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Performance of Various Texture Model for Face Recognition

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Abstract*– In this paper, a texture pattern and retrieval algorithm using Local Binary pattern (LBP) and Local Directional Pattern for content-based image retrieval (CBIR). This proposed pattern encodes the relationship between the referenced pixel and its surrounding neighbours by computing eight directions value is calculated for one pattern. The proposed method encodes the relationship between the training image and its test images by applying the classification part. The performance has been evaluated using YALE and CMU-PIE databases containing more than 1500 images. The Results show that LDP perform much better than the LBP-based methods
***Keywords* – face recognition, texture analysis and texture features.**

I. INTRODUCTION

Automatic face recognition system has been an active and popular research topic in computer vision and pattern recognition due to its wide applications in security, forensic investigation access control and law enforcement [1]. Existing face recognition method is mainly classified into appearance (holistic) based method and feature-based method [2]. In holistic method the entire face image is represented as a high dimensional vector. Due to curse of dimensionality such vectors cannot be compared directly. Hence holistic methods use dimensionality reduction techniques to resolve these problems.

As compared to holistic approaches, feature based methods have several advantages. They are robust to variations in pose, illumination, occlusion, expression and localization errors. The face recognition system has to tolerate the real time challenges due to illumination changes, expression, pose, partial occlusion, ageing and so on. An illumination change is considered as a very crucial factor for face recognition. Several illumination pre-processing methods has been proposed [3] to handle the lighting variations.

Among that illumination normalization has strained much attention due to its simplicity and fidelity. Hence, in this paper four admired illumination normalization methods are combined with texture descriptors for face recognition. Most of the face recognition methods were initially developed with face image acquired under well-controlled conditions.

A. Motivation and justification of the proposed Approach

Face can be seen as a composition of micro patterns of textures. In recent years, the texture analysis community has developed a variety of different descriptors for face recognition. Texture provides a normalized shape-free image. It effectively captures the information about the spatial relations, which is very useful for face recognition. Motivated by this concept, this paper attempts to implement And evaluate a few texture models for face recognition.LBP was originally proposed for texture description and has been widely exploited in many applications such as video retrieval, aerial image analysis and visual inspections. Recently, LBP have been extensively exploited for facial image analysis, including face detection, face recognition, facial expression analysis gender/age classification and so on.The LDP image is derived from the edge response values in different eight directions Next, the LDP image is directly inputted in 2D-PCA algorithm and nearest neighbour classifier is applied to recognize unknown user. Remark that the proposed face recognition system is very different approach when compared to previous works, because most of previous works were used the local pattern descriptors to extract the histogram features. Texture features can characterize regularity, randomness, directionality and coarseness properties of patterns. A face can be viewed as a texture pattern exhibiting symmetry and regularity. Hence texture plays an important role in computer vision and pattern recognition. Though texture based face recognition are so common, the success of these techniques depends on illumination invariant features of textures. Hence illumination normalization techniques can be applied as pre-processing methods for texture based face recognition. Motivated by this, an attempt is made in this paper to propose illumination invariant face recognition. Since texture feature measures the surface property of image, with lighting variations the textural property will also change. Hence, the pre-processing techniques are applied to remove the lighting variations. The histogram manipulation automatically minimizes the contrast in areas too light or too dark of an image. Hence it generates a resulting image whose histogram is approximately uniform.

B. Outline of the proposed approach

In this paper, LBP and LDP are experimented for the face recognition problem. A pre-processing technique is used to resize the training and testing images. During the training phase, global textural features extracted from the training images are stored in the database. Textural features extracted from the testing images are compared with the stored features in the database by using K nearest neighbor classifier [5],[6], which uses the log-likelihood measure as the distance metric. Fig. 1 shows an overview of the face recognition system.

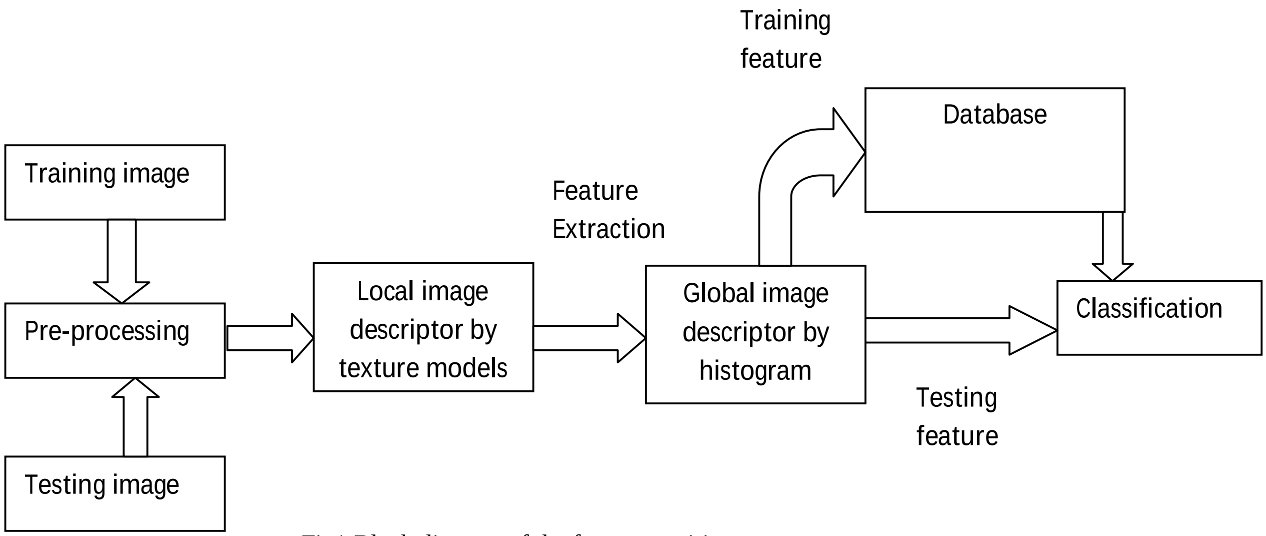

Fig1 Block diagram of the face recognition system

C. *Organization of the paper*

The remaining part of the paper is organized as follows: Section 2 describes the LBP and LDP based texture models in detail. Section 3 explains the classification principle. In Section 4, extensive experiments were conducted on the YALE and CMU-PIE databases and the results are presented. Section 5 concludes the paper.

II. TEXTURE MODELS

A. *Local binary pattern*

LBP is computationally simple yet very efficient local texture operator. These features are invariant to monotonic gray scale changes. LBP value of a sample 3 * 3 image is calibrated as,

$$LBP = \sum_{i=0}^{7} s(g_p - g_c)2^p \quad (1)$$

Where

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \qquad (2)$$

Where, $g_c$is the gray level value of the central pixel $g_p$is the grey value of its neighbours around $g_c$and p is the number of neighbours. A binary code is computed by comparing $g_c$value with those of its neighbourhood. Fig.2 illustrates the basic LBP operator.

1	1	0
0		1
0	1	0

95	76	55
40	76	89
50	81	68

Binary value: 11010100

Fig 2 Calculation of LBP pattern

Conventional LBP requires 256 bins to store all possible patterns. The concept of uniform patterns is introduced to reduce the number of possible bins. It effectively captures the fundamental information of textures. A uniformity measure U is defined as

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$$U(LBP) = |S(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{p-1} s(g_p - g_c) - s(g_{p-1} - g_c) \quad (3)$$

The binary pattern having U ≤ 2 is designated as uniform pattern and is signified by nine separate bins. The pattern having U >3 are termed as non-uniform patterns and are represented in a single bin. Hence, LBP requires totally ten bins to store all the binary patterns.

Utilizing this assumption the region can be weighted based on the importance of the information they contain. For example the weighted Chi square distance can be defined as

$$X_w^2(X, \varepsilon) = \sum_{j,i} w_j \frac{(x_{i,j}-\epsilon_{i,j})^{2}}{x_{i,j}+\epsilon_{i,j}} \quad (4)$$

In which X and ϵ are the normalized enhanced histogram to be compared, indices i and j refer to i-th bin in histogram corresponding to the j-th local region and w_j is the weight for region j.

B. Local directional pattern

LDP was implemented by Zhang et.al [4].the LBP operator labels the pixels of an image by thresholding a 3x3 neighbourhood of each pixel with the centre value and considering the results as a binary number, of which the corresponding decimal number is used for labelling. The derived binary numbers are called local binary patterns or LBP codes. While the LBP operator uses the information of intensity changes around pixels, LDP operator use the edge response values of neighbourhood pixels and encode the image texture. The LDP assigns an 8 bit binary code to each pixel of an input image. This pattern is then calculated by comparing the relative edge response values of a pixel by using Kirsch edge detector. Given a central pixel in the image, the eight-directional edge response values $m_i(i = 0,1, \dots\dots\dots, .7)$are computed by Kirsch masks as shown in Figure 3. Since the presence of a corner or an edge shows high response values in some particular directions, thus, most prominent directions of number with high response values are selected to generate the LDP code. In other words, directional bit responses, are set to 1, and the remaining bits are set to 0. Finally, the LDP code is derived by

$$LDP = \sum_{i=0}^{7} b_i(m_i - m_k) * 2^i , \quad (5)$$

Where

$$b_i(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (6)$$

Where m_k is the k-th most significant directional response.

M3	M2	M1
M4	X	M0
M5	M6	M7

b_3	b_2	b_1
b_4		b_0
b_5	b_6	b_7

Fig 3 Edge response and LDP Binary Bit Positions

The Local directional pattern code with k=3.

85	32	26
53	50	10
60	38	45

→

313	97	503
537	X	399
161	97	303

→

0	0	1
1	X	1
0	0	0

LDP binary code: 00010011

LDP decimal code: 19

Fig 4 LDP code with k=3

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C. Global image description by 1D histogram

In all the texture models, a local texture is characterised by its corresponding texture patterns. It is expected that the statistics of the occurrence frequency of the texture information of the image to be analysed. Hence, to describe the global texture feature of an image, local patterns over the image will be collected in a 1D histogram. The basic histogram can be extended into a spatially enhanced histogram which encodes both the appearance and the spatial relations of facial regions

III. FACE RECOGNITION ALGORITHMS

Face recognition algorithm consists of two phases namely training phase and testing phase.

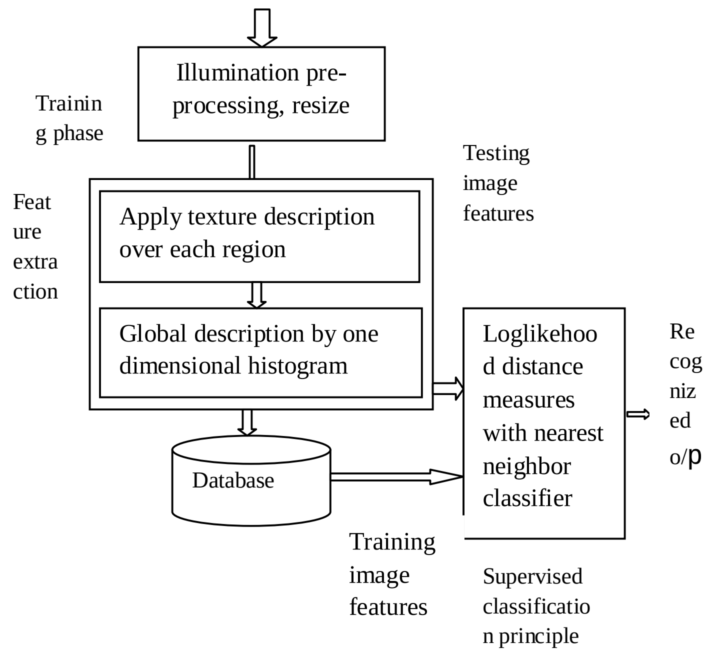

Fig 5 Face recognition execution diagram

A. Training Phase

1) Load the image
2) Apply any one of the illumination normalization techniques among histogram equalization over an image.
3) Divide the image into non overlapping region of size $N * N$.
4) Apply any one of the local texture descriptor such as LBP and LDP over the sub region.
5) Construct a one dimensional histogram for each sub region.
6) Concatenate the histogram over each sub regions to get global description.
7) Store this training feature in the database.

B. Testing phase

1) Steps 1 to 6 of training phase are repeated to extract the testing feature from an image.
2) Retrieve the training features from the database.
3) Find the similarity between training and testing features using G statistic distance.

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$$\boldsymbol{G} = \left[\begin{array}{c} \left[\sum_{s,m}\sum_{i=1}^{n} f_i \log f_i\right] \\ -\left[\sum_{s,m}\left(\sum_{i=1}^{n} f_i\right)\log\left(\sum_{i=1}^{n} f_i\right)\right] \\ -\left[\sum_{i=1}^{n}\left(\sum_{s,m} f_i\right)\log\left(\sum_{s,m} f_i\right)\right] \\ +\left[\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\log\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\right] \end{array}\right] \quad (7)$$

where, s is the histogram of the test sample and m is a histogram of the texture measure distribution of the train sample, n is the total number of bins in a histogram and f_i is the frequency at bin i.

4) Choose the nearest neighbor as correct match for the corresponding training image.

IV. PERFORMANCE EVALUATION

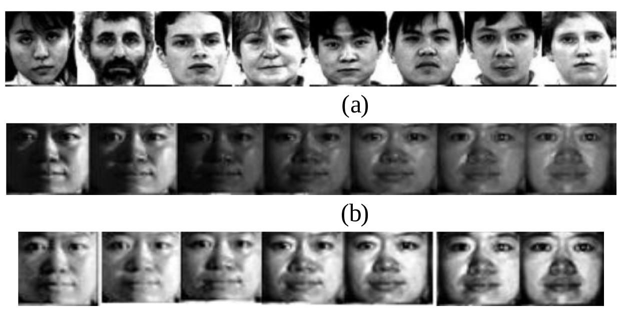
A. *Performance Metric*

In order to evaluate the performance of the proposed model, an extensive experimental investigation is carried out, covering face recognition under different lighting variations. The experiments were conducted on Yale B and CMU-PIE databases which contain face images under different lighting conditions appropriate for face recognition. The closest match of the testing sample with any one of the training sample has been identified using nearest neighbor classifier and such match is validated as either correct or incorrect based on the supervised knowledge. The Recognition Rate is calculated by,

$$Recognition\ Rate(\%) = \frac{No.of\ correct\ matches}{No.of\ test\ matches} * 100 \quad (8)$$

B. *Experiment Analysis*

1) *Results on CMU-PIE Database:*



(a)

(b)

(c)

Fig.6.(a). Sample Images of different subjects; (b). Images of one subject under different illumination; (c). Images obtained by Histogram Equalization.

The CMU-PIE database contains 68 subjects with different pose, illuminations and expressions. [7] Frontal face images with controlled illumination variation are taken for training. Five samples per subject are kept in the training set and remaining images per individual are kept in the testing set. Fig.6 represents sample images from CMU-PIE database.

Table1Recognition Rate under Different Illumination Condition on CMU-PIE database

Texture model	Recognition rate (%)	
	Without pre-processing	With pre-processing
LBP	78.5	83
LDP	86.6	87

In order to analyze the performance of various illuminations pre-processing methods, an experiment is carried out in this section on CMU-PIE database. The local texture descriptors used are LBP and LDP. The results obtained for the experiment is listed in Table.1. Pre-processed images preserve more facial feature than non-pre-processed images. Hence, face recognition rate on original face image without illumination pre-processing also included. The table shows the histogram equalization is some noise is

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remove the images to clear to identify images as input to given.

2) *Results on Yale B Database:*

(a)

(b)

(c)

Fig.7. (a). Sample Image different subjects; (b). Images of one subject under different illumination conditions; (c). Images obtained by Histogram equalization.

Yale face database from Yale centre for Computational Vision and control contains images of 38 subjects in 9 poses and 64 illuminations per pose [8]. We only use the frontal face images under 64 illumination conditions for evaluation. In our experiments, the images which are captured under the azimuth angle of 12^0 from the optical axis are considered for experimental investigation. The Fig.7 shows the sample images from the database. The original image size is 320 * 243. All images are rescaled to the size of 240 * 240. It is of importance to pay attention to different factors that manipulate the performance of face recognition system. The number of training images per subject is recognized as one of the key factor for a face recognition problem. This database is used for performance analysis of different preprocessing methods with different number oftraining and testing images. Number of training images per subject is varied from 1to 5 where as the testing image is kept as constant value of 12. None of the training and testing images is overlapped.

Table 2 represents the recognition rate of different methods with different number of training and testing images per subject.

No. of Training images	Texture model	Recognition Rate (%)	
		Without pre-processing	With pre-processing
1	LBP	52	59
	LDP	58	69
2	LBP	60	63
	LDP	65	69
3	LBP	72	78
	LDP	78	80
4	LBP	76	78
	LDP	80	83

The performance of individual methods gradually increases with the increase in number of training images per subject. LDP offers better results among others because it encodes the images with four distinct values. Hence it is able to extract more detailed information from the images among all other methods considered for exploration. It combines Illumination normalization and contrast enhancement techniques together.

V. CONCLUSION AND FUTURE SCOPE

In this paper, efficient illumination normalization techniques for face recognition are presented. Illumination preprocessing technique Histogram Equalization exercised prior to facial feature extraction. These methods effectively eliminate unwanted illumination effect and enhance the local features of facial images, which play a vital role in recognition. Texture based face recognition are most successful and recently used techniques. Hence local descriptors LBP and LDP are used for face recognition. The combination of normalization techniques and local descriptors provides very promising performance on Yale B and CMU-PIE datasets that contain face images of widely varying lighting conditions. Among all the normalization methods considered MHF offers superior results because it captures micro pattern information of face images. It eliminates illumination effect and enhances the contrast by histogram equalization. In future the effect ofdirectional illumination variation can also be experimented by the proposed approach to prove the efficiency of our method for face recognition

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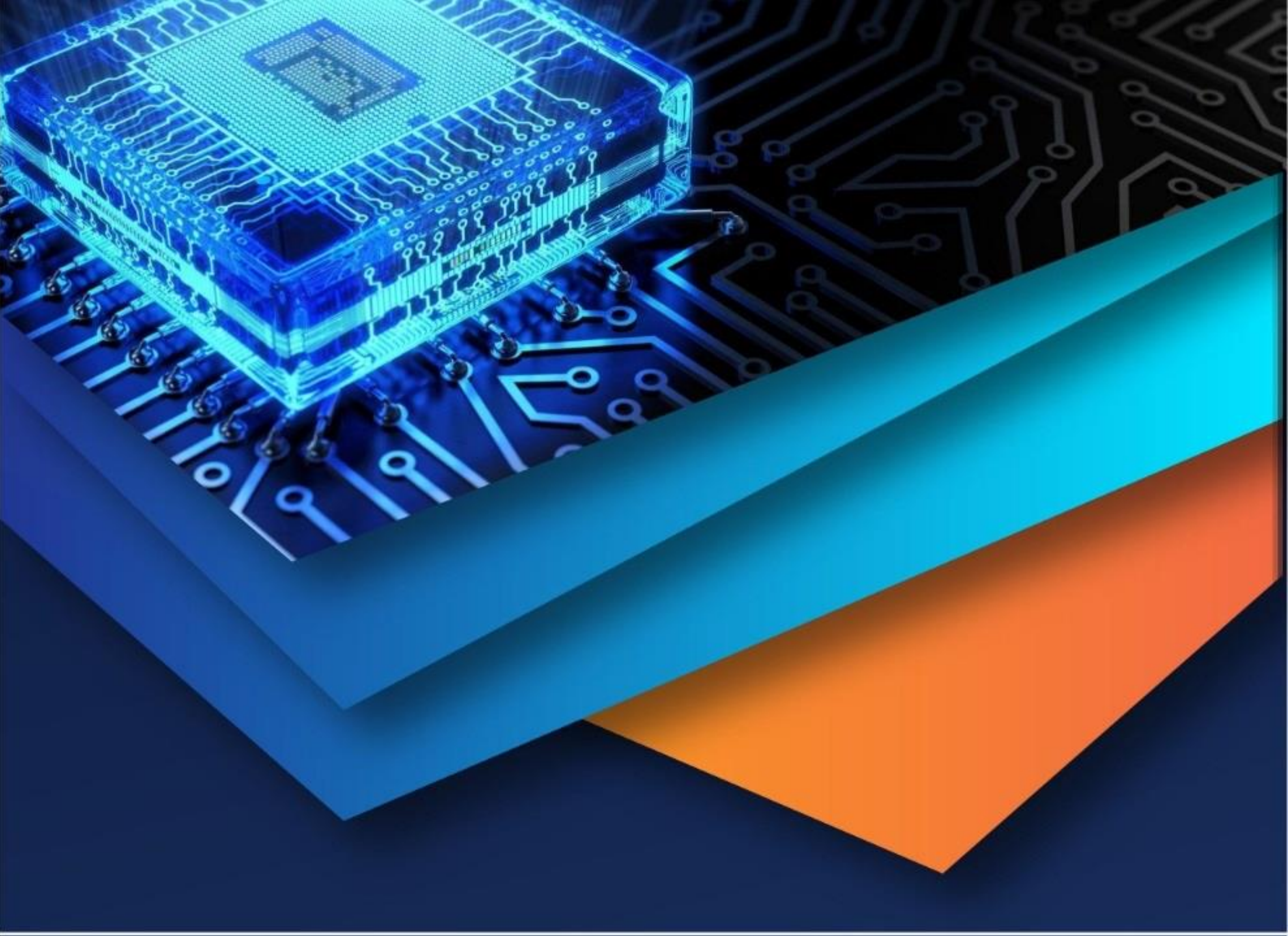

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