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Classification of Synthetic Aperture Radar Images using Fuzzy SVMs

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Abstract: In this study, the classification of synthetic aperture radar images are analyses using fuzzy support vector machines. The issues in the classification of SAR images are not addressed properly and remains an unsolved problem in few instances. This study provides one of the best methodology to classify SAR based image databases with fuzzy support vector machines. All the concepts which are derived and applied are based machine learning algorithms. The designed and developed methodology has got many applications in the area like weather forecasting, flood impact monitoring, designing crop calenders, early detection of drought and many more. All the algorithms applied in this study are pixel oriented. This study is carried out on the SAR images collected from the publicly available AXA EORC data set. We designed a model based mathematics and statistics which is developed in the python programming language. Several algorithms are designed to analyze SAR images in which fuzzy support methodology is exhibited high performance. Reports discussed in this study shown that the efficiency of fuzzy support vector machines to classify synthetic aperture radar image is 95.3% without any heuristic information.
Keywords: Fuzzy SVMs, Synthetic aperture radar image, remote sensing data and analytic algorithms.

I. INTRODUCTION

Images obtained from the satellites are considered as synthetic aperture radar images that are applicable in the area like agriculture, flood mapping, soil moisture, oceanography, geology, earthquake studies, forest density, hydrological applications and oil spill. SAR image classification is performed based on the mathematical models and texture extraction algorithms. SAR image analysis is applicable in the specific domains like coconut plantation, cashew plantation, harvested paddy fields, late transplant paddy and early transplant paddy.

Study of the spillage from boats and ships in oceans can be analyzed effectively with fuzzy support vector machines. This methodology is based on machine learning methods in which we applied supervised learning approach. There are some instances where we applied unsupervised learning in which training is not involved.

II. RELATED WORK

Synthetic aperture radar images are special type of images that contains high resolution and contains accurate information. This accurate information plays very important role in the analysis of hydrological applications and earthquake studies. SAR images plays an important role in the analysis of atmosphere as it contains variety structure and in different formats [1]. Multi layered model used attributes related semantic properties to interpret crop images [2]. Several methods like model based procedures, statistical based procedures and texture based algorithms are used to interpret forest density, geology, oceanography and forest density [3, 4, 5]. Statistical properties like mean, variance, covariance and correlation coefficient are used to analyze cashew plantation, coconut plantation and harvested field [6, 7]. Gabor filter, GLCM algorithm, Fisher and Lognormal models are used in the classification of earth and planet mapping [8]. Markov random algorithms form the basis to interpret SAR images related to oil spill and hydrological application [9, 10]. SAR images plays significant role in non military and military applications such as positioning the systems and guided application systems. SAR image analysis is used in variety applications like mining [11], oil pollution monitoring [12, 13, 14], oceanography [15, 16, 17, 18]. Images collected from different SAR image databases is extensively used in the classification of space borne and airborne images [19,20, 21].

III. FEATURE ANALYSIS OF SAR IMAGE

Texture is very important property of synthetic aperture radar image and is used to understand other features like smoothness, regularity and coarseness of image. All the regions of interest of SAR image are interpreted with the help of various types of textures present in the image under consideration. Textures plays very important role in the analysis and classification of regions of interest of the SAR image analysis and classification. Thematic data of SAR images is used to improve the classification accuracy by concatenating texture data to the original SAR image data. Texture principals form the basis for recognition and analysis of the SAR image texture analysis. Qualitative and quantitative properties of SAR images are obtained through image processing methodology.

A. Analysis with GCM Methodology

GCM methodology is a tool that identifies features like coarseness, smoothness and regularity [16]. This methodology based on the intensity levels of digital image and grey levels of SAR images. These two intensity levels are prominent in interpreting EORC database to forecasting the weather conditions.

GCM is a two dimensional table in which we have m rows and m columns. All the entries of this matrix is represented by different intensity pixel values with different levels. All adjacent pixels are separated by an angle θ and distance

$$\begin{pmatrix} q(0,0) & q(0,1) & \dots & q(0,m-1) \\ q(1,0) & q(1,1) & \dots & q(1,m-1) \\ \dots & \dots & \dots & \dots \\ q(m-1,0) & q(m-1,1) & \dots & q(m-1,m-1) \end{pmatrix}$$

This covariance matrix is used to classify SAR images more accurately with very few samples. Eigen values and Eigen vectors of GCM matrix represents important properties of SAR images. These Eigen values and eigenvectors are used to significant features of the SAR images.

Entries in the GCM matrix is calculated joint probabilities and conditional probabilities with distributions with angles 0, 45, 90 and 135 degrees.

$$\theta = 135; |y1 - y2| = 0, |x1 - x2| = e(1)$$

$$\theta = 45; |y1 - y2| = +d, |x1 - x2| = -d(3)\ \theta = 90; |y1 - y2| = e, |x1 - x2| = 0(2)$$

$$\theta = 0; |y1 - y2| = -d, |x1 - x2| = 0(4)$$

Here (x1,y1) is the first pixel and (x2,y2) is the second pixel.

Gray level matrix is used segment the texture information of the SAR image. The complete and detailed explanation of a local SAR image is calculated by Baye's theorem [17], occurrence probabilities and joint probabilities. For each texture feature present in SAR image, parameters like energy EN, correlation coefficient COC, sum average SA and contrast CN [18] are computed by following formulas.

$$EN = \sum_{i=0}^{m-1} \sum_{j=0}^{m-1} q^2(i,j)(5)$$

$$COV = \sum_{i=0}^{m-1} \sum_{j=0}^{m-1} \frac{(i-\sigma_x)(j-\lambda_y)q(i,j)}{\psi_x \psi_y}(6)$$

$$\sigma_x = \sum_i i \sum_j q(i,j)(7)$$

$$\lambda_y = \sum_j j \sum_i p(i,j)(8)$$

$$\psi_x = \sum_j (j-\mu_y)^2 \sum_i p(i,j)(9)$$

$$\psi_y = \sum_i (i-\mu_x)^2 q(i,j)(10)$$

$$SV = \sum_{n=0}^{2m-2} \sum_{i=0}^{m-1} \sum_{k=0}^{m-1} mq(j,k) (11)$$

IV. CLASSIFICATION OF SAR IMAGES WITH FUZZY SVM

Fuzzy SVM is more efficient compare to ordinary SVM in classifying multi label SAR image data. These are the support vector machines which classify complex SAR data by using member function.

$$\min Q(\tau,\tau^*) = \frac{1}{2}(\tau^* - \tau)^T K(\tau^* - \tau) - (\tau^* - \tau)^T d + \varepsilon(\tau^* - \tau)^T (12)$$

Where τ is biased variable and K is the kernel function

Figure. 1 represents fuzzy support vector machine classification process in which first phase is to collect SAR images from publicly available SAR image database. Image processing and enhancement is the second phase, Feature extraction is the third phase of the fuzzy SVM classification process.

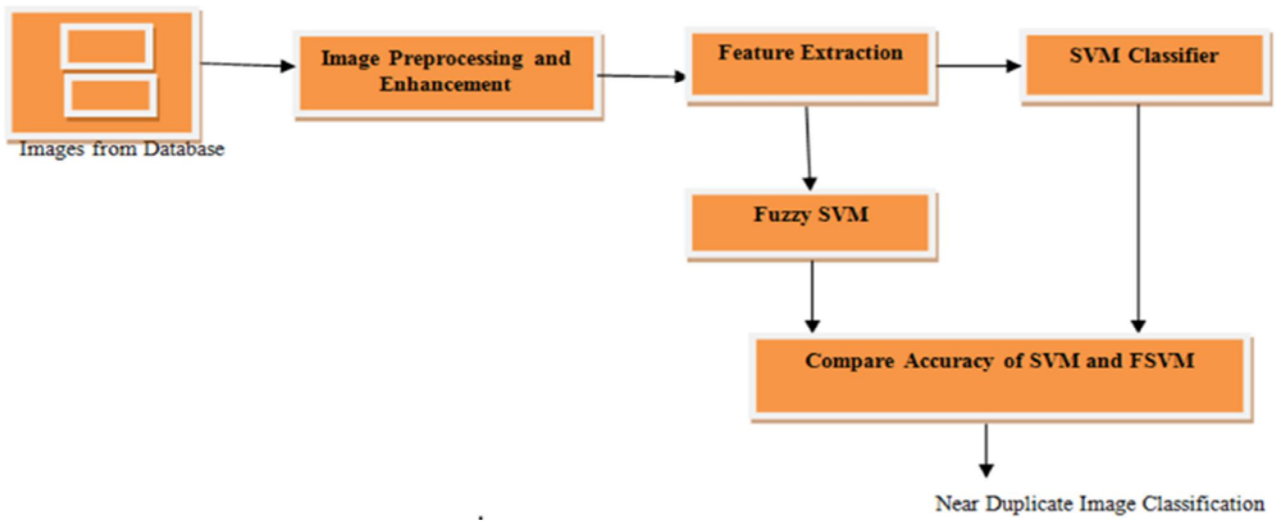

Figure 1. Fuzzy Support vector machine classification process

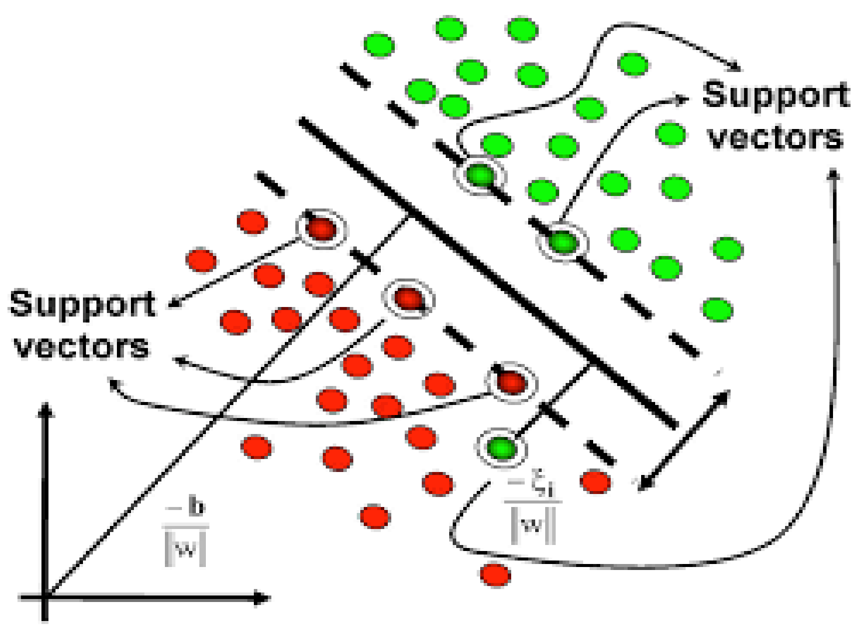

Figure 2.Two dimensional Examples with support Vectors

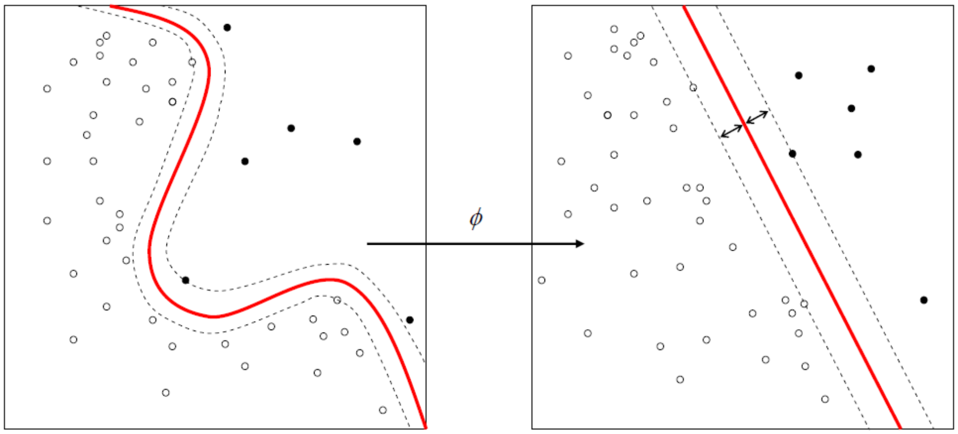

Figure 3. Support vectors with Linearly separable and in separable data

Duplicate image classification can overcome by fuzzy support vector machines as shown in Figure.1. Figure 2 describes the linearly separable data and also gives illustration of support vector machines. Figure 3 represents mapping between non linearly separable data into linearly separable data. This can be performed by appropriate kernel function. The optimal margin between two hyper planes is calculated by the following formulas.

$$2/||w|| \quad (13)$$

$$f(x) = \text{sgn}\left\{\sum_{xj} a_i * yj < xi.x >\right\} + b * (14)$$

$$Kernel = \exp\left(-\frac{||xi - xj||^2}{2\omega^2}\right)(15)$$

SAR image analysis is performed with the help of the category of non linear classification to resolve the issues related to speckle present in SAR images. Lagrangian multipliers and Kunteker conditions are used to construct soft margin to analyze SAR based images of EORC database. Slack and surplus variables are used to construct equalities which leads to form the basis matrix. There is various type of SVMs such as binary classifier and multi class classifier for segmentation and classification SAR images. Number of classifiers are depends on the type of the problem formulated by considering different SAR images. We need n classifiers for n type problems and n(n-1)/2 classifiers in the case one against one method.

V. DESIGNED ALGORITHM

A. Divide and evaluate the attributes of SAR image data with the help of GCC matrix and MCSM algorithm
B. Attribute space is formed by the attributes obtained in step1. Unnecessary attributes are removed with the help of sequential backward extraction algorithm
C. accurate classification of SAR images.
D. Analyze and identify the learning samples of SAR image from step3
E. Compute decision function and kernel function of support vector machines from the learning samples identified in step4Compute accuracy of classification with help of testing samples as shown in Figure.9
F. Trained classifier is used to analyze accuracy of each SAR images which are obtained from EORC image database

VI. METHODOLOGY AND RESULTS

All the L-band SAR images and C-band SAR images are used in this study are collected from EORC database. In this paper two types of SAR images are considered in which is first one is related crops maize, rice and yam and second one is associated with the crops cotton, cereals as shown in Figure4. Figure 5 describes the box plot analysis of crops like cotton, maize, rice, yam and rice by fuzzy support vector machines. Box plot analysis gives more insight to classify and analyze SAR based images compare bar chart diagrams as shown in Figure 5. Figure 6 illustrate several attributes about classified SAR images by taking different input parameters from user.

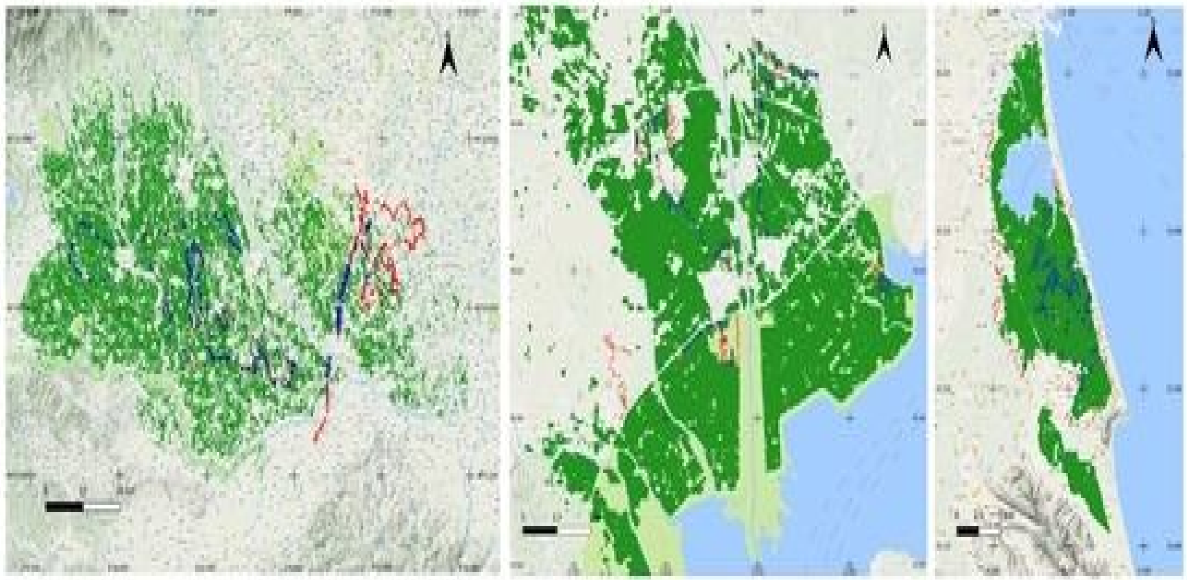

Figure. 4 Example of trained SAR image

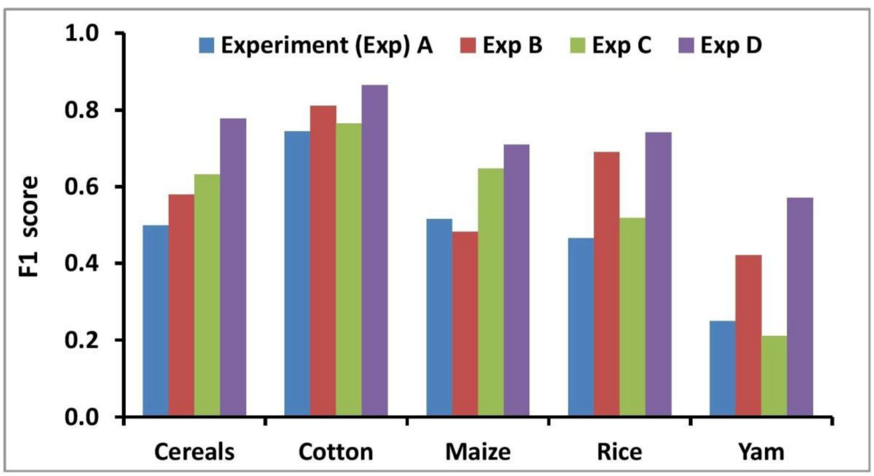

Figure. 5 F1 Score Analysis of different crops

Figure. 6 Accuracy Fuzzy entropy applied to different number of features

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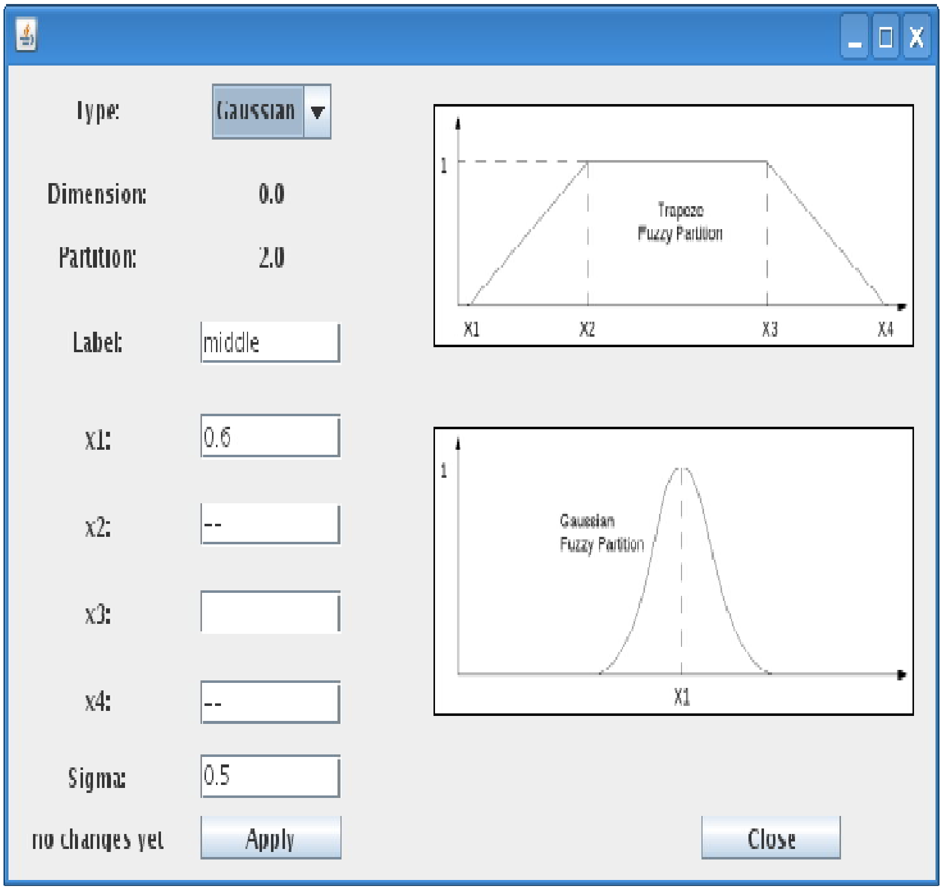

Figure. 7 Applet program out put SAR image for SAR image classification

	F1 SCORE					
TEST	1	2	3	4	5	6
1	1228	340	0	0	0	93%
2	532	1032	0	0	1	82.4%
3	0	0	1400	180	0	95%
4	0	0	100	1075	375	94%
5	110	115	0	189	1400	89%

Table 1. Accuracy results of different SAR images F1 Score

	F2 SCORE					
TEST	1	2	3	4	5	6
1	1328	440	0	0	0	93.2%
2	632	1134	0	0	1	78.1%
3	0	0	1500	280	0	92.45%
4	0	0	45	1111	310	92.83%
5	40	45	0	149	1340	85.24%

Table 2. Accuracy results of different SAR image of F2 Score

F-SVM		Maize	Cotton	Yam
	SVM	0.73	0.45	0.654
	SVM+RIM	0.89	0.92	0.89
F-SVM		Rice	Cotton	Yam
	SVM-1	0.415	0.538	0.5317
	SVM-2	0.335	0.3223	0.473
	RIM+SVM Linear	0.92	0.92	0.97
	RIM+SVM RBF	0.93	0.94	0.98
	RIM+SVM Poly	0.92	0.93	0.93
F-SVM		Rice	Cotton	Yam
	SVM-1	0.5285	0.538	0.531
	RIM+SVM	0.92	0.91	0.92
GV-SVM		Maize	Yam	Cotton
	SVM-1	0.527	0.5376	0.5337
	RIM+SVM	0.475	0.473	0.5872
CV-SVM		Maize	Cotton	Yam
	SVM-1	0.93	0.86	0.91
	RIM+SVM	0.96	0.98	0.99

Table 3. Accuracy results of Fuzzy SVM with other SVMs

Here 1 represents data related to Rice
represents data related to Maize
represents data related to bare Cotton
represents data related to cereals
broad leaves crop and 6 represents Yam

The rice field, cotton field related SAR data are classified more accurately compare to other data as they have less greenery property and double bounce property. Texture feature played significant role in classifying rice field.

Results in the Table 1, Table 2 and Table 3 compares the classification of SAR images consisting of rice crop, cotton crop, yam crop and maize crop. These results shows that fuzzy support vector machines show significant improvement in classifying the images of different types. Volume scattering and double bounce are the major reasons for misclassification small stem crops SAR image data. The data related to rice are classified correctly in most of the cases.

VII.CONCLUSION

F-SVM method is general purpose method for classifying asymmetric and symmetric SAR based image data. Fuzzy Support vector machines used membership function of fuzzy logic to enhance the classification accuracy. Member function and feature extraction played major role in the classification task SAR images of different crops. Results proved that SVM embedded with fuzzy logic is accurate and effective in the classification SAR images.

In this study, we designed fuzzy SVMs based on statistical learning theory used to segmentation of targets in SAR crop related images. We systematically analyzed the performance of support vector machines on huge and variety number of SAR targets under different illumination conditions and backgrounds. The methods of performance that we used are segmentation precision, probability of recognition and wrong alarm rate.

The combination of support vector machines with fuzzy logic gives significant results in the analysis of SAR images related different crops. This F-SVM algorithms are more suitable to choose appropriate parameters. This paper proves that the performance of fuzzy support vector machines performance in improved with the help of member function associated with fuzzy logic.

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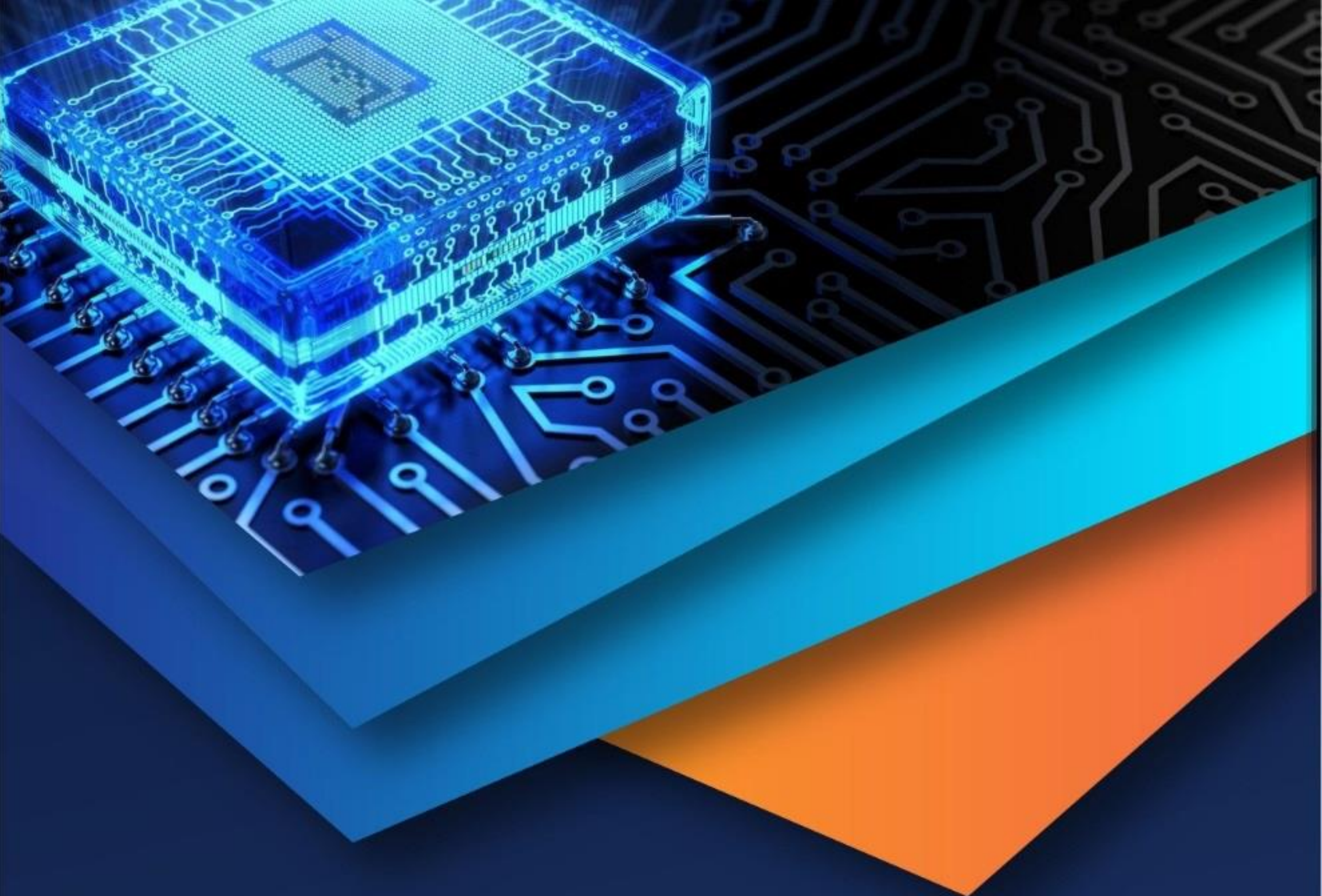

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