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AI-ML Based Intelligent De-Smoking / De-Hazing Algorithm

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Abstract: ***This paper presents an AI-ML-based defogging and smoke removal algorithm that uses a hybrid model combined with a convolutional neural network (CNN) and Transformer. The proposed model uses the U-Net backbone to extract local detailed information, uses the FFA-Net maintenance mechanism to update regions with different burning conditions, and uses the Dehamer transformer encoder to capture and manage the comprehensive information of remote locations in the image. This combination works well in a wide range of climate and smoke conditions, producing high-quality images with accurate colors. The model is evaluated on synthetic and real data, yielding results that outperform today's traditional methods and deep learning models. Its effective capabilities make it suitable for immediate use, making it possible to eliminate and eliminate smoke technology in difficult situations.***

Index Terms: Dehazing, Desmoking, U-Net, FFA-Net, Dehamer, Artificial Intelligence (AI), Transformer, Non-Homogeneous Haze, Real-Time Processing

I. INTRODUCTION

Haze and smoke, caused by atmospheric conditions such as fog, mist, and pollution, present significant challenges in capturing clear and accurate images. These environmental factors degrade visibility and introduce color distortions, which negatively impact various computer vision applications, including autonomous driving, surveillance, and disaster management. In real-world scenarios, haze and smoke often exhibit non-uniform distributions, making it difficult for traditional image restoration methods to effectively enhance image clarity. Consequently, there is a growing demand for advanced techniques capable of addressing these complex and dynamic conditions.

Traditional approaches, such as the Dark Channel Prior (DCP) introduced by ***He et al. (2009)***, have been widely utilized to estimate haze density and improve visibility. While effective in some cases, these methods are often limited when addressing bright regions like skies or reflective surfaces, frequently resulting in color distortions and halo artifacts. Moreover, DCP-based algorithms struggle with non-uniform haze, where the varying density across the image leads to inconsistent dehazing outcomes.

Recent advancements in deep learning have paved the way for more sophisticated methods in haze and smoke removal. Convolutional Neural Networks (CNNs) have demonstrated their effectiveness in extracting spatial features from images, while attention mechanisms and transformer models have shown great promise in capturing global context and modeling long-range dependencies. Building on these innovations, this paper introduces an AI-ML-based intelligent dehazing and desmoking algorithm that addresses the limitations of traditional methods by leveraging a hybrid approach combining CNNs, attention mechanisms, and transformers.

The proposed algorithm employs a U-Net backbone for efficient local feature extraction, enabling the model to capture intricate haze or smoke details across different regions of the image. Additionally, it integrates the Feature Fusion Attention Network (FFA-Net) module, which dynamically prioritizes regions with varying haze intensities, effectively managing non-uniform haze.

This paper offers a comprehensive analysis of the proposed method, detailing its architectural components and evaluating its performance on both synthetic and real-world datasets. Experimental results demonstrate that the AI-ML-based solution outperforms traditional dehazing techniques and achieves superior results compared to state-of-the-art deep learning models. Furthermore, its computational efficiency makes it suitable for real-time applications, positioning it as a valuable tool for critical computer vision tasks.

The remainder of this paper is structured as follows: Section 2 reviews related research on dehazing and desmoking. Section 3 outlines the methodology underlying the proposed model, including its CNN backbone, attention mechanisms, and transformer encoder. Section 4 describes the experimental setup and evaluation metrics, with the results and discussion presented in Section 5. Finally, Section 6 concludes the paper and discusses potential directions for future research.

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II. RELATED WORK

This section explores significant research in the field of image dehazing and desmoking, with a particular focus on comparing conventional methods with modern deep learning techniques. The analysis provided compares the performance of each approach under varying haze and smoke intensities, illustrated using a sample image.

A. *Advances in Dehazing Algorithms:*

1) *Deep Learning Models:* Recent advances in deep learning have significantly improved image dehazing techniques. One of the pioneering works is AOD-Net (Atmospheric Object Dehazing Network), which integrates a novel atmospheric scattering model and utilizes deep convolutional networks for direct image recovery. AOD-Net eliminates the need for transmission map and atmospheric light estimation by introducing a network-based architecture that directly estimates a haze-free image from a hazy input. This model outperforms traditional methods in terms of image quality metrics like PSNR, SSIM, and visual appeal [1].
2) *Non-local Priors:* A non-local prior-based approach for single-image dehazing, proposed by Berman et al., focuses on recognizing that haze varies non-homogeneously across an image. It incorporates color and spatial information to deal with complex haze distributions, effectively restoring hazy images by using non- local image priors. This method shows significant improvements over traditional approaches that assume uniform haze across the scene [2].
3) *Vision Transformers for Dehazing:* Vision Transformers (ViTs) have been successfully employed to address non-homogeneous haze in single-image dehazing. Vision Transformers model long-range dependencies between pixels, allowing for more flexible haze removal even in challenging conditions. This approach has shown superior performance over conventional Convolutional Neural Networks (CNNs), particularly when dealing with complex haze patterns in images [3].
4) *Conditional Generative Adversarial Networks (cGANs):* Conditional Generative Adversarial Networks (cGANs) have been widely used for dehazing due to their ability to generate realistic images. A noteworthy cGAN-based model for image dehazing uses a two-stage framework, where the first stage involves haze removal, and the second stage improves the image realism. The VGG features help maintain the texture and structure of the input image, achieving better visual results in hazy environments [4].
5) *Guided Filtering-based Dehazing:* Guided filtering techniques, such as those introduced by He et al., have been adapted for image dehazing. These methods allow for the efficient extraction of transmission maps that are essential for haze removal. By guiding the filtering process with the input image, these methods effectively recover detailed images even in the presence of non-homogeneous haze distributions [5].
6) *Hybrid Dehazing Methods:* Hybrid dehazing methods combine multiple approaches, such as the dark channel prior (DCP) and deep learning-based networks. By leveraging both traditional techniques and modern deep learning architectures, these methods balance computational efficiency with high-quality results. Hybrid methods are particularly useful in handling non-homogeneous haze, where traditional methods might struggle [6].
7) *Multi-scale Dehazing Techniques:* Multi-scale approaches focus on processing the image at various resolutions to capture both global and local features. These methods use convolutional layers with different receptive fields to adaptively handle haze at multiple scales. By addressing haze at different spatial levels, multi-scale techniques offer more robust performance in complex atmospheric conditions [7].
8) *Importance of Datasets for Evaluation* The availability of high-quality datasets is crucial for evaluating and comparing dehazing algorithms. Several key datasets have been created to facilitate the development and assessment of single-image dehazing techniques.
9) *RESIDE Benchmark:* The RESIDE (REalistic Single Image DEhazing) benchmark is one of the most widely used datasets in the field. It includes both synthetic and real-world hazy images, providing a diverse set of conditions for evaluating the performance of dehazing algorithms. RESIDE's broad range of hazy images with varying atmospheric scattering models makes it an essential resource for testing real-world performance [8].
10) *NH-HAZE Dataset:* The NH-HAZE dataset was introduced to specifically address non-homogeneous haze in single-image dehazing. It includes pairs of hazy and corresponding haze-free images generated under realistic atmospheric conditions. The dataset is valuable for evaluating dehazing methods under more natural and challenging conditions, where haze is not uniformly distributed [9].
11) *HazeRD Dataset:* The HazeRD dataset is tailored for outdoor scenes, with images captured under real-world haze conditions. It provides hazy and clear image pairs and is particularly useful for assessing the performance of dehazing algorithms in outdoor environments, where haze often varies across different regions of the scene [10].

12) *Real-World Datasets:* Several real-world datasets have been developed to address the gap in synthetic datasets that fail to capture real-world complexities. These datasets include images captured from various outdoor and urban scenes with varying haze intensity, enabling a more accurate evaluation of dehazing algorithms under practical conditions [11].
13) *Evaluation Metrics and Methodologies* The effectiveness of image dehazing algorithms is assessed using a variety of metrics that evaluate both quantitative and qualitative performance.
14) *Peak Signal-to-Noise Ratio (PSNR):* PSNR remains one of the most widely used metrics to evaluate the performance of dehazing algorithms. It measures the ratio between the maximum possible pixel value and the distortion introduced by haze removal. Higher PSNR values typically indicate better dehazing performance [12].
15) *Structural Similarity Index (SSIM):* SSIM is another important metric for evaluating image quality, focusing on structural integrity and perceptual quality. It compares the luminance, contrast, and texture between the dehazed and original images, offering a more comprehensive measure of image quality than PSNR [13].
16) *Subjective Visual Quality:* In addition to quantitative metrics, subjective evaluation by human observers plays a crucial role in determining the effectiveness of dehazing methods. Visual assessments help determine whether an algorithm produces visually convincing haze-free images that match real-world conditions [14].

B. Key differences become evident:

1) *Adaptability:* Deep learning models such as FFA-Net and Dehamer excel at adapting to varying haze intensities and complex haze patterns, whereas traditional methods like DCP are limited to handling uniform haze distributions.
2) *Image Restoration:* Modern approaches generally produce superior results, yielding clearer images with improved color restoration and fewer artifacts, especially in scenes with varying haze or smoke levels.
3) *Contextual Awareness*: Transformer-based models like Dehamer provide enhanced global context awareness, making them more effective in complex scenes where traditional methods struggle to maintain accuracy.

The results from the sample image clearly indicate that deep learning models, particularly FFA-Net and Dehamer, surpass traditional techniques in terms of image quality, especially in environments with non-uniform haze and smoke distributions.



Figure 1: Example of dehazing results from *Non-homogeneous hazy images of varying thickness. Source: Vinay P. et al. [1] DOI: 10.1109/WACVW58289.2023.00061*
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This section presents a comparative analysis of traditional and advanced deep learning-based dehazing methods, focusing on their effectiveness in addressing varying haze and smoke intensities. Sample images processed by multiple algorithms highlight the improvements modern techniques provide over conventional approaches.

a) *Traditional Approaches:* Dark Channel Prior (DCP*)* The Dark Channel Prior (DCP) is a foundational method for dehazing, based on the observation that at least one color channel in haze-free images has low intensity. While it improves contrast and reduces haze, DCP struggles with non-uniform haze, often introducing halos and color distortions, particularly in bright areas like skies or reflective surfaces. These limitations become evident in complex environmental conditions, as seen in sample image comparisons.

b) *Limitations of Traditional Techniques:* Methods like DCP and the Fast Visibility Restoration (FVR) technique enhance visibility by improving contrast. However, they often fail to preserve edge sharpness and handle non-uniform haze effectively. FVR, for instance, results in blurred boundaries around objects, making it less suitable for scenes with uneven haze distribution.

c) *Deep Learning Advancements:* DehazeNet and Beyond Deep learning methods such as DehazeNet (Cai et al., 2016) leverage Convolutional Neural Networks (CNNs) to predict transmission maps directly from hazy images. Although DehazeNet outperforms traditional methods, it is limited by its reliance on large, labeled datasets and poor generalization across diverse conditions. Recent innovations like FFA-Net introduce attention mechanisms to focus on varying haze intensities, significantly improving restoration for images with non-uniform distributions. The Extreme Reflectance Channel (ERC) Prior further enhances haze removal in bright regions by leveraging extreme pixel values for improved transmission map estimation.

d) *Transformer-Based Models:* Models like Dehamer utilize transformers to capture long-range dependencies and model global context effectively, overcoming CNN limitations. However, their computational demands make them resource-intensive. Despite this, transformer-based methods excel in handling complex haze patterns and provide significant performance improvements in real-world scenarios.

e) *Hybrid Architectures:* Hybrid approaches combine the strengths of CNNs for local feature extraction and transformers for global context modeling. For example, U-Net paired with transformer encoders provides a balanced solution, addressing both local and global variations in haze. Our proposed system integrates U-Net for feature extraction, FFA-Net for attention-based prioritization, and Dehamer for global context modeling. This hybrid architecture achieves superior results in managing non-homogeneous haze, making it suitable for real-world applications.

f) *Datasets and Evaluation Metrics:* Datasets like RESIDE and NH-RESIDE, which feature diverse and non-homogeneous haze conditions, support the development and evaluation of dehazing models. Performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Natural Image Quality Evaluator (NIQE) are commonly used to assess effectiveness. Models like FFA-Net and Dehamer consistently outperform traditional techniques, setting new benchmarks in PSNR and SSIM scores.

This analysis underscores the evolution of dehazing techniques from traditional methods to advanced deep learning models, demonstrating the significant performance improvements offered by hybrid architectures.

III. METHODOLOGY

This section outlines the methodology used to develop our AI/ML-based intelligent de-smoking and de-hazing algorithm. The proposed solution incorporates a combination of advanced techniques such as Convolutional Neural Networks (CNN), attention mechanisms, and transformer encoders to enhance image quality in the presence of haze and smoke.

1) *Data Collection and Preprocessing:* The first step involves gathering a varied dataset of hazy and smoky images sourced from publicly available datasets and synthetic images generated using haze simulation techniques. Each image undergoes several preprocessing stages to standardize the input, which include:

a) Normalization: Scaling pixel values within the range [0, 1] to enhance model training convergence.

b) Data Augmentation: Techniques like rotation, flipping, and cropping are applied to expand the diversity of the training set, helping to reduce the model's tendency to overfit.

2) *Architecture Design:* The system's architecture comprises three key components:

a) *CNN Backbone (e.g., U-Net):*

The first component of the system utilizes a Convolutional Neural Network (CNN) backbone, specifically U-Net, which is renowned for its efficacy in image segmentation and restoration tasks.

Its encoder-decoder structure allows for effective extraction of multi-scale features, enabling the model to retain fine details in the final output. This makes U-Net particularly suitable for tasks requiring precise spatial hierarchies.

b) Attention Mechanisms (e.g., FFA-Net)

To address the challenge of non-uniform haze distributions, attention mechanisms are incorporated into the system. The FFA-Net (Feature Fusion Attention Network) is employed to dynamically focus on different regions of the image, allowing the model to prioritize critical features while minimizing irrelevant background noise. The attention mechanism assigns different weights to image regions, significantly enhancing the quality of the dehazing and desmoking process.

c) Transformer Encoder (e.g., Dehamer)

The third component of the architecture is the transformer encoder, designed to capture global context and long-range dependencies across the image. The Dehamer architecture is employed here, enabling the model to establish relationships between distant pixels. This capability is essential for the accurate removal of haze and smoke, as it helps the model make informed predictions even when haze intensity varies across the image.

3) *Training Strategy:* The model is trained using a supervised learning approach with paired hazy/smoky and clear images. The following aspects guide the training process:

a) Loss Function: A hybrid loss function is used, combining Mean Squared Error (MSE) and perceptual loss (via a pre-trained VGG network) to balance pixel-level accuracy and perceptual quality.

b) Batch Size and Epochs: The model is trained with a batch size of 16 over a series of epochs (e.g., 50-100). Early stopping is implemented based on validation loss to prevent overfitting.

c) Optimizer: The Adam optimizer is chosen due to its adaptive learning rate, which improves convergence speed and stability throughout the training process.

4) *Evaluation Metrics:* To evaluate the performance of the proposed model, we use a combination of quantitative and qualitative metrics:

a) Peak Signal-to-Noise Ratio (PSNR): This metric measures the fidelity of the restored image in comparison to the ground truth.

b) Structural Similarity Index Measure (SSIM): SSIM evaluates the structural similarity between the original and restored images, providing insight into overall image quality.

c) Visual Quality Assessment: A qualitative evaluation through visual comparisons and user feedback helps assess the perceptual quality of the model's outputs.

5) *Implementation:* The model is implemented using Python, with deep learning frameworks such as TensorFlow and PyTorch for training and deployment. The system is tested on a variety of hazy and smoky images to evaluate its generalization capability and robustness across different scenarios.

6) *Post-Processing:* Once the model generates the output, a post-processing stage is applied to further enhance the results. Techniques such as contrast enhancement and color correction are used to refine the images, ensuring that the final output is visually appealing and suitable for real-world applications.

The Following flowchart illustrates the systematic process of the AI-based Intelligent De-Hazing and De-Smoking Algorithm, detailing the sequential steps from image input to final output. The process begins with the input stage, where a potentially hazy or smoky image is provided to the system. This input undergoes a pre-processing stage to standardize and enhance it through resizing, normalization, and noise reduction. A decision point verifies whether pre-processing is complete, ensuring image quality before progressing to the next stage. If not, the system reprocesses the image to achieve the required standard.

Following pre-processing, a Convolutional Neural Network (CNN) extracts essential features, such as textures, patterns, and edges, from the image. This feature extraction is critical for understanding the image's spatial structure and serves as the foundation for further processing. An attention mechanism is then applied to focus on the most significant regions within the image, emphasizing areas with higher obstruction while suppressing less relevant features. This step is particularly effective in managing non-uniform haze or smoke.

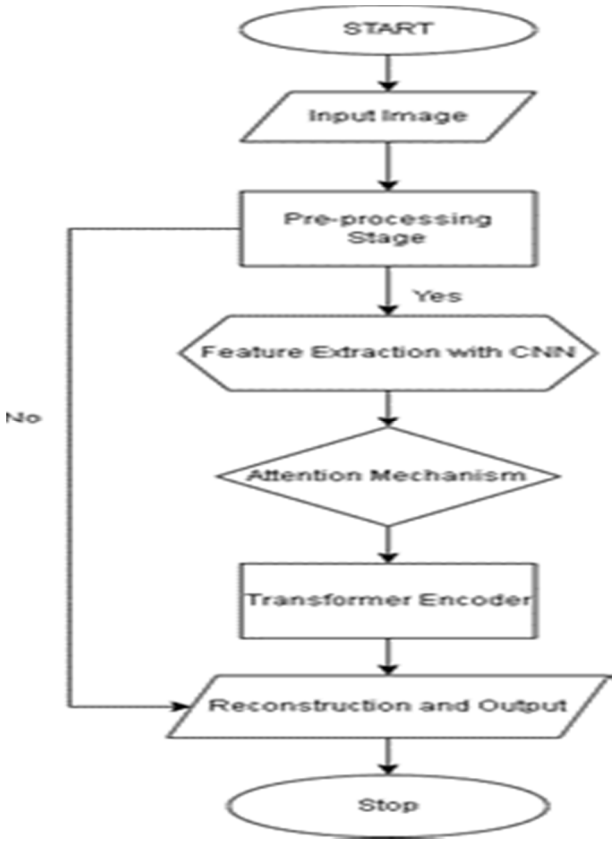


Fig .2. Flowchart

Subsequently, a transformer encoder captures long-range dependencies and global spatial relationships within the image, leveraging its ability to process contextual information comprehensively. This stage refines the processed data, ensuring that the algorithm can effectively handle complex haze and smoke patterns. Finally, the processed features are used to reconstruct a clear, de-hazed, or de-smoked image. The system produces an output that retains natural color, detail, and structure, ensuring usability in applications such as surveillance, autonomous driving, or environmental monitoring. The process concludes, ready for further iterations If needed.

IV. CONCLUSION

This research paper presents a comprehensive approach to addressing the challenges posed by haze and smoke in outdoor imagery through an AI-ML-Based Intelligent De-Hazing and De-Smoking Algorithm. Leveraging advancements in deep learning, the proposed system combines the strengths of Convolutional Neural Networks (CNNs), attention mechanisms, and transformers within a hybrid architecture. The integration of U-Net for local feature extraction, FFA-Net for region-specific focus, and Dehamer for global context modeling enables the system to effectively manage non-uniform haze and smoke conditions.

Traditional dehazing techniques, such as the Dark Channel Prior (DCP) and Fast Visibility Restoration (FVR), have provided foundational methods but suffer from limitations, including artifacts, color distortions, and poor handling of bright or non-homogeneous haze regions. While these methods are computationally efficient, they lack the robustness required for complex real-world scenarios. Conversely, recent deep learning advancements, including attention mechanisms and transformer-based models, address these challenges by improving clarity, color fidelity, and structural integrity in processed images.

This research highlights the transformative potential of combining CNNs, attention mechanisms, and transformers, setting new benchmarks in dehazing and desmoking performance. Future work could explore optimizing computational requirements for transformer components, integrating real-time dynamic feedback mechanisms, and extending the system to handle other atmospheric disturbances, such as rain or dust. This study thus represents a significant advancement in image restoration, offering a reliable solution for critical computer vision tasks in challenging environments.

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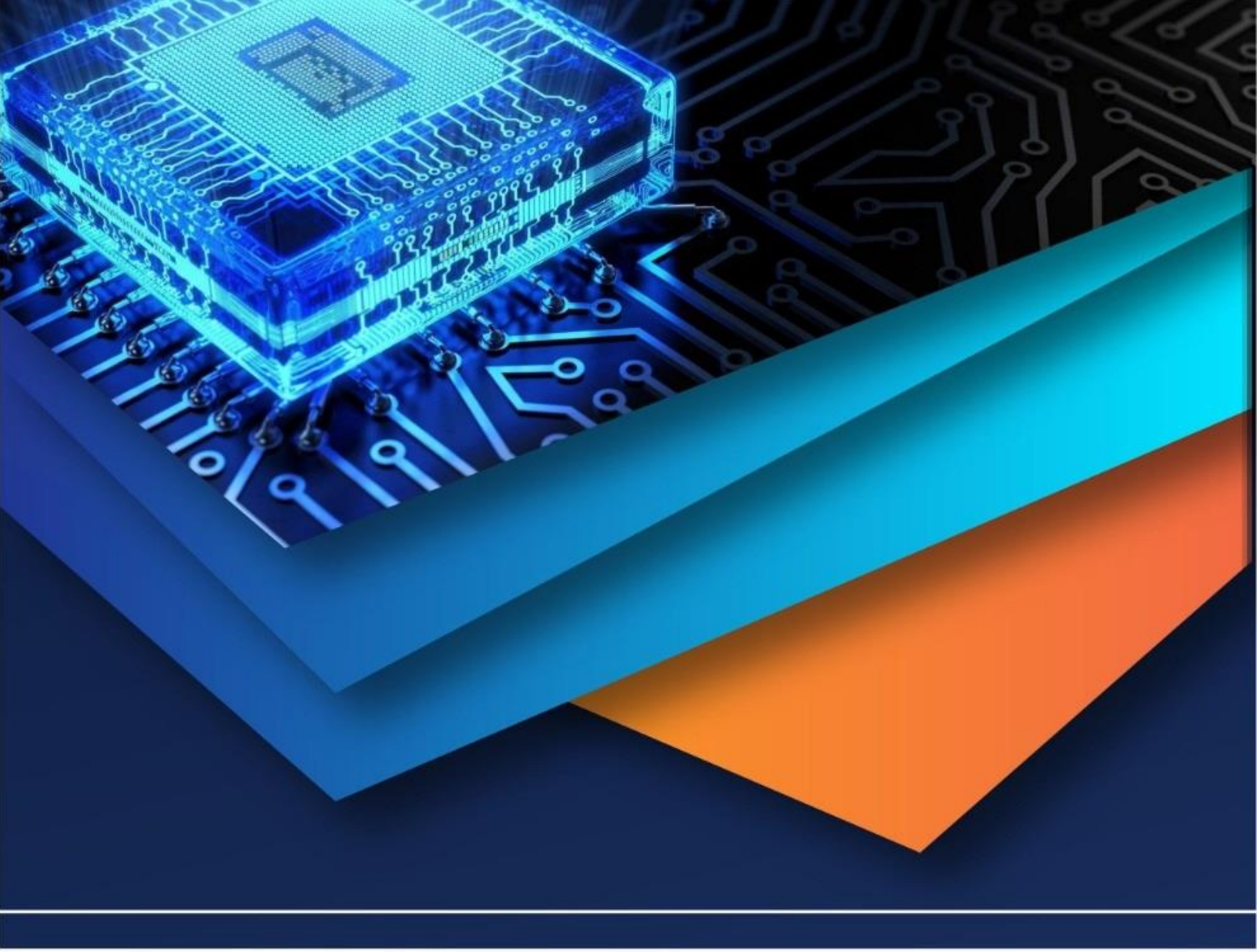
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