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Path Planning for Robot Navigation

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Abstract: This paper focuses on finding the best path for a mobile robot to follow, especially when it's sent to remote or rough areas. Often, we can use aerial images—taken by satellites or drones—to plan a rough route for the robot. These images are analyzed and divided into different terrain types based on how bright or dark the areas appear.

Each type of terrain is given a "cost," which could represent things like energy use or the risk of an accident. These costs are put into a map called a "cost map," where each spot on the map has a number showing how hard it is for the robot to travel there. This map is then used with the A* algorithm—a popular method for finding the shortest and safest path.

The A* algorithm uses this cost map to figure out the most efficient route for the robot. The result is shown as a path drawn over the aerial image, and this process is tested with different image resolutions and sample sizes. The goal of this work is to improve path planning, even when there's uncertainty, to ensure smooth and safe travel for the robot.While higher-resolution images give more accurate results, they also take much more time and computing power to process. It also includes a practicality involvement of SLAM Algorithm for the classification of different terrains of Grass, Road, or objects. It is used in a dynamic environment.

All these algorithms are used here to get trace the optimal path to the Goal state, so that the robot can be able to map out the path in which it has to traverse safely without any obstruction.

Index Terms- A* Algorithm, Gaussian Processes Bayesian Classifier, Path Planning, SLAM Algorithm, LiDAR Sensors

I. INTRODUCTION

This paper guides a stepwise walkthrough of how the path to the Goal point gets traced in the map.Robotics is the broad field dealing with designs, construction, operational implementation and application of robots, which focuses on building robots that are autonomous. It's being challenging in this field of robotics to get the robot navigate through the shortest path from one point to other as it requires a high quality processors and hardware with efficient ability to perform.

Planning a path for a mobile robot can be tricky because it needs detailed information about the area where it will move. This data is generally provided with the aerial map of the area. Using this map, the robot finds its way from the starting point to the destination by following the shortest and safest path. A good path planning system makes sure the robot avoids obstacles and chooses the quickest route possible. Most importantly, the algorithm must always find a valid and efficient path based on the map.

It often happens to send the mobile robot to travel for long missions in the geographical locations in the outdoor, hostile or any uneven terrain rather than humans avoiding prolong traveling and risking their lives. So it would be important to plan a path in order to trace the map. Only map that we have is aerial map either through satellite or through drone camera for surveillance purpose which produces a noisy image. So it is difficult to get a clean systematic planned path from this noisy image.

We have also used the SLAM Algorithm for the classification purposes of various terrains so that the robot can navigate with fairly judgment of the path of the map.

The main purpose of this paper is to deal with this uncertain path planning to make it in an optimal manner for obstruction free traversal.

Some of the algorithms that would be helpful to achieve this:

A. A Algorithm:*

The A* search algorithm finds the best path by combining two things:

1) The real cost it has taken so far to get to the current spot (called g(n)), and
2) A smart guess of how much further it is to the destination (called h(n), a heuristic cost function of n).

A function f(n), which is the estimate optimal approach to the goal state, is equal to the sum of the g(n) and h(n).

B. SLAM Algorithm:

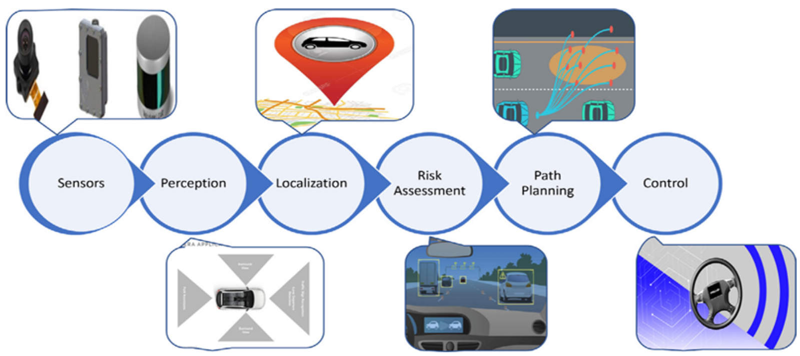
This is a smart technique often used in robotics and self-driving vehicles. It helps them create a map of a place they've never been to, while also figuring out where they are in that space at the same time. By using sensors like Lidar, cameras, and other tools, the system can track the vehicle's position and build an accurate map of the surroundings—even if the environment is changing.

II. NAVIGATION PROBLEM DEFINITION AND ITS SOLUTION

The aim is to help a robot move from a starting point (S) to goal point (G). To do this, we are given an aerial image of the area where the robot needs to travel. This area is divided into different types of terrain, such as roads, grass, and obstacles — each one is considered a different terrain class (C).

Each type of terrain has its own travel cost, which reflects how easy or difficult it is for the robot to move through that area. These costs take into account various real-world factors, like surface type, energy use, or time required.

Using A* algorithm, we calculate the total cost for different possible paths from the start to the goal state. The algorithm then chooses the most efficient path — the one with the lowest total cost, based on the terrain types along the way.



The Robot consists of sensors and has its own perception to find out its location in the map. It completely detect the environment whether there is risk, to take risk or not. It also plans the path as per its calculations of the sensors and condition in that point of time as seen in Figure 1.

Path planning [1-2] all conceptual about the getting the safest path of the map. This usually happens in two steps:

1) Global path planning Technique creates a rough route from the starting point to the destination using GPS and a preloaded map.
2) Local path planning fine-tunes the route by avoiding any nearby obstacles to make sure the vehicle doesn't crash while following the global path.

The tricky part is that finding the shortest and safest route isn't easy — it's like solving a very complex puzzle. As the number of possible paths increases, it takes much more time and effort to find the best one.

The A* algorithm is especially useful for real-world applications where we need to find the best path across a terrain, such as in aerial images of an operational area. To do this, we first convert the aerial image into a grid. Each cell of the grid represents a small portion of the terrain, and we classify grid every cell as either road, grass, or obstacle.

To directly identify different types of terrain in an image (like roads, lawn, and obstacles), we use a machine literacy system called a Gaussian Process Bayesian classifier. This classifier learns from sample points taken from the image the further samples we give it, the better it gets at feting the terrain. But using further samples also means it takes further time to reuse.

Once the image is classified, we produce a cost chart. This is like a chart that shows how delicate or expensive it's to move through each part of the area. For illustration, roads are easy to drive on and get a low cost, lawn is harder and gets a advanced cost, and obstacles are blocked fully.

A* looks for the path with the smallest total cost, avoiding obstacles and preferring easier class to traverse. One factor that affects the quality of the path- is the resolution of the image that is done on its pixels to classify the path more clearly. High- resolution images give further detail, so the path is generally more accurate. But they also take longer to reuse. To break this, we shrink the image using a system called Bilinear Interpolation, which keeps enough detail to make good opinions but pets up the calculation.

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In short, we combine smart image bracket with effective path finding to move through complex surroundings, and we acclimate image size to keep the system fast and effective.

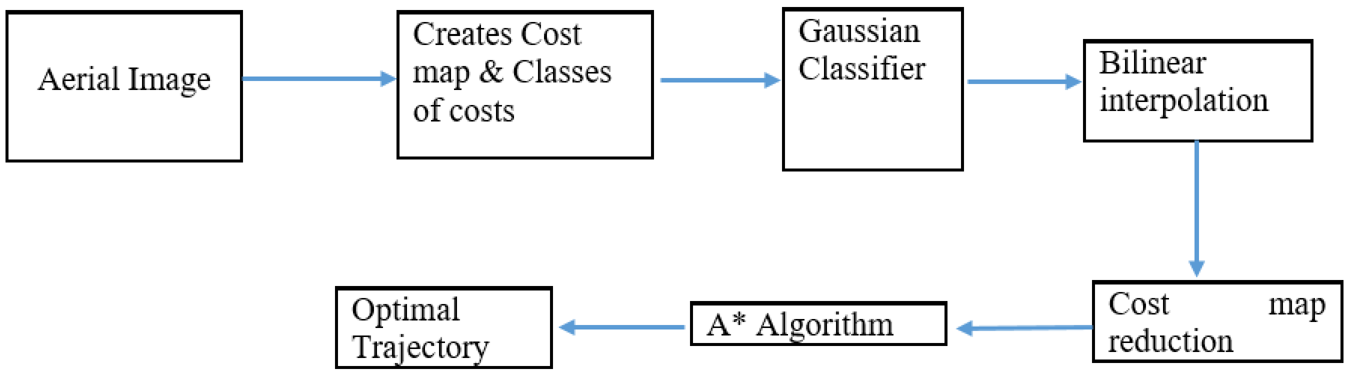

FIGURE (2)

The figure 2 explains the whole procedure about the path planning of the Robot.
The Algorithm for the path planning is as:

1) Load and prepare the image
2) Sample pixels for training purpose.
3) Define colors (approximate)
4) Sample training data
5) Train GPC(Gaussian Process Classifier)
6) Predict over entire image
7) Terrain cost map for A*
8) Apply A* Algorithm on the sampled data.
9) Define start and goal (can be replaced with dynamic selection)
10) Overlay path on classified image
11) Plot the results of the process

III. GAUSSIAN PROCESSES BAYESIAN CLASSIFIER

To make a cost map from an aerial image, we treat each pixel in the image as a small square (or grid cell) representing a part of the area where the robot will move. Each part of this area is categorized into different types of terrain, like roads, grass, or obstacles.
To figure out which terrain type each pixel belongs to, we use a statistical method called a **Bayesian classifier**. This method works by learning from a few sample areas of each terrain type. We look at their features — like their color (RGB values) — and use that as training data. Once the classifier has learned from these examples, it can then automatically identify terrain types in the rest of the image. Each type of terrain is represented by a label (like C_1, C_2, etc.).

$$P(C_i \mid RGB) = \frac{P(RGB \mid C_i) \times P(C_i)}{\sum_i P(RGB \mid C_i) \times P(C_i)}$$

Bayesian process is a probabilistic theory to infer that revises earlier methods by making use of observed dataset. It relies on Bayes' theorem, where the prior distribution and a new evidences are combined to result a posterior distribution. This methodology permits an adaptive learning as well as the measurement of uncertainty as per the surrounding condition.

$$P(C_i) = \frac{|samples(C_i)|}{\sum_i |samples(C_i)|}$$

We count how many sample points we have for each terrain type (like roads, grass, etc.), which we call class **C_i**. Then, for every small square (or grid cell) in the image, we calculate how likely it is to belong to each terrain type using those samples.
Whichever class has the highest probability is chosen as the label for that grid cell. Based on that label, we assign a travel cost to the cell. All these costs together form the **cost map**, which is then used by the **A*** algorithm to find the best path for the robot.

IV. GRAPH SEARCH FOR ROBOTIC NAVIGATION

The A* Algorithm is a smart way to find the best path through a map, like how GPS finds the shortest route. It's designed to always find the best possible path if one exists.It works by checking many possible paths and choosing the one that looks the most promising based on a cost score. In each step, it picks the point (or "node") with the lowest score, explores where it can go next, and keeps track of places it's already checked.Using a more detailed map (higher resolution) gives better results, but it also takes much more computing power and time.The A* algorithm works by combining three types of costs to find the best path:

1) g(n) – This is the actual cost it takes to reach a certain point (or node) from the starting point.
2) h(n) – This is a guess (an estimate) of how much more it will cost to get from that point to the goal.
3) The total helps A* decide which path to follow.

The value of **h(n)** doesn't have to be exact — it's just an estimate. But for A* to always find the best path, this estimate must not overstate the real cost (it should always guess equal to or less than the true cost). If it guesses too high, the algorithm might miss the best route.The cost map generated from is first compressed to reduce its resolution using a bilinear interpolation technique. Each grid in the smaller resolution Cost map is a state of the A* algorithm.

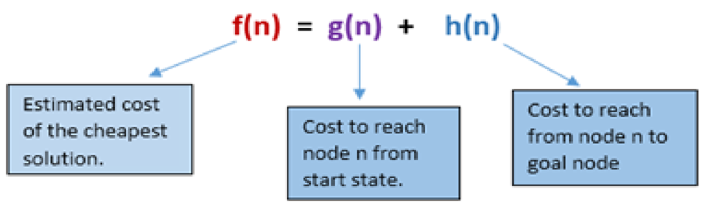

FIGURE (3)

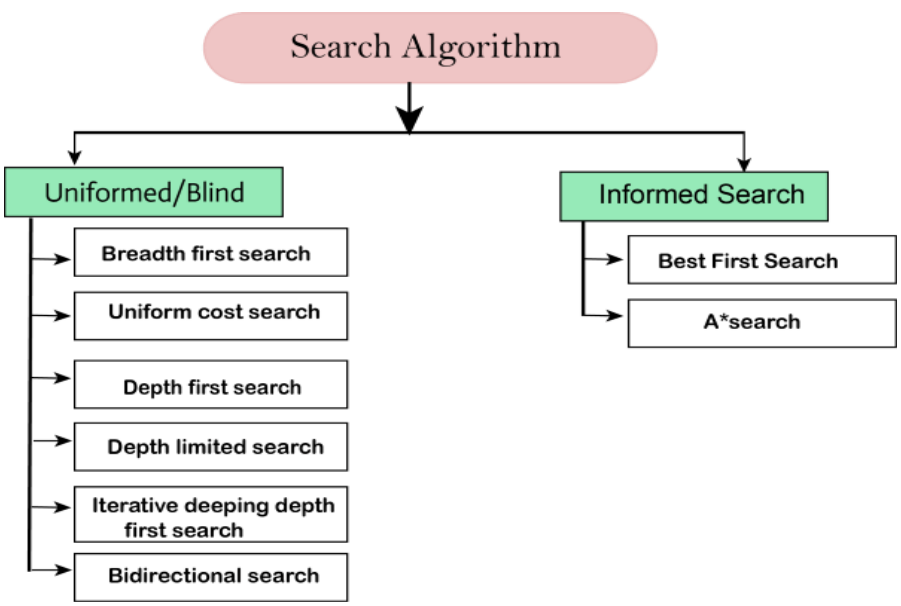

FIGURE (4)

The computed by the A* algorithm is a low resolution computed cost map representation. The path is measured up to an original cost map. The path is traced on the aerial image of the map.

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V. RESULTS OF A* ALGORITHM

In order to test the algorithm, we took a large number of images from [Approx.. 50]. The original image that we had taken here is shown below Figure 6. The figure shows an aerial image of an airport site [4]. As it consists of obstacles which cannot be traversed by the robot and are taken their cost as infinity; well-built roads which are the easiest to traverse are associated with cost 1; and grasslands which can be traversed but with some difficulty and have a cost of 10.

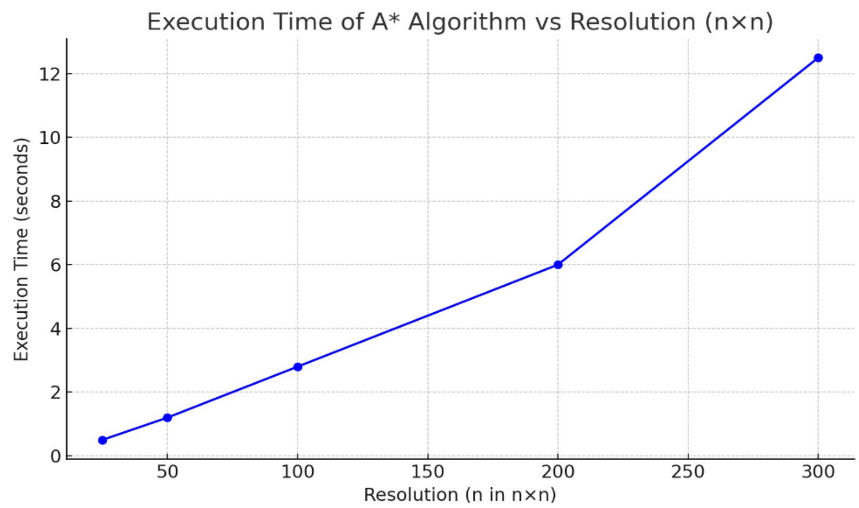

FIGURE (5)

Here's the plot showing the relationship between the resolution [3] (n×n) and the execution time of the A* algorithm. As the resolution of the image pixel increases, the execution time rises significantly, indicating a trade-off between path accuracy and computational efficiency.

VI. RESULTS OF GAUSSIAN CLASSIFICATION

We used a Gaussian Process Bayesian classifier [9-11] to categorize different areas of the terrain into three types: road, grass, and obstacle. To train the classifier, we randomly selected 10 to 20 sample points from each of the three classes. For each class, we calculated the average (mean) and variation (variance) of the samples. These values helped us calculate the likelihood and prior probability for each class. Finally, we used these probabilities to classify every point in the image by computing the posterior probability, which tells us the most likely class for each point.

Figure (6)

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In the given below figure 7 and 8, we can see that the type of the door and girding areas is mainly accurate. Still, there are still some queries, where one class is confused with another pixel of the image because of noise in the it. These misapprehensions reflect the query in the classification. However, we can reduce this query though it may take farther time to exercise. If we increase the number of training samples for each class.

The results for an advanced number of samples are also shown in the figure 7. As the number of samples increases, the query decreases. For illustration, in the field, road, and handicap areas, we can see lower black and white markings (which indicate query), showing that the type has come more confident and accurate. In figure 6 the red color path traced is done by Gaussian classifier which has classified the field and multitudinous analogous terrains as value 0 ie. Black in color.

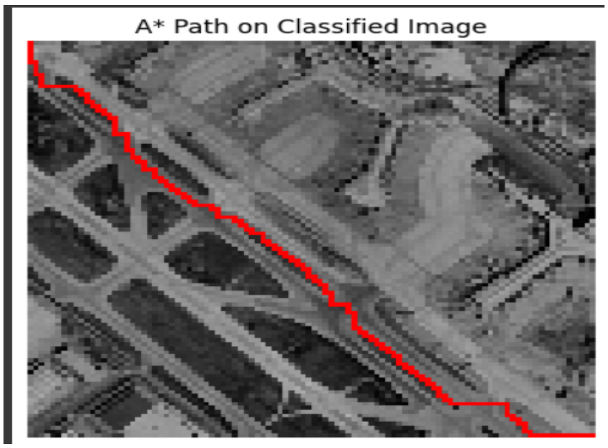

FIGURE (7)

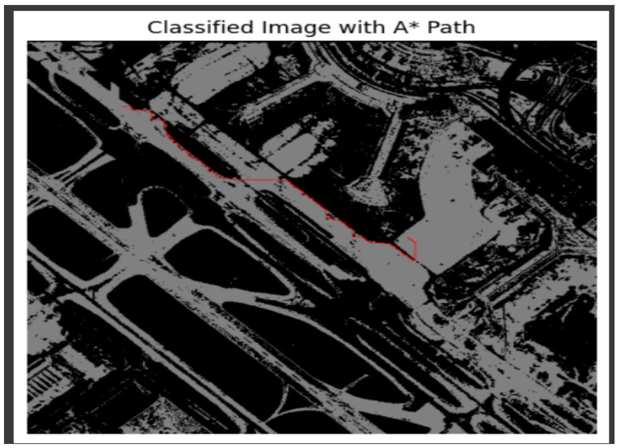

FIGURE (8)

In the figure 7 the terrain is largely pixel acquainted and resolved and is classified predicated on which is much farther effective in getting an optimal path to the thing using A * algorithm as it's mentioned in figure 7.

VII. CLASSIFICATION AND PATH RESULT USING SLAM ALGORITHM

FIGURE (9)

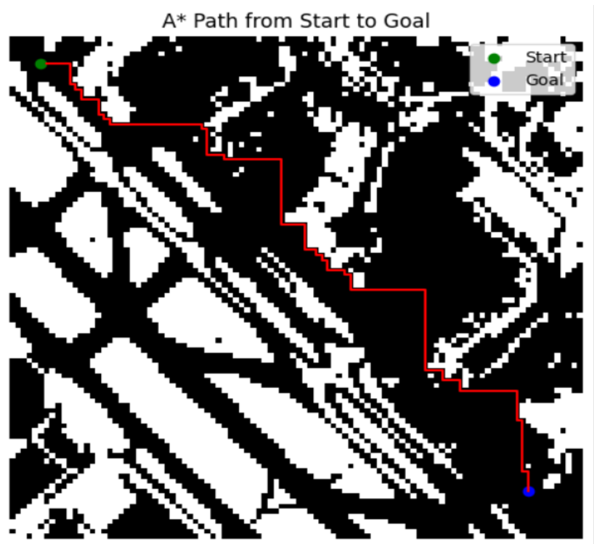

FIGURE (10)

The figure 9. classification has done by the SLAM Algorithm to classify the environment in classes in white and black, since as I have set the pixel intensity value as white and black. The path in Figure 10. Red and Blue marked points are planned by the A* Algorithm to trace the optimal in the map of the aerial image [4-7] from the satellite. If we don't want to get the traced path the robot just classify the environment and move through the environment as the map created by SLAM through the LiDAR sensor usage [8-13].

The main goal of localization and mapping is to figure out the exact position of a vehicle within its environment. There are three common methods used for this: combining GPS with an IMU (inertial measurement unit), using SLAM (Simultaneous Localization and Mapping), and using pre-built maps.

Robots can explore and understand their surroundings in different ways. One common method is LiDAR-based SLAM, which uses data from a LiDAR sensor to create a map made of 3D points (called a point cloud). LiDAR is very accurate when it comes to measuring distances. However, the process of matching new sensor data with the existing map needs to be detailed and precise to work well.

The advantage of SLAM is that it doesn't require any previous knowledge of the environment—it can build a map from scratch as the robot motion. That means it can be used in new or unknown places without needing preloaded maps.

Perception tasks.

Task	Idea	Sensors	Steps and algorithms
Image-based 2D Object detection	Detect if specific objects exit in the image, determine its location and size using a rectangular bounding box.	Cameras	Single stage: YOLO, SDD, two-stage: faster. RPN. Single stage faster.
Image segmentation	Semantic Seg. classifies pixels in images, instance seg. classifies objects based on box boundaries.	cameras	RNN, Pyramids Networks, Transposed Convolutions Networks, Slow.
3D object detection	depth information should be considered to convert the 2D objects into 3D objects.	3D stereo cameras, LiDAR, Radar	Euclidean clustering , VeloFCN, VoxelNet network.
Object tracking	Detect the dynamic object trajectory velocity to predict the future location of the object	cameras, LiDAR, Radar	1- occupancy map as a single frame for all sensors. 2- data association (nearest neighbor, Image, Point cloud based) 3- filtering for smoothing (Bayes, Kalman, particle filters).
Road and lane Detection	Find the drivable region for the autonomous vehicle.	cameras, lidar, radar	1- data pre-processing (color correction, map-based filtering). 2-lane feature extraction. 3- construct the continuity of lanes (geometric parametric and non-parametric alg.). 4- temporal integration for smoothing (Kalman, particle filters).

VIII. CONCLUSION

In this paper, we developed a method to create a detailed map (called a costmap) using aerial images, which helps in planning paths for robots. First, we used a machine learning model (the Gaussian Process classifier) to classify different types of terrain in the image, such as roads, grass, or obstacles. Based on this classification, we created a costmap where each type of terrain has a different movement cost. For better accuracy, we found that using more sample data improved the quality of classification, and therefore, the costmap.

We then used the A* pathfinding algorithm to find the best path for the robot by treating each part of the map as a node with a specific cost. The algorithm found the most efficient route across the map based on these costs.

We then used another algorithm in this path planning method SLAM Algorithm which helps to get an optimal map classification and path tracing ahead.

Looking ahead, we plan to improve this approach by including uncertainty in the cost values — essentially creating a costmap that shows not just a single cost, but a range of possible costs for each area. This probabilistic approach will be more realistic but also more complex, since standard A* algorithms aren't designed to handle probabilities. We also aim to build a larger dataset of different terrain types to automate classification and reduce the need for manual labelling. Lastly, we plan to test this system with real robots to verify its performance in practical scenarios.

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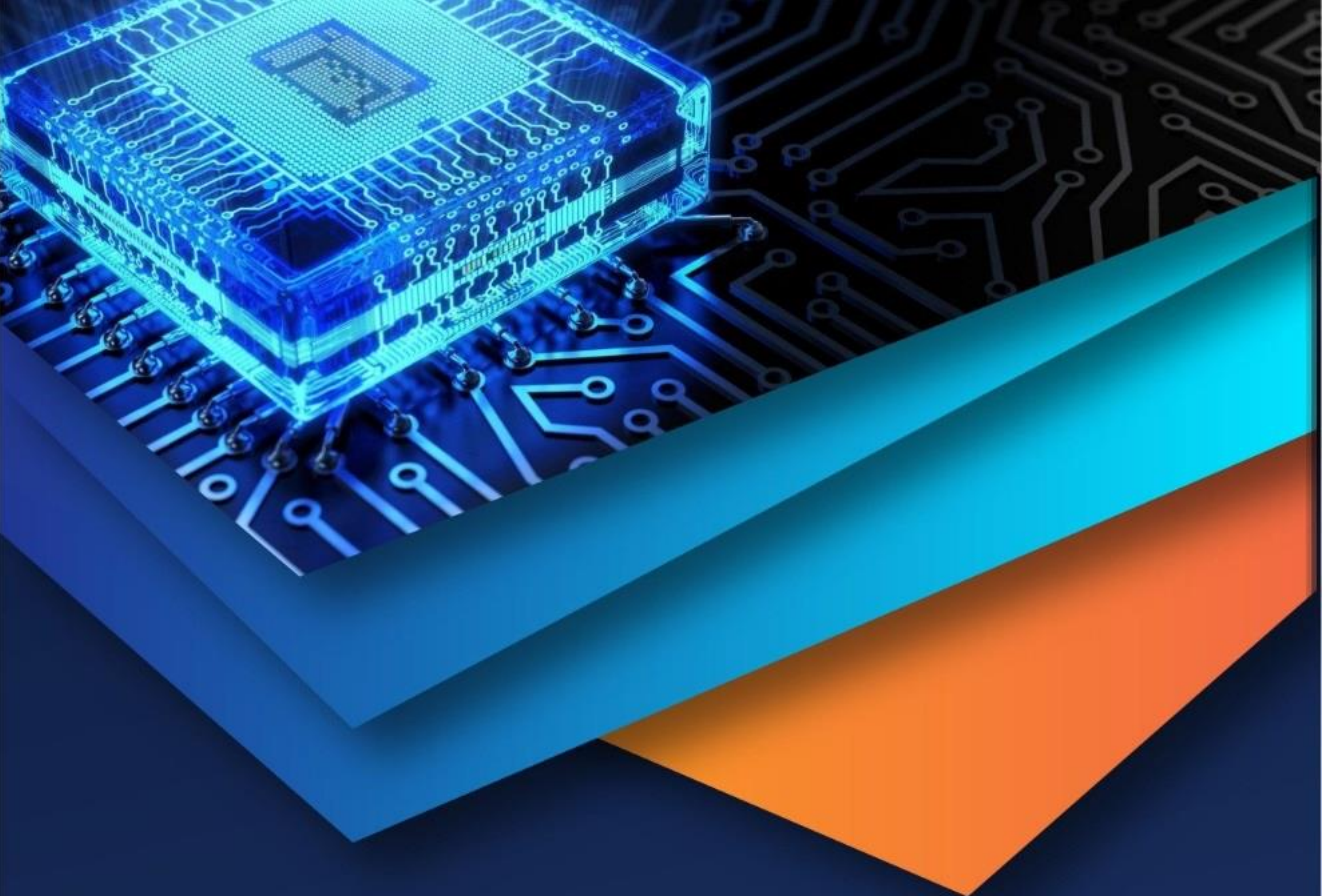

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