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Generative Adversarial Network Powered Image Transformation Enhancing, Completing and Converting Visuals

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Abstract: This study addresses conventional image processing shortcomings via one cohesive system integrating SRGAN, DeepFillv2, and CycleGAN (Generative Adversarial Networks). Image enhancement along with clever completion also versatile style transformations including colorization and decolorization are accessible through an intuitive Streamlit web interface. SRGAN is known to excel at improving image resolution and DeepFillv2 reconstructs damaged areas skillfully with full contextual awareness. CycleGAN eases style changes between domains without need of matched datasets. The system performs during real-time, features dependability, and outputs superior visuals. SSIM evaluation validates its utility. It makes this an important instrument for artists, designers, and photographers.
Keywords: Generative Adversarial Networks (GANs), SRGAN, DeepFillv2, CycleGAN, Image Processing, as well as Image Enhancement, Image Completion (Inpainting), Image Conversion (Colorization and Decolorization), Structural Similarity Index (SSIM), Streamlit web interface.

I. INTRODUCTION

Artificial intelligence advancements in image processing have changed rapidly via deep learning models. Among all of these, Generative Adversarial Networks (GANs) stand out because of how they can manipulate images in different ways. In 2014 Ian Goodfellow introduced GANs, and they have emerged as a powerful framework for image creation and modification, pushing the boundaries of what was previously conceivable.

Using GAN-based models, this study specifically addresses three key areas within image manipulation: improvement, completion, also conversion. For image enhancement, SRGAN is used to increase resolution and sharpness. This is particularly valuable in satellite image analysis as well as in improving the quality of highly compressed images.

DeepFillv2 conducts the image completion process known as inpainting. This model is able to understand contextual patterns and is able to predict them, cleverly filling areas that are missing or damaged within an image. CycleGAN tackles the transformation of images plus it is a strong model. CycleGAN eases flexible domain adaptation and style transfer without paired datasets.

The unique architecture that CycleGAN has allows for transformations between distinct visual styles that are smooth. New images can have specific artistic styles adapted or day to night scenes converted by it. This study analyses the effectiveness concerning these GAN architectures in real-world scenarios, and it examines their potential impact on diverse fields including digital art, photography, and automated content generation.

II. LITERATURE SURVEY

The rapid advancements in artificial intelligence have revolutionized the realm of image processing, particularly through deep learning models. Among these, Generative Adversarial Networks (GANs) have demonstrated remarkable capabilities, transforming images in ways once thought impossible. This work specifically focuses on three critical aspects of image manipulation: image completion (inpainting), image-to-image translation, and image super-resolution, leveraging various GAN architectures to achieve high-quality results.

The foundational work by Isola et al. (2017) proposed a conditional GAN framework, a powerful asset for artists, designers, photographers, and researchers. This framework is particularly well-suited for tasks where paired data is available, such as image inpainting, edge-to-image translation, and image colorization. This approach laid the groundwork for many subsequent advancements in image-to-image translation tasks[1].

Building on the concept of image-to-image translation, Park and Isola (2017) introduced **CycleGAN**, enabling translation between image domains even without paired examples. Their model incorporated a novel cycle-consistency loss to ensure the reversibility of transformations, such as grayscale-to-color conversion. This innovation significantly expanded the applicability of GANs to a wider range of image manipulation challenges[2].
Mehralian and Karasfi (2018) contributed to the field by introducing DCGANs for learning image features without labelled data. Their work focused on improving image resolution and quality through unsupervised learning, thereby paving the way for advanced image enhancement techniques using convolutional GANs. This research was crucial for developing models that can learn robust representations directly from image data[3].
More recently, Dhanasekaran and Raghu (2022) combined SRGAN with Discrete Wavelet Transform to enhance MRI image resolution. This research demonstrated improvements in PSNR and SSIM values, making it highly suitable for medical imaging applications. This highlights the practical utility of GANs in specialized domains requiring high-fidelity image reconstruction[4].

III. OBJECTIVE

The main objective of this project is to develop an integrated system to perform multi-functional image transformations that leverages Generative Adversarial Networks (GANs), specifically image enhancement, smart completion (inpainting), as well as versatile conversion (colorization and decolorization). The system uses GAN architectures that are specialized such as the SRGAN, the DeepFillv2, and the CycleGAN. The system seeks to improve processing efficiency in conjunction with realism and visual quality. Additionally, one key goal would be to ensure that the tool is both accessible and also user-friendly because we deploy it as a web application through Streamlit, which is valuable for artists, designers, plus photographers.

IV. SYSTEM ANALYSIS

A. Existing System

Existing image processing systems often rely on traditional GAN models like DCGAN for image enhancement, which can lead to artifacts, slower processing, and inconsistent results. For image completion, models like Pix2Pix are used, but they often have limited accuracy when filling large missing areas. Image conversion frequently depends on Pix2Pix and CycleGAN, which can result in inaccurate colors and poor-quality transformations. Common drawbacks of these systems include blurry or unnatural textures, color mismatches, long training times, limited flexibility across different image types, and less realistic outputs due to insufficient training data or mode collapse.

B. Proposed System

The proposed system directly addresses these limitations by integrating specialized GAN architectures for enhanced image transformations. For image enhancement, it utilizes SRGAN, which provides high-quality upscaling with better detail preservation and clearer images. Image completion is performed using DeepFillv2, ensuring high-quality and accurate reconstruction of missing or damaged regions. For image conversion, CycleGAN is employed to achieve realistic colorization and correct conversions between visual domains. This integrated approach offers several advantages, including faster results due to optimized GAN models, flexible performance across various transformation tasks, consistent output quality, and multi-task capabilities within a single framework.

V. SYSTEM ARCHITECTURE AND METHODOLOGY

A. System Architecture

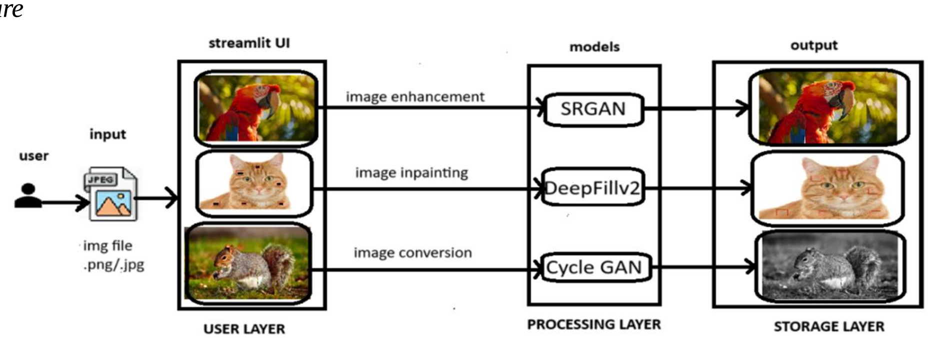

Fig.1System Architecture: GAN-powered image transformations

The diagram illustrates the architecture of the GAN-powered Image Transformation system, broken down into three main layers: User Layer, Processing Layer, and Storage Layer. In the User Layer, users interact with a Streamlit UI, where they upload image files (.jpg) for processing. The interface allows users to select one of three transformation tasks. In the Processing Layer, based on the selected task, the system routes the image to the appropriate GAN model: SRGAN is used for image enhancement, and improving the visual quality. DeepFillv2 is used for image inpainting, filling in missing or masked parts of the image. Cycle GAN handles image conversion, such as converting colored images to grayscale or vice versa. Finally, in the Storage Layer, the output image generated by the selected model is displayed to the user and stored for download.

B. Methodology

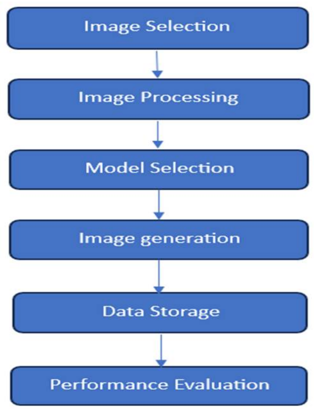

Fig.2 Block diagram: GAN-powered image transformations

1) Image Selection
- The user uploads an image through the web interface.This image can be a standard photograph for enhancement or style conversion, or a masked image specifically prepared for the image completion task.

2) Image Preprocessing
- The uploaded image undergoes essential preprocessing to convert it into a standardized format compatible with deep learning models.
- This involves operations such as resizing the image to a uniform input dimension (e.g., 256x256 pixels), normalizing pixel values (e.g., scaling to a range of -1 to 1), and ensuring consistent color channels (e.g., RGB).

3) Model Selection
- Based on the user's chosen transformation task from the interface, the system dynamically selects the appropriate pre-trained GAN model.
- SRGAN is activated for image enhancement (super-resolution), DeepFillv2 for intelligent image completion (inpainting), and CycleGAN for versatile image conversion (e.g., colorization/decolorization).

4) Image Generation
- The pre-processed image is fed into the selected GAN model, which then performs its specialized generative task.
- The chosen model produces a new image that is either enhanced in resolution, has missing regions intelligently filled, or is transformed into a different style/color domain.

5) Data Storage
- The newly generated image is temporarily stored in the system's memory for immediate display to the user.
- Users are provided with a clear option to download the final transformed image for their personal or professional use.

6) Performance Evaluation
- To quantitatively assess the results, the system computes the Structural Similarity Index (SSIM) when a "ground truth" image is provided by the user. SSIM serves to measure the perceptual similarity separating the generated image from its original counterpart.

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VI. RESULTS AND ANALYSIS

A. Results

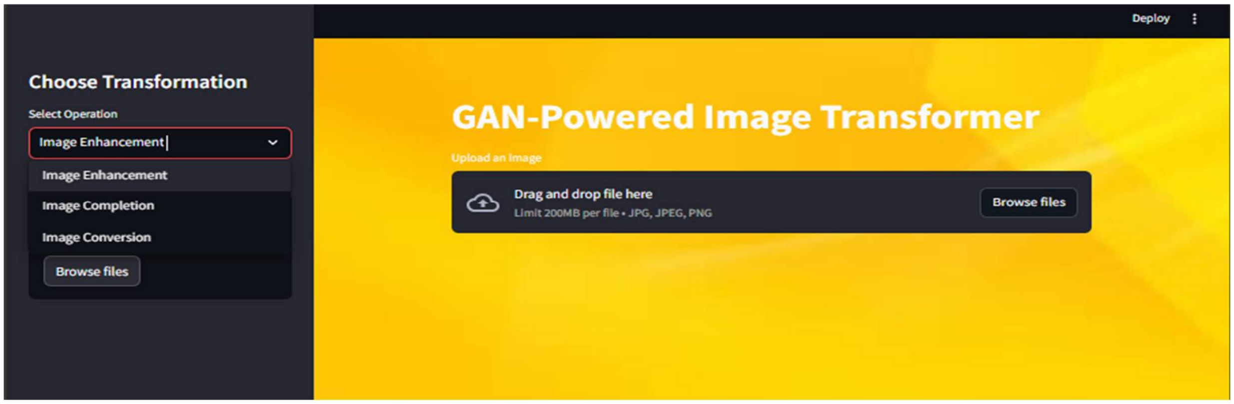

Fig.3Layout of Choose Transformations[Image Enhancement, Image Completion, Image Conversion]

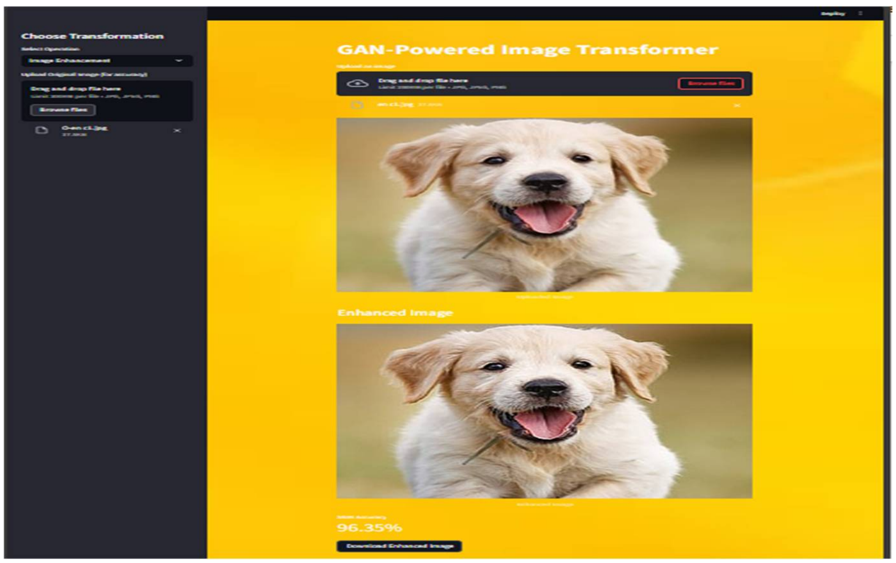

Fig.4Image Transformation: Enhancement

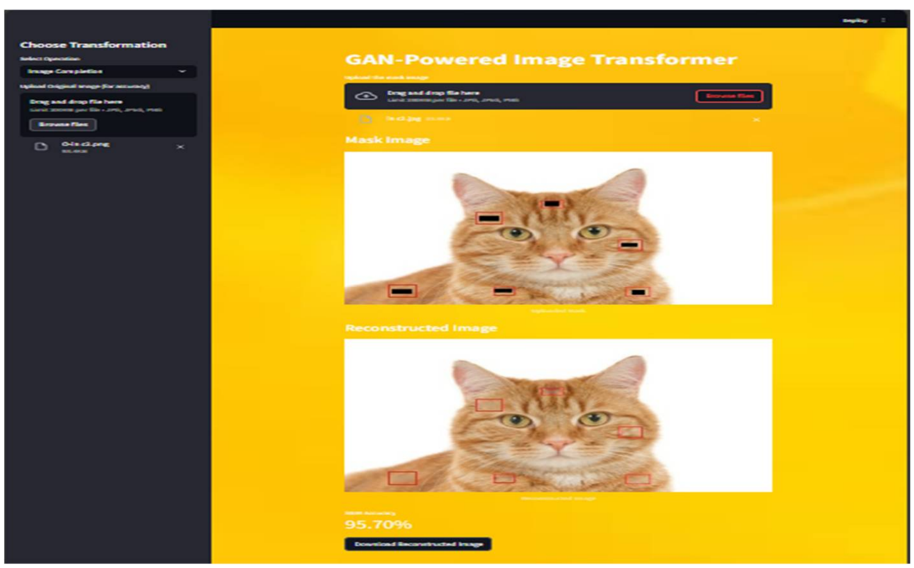

Fig.5Image Transformation: Inpainting(Completing)

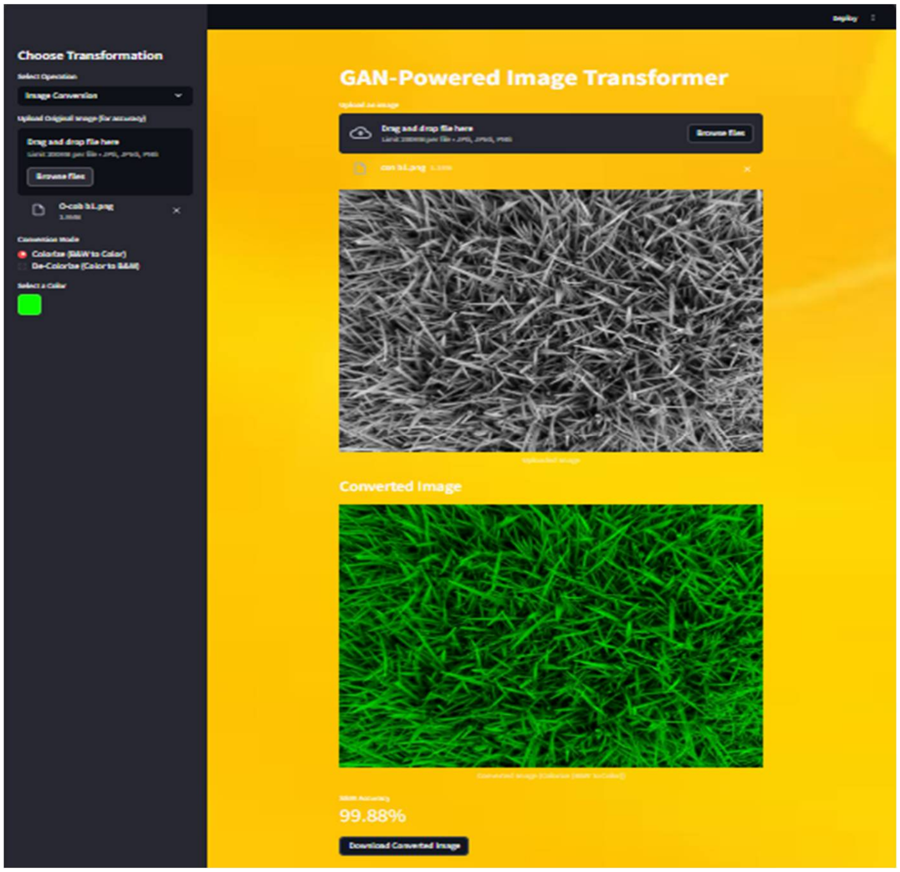

Fig.6Image Transformation: Conversion [COLORIZATION]

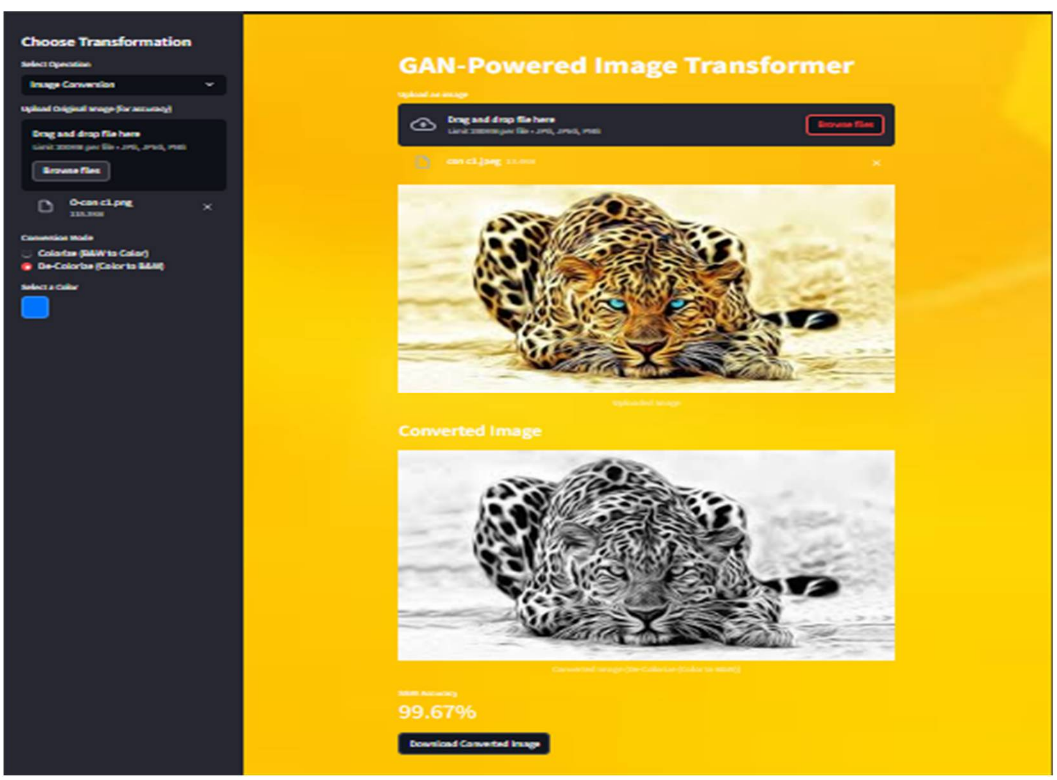

Fig.7Image Transformation: Conversion [DE-COLORIZATION]

B. ANALYSIS

SNo	Transformation Task	Model Used	Existing System Accuracy	Proposed System Accuracy
I	Image Enhancement	SRGAN	89%	95.3%
II	Image Inpainting	DeepFillv2	85%	91.1%
III	Image Conversion	CycleGAN	92%	98.9%

Table 1.Accuracy Score of Image Transformation

VII. CONCLUSION AND FUTURE SCOPE

This project effectively demonstrates a deep learning system for image transformation, powered by Generative Adversarial Networks (GANs), capable of performing image enhancement, completion, and conversion within a unified platform. By leveraging SRGAN, DeepFillv2, and CycleGAN architectures, the system provides high-quality, realistic visual outputs across a variety of image transformation tasks. The Streamlit-based interface ensures accessibility for users with varying technical expertise, allowing them to interact with the system easily and effectively. Overall, this approach simplifies complex image editing processes and has strong potential in domains such as digital art, media restoration, and automated visual content generation.

There are several opportunities to enhance this GAN-powered image transformation system in future versions. The platform can be extended to include additional functionalities such as noise removal, object manipulation, and background editing to increase its versatility. Incorporating real-time input from devices like cameras or drawing tablets could expand its use in creative and professional workflows. The integration of more advanced GAN variants or hybrid models could further improve output quality and model robustness. Additionally, deploying the system on cloud platforms would allow broader access, support real-time processing at scale, and make it feasible for deployment in industries such as entertainment, design, and e-commerce.

VIII. ACKNOWLEDGEMENT

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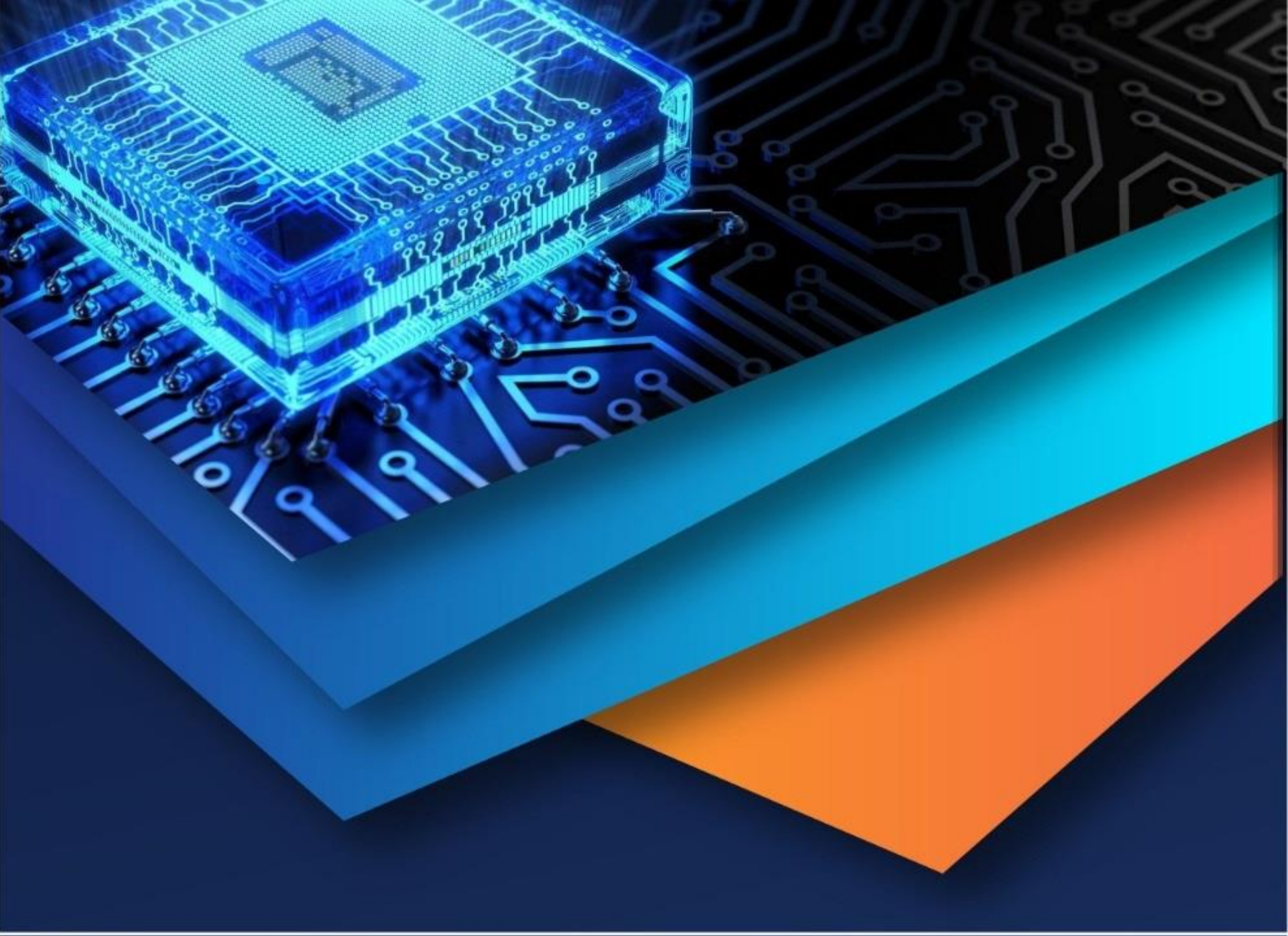

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