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Wildfire Detection : Review of Emerging Technologies and Methodologies

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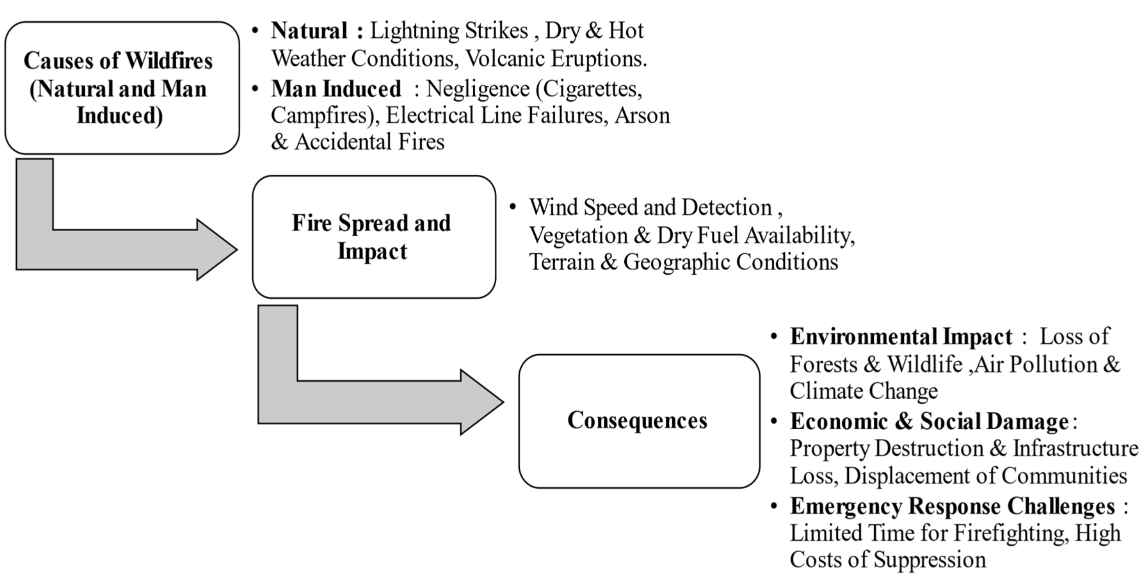
Abstract: Wildfires are uncontrolled fires that very quickly spread across forests, vegetation and grasslands powered or intensified by dry weather conditions, high temperatures and strong winds. These fires not only devastate ecosystems but also threaten human lives and infrastructure, which can lead to potential significant economic and environmental losses. With the climate change adding to their increasing frequency and intensity, the need for effective wildfire detection methods is becoming more crucial. Motivated on exploring solutions for this huge challenge in front of humans , in this study we explore the evolution of wildfire detection technologies, from traditional methods like manual surveillance to advanced systems incorporating satellite imagery, UAV (drones) monitoring, sensor networks, and analysis done by Artificial Intelligence. Each approach offers unique strengths and faces specific challenges, making it crucial to understand their roles in modern wildfire management. We explore how wildfire detection methods have developed over time, offering a clear and practical look at the various different solutions. By taking this approach, we hope to help spark fresh perspectives and inspire innovations potentially contributing to faster, more accurate and proactive wildfire detection strategies that help protect both natural ecosystems and human lives.

Keywords: wildfire, emerging, AI, satellite based monitoring, UAV surveillance.

I. INTRODUCTION

Wildfires were a natural phenomenon for centuries, but recent time has seen a sharp increase in their frequency and intensity due to climate change, urban human expansion, and other human activities. [[1], [2]]. The rapid spread of these fires not only endangers the natural ecosystems but also puts human life and property at risk [[3], [4]]. Early detection is therefore very crucial to mitigate these impacts, allowing for quick responses that can potentially help contain, control and extinguish fires before they can become uncontrollable [[5], [6]].



(Fig. 1 - Causes and Consequences of Wildfires The Need for Early Detection)

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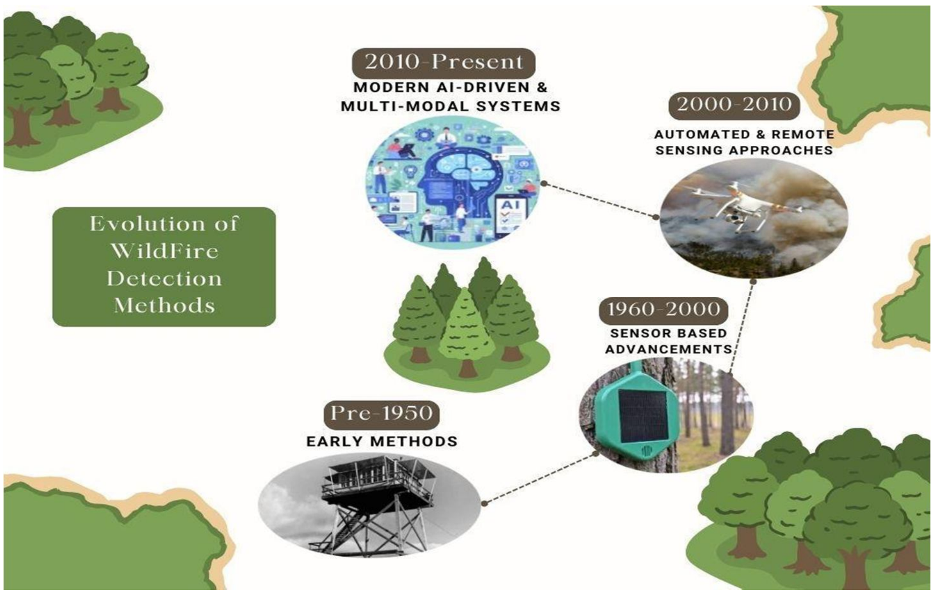
Historically, wildfire detection relied on human observation, which was fire lookout towers and ground patrolling [[7]]. Early sensor networks were very innovative and effective at that time, however they were limited by their slow response times and limited localized coverage [[5], [6]]. For instance, early systems often used basic thermal sensors or simple smoke detectors that could trigger false alarms under adverse weather conditions [[8]].

Rapid advancements in the technology over the past twenty years have revolutionized this field of study [[9], [10]]. The integration of satellite remote sensing [[11], [12], [13]], UAV (drones) technology [[14], [9], [15], [16]], and artificial intelligence [[17], [18], [19], [20]] has enabled the development of sophisticated, intelligent and automatic wildfire detection systems. These modern methods increase the speed of detection and also improve accuracy by analysing the vast amounts of data from multiple data sources [[14],[21] , [22]]. This review categorizes wildfire detection approaches into four main types: satellite-based detection, UAV-based detection, sensor network-based detection, and AI-driven methods. In doing so, we try to provide a detailed analysis of how each technology contributes to modern wildfire detection and discuss the evolution from traditional methods to the current state-of-the-art solutions [[23], [15], [24]].



(Fig. 2 - Evolution of wildfire detection methods)

II. GAPS AND CHALLENGES

Despite the significant progress made several key challenges continue to affect the efficiency and reliability of wildfire detection systems.

Challenge	Description	Potential Solution
False Positives	Incorrect detections waste time, resources and causes unnecessary alarms.	Improve AI models with diverse datasets & better training on existing data.
Real-time Processing	Delays in the detection reduce effectiveness in wildfire control.	Use of edge computing & optimized ML models for faster processing.
Limited Data	Lack of diverse training datasets can reduce the detection accuracy.	Utilize synthetic data & crowdsourced wildfire reports.
Environmental Factors	Smoke, fog, and cloud cover affect sensor accuracy.	Implement multi-sensor fusion & AI-based filtering techniques.
Costs	High costs make large-scale wildfire detection difficult.	Use of open-source AI models & cloud-based solutions to make it accessible.

(Fig. 3 - Gaps and Challenges in Detection of wildfire)

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A. *False Positives and False Negatives*

One of the major issues in wildfire detection is the occurrence of the false alarms. Many systems, particularly those that are based on the optical sensors, have hard time distinguishing between wildfire smoke and other occurrences such as industrial emissions, dust storms, or even fog [[25], [26]]. Such misclassifications not only lead to unnecessary emergency responses but also damage the credibility of detection systems. Although AI models have improved discrimination capabilities, optimizing them for diverse environmental conditions remains a critical research challenge [[27] ,[19]].

B. *Real-time Processing*

For wildfire detection systems to be truly effective, they must operate in near real-time state. This requirement is very critical in remote areas where rapid response means the difference between a minor incident and a huge disaster. However, high-resolution satellite images and data from UAVs often involve large data volumes that require intensive computational resources for processing and analysis [[21], [28]]. A significant challenge, especially in old legacy systems is the delay between capturing the data and deriving the actionable insights[13].

C. *Data Availability and Labelling*

AI-driven approaches depend heavily on large, accurately labelled datasets to train robust machine learning models. Unfortunately , obtaining such datasets in the context of wildfire detection is quite a challenging task. Wildfires are unpredictable events which can occur anytime , and gathering a comprehensive dataset that captures all possible scenarios with varying intensities, weather conditions, and geographic features—is a tedious task [[29], [30]]. To address this challenge, researchers are exploring synthetic data generation and transfer learning, yet the lack of high-quality datasets remains a significant obstacle[31].

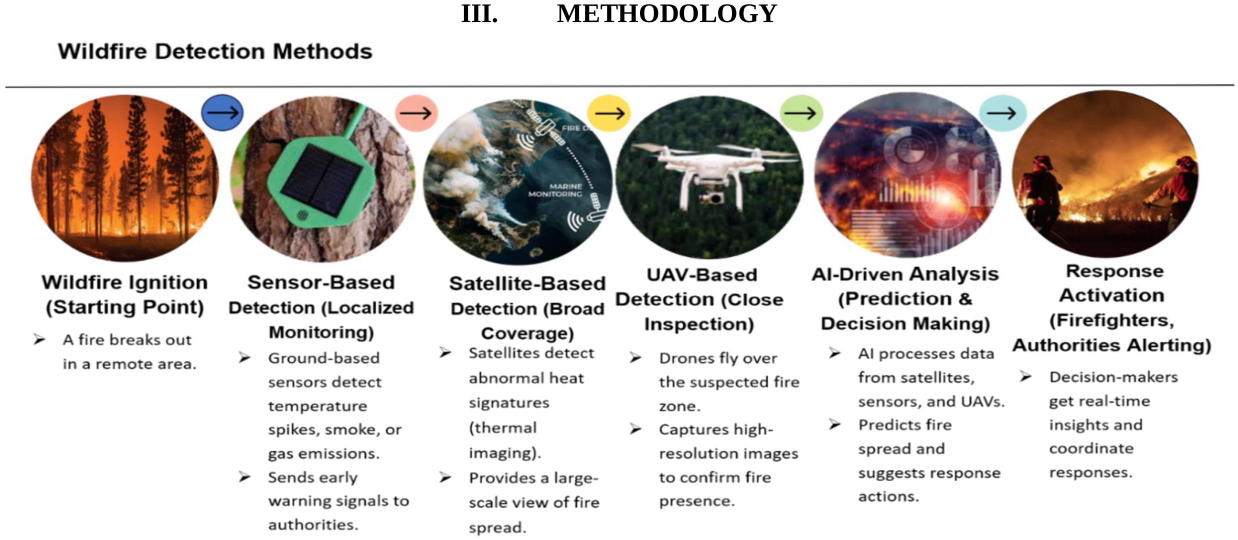
D. *Energy Efficiency*

Managing the energy consumption is very crucial for the efficiency and lifespan of sensor-based systems and UAV operations . Many of these devices operate on limited battery power, and extended deployment of these devices require efficient energy management techniques[[32],[10]].Improving energy efficiency without compromising detection accuracy is essential, particularly for systems intended for long-term monitoring in remote or inaccessible areas [[1],[33]].

E. *Integration and Standardization*

Another significant challenge is the integration of various detection technologies into a one unified system. Currently, many wildfire detection solutions operate in isolation. Satellite-based systems, UAVs, and ground sensors often use different data formats and communication protocols [[34], [7]]. This lack of standardization hampers the ability to combine data from multiple sources, which is essential for creating a comprehensive situational picture. Developing standardized frameworks and interoperability protocols is vital for enhancing the overall efficiency and responsiveness of wildfire monitoring systems [[1], [35]].

III. METHODOLOGY



(Fig. 4 - Wildfire Detection Methodologies and Their Workflow)

A. *Sensor based Systems*

Ground-based sensor systems make up for a critical component of the wildfire detection system. Wireless sensor networks (WSN's) and IOT based services help monitor the environmental conditions[[32],[10],[4]].

1) *Distributed Monitoring* **:** Sensors can be deployed across large areas to continuously monitor the temperature, humidity, gas concentrations, and other indicators of fire. This distributed network provides granular data that can be used to detect early signs of wildfire ignition [[5]].
2) *IoT Integration* : The advent of the Internet of Things (IoT) has further enhanced the sensor networks by enabling real-time data transmission and cloud-based analytics. These systems can alert authorities almost instantly when abnormal conditions are detected [[7]].
3) *Limitations* : Sensor networks face challenges such as limited range, the need for regular maintenance, and potential damage from extreme weather or fire events. Additionally, the cost of deploying and maintaining a dense sensor network across vast areas can be prohibitive [[32], [4]].

B. *Satellite based Detection*

Satellite imagery has transformed wildfire detection by providing extensive coverage and constant frequent updates. Modern satellites like Landsat-8 and Himawari-8 are equipped with advanced sensors that can detect thermal anomalies, making it possible to identify active fires [[11], [12],[37]].

1) *Global Coverage and Monitoring* **:** Satellite systems offer the advantage of monitoring vast regions, making them ideal for detecting wildfires in remote or inaccessible areas. Geostationary satellites provide near-continuous coverage, while polar-orbiting satellites deliver high-resolution images at regular intervals [[2], [11]].
2) *Advanced Imaging Techniques* **:** Modern satellites use a combination of visible, infrared, and thermal imaging to detect fires. These multi-spectral approaches enable the differentiation between fire and non-fire events. In addition, recent developments in machine learning have facilitated the automated processing of satellite images to identify potential wildfires more quickly [[38], [12]].
3) *Limitations* **:** Despite these advances, satellite-based detection is not without its limitations. Cloud cover, atmospheric disturbances, and the temporal resolution of satellite passes can delay detection. Moreover, the volume of data generated requires significant processing capabilities, which can introduce further delays in real-time.applications[[13],[35]].

C. *UAV-based Detection*

Unmanned Aerial Vehicles (UAVs) have emerged as a flexible and effective tool for wildfire detection. Equipped with high-resolution cameras and thermal sensors, UAVs can provide real-time aerial views of fire-prone areas [[14], [16]].

1) *Real-time Aerial Surveillance :* UAVs can rapidly deploy to areas of interest, offering real-time insights that are critical during the early stages of a wildfire. Their mobility allows them to reach areas that are too hazardous or inaccessible for human responders[[9],[26]].
2) *Integration with Deep Learning* : Recent research has integrated UAVs with deep learning models, such as YOLO and Faster R-CNN, to automatically identify and track fires from the air. This integration enhances detection accuracy and speeds up the decision-making process by reducing the reliance on human interpretation [[30], [39]].
3) *Operational Limitations* : The effectiveness of UAVs is sometimes constrained by limited battery life, weather conditions, and regulatory restrictions regarding airspace usage. Addressing these challenges is crucial to unlocking the full potential of UAV-based wildfire detection [[9], [16]].

D. *AI Driven Approaches*

In recent years, the application of deep learning and artificial intelligence (AI) has revolutionized wildfire detection. Advanced algorithms can process large datasets from various sources and identify fire signatures with high accuracy [[18],[24], [17]].

1) *Automated Recognition :* Deep learning models such as YOLOv3, Faster R-CNN, and LSTMs have been successfully applied to both satellite imagery and UAV-captured video to automate the detection of fire and smoke. These models learn complex patterns and can differentiate between actual fire events and false alarms [[40], [17], [25]].
2) *Data Fusion* **:** AI-driven systems are now being designed to integrate data from multiple sources—combining satellite images, UAV footage, and ground sensor readings—to create a comprehensive view of wildfire activity. This multi-modal approach significantly improves detection accuracy and response times [[14], [21], [22]].

3) *Computational Challenges* : Despite their promise, deep learning approaches require significant computational resources and large, annotated datasets for effective training. The development of lightweight models that can operate on edge devices is an ongoing area of research [[18], [33], [20]].

Method	How it works	Strengths	Limitations	Real World Use
Sensor	Ground sensors measure temperature, humidity, smoke, and gases linked to fire outbreaks.	Ground sensors measure temperature, humidity, smoke, and gases linked to fire outbreaks.	Only covers small areas, needs many sensors for accuracy, and requires maintenance.	Installed in wildfire-prone forests to send early fire alerts.
Satellite	Satellites scan vast areas using thermal imaging and sensors to spot heat and smoke.	Covers large regions, provides continuous updates, and helps in early detection.	Data can be delayed, weather conditions may interfere, and image resolution is sometimes low.	Used by agencies like NASA and NOAA to track wildfires globally.
UAV/Drone	Drones fly over at-risk areas, capturing real-time images with thermal and optical cameras.	Provides high-resolution images, rapid response, and can reach remote locations.	Limited flight time, costly for large-scale monitoring, and requires trained operators.	Fire departments use drones for situational awareness and search-and-rescue efforts.
AI (Deep Learning and Computer Vision)	AI processes images from satellites, drones, or sensors to identify fire patterns.	Fast and accurate detection, integrates multiple data sources, and continuously improves.	Needs large amounts of data for training, can be expensive, and may produce false alarms.	AI-powered fire detection in surveillance cameras and automated firefighting systems.

(Fig. 5 - Comparison of Wildfire Detection Methodologies)

IV. CONCLUSION

The evolution of wildfire detection methods—from manual observation and early sensor networks up to sophisticated AI-powered systems—demonstrates a significant advancement in our ability to monitor and respond to the wildfires. Modern detection systems now integrate satellite imagery, UAV-based surveillance, ground sensors, and deep learning models to provide near real-time detection and improved accuracy. However, despite these advancements, several challenges continue to persist. Issues such as false positives, real-time processing limitations, data scarcity, energy efficiency, and the lack of standardized integration frameworks throughout the world continue to affect the performance and reliability of wildfire detection systems.The future research in wildfire detection can benifit by exploring several key areas to enhance the efficiency and reliability of the systems. One important aspect is the development of multi-modal integration, in which standardized platforms can seamlessly combine the data from satellites, UAVs, and ground sensors. Using this integration will be vital in making a unified and comprehensive wildfire monitoring system. Also since acquiring diverse and annotated wildfire datasets remains a challenge, leveraging synthetic data generation and transfer learning techniques can help address data scarcity in turn improving the accuracy of AI-driven detection models. Energy-efficient design is also a very critical factor, particularly for sensor networks and UAVs used in remote locations. Advancements in battery management and low-power sensor technology will be very essential to ensure the continuous and long-term monitoring without their frequent maintenance or power limitations. Additionally, real-time analytics should be enhanced to accelerate decision-making in wildfire detection. And finally, the standardization and interoperability of various detection systems must be prioritized. Establishing universal data-sharing protocols and integration frameworks can allow different technologies to work together, improving coordination and creating a more effective wildfire management strategy. Addressing these research areas will be helpful in advancing wildfire detection capabilities and minimizing their devastating impact.

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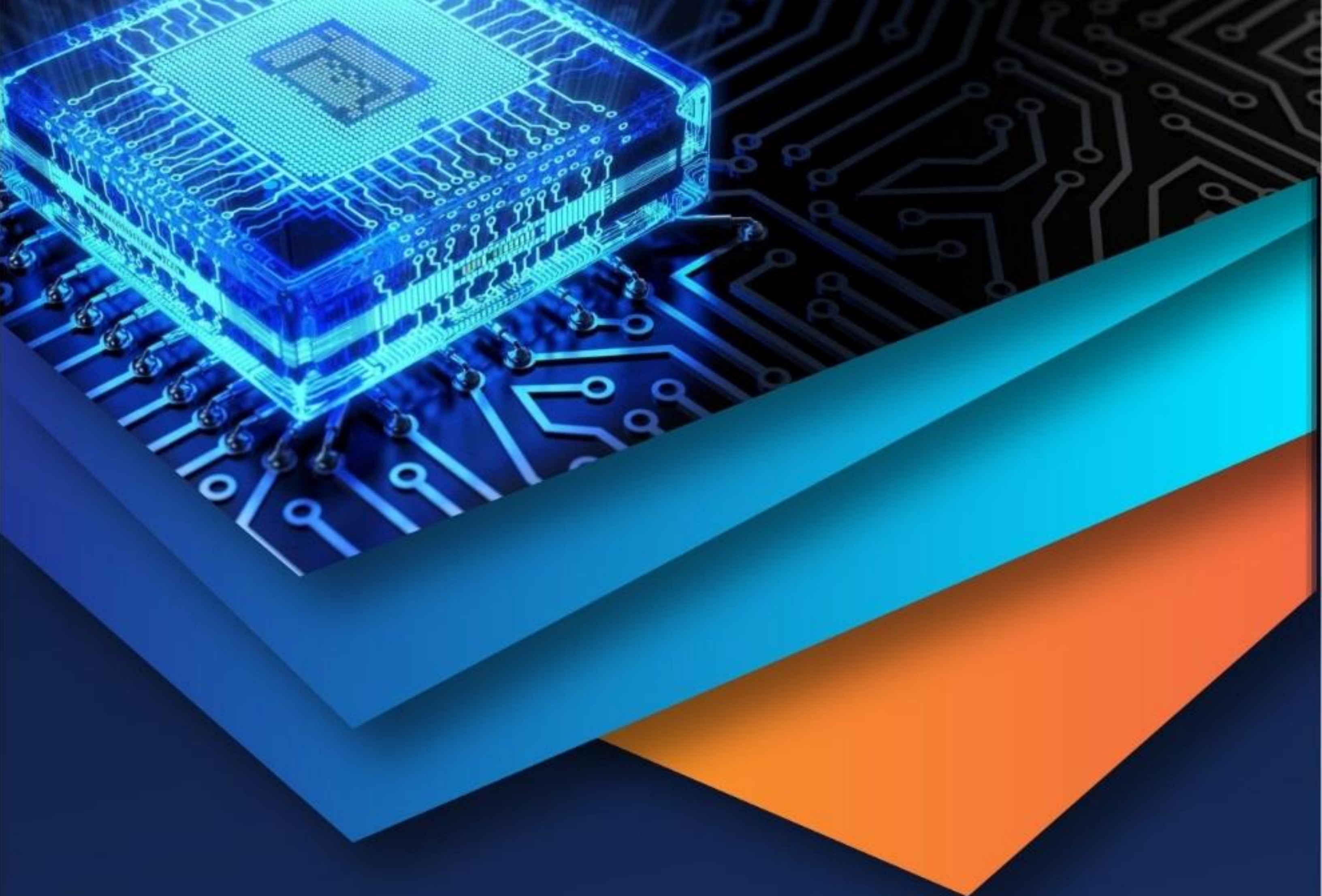

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