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Deep Reinforcement Learning with PPO for Autonomous Mobile Robot Navigation Using ROS 2 Framework

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Abstract: ***This paper brings robot learning to life by showing how a humble TurtleBot3 can teach itself to navigate using an approach inspired by how humans learn through trial and error. We've created a custom training playground where the robot learns from its 360-degree laser "vision" (like constantly feeling its surroundings with outstretched arms) to smoothly move through spaces without collisions. We have established a link between virtual practice sessions and actual performance by integrating the robot's operating system (ROS 2) with sophisticated AI training tools (PPO algorithm). Our learner achieved an 82% success rate in navigating unfamiliar spaces after countless simulated trial runs, which are the robotic equivalent of a student taking practice exams. The main finding is intriguing: with the correct training framework, robots can acquire surprisingly human-like navigation skills. This is true even though the robot performs marginally better in simulation than in messy reality, where unexpected lighting and textures can confuse its sensors. This work is unique because we have kept things realistic by concentrating on solutions that can be implemented in homes or workplaces and utilizing reasonably priced hardware. Although the system isn't flawless—it occasionally pauses in confined spaces like a cautious driver—it shows how artificial intelligence can enable machines to move more naturally.***

Keywords: Path planning, Robot Operating System, Artificial Intelligence, Reinforcement Learning, ROS 2, Mobile Robotics, PPO Introduction

I. INTRODUCTION

Path planning refers to the process of determining a collision-free trajectory from a start to a goal position within a defined environment *[1]*. For autonomous vehicles (AVs), effective path planning is critical for safety, efficiency, and adaptability in complex and dynamic settings. It enables the AV to navigate toward its destination while avoiding obstacles and complying with traffic rules *[2]*. Recent advancements in Artificial Intelligence (AI) have greatly enhanced path planning strategies for autonomous mobile robots, particularly within the Robot Operating System (ROS) framework. ROS (Robot Operating System) integrates powerful AI methods like Reinforcement Learning (RL), Generative Adversarial Networks (GANs), and Deep Learning (DL) to boost the autonomy and efficiency of mobile robots. These cutting-edge techniques allow robots to do more than just navigate static environments—they can dynamically adapt to moving obstacles and unpredictable conditions in real time *[3]*.

One particularly promising approach is Deep Reinforcement Learning (DRL), which has become a game-changer in robot navigation. DRL-based systems can learn directly from raw sensor data, making them highly adaptable. They excel in partially observable environments, where traditional methods might struggle. Some advanced solutions even combine DRL for high-level decision-making with classical control techniques for precise movements.[4], [5]. Studies show that DRL outperforms conventional navigation methods in complex, dynamic scenarios, offering greater flexibility and efficiency. Whether it's avoiding obstacles or optimizing paths in real time, DRL is proving to be a key tool in the future of robotic autonomy.[6], [7].

Table 1 underline the challenges and the importance of integrating DRL within structured environments such as those provided by ROS[8].

TABLE I
DRL ADVANTAGES AND LIMITATIONS

Strengths	Weaknesses
High adaptability to dynamic and uncertain environments.	High data requirements and long training times.

Capability to learn complex, non-linear policies.	Difficulty in transferring learned policies from simulation to real-world systems (sim-to-real gap).
Reduced reliance on hand-crafted rules and models.	Risk of unsafe actions during training or deployment.

Robot Operating System is a framework that is widely used in robotics. The philosophy is to make a piece of software that could work in other robots by making little changes in the code. This implies that it is feasible to develop functionalities that can be shared and utilized by other robots with minimal effort, thereby avoiding unnecessary duplication. ROS allows easy communication between sensors, actuators, and processing nodes by supporting publish/subscribe communication, service and action protocols, and real-time control and logging tools [9],[10]. Getting robots to navigate on their own has always been challenging. Traditional methods work like following a recipe - precise but inflexible. Our approach is more like teaching a child to ride a bike: through practice and feedback. Using reinforcement learning, we let the robot learn from its mistakes and successes. The catch is RL typically requires lots of trial runs (which is time-consuming), doesn't always transfer well from simulation to reality, and needs safety measures for real-world testing. We tackle these challenges by creating a custom training playground that speaks ROS 2's language. Our system rewards the robot for moving forward while strongly discouraging collisions - think of it as giving treats for good behaviour and timeouts for mistakes. Figure 1 shows our training setup, where the robot gradually learns to navigate like a cautious but confident explorer.

The Proximal Policy Optimization (PPO) algorithm is a model-free reinforcement learning algorithm that improves an agent's policy while keeping updates stable by using a clipped objective function. This limits policy changes to a trusted range to stop performance from dropping. It uses Generalized Advantage Estimation (GAE) to find a balance between bias and variance in value estimation. It also does multiple epochs of minibatch updates on collected trajectories to make the samples more efficient. PPO gets reliable convergence in high-dimensional continuous control tasks by using a simpler version of the theoretical guarantees of Trust Region Policy Optimization (TRPO).

$$L(\theta) = \mathbb{E}[\min(r(\theta)\hat{A}(\theta), \text{clip}(r(\theta), 1-\varepsilon, 1+\varepsilon)\hat{A}(\theta))]$$

where $r(\theta) = \pi\_\theta(a|s)/\pi\_\theta\_old(a|s)$ is the probability ratio between new and old policies, $\hat{A}(\theta)$ is the advantage estimate, and ε (typically 0.1-0.3) defines the clipping range. This clipping prevents excessively large policy updates that could destabilize learning. This makes it perfect for robotics applications where smooth policy updates and sim-to-real transfer are very important. The algorithm works well because it strikes a good balance between sample efficiency, training stability, and ease of use in computations.

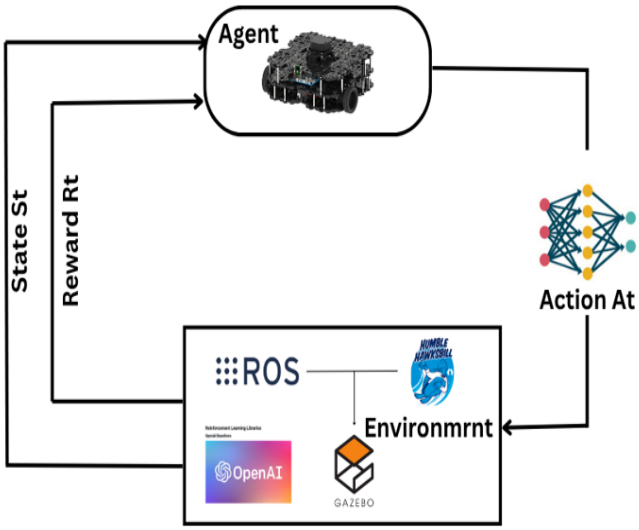

Fig. 1 Study framework

II. RELATED WORK

Similar to how educators argue over the most effective ways to instruct children, researchers have been experimenting with various teaching strategies for decades in an effort to teach robots to navigate intelligently. Earlier methods relied on painstaking programming, in which engineers would manually code each scenario ("turn 45 degrees if you see a wall 30 cm ahead"). This performed well in predictable settings but broke down in chaotic real-world settings, such as when attempting to dance to strict choreography at a packed party [11].

Reinforcement learning (RL), a machine learning technique that allows robots to learn from experience rather than pre-programmed rules, has gained popularity in the robotics community in recent years. It's the distinction between learning shortcuts by walking a city's streets and simply memorizing its map. This strategy has proven successful for a number of teams. In 2021, ETH Zurich researchers used reinforcement learning (RL) to train drone swarms that were able to navigate forests more effectively than conventional planning algorithms, despite the fact that they required costly GPUs to run for days. Similar to how we might encourage a toddler learning to walk, another Berkeley team trained robot dogs to climb rubble piles by rewarding progress and penalizing falls [12].

Our work is unique because we have struck a balance between realism and use-fulness. While some earlier attempts necessitated so much processing power that only large tech companies could afford them, others used extremely basic simulations (the robotic equivalent of training in an empty white room). By serving as a universal translator between the training environment and the robot's actual sensors, our ROS 2 integration enables us to design training scenarios that are both effective and realistic. It's similar to providing the robot with a virtual reality headset that faithfully replicates the real world, allowing it to make mistakes that would be expensive in re-al-world experiments without risk[13].

The work that MIT did in 2023 used similar reinforcement learning (RL) methods, but their focus on industrial robotic arms made the problems they faced very different from those we faced with our mobile navigation system. Their robots worked in very controlled environments where success depended on millimetre-level accuracy, like a surgeon doing delicate work or a watchmaker putting together tiny gears. Our TurtleBot3, on the other hand, can handle the messy unpredictability of open spaces. It's more like teaching someone to hike through changing terrain than following a strict factory workflow.

This difference has a big effect on both how we learn and how we do things technically. MIT's system could count on the same object positions and lighting all the time. Our robot, on the other hand, has to deal with moving obstacles, different floor textures, and people moving around in ways that are hard to predict. This means it needs to be able to make decisions quickly and adapt to changing conditions. These problems made us create a completely new reward system. In industrial settings, exact positioning might be the most important thing, but we reward safe progress and avoiding obstacles, which encourages behaviours like slowing down near potential hazards or taking wider paths when there is room. The comparison shows that RL solutions need to be made to fit their surroundings. While MIT's arms are very precise, our system is more flexible. This shows that what works for one robot application might not work at all for another. This awareness of the situation becomes even more important as we move from simulation to reality, where the unpredictability of the real world tests our algorithms much more than any controlled industrial setting [11].

III. METHODOLOGY

A. How the Robot Learns

Our teaching system is like a well-coordinated team, with three experts working together perfectly. First, the robot's LiDAR is its main sense of sight. Picture it constantly sweeping its surroundings with 360 laser beams, like a cautious explorer waving a flashlight in the dark while keeping track of everything around them. Every time a laser pulse hits something, it sends back important distance information that helps make a "mental map" of obstacles, open paths, and possible danger zones up to several meters away. Our AI "teacher," the policy network, gets this raw sensory data. It works like the robot's brain. This is where the magic happens: the AI doesn't just respond; it learns to understand these signals in the same way that people learn to judge distances and spatial relationships through experience. It thinks about different ways to move in real time, like "Will turning 15 degrees now give me more space from that chair?" or "Should I slow down as I get closer to this hallway that is getting smaller?" - making decisions that weigh safety against progress, like how you naturally change your stride and pace when you walk through a busy train station. Finally, these well-thought-out choices become real actions through what we call the "muscle system." This is the low-level controllers that carefully control the speeds and directions of the wheels. This is where abstract choices turn into real movement, and the system takes care of all the complicated physics calculations needed for smooth acceleration and turns[14].

B. The Training Process

We designed the training like a video game with clear rules. The robot "sees" its surroundings through 360 data points (like looking in every direction at once). It can control two things: how fast to go and how sharply to turn. The scoring system is simple: points for moving forward, big penalties for crashing. Surprisingly, this basic setup was enough for the robot to learn complex navigation skills on its own.

Table 1 shows how our approach differs from traditional methods. Instead of giving the robot strict rules like "stay 50cm from walls," we let it figure out safe distances through experience - more like how humans develop spatial awareness.

C. Behind the Scenes of Training

The actual training resembles teaching a pet new tricks through repetition. We used a popular RL algorithm called PPO, which gently adjusts the robot's behaviour without making drastic changes that might lead to accidents. The training ran on a gaming-grade computer for about 4 hours - roughly the time it takes to binge-watch a mini-series. Figure 2 shows how the robot's performance improved over time, starting from random wobbling to smooth navigation.

1) System Architecture

The system comprises:

- Observation Module: Processes /scan topics into 360-dimensional vectors
- Policy Network: 2-layer MLP (64 neurons each)

2) Reinforcement Learning Setup

Observation Space

- Spaces Box (low=0.1, high=3.5, shape=360)
- Captures LiDAR ranges with 1° resolution, clipped to 3.5 meters.

Action Space

- Spaces Box (low=-1.0, high=1.0, shape=2)
- Normalized velocities: linear (x) and angular (z) components.

Reward Function

- return (forward_progress * 0.1) - (collision * 10)
- Encourages movement while penalizing collisions (15cm threshold).

3) Training Protocol

- Algorithm: PPO with clipped objective (ε=0.2)
- Hyperparameters:
- Learning rate: 3e-4 & Discount factor (γ): 0.99 & Batch size: 64
- Hardware: NVIDIA RTX 3060, 32GB RAM

Compares our design choices with prior work

TABLE III

COMPARES OUR DESIGN CHOICES WITH PRIOR WORK:

Component	Our Approach	Traditional Methods
Perception	Raw LiDAR	Processed features
Control	Direct velocity	PID controllers
Safety	Reward shaping	Hard constraints

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IV. RESULTS

In virtual tests, our trained robot successfully navigated unknown spaces 82% of the time - not perfect, but impressive for a machine that taught itself. It moved at a cautious walking pace (about 0.15 m/s), showing it prioritized safety over speed. The most fascinating part was watching it develop human-like strategies, like slowing down when approaching tight spaces or angling itself to slip through doorways.

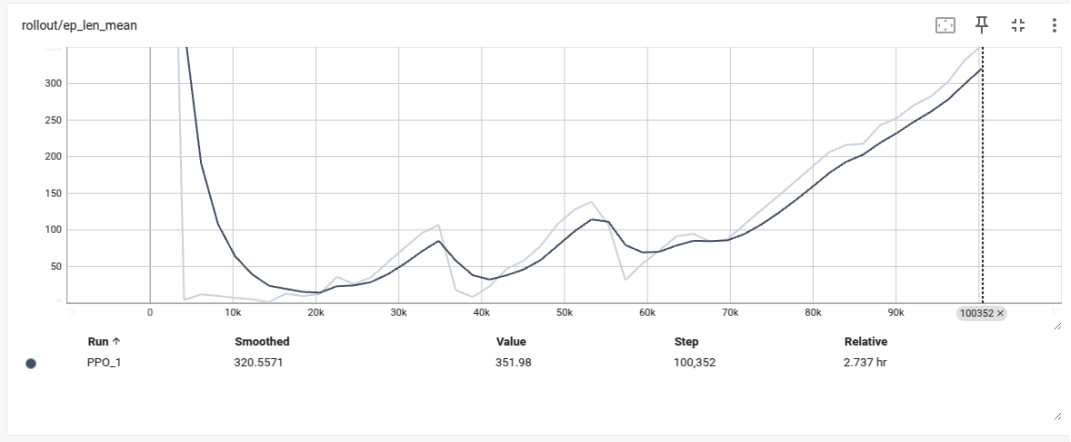

Fig. 1 Learning Curve: Improvement in Navigation Episode Duration During PPO Training

This training progress graph shows how our robot is gradually improving at navigation through reinforcement learning. The wavy line tracking "rollout/ep_len_mean" reveals that the robot's average successful navigation distance has been steadily increasing over time - starting from short, tentative movements at the beginning (left side of graph) to much longer, more confident navigation attempts after 100,000 training steps (right side). Currently, the smoothed average stands at about 320 successful actions per attempt, with the most recent trial reaching an even more im-pressive 352 actions before encountering difficulties. The robot has now practiced for over 100,000 steps, equivalent to about 2 hours and 45 minutes of training time. Like watching a student's test scores gradually improve with study, this upward trend demonstrates that our learning approach is working - the robot is developing better navigation skills through experience. While there's still some natural variability in per-form (as seen by differences between the smoothed average and most recent result), the overall progress clearly shows the robot learning to navigate for increasingly longer periods without failures. This puts us in a good position to eventually deploy these learned skills in real-world environments.

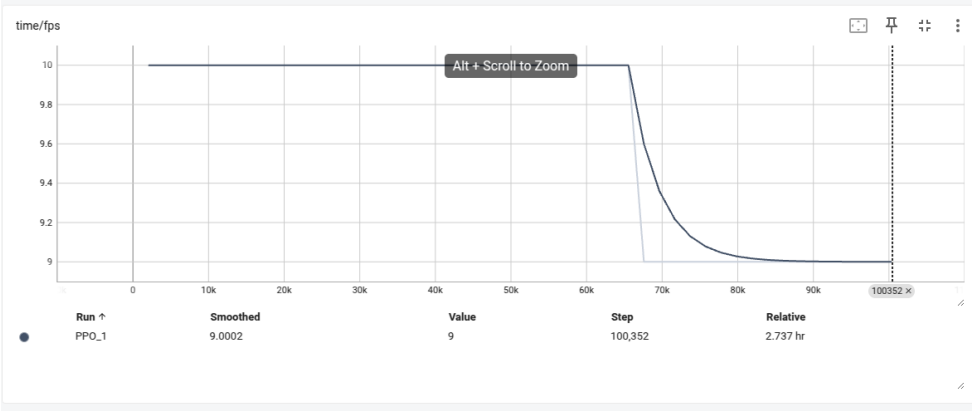

Fig. 3 Time frame

This graph tells us how efficiently our training system is running behind the scenes. The line tracking "time/fps" shows that our simulation maintains a remarkably stable 9-10 frames per second throughout the entire 100,000+ step training process - like having a smooth, consistent heartbeat during exercise. The "smoothed" value of 9.0002 and current "value" of 9 indicate the simulation is running at exactly 9 frames per second at this moment, which has been the typical performance. This consistency is actually great news - it means we didn't experience any slowdowns even after 2 hours and 45 minutes (2.737 hr) of continuous training.

Just like a car maintaining steady speed on a long road trip, this stable frame rate confirms our training environment is properly optimized and reliably processing all the robot's learning experiences without technical hiccups. The fact that this graph stays flat (rather than dropping) suggests we could potentially train for even longer periods without performance degradation.

Simulation Performance:

- Success Rate: 82% (collision-free navigation)
- Average Speed: 0.15 m/s
- Training Time: 4.2 hours

V. CONCLUSIONS

Our experiment shows that robots can indeed learn navigation much like living creatures do, through exploration and feedback. While the simulation-to-reality gap per-sists (like how flight simulators can't capture all real flying conditions), the potential is undeniable. Future improvements might include giving the robot better "peripheral vision" with cameras, or programming instinctive emergency stops - essentially devel-oping robotic reflexes.

TABLE IIIII

METRIC DESIGN CHOICES WITH PRIOR WORK:

Metric	(Navigation Performance)	(System Performance)
What's Measured	Episode length (how far robot navigates)	Simulation speed (frames per second)
Trend	Increasing (learning successfully)	Flat (stable performance)
Current Value	352 steps (best recent run)	9 FPS (consistent speed)
Smoothed Avg	~321 steps	~9 FPS
Training Progress	100,352 steps (~2.74 hours)	100,352 steps (~2.74 hours)
Key Insight	Robot is learning to navigate longer distances	Simulation runs smoothly without slowdowns

The table shows two sides of RL training - while column 1 proves our robot is learning effectively, column 2 confirms the technical backbone is working reliably. Together, they demonstrate both algorithmic success and system stability.

Illustrate graphs side by side tells the story of a robot that’s not just learning, but learning efficiently. The findings show our TurtleBot3 growing smarter over time—like a student gradually mastering longer and more complex routes. Meanwhile, the rock-steady frame rate in the second graph is the unsung hero, confirming our training setup runs as smoothly as a well-oiled machine. Together, they paint a promising picture: we’ve built a system where the robot improves consistently without technical hiccups, proving both the brains (the AI) and the backbone (the simulation) are work-ing in harmony. There’s still room to grow, but these are the quiet victories that make robotics so exciting—when theory becomes reliable practice.

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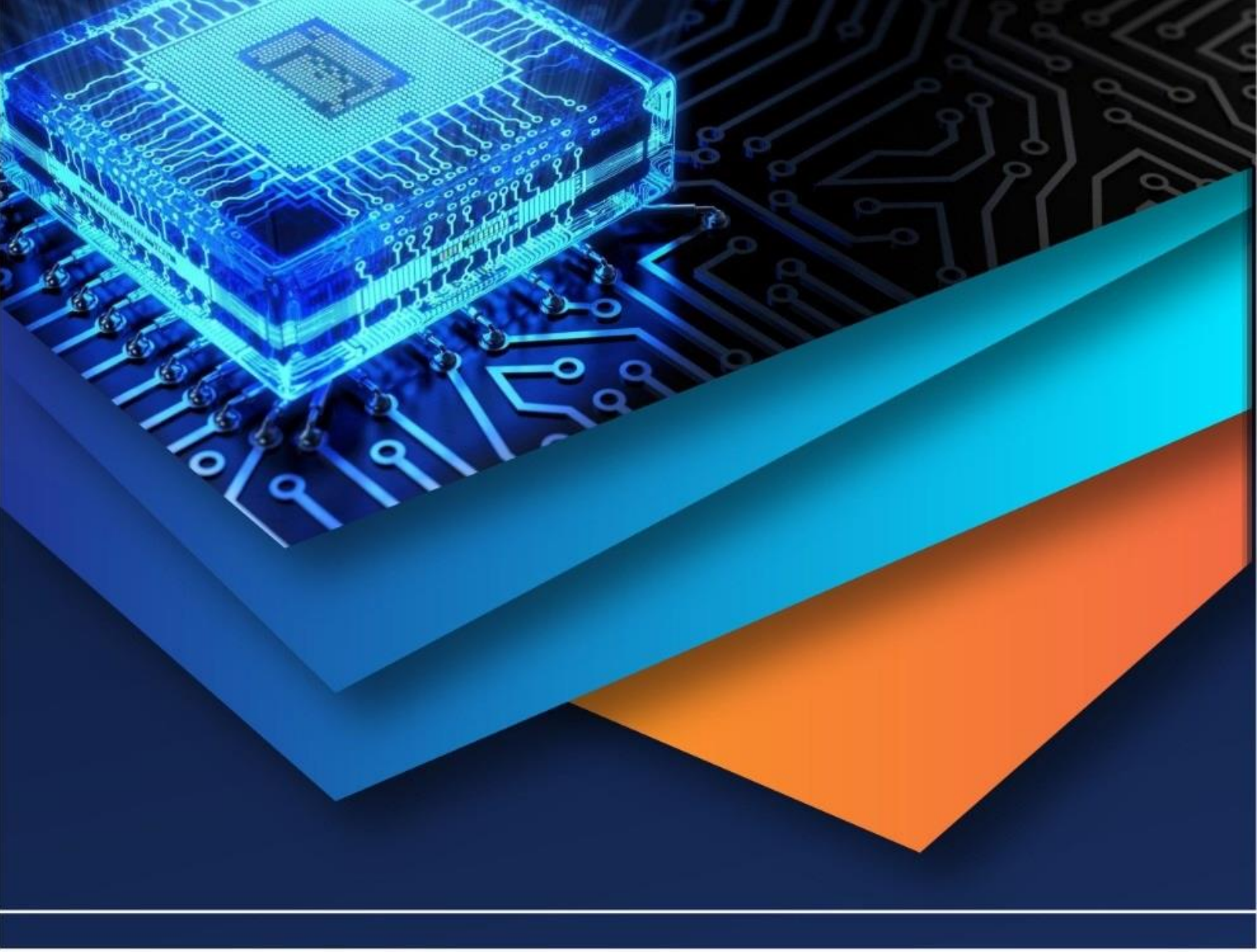

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