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Optimal Multi- Level Thresholding for Color Image Using Kapur's Entropy and Bacterial Foraging Algorithm

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***Abstract*—This paper presents, a multi-thresholding approach for a class of 481 x 321 sized standard colour test images using Kapur's entropy function and Bacterial Foraging Optimization (BFO) optimization algorithm. In this work, maximization of the Kapur's entropy is chosen as the cost function and the BFO algorithm is allowed to explore the RGB histogram, till the threshold value is attained. The performance of the classical BFO algorithm is also enhanced using Brownian Walk (BW) strategy. The capability of BFO assisted segmentation with Kapur's function is validated in association with Particle Swarm Optimization (PSO) and classical BFO algorithms using Kapur's entropy value and search iteration taken by the algorithm. Proposed approach also confirmed using the image quality measures, such as RMSE, PSNR, SSIM, NAE and NCC.**
***Keywords*—Colour image; Kapur's entropy function; BFO algorithm; PSO algorithm; image quality values.**

I. INTRODUCTION

Image segmentation based on multi-level thresholding is widely adopted by the researchers and scientists to extract the image features from a digital image frame. Due to its significance, it is widely considered for traditional image segmentation [1-3], hyper-spectral image processing [4], satellite image processing [5] and biomedical image processing [6-8] applications. In general, image multi-thresholding is carried using manual segmentation procedure or by using the processing unit such as a computer. In this method, with the help of a specified guiding procedure, the digital images are separated in to various layers based on the threshold values.

In the literature, a considerable segmentation procedure is available for the gray scale images and colour (RGB) images [9,10]. For the gray scale image, the threshold level will be of the range [0, L-1], where L=256, but for the RGB image, the threshold value is complex and it can be represented mathematically as $[0, L-1]^3$, which is the combination of Red (R) [0, L-1]; Green (G) [0, L-1] and Blue (B) [0, L-1].

Due to the complex threshold value, segmentation of RGB image is a tedious and time consuming work compared to gray scale images. The complexity in RGB image thresholding can be minimised by employing the heuristic search approaches.

Heuristic algorithm based optimization is widely adopted in various engineering optimization problem because of its robustness, cost effectiveness and ease of implementation [10]. Recently, heuristic algorithm based multi-level thresholding is proposed and implemented for a class of RGB images as discussed below;

Sarkar and Das presented Tsallis entropy and differential evolution based RGB image thresholding process and confirmed this procedure using a class of RGB images using 2D histogram technique [11]. Su and Hu presented a colour image processing technique using self-adaptive differential evolution algorithm [12]. Rajinikanth and Couceiro discussed RGB histogram assisted multi-thresholding using firefly algorithm [13]. They also presented RGB image segmentation work for the breast cancer image dataset using the Lévy flight based BFO algorithm [14]. Rajinikanth et al. discussed Otsu and cuckoo search assisted colour image segmentation for a class of traditional and noise stained images [15]. Preethi and Rajinikanth presented Otsu and firefly algorithm based image segmentation procedure for biopsy breast cancer image dataset [16]. Raja et al. presented Otsu and improved PSO based multi-thresholding for the cancer infected breast thermal image dataset [17]. Balan et al. proposed Otsu based multi-thresholding method to improve the visibility of plasmodium species in thin blood smear malaria image [18]. In this paper, multi-thresholding is implanted for 481 x 321 sized standard RGB images, such as Butterfly, Star fish, Snake, Bird and Train obtained from the Berkeley image segmentation dataset using Brownian Walk based Bacterial Foraging Optimization (BWBFO) algorithm recently discussed by Raja and Rajinikanth [19]. The supremacy of BWBFO is confirmed with the traditional Particle Swarm

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Optimization (PSO) algorithm and BFO algorithm existing in the literature.

Image quality measures, such as RMSE, PSNR, SSIM, NAE and NCC are also computed to evaluate the quality of the proposed segmentation process.

II. KAPUR'S FUNCTION

In general, the entropy is a fundamental thermodynamic conception that is connected with the order of irreversible processes in the universe. Physically it can be connected with the amount of chaos in a physical system. In this section, a uncertain probability entropy method generally known as Kapur entropy is considered. It was originally proposed in 1985 to segment the gray scale image using the entropy of the histogram [20].

This method finds the optimal *Th* which maximizes overall entropy. Let, $Th = [th_1, th_2, ..., th_{k-1}]$ is a vector of the image thresholds. The Kapur's entropy can be expressed as;

$$J_{max} = f_{kapur}(Th) = \sum_{j=1}^{k} H_j^C \quad for \quad C\{1,2,3\} \qquad (1)$$

Generally, each entropy is computed independently based on the particular *Th* value. For multi-level thresholding problem, it can be expressed as;

$$\begin{aligned} H_1^C &= \sum_{j=1}^{th_1} \frac{Ph_j^C}{\omega_0^C} ln\left(\frac{Ph_j^C}{\omega_0^C}\right), \\ H_2^C &= \sum_{j=th_1+1}^{th_2} \frac{Ph_j^C}{\omega_1^C} ln\left(\frac{Ph_j^C}{\omega_1^C}\right), \\ &\vdots \\ H_k^C & \sum_{j=th_k+1}^{L} \frac{Ph_j^C}{\omega_{k-1}^C} ln\left(\frac{Ph_j^C}{\omega_{K-1}^C}\right) \end{aligned} \qquad (2)$$

where Ph_j^C is the probability distribution of the intensity levels and $\omega_0^C, \omega_1^C, ...\omega_{k-1}^C$ probability occurrence for *k* levels. Detailed explanation for the Kapur's function can be found in [1,21,22].

III. HEURISTIC ALGORITHM

This section presents the heuristic algorithms considered in this paper.

A. PSO Algorithm

PSO is a widely adopted heuristic procedure to solve various engineering optimization problems [3].

The PSO algorithm has two basic equations such as velocity update and position update equation and is given below;

$$V_i(t+1) = W^t.V_i^t + C_1R_1(P_i^t - S_i^t) + C_2R_2(G_i^t - S_i^t) \qquad (3)$$

$$X_i(t+1) = X_i^t + V_i(t+1) \qquad (4)$$

Where W^t is inertia weight assigned as 0.8, V_i^t is the current velocity of particle, $V_i(t+1)$ -updated velocity of particle , X_i^t - current position of particle, $X_i(t+1)$ -updated position of particle, R_1, R_2 are the random numbers [0,1] and C_1 =0.7 and C_2=2.0.

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B. BFO Algorithm

The BFO algorithm is initially proposed by Passino in 2002 based on the mathematical model of the foraging manners in Escherichia coli (E.coli) bacteria [23]. Due to its superiority, it is widely considered to solve a variety of engineering optimization problem [24,25]. In this work, the BFO algorithm discussed in [25] is adopted.

The initial BFO parameters are assigned as follows:

$$N = 20 ; N_c = \frac{N}{2} ; N_s = N_{re} \approx \frac{N}{3} ; N_{ed} \approx \frac{N}{4} ; \quad N_r = \frac{N}{2} ; \; P_{ed} = \left(\frac{N_{ed}}{N + N_r} \right) ; \; d_{attract} = W_{attract} = \frac{N_S}{N} ; \; and \; h_{repell} = W_{repell} = \frac{N_C}{N} \tag{5}$$

Where, *N*- number of *E.Coli* bacteria, *Nc*-number of chemotactic steps, *Ns*-Swim length during the search, N_{ed}-number of elimination - dispersal events,N_r-number of bacterial reproduction, P_{ed}- probability of the bacterial elimination, $d_{attract}= W_{attract}$ -width and depth of attraction, $h_{repell}= W_{repell}$- height and width of repellent signal.

C. BWBFO Algorithm

It is a recent version of BFO algorithm, in which the chemo-taxis operation is mutated with the Brownian walk strategy [2, 26]. The major advantage of this procedure is that, it offers better convergence compared with the traditional BFO algorithm.
Let us consider the search operation of i^{th} bacterium at j^{th} chemotactic, k^{th} reproductive and l^{th} elimination-dispersal can be represented as;

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^t(i)\Delta(i)}} \tag{6}$$

where *C(i)* is the step size in the random direction and *Δ(i)* is a random vector of size [-1,1].
In this work, eqn. (6) is modified as follows:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + \frac{\Delta(i)}{\sqrt{\Delta^t(i)\Delta(i)}} \oplus B(s) \tag{7}$$

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + \frac{\Delta(i)}{\sqrt{\Delta^t(i)\Delta(i)}} \oplus B(s) \tag{7}$$

where the symbol ⊕ represents the entry wise multiplication and *B(s)* is the BW strategy [2,26].

IV. IMPLEMENTATION

Multi-level thresholding problem is used to find optimal thresholds within the RGB histogram range [0, L−1]3 that maximize an objective function J_{max}. Kapur's entropy function is employed in this paper to find the R, G, B thresholds based on the assigned *Th* value using a chosen heuristic algorithm.
In this work, in order to obtain a reasonable assessment, all the heuristic algorithms are allocated with similar algorithm parameters, such as number of agents (N=20), maximum number of iteration (2000), search dimension (D=*Th*) and stopping criteria (J_{max}). The quality of the segmentation outcome is assessed using the following image quality measures [27,28];

$$MSE(x,y) = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left(x_{j,k} - y_{j,k}\right)^2 \tag{8}$$

$$PSNR(x,y) = 20\log_{10}\left(\frac{255}{\sqrt{MSE(x,y)}}\right) \tag{9}$$

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$$SSIM(x,y)=\frac{(2\mu_x\mu_y+G_1)(2\sigma_{xy}+G_2)}{\left(\mu_x^2+\mu_y^2-G_1\right)\left(\sigma_{x^2}+\sigma_{y^2}+G_2\right)} \tag{10}$$

$$NAE(x,y)=\sum_{j=1}^{M}\sum_{k=1}^{N}\left|x_{j,k}-y_{j,k}\right| \Big/ \sum_{j=1}^{M}\sum_{k=1}^{N}\left|x_{j,k}\right| \tag{11}$$

$$NCC(x,y)=\sum_{j=1}^{M}\sum_{k=1}^{N}x_{j,k}.y_{j,k} \Big/ \sum_{j=1}^{M}\sum_{k=1}^{N}x^2{}_{j,k} \tag{12}$$

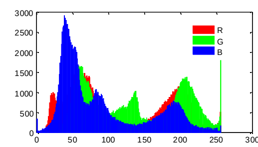
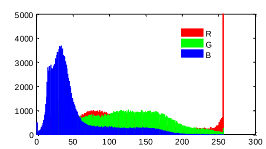
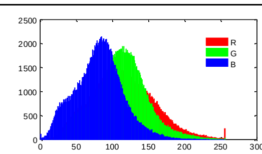
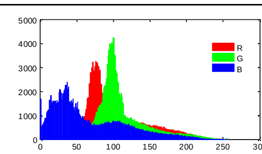
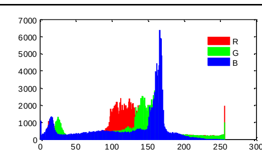
where x- is the original image and y-thresholded image.

V. RESULTS AND DISCUSSIONS

This section presents the simulation results obtained with the proposed multi-thresholding process. The simulation work is implemented using Matlab 2010a software. The benchmark RGB images are obtained from the Berkeley image segmentation dada set [29].

Table I presents the considered 421 x 381 sized RGB dataset and its RGB histogram value. From this, it can be noted that the RGB image is the combination of the Red, Green and Blue colored pixels.

TABLE I. RGB TEST IMAGES AND CORRESPONDING HISTOGRAM VALUES

	Test image	RGB histogram
Butterfly		
Star fish		
Snake		
Bird		
Train		

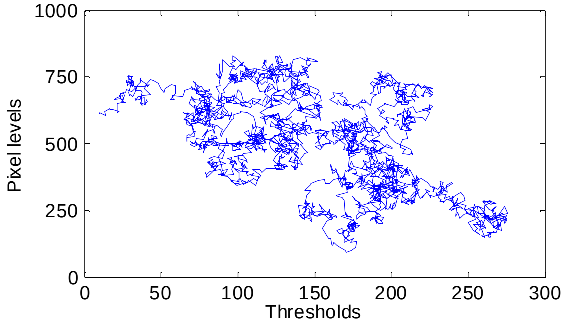


Fig. 1 Brownian walk based search

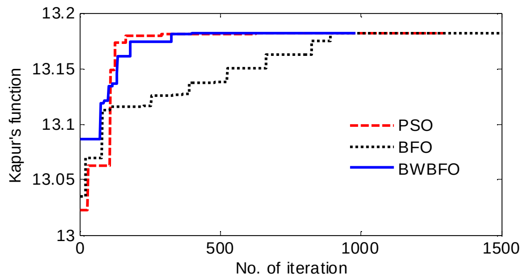


Fig. 2 Convergence of optimization search for *Th*=2

Table II. Comparison of proposed and existing algorithms

	Th	**Kapur's entropy**			**No. of iterations**		
		PSO	**BFO**	**BWBFO**	**PSO**	**BFO**	**BWBFO**
Butterfly	**2**	13.7856	13.7857	13.7859	677	992	418
	3	14.2984	14.3388	14.3391	810	1043	806
	4	15.2385	15.2649	15.3027	1103	1115	1128
	5	17.0037	17.0647	17.0739	1385	1293	1275
Star fish	**2**	12.0543	12.1866	12.1794	729	815	736
	3	14.1864	13.9754	14.1868	965	904	846
	4	14.9753	14.9277	14.9862	1332	1164	1082
	5	15.1688	15.1493	15.1782	1394	1403	1170
Snake	**2**	11.3873	11.3927	11.4084	518	612	604
	3	13.2084	13.2188	13.2503	828	749	841
	4	13.9475	13.5793	13.8732	1055	968	975
	5	14.2945	14.1938	14.3028	1253	1164	1109
Bird	**2**	10.3948	10.5885	10.5913	492	529	508
	3	10.9765	11.0954	11.0486	770	810	792
	4	11.3774	11.4992	11.5003	916	928	826
	5	12.0865	12.0948	12.1109	1064	1016	962
Train	**2**	12.7538	12.6775	12.5076	512	719	502
	3	12.9755	12.8116	12.8664	803	851	664
	4	13.0064	13.0175	13.0194	932	977	719
	5	13.0578	13.0614	13.0642	1125	1084	941

TABLE III. IMAGE QUALITY MEASURES OBTAINED WITH BWBFO

	Th	RMSE	PSNR	SSIM	NAE	NCC
Butterfly	**2**	76.6936	10.4356	0.4001	0.5638	0.4696
	3	65.1582	11.8514	0.5871	0.4759	0.5441
	4	36.0924	16.9825	0.6600	0.2686	0.8111
	5	34.0825	17.4802	0.6844	0.2543	0.8223
Star fish	**2**	60.3926	12.5111	0.3608	0.5122	0.5847
	3	46.5299	14.7762	0.4768	0.3910	0.6860
	4	39.2887	16.2454	0.5301	0.3208	0.7627
	5	27.2671	19.4180	0.7126	0.2335	0.8203
Snake	**2**	63.2883	12.1043	0.4949	0.4828	0.5642
	3	46.9078	14.7059	0.6527	0.4133	0.6250
	4	34.4194	17.3947	0.7488	0.2939	0.7212
	5	27.3261	19.3992	0.8221	0.2306	0.7998
Bird	**2**	74.1012	10.7343	0.2394	0.6827	0.4338
	3	40.2904	16.0268	0.6973	0.3680	0.6826
	4	35.2419	17.1896	0.7809	0.3229	0.7164
	5	31.5423	18.1529	0.8313	0.2907	0.7447
Train	**2**	75.0919	10.6189	0.5358	0.5441	0.4958
	3	46.1694	14.8437	0.7494	0.3244	0.6821
	4	29.2925	18.7957	0.8246	0.2101	0.8063
	5	25.0921	20.1401	0.8684	0.1795	0.8364

Initially the proposed multi-thresholding procedure is implemented on the Butterfly image with PSO, BFO and BWBFO algorithm for *Th* = 2. Fig. 1 shows the search pattern offered in the BWBFO algorithm. From this, it can be noted that, BW strategy helps the BFO to efficiently explore the entire search space *D*.

Fig. 2 sows the convergence of the heuristic search for the Butterfly image when *Th* =2. From this, it can be observed that, BWBFO offers better convergence compared with PSO and BFO algorithms.

The segmentation process is repeated 10 times for each image and for each threshold value and the mean value is presented in Table II and Table III.

The PSO algorithm based search steadily explores the entire the search space in order to find the optimal threshold from $[0, L\text{-}1]^2$ thresholds. In BFO based search, finds the value very slowly due to its slow tumbling and swimming operation. In BWBFO algorithm, the tumble-swim operation is enhanced using the BW strategy, which helps to achieve faster convergence.

From Table II, it is confirmed that, for most of the cases, the Kapur's entropy and number of iterations offered by BWBFO is better compared with the PSO and BFO algorithms.

Table III presents the mean values of Root Mean Square Error (RMSE), Pixel Signal Noise Ratio (PSNR), Structural Similarity Index (SSIM), Normalized Absolute Error (NAE) and Normalized Cross Correlation (NCC) obtained with BWBFO and Kapur's function for *Th* = {2,3,4,5}.

From Table IV, it can be noted that, when the required threshold *Th* = 2, the proposed approach segments the image in to region of interest and back ground. When the *Th* value increases, based on the assigned *Th*, the algorithm groups the RGB pixels in order to enhance the required image portion.

Table V presents the SSIM map obtained for the original image (x) and the thresholded image (y) for *Th* = {2,3,4,5}. SSIM map is used to find the percentage of fit between x and y graphically. This table offers the SSIM map for the Butterfly, Star fish, Snake, Bird and Train for *Th* = {2,3,4,5}.

From this table, it is evident that, when the threshold value increases, the percentage fit in SSIM map also increases.

From these results, it is confirmed that, proposed BWBFO and Kapur's entropy based approach offers better segmentation result for the RGB images considered in this study compared with the PSO and BFO algorithms. In future, this segmentation procedure can be considered to solve the complex medical RGB image segmentation problem and hyper spectral satellite image segmentation

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problems.

TABLE IV. SEGMENTED RGB IMAGES FOR *Th* = {2,3,4,5}

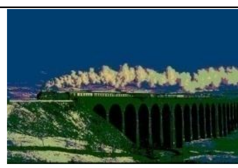
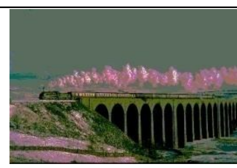
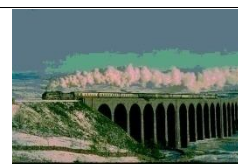
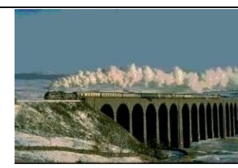
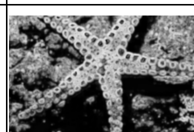
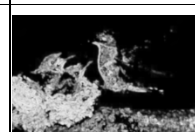
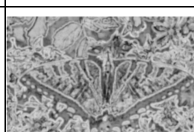
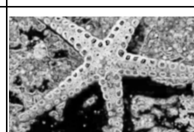
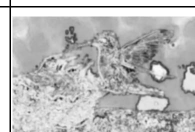
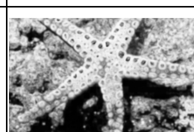
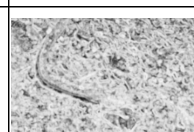
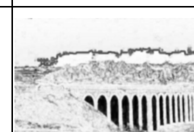
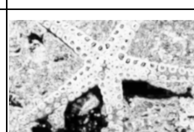
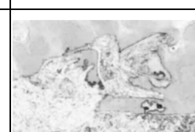
	Th =2	*Th* =3	*Th* =4	*Th* =5
Butterfly				
Star fish				
Snake				
Bird				
Train				

TABLE V. SSIM MAP BETWEEN SEGMENTED AND ORIGINAL IMAGE FOR *Th* = {2,3,4,5}

Th	Butterfly	Star fish	Snake	Bird	Train
2					
3					
4					
5					

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VI. CONCLUSIONS

In this paper, RGB image multi-level thresholding problem is addressed using the Brownian walk based BFO algorithm and Kapur's function. In this work, the threshold values are chosen as *Th*={2,3,4,5} and it is implemented for 421 x 381 sized standard RGB benchmark images. In order to verify the effectiveness, proposed method is validated with PSO and BFO algorithm. Initially the Kapur's function and number of iteration is considered to assess the performance of PSO, BFO and BWBFO. Later the image quality measures, such as RMSE, PSNR, SSIM, NAE, NSS and SSIM map are considered. The simulation result confirms that, BWBFO based segmentation helps to achieve better result compared with the PSO and BFO.

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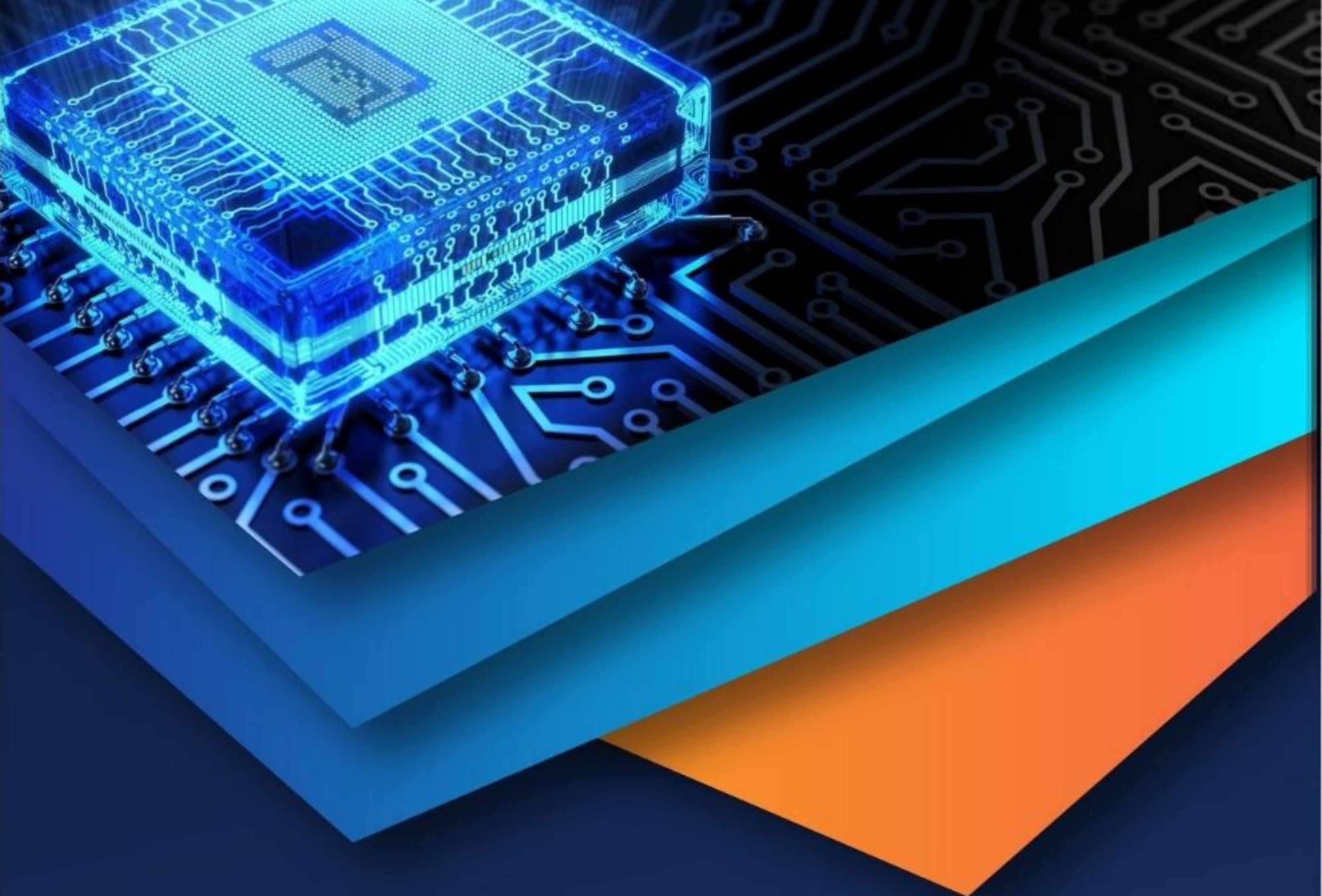

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