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Hybrid Algorithm Analysis for Brain Tumor Detection using Segmentation Technique with Efficient Intensity Adjustment in MRI Images

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Abstract*: The proposed paper presents a Hybrid algorithm for MRI Images which has been developed along with the image segmentation, edge detection techniques and intensity enhancement to detect Brain Tumor Efficiently. The developed Technique using K-means clustering algorithm is integrated with the Fuzzy C-means (KIFCM) and Edge Detection for abnormal MRI images is a novel image segmentation approach to overcome the limitations and to make it more beneficial. The performance of proposed Technique has been analyzed in terms of Tumor Area, White pixels, Black pixels, Tumor detected area, Accuracy value, Processing time, Precision value, and Recall value. The accuracy was evaluated by the ground truth of each processed image. The experimental results clarify the effectiveness of proposed approach to deal with a higher number of segmentation problems via improving the segmentation quality and accuracy in minimal execution time. The Experiment Proposed on Dataset of images giving 100% Accuracy. The proposed technique is quite sensitive towards the detection, specification and highlighting the detected Tumor Area. The work was implemented using MATLAB R2015a (8.5.0.197613)-64Bit.

Keywords: Medical Image Segmentation, K-means clustering, Fuzzy C-means, Level Set, Edge Detection, Intensity Adjustment, Brain Tumor, MRI Images

I. INTRODUCTION

The brain is a very complex structure of body and it is tightly bounded within the skull because of this it is more difficult to diagnose its diseases. The abnormal growth in brain cells creates a cluster known as brain tumor which is a very complicated to diagnose. There are two general classifications of tumors; benign tumor or malignant tumor. In the case of a benign tumor, the tumorous mass lacks the ability to attack adjacent healthy cells which means that it is unable to metastasize therefore it is termed as non-cancerous. [2] A tumor is a name for a neoplasm or a solid lesion formed by an abnormal growth of cells (termed neoplastic) which looks like a swelling. The tumor is not synonymous with cancer.

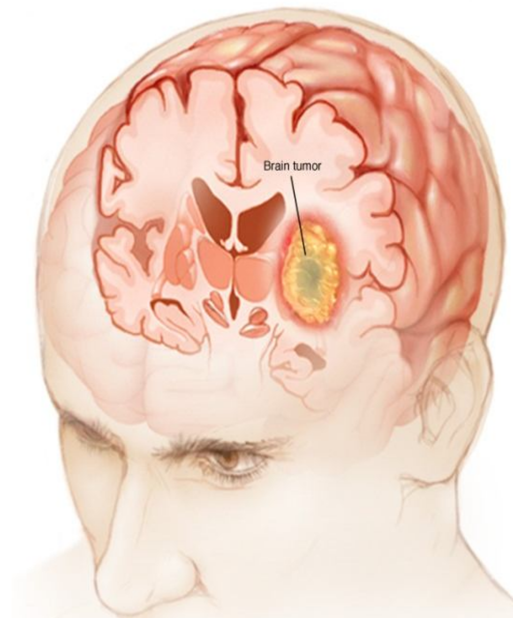

Fig. 1 Image of Brain Tumor [22]

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II. MAGNETIC RESONANCE IMAGING (MRI)

Magnetic Resonance Imaging (MRI) scan or Computed Tomography (CT) scan are the techniques used to scan the anatomy of the brain. The MRI scan does not use any radiation and is more comfortable than CT scan for diagnosis thus it does not affect the human body. MRI is based on the Magnetic Field and Radio Waves. [1]

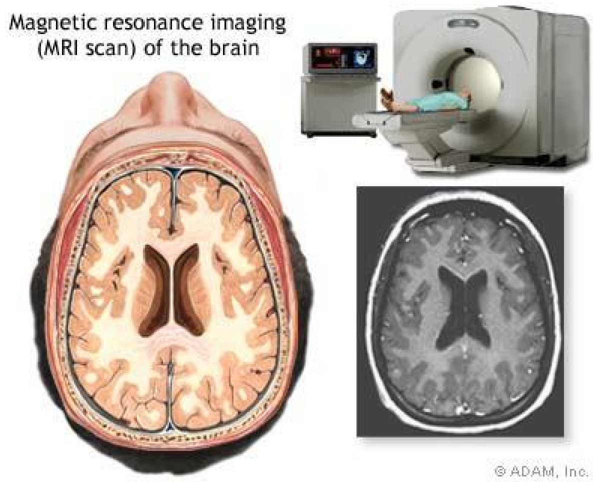
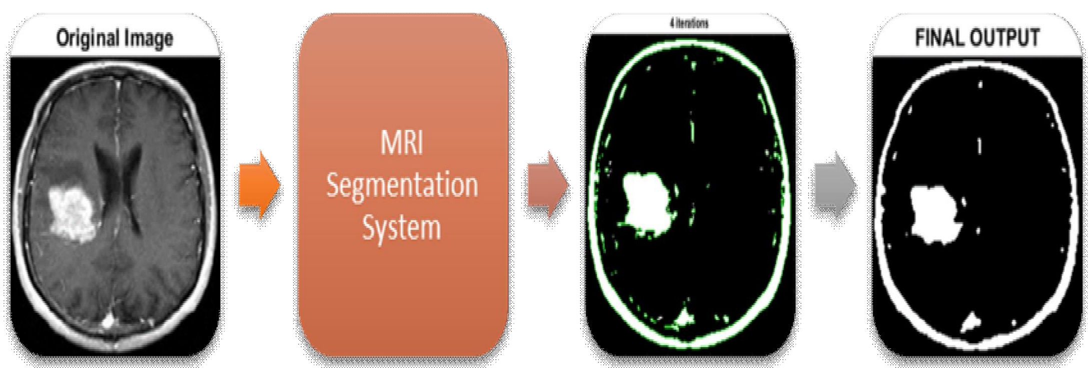


Fig. 2 Image of Magnetic Resonance Imaging (MRI) scan [23]

III. IMAGE SEGMENTATION

Image segmentation is the process of partitioning a digital image into multiple regions. The goal of segmentation is to change the representation of an image. It is more meaningful and easier to analyze and used in order to locate objects and boundaries in images. The result of image segmentation occurs as a set of regions that collectively covers the entire image. [1]



Input (MRI) Output (Label Field)

Fig. 3 Image Segmentation Process

IV. PROPOSED MEDICAL IMAGE SEGMENTATION SYSTEM

For a Mass Tumor, it is easy to run K-means algorithm which is simple and fast to work on Larger size of Dataset. On the other hand, for a Malignant Tumor it results in an incomplete detection of tumor. There are some medical image segmentation systems which use K-means algorithm for detecting mass tumor in brain [22]. As other systems use Fuzzy C-means algorithm because it retains the more information of the original image to detect malignant tumor cells accurately compared to the K-means [23]. These systems are sensitive to noise and outliers, and they take long execution time. In our proposed medical segmentation system approach, we used last two algorithms to get more benefit. The main purpose of doing the integration is to decrease the number of iterations done by initializing the right cluster centers to Fuzzy C-means clustering techniques that reduces execution time and results qualitative output. The results of these experiments resulted that our hybrid clustering method (KIFCM) can detect a tumor that cannot be detected by Fuzzy C-means with less execution time. The projected medical image segmentation system consists of four stages Pre-Processing, Clustering, Tumor Extraction and Contouring, and Validation Stages.

Table I
The pseudocode of the proposed Hybrid KIFCM system.

1. READ image
2. APPLY Timing Calculations and Iterations
3. CONVERT to Gray Scale image
4. DISPLAY the converted image
5. START KIFCM algorithm
6. FIND cluster center *MU*
7. Search for minimum value
8. calculating New Centroid
9. CALCULATE image size, max X, max Y
10. CONCATINATE the dimensions
11. SAVE Clustering image
12. DISPLAY clustering image KIFCM image, execution time, and iteration Numbers
13. BINARIZE image
14. APPLY median filter
15. SAVE thresholding image
16. CALL level set function
17. SAVE resulting image
18. START Efficient intensity adjustment
19. SUBTRACT and filter non required part of image
20. DISPLAY Image Opening, Subtraction 1, Subtraction 2, Subtraction 3 image subplots
21. APPLY median filter
22. DISPLAY noise removed image
23. ADJUST the intensity of image
24. DISPLAY the segmenting image with contoured tumor regions
25. CALCULATE total pixels = numel (BW)
26. CALCULATE white pixels nwhite = $\sum BW(:)$

(1)

27. CALCULATE black pixels nblack = total pixels – nwhite
28. CALCULATE ratio = $\frac{nwhite}{nblack}$
29. DISPLAY Total area of Tumor
30. ADJUST the intensity in the final output
31. DISPLAY final output
32. CALCULATE true positive TP
33. CALCULATE true negative TN
34. CALCULATE false positive FP
35. CALCULATE false negative FN
36. CALCULATE precision
37. CALCULATE recall
38. CALCULATE accuracy

A. Pre-Processing Stage

In this phase a series of initial processing procedures is implemented on the image before any special purposes processing, which improves the image quality and removes the noise. This stage consists of the following two sub-stages:

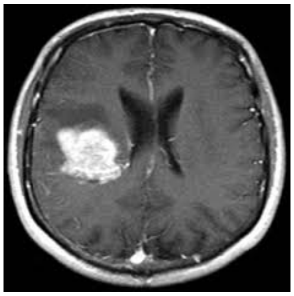


Fig. 4 Image before Pre-Processing

1) Initial Values: In this step, the initial values for the computation of Maximum number of Iterations is defined along with Iteration Number, the elapsed time during the initial process of proposed approach is given to the algorithm such that the total elapsed time from start to the end of processing will be calculated.

2) Image Conversion: Pre-processing step translate the image, completes filtering of noise, sharpening the edges, RGB to gray conversion, Reshaping and other parameters in the image. It enhances the quality of the images and make the segmentation and feature extraction phase more reliable.

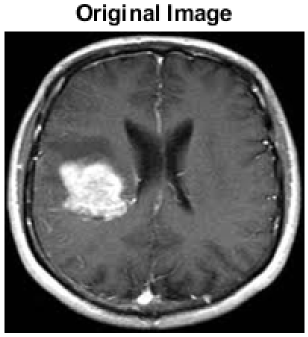


Fig. 5 Image after Pre-Processing

Fig. 6 Image Segmentation Process

B. *Clustering Stage*

The images are fed to KIFCM technique by setting cluster numbers k, max iterations, and termination parameter after Pre-Processing. The pseudo-code of the proposed KIFCM is listed in Table 1. The cluster centers are calculated by:

$$MU = \frac{(1:k)\,m}{(k+1)} \tag{2}$$

Where *MU* is the initial means that can be calculated due to k (number of clusters).
m is defined as:

$$m = \max\,(\text{MRI image}) + 1 \tag{3}$$

1) Assign each point to the nearest cluster center based on a minimum distance by checking the distance between the point and the cluster centers then re-compute the new cluster centers.
2) It is repeated until some convergence criterion is obtained.
3) Also, there are some points scattered and distant from any cluster center.
4) The resulted new cluster centers, the clustered points, and the scattered points can be entered in the same time to the looping step that calculates the new distances and clustering the points due to membership value.
5) The membership and means values are then updated by determining the condition of closing.

The initial centers of the clusters were not randomly chosen which saves time and effort, thus looping step takes less number of iterations than the random selection. Although, the points were re-clustered due to its membership. There is no huge change done by the re-clustering process therefore there is no inference between points in their clusters [15]. The output of the technique is the clustering image, execution time, and iteration numbers that are recorded to compare with other clustering methods. In this stage, we make a hybrid clustering method based on hard and soft clustering. The hard clustering technique put each point to belong to only nearest cluster. Whereas, the soft clustering technique gives every point a degree of membership, rather than belonging wholly to just one cluster.

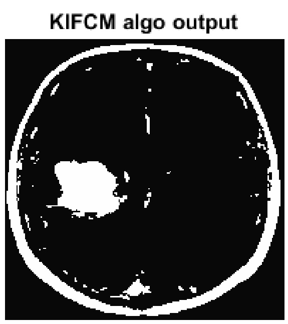


Fig. 7 Image after KIFCM Process

C. *Extraction and Contouring Stage*

In this phase, we used two segmentation methods: thresholding and active contour level set methods:

1) Thresholding Segmentation: Thresholding or image binarization is intensity-based segmentation and is used to extract the object from the background. The segmented image obtained by thresholding is of smaller storage space, fast processing speed, and ease of manipulation, compared with gray level image which generally contains a large number of gray levels (maximum 256 levels). The result output is the segmenting image with dark background and lighting tumor area.

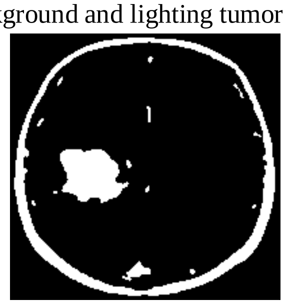


Fig. 8 Image after Thresholding Segmentation

2) De-Noising by Median Filter: Since, the brain images are more sensitive than other medical images; they should be of minimum noise and maximum quality. It may reach due to the thermal effect. The main purpose of this paper is to detect and segment the tumor cells, but for the complete stage it needs the process of noise removal.

MRI images are usually corrupted by disturbances like Gaussian and Poisson noise. The vast majority of the de-noising algorithms assume additive white Gaussian noise. There are some algorithms that designed for Gaussian noise elimination, like edge preserving bilateral filter, total variation, and non-local means. In this paper, median filter is used which works by moving pixel by pixel through the image, replacing each value with the median value of neighboring pixels. The median is calculated by first sorting all the pixel values from the window (pattern of neighbors) into numerical order, and then replacing the pixel being considered with the middle (median) pixel value. Image processing researchers commonly assert that median filtering is better than linear filtering for removing noise in the presence of edges [14]. The output of this sub-step in preprocessing is the free noising MRI image.

Fig. 9 Image after De-Noising by Median Filter

3) Active Contour by Level Set: Active contours have been used for image segmentation and boundary tracking. The basic idea is to start with initial boundary shapes represented in a form of closed curves, i.e. contours, and iteratively modify them by applying shrink/expansion operations according to the constraints. The used active contour method shows robust segmentation capabilities in medical images where traditional segmentation methods show poor performance [11]. An advantage of the active contours as an image segmentation method is that they partition an image into sub-regions with continuous boundaries. While the edge detectors based on the threshold or local filtering, it often results in discontinuous boundaries. The use of level set theory has provided more flexibility and convenience in the implementation of active contours. Depending on the implementation scheme, active contours can use various properties used for other segmentation methods such as edges, statistics, and texture [13].

a) The clustering image is entered to the binarization process using inverse thresholding method with iteration number equals 3.
b) The noise of the image is removed by using the median filter that eliminates the small regions that are far away from the tumor cluster.
c) We can consider this step as a post processing step in our system. Of course, these two steps can be converted to one step if the classical FCM is used which user can enter the cluster to be a threshold or appeared only in image. In our proposed technique, we get rid of user interaction that may be true or false. After that, the thresholding image with the lighting tumor cluster is fed to the level set.
d) Level set contours the tumor area of the thresholding image on the original image.
e) The output of this step is the thresholding image and original free noising image with contouring tumor area.
f) The tumor area can be calculated by computing the white pixels of total pixels of the image.

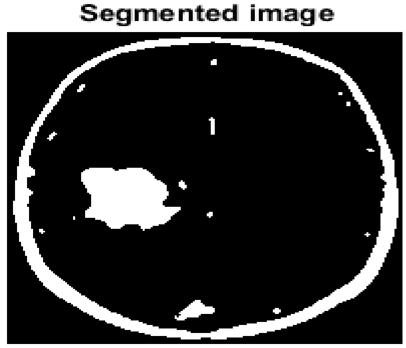


Fig. 10 Image after Active Contour by Level Set

4) Intensity Adjustment: The Novel Intensity Adjustment Approach has been introduced with Image segmentation. Intensity adjustment is an image enhancement technique that maps intensity values of an image to a new range. This technique modifies the Low contrast of an image to high contrast value along with removing and subtracting the image portion which is not required. It increases the processing speed and the results are more refined by adjusting the contrast of the experimented image.

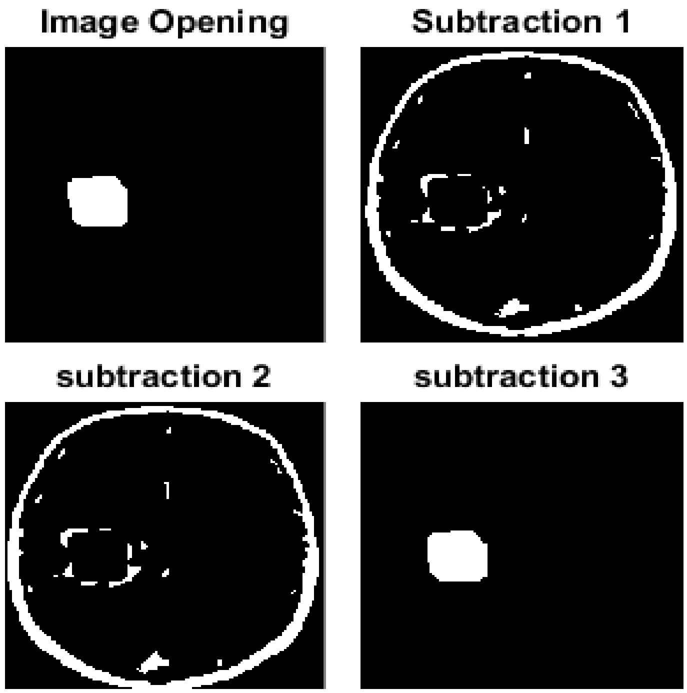


Fig. 11 Image after Intensity Adjustment

V. EXPERIMENTAL RESULTS

A. Data Sets

In order to check the performance of our image segmentation approach, we used the available MRI data sets. The suggested algorithm was successfully run on fifteen MRI images publicly available Brain Tumor Segmentation (BRATS) challenge dataset. The data set consists of multi-contrast MRI scans (both low-grade and high-grade)

B. Results and Discussion

In this section, we show the results of our proposed image segmentation technique that obtained using real MRI brain images from different data sets. This work was implemented using MATLAB R2015a (8.5.0.197613)-64Bit. We run our experiments on a core i3/1.8 GHZ computer with 4 GB RAM and intel HD Graphics 4000 VGA card. After that, the images are smoothed by median filter. Then, they are clustered by the proposed KIFCM technique and segmented by using thresholding and contouring the tumor region by level set.

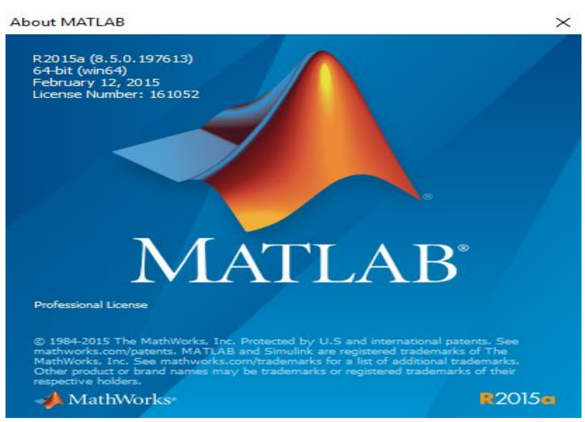


Fig. 14 Image of MATLAB R2015a (8.5.0.197613)-64Bit

C. The final Output Shows Calculating the Area of the Tumor.

The result is apparent for the user to discover the tumor with his eyes before doing thresholding and level set stages. For the proposed algorithm in some images, we found that the KIFCM method is more accurate. Comparing with the previous research in the same field, we can say that their iteration number is 8 and elapsed time is 12 seconds but in our hybrid method technique iteration number is 7 and elapsed time is 6.38 seconds.

The comparison was done and tested using hybrid technique according to the following performance measures:

$$True\ Positive\ (TP) = \frac{No.of\ resulted\ images\ having\ brain\ tumor}{total\ No.of\ images} \quad (4)$$

$$True\ Negative\ (TN) = \frac{No.of\ images\ that\ haven't\ tumor}{total\ No.of\ images} \quad (5)$$

$$False\ Positive\ (FP) = \frac{No.of\ images\ that\ haven't\ tumor\ and\ detected\ positive}{total\ No.of\ images} \quad (6)$$

$$False\ Negative\ (FN) = \frac{No.of\ images\ have\ tumor\ and\ not\ detected}{total\ No.of\ images} \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (10)$$

Table II
Output Results shows calculating the area of the Tumor

Cluster Centres	0.2301	
		0.7757
Total pixel		40000
White pixel		5190
Black pixel		34810
ratio		0.1491
Area of tumor		5.2974e+03
Elapsed time is 6.387651 seconds.		
TP	=	100
TN	=	0
FP	=	0
FN	=	0
Precision	=	1
Recall	=	1
ACCURACY	=	100

VI. CONCLUSION

Image segmentation plays a significant role in medical image. In the field of medical diagnosis, an extensive diversity of imaging techniques is available presently, such as CT and MRI. MRI is the most effective image model used for diagnostic image examination for brain tumor. The MRI scan is more comfortable than CT scan for diagnosis. On the other hand, K-mean algorithm can detect a brain tumor faster than Fuzzy C-means, but Fuzzy C-means can predict tumor cells accurately. Therefore, we have used K-means clustering technique integrated with Fuzzy C-means algorithm and along with the efficient intensity adjustment method to detect brain tumor accurately and more precisely in minimal execution time. Our framework consists of four stages: pre-processing, clustering (integration of Kmeans and Fuzzy C-means), extraction and contouring (thresholding and level set), and validation stages. We are getting the improved results as compared to the previous work in the same field [1]. We have done this hybrid method work for 7 Iterations, and some images from the dataset are showing results even for the 4th or 5th Iteration number. From the experimental results, we proved the effectiveness of our approach in brain tumor segmentation by comparing it with previous work. Our proposed system determines the initial cluster k value to minimize the execution time. The performance of the proposed technique, its minimization time strategy, and its quality has been demonstrated in several experiments. An intensity adjustment process has been provided for more challenging and refined results of the segmentation techniques to the MRI brain tumor segmentation.

VII. FUTURE SCOPE

The proposed method gives more accurate result. In future the 3D evaluation of the brain tumor detection using 3D slicer of brain using 3D slicers with MATLAB can be developed. The work can be extended by using network training for auto analyzing and determining the affected area by saving using fuzzy logics. Also we can use more advance processors to enhance the processing speed.

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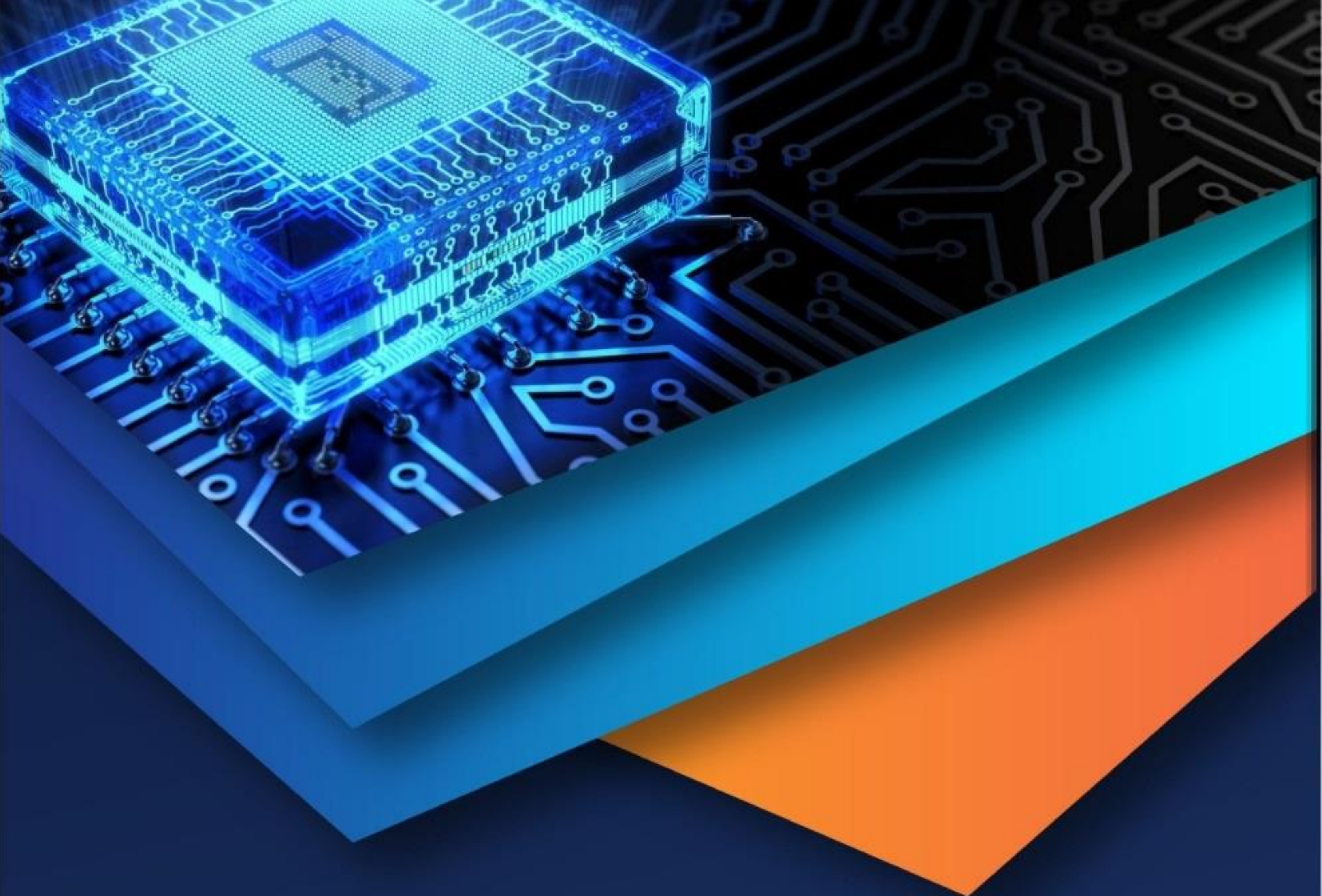

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