iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 **Issue:** V **Month of publication:** May 2024

DOI: https://doi.org/10.22214/ijraset.2024.62740

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue V May 2024- Available at www.ijraset.com

A Triadic Approach for Enhancement of Underwater Images Using Adaptive Colour Correction with Unsharp Masking and CLAHE Implementation

Sumbul Zaheer[1], Shweta Dwivedi[2], Yashvi Srivastava[3], Prof. Awanish Kumar Shukla[4]
Department of Electronics & Communication Engineering, SRMCEM, Lucknow, Uttar Pradesh, India

Abstract: The underwater domain has distinct challenges for capturing and examining images both. This is due to absorption and dispersion of light, which diminishes visual clarity and also distorts colour. In this context, we present an extensive method for enhancing underwater images with the objective of restoring true colours, uplifting contrast, and emphasizing minute details. Adaptive colour correction, detail sharpening, and contrast enhancement techniques drafted for underwater environments are all included in our project. Using objective picture quality standards includes the Underwater Image Quality Measure (UIQM), Underwater Colour Image Quality Evaluation (UCIQE), Patch-based Contrast Quality Index (PCQI), and Image Entropy (IE), we evaluate the effectiveness of our technique. With latent uses in oceanology, archaeology, environmental impact analysis, underwater inspection, and photography, the results show significant evolution in visual accuracy and details extraction.
Keywords: Adaptive colour correction, Unsharp masking, CLAHE, UIQM, UCIQE, PCIQE, IE etc.

I. INTRODUCTION

Significant technological breakthroughs have recently been made in underwater imaging, which includes photography and videography, providing useful tools for commercial, scientific, and recreational uses. The underwater world is a captivating subject to photograph, but it also poses a number of difficulties. The light entering the water from the air is absorbed by the water and scattered. Generally, the red light is absorbed first due to the long wavelength. Additionally, scattering is caused by suspended particles in water, including forward scattering and background scattering. Forward scattering causes the underwater image to be blurred, and background scattering is the main reason for the low contrast of the underwater image and the occurrence of haze-like [38]. Due to wavelength-dependent and selective light absorption, underwater images always suffer from colour castes and look bluish [20]. We have categorized underwater image low visibility problems into colour distortion, light attenuation, and decreased visibility from light absorption and scattering. Underwater image quality, contrast, and colour accuracy are compromised by these factors, necessitating the use of specialist equipment and augmentation procedures. Therefore, order to promote the subsequent research and application, it is necessary to enhance underwater image [26]. It is essential to several different fields of study, including oceanography, marine biology, environmental protection, archaeology, and marine resource management. Additionally, it promotes awareness and education about marine conservation while enhancing leisure pursuits like scuba diving and snorkelling.

II. LITERATURE SURVEY

For underwater image enhancement [1] has employed method for backscattered light estimation and image restoration in turbid water. [2] implemented recursive-overlapped contrast limited adaptive histogram specification and dual-image wavelet fusion. [3] proposed a colour balance algorithm from multiple images to improve the overall quality of underwater images. [4] proposed locally adaptive contrast enhancement method focuses on preserving colour. [5] implemented retinex-inspired color correction and detail preserved fusion to improve colour distortions and fuse details in underwater images effectively. [6] proposed colour balance, contrast optimization, and histogram stretching to restore and enhance underwater images. [7] proposed dual-purpose method for underwater images. [8] used low-light image enhancement via image layer separation, deep learning techniques, specifically a deep residual framework, [9] proposed a method that learns representations of underwater images insensitive to change in water types to enhance underwater images effectively. [10] employed correction of colour distortions and adjusting illumination to improve the visual quality of underwater images.

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[11] proposed a method using the Retinex Model which calculates background illumination and colour correction method Based on colour filter array (CFA). [12] utilized the unsharp masking technique emphasizes edges and features in an image by blurring and eliminating a copy of the image. [13] proposed multi scale retinex colour restoration, CLAHE. [14] proposed triplets are used by triplet-based colour correction modules and recurrent dehazing models to address severe distortions. [15] proposed histogram equalization and adaptive histogram equalization that disperse pixel intensities. [16] implemented adaptive colour correction, white balance adjustment, image decomposition to improve the overall image contrast by fortifying edge contrast. [17] proposed transmission map (TM) that improve estimations based on image attributes in order to account for colour distortions. [18] proposed bilateral filtering method for enhancing edges and fine details without sacrificing structural information. [19] proposed a method that adjusted brightness levels and pixel intensities for a balanced distribution, gamma correction, multiscale fusion technique. [20] proposed blurriness estimation and image restoration method. [21] proposed a restoration method for both image blurriness and image absorption.

III. PROBLEM STATEMENT

The Problem statement of this project is that, underwater images always struggle with problems due to light absorption and scattering, that cause poor visibility, colour distortion, and haze. Red light is rapidly lost, leading to a blue-green colour tint in the images. Refraction further distorts images. These issues complicate in obtaining visible and original reference images and therefor requires efficient technique to address it. This project aims to create an adaptive colour correction and enhancement techniques to improve the underwater image quality, which provides benefit to marine research, exploration, and also environmental monitoring.

IV. PROPOSED SYSTEM

1) We first implement Adaptive Colour Correction that includes Channel Compensation and Colour Balance.
2) Next, we perform an image sharpening technique, which is unsharp masking, to enhance edge details of the image.
3) In the last we incorporate contrast enhancement technique, Contrast-Limited Adaptive Histogram Equalization (CLAHE). To, improve the overall contrast of the image.
4) On the other hand, we evaluate the quantitative parameters such as UIQM, UCIQE, PCQI, IE.
5) Also conduct a comparative analysis of our proposed methodology with some existing techniques for underwater images. Evaluate the performance in terms of visual quality and quantitative metrics.

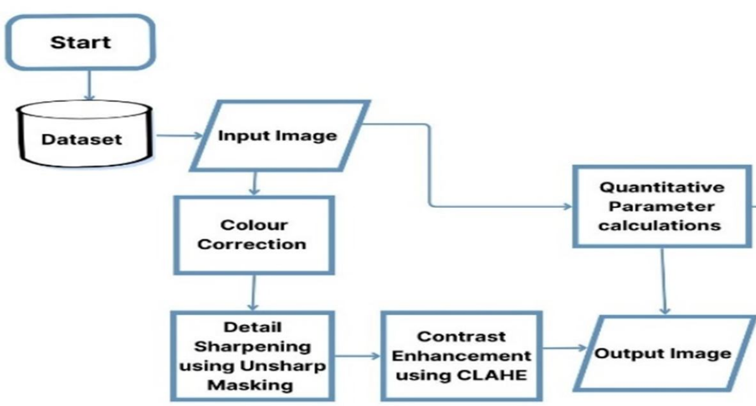

Fig 1. Block Diagram of Proposed Methodology

A. *Adaptive Colour Correction*

We have followed an adaptive colour correction technique [16], that comprises of two components which are colour balancing and channel compensation, they are used to successfully eliminate colour cast.

The average pixels for the red, green, and blue channels are depicted by the symbols Ir, Ig, and Ib, respectively. We know that the green channel is frequently better maintained [16], if

$$\frac{Ir+Ib}{Ir+Ib+Ig} < \frac{1}{3} \tag{1}$$

The red and blue channels are certainly lost if equation (1) is true. Consequently, colour balance can eliminate the colour cast without requiring channel correction. On the distorted images, channel compensation must have to be applied if inequality (1) is not fulfilling.

The uneven hue distortion is generally caused by the intricate undersea environment. As a result, it ought to adjust the red, green, and blue channels independently, which is represented by following equations,

$$\overline{ir}(x)= \overline{ir}(x) +\alpha(\overline{ig}- \overline{ir})(1 - \overline{ir}(x)\, \overline{ig}(x)) \tag{2}$$

$$\overline{ig}(x) = \overline{ig}(x) + \beta(\overline{ig} - \overline{ib})(1 -\overline{ig}(x)\, \overline{ib}(x)) \tag{3}$$

$$\overline{ib}(x) = \overline{ib}(x) + \gamma(\overline{ig}- \overline{ib})(1 -\overline{ib}(x)\, \overline{ig}(x)) \tag{4}$$

here α, β, and γ are representing the corresponding compensation coefficients of the red, green, and blue channels, and $\overline{ir}(x)$, $\overline{ig}(x)$ and $\overline{ib}(x)$ representing the pixel values of the red, green, and blue channels, respectively. The compensation coefficients computation process is explained with the help of some cases:

Let Ω be the channel loss level measurement parameter. A too-small value of Ω will result in overcompensation. An excessively large Ω value will result in under-compensation. The experiment demonstrates that it can effectively balance the variation in loss level among channels when we consider $\Omega = 0.1$.

First Case:

If $|Ig - Ib| \leq \Omega$, then

$$\alpha=1-\ln(Ig-Ir),\ \beta=0,\ \gamma=0. \tag{5}$$

Here we just need to concentrate for the red channel because the loss of the blue and green channels is minimal as clearly depicting in above equation (5).

Second Case:

If $|Ib-Ig| > \Omega$, then

$$\alpha =1-\ln(Ig- Ir),\ \beta = 0,\ \gamma = -\ln(Ib -Ig). \tag{6}$$

The image appears bluish in this instance, suggesting that the blue channel is well intact while the red and green channels have been severely lost. As a result, we will solely adjust for the red and green channels.

Third Case:

If $Ig-Ib > \Omega$ and $Ig- Ib \leq \Omega$, then,

$$\alpha=1-\ln(Ig- Ir),\ \beta = (1 - \ln(Ig - Ir))^{-1},\ \gamma = 0. \tag{7}$$

Since the image in this instance leans green, we only need to adjust for the red and green channels.

Fourth Case:

If $Ig - Ib > \Omega$ and $Ir - Ib > \Omega$, then

$$\alpha=0,\ \beta=1-\ln(Ig-Ib),\ \gamma=0. \tag{8}$$

We simply do adjustments for the blue channel in this instance because the image is yellowish, showing that the red and green channels are largely retained but the blue channel is significantly lost.

Once the image has been compensated, we apply a colour balance to correct the global tone of the image. Let Ik be the average value of the compensated picture in the K channel for K∈ {R, G, B}. Then, we can define,

$$qk,1 = 0.005\frac{maximum\{Ir,Ib,Ig\}}{Ik},$$
$$qk,2=1-qk,1 \tag{9}$$

Assuming Q(qk,1), Q(qk,2) represents the image's quantile pixel values in the channel K, then we carry out the subsequent procedure.

$Ik =$

$$\{ \begin{array}{l} Q(qk,1),\ Ik(x) < Q(qk,2) \\ Q(qk,2),\ Ik(x) > Q(qk,2),\ K \in \{R<G<B\} \\ Ik\ (x),\ others. \end{array} \quad (10)$$

To successfully acquire the image Ik(x). Ultimately, we extend the image Ik(x) to acquire the colour-corrected version, specifically,

$$Ik = \frac{Ik - Ik,min}{Ik,max - Ik,min} \quad (11)$$

where Ik,max and Ik,min stand for the maximum and minimum values in the K channel, respectively. Consequently, we are left with the colour-corrected image Ik.

B. Unsharp Masking

Unsharp masking is a sharpening technique that aimed to improve the details and edges of images. To incorporate the mathematical processes, the input image (here colour corrected image we get from previous section) is transformed into a double precision format. This gives us accuracy while doing computations on the image, then a Gaussian filter is used. This filter is used here to produce a blurred version of the image. Note that we have implemented unsharp masking from [22].

This can be represented as:

$$blurredImg(x, y) = G \times I(x, y) \quad (12)$$

where G is the Gaussian kernel, I(x,y) is the input image and x, y denotes the pixel values.

The input image is subtracted from the blurred image to generate the high-pass component, which represents the sharpening effect.

Mathematically:

$$Hp\ (x, y) = I\ (x, y) – blurredImg\ (x, y) \quad (13)$$

The high-pass component is considered to the strength parameter, which can regulates the sharpening effect's intensity.

Now finally we get:

$$S'(x, y) = I(x, y) + K \times Hp(x, y) \quad (14)$$

Where S'(x, y) denotes the sharpened image and K is the strength parameter, we have used K=0.6.

Also, we have done one more step to make sure the sharpened image values stay within the acceptable intensity range of 0 to 255, the sharpened image is clipped after being sharpened. This can avoid any problems with overflow or underflow.

Mathematically:

$$S'(x, y) = \max\ (0, \min\ (S'(x, y), 255)) \quad (15)$$

In order to represent the pixel values as integers in the range of 0 to 255, the sharpened image is finally transformed back to the uint8 format which is unsinged integer format. In general, this transformation improves the visual clarity of the image as well as the detail of the input image by sharpening it according as per the strength parameter.

C. CLAHE

To improvise the contrast in images there are two techniques used namely Adaptive Histogram Equalization (AHE) and its revamped edition Contrast Limited Adaptive Histogram Equalization (CLAHE). For local contrast enhancement AHE works with the fraction of pictures into modest sections followed up by histogram creation for every region and then applying histogram equalization separately. The unfettered amplification by AHE of the pixel intensities causes excessive amplification in regions of homogeneity, even after its successful ability of attaining defined edges and enhanced interest. Consequently, with the view to subdue this limitation, CLAHE is used to add a clip limiting factor that modulates the amount of amplification which is made used during histogram equalization. The excessive value above the clip limit is made to redistribute so as to avert the over amplification while retaining the defined edges and contrast.

In this the AHE advantages are incorporated with the extra control offered with the clip limit factor leading to a better contrast enhancement technique for resilient photographs. The following is the algorithm, taken from [23].

D. Tile Generation
The input image is segmented into many tiles in vertical and horizontal dimensions both the number of rows (columns) is divided by the tile number in the particular direction for determination of the tile size. An even integer should be used for tile size calculation if not so, pad the input image in symmetry.

E. Histogram Equalization
The five phases of histogram equalization are as mentioned: histogram calculation, total access calculation, total access distribution, cumulative distribution function (CDF), scaling and mapping.
The clip limit value is used to compute the excess value from each bin. Following formulae is used to calculate clip limit:

$$CL = minCL + round\ (normCL \times (numPixInTile - minCL)) \quad (16)$$
$$minCL = ceil(numPixInTile / numBins) \quad (17)$$

where CL is clip limit, minCL is minimum clip limit, and normCL is normalized clip limit.
By adding up the excess value obtained from each bin total surplus value is formed.For excess distribution following two variables are taken into account and calculated as:

$$AvgBIn = totalExcess / numBins \quad (18)$$
$$upperLim = CL - AvgBIn \quad (19)$$

where AvgBIn is average bin increment, numBins is number of bins and upperLim is upper limit.

The histogram value is computed on three criteria:
1) The clip limit value is used in replacement if histogram value is exceeded.
2) If histogram value is bounded between clip limit and upper limit then it is replaced with clip limit and total excess value is reduced using number of added pixels which equals (CL - histV), where histV is histogram value.
3) If the bin value is less than upper limit then it is increased by average bin increment. The average bin increment is applied to the overall excess value.

F. Excess Redistribution
The spillover or excess values above clip limit of the bins are further redistributed to the histogram part. This provides not discarding the histogram part but to equally distribute it.

G. CDF Calculation
The final step is the CDF computation in histogram equalization process. It helps to maintain a linear trend indicating equalization in every part of the region.

H. Bilinear Interpolation
Finally, the tiles a stitched together using bilinear interpolation while keeping the edges smooth and even. The four tiles are further split into four sections each and the pixel values of the resultant image is calculated.
For computation one component from each tile is taken and combined. For a pixel value calculation of the output image, position of a pixel with regard to each tile as well as the intensity information at that point the takes into account. Using the input image pixel value at the same position, the intensity information at each corresponding tile position is derived using the CDF function of histogram equalization. And at last, the derived values from the CDF function are scaled.

V. RESULT & IMPLEMENTATION
A significant number of raw underwater photos, mostly from [27], are used to evaluate our method to confirm its effectiveness. We present a subjective assessment and objective assessment, further they contain two subsections, one is subjective, objective calculations of our proposed method and second section has comparison of our proposed method with four most recent methods for underwater picture enhancement, which are ACIR [16], IBLA [21], CFA [12], ULA [20].

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A. Subjective Assessment

The raw underwater images are obtained by UIEB [27], the following figures 2, 3 &4 show the subjective evaluation of various photos using our proposed method. It clearly represents that our proposed method has significantly enhanced the raw degraded images. Similarly Figure 5, 6 illustrates, the comparison with different techniques. The IBLA algorithm struggles to address colour deterioration issues in images. On the other-hand ACIR is able to handle different colour distortions and also maintains the natural texture of the image. Similarly in Figure 6, CFA is unable to improve the visual quality of the whole image, however CFA can effectively recover the original colours of underwater images. ULA results show that colour distortions. Thus, our proposed algorithm can address several degradation issues, including colour correction, sharpening and contrast enhancement. In summary, our proposed algorithm can enhance the underwater images' subjective visual impact more effectively.

B. Objective Assessment

To objectively demonstrate the efficiency of our proposed method, PCQI [25], UCIQE [26], UIQM [24], and IE indices are chosen as the metrics for evaluating various algorithms. The contrast difference between two photos is compared using PCQI. A higher value of PCQI rating denotes improved enhanced image visibility. The chroma, saturation, and contrast of underwater photos are reflected by metric indices UCIQE. The image quality is significantly improved with a higher UCIQE value. Human vision, which captures the colour contrast, and visual clarity of underwater images, is highly linked to UIQM. Greater consistency in the upgraded photos is indicated by a higher UIQM value. IE displays the depth of picture data. The enhanced image has more detailed information the higher its IE rating.

The UIEB [27] datasets were used for the objective comparisons. There are approximately 890 photos of various underwater sceneries in the UIEB dataset. Table 1, 2, 3 displays the results of the objective evaluation we have obtained by our proposed method. In the same way table 4, 5 represents the objective comparison with our method to the results produced by the techniques [16], [21], [12], [20], respectively. Note that tables represent the average values of indices Therefore, it is clear from that, our algorithm performed the highest and second highest on the PCQI, UCIQE, UIQM, and IE indexes on the UIEB datasets.

Fig 2. Subjective comparisons of (a) degraded image with (b) enhanced image by our method

Fig 3. Subjective comparisons of (a) degraded image with (b) enhanced image by our method

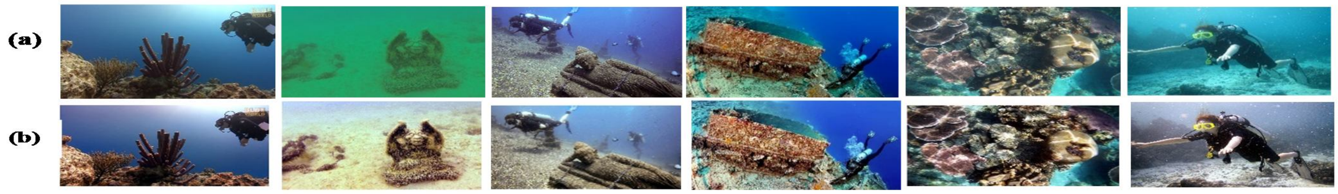


Fig 4. Subjective comparisons of (a) degraded image with (b) enhanced image by our method

Parameters	UCIQE	UIQM	PCQI	IE
Degraded image	0.5746	1.9408	1.0000	7.0723
Enhanced image (Our Method)	0.6394	3.7060	1.2881	7.7176

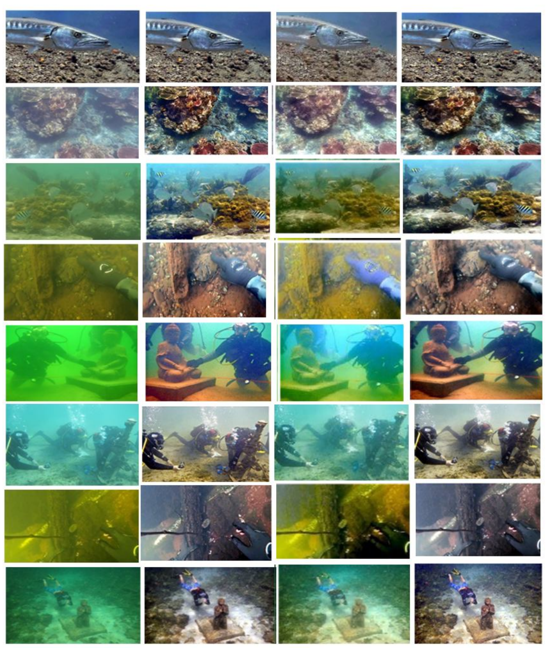
Table 1. Quantitative comparisons for Fig 2

Parameters	UCIQE	UIQM	PCQI	IE
Degraded image	0.5042	1.6445	1.0000	6.5052
Enhanced image (Our Method)	0.6267	0.3886	1.2172	7.7079

Table 2. Quantitative comparisons for Fig 3.

Parameters	UCIQE	UIQM	PCQI	IE
Degraded image	0.5667	2.2137	1.0000	7.0649
Enhanced image (Our Method)	0.6477	3.7059	1.1478	7.6559

Table 3. Quantitative comparisons for Fig 4.



(a) Distorted (b) ACIR [16] (c) IBLA [21] (d)Ours-Method

Fig 5. Subjective comparisons of different algorithms

(a) Distorted (b) CFA [11] (c) ULA [20] (d) Ours Method

Fig 6. Subjective comparisons of different algorithms

Parameters	Ours Method	ACIR [16]	IBLA [21]
UCIQE	0.6323	0.6249	0.5990
UIQM	4.0252	4.0392	2.9324
PCQI	1.2281	1.1871	1.0744
IE	7.6462	7.5891	6.9327

Table 4. Quantitative comparisons of different methods for Fig 5.

Parameters	Ours Method	CFA [11]	ULA [20]
UCIQE	0.62	0.48	0.46
UIQM	4.77	4.39	3.40
PCQI	1.24	-------	------
IE	7.72	7.73	7.18

Table 5. Quantitative comparisons of different methods for Fig 6

VI. CONCLUSIONS

Our proposed method has successfully applied three different algorithm which are Adaptive Colour Correction, Unsharp Masking, and at the last Contrast-Limited Adaptive Histogram Equalization (CLAHE) all these are collectively used to improve the image quality through a combination of subjective and objective evaluations. Several real-world underwater images are provided as input and subjective evaluation depicted our results visually, whereas objective comparisons have been done on the basis of four quantitative measures like UIQM, UCIQE, PCQI and IE have demonstrated significant progress. The foundation for future image enhancement techniques, we will parameters refer to other robust algorithms which aim to strike a balance between perceived quality of the image and values of parameters

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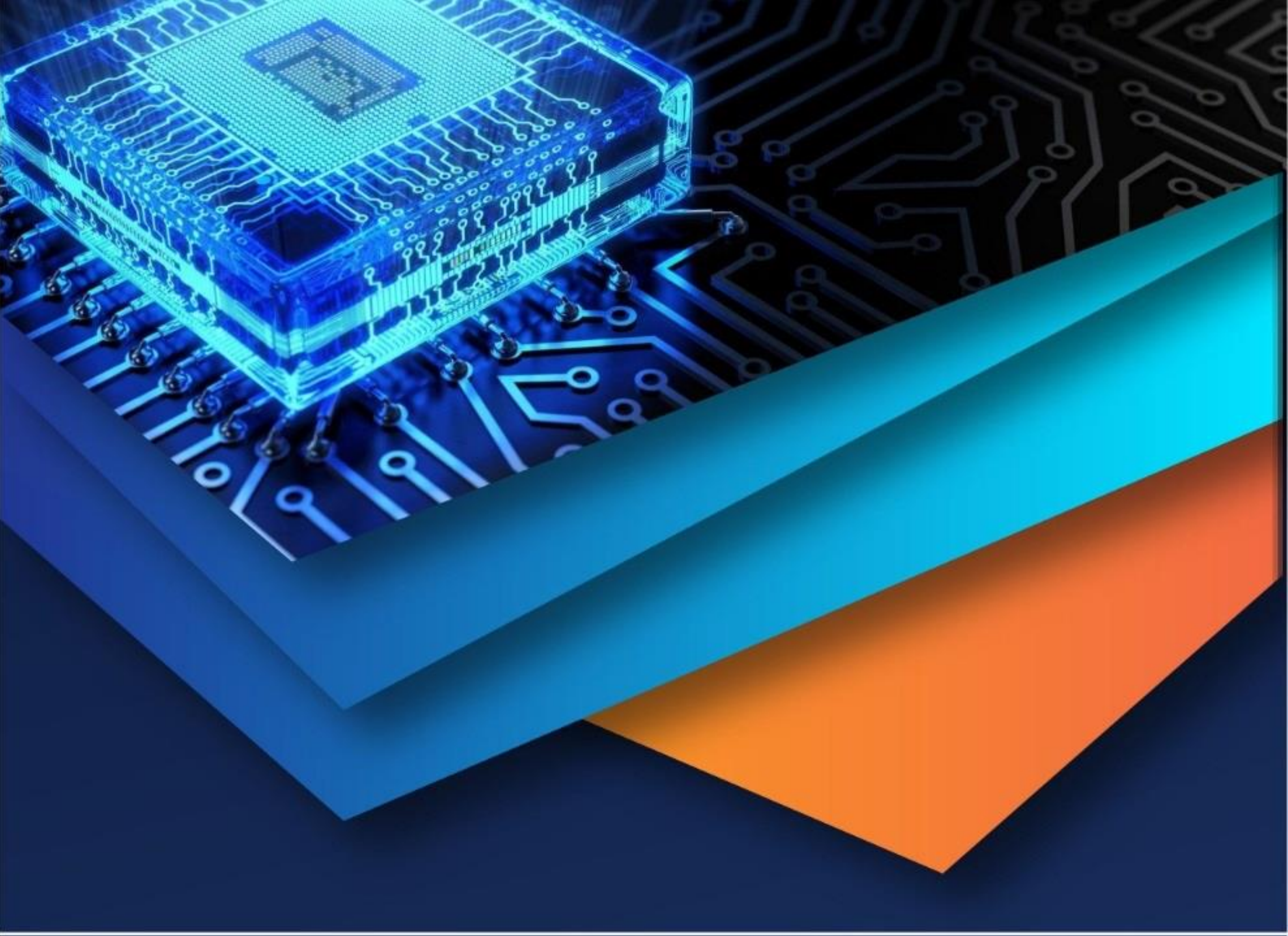

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