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Smart Transportation Through Ontology-Based Sensor Integration for Safer Driving Environments

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Abstract: This research proposes an ontology-driven design for a traffic sensor network that aims to enhance the driving environment. Based on data collected by the sensors, the system carries out a number of automated processes meant to improve the driver's comfort and safety. Enhancing real-time traffic management and decision-making, the suggested system combines data from numerous sensors—including traffic signals, road segment monitors, and vehicle detectors—within a semantic framework. Dynamic adaptations to traffic conditions are made possible by using ontologies, which provide interoperability and meaningful interpretation of diverse sensor data. The findings show that adaptive control systems that use semantic reasoning greatly enhance traffic flow and decrease vehicle travel time. The results show that smart transportation systems may be improved with the help of ontology-driven sensor integration, which can reduce congestion and optimize vehicle flow via coordinated modifications to traffic lights, making roads safer for everyone.
Keywords: Vehicle, Traffic, Sensor, Transportations, Ontology.

I. INTRODUCTION

Interest in using cutting-edge technology to improve road safety and efficiency has been on the rise in recent years, thanks to the fast growth of ITS. The idea of smart transportation in particular has been getting a lot of buzz because of the revolutionary changes it may bring to the transportation industry, replacing antiquated systems with ones that are more user-cantered, intelligent, and adaptable. When it comes to improving traffic safety and efficiency, one of the most exciting new directions is the use of sensor technology backed by ontology-based systems. Sensor integration with ontologies for semantic knowledge representation allows for real-time fusion and interpretation of heterogeneous data streams, which improves decision-making for humans and machines alike. [1] There is a proliferation of sensors in today's transportation networks, found in a wide variety of vehicle, infrastructure, and mobile device kinds. These sensors record a wide range of information, including but not limited to: location, speed, road conditions, traffic patterns, weather, and driver behavior. [2] Nevertheless, processing and interpreting this sensor data may become complicated due to its sheer amount and variability. Smart transportation systems aren't making the most of their capabilities since there isn't a standard way to interpret and combine this data. Integrating based on ontologies is crucial in this context. With the help of ontologies, which provide a structured way to express domain-specific knowledge, computers can analyze sensor data, make conclusions, and work together with different types of systems. [3]

Integrating sensors based on ontologies enables meaningful data fusion by outlining the connections and context of different parts of the transportation system. It makes sure that sensor readings from various brands, formats, and communication protocols may be understood consistently. For instance, it's not uncommon for weather sensors mounted on traffic signal poles and temperature sensors in vehicles to gather comparable environmental data. As long as there isn't a shared semantic interpretation, this data could stay in pieces. In order to conduct a thorough evaluation of driving dangers, such as ice roads or foggy conditions, ontology may contextualize both sources and relate them to a common environmental state. Driving in safer and smarter surroundings is made possible by semantic data fusion, which allows for real-time decision-making, risk assessment, and adaptive control of infrastructure components and cars. [4] Smart transportation systems that integrate sensors based on ontologies not only help drivers have better situational awareness, but they also pave the way for fully autonomous and semi-autonomous vehicles. [5] These systems can comprehend complicated traffic situations, anticipate possible crashes, and implement preventative measures thanks to the real-time semantic interpretation of data collected by sensors. For instance, integrating proximity sensors, lane-keeping systems, and driver fatigue detectors through a common ontology can help detect a potential crash risk and issue timely alerts or corrective commands. Furthermore, these systems are capable of adjusting their actions in response to changing traffic conditions or the particular driving circumstances of a certain location, such construction zones, school zones, or heavily populated crossroads. [6]

Vehicles, traffic lights, emergency services, and pedestrians are just a few of the transportation ecosystem agents that benefit from the ontology-driven approach's enhanced communication and coordination capabilities. Important for both the smooth flow of information and the promptness of interventions, this coordination is known as Vehicle-to-Everything (V2X) communication. By using ontology-based models, these agents can communicate and understand data in a consistent way, which improves the reliability of automated choices by removing grey areas. This becomes even more crucial in scenarios where autonomous cars and human drivers coexist, known as mixed traffic. Ontologies ensure that all participants share a common understanding of road rules, traffic priorities, and safety protocols. [7]

Integrating sensors based on ontologies also helps with proactive safety management and predictive analytics, which are two big advantages. By analysing historical and real-time data within a semantic framework, transportation authorities can identify accident-prone areas, predict congestion patterns, and implement preventive measures such as dynamic traffic signalling, speed regulation, or route optimization. Ontologies also support scalability and customization, allowing transportation systems to adapt to specific regional or urban needs. For instance, a smart transportation system in a mountainous region may prioritize slope stability and weather data, while an urban system may focus on pedestrian movement and air quality. [8]

Despite its potential, the implementation of ontology-based smart transportation systems also presents several challenges. Developing comprehensive and universally accepted transportation ontologies requires extensive domain knowledge, collaboration among stakeholders, and continuous updates. The accuracy and reliability of sensor data are critical for effective ontology-driven reasoning. Inconsistencies, noise, or delays in sensor outputs may lead to incorrect inferences, which can compromise safety. Moreover, real-time processing of semantically rich data requires significant computational resources and robust communication infrastructure. Ensuring data privacy and cybersecurity in such interconnected systems is also an essential consideration, especially when dealing with personal information or critical transportation controls.[9]

Nevertheless, on-going research and technological advancements continue to improve the feasibility and effectiveness of ontology-based sensor integration in transportation. [10] Open-source ontology libraries, cloud computing, edge processing, and AI-driven reasoning engines are facilitating the adoption of these technologies in real-world scenarios. Governments and transportation agencies are increasingly investing in smart city projects that incorporate these concepts to improve road safety, reduce congestion, and lower emissions. In smart transportation through ontology-based sensor integration represents a significant step toward creating safer, more intelligent, and adaptive driving environments. By enabling meaningful interpretation and fusion of sensor data, ontologies bridge the gap between complex data streams and actionable insights. They support real-time decision-making, predictive analytics, and system-wide interoperability, which are crucial for the development of future transportation systems. [11] As urbanization accelerates and mobility demands rise, embracing ontology-driven smart transportation is essential for building resilient, responsive, and inclusive mobility networks that prioritize safety, sustainability, and efficiency.

II. REVIEW OF LITERATURE

Saafi, Nesrine&Dhouib, Karima. (2024) [12] A developing trend in urban planning is the increasing interconnection of city services, which means that more and more urban systems and services are being integrated and networked via data and technology. Smart city programs aim to optimize infrastructure and resource consumption in order to create more sustainable and efficient urban settings. We provide "TrafCsOnto," a traffic ontology that includes all sorts of traffic ideas, in this study. In the context of smart cities, reducing traffic congestion is the main objective of this ontology. With the help of the OWL language and the protégé tool, this ontology has been formalized. We make an effort to show how the traffic ontology may be used in practice by manipulating real-world examples and conclusions.

Hira,. (2023) [13] The goal of intelligent transportation systems is to provide a more streamlined driving experience by integrating various smart technologies. It is essential for these systems to work that cars can communicate data with various parts of the road network via various apps. In this study, we provide an ontology that allows each vehicle to experience independently. This interchange of traffic information and representation of knowledge utilizing the protégé can only operate inside an intelligent transportation system architecture that allows for complexity. The creation of an ontology in the ITS domain is being informed by methodologies that have been proposed and implemented for traffic density estimates.

Shakya, Harish et al., (2022)[14] A relatively recent technological development, intelligent transportation systems (ITS) aim to enhance transportation system performance and safety.Information sharing is a crucial part of intelligent transportation systems (ITS) since it allows cars to communicate with each other and with other ITS components on the road. However, for ITS data transmission and collection between cars and road segments, Internet of Things (IoT) sensors are crucial.

In order to drive safely in traffic, the data collection gives the most up-to-date information on traffic and weather. Nonetheless, electric vehicle (EV) integration with ITS has energy savings as one of its primary goals. To enhance the driving experience as a whole, we present an ontology-based design for electric vehicles that makes use of data gathered from an Internet of Things (IoT) sensor network. The system performs a variety of tasks based on data collected from Internet of Things (IoT) sensors to guarantee the driver's comfort and safety on the road. An Eclipse SUMO simulator is used to run the simulation, and the results are presented. According to the simulation findings, the suggested intelligent model outperforms current ITS models in terms of decision efficiency when considering both weather and traffic circumstances.

Fernández, Susel& Ito, Takayuki. (2018) [15] The goal of intelligent transportation systems is to improve road transport management via the provision of new services, the dissemination of more accurate information to users, and the promotion of more orderly and secure network use. For these systems to work, it is essential that cars can communicate with one another and with various parts of the road network via various apps. Sensors are a crucial part of these types of systems since they collect data. Bridges and traffic signs are examples of infrastructure elements that could have sensors. In order to enhance the driving experience, the sensor may give data pertaining to traffic and weather. To enhance the driving environment, this research proposes a multi-agent system that makes use of ontologies. Using data collected from sensors, the system carries out a number of operations automatically, all with the goal of improving the driver's safety and comfort.

Zhao, Lihua et al., (2015) [16] To ensure safe autonomous driving, it is essential to represent driving environment information in a structured machine-readable way. We enhance smart car safety by representing the knowledge of maps, drivingpaths, and driving surroundings using ontologies. To aid in the creation of ADAS, we provide the fundamental ontologies in this study. Smart car knowledge bases and other forms of advanced driver assistance systems may be built using the ontologies and expanded upon in the future.

Zhao, Lihua et al., (2014) [17] Advanced Driver Assistance Systems (ADAS) use Intelligent Speed Adaptation (ISA) and other technologies to help drivers stay under the speed limit and thereby minimize the number of incidents that occur on the road. Autonomous vehicles cannot sense their driving environments without context awareness, which is essential for representing information in a machine-understandable fashion. In order for computers to mimic human thinking, ontologies must be able to express knowledge in a way that computers can comprehend. In this study, we provide an ISA system that uses an ontology-based Knowledge Base (KB) to identify instances of overspeed. We used both simulated and real-world data acquired by an intelligent vehicle in our tests. To access the Knowledge Base, we transform sensor data into RDF stream data and build SPARQL queries and a C-SPARQL query. The results of the experiments demonstrate that the ISA system can quickly identify overspeed scenarios by consulting the Knowledge Base, which is built on ontologies.

III. MATERIAL AND METHODS

Four layers are recommended for the system. The road infrastructure has the sensor network layer, as shown in Figure 1. [18] These sensors measure traffic flow and weather. Sensor data is stored in a database on the second level. The ontology layer semantically processes raw data. We created a comprehensive ontology in the ontological layer to describe road traffic concepts including autos, infrastructure, sensors, and driver behaviors. We have also defined reasoning rules for the ontology and its relationships. In the last layer, agents do all essential procedures to improve driving. Agents interact with one other and the ontologies to complete tasks. [19]

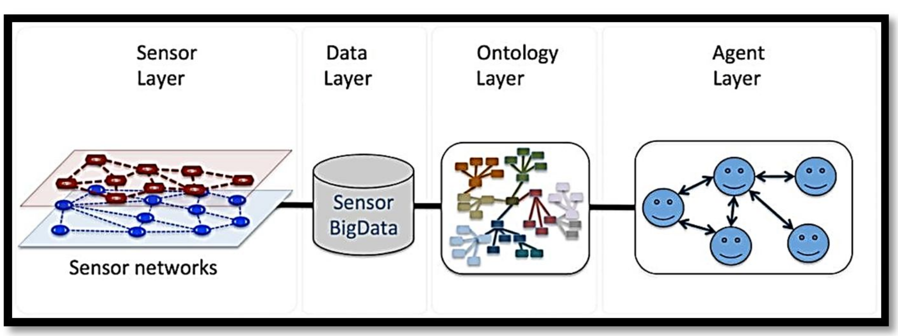

Figure 1.A System Architecture

Sensors, automobiles, weather components, and agents are hierarchically organized like holonic traffic architecture. [20]

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IV. RESULT AND DISCUSSION

We simulated traffic scenarios in multiple experiments. This experiment provides a simple approach to evaluate if traffic lights automatically synchronize their durations. [21] Figure 8 depicts a typical traffic scenario with four intersections and four traffic lights. The system uses vehicle location, speed, lane segment length, and traffic light duration to calculate when each vehicle arrives at its destination depending on the route. [22]

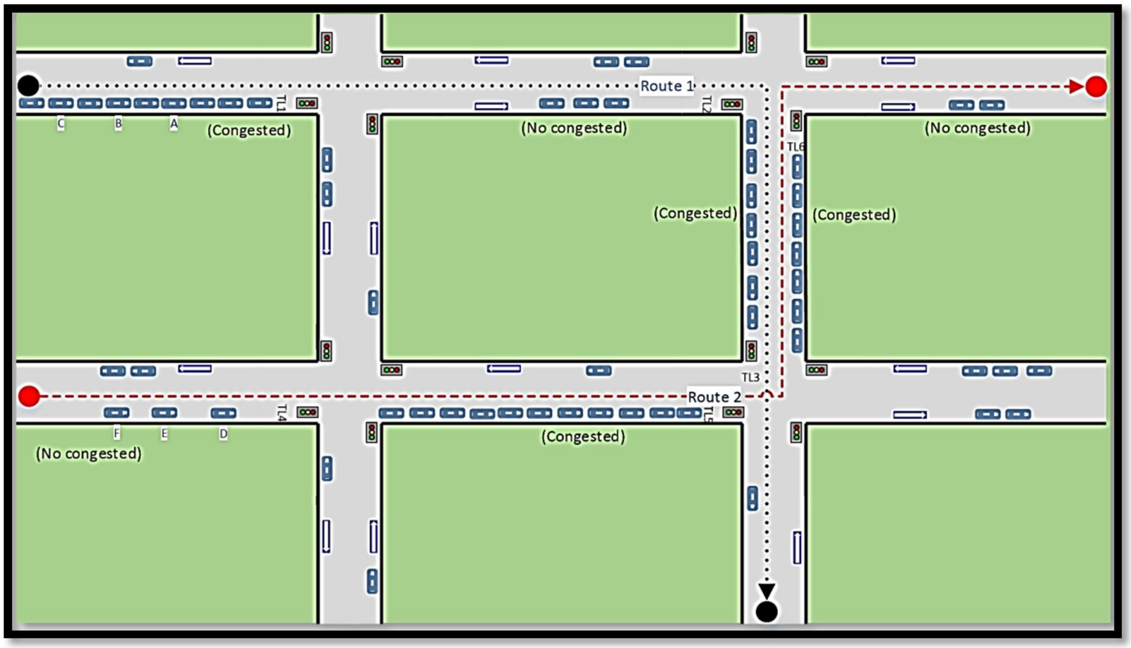

Figure 2.Example of traffic light length

Roads, lanes, traffic signs, and infrastructure are covered under the traffic ontology. [23] However, the SSN ontology gives sensor data. Agents obtain ontology information via SPARQL queries. [24]

In this example, black dotted lines indicate the first route while red dashed lines indicate the second. The figure shows automobiles A, B, and C on route 1 and D, E, and F on road 2. [25]

Table 1.Initial simulation traffic light and segment statuses setup.

S_{11}-TL1	S_{12}-TL2	S_{13}-TL3	S_{21}-TL4	S_{22}-TL5	S_{23}-TL6
Congested	Not congested	Congested	Not congested	Congested	Congested
Red	Red	Green	Red	Red	Green

Table 1 shows the beginning arrangement of the traffic lights and segment statuses for the experiment. Traffic fluctuated throughout the network. The traffic light on Segment S11-TL1 has gone red, indicating a traffic halt in a congested area. S12-TL2 is not blocked, however its signal is red, which may hinder travel even on clear routes. However, S13-TL3 is jam-packed but has a green signal, so traffic may move through a crowded area. This might improve or worsen congestion depending on downstream constraints. [26]

The second row of segments of S21-TL4 is uncongested and controlled by a red light, suggesting that road capacity is being misused. However, S22-TL5 is red-lighted owing to congestion, which may deter traffic on the overloaded portion. Finally, S23-TL6 is packed but has a green signal, suggesting a strategy to move traffic and remove the bottleneck.

In general, the first configuration uses a mix of management measures to restrict congestion increase and selectively allocate green lights to relieve congestion. [27]

Table 2.Vehicle travel time via road segments.

	Time with Traffic Light Duration Adjustment					Time with Default Traffic Light Duration				
	S11	S12	S13	S14	Sum	S21	S22	S23	S24	Sum
A	6 + 10 = 16	12	12	12	52	6 + 15 = 21	12 + 15 = 27	12 + 15 = 27	12	75
B	7.5 + 10 = 17.5	12	12	12	53.5	7.5 + 15 = 22.5	12 + 15 = 27	12 + 15 = 27	12	76.5
C	9 + 10 = 19	12 + 15 = 27	12 + 10 = 22	12	80	9 + 15 = 24	12 + 15 = 27	12 + 15 = 27	12	88
D	4.2 + 15 = 19.2	12 + 10 = 22	12 + 10 = 22	12	75.2	4.2 + 15 = 19.2	12 + 15 = 27	12 + 15 = 27	12	85.2
E	6 + 15 = 21	12 + 10 = 22	12	12	67	6 + 15 = 21	12 + 15 = 27	12	12	72
F	9 + 15 = 24	12 + 10 = 22	12	12	70	9 + 15 = 24	12 + 15 = 27	12	12	75

Table 2 displays automobile travel times on various route segments with altered traffic signal durations and default durations. [28] According to statistics, changing traffic signal lengths reduces travel time for all vehicle routes (A to F). With modified durations on Route A, automobiles save 23 seconds, reducing the journey time from 75 seconds to 52 seconds. Route B also improves, from 76.5 to 53.5 seconds. Route C improves less, from 88 to 80 seconds. Route D also improves somewhat, going from 85.2 to 75.2 seconds. The adjustment saves 5 seconds each route, therefore routes E and F are least impacted. [29] Our results imply that altering traffic light duration might improve travel efficiency, especially on routes with congestion or signal timing. Since these modifications are less evident on roads with fewer lights or busier parts, their efficiency may vary by route. [30]

Table 3.Simulation results showing percentages of vehicles experimenting and not experimenting time gains and average time improvements..

Number ofExperiments	Number ofVehicles	% Gain Time	Average Gained Time	% Not Gain Time
150	300	78%	134.52 s	22%

Table 3 summarizes simulation experiments and shows that traffic light length adjustments worked. Out of 300 automobiles examined in 150 trials, 78% noticed a reduction in travel time, confirming the improvements worked. [31] The average time gained of 134.52 seconds across these autos showed significant travel efficiency. Optimization benefited most automobiles, but 22% showed no time gain, suggesting it may not work for all traffic patterns or routes. The data demonstrate that adaptive traffic signal management saves time for most network vehicles. [32]

V. CONCLUSION

Finally, smart transportation systems that use ontology-based sensor technologies have tremendous promise for improving road safety and efficiency. Accurate, real-time decision-making, better situational awareness, and seamless communication among cars, infrastructure, and road users are all made possible by ontologies, which provide a structured semantic framework for understanding different and heterogeneous sensor data. In order to reduce hazards, avoid accidents, and improve traffic flow as a whole, this method makes sure that data gathered from different sources is standardized and used properly. These sources include traffic signals, in-vehicle sensors, weather stations, and road monitoring systems. In addition to bolstering conventional traffic management via the implementation of proactive safety interventions and dynamic responsiveness to road conditions, the use of ontology-based models bolsters the growth of semi-autonomous and autonomous driving systems. To fully reap the advantages of this technology, however, issues including data quality, standards, computing needs, and privacy concerns need to be resolved. Overcoming these challenges need ongoing research, stakeholder engagement, and investments in smart infrastructure. The creation of smart cities and sustainable urban development are overarching aims, and ontology-driven smart transportation play a crucial role in achieving these larger objectives by facilitating the construction of intelligent, inclusive, and safe mobility solutions.

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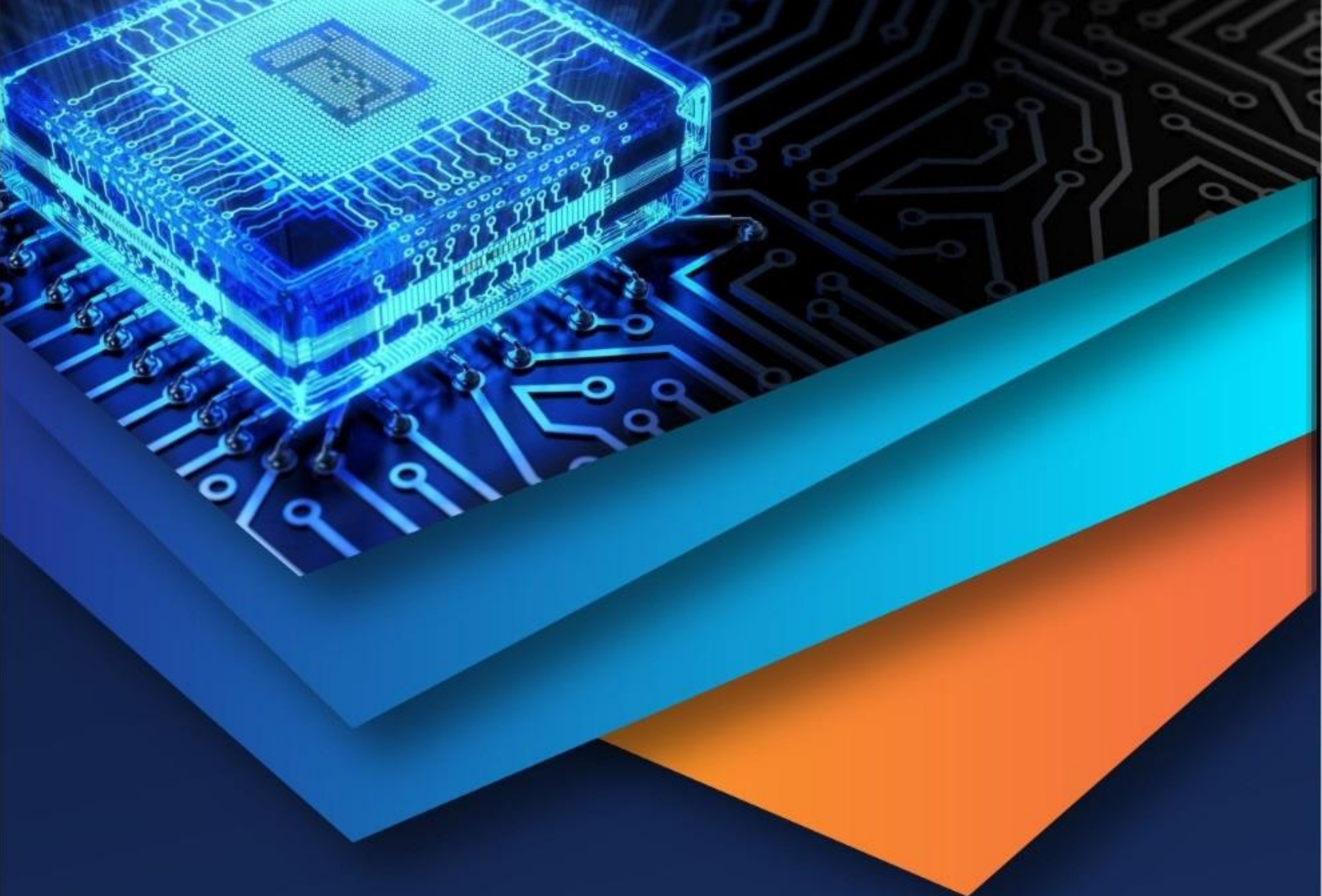

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