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A Review of the Existing Literature on 3D Reconstruction Methods

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Abstract: Using deep neural networks, supervised 3D reconstruction has made significant progress. However, large-scale annotations of 2D/3D data are necessary for this performance boost [4]. How to effectively represent 3D data to feed deep networks remains a challenge in 3D deep learning. Volumetricor point cloud representations have been used inrecent works, but these methods have a number of drawbacks, including computational complexity, unorganized data, and a lack of finer geometry [7]. The ultrasound (US) examination is one method usedto diagnose carotid artery disease. The flow conditions in the artery also play a role in the onset and progression of vascular diseases [5]. Stenting the carotid artery is a treatment option for carotid atherosclerosis. It is impossible to know for sure where an injection with a needle will begin. The place of the conduits is in the body, thusly, decidingthe beginning stage of needle infusion is finished byassessment just and can't not entirely set in stone. The first thing that must be done is to locate the carotid artery in order to identify it. To determine it,we propose a modified template matching based on the ellipse feature for a 3D reconstruction of the carotid artery [1]. Data acquisition, pre-processing, segmentation, outlier selection for ellipse parameter fitting, and visualization are all used to process it. In comparison to the template matching method and the Hough Circle method, the proposed procedure with pre-processing produces the highest accuracy [1]. The objective of this research was to create three- dimensional (3D) ultrasound imaging of the carotid arteries to lessen the variability of volume measurements between and within examiners duringfollow-up scans of atherosclerotic plaques.
Keywords: Carotid artery; 3D reconstruction; atherosclerosis; Ultrasound imaging; Deep learning; vasculature; Surgical guidance; Automatic segmentation;

I. INTRODUCTION

One of the cardiovascular illnesses that affects people is carotid artery stenosis (CAS). It is critical to get this disease caught early because if it is not treated properly, it may lead to worsening effects likea crippling stroke. The classic computer vision problem of inferring the 3D geometry of an object orscene from its 2D projection on the image plane hasnumerous applications, such as object recognition, scene understanding, medical diagnosis, animation, and more [3]. A large number of images has traditionally been used for dense 3D reconstruction from images.

Dense matching, direct minimization, or reprojection errors extract geometry. Implicit volumetric reconstruction and explicit mesh-based approaches are two examples of common approaches[6]. This becomes even more appealing and motivating when millions of 3D CAD models from various categories are made publicly available online[7]. Currently, the modalities of Magnetic Resonance (MR), Compute Tomography (CT), and Ultrasound (US) are typically used to detect and quantify carotidstenosis. In interventions, they aid in the decision- making process. The outcomes of this intervention can be used to help insert a catheter or use a thrombus aspiration machine to remove the plaque.

MR or CTscan angiography has been used to locate carotid arteries in previous studies. Mechanical scanning, anoptical tracker, and a magnetic tracker all play a rolein reconstruction. The distance between the ultrasound probe's marker and the world coordinate must be determined using the tracker. The goal of this study is to use two-dimensional B-mode imagesto reconstruct the CA lumen area's 3D object. The reconstruction was carried out using data collecting, pre-processing, segmentation, choosing outlier segmentation, ellipse parameter fitting, and visual analytics. [1].

The proposed paper contains different sections like image analysis, data acquisition, pre-processing, related works, segmentation and outlier selection, results and discussion, conclusion.

II. 3D RECONSTRUCTION OF THE CAROTID ARTERY

The patient's carotid artery is 3D reconstructed usingthe patient's unique clinical imaging data. One of thekey problems is the small number of 2D transversal cuts in the patient data set that was employed. The generalized model served as the foundation for resolving the issue of missing cuts, which was then enhanced using the available data [5].

The carotid artery (CCA) transversal cut (shown in Fig. by the B line)1) as well as the external carotid artery (ECA; Fig. C line denotes lower segment).1) is utilized to define the cross-sectional shapes of these segments' carotid arteries. The internal carotid artery (ICA) longitudinal cut (shown in Fig. by the A segment)1) is used to extract the ICA's center line and diameters from this segment, while the ICA's transversal cuts (the C line in the upper segment and the D line in the cross-section in Fig.)1) are also utilized to provide a more precise definition of thesespecific cross-sections. Based on the data gathered from the cuts, the lengths of the branches are determined.

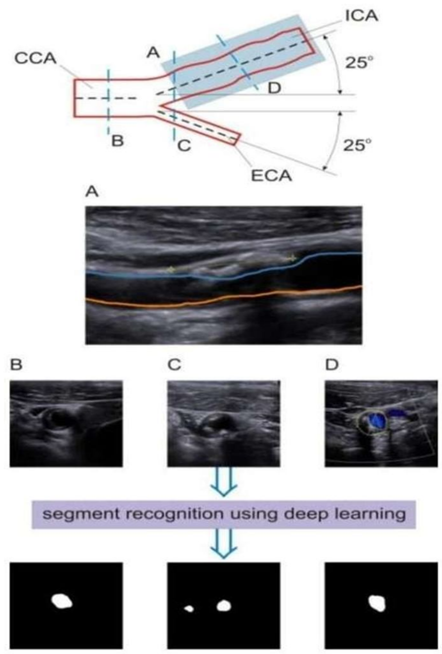
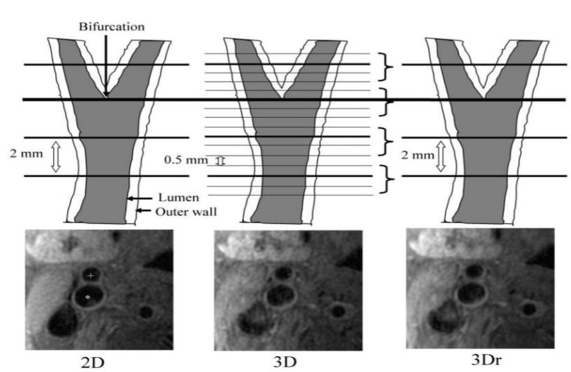


Figure 1. The adaptation of the generalised model ofthe carotid artery using ultrasound images acquired for a specific patient.

III. IMAGE ANALYSIS

In order to improve image registration between the two scans, the bifurcation of the index side was the focal point of the 2D and 3D scan geometries, whichis the side with the increased stenosis in the ultrasonography. The index side artery was the focusof each and every subsequent analysis. A previouslypublished five-point scale was used to evaluate the image quality: exams with image quality below twowere not included in the review process. To match picture locations between scans, the common carotidartery's bifurcation into the internal and exterior carotid arteries was independently located on both 2D and 3D image sets. To assess the role of the partial volume effect and improvements with a thinner slice thickness, the original 3D pictures wereadditionally reformatted to a 2D-like dataset (referred to as 3Dr below). [28]. Four adjacent 3D slices with a 0.5-mm slice thickness that anatomically matched a corresponding 2D image were summed per pixel during this procedure. Figure depicts the scheme for matching images and reconstructing 3D data, as well as examples of native and reformatted images. As a result, three sets of images: review and quantitative measurements couldbe done with 2D, 3D, and 3Dr.



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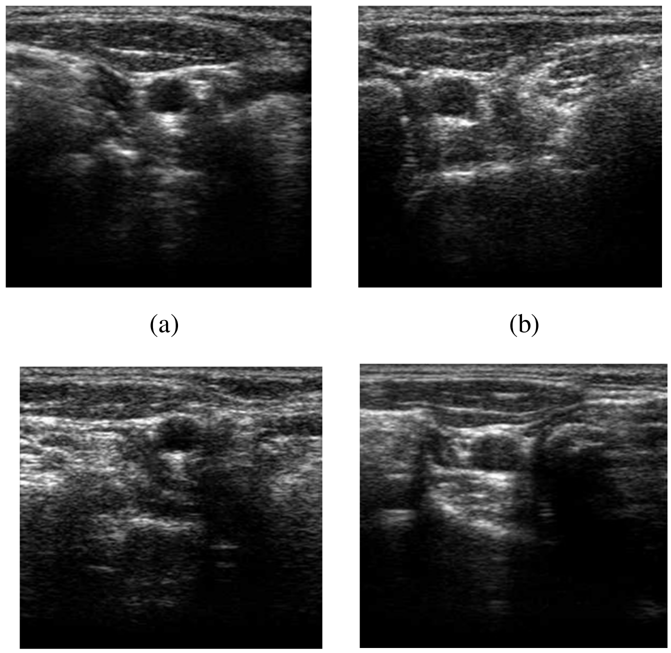
IV. PROPOSED PROCEDURE

A. Data Acquisition

The method for 3D reconstruction of the carotid artery utilising US pictures as input was developed and validated using a collection of original and annotated US images from the Toshiba test. The annotated photos were utilised for processing and training, while the original images were used for validation. For each patient, transversal and longitudinal projections show the common carotid artery, its branches, and the carotid bifurcation. B- mode was used for the examination. In keeping with the safety and security of the data, all imaging data were anonymized [32]. There are various frames in each data set depending on the probe's speed. The position and constant direction of the probe influence the ability to retrieve data. The image contains spatial data, and it is expected that position data is sequential from the data acquisition's beginning to its conclusion.



(a) (b)

(c) (d)

Figure 1. Samples of carotid artery US images.

B. Pre-processing

The goal of the pre-processing step is to better prepare the data for the segmentation step. An elliptical morphology feature is the one used. In order to make the ellipse's characteristics more apparent, data on the carotid artery's surface area are exposed. So the pre-processing step is to make images that show the carotid artery's location. A stage of pre-processing that uses median filters, histogram equalization, and a series of Gaussian filters. The image is processed using gaussian filters to produce more uniform data in certain areas with finer results. The image is processed using gaussian filters to produce more uniform data in certain areas with finer results. The value of the standard deviation parameter (σ) is 0.5. Histogram Equalization follows the Gaussian filter process's output. The data have salt and pepper noise, which can make it hard to segment the data. To circumvent this problem, the median filter is employed. In some sections of the image data, the divided piece with holes in the surrounding area can offer a high gradient value. It is overcome by the application of dilation morphology.[1].

C. Segmentation

The information about texture, shape, and contours, among other things, is used in the traditional image segmentation techniques perform well when there is less noise in the images. However, it has been discovered that the objective function is typically much more complex in the context of medical images. As a result, the number of classical techniques that can be used is limited. Using anisotropic diffusion or geodesic active contours, the segmentation method that is used to measure the IMT was suggested in some papers. A novel approach to the processing of B-mode ultrasound images that makes use of all of the data in the image to reduce anisotropic noise was developed by others. It is currently being made available for RF ultrasound data as well as 3D carotid image data[2].

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V. RELATED WORK

The study of reconstructing 3D shapes from 2Dimages has increased thanks to recent advancementsin 3D representation learning, reconstruction, and completion in 3D computer vision field. Based on the quantity of input images, this research can be dividedinto the following categories: single-view and multi-view three-dimensional shape reconstruction. However, the associated work can also be characterised as voxel-based 3D shape reconstruction, point cloud-based 3D shape reconstruction, or mesh-based 3D shape reconstruction according to various representation forms of 3D shapes. In particular, the single-view 3Dshape reconstruction that is based on point clouds includes the 3DAttriFlow that is proposed in this paper. For convenience, the discussion of related work will be arranged in accordance with 3D shape output forms.

Author	Year	Algorithm	Advantages	Disadvantages
C. B. Choy etal.,[5]	2016	Multi view stereo (MVS) analysis	• Accurate and effective 3D acquisition techniques. • Minimal supervision needed.	• When reconstructing objects with high texture levels, this technique performed worse. • Fail to reconstructas many details when more than 30 different views are given.
Jun Young Gwaket al.,[6]	2017	–	• Effectively produce an excellent reconstruction from subpar 2D supervision. • Improved generalisation capabilities despite noisy perspective labels.	• It harms reconstruction oncomplex shapes.
Tijana Djukicet al.,[7]	2021	Finite element procedure	• Makes morphological parameter extraction andsegmentation efficient. • It allowed for quicker diagnosisand improved clinical judgement.	• When making data collecting, ittakes the expertise, knowledge, and abilities of the expert. • Images producedby various sonographers could vary.
Christian Haneet al.,[8]	2017	Hierarchical surface prediction	• Facilitates high resolution 3 dimensions reconstruction of objects. • Prediction is feasible and improved quality.	• They only forecast a voxel grid with a coarse resolution, whichpoorly captures the surface of theobjects.

Jhony K Ponteset al.,[9]	2018	Image 2 mesh framework	• Simple and effective learningframework. • A low dimensional space contains a3D mesh object.	• Demand for astrong embedding graph. • Do not synthesisea background thatlimits work to white backgrounds.
Edward Smithet al.,[10]	2018	Orthographic depth maps (ODM) and a framework formulti-view decomposition	• Generate sharpedges more easily. • Accurately predicting novel objects at its highest resolutions.	• ODM with a narrow-band adaptive averaging filterthat only takesinto account nearby pixels.
Weiyue Wanget al.,[11]	2019	Approach using a deep implicit surface network	• Capable of capturing minutedetails. • Produce excellent 3Dmodels.	• Only objects with transparent backgrounds can be handled by the technique.
Mateusz Michalkiewicz1 et al.,[12]	2020	_	• Higher reconstructionquality with highest shape resolution. • Improve performance and interpretability.	• Only works witha large dataset.
Jiongchao Jinet al.,[13]	2019	Metrics for Differentiable Visual Similarity	• The networks performed better in terms of visualshape similarity criteria. • Analysis can be carried out in both qualitativeand quantitative ways.	• On the projectedimages, errors aren't noticeable.
Xueting Li et al.,[14]	2020	Self-supervision and consistency in semantics	• Reduces ambiguities. • Accurately depictthe most definingaspects of an object's shape and meaning.	• It ignores certain information, which prevents the discovery of significant piecesfor a particular category.
Yifan Xu et al.,[15]	2020	Algorithms based on Farthest Point Sampling and SGD-based optimization	• Rebuild a high-quality mesh that contains precise geometrical details.	• It is challenging due to the wide variances in shape and structure among things.

Xin Wenet al.,[16]	2022	3D attribute flow method	• Consumption oflight weight storage. • The capacity to depict a variety of complex shapes.	• Data loss or compression during the globalpicture feature extraction process.
Weiyang Liuet al.,[17]	2022	Structural Causal Reconstruction (SCR) framework	• Recreate precise geometrical details. • Find more accurate forms.	• Assumptions for disentanglement can be strong butunrealistic sometimes.
Zhen & Chen et al.,[18]	2022	Method for contrastive learning that is 3D aware	• Choose shape priors and combine shape priors and visual features to reconstruct three - dimensional objects.	• For the category with subtle shapedifferences, the model is unable to produce good reconstruction results.
Zhen Xing et al.,[19]	2022	Semi-Supervised learningand state-of-the-art method	• Use of unlabelled data for effectiveand reliable reconstruction. • Consistent androbust to data augmentation.	• Use of a large number of labelled and unlabelled visualsand time consuming fine- grained three dimensional shapes.
A Delcker and HC Diener et al.,[20]	1994	Watershed algorithm	• Visualising the human lumen of vessel with the high resolution and reliability.	• Possibility of error in plaque volume evaluation due to manual tracking.

A. *Outlier Selection*

Selection of outlier is the process of calculating a data's segmentation error using all of the available data. The carotid artery may not be correctly segmented throughout the segmentation process. The segmentation method saves ten of the best elliptical data, which can be utilised to fix the segmentation error. Calculating the standard deviation () isnecessary to spot anomalous carotid arterysegmentation results [1].

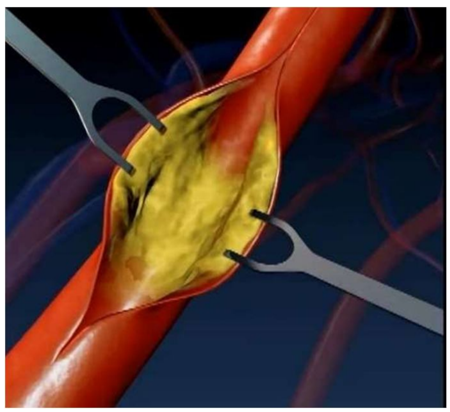
B. *Visualisation*

Using a 3D point cloud, the polynomial fitting functions for the parameters x, y, a, and b are visualised. To draw the ellipse, a polynomial fitting function is applied to each parameter. Each ellipse isseparated by 0.01 cm, while the beginning and last ellipses are separated by 5 cm. Leveraging the CloudCompare application for visualisation, the smooth visualisation is achieved by using the close spacing between the ellipses.

VI. RESULTS AND DISCUSSION

This work created a 3D reconstruction of an artery that allowed to visualise surfaces based on ellipses that represent arterial walls. Data collection, pre- processing, segmentation, outlier selection, curvefitting with polynomial fitting, also point cloud visualisation are the first steps in this study. Ten datasets are produced by data collecting from 10 individuals. The number of pictures in each dataset varies depending on how quickly the probe moves during the data collecting process. The same frequency and depth parameters are used during datacollecting. Whether a good or awful image is createdfor each person determines the gain setting, which ranges from 85% to 95% [1].

Patients who have cardiac arrhythmia are another category of patients for whom 3-D ultrasound imaging poses challenges because freehand 3-D ultrasound is not a real-time imaging technique that relies on ECG-gated acquisition to capture serialimages of the vessel at the same point in the cardiaccycle. Unless combined ECG- and respiratory-gatedacquisition is used, patients who have trouble breathing should also be thought of for exclusion from 3-D ultrasound assessment to preventsignificant motion artefacts from being introduced into the reconstruction. Respiratory motion was not found to introduce significant artefacts for the majority of patients scanned in this study, however. It is still unknown how useful measures like plaque volume and volumetric stenosis are in the clinical setting. Some of these measurements may help in theidentification and management of high-risk patients by offering a measure that more accurately reflects the true severity of the disease in relation to the dimensions of the vessel wall or by tracking plaque progression shown by changes in serial measurements [19].



VII. CONCLUSION

The surface artery was visualized in three dimensions as a result of this study. The stages of thisstudy are as follows: segmentation, selection of outliers, ellipse fitting parameters, and visualizationare all part of the data acquisition process. In the proposed method, segmentation without pre-processing yields results with lower accuracy than those with pre-processing. The proposed approach with pre-processing, compared to the template matching and hough circle methods, obtains the maximum accuracy with a 99.41% accuracy rate andthe smallest standard deviation of 0.05. The polynomial equation, which is the best match for alldata, has the minimum mean error value in the 22ndorder, 0.26303. Therefore, the carotid artery positionon the B-mode ultrasound image can be seen in threedimensions using the modified template matching with ellipse feature.

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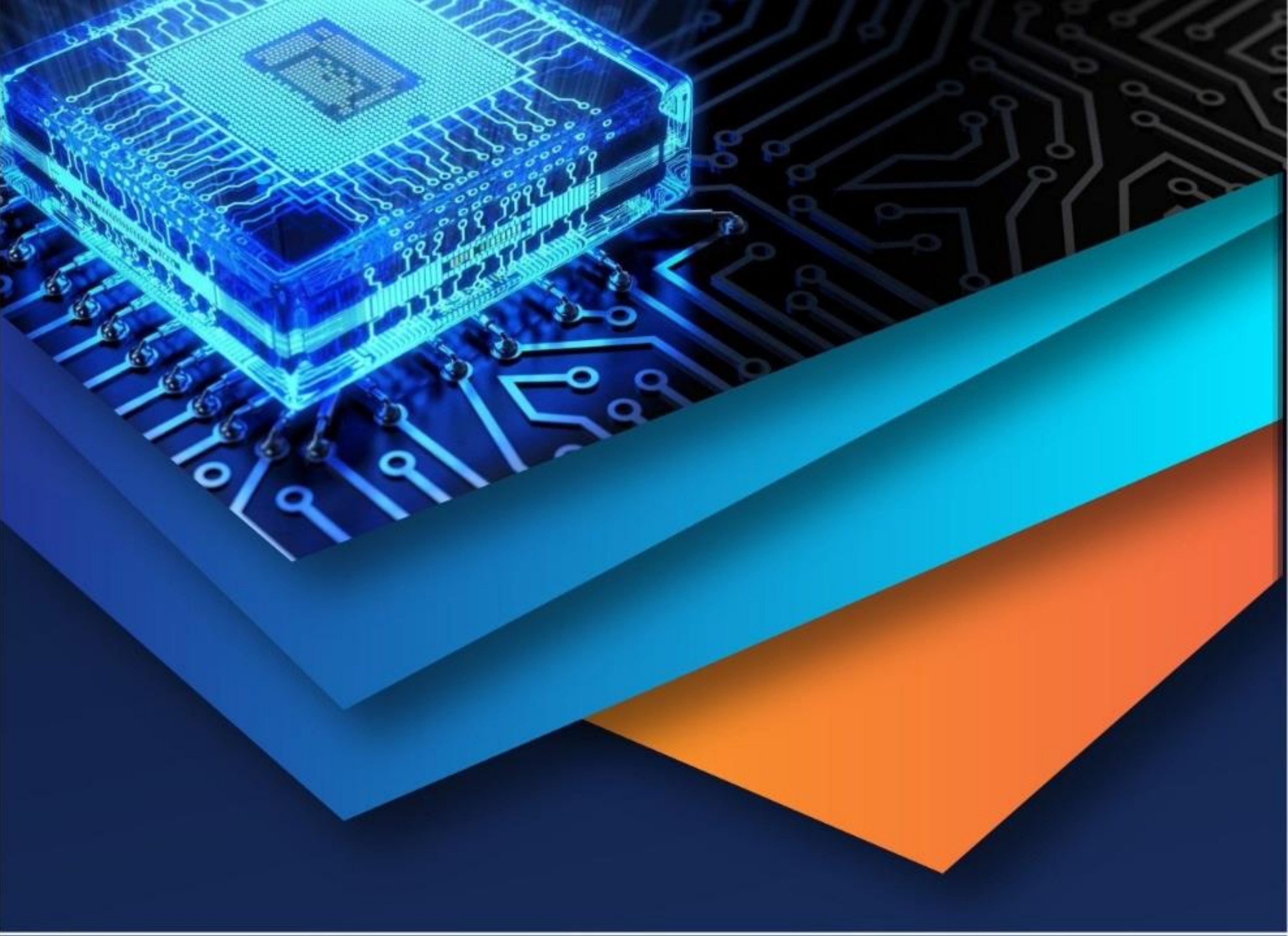

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