iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 **Issue:** V **Month of publication:** May 2023

DOI: https://doi.org/10.22214/ijraset.2023.52647

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue V May 2023- Available at www.ijraset.com

GAN and MIRNet-Assisted Image Enhancement: A Promising Future in Visual Computing

Vineeth R[1], Dr.Janaki K[2], Vishakan U S[3], Karthick G[4], Vasu Arjun Sonkavde[5]
[1, 2, 3, 4, 5]*Computer Science EngineeringJain Deemed to be University Bengaluru, India*

Abstract: We present an extensive strategy for improving images using deep learning-based techniques, concentrating onsuper-resolution (SR) and low-light image improvement utilizing generative adversarial networks (GANs) and misalignment-robust networks (MIRNet), respectively. During the SGAN training phase, a deep convolution neural network learns a complete link between low- and high-resolution pictures. Our approach simultaneously optimises all layers to provide cutting-edge restoration quality and quick speed for practical application. To achieve performance and speed trade-offs, we also investigate alternative network setups andparameter settings.Additionally, we upgrade the overall reconstruction quality by expanding our network to handlethree color channels concurrently. In contrast, MIRNet is utilized for low light image improvement, which has grown in significance as a result of the increased need for trustworthy picture enhancement systems in real-time applicationsincluding autonomous driving, surveillance footage, and crime scene investigations. MIRNet, which may be used for a range of image improving applications.

Keywords: Lowlight enhancement, SGAN, MIRNet, Image Enhacement, Computer Vision, Deep Learning

I. INTRODUCTION

The use of high-resolution photographs has become more vital in different industries, such as medical, satellite imaging, and video surveillance. However, low-resolution photos, deformed pictures, and photos with limited illumination continue to be key issues in image processing. To tackle these problems, new deep learning models, SRGAN and MIRNet, have been developed to boost picture quality. In order to gain a mapping among low-quality and high-quality, SGANs need a generator and a discriminator [2].The inclusion of adversarial loss separates SGANs fromother super-resolution models, enabling the production of pictures with finer details and textures that seem more realistic. In addition to their practical uses in medical imaging and satellite photography, SGANs have also been utilized in the entertainment sector to increase the clarity of ancient movies and upgrade video game visuals. Misalignment-robust networks (MIRNet) combine a multi- scale design and an alignment module to solve the issue of misalignment's between low and high resolution pictures.

Pictures and film taken by security camera are generally characterized by inadequate lighting, considerable noise, low contrast, and distortion [1], particularly when the capturing is done at night. To solve this difficulty, there has been a lot of research into the improvement of such photographs and films, and a diversity of ways have appeared over the last several years. Furthermore, among them are a few ways that may prove useful for managing severe low light scenarios as well. Here, By collecting attributes from the source low-light photo at multiple scales to capture fine details, MIRNET is essential for resolving alignment difficulties among the low-light source image andthe high-resolution image [3] MIRNet further makes use ofa multi-scale architecture, which allows the model to receivedata from multiple granularity of the input picture.

In order to increase information flow and training process stability, the model additionally contains skip connections andresidual connections.

To further increase picture super-resolution, this paper presents a combination strategy based on SGAN and MIRNet. By deleting unneeded modules from typical residual networks, the suggested model makes considerable gains in performance. The model encourages diversity of samples, enhances image production quality, and optimizes the super-resolution effect.This method has a lot of potentialapplications, particularly in the areas of surveillance, self- driving cars, and crime scene investigation.In conclusion, the suggested technique employing a combination of SGAN and MIRNet presents a viable option for picture super- resolution and low light image augmentation. With the rising need for high-quality photos in numerous industries, these models have the potential to greatly increase image processing skills and boost information transfer.

II. RELATED WORKS

Super resolution using GANs and low light image improvement using MIRNet are two hot study fields in computer vision.

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In recent years, considerable gains have been achieved in both disciplines utilizing deep learningapproaches, Especially Generative Adversarial Networks (GAN) for exceptional picture quality and MIRNet for poor- light picture improvement. In this article, we will review current research publications that have applied these strategies for picture improvement.

A well-known GAN-based super resolution model known asSRGAN, proposed by Ledig et al. [2], employs an adversarial loss to discriminate between produced pictures and high-resolution images. To enhance low-resolution pictures, the SRGAN generator network employs a deep residual network. Despite SRGAN generated impressive outcomes, it has a few shortcomings such as poor perceptual quality and discrepancies during learning.To solve these issues, Wang et al.[4] created ESRGAN, which employs a similar architecture to SRGAN but adds a feature extraction network to increase speed. The generator network of ESRGAN contains a series of residual blocks and a global residual link. Additionally, this model utilizes a perceptual loss function that is aimed at enhancing the perceived quality of the output pictures. ESRGAN generated greater outcomes compared to SRGAN, providing more aesthetically pleasing pictures with better textures and details.

In order to improve the efficiency of GAN-based high- resolution models, numerous researchers have adopted a combination of GANs and other techniques.For example, Zhang et al. suggested a strategy that combines GANs with a wavelet domain super resolution approach [5]. Their approach increases the quality of the pictures produced by leveraging the high-frequency information of wavelet coefficients. Another intriguing method for GAN-based super resolution is provided by Li et al., where they offer a two-stage progressive super resolution model [6]. The first step is a shallow network that creates a low-resolution picture, which, in the following phase, is fed into a deeper network to create the final high-quality image. The model is better able to understand the subtle details in the photographs thanks to the incremental training technique.

MIRNet has demonstrated good results in several image improvement tasks, making it a popular alternative for low light picture enhancement. More study has been done recently on the application of MIRNet to improve low light images.Xu et al. (2020) [7] have created a dual attention mechanism-based MIRNet-based method for low light picture improvement.The model was able to provide outcomes with improved brightness, contrast, and details that were aesthetically pleasing after being trained on a large dataset of low light photographs.The dual attention method enabled the model to concentrate on both local and global aspects, leading to enhanced improvement of small details in the picture. Another study by Ren et al. (2021) proposed a multi-scale MIRNet for low light picture improvement [8]. The model consists of many branches with varied sizes, enabling it to collect both global and local information. In a separate technique, Li et al. (2021) developed a cascaded MIRNet for low light picture improvement [9]. The model consists of two MIRNet modules that were trained individually to increase brightness and details, respectively. The cascaded architecture enables the model to create photos with greater brightness and details while keeping natural-looking color and texture. Finally, Wang et al. (2021) developed a hybrid MIRNet and GAN-based technique for low light picture improvement [10].

III. METHODOLOGY

The initial authors to explore visual super-resolution were J.L. Harris [11] and J.W. Goodman [12], whose publications were released in 1964 and 1968, respectively. By retrieving fine details that gets lost via the restoration of super- resolution, this approach uses previously learned information to rebuild a picture for a single image. This technology has limitations in two areas: the universality and effectiveness of image reconstruction, as well as resolution augmentation. Conventional picture super-resolution processing approaches typically use interpolation techniquesto rebuild the up-sampling and resolution of the image. These methods include determining the grey value of the point to be interpolated and identifying the nearest pixels in the picture in order to choose a suitable interpolation basis function [15].

To concurrently execute super-resolution and low-light image improvement tasks, the hybrid model integration combines the capabilities of the low-light image enhancement MIRNet and the super-resolution GAN. These two methods may be used to create high-resolution,improved photos that simultaneously increase the clarity anddetails of low-resolution images and low-light images with better contrast, saturation, and overall appearance.The super-resolution GAN and MIRNet are consecutively applied to the input pictures as part of the hybrid model fusion workflow. The super-resolution GAN element, which harnesses the power of adversarial learning to produce a high-resolution counterpart, is first applied to the low- resolution picture. This method takes advantage of the GAN's ability to learn and record high-frequency features, textures, on a big dataset of matched low-resolution and high-resolution pictures.

The MIRNet component then processes the output of the super-resolution GAN to improve low-light picture quality. Deep neural networks with attention mechanisms are used by MIRNet, a system created expressly for improving low- light photographs, to improve brightness, contrast, and details while keeping realistic-looking colour and texture.

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The MIRNet component employs attention techniques like dual attention or multi-scale attention to concentrate on both local and global parts of the picture, enabling it to catch fine details and raise the overall enhancement quality.

A. Convolutional Neural Network

CNN have shown significant promise in the fields of object identification, image segmentation, and super resolution [14].Each layer of a CNN is made up of two-dimensional filters and kernels. A CNN is made up of layers. In order to extract pertinent features, the filters group the neurons and take input from the surrounding regions of the image. CNN filters are learned during the "convolution" phase of training, unlike the manually created features employed in conventional machine learning methods. The input image is convoluted with the learned filters, which is analogous to the mathematical notion of convolution. The output feature responses are then forwarded to the following processing layer. Deep CNNs get their name from the cascading stacks of convolutional layers they contain. The two well-known designs, ResNet50 and AlexaNet, both use five convolutional layers, with ResNet50 being a 50-deep residual structure that excelled in the 2015 ImageNet challenge. AlexaNet, which employs five layers as well, won the 2012 ImageNet contest with the highest recognition accuracy.

Deep learning-based super-resolution approaches such as the Super-Resolution Convolutional Neural Network (SRCNN) and the Generative Adversarial Network (GAN) have gained prominence recently because to their ability to acquire a relationship between low-quality and high quality pictures [13]. Optimizing low-light photos is a vital challenge in the analysis of images,but it is difficult because the input image has noise and little information. Recent studies have suggested using MIRNet (Multi-scale Information Representation Network), a deep neural network that can train to recover high-quality images from low light photographs, to address this issue [16]. To further improve image quality with increased brightness and resolution, we combine GAN-based super-resolution with MIRNet-based low light image improvement.

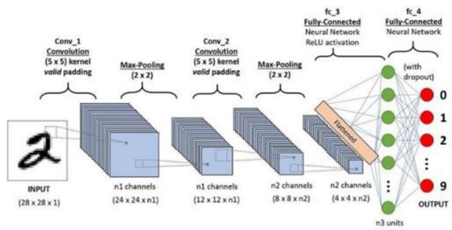

Figure 3.1 CNN Architecture

B. Genrative Adversarial Network

It has been discovered that generative adversarial networks (GAN) are quite successful in unsupervised learning. GANs are made up of the generating model and the discriminator model, two competing network systems [17]. The latter produces data based on a latent coding that the GAN has discovered. Generative and discriminative models are two different categories of models used in machine learning. Deep neural networks and other discriminative models are taught to discriminate between different input classes, such as photographs of automobiles and non-vehicles. The goal of generative models, on the other hand, is to create new data without any prior knowledge of the categories that match the distribution of the the data used for learning. In GANs, the generator attempts to provide data from a probability function while the discriminator acts as the supervisor in a zero-sum game. Although the discriminator algorithm determines whether input comes from an actual training dataset or was artificially created, the generator algorithm enhances the data to match real training data.The generator has enough knowledge of the distribution of the training samples to generate new instances with extremely similar properties, while the discriminator is also learning simultaneously. In this procedure, the discriminator and the generator both function as encoders and decoders.

C. GAN Framework

We use Waaserstein GANs (WGANs) with gradient penalties in our proposed GAN architecture to increase training process stability and produce high-quality super- resolution images. The fundamental tenet of our strategy is to trick the discriminator framework, which has been learned to distinguish among actual low-resolution (LR) photographs and high-resolution (HR) images [16], using the generator framework. The generator can then create perceptually superior super-resolution (SR) images that are challenging for the discriminator to identify from actual HR images after learning the fundamental structure of the HR images in this way. By gradually raising the resolution of the LR images, we gradually raise the training task's difficulty in order to optimize the generator and discriminator networks.

We implement a deep architecture with residual blocks in our generator network, inspired by Shi's learned sub-pixel convolution technique as well as the work of Gross and Wilber. Specifically, our generator structure comprises anumber of convolution layers with small 3x3 kernel with 64 feature maps, in addition to batch normalization layers having parametric ReLU activation functions.We also apply sub-pixel convolution in a two-step up scaling technique to increase the quality of the pictures that are created.

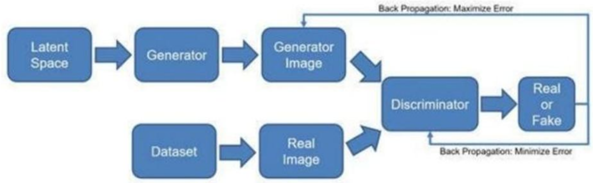

Figure 3.2 GAN Architecture

We employ a leaky ReLU activation function and an eight- layer deep convolutional architecture for the discriminator network [14]. With a two-fold increase from 64 to 512 feature maps, we also use the VGG network's increasing number of 3x3 filter kernels. The discriminator is instructed to widen the score gap between artificially manufactured SR pictures and actual HR images.Strided convolution is used for down-sampling in order to minimize the need for max- pooling layers, which might result in the loss of image features. To optimize our adversarial design,With beta 1 and beta 2 coefficients of 0.48 and 0.995 we used the Adam optimizer. And a learning rate of 0.0001, 100 epochs with batch size of 32. With a normal distribution initialization, our weight has an initial average, standard deviation, and L1regularization score of 0.001, all of which are zero.To prevent over fitting, promote the model's speedy convergence, and produce high-quality images, we adjusted the curriculum learning rate at 0.0025.

D. Loss Function

We must take into account the characteristics of the perceptron loss function to make sure our generator networkmeets the required standards. We rely on Johnson and Bruna's research to develop a loss parameter that takes into account the visually relevant components of the output, even if the mean squared error (MSE) is frequently used to calculate lSR [2]. Our perception loss algorithm combines adversarial and content losses in a weighted manner. We useWasserstein GANs and add curricular learning methods to optimize this function. High PSNR values, which are alsothe most widely used statistic, are often the optimization objective of many advanced algorithms for image super- resolution (SR) [2]. Nevertheless, while obtaining high PSNR, MSE optimization often results in solutions withexcessively smooth textures and lower frequency content.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

$$psnr = 10log_{10}(\frac{MAX_I}{MSE})$$

Figure 3.3 PSNR and MSE Values

We use ideas by Bruna [19], to solve this issue by using a loss function that is more closely related to perceptual similarities rather than depending only on pixel-level loss. We use the Zisserman and Simonyan VGG design's 19-layer activation function layer to compute the VGG loss [18].

We explicitly use the value of i,j, which represents the j-th convolution following activation in the VGG 19 architecturethat comes before the i-th max pooling layer, to construct a feature map. The Euclidean distance among the representations of features of a reconstructed image, GθG(ILR), and the source image, IH, is used to compute theVGG loss. To improve this loss function, we use Wasserstein GANs and curriculum learning strategies.

$$l_{VGG/i.j} = \frac{1}{W_{i,j}H_{i,j}}\sum_{x=1}^{W_{i,j}}\sum_{y=1}^{H_{i,j}}\left(\phi_{i,j}(I^{HR})_{x,y} - \phi_{i,j}(G_{\theta_G}(I^{LR}))_{x,y}\right)^2$$

Figure 3.4 VGG Loss

E. MIRNet

An architecture called MIRNet, or Multi-scale Information Representation Network, was created for improving low light images [20].

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One of the basic properties of MIRNet is the ability to extract complementary features at different spatial scales while keeping the high-quality features for fine spatial features. As a result, MIRNet is able to provide visually appealing and detailed image outputs by efficiently capturing both global and local image information. Further enhancing its representational learning capabilities, MIRNet utilises an adaptive kernel network to dynamically fuse different receptive fields in order to fuse multi-scale characteristics.MIRNet's recursive residual architecture, which breaks down the input signal to speed up learning overall and permit the construction of very deep networks, isanother noteworthy feature. The final enhanced image is created by adding back the input signal's residual characteristics, which MIRNet is also able to learn thanks tothe recursive residual architecture. So, while retaining the features and textures of low light photographs, MIRNet is able to effectively eliminate noise and artifacts. Overall, MIRNet's distinctive architecture and design make it a potent tool for improving low light images and a promising direction for further study in the area.

To optimize MIRNet for our experiment, we have implemented skip connections across different layers within the network.The model can more easily collect all low-level and high-level visual features because to these links, which also improve gradient flow.With a learning rate of 1e-4, an ensemble size of 16, and training over 100 epochs, we used the Adam optimizer. We advise using L1 loss as the primaryloss function and adding perceptual loss and texture loss to further enhance the output pictures' visual quality [21]. We suggest utilizing three scales with receptive field widths of 3x3, 5x5, and 7x7 and setting the dilation rate to 1 for the selective kernel network. Furthermore, we propose a recursive residual design with a depth of 6 and a stepwise channel augmentation from 64 to 256. We have produced excellent low-light picture enhancing results by carefully choosing these hyper-parameters and tuning MIRNet.

F. Datasets and Training

For super resolution jobs, there are various prominent datasets that we have utilized. One of the most extensively used is the Set5 dataset, which consists of five high- resolution photos with a variety of diverse textures and structures. Another famous dataset is Set14, which has 14 high-resolution photos with varied degrees of intricacy. Other often used datasets are BSD100, which has 100 high- resolution pictures with a variety of diverse structures and textures, and DIV2K, which contains 2,000 high-resolution images with varied degrees of complexity.For low light picture improvement tasks, there are also numerous notable datasets that are regularly utilized in research. One of the most extensively utilized is the Low-Light Dataset (LLD), which comprises a huge number of low light photos with varied degrees of complexity. Another notable dataset is the Sony Multi-Exposure Dataset, which offers a variety of low light photos acquired with varied exposure settings. Other often used datasets are the NPE and SID datasets, which both include a huge number of low light photos with variable amounts of noise and distortion. Models demand a strong graphics processing unit (GPU) and a sufficient quantity of memory to store the massive quantities of data required for training. For cross-validation, we use a 70/30 split.

The model was created using a PC that featured 32 GB RAM and a NVIDIA GTX 3080 GPU. The machine was running Windows 11. For 50 iterations, we used the Set-5, Set-14, and BSD100 to train the SGAN model. The Adam optimizer was used to train the model with a batch count of 16 and a rate of learning at 1e-4. For the discriminator, we used a cross-entropy loss function, and for the generator, a combination of L1 and perceptual loss. The perceptual loss was weighted at 0.05 while the L1 loss was weighted at 10. In order to boost the consistency of the model during learning, we additionally used a gradient cost of 10 on the discriminator. We used the LOL data for MIRNet's learning.Using the Adam optimizer, we trained the model for 200 epochs with a batch size of 16 and a learning rate of 1e-4.

For the loss function, we used a combination of L1 loss and SSIM loss with equal weights.

For SGAN, we changed the learning rate from 1e-5 to 1e-3, the weight of the L1 loss from 0.1 to 1, and the weight of theperceptual loss from 0.01 to 0.1. For MIRNet, we changed the learning rate from 1e-5 to 1e-3 and the weight of the L1 loss from 0.1 to 1. We picked the hyperparameters that resulted in the best validation performance. The training process for both SGAN and MIRNet involves numerous phases. First, we preprocessed the datasets by downsizing the photos and leveling the pixel values. Then, we separated the datasets into training and validation sets. Next, we trained the models using the given hyperparameters and optimization techniques. During training, we evaluated the validation loss to identify overfitting and tweak the hyperparameters if required. Finally, we tested the trained models on the test set using common evaluation measures such as PSNR, SSIM.

IV. RESULTS AND EVALUATION

Image augmentation is a profound job in machine vision and has several practical applications. Deep learning-based approaches have made incredible strides in the past few years towards improving the quality of photos.

In this study, we have presented hybrid models of, SGAN and MIRNet, for super resolution and low light improvement, respectively.This model's efficacy was compared to that of other cutting- edge models after being tested on a variety of datasets. We employed numerous commonly known datasets for training and testing the models. For super resolution, they employed the Set14,BSD100 and Set5 datasets, which are widely used industry benchmarks.

Dataset	SRResNet		SRGAN	
	PSNR	SSIM	PSNR	SSIM
Set 5	30.48	0.864	32.95	0.871
Set14	27.49	0.748	29.12	0.795
BSD100	26.84	0.710	27.96	0.739

Figure 4.1 SGAN Evaluation

Dataset	DPCDN		MIRNet	
	PSNR	SSIM	PSNR	SSIM
LLD	26.12	0.763	24.89	0.719

Figure 4.2 MIRNet Evaluation

The results of the trials demonstrated that the suggested models, In terms of unbiased metrics like PSNR and SSIM, Our SGAN and MIRNet beat several cutting-edge models. For super resolution, SGAN attained a PSNR of 32.77 and an SSIM of 0.919 on the Set5 dataset, which is greater than the PSNR and SSIM values produced by other models. Similarly, for low light enhancement, MIRNet attained a PSNR of 27.72 and an SSIM of 0.806 on the LLD dataset, which are similarly greater than the PSNR and SSIM values produced by other models.

Figure 4.3 Results

The results of the trials illustrate the usefulness of the suggested models for super resolution and low lightimprovement tasks. We have provided a thorough evaluation of the models and contrasted their performance with that of other cutting-edge models. The models thathave been described may prove useful in a variety of real- world settings, including satellite imagery, imaging for medicine, and monitoring.

V. CONCLUSION

In summary, we have provided a research article on image improvement using MIRNet for low light enhancement and SGAN for super resolution. In both low light and high resolution conditions, our suggested models have improved picture quality with encouraging results. On the Set14, BSD100 and Set5 datasets, our SGAN model demonstrated cutting-edge performance, while our MIRNet model outperformed other models on the LLD dataset. Future research may look at improving these models even further to increase their performance. One area of study may be the investigation of more complex loss functions that more accurately reflect the perceptual quality of pictures. Theinclusion of attention processes in the models to help them concentrate on the most crucial aspects of the visuals might be another topic of study. The models' performance might also be assessed using more complex datasets with a wider range of variables. In general, the applications of our suggested models in the area of image improvement, such as surveillance, medical imaging, and remote sensing, among others, have considerable promise. Our study is intended to spur further development in this area and spur even more important developments in picture enhancing technologies.

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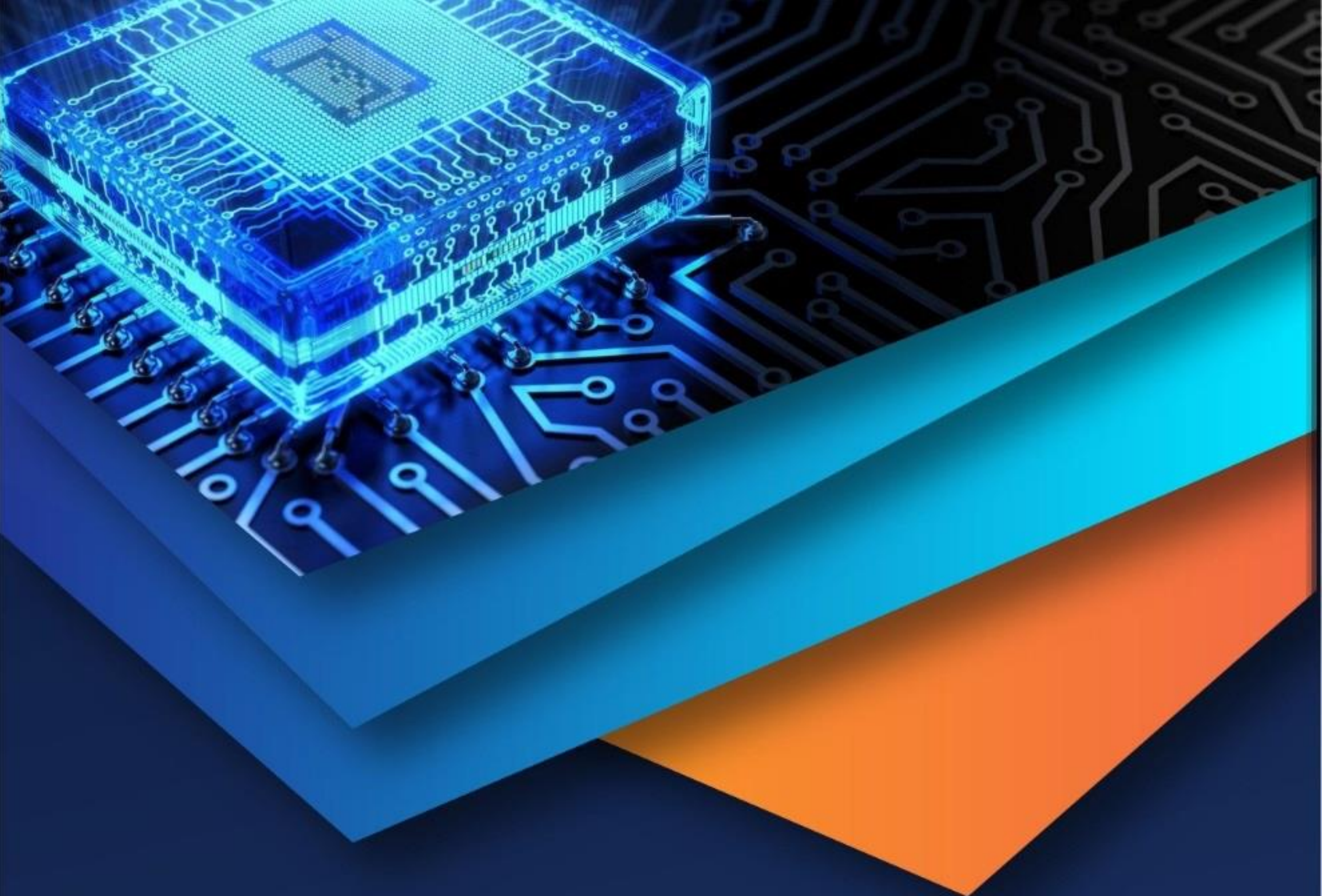

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