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Emphysema Detection usingRegion Growing based Active Contour ModelSegmentation

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Abstract-----Emphysema has large prevalence rate and remain as a healthcare challenge worldwide. Computer Aided Diagnosis (CAD) has become a major research interest in diagnostic radiology and medical imaging diagnostics. The basic goal of CAD is to provide a computer output as a second opinion to assist the technicians by reducingimage interpretationtimeand improving diagnostic accuracy. In this work region growing based active contour segmentation technique is attempted for extracting the lung parenchyma in the CT lung images in order to detect emphysema. The active contour method provides an effective way for segmentation, in which the boundaries of the objects are detected by evolving curves. In this work region growing output image is used as the mask for the active contour model and then texture features are extracted and the extracted features are classified using Extreme learning Machine classifier. Result shows that the automated method can detect emphysema efficiently.

Key words: Emphysema, Region Growing, Active Contour Model, ELM Classifier

I. INTRODUCTION

Chronic Obstructive Pulmonary Disease (COPD) is one of the fastest growing healthcareproblem in worldwide [1]. Emphysema is defined as a lung condition characterized by the destruction of the alveolar walls leading to a loss of elastic tissue and an increase in compliance. Chest imaging technologies with computer aided analysis can be used to diagnose the lung diseases with high accuracy and less computation time. High-resolution Computed Tomography (CT) now provides images of airways as small as 2 mm and indices of parenchymal density that correlate well with diffusing capacity. Radiographic pattern observed from lung CT are often varied and subtle and that human observer does not usually see early abnormal lung pathology on CT Images. Also examining every CT slice from a patient's CT data set can be time consuming. Hence a computer-aided diagnosis for physicians is very much essential to improve the diagnostic accuracy and ease of use. methods aim at recognizing and delineating the boundaries of objects. YasuoSekine et al [5] reviewed about the early detection of COPD and significant risk factor for the lung cancer. They concluded that CT imaging modality is an effective procedure for the early detection of lung cancer in high risk patients.

A report on emphysema distribution and annual changes in pulmonary function in male patients with COPD disease has been submitted in 2012 Respiratory research organization [6] [Naoya Tanabe].

Computer-aided diagnosis is a young interdisciplinary technology combining artificial intelligence and digital image processing with radiological image processing [4]. A CAD system analyzes the images in several steps like preprocessing, segmentation, structural or textural feature analysis for region of interest and evaluation or classification.

Various segmentation techniques have been used for the segmentation of lung parenchyma in CT images. Manual cropping, semi-automatic and automatic segmentation techniques have been proposed.

A method has been proposed for quantification of pulmonary emphysema from lung CT image using texture based adaptive multiple feature method by Uppalapuri . Quantitative texture analysis using adaptive multiple features holds promise for the objective noninvasive evaluation of pulmonary parenchyma.

Khairulmuzzamin et al [7] proposed a method for diagnosis of emphysema on lung CT images by segmenting the emphysema tissues by threshold based method.

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Baidya et al [8] proposed a method for detecting multiple objects by using quad tree based approximate segmentation and modified Adaboost algorithm. Saha et al proposed a snake validation scheme using PCA. Their method places seeds on the entire image and evolve one snake from each seed.

A distance regularized level set evolution for the segmentation of level set methods has been used by Chunming Li. Seokyoon Choi and Changsoo Kim [9] proposed automatic initialization of active contour model for the segmentation of chest wall in CT image using mean shape GVF.

Chunming Li [10] proposed an automatically initializing and splitting of snakes for the segmentation using Edge preserving GVF.VeronicaVasconcelos et al [11] compared the various Statistical Textural Features for Classification of Lung Emphysema in CT Images.

In this work region growing based active contour segmentation technique is attempted for extracting the lung parenchyma in the CT lung images in order to detect emphysema. The active contour method provides an effective way for segmentation, in which the boundaries of the objects are detected by evolving curves. In this work region growing output image is used as the mask for the active contour model.By using this method number of iterations to detect the boundary line can be reduced, hence the energy required for the active contour model can be minimized. The texture features are extracted for the segmented lung parenchyma and the features are given to train and test the classifier to differentiate normal and abnormal subjects

II. METHODOLOGY

The images used for detection of lung disease are collected from the Computed Tomography Emphysema Database. The data comes from a study group comprising 39 subjects (9 never-smokers, 10 smokers, and 10 smokers with COPD) that were all CT scanned CT image [28].

CT lung image is preprocessed using the histogram based threshold method and the preprocessed image is segmented by automatic region growing segmentation. The resultant image obtained from the RG algorithm is given as the mask input to the Active Contour algorithm to detect the boundaries of the lung parenchyma by the evolving snakes.MATLAB is used as the software for the implementation of this paper.

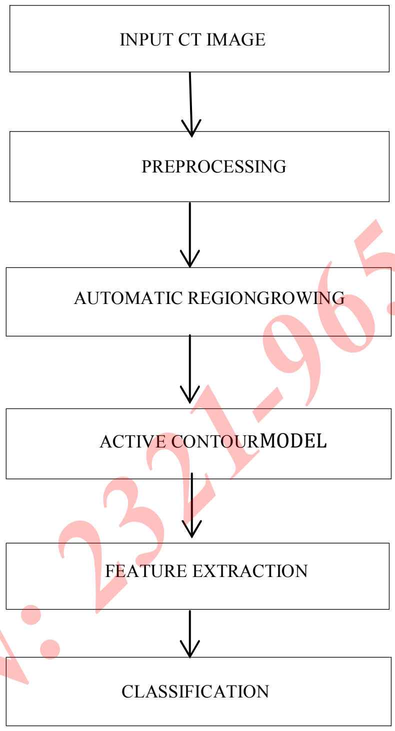

Fig 1. Flow Diagram

A.Region Growing:

Region growing is a simple pixel basedimage segmentation method,it involves the selection of initial seed points.This approach to segmentation examines neighboring pixels of initial seed points and determines whether the pixel neighbors should be added to the region based on the selection rules [16].

I. If the intensity *I* is greater/lower than a certain threshold, the pixel is included in the growing region.
II. The intensities of the pixel and its neighbors are averaged; if the average is greater/lower than the threshold , the pixel is included in the growing region

The main problem of a RG algorithm relies in the selection of a proper seed point, which is usually done by hand. As our aim is the implementation of an automated CAD system, the seed point could be automatically selected.

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(i)*Preprocessing:*

First the given input image is preprocessed by histogram based binary image conversion method [16].

- The CT gray-tone histogram is divided into two regions with equal number of bins and the mean values of the bins in the two regions are computed;
- The previously computed mean values are averaged and the bin having the intensity nearest to the new mean is selected as the threshold to divide the histogram
- The routine is iterated until the threshold bin does not change anymore.

By the application of preprocessing the muscles and vascular tree regions are eliminated.

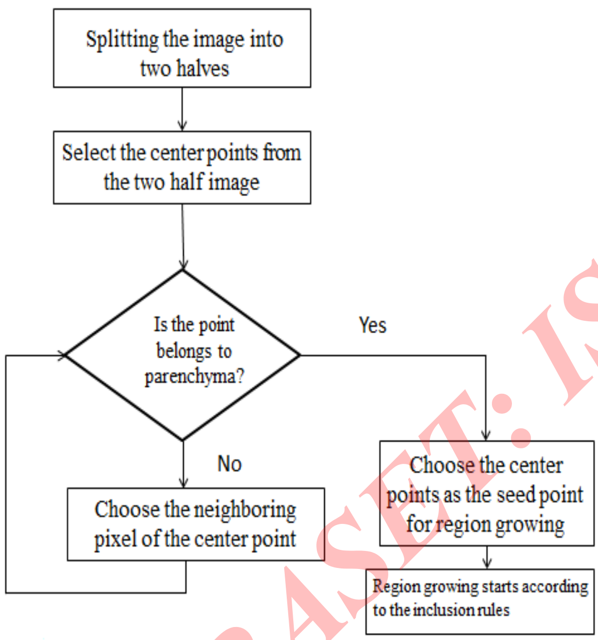

Fig 2.Automatic region growing Flow diagram

(ii)Automatic seed selection:

The preprocessed image is divided into two equal halves in order to select seed points. The center points are selected from the two halves as seed points and these seed points are used to segment right and left parenchyma individually. If the center point is equal to '0' the co-ordinate values of the center point will be taken as seed point, else the neighboring pixel which has the zero value will be taken as the seed point.

Once the seed points are selected the region growing starts. Finalimage obtained from the region growing is given as a mask input to the Active contour model.

B.Active Contour Model:

Active contour methods for image segmentation allow a contour to deformiteratively so as to partition an image into regions corresponding to thescene represented by the image.Detecting and locating curves corresponding to object boundaries in an image is vital in segmentation and using these boundary detectors to iteratively move towards their final solution is the underlying principle of Active Contours. These boundaries are represented as spline curves and undergo numerous shrinkage or expansion operations based on an energy minimizing function [12].

A contour is a parameterized curve in an image domain and minimizing an energy functional whose argument is an entire contour is the mathematical problem of segmentation.

Snakes, Intelligent Scissors and Level Sets are three types of the active contour technique. The Snakes technique uses an energy-minimizing 2D spline curve that evolves towards features such as strong edges, i.e. regions of high pixel-intensity change. While, the Intelligent Scissors technique allows for real-time curve sketching of the object boundaries by computing a least cost path between specific points of the image. It optimizes the contour and draws a better curve depicting high-contrast edges. The Level Sets technique is based on representing a contour as a signed function, where the zero set of the characteristic function corresponds to the actual contour. This allows for incorporating region-based statistics and facilitates topology change of the contours, an importantprocess that could not be tackled by the former two techniques [17].

The primary drawback of level set methods is that they are slow tocompute. In their truest form, many computations are required to maintain Φas the contour changes. This has led to proposals of various narrow-bandalgorithms that reduce the computational complexity by only performing calculations near the zero level set. The sparse field method (SFM) is one of the most efficient algorithms tomaintain a minimal, but accurate representation of Φ. Using the SFM candrastically reduce computation times for level set methods [22].

In this paper, a binary image obtained from the region growing is taken as the label map (label), The binary image have values 0 and 1 where 1's represent foreground pixels, and 0's represent background pixels.

Once the label have been initialized, the level sets may be deformed in order to minimize some segmentation

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energy. One of the active contour energy called Chan-Vese energy is given by

$$E=\int_{interior}(I-\mu_1)^2+\int_{exterior}(I-\mu_2)^2 \quad (1)$$

which has the corresponding evolution equation

$$F=(I-\mu_1)^2-(I-\mu_2)^2 \quad (2)$$

F has been computed along the zero level set and normalized such that |F| < 0.5 at each iteration.

When computing the movementof the contour, it is often desirable to track when a point crosses the zerolevel set thus changing from an interior point to an exterior point or viceversa.

This can be accomplished by checking the sign of Φ before andafter adding F to the value of Φ for points on the zero level set.

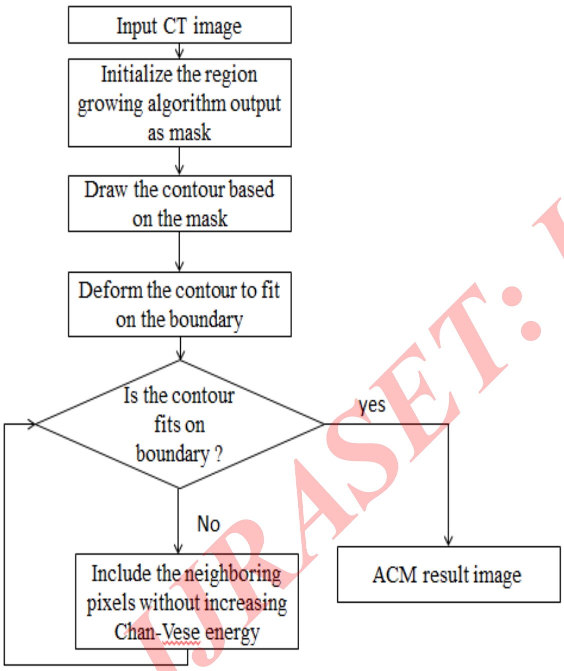

Fig 3 Active contour model flow diagram

C. Feature extraction:

Co-occurrence matrix captures numerical features of a texture using spatial relations of similar gray tones. Numerical features computed from the co-occurrence matrix can be used to represent, compare, and classify textures . In this approach five Haralick features are computed using the following formulas [11].

Energy is the sum of squared elements in the co-occurrence matrix.

$$\text{Energy}=\sum_i\sum_j\{P(i,j)^2\} \quad (6)$$

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

$$\text{Entropy}=\sum_i\sum_j\{P(i,j)\log_2 P(i,j)\} \quad (7)$$

Contrast returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.

$$\text{Contrast}=\frac{1}{(N-1)^2}\sum_i\sum_j(i,j)^2\,P(i,j) \quad (8)$$

Homogeneity returns a value that measures the closeness of the distribution of elements in the co-occurrence matrix to the co-occurrence matrix diagonal.

$$\text{Homogeneity}=\sum_i\sum_j\frac{1}{1+(i-j)^2}P(i,j) \quad (9)$$

Correlation returns a measure of how correlated a pixel is to its neighbor over the whole image.

$$\text{Correlation}=\frac{1}{\sigma_x\sigma_y}\sum_i\sum_j(i,j)P(i,j)-\mu_x\mu_y \quad (10)$$

D. Extreme learning machine classifier:

A new learning algorithm for Single Hidden Layer Feed-Forward Networks (SLFNs), called Extreme Learning Machine (ELM). Traditional Artificial Neural Networks (ANNs) approaches, such as BP algorithms, usually face difficulties in manually tuning control parameters, but ELM can avoid such issues and reaches good solutions analytically, and learning speed of ELM is extremely fast. The reason is that ELM randomly chooses the input weights and bias of the SLFNs instead of tuning [27].

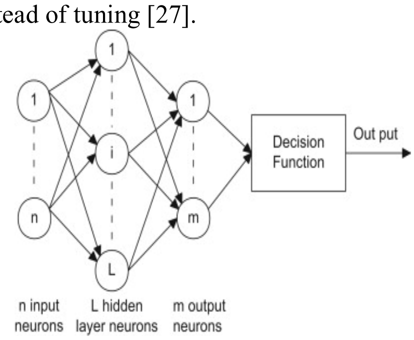

Fig 4.ELM architecture

In ELM, the input weights and hidden biases are randomly generated instead of being tuned. Hence the nonlinear system has been converted to a linear system:

$$H\beta = T \quad (11)$$

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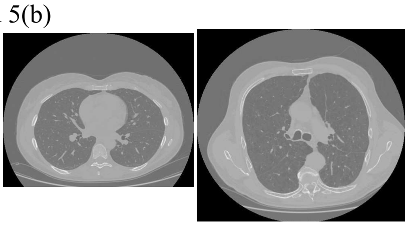
where H is the hidden-layer output matrix, β is the matrix of output weights, T is the matrix of targets. Different basis functions of ELM which include sigmoid, sine, hard limit, triangular basis and radial basis functions are considered.

III. RESULTS AND DISCUSSION

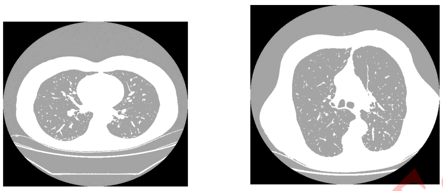
The typical normal and emphysema lung images are shown in Fig 5(a) and 5(b)



(a) (b)

Fig 5.Typical lung images (a) Normal (b)Abnormal

For the histogram based preprocessing procedure 133 and 163 are obtained as the optimal threshold value for the normal and abnormal images respectively. By using this threshold value the muscle and fat tissues are removed from the CT lung images. Preprocessed image output is shown in fig 6.



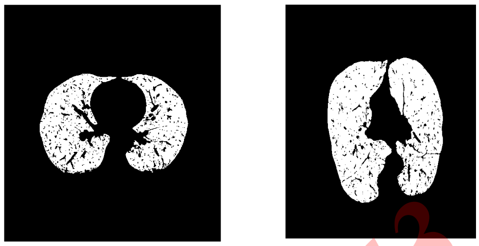
(a) (b)

Fig 6. Preprocessed Image (a)Normal (b)Abnormal

The preprocessed image is automatically segmented by using region growing algorithm. The output obtained from the region growing algorithm is shown in fig 7 and the postprocessed output is shown in fig 8 .

Table 1.Statistical Analysis of features

FEATURE	Mean ± Standard deviation	
	NORMAL	ABNORMAL
Auto correlation	0.97±0.02	0.90±0.03
Contrast	0.60±0.19	0.68±0.19
Energy	0.95±0.06	0.90±0.06
Entropy	0.81±0.10	0.73±0.09
Homogeneity	0.993±0.004	0.920±0.004



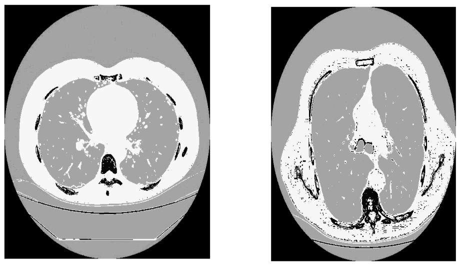
(a) (b)

Fig 7. Region growing output(a)Normal (b)Abnormal

(a) (b)

Fig 8.Postprocessed output used as the mask (a)Normal (b)Abnormal

The post-processed image is saved as the mat file and this mat file is used as the mask , which specifies the background pixels by ‘0’ and foreground pixels by ‘1’.The final Active contour image output shows the boundaries of the lung parenchyma as shown in fig 9.



(a) (b)

Fig 9.Active contour model output (a)Normal (b)Abnormal

The Haralick features are extracted for the region of interest. The mean and standard deviation of features extracted are presented in Table 1.

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The difference in values for normal and abnormal values could be used for classification. The difference between normal and abnormal images is presented as a graph in Fig 10

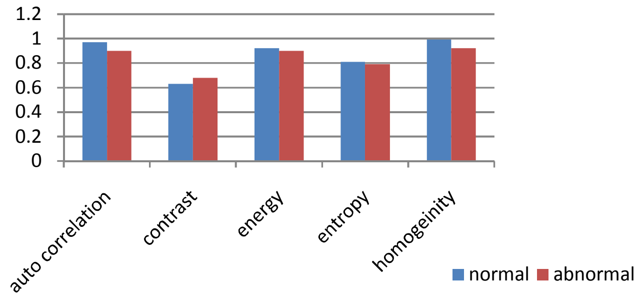

Fig 10. Graphical representation of normal and abnormal image features

The performance of classifier is given in Table 2. The overall accuracy achieved in ELM classifier for the sine activation function and 20 hidden neurons is 96.67%.

Table 2. Classifier Performance

ELM ACTIVATION FUNCTION	**ACCURACY (%)**
Sine function	96.67
Sigmoid function	90
Radial basis function	93.3
Triangular basis function	96.6
Hard limit function	66.67

IV. CONCLUSION

CT imaging technology is used as the technique to detect COPD, by automating the evaluation CT images the accuracy can be improved and time consumption can be reduced. In this work, lung parenchyma is segmented using region growing based Active contour model and features are extracted. The features are subjected to Classification using ELM. The result shows that this automated analysis is able to detect Emphysema. Hence this approach can be efficiently used in medical imaging field to assist the technicians for disease quantification.

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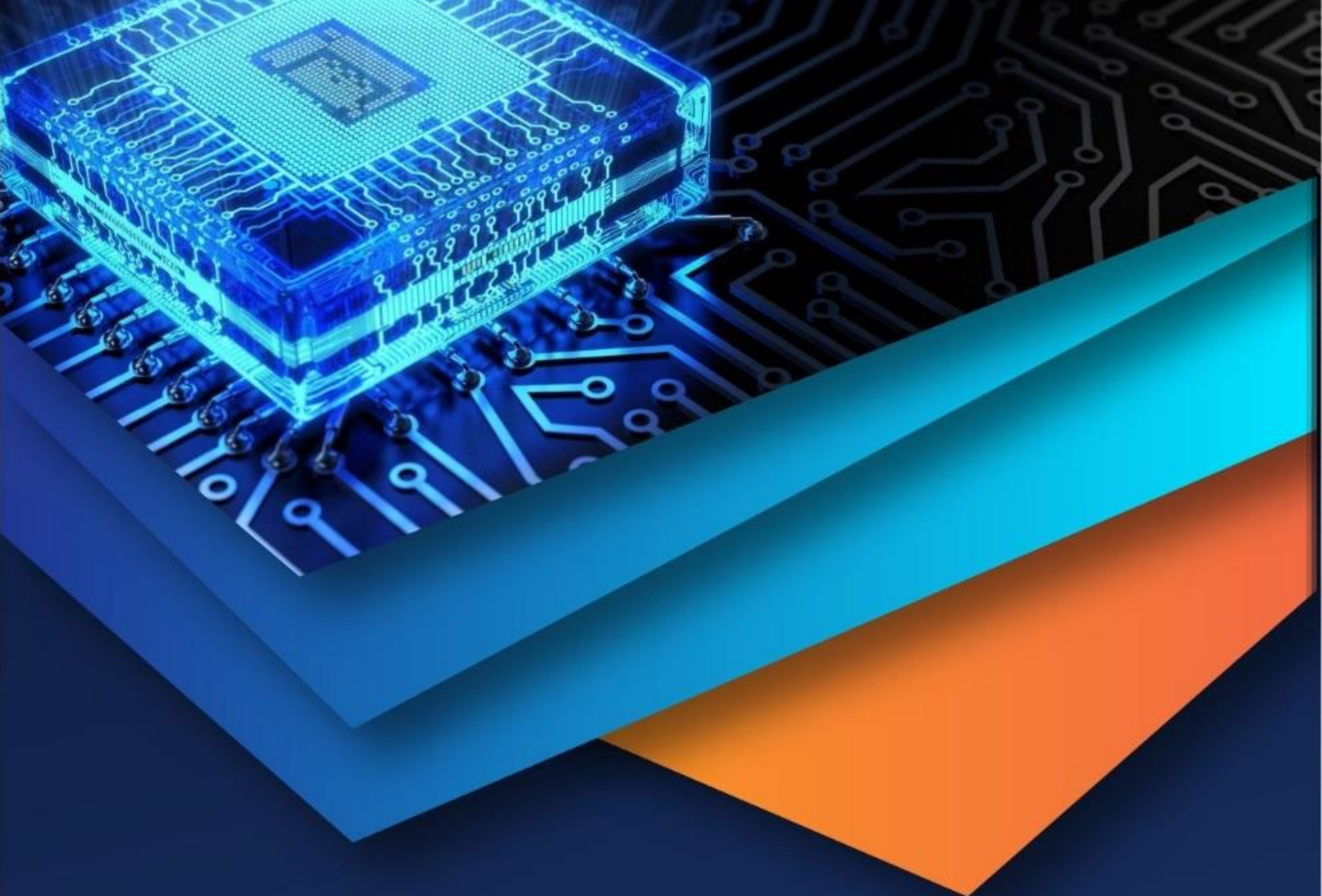

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