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Brain Tumor Segmentation Using Convolution Neural Network

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Abstract*: The Automatic Upkeep Intelligent System is used to detect Brain Tumor through the blend of neural network and FLS. It helps in the analytical and aid in the treatment of the brain tumor. The recognition of the Brain Tumor is a perplexing problem, due to the organization of the Tumor cells in the brain. This project presents an critical method that enhances the detection of brain tumor cells in its initial stages and to analyze anatomical structures by training and sorting of the samples in neural network system and tumor cell segmentation of the sample using fuzzy clustering algorithm. The ANN will be used to train and classify the stage of Brain Tumor that would be benign, malignant or normal.
Keywords*: Fuzzy logic system(FLS), Fuzzy Clustering Algorithm (FCA), Artificial Neural Network (ANN), Probablistic neural network (PNN), Karhunen–Loève transform (KLT)

I. INTRODUCTION

Automated classification and detection of tumors in different medical images is motivated by the necessity of high accuracy when dealing with a human life. Also, the computer assistance is demanded in medical institutions due to the fact that it could improve the results of humans in such a domain where the false negative cases must be at a ve ry low rate. It has been proven that double reading of medical images could lead to better tumor detection. Butte cost implied in double reading is very high, that's why good software to assist humans in medical institutions is of great interest nowadays conventional methods of monitoring and diagnosing the diseases rely on detecting the of presence of particular features by a human observer. Due to large number of patients in intensive care units and the need for continuous observation of such conditions2, several techniques for automated diagnostic systems have been developed in recent years to attempt to solve this problem2. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objectiv quantitative feature classification problem

In this project the automated classification of brain magnetic resonance images by using some prior knowledge like pixel intensity and some anatomical features is proposed. Currently there are no 9methods widely accepted therefore automatic and reliable methods for tumor detection are of great need and interest. The application of PNN in the classification of data for MR images problems are not fully utilized yet. These include the clustering and classification techniques especially for MR images2 problems with huge scale of data and consuming times and energy if done manually . Thus, fully understanding the recognition, classification or clustering techniques is essential to the developments of Neural Network systems particularly in medicine problems.

Segmentation of brain tissues in gray matter, whith matter and tumor on medical images is not only of high interest in serial treatment monitoring of "disease burden" in oncologic imaging, but also gaining popularity with the advance of image guided surgical approaches. Outlining the brain tumor contour is a major step in planning spatially localized radiotherapy (e.g., Cyber knife, iMRT) which is usually done manually on contrast enhanced T1-weighted magnetic resonance images (MRI) in current clinical practice. On T1 MR Images acquired after administration of a contrast agent (gadolinium), blood vessels and parts of the tumor, where the contrast can pass the blood–brain barrier are observed as hyper intense areas. There are various attempts for brain tumor segmentation in the literature which use a single modality, combine multi modalities and use priors obtained from population atlases.

II. METHEDOLOGY

A. Discrete Wavelet Transform

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A function is called an Ortho normal wavelet if it can be used to define a Hilbert basis, that is a complete Ortho normal system, for the Hilbert of square integrable functions. The Hilbert basis is constructed as the family of functions for integers. This family is an Ortho normal system if it is ortho normal under the inner product where is the Kronecker delta and is the standard inner product on the requirement of completeness is that every function may be expanded in the basis as with convergence of the series understood to be convergence in norm. Such a representation of a function *f* is known wavelet series. This implies that an ortho normal wavelet is self-dual.

B. Fractal Feature Extraction

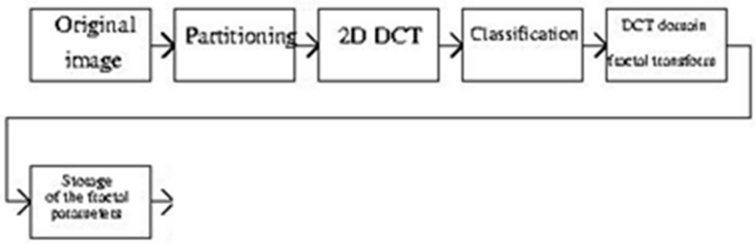

Fig. 2 Block diagram of fractal feature extraction

Fractal dimension is a ratio providing a statistical index of complexity comparing how detail in a pattern (strictly speaking, a fractal pattern) changes with the scale at which it is measured.It has also been characterized as a measure of the space-filling capacity of a pattern that tells how a fractal scales differently from the space it is embedded in; a fractal dimension does not have to be an integer

Fractal dimension is given as:

$$\log_\epsilon N = -D = \frac{\log N}{\log \epsilon}$$

And,

$$N \propto \epsilon^{-D}$$

Fractal features represent real world texture patterns and therefore are a good descriptor of the texture features of an image.

C. Knn classifier

In pattern recognition, the k-nearest neighbor algorithm (k-NN)2is a method for classifying objects based on closest training examples in the feature space.K-NN is a type of instance-based learning, or lazy learning where the function is only approximated locally and all computation is deferred until classification.The k-nearest neighbor algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors(k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of its neares neighbour.

The same method can be used for regression, by simply assigning the property value for the object to be the average of the values of its k nearest neighbors. It can be useful to weight the contributions of the neighbours, so that the nearer neighbors contribute more to the average than the more distant ones. (A common weighting schemeis to give each neighbor a weight of 1/d, where d is the distance to the neighbour. This scheme is a generalization of linear interpolation.)

D. Principal component analysis

PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of observations ofpossibly corr elated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding2component in turn has the highest variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, it is also named the discrete Karhunen–Loève transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD).

III. DESIGN AND IMPLEMENTATION

A. Set the initial threshold T= (the maximum value of the image brightness + the minimum value of the image brightness)/2.

B. Using T segment the image to get two sets of pixels B (all the pixel values are less than T) and N (all the pixel values are greater than T);

C. Calculate the average value of B and N separately, mean ub and un.

D. Calculate the new threshold:T= (ub+un)/2

E. Repeat Second steps to fourth steps up to iterative conditions are met and get necessary region from the brain image.

F. probabilistic neural networks (pnn)

Probabilistic (PNN) and General Regression Neural Networks (GRNN) have similar architectures, but there is a fundamental difference: Probabilistic networks perform classification where the target variable is categorical, whereas general regression neural networks perform regression where the target variable is continuous. If you select a PNN/GRNN network, DTREG will automatically select the correct type of network based on the type of target variable.

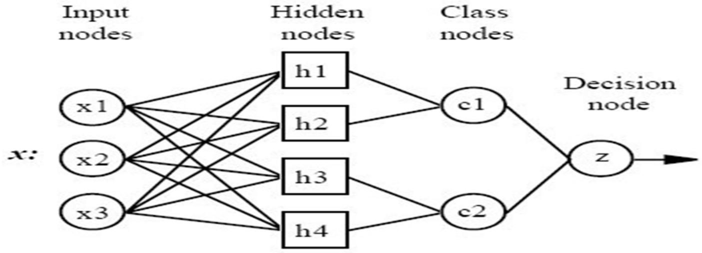

Fig. 3.1 Architecture of PNN

1) All PNN networks have four layers

a) Input layer - There is one neuron in the input layer for each predictor variable. In the case of categorical variables, *N*-1 neurons are used where *N* is the number of categories. The input neurons (or processing before the input layer) standardizes the range of the values by subtracting the median and dividing by the inter quartile range. The input neurons then feed the values to each of the neurons in the hidden layer.

b) Hidden layer – This layer has one neuron for each case in the training data set. The neuron stores the values of the predictor variables for the case along with the target value. When presented with the *x* vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma value(s). The resulting value is passed to the neurons in the pattern layer.

c) Pattern layer / Summation layer – The next layer in the network is different for PNN networks and for GRNN networks. For PNN networks there is one pattern neuron for each category of the target variable. The actual target category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's category.For GRNN networks, there are only

two neurons in the pattern layer.One neuron is the denominator summation unit the other is the numerator summation unit. The denominator summation unit adds up the weight values coming from each of the hidden neurons. The numerator summation uni adds up the weight values multiplied by the actual target value for each hidden neuron.

d) Decision layer - The decision layer is different for PNN and GRNN networks. For PNN networks, the decision layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

For GRNN networks, the decision layer divides the value accumulated in the numerator summation unit by the value in the denominator summation unit and uses the result as the predicted target value.

The following diagram is actually proposed in our project

i) *Input layer:* The input vector, denoted as **p**, is presented as the black vertical bar. Its dimension is $R \times 1$. In this paper, $R = 3$.

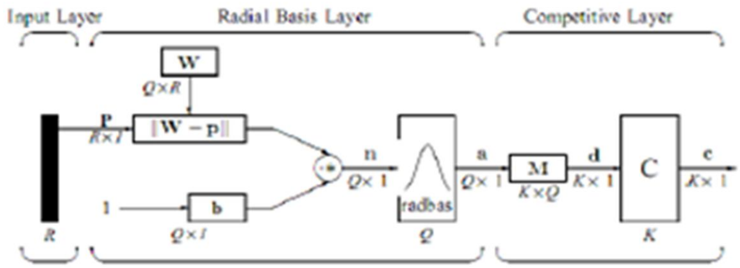

Fig. 3.2

ii) *Radial basis layer:* In Radial Basis Layer, the vector distances between input vector p and the weight vector made of each row of weight matrix W are calculated. Here, the vector distance is defined as the dot product between two vectors [8]. Assume the dimension of W is $Q\times R$. The dot product between p and the *i*-th row of W produces the *i*-th element of the distance vector ||W-p||, whose dimension is $Q\times 1$. The minus symbol, "-", indicates that it is the distance between vectors. Then, the bias vector b is combined with ||W- p|| by an element-by-element multiplication. The result is denoted as n = ||W- p|| ..p. The transfer function in PNN has built into a distance criterion with respect to a center.

iii) Each element of n is substituted into Eq.1 and produces corresponding element of a, the output vector of Radial Basis Layer. The *i*-th element of a can be represented as ai = *radbas* (||Wi - p|| ..bi)

iv) where Wi is the vector made of the *i*-th row of W and bi is the *i*-th element of bias vector b.

Some characteristics of Radial Basis Layer:

The *i*-th element of a equals to 1 if the input p is identical to the *i*th row of input weight matrix W. A radial basis neuron with a weight vector close to the input vector p produces a value near 1 and then its output weights in the competitive layer will pass their values to the competitive function. It is also possible that several elements of a are close to 1 since the input pattern is close to several training patterns.

v) *Competitive Layer*:

There is no bias in Competitive Layer. In Competitive Layer, the vector a is firstly multiplied with layer weight matrix M, producing an output vector d. The competitive function , denoted as C in Fig.2, produces a 1 corresponding to the largest element of d, and 0's elsewhere. The output vector of competitive function is denoted as c. The index of 1 in **c** is the number of tumor that the system can classify. The dimension of output vector, *K* is 5 in this paper.

G. *Morphological Process*

1) *Erosion And Dilation:* The erosion of a binary image *f* by a structuring element *s* (denoted *f* *s*) produces a new binary image *g* = *f* *s* with ones in all locations (*x*,*y*) of a structuring element's origin at which that structuring element *s* fits the input image *f*, i.e. *g(x,y)* = 1 is *s* fits *f* and 0 otherwise, repeating for all pixel coordinates (*x*,*y*).

Erosion with small (e.g. 2×2 - 5×5) square structuring elements shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions. The holes and gaps between different regions become larger, and small details are eliminated:

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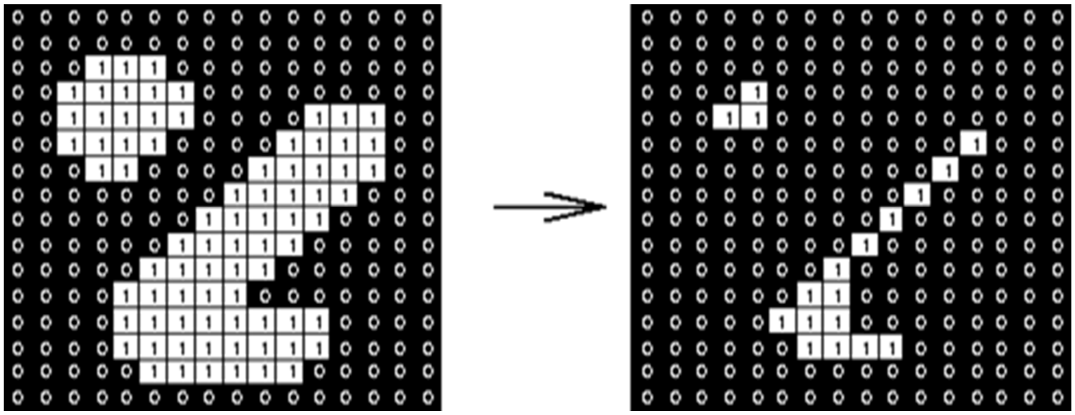

Fig. 3.3 Erosion: 3×3 square structuring element

Larger structuring elements have a more pronounced effect, the result of erosion with a large structuring element being similar to the result obtained by iterated erosion using a smaller structuring element of the same shape. If s_1 and s_2 are a pair of structuring elements identical in shape, with s_2 twice the size of s_1, then $f\ s_2 \approx (f\ s_1)\ s_1$.
Erosion removes small-scale details from interested image by subtracting the eroded image from the original image, boundaries of each region can be found: $b = f - (f\ s)$ where f is an image of the regions, s is a 3×3 structuring element, and b is an image of the region boundaries.
The dilation of an image f by a structuring element s (denoted $f\ s$) produces a new binary image $g = f\ s$ with ones in all locations (x, y) of a structuring element's orogin at which that structuring element s hits the the input image f, i.e. $g(x, y) = 1$ if s hits f and 0 otherwise, repeating for all pixel coordinates (x, y). Dilation has the opposite effect to erosion – it adds a layer of pixels to both the inner and outer boundaries of regions.
The holes enclosed by a single region and gaps between different regions become smaller, and small intrusions into boundaries of a region are filled in:

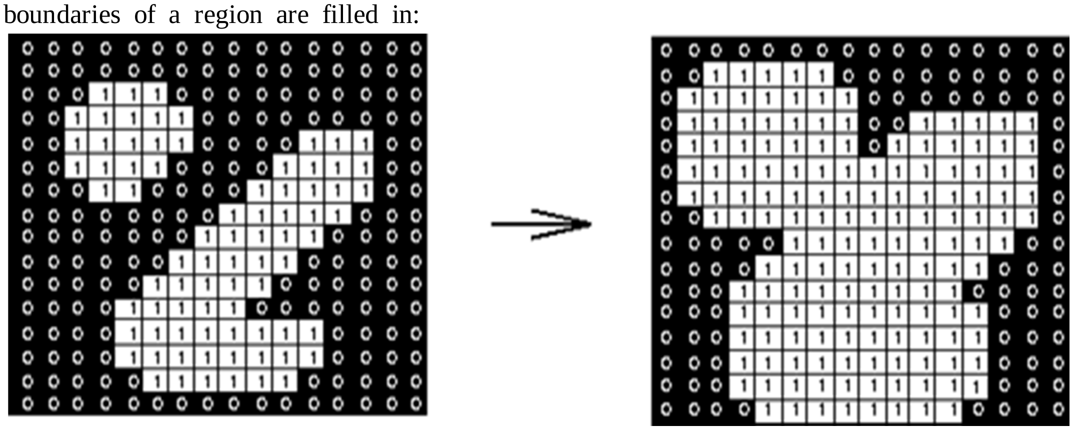

Fig. 3.4 Dilation: a 3×3 square structuring element

Results of dilation or erosion are influenced both by the size and shape of a structuring element.
Dilation and erosion are dual operations in that they have opposite effects. Let f^c denote the complement of an image f, i.e., the image produced by replacing 1 with 0 and vice versa. Formally, the duality is written as
$f\ s = f^c s_{rot}$
where s_{rot} is the structuring element s rotated by 180. If a structuring element is symmetrical with respect to rotation, then s_{rot} does not differ from s. If a binary image is considered to be a collection of connected regions of pixels et to 1 on a background of pixels set to 0, then erosion is the fitting of a structuring element to these regions and dilation is the fitting of a structuring element (rotated if necessary) into the background, followed by inversion of the result.

IV. RESULTS AND DISCUSIION

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The test of projected technique to discover and segment brain tumor is performed using MR images. Each tested image has brain tumor of diverse intensity, size and shape. Manual examination is done to check the correctness of automatically segmented tumor area. The experimental result for MR images containing tumor is discussed below.

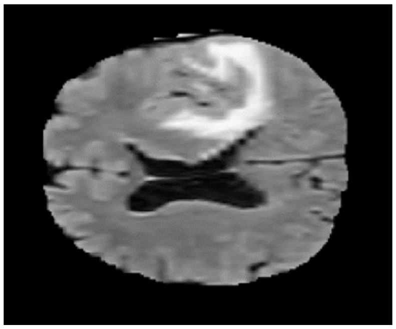

Fig. 4.1 Input MRI image

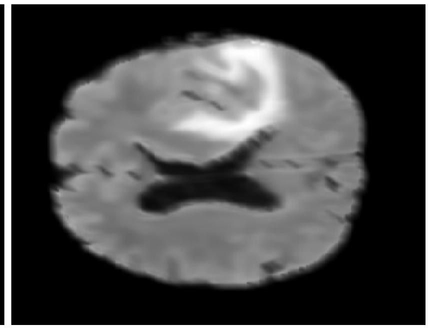

Fig. 4.2 Trilateral filtered image

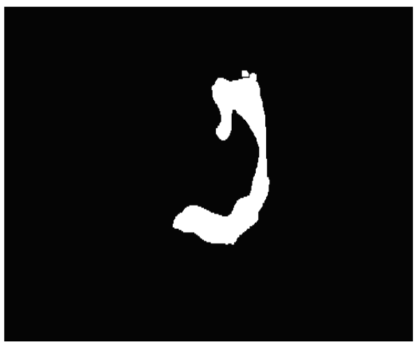

Fig. 4.3 Filtred input for EM-GM Segmentation

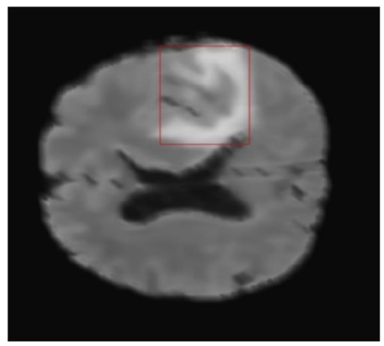

Fig 4.4 EM-GM segmented image

In Fig 4.1, it is one of the MRI image containing tumor which is taken as the input. Fig 4.2 shows the resultant image after the Trilateral filtering process. Fig 4.3 shows the filtered input image for EM-GM Segmentation and the Fig 4.4 shows the resultant image of EM-GM Segmentation.

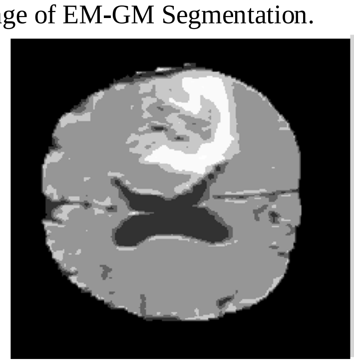

Fig. 4.5 Color Quantized Image

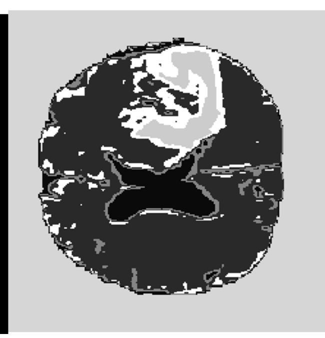

Fig. 4.6 Segmented image

Fig. 4.7 Tumor masked image

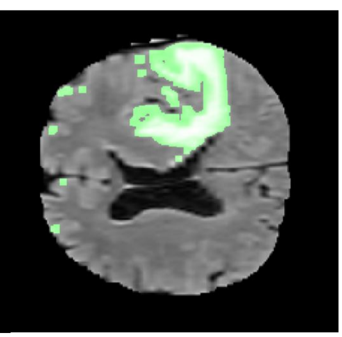

Fig. 4.8 Tumor detected

After the EM-GM Segmentation the resultant image is color quantized, this is shown in the Fig 4.5. Later we will train the SOM (Self-organizing map) which is a type of artificial neural network. It is trained using unsupervised learning to produce a two dimensional discretized representation of the input space of the training samples. Fig 4.6 shows us the Classified and Segmented image which is done after the color quantization process. After the Segmentation process the tumor will be masked and the Fig 4.7 shows the resultant image of the tumor masked region/area. Morphological cleaning is done after masking the tumor and the final stage is tumor detection which is shown in the resultant image Fig 4.8, the region which is highlighted by green colour shows us the presence of tumor in the MR image.

V. CONCLUSION AND FUTURE WORK

The project presented that automated brain image classification for early stage abnormality detection with use of neural network classifier and spotting of tumor was done with image segmentation. Pattern recognition was performed using probabilistic neural network with radial basis function and pattern will be characterized with the help of fast discrete curvelet transform and haralick features analysis. Here. Spatial fuzzy clustering algorithm was utilized effectively for accurate tumor detection to measure the area of abnormal region. From an experiment, system proved that it provides better classification accuracy with various stages of test samples and it consumed less time for process.

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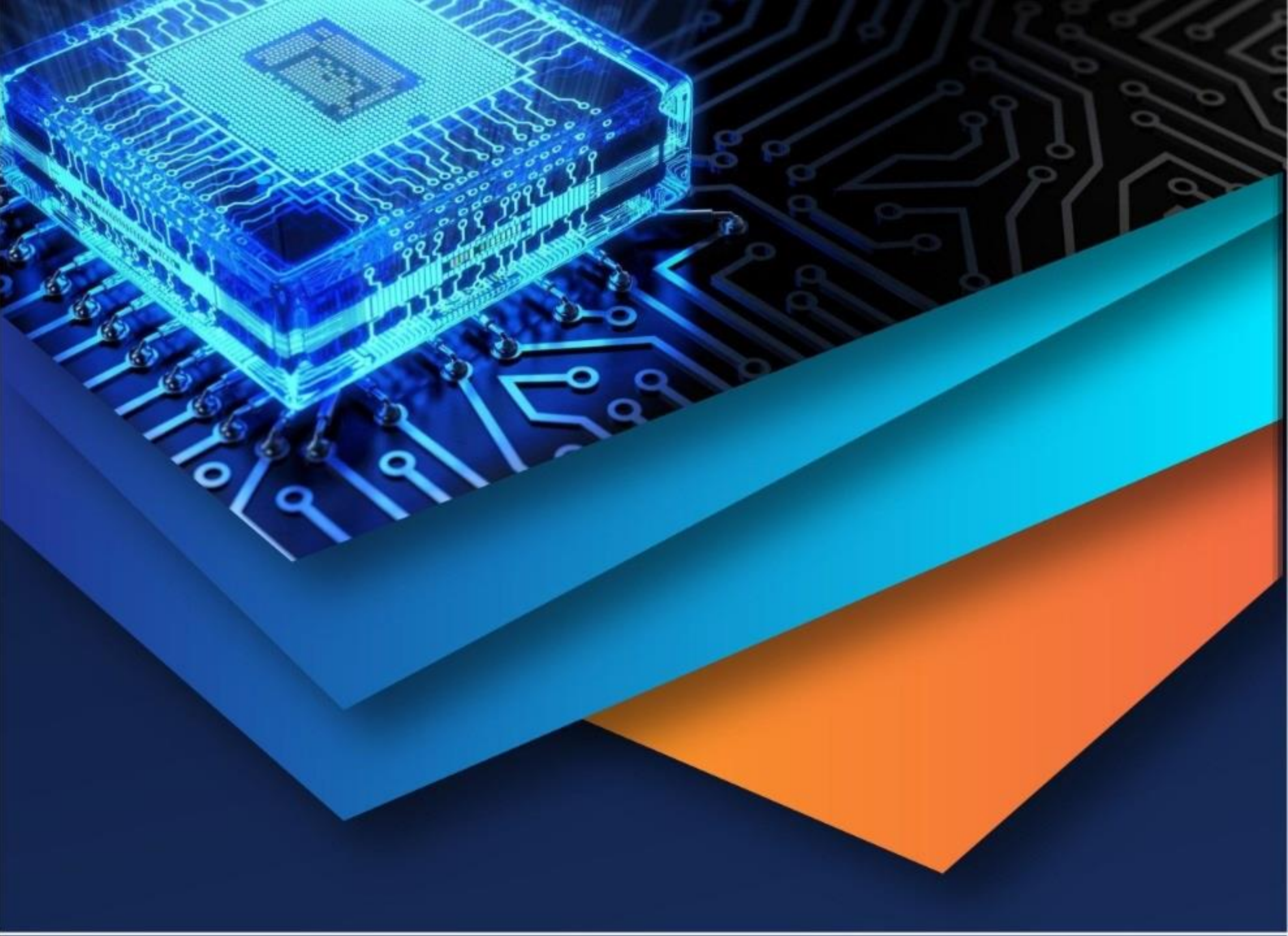

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