflow

8.1 DnCNN

8.1.1 FIRST LAYER (Conv+ReLu)

64 filter layer of 3x3xC that is c is number of image channel turns to 64 feature map and rectified linear units ReLu C=1 denotes gray C=3 denotes various color

8.1.2 SECOND LAYER (Conv+bn+relu)

64 filter layer of size 3x3x64 are then trained with the intermediate as BN-Batch Normal

8.1.3 third layer conv

last layer, c filters of size 3 x 3 x 64 are used to reconstruct the output.

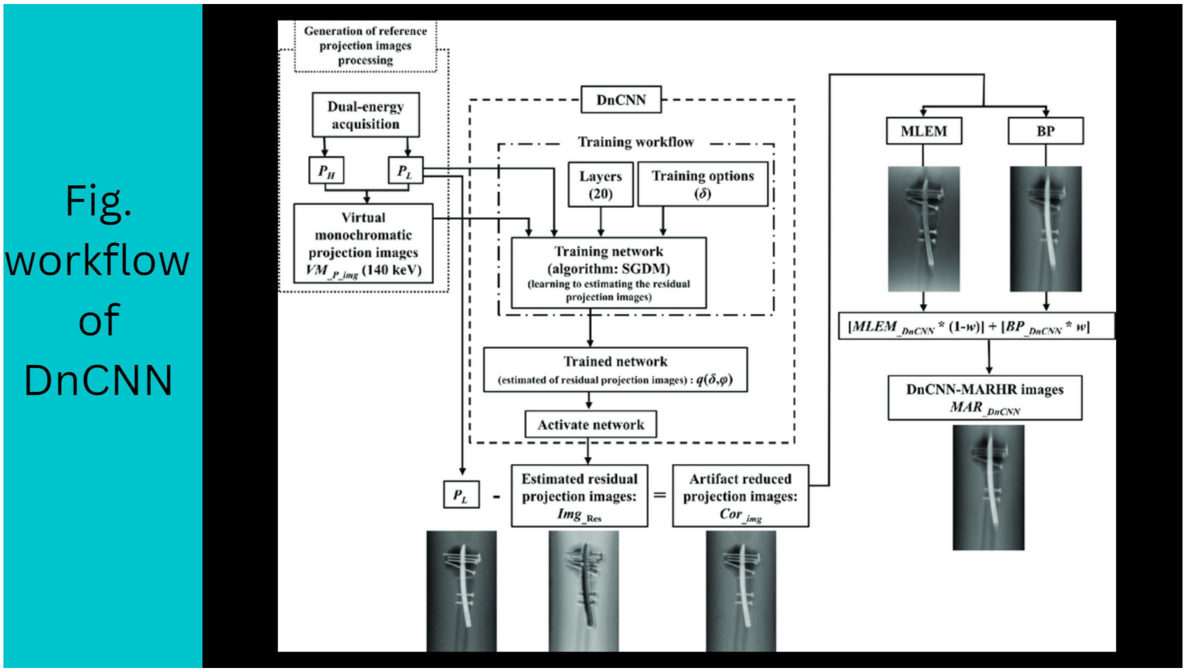


Figure 4: DnCNN Workflow

8.2 RIDNet

The performance of deep convolutional neural networks is limited on real-noisy images and necessitates multi-stage network modelling. Deep convolutional neural networks perform better on images including spatially invariant noise (manufactured noise). This research offers a unique single-stage blind real image denoising network (RIDNet) using a modular architecture to increase the applicability of denoising techniques. To facilitate the flow of low-frequency information, we employ a residual on the residual structure, and we employ feature attention to take advantage of the channel dependencies. Additionally, the comparison of our RIDNet's performance to 19 cutting-edge algorithms using quantitative parameters and visual quality on three synthetic and four actual noisy datasets shows its supremacy.

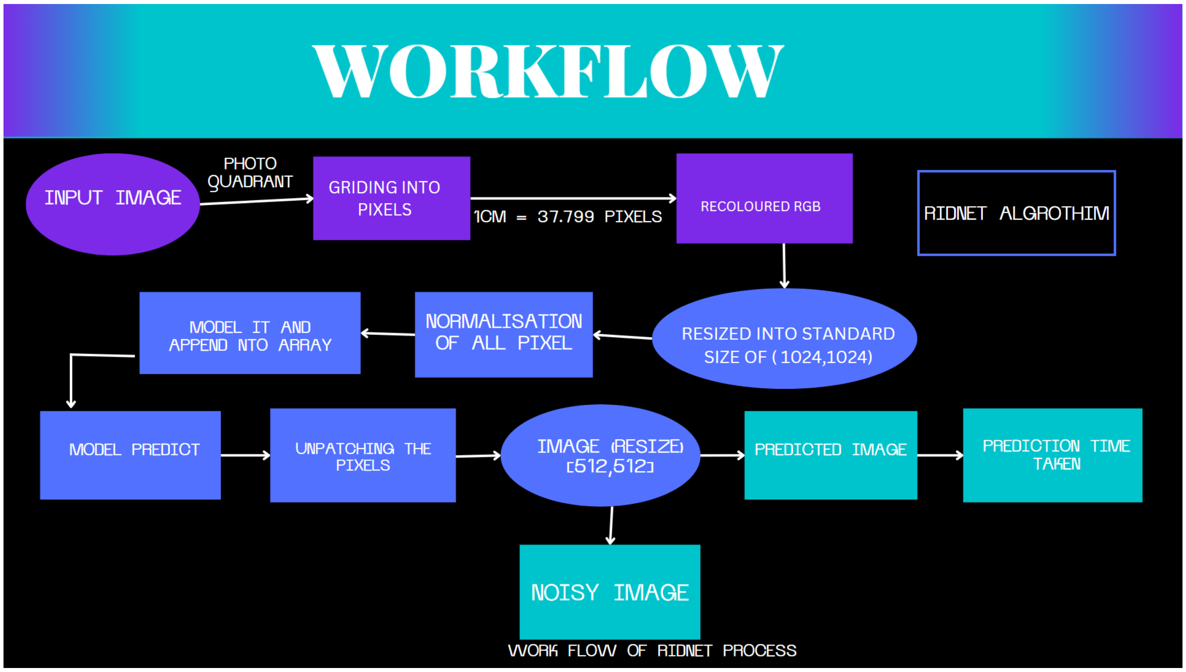
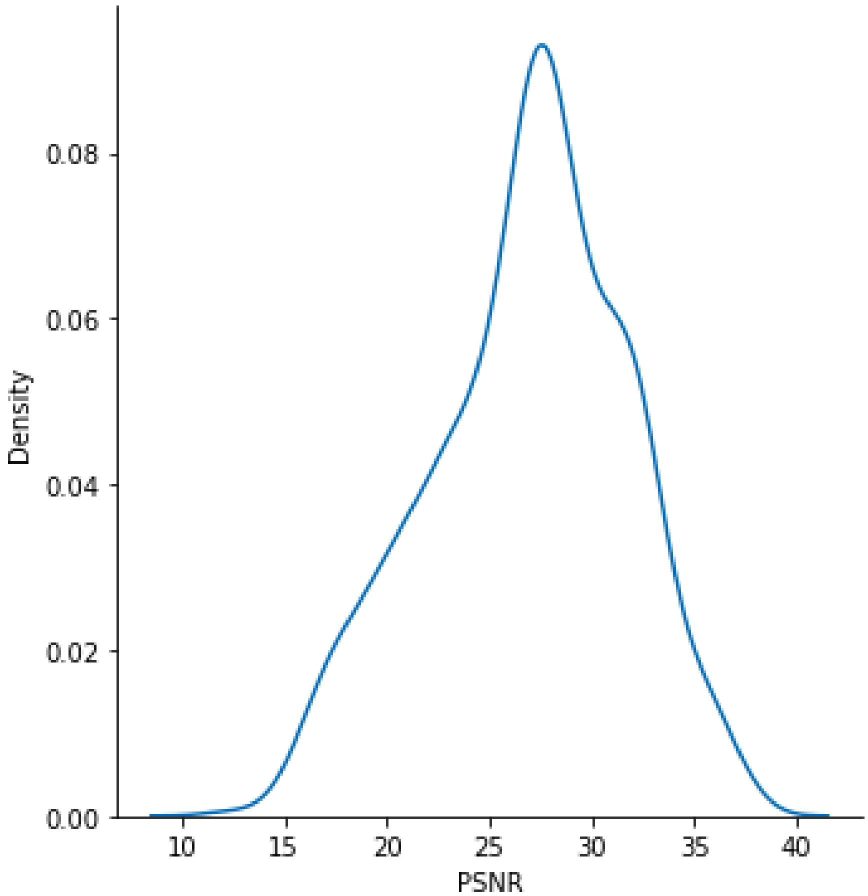


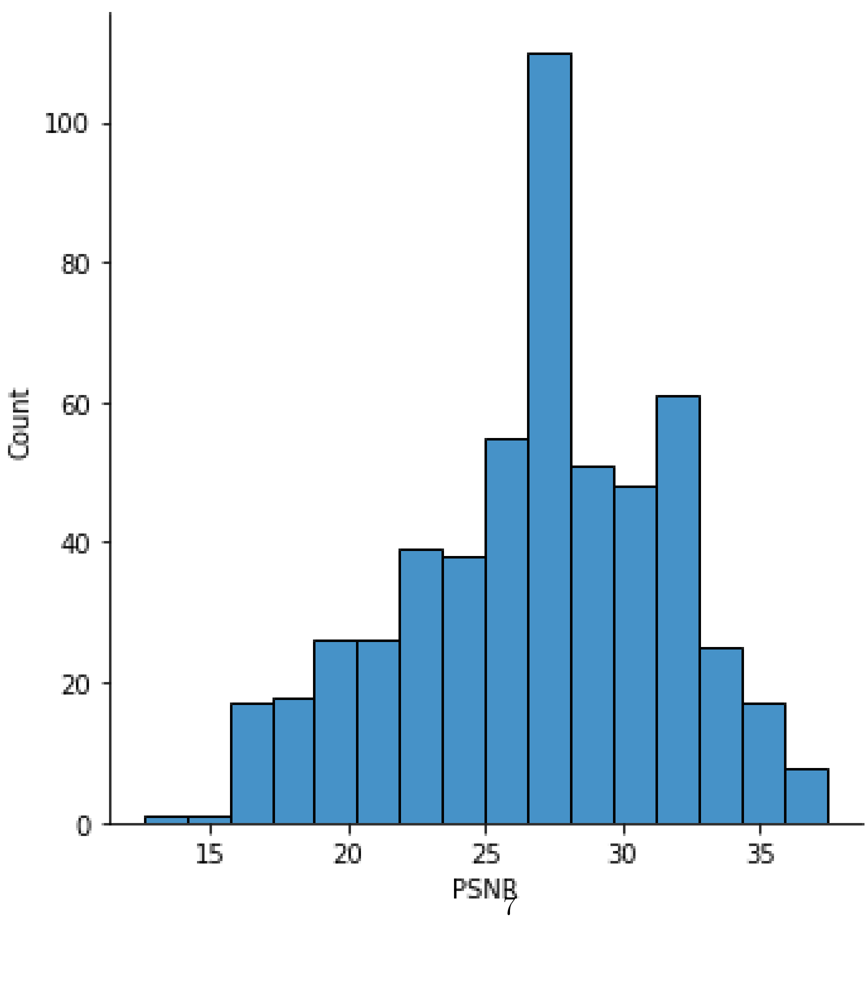
Figure 5: RIDNet Workflow

9 Key Parameters of This Model

9.0.1 Peak Signal to Noise Ratio (PSNR)

The degree to which a signal is accurately represented depends on the relationship between the maximum strength of the signal and the power of the corrupting noise. PSNR is typically stated on a logarithmic decibel scale since signals can have a wide range of levels. It is important to compare an image to a perfect, clean image with the most power in order to assess its PSNR. The quality of the compressed or rebuilt image improves with increasing PSNR. Log10(), which forms the foundation of psnr, has a negative range if the quantity whose log is being taken is less than 1. PSNR can be negative, particularly when there is more noise than signal. Peak dynamic range is used to define PSNR

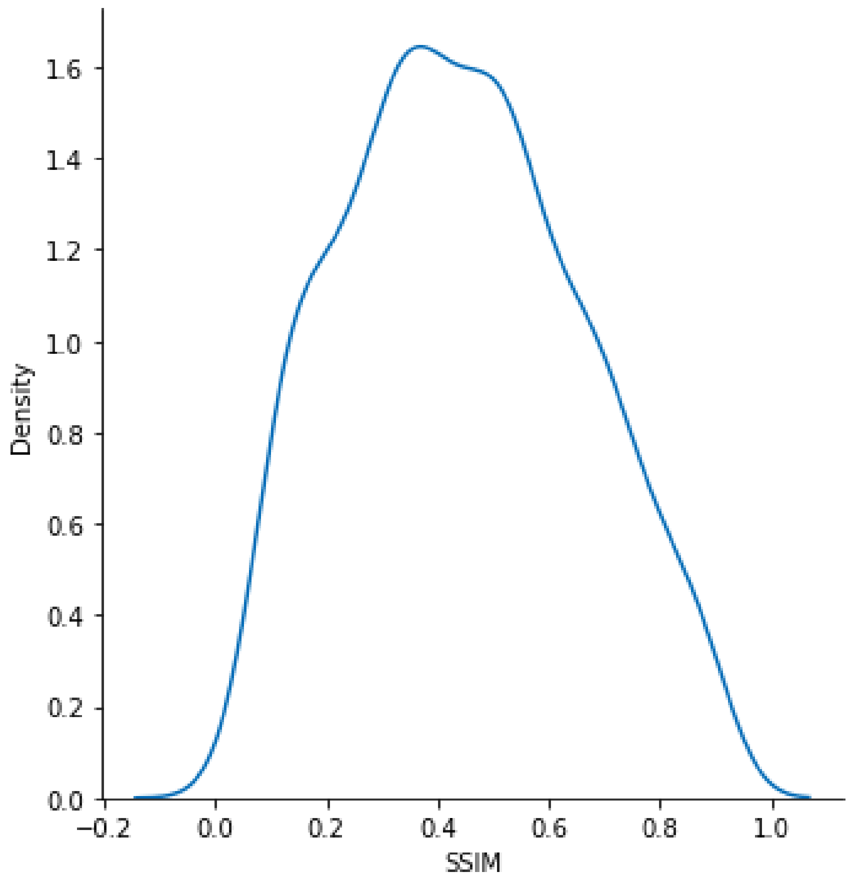

Density
0.00
0.02
0.04
0.06
0.08
10
15
20
25
30
35
40
PSNR


Count
0
20
40
60
80
100
15
20
25
30
35
PSNR

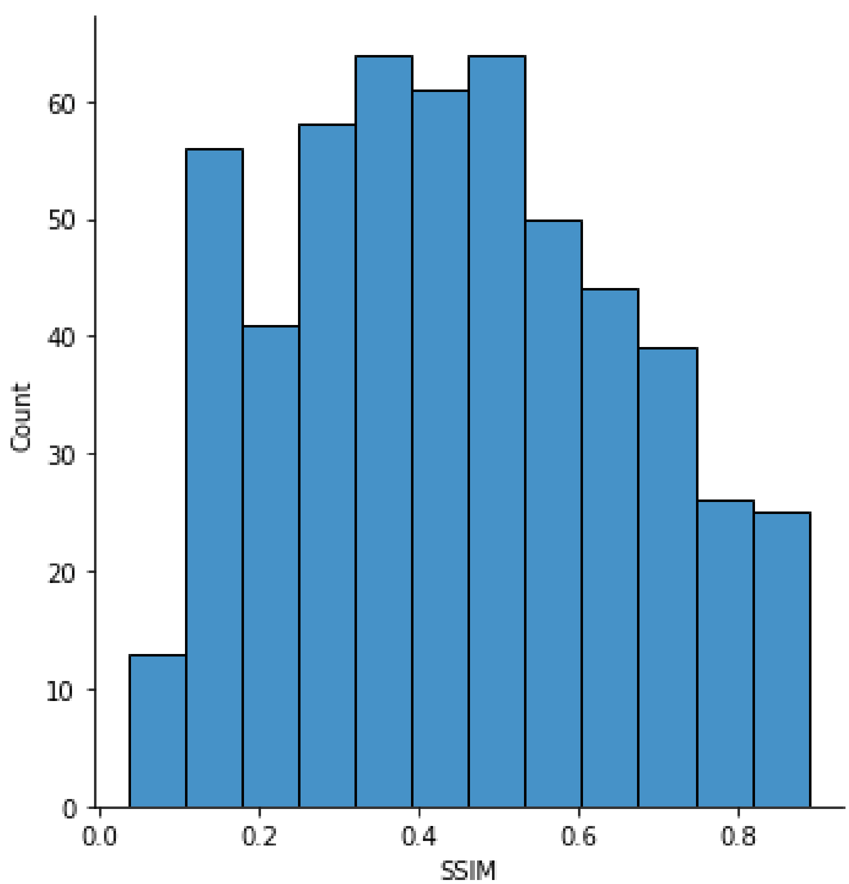
9.0.2 Structural Similarity Index (SSIM)

By concentrating primarily on the structural information from a scene and highlighting the contrasts between the information taken from a reference and a sample scene, it calculates the similarity between two provided images. It is thought that this is how the human visual perception system functions. As a result, this statistic is useful for assessing image quality.

Luminance, contrast, and structure are the three qualities that this metric extracts. These characteristics are used to compare two photographs. The Structural Similarity Index (SSIM) is a perceptual assessment of structural similarity. The Structural Similarity Index (SSIM) is a perceptual metric that measures the loss in image quality* brought on by data transmission losses or other processing steps like data compression. The SSIM values range from 0 to 1, with 1 denoting a perfect match between the recreated image and the original. Standard SSIM scores for good quality construction techniques are 0.97, 0.98, and 0.99.



Density
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
SSIM



Count
60
50
40
30
20
10
0
0.0
0.2
0.4
0.6
0.8
SSIM

10 FEASIBILITY

10.1 PRIMARY GOAL

Our primary goal is to eliminate reliance on foreign OEMs for specialised technology and produce clearer, higher-quality images based on our industry. It is therefore highly likely to be incorporated into our daily life. There are no start-up costs. To simplify setup, we can distribute software in advance. We also have a variety of machine learning algorithms, such as "CLAHE,OPENCV,LMS,NLMS,EMD," as well as deep learning methods, such as "Deep Convulutional

10.2 TECHNOLOGY USES

Neural Network model (DnCNN),Real Image Denoising with Feature Attention,GAUSSIAN FILTER,DST[DISRETE SIGNAL EXTRACTION],POLARISATION," and "noise removal algorithms, such as Recurrent Neural Networks, LSTM, GRU," and also with parameters include "MSE,SNR(SIGNAL NOISE RATIO),UIQM(UNDER WATER IMAGE QUALITY MEASURE)."

10.3 MARKET AND RIVALS

It won't cost much money because this approach is totally based on algorithms, as we already mentioned, but it will take up most of our time to think about a particular algorithm. In addition, the hardware is close to 25–30k INR in price The product must, in everyone's opinion, be easily accessible, reasonably priced, in good working order, and have the best result with the least amount of time complexity. Due to its ability to fulfil all of the aforementioned needs of the individual, our invention can easily increase the demand for this product. When working with a picture or video, this workflow strategy can enhance resolution and pixels in places where it would not often be possible for people to work easily. As a result, the product satisfies the customer's needs

11 EXECUTION TIMELINE

12 PROJECT COST

It won't cost much money because this approach is totally based on algorithms, as we already mentioned, but it will take up most of our time to think about a particular algorithm. In addition, the hardware is close to 25–30k INR in price

13 SWOT Analysis:

13.1 Strength:

With the development of new technologies, this device has improved strengths in providing high resolution photographs with good pixel quality and eliminating noise in pictures. Consequently, the photograph offers a clear perspective of an object that percepts

13.2 Weakness:

Our approach generates high-quality images, but when the noise exceeds the signal, the PSNR can be negative, which results in some of the picture's information being lost and may cause data loss.

13.3 Opportunity:

Due to its access to a number of new technologies and ability to separate specialised technology from OEM, this model has the potential to present a number of opportunities in the future.

13.4 Threats:

Our model offers great pixel output while eliminating all sounds. The data may become interrupted during the noise cancellation process, resulting in the loss of data and information.

14 Existing solution and market audience:

High system requirements, Sluggish processing, Paid updates one year later, RAW AI model need development, Inadequate input settings, Creates extremely big DNG files and is occasionally slow.

	Noise Level	Noise Image	AutoEncoder	DnCNN	RIDNET
0	15.0	24.845110	32.388158	32.270786	32.473852
1	20.0	22.390184	32.346889	31.923581	32.386050
2	25.0	20.512513	31.911771	31.159505	31.863160
3	30.0	19.020924	29.952373	29.618193	29.922082
4	40.0	16.713513	24.626888	24.878584	24.568452
5	45.0	15.823676	22.879885	23.087721	22.847336

Figure 8: Comparison of models

15 Conclusion:

The algorithm put out in this research is a tool for improving marine optical image quality. The suggested technique uses a "DnCNN," "RIDNET[EAM]," and parameters like "PSNR," "SSIM," and "MSE" to improve the image by lowering the noise. Finally, CLAHE is used to boost the image's contrast. It deals with the haze, back scattering noise, and large particle noise in the image. The quality of the produced image will be better the higher the PSNR value. MSE is employed in the PSNR calculation. Two metrics that are frequently used in evaluating the quality of images are peak signal to noise ratio (PSNR) and structural index similarity (SSIM). These two measurement devices are used to gauge the degree of imperceptibility, particularly in steganography images.