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Detection of Built-up Areas from High Resolution Satellite Images

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Abstract- *With the advancement in remote sensing technology, high resolution remote sensing have become a key source of information in many application platforms such as urban development, agriculture monitoring, military, intelligence, disaster relief is a high resolution remote sensing applications. Since there is a tremendous advancement in remote sensing technology, Among many of its applications, built-up area detection and land development management is an important application domain of high resolution satellite imagery, because it provides quantitative analysis in the distribution of population of a particular area of interest. This paper proposes an approach to simultaneously detect the manmade areas from the satellite images. Our approach consist of two major steps: preprocessing using a nonlinear filtering to enhance the images and its components and active contour without edge model to simultaneously extract the boundaries of built-up areas. Nonlinear Filtering helps to remove noisy image components to the large extent and Active Contour model has an advantage to detect an object in noisy 2D images. This model works on the principle of evolving a curve from a given image, in order to detect the objects from the images.*

Keywords— *Built-up area detection, preprocessing, Median filtering, Segmentation, Active contour without edge.*

I. INTRODUCTION

A dynamic and challenging problem in urbanization is built-up area detection on the land. Cities are fast developing with the world's population and have experienced continuous growth. With the advancement in remote sensing technologies, high-resolution remote sensing images have become critical sources of information fields such as city planning, geography, surveillance etc. Built-up area represents an environment on the land which is composed of both manmade and natural objects. Major approaches for built-up area detection are based on texture analysis, because the texture of the scene is distinct from that of the natural scene. Thus, it is tedious task for a human expert to extract the information from the satellite images. Automated urban-area and building-detection methods using VHR satellite and aerial images by scale invariant feature transform (SIFT) along graph theory to detect buildings and built-up areas from satellite images is proposed in [5]. One of the most important characteristics associated with the panchromatic satellite

images is that most of the urban area represent straight line feature. Cem ünsalan, member, *ieee*, *et al*, uses this straight line feature to classify land development in panchromatic satellite images in [4]. According to [9], corner detection is important in many applications, such as image registration, mobile robots, and computer vision. In image processing corner detection is a popular research area, therefore many corner detectors have been presented and among them some are widely used in industries. According to [17] and [18], common corner detection methods can be divided into three groups: 1) template based corner detection; 2) contour based corner detection; 3) direct corner detection. Contour based corner detection methods are based on edge detection in which edges in the image are detected first and the corner is detected along the contour. Generally direct corner detection methods are mathematical computations. In this category of methods usually some statistical operations are used first. Then corners are detected based on statistical information.

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SUSAN detector, Harris detector, wavelet based detector and blob detector are some famous corner detection techniques. SUSAN can work well when the noise is present because this corner detector does not require derivative. In [10], authors compared the performance of those two detectors in terms of complexity, stability, and execution time. The simulation results showed that Harris detector is better performing than SUSAN detector. Recently, an improved Harris method with using the multi-scale topological features was presented in [19]. This technique uses topological features to reduce the range of Harris corner detector. Remote sensing is a process of acquiring the information about the area or object at the earth surface without being in direct contact with the area of interest or object. Principle step in differentiating manmade areas and natural scenes is the texture of scene, because the texture of the manmade scene is different from natural scene. For this reason, many manmade or built-up areas techniques are based on the basis of texture analysis. An unsupervised approach is proposed based on the frequently recurring pattern of manmade object (e.g. building) is presented in [1]. Using Ikonos and Quickbird images as a data set in [1], accuracy up to 86% is obtained. A technique based on morphological segmentation proposed in [6], uses Gabor filter to extract the local feature points. Afterwards spatial voting used in [6] to vote the candidate built-up areas. With the advancement in remote sensing technology, the resolution of satellite image gets increased. Quite simply, high resolution means more information can be extracted from it. From the high resolution satellite images, our aim is to simultaneously detect the entire built-up areas from them. Our approach is divided into two major steps: firstly preprocessing, wherein, the image conversion and noise removal are performed for better results. In the second step, detection of built-up and non-built-up areas is performed. For built-up area boundary detection, we have used the active contour model without edge. This model has a most achievable background in the image processing application. Active contour model, also called as Snake, is a framework for delineating an object outline from possibly noisy 2D images [2]. In [3], based on techniques of curve evolution, Mumford–Shah functional for segmentation and level sets, the model for active contours to detect objects in a given image is presented. Afterwards, the color classification based on built-up and non-built-up areas are performed.

II. DESCRIPTION OF THE WORK

With the advancement of remote sensing technology, high resolution satellite images become more important in providing the valuable source of information in many application platforms. From the set of high resolution satellite images, our aim is to simultaneously detect the built-up areas from them. Our work is divided into two major steps:

- i) Preprocessing and ii) detection of built-up areas with boundaries.

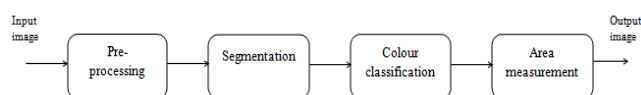


Fig. 1 Flow diagram of proposed approach

A) Preprocessing

Generally, images are often corrupted by random variations in intensity, illumination, or have poor contrast. In order to improve the quality and enhance the image features, preprocessing is performed. Image Preprocessing aims at performing geometric and radiometric correction in order to enhance the characteristic of the images. In our method we have used median filtering to improve the quality of the noisy image. Filtering is a process which transforms pixel intensity values to reveal the certain image characteristics. In median filtering, each pixel value is replaced with the median of gray values in the region of pixels. Median filtering method is very effective in removing salt and pepper and impulsive noise while preserving the details of images.

B) Boundary extraction of built-up areas

From the given set of high resolution satellite images, our main goal is to simultaneously detect the built-up areas. Active contour without edge model is used, to detect the boundaries of manmade (i.e. built-up) areas in high resolution satellite images. According to [2], Active contour based on curve evolution, Mumford shah functional segmentation and level set methods are used to detect the boundaries of manmade areas in high resolution satellite images. This model has good performance index in image processing applications.

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Active contour model, also called as Snake is a framework for delineating an object outline from possibly noisy 2D images. In order to detect objects in the images, basic idea of active contour models or snakes is used to evolve a curve. The curve moves towards the interior side of object to be detected and has to stop on the boundary of the object.

According to [2], a general edge detector can be defined by a positive decreasing function ' g ' depending on the gradient of the image u_0 as

$$\lim_{z \rightarrow \infty} g(z) = 0 \quad (1)$$

where, g is positive decreasing function

For instance,

$$g(|\nabla u_0(x, y)|) = \frac{1}{1 + |\nabla G_\sigma(x, y) * u_0(x, y)|^p} \quad p \geq 1$$

(2)

Where $G_\sigma * u_0$, a smoother version of u_0 is the convolution of the image u_0 with the Gaussian function $G_\sigma(x, y) = \sigma^{-1/2} e^{-|x^2+y^2|/4\sigma}$. The function $g(|\nabla u_0|)$ is positive in homogeneous regions, and zero at the edges. In order to obtain a mathematically easier minimization problem, Active contour [2] introduced a piecewise constant approximation to the well-known functional formulation of image segmentation by Mumford and Shah [3]. In the active contour models or snakes, the idea is to evolve a curve subject to constraints from a given image u_0 in order to detect the objects in that image. The fitting term is given by,

$$F_1(C) + F_2(C) = \int_{\text{inside}(C)} |u_0(x, y) - c_1|^2 dx dy + \int_{\text{outside}(C)} |u_0(x, y) - c_2|^2 dx dy \quad (3)$$

Where, C is any other curve variable $\text{inside}(C)$ denotes region ω inside C and $\text{outside}(C)$ denotes region $\Omega \setminus \omega$. c_1 and c_2 constants are the averages of u_0 inside C and outside of C respectively, depends on C . An energy associate with lines, which represent the

object boundaries or the moving contour. Then an evolution equation for the moving contour is derived to find the object boundaries by minimizing the total energy. The level set framework is used for the moving contour to handle the topological changes. Fitting term minimization is dependent upon parameter $F_1(C)$ and $F_2(C)$. To do this, fitting term minimizer is given by,

$$\inf_C \{F_1(C) + F_2(C)\} \approx 0 \approx F_1(C_0) + F_2(C_0) \quad (4)$$

The conditions for the above equation are

$F_1(C) > 0, F_2(C) \approx 0$; If curve C is outside the object

$F_2(C) > 0, F_1(C) \approx 0$; If curve C is inside the object

Finally, the fitting energy is minimized if;

$$C = (C_0) \quad (5)$$

Which means curve is on the boundary of the object.

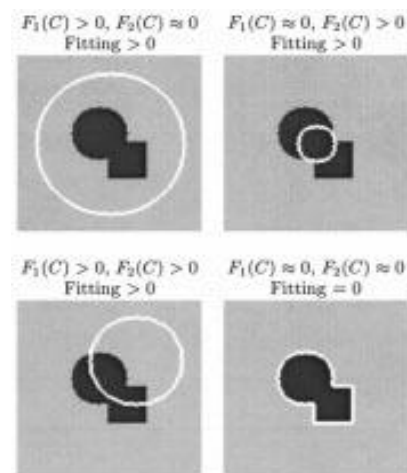


Fig.2. Cases in the position of the curve. When the curve is on the boundary of the object the fitting term is minimized

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The Mumford-shah functional can be define as

$$F^{MS}(u, C) = \mu \cdot \text{Length}(C) + \lambda \int_{\Omega} |u_0(x, y) - u(x, y)|^2 dx dy + \int_{\Omega/C} |\nabla u(x, y)|^2 dx dy \quad (6)$$

With the parameters, $v = 0, \lambda_1 = \lambda = \lambda_2$. The parameters λ and μ are the positive parameters.

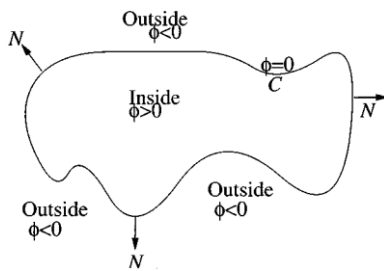


Fig.3 Curve $C = \{(x, y): \phi(x, y) = 0\}$ propagating in normal direction

Therefore, we consider the minimization problem:

$$\inf_{c_1, c_2, C} F(c_1, c_2, C).$$

In this model, for the minimum partitioning problem;

The conditions are;

$$u_0 \begin{cases} \text{Average } (u_0) \text{ inside } C \\ \text{Average } (u_0) \text{ outside } C \end{cases}$$

Further, solution for the level set formulation can be given by this model as,

$$u(x, y) = c_1 H(\phi(x, y)) + c_2 (1 - H(\phi(x, y))), (x, y) \in \bar{\Omega} \quad (7)$$

An important step for the Chan-Vese algorithm, which we can refer as the “fitting energy” functional. The goal of this segmentation algorithm will be to minimize this fitting energy

for a given image, and the minimizing level set function ϕ will define the segmentation. For minimizing energy, model presented in [2], keeps ϕ fixed.

Thus, c_1 and c_2 are given as follows.

$$c_1(\phi) = \frac{\int_{\Omega} |u_0(x, y)| H(\phi(x, y)) dx dy}{\int_{\Omega} H(\phi(x, y)) dx dy} \quad (8)$$

If,

$$\int_{\Omega} H(\phi(x, y)) dx dy > 0$$

And

$$c_2(\phi) = \frac{\int_{\Omega} |u_0(x, y)| (1 - H(\phi(x, y))) dx dy}{\int_{\Omega} (1 - H(\phi(x, y))) dx dy} \quad (9)$$

If,

$$\int_{\Omega} (1 - H(\phi(x, y))) dx dy > 0$$

The c_1 and c_2 are given by

$$\left. \begin{aligned} c_1(\phi) &= \text{average } (u_0) \text{ in } \{\phi \geq 0\} \\ c_2(\phi) &= \text{average } (u_0) \text{ in } \{\phi < 0\} \end{aligned} \right\} \quad (10)$$

Further, the initial level set is evolve by using partial differentiation, given by

$$\frac{\partial \phi}{\partial t} = \partial \phi \left[\mu \nabla \left(\frac{\nabla \phi}{|\nabla \phi|} \right) - v - \lambda_1 (1 - c_1)^2 + \lambda_2 (1 - c_2)^2 \right] \quad (11)$$

In order to solve this PDE numerically, we must discretize it. Let $\phi_{i,j}^n$ denote the value of the level set function ϕ at pixel

(i, j) at iteration n. For finding, ϕ^{n+1} i.e. reinitializing factor, the equation is referred by [2], this factor is used to reinitialize the parameters to define boundary on object (or built-up areas). Thus initialization factor mathematically expressed as follows. When working with level sets and Dirac delta

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functions, a standard procedure is to reinitialize to the signed distance function to its zero-level curve. This prevents the level set function to become too flat, or it can be seen as a rescaling and regularization.

$$\begin{aligned} & \frac{\phi_{L,j}^{n+1} - \phi_{L,j}^n}{\Delta t} \\ &= \delta_h(\phi_{L,j}^{n+1}) \left[\frac{\mu}{h^2} \Delta x - \left(\frac{\Delta x + \phi_{L,j}^{n+1}}{\sqrt{\frac{(\phi_{L,j+1}^n - \phi_{L,j-1}^n)^2}{h^2} + \frac{(\Delta y + \phi_{L,j}^n)^2}{(2h)^2}}} \right) + \frac{\mu}{h^2} \Delta y - \right. \\ & \quad \left. \left(\frac{\Delta y + \phi_{L,j}^{n+1}}{\sqrt{\frac{(\phi_{L,j+1}^n - \phi_{L,j-1}^n)^2}{h^2} + \frac{(\Delta y + \phi_{L,j}^n)^2}{(2h)^2}}} \right) - v - \lambda_1 (u_{0,i,j} - c_1(\phi^n))^2 + \right. \\ & \quad \left. \lambda_2 (u_{0,i,j} - c_2(\phi^n))^2 \right] \end{aligned} \quad (12)$$

Further, the Heaviside function (H) is a non-continuous function, it is an integral of Dirac delta function i.e. $H' = \delta$

Expanding Heaviside function as,

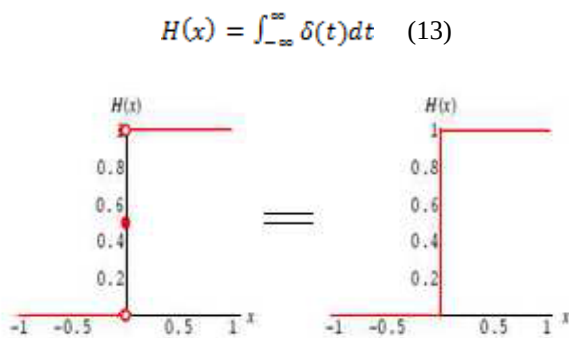


Fig. 4 The Heaviside step function, using the half-maximum Convention

The following are the various steps used in our work:

Step 1: Insert input image in proper format.

Step 2: Apply median filter to input image.

Step 3: Initialize ϕ^0 by ϕ_0 , $n=0$ in (2)

Step 4: Compute the values of c_1 and c_2 from equation (8) and (9) respectively.

Step 5: Evolve level set function for active contour

Step 6: Apply sign distance function (SDF) to the curve.

Step 7: Check whether solution is stationary. If not, $n=n+1$ and repeat step 4

Step 8: Perform color classification on image

Step 9: Measure area of respective image, which is the required built-up area.

III. EXPERIMENTAL RESULTS

High resolution satellite images covering different scenes of different cities are used as test images. The images are taken from different satellite of different spatial resolutions along with aerial images covering different scenes of earth. Also images from the highly density areas (like Mumbai, Ukraine) taken to observe the robustness of the proposed method. All the images are available on the following sources.

a. www.satelliteimagingcorp.com

b. visibleearth.nasa.gov

c. www.digitalglobe.com

d. maps.google.com

To quantify the detection results, we have used the evaluation measures widely accepted for built-up region extraction, which are true positive rates (TPRs) and false positive rates (FPRs). The detection result are shown in table (2). Here we

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have calculated FPRs and TPRs for each images, and mean of each dataset is presented in table to clearly quantify the accuracy on the basis of data sets. On the basis of our calculated results, proposed approach provides average TPR of 96% and average FPR of 2.6% , which is considered as a very good detection result.

Table -I: Description of data set

Satellite name	No. of images
Aerial images	24
Geo Eye	10
IKONOS	10
Quick bird	7
Pleiades	3
World view-II	2
Total images	56

Further to clearly different between the built-up and non-built-up areas, color classification on high resolution satellite images is also performed.

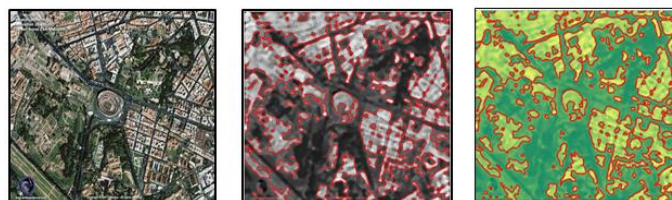
IV. CONCLUSIONS

In this paper, we implemented a method to detect the built-up areas from the high resolution satellite images. Preprocessing is performed in the first step. Mumford-shah segmentation technique based active contour model is used for delineating the boundaries man made areas. The model is able to detect an object whose boundary is no necessarily defined. The active contour model also deals with mean curvature flow, while evolving the boundary stopping term parameter does not depends upon the gradient of image, it will stop at desired boundary. We have also implemented the color classification technique in our work. On the basis of the results obtain, we can say the accuracy of the built-up areas detected the high resolution satellite images is 96% on an average.

Table II: Average values of computational time, FPR and TPR results obtain from total 56 images

Dataset	Avg. time in sec	Avg. FPR in %	Avg.TPR in %
Aerial	5.5245	2.8415	96.665
Geo Eye	4.0191	2.2967	96.483
IKONOS	4.8936	2.7675	96.735
Quick bird	4.5378	2.4495	96.612
Pleiades	5.7833	2.5691	96.277
World view-II	4.6631	2.7675	96.735

A) Built-up area detection result



(a) input image 1 classification

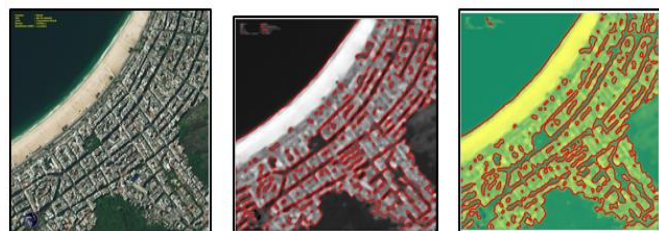
(b) boundary detection (c) color



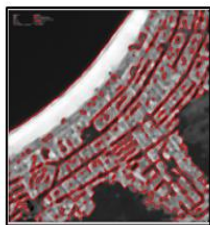
(a) input image 2 classification

(b) boundary detection (c) color

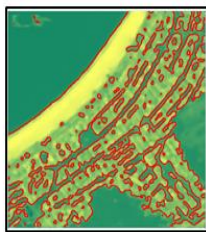
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(a) input image 3
classification



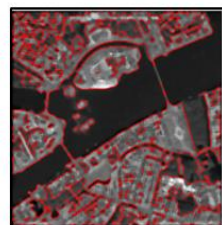
(b) boundary detection



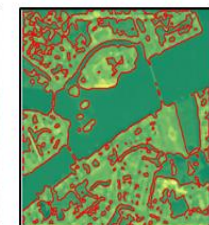
(c) color
classification



(a) input image 4
classification



(b) boundary detection



(c) color
classification

Fig.5 Built-up area detection results

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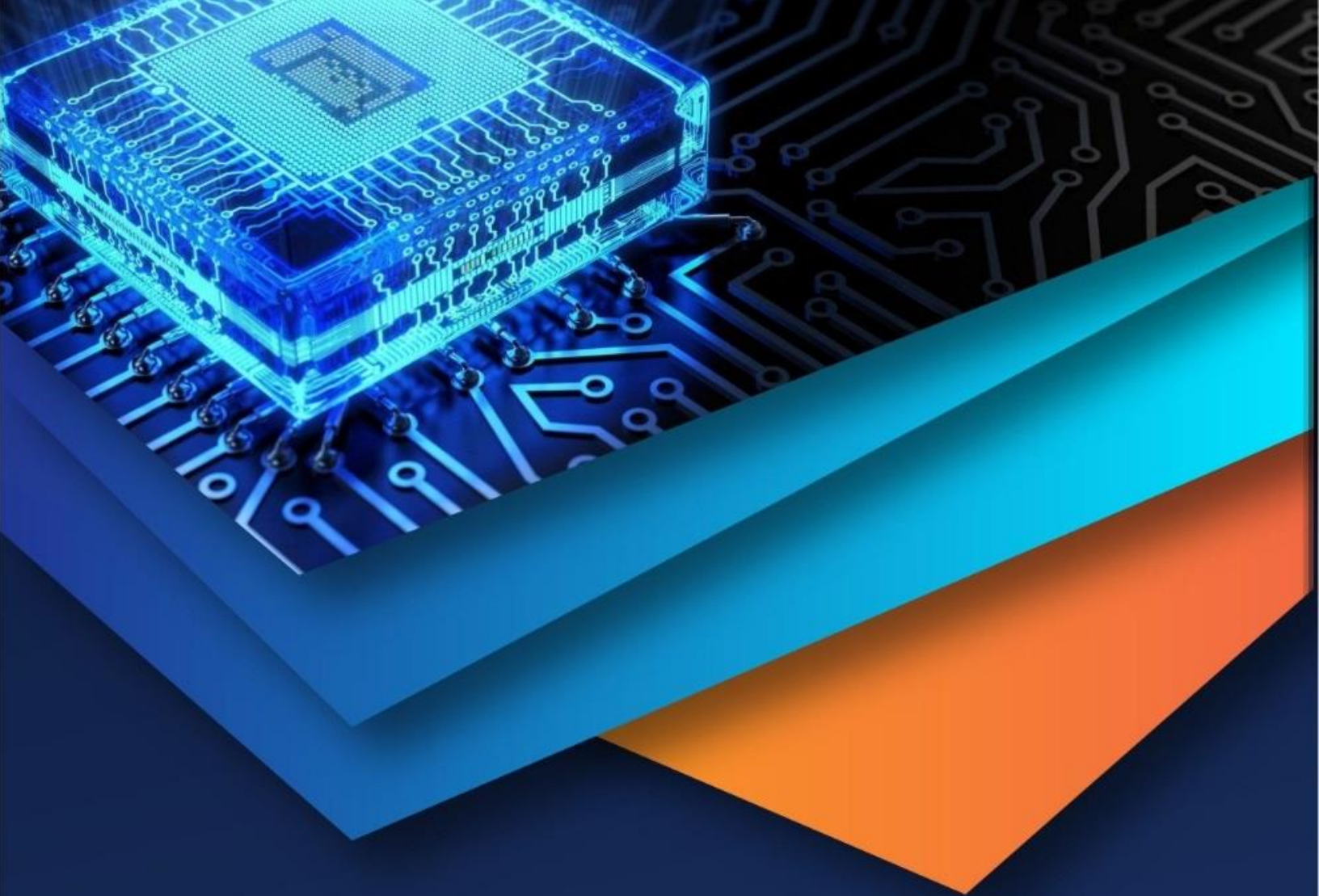
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