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A Review of Datasets for 3D Indoor Modeling

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Abstract: Indoor modeling has witnessed a substantial transformation in recent years, driven by advancements in 3D sensing technologies and data processing techniques. Point cloud datasets, representing detailed geometric information of indoor environments, play a pivotal role in enabling various applications such as architectural design, navigation, and augmented reality, and Building Information Modeling (BIM). This paper provides a comprehensive overview and comparision of the state-of-the-art datasets specifically curated for indoor modeling.
Keywords: Computer Vision, Deep Learning, 3D Vision, Point Clouds, Building Information Modeling.

I. INTRODUCTION

3D modeling is the process of creating virtual three-dimensional representations with reference to an object or a surface in the real world. 3D models assist professionals across a multitude of fields to visualize, plan, optimize, and understand the intricacies of the physical entities they are faced with, improving efficiency and reducing costs of the project.

It is thus no surprise that 3D modeling has propelled the field of architecture and interior designing into the digital era, revolutionizing the way professionals conceptualize, plan, and design projects.

Tools like AutoCAD, Autodesk Revit, Blender, and the Adobe Creative Suite are widely used to design 2D and 3D models in 3D Indoor Modeling.

These tools empower designers and architects to create detailed and realistic representations of indoor spaces.

In the last decade, 3D Indoor Modeling has significantly advanced due to the integration of 3D vision techniques like point clouds, depth sensors, and RGB-D imaging.

Dense point clouds are among the most accurate methods of capturing 3D data, and are widely used in Building Information Modeling (BIM). BIM is a digital representation of the physical and functional characteristics of a building or infrastructure, and is commonplace in the architecture, engineering, and construction (AEC) industries.

In this paper, we provide a detailed review of datasets commonly used and related to 3d indoor modeling and BIM. As opposed to reviews [1, 2, 3, 4], we specifically compare and analyse datasets rather than methods developed on these datasets using deep learning. We consider the most impactful datasets from 2015 to 2023, and provide a summary of the most influential and useful datasets that have shaped research and applicationsin this domain.

The paper is organized as follows: Section 2 reviews related survey papers that have studied similar topics. Section 3 discusses challenges encountered by professionals while using 3D data. Section 4 studies state-of-the-art datasets in 3D modeling and compares the tasks associated with them. Section 5 discusses future applications of 3d modeling in various fields.

II. RELATED WORK

Several comprehensive surveys and reviews have systematically documented the various models proposed for tasks like 3D object recognition, point cloud segmentation, and scene understanding. These surveys provide valuable insights into the evolution of techniques and the comparative performance of different models.

[5] investigate data acquisition and validation methodologies for point clouds in the context of BIM. They detail the numerous devices used to capture point clouds and study the device configuration, capture time, and processing time needed to completely capture the target area in a determined resolution. [6] take a look at five datasets for indoor modeling that were produced shortly after the Microsoft Kinect, a consumer-level RGB-D camera was released. [3, 1, 4] comprehensively explore and categorize the many models developed over the years. They also examine various datasets used and compare evaluation metrics in 3D tasks like shape classification, object detection, and semantic segmentation. \cite{ardlsspc} focus specifically on semantic segmentation in point clouds.

[7] focus on label-efficiency in point cloud learning. Label-Efficient learning attempts to train models with minimal accuracy while still achieving a desired accuracy. They examine label-efficient learning in other modalities and also detail techniques like data augmentation, domain transfer learning, and weakly-supervised learning for point clouds.

[8] is a thorough survey on point cloud registration. The authors explore commonly faced challenges, and propose a taxonomy that categorizes the types of registration according to the solutions developed to counteract these challenges.

III. CHALLENGES

There are many challenges that scientists may encounter while dealing with point clouds and RGB-D data. We broadly classify them into 4 categories

A. Data Collection

Frequently, point clouds are sparse, devoid of the density required for precisely identifying intricate or minute items in a scene. Furthermore, it could be difficult to infer object features from their visual appearance because they might not contain color information.

The quality and density of point clouds are subject to a myriad of variables, including the specific sensing device used, the environmental conditions, weather, lighting, and the number of devices involved in data collection [7]. These factors can introduce substantial variations in data quality and density, which can complicate subsequent analysis.

Indoor environments, with their intricate interior structures, pose a particularly demanding challenge. The complex layout of indoor spaces can make object detection and modeling a formidable task, especially when dealing with consumer-grade sensors that may produce lower-quality data. Furthermore, unavoidable clutter and occlusions within indoor settings can disrupt the data collection process, hindering the creation of accurate and comprehensive point clouds [9].

B. Data Annotation

Data annotation in a 3D context demands expertise and careful attention. Annotators often require specialized knowledge to accurately label objects, or they must undergo extensive training to develop this expertise. The three-dimensional nature of point cloud data can be tricky to navigate, and annotators may become easily confused or disoriented, especially when working with data lacking color or relevant metadata like scene images to provide context.

Consumer-grade sensors, which sometimes produce lower-quality data, further compound the difficulties of annotation. Poor data quality can obscure important details, making it a demanding task for annotators to interpret and label objects accurately.

The presence of unavoidable clutter and occlusions in point clouds can significantly disrupt the annotation process. Objects or structures vital to the annotation task may be obscured by these occlusions, requiring extra effort to compensate for their presence.

C. Data Preprocessing

Despite its compute-heavy and time-consuming nature, effective preprocessing significantly accelerates both the training and inference phases.

One of the primary concerns during data preprocessing is the potential loss of information [2]. Certain transformations or simplifications applied to point cloud data may inadvertently result in the loss of critical details. Additionally, handling sparse and low-quality data to convert it into high-information representations is a formidable task [4].

In the context of point cloud registration, where multiple scans are combined to create a unified model, several formidable challenges emerge. Data overlaps and mismatches between scans, variations in scale and rotation, and differences in data modalities across sensors must be addressed. Detecting and closing loops in the trajectory while ensuring consistent registration, a challenge known as "loop closures," is another intricate aspect of this process.

The presence of clutter and occlusions in point cloud data may lead to inaccurate or distorted representations, necessitating thorough preprocessing to mitigate these issues. Furthermore, when data is collected using a mobile sensor, accounting for localization uncertainty becomes imperative to ensure the accuracy of the final point cloud representation[10].

D. Data Modeling

Addressing the challenge of training a model on one dataset and testing it on another is crucial. It's essential to develop robust methods capable of handling variations in quality and density across different configurations of point cloud data. These variations can impact the model's performance, necessitating careful consideration during training and testing phases.

Point clouds, due to their unstructured and permutation-invariant nature, pose a challenge when it comes to incorporating them into models. Handling the scale and viewpoint invariance inherent in point cloud data is a complex task, requiring innovative approaches to effectively capture the features and relationships within the data.

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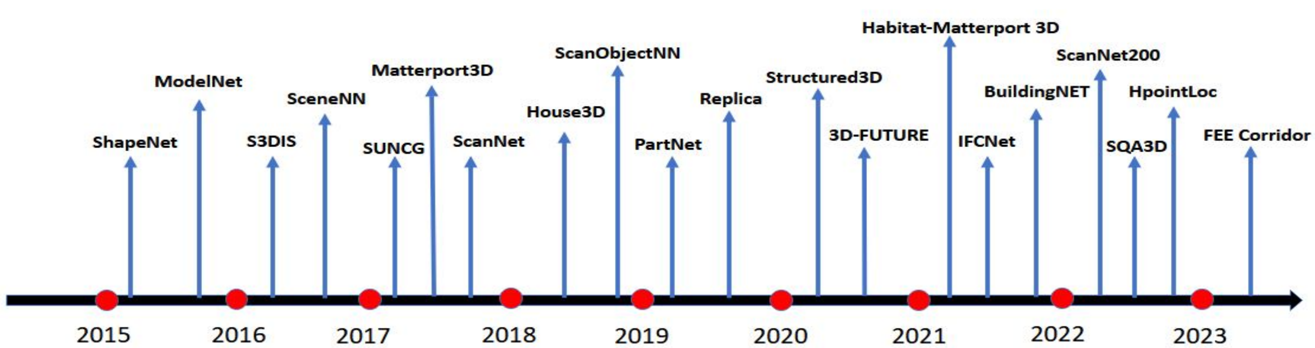
Developing robust models for point clouds demands a diverse and substantial dataset for training, encompassing various scenarios and conditions. Large and diverse data not only aids in enhancing the model's generalization but also empowers it to deal with the inherent complexities of real-world point cloud data. Indoor scenes, often characterized by intricate interior structures, add another layer of complexity to data modeling. Detecting and classifying objects within these spaces is challenging due to their complexity, diversity, and variations in lighting and geometry. The sheer volume of 3D data can be daunting, requiring vast storage capacity. Handling and managing such large datasets for training and inference introduces storage and computational challenges. Models need to be efficient in storage usage and computational requirements to be practical for real-world applications.

IV. DATASETS

With meticulously annotated and well-structured datasets, researchers can confidently develop and assess their models and algorithms. These datasets serve as a standard for evaluating performance, facilitating comparisons among various methodologies, and encouraging the creation of more powerful and streamlined solutions across diverse applications.

TABLE I
COMPARISION OF DATASETS SURVEYED

Name	Year	Classes	Scale	Real/Synthetic	Data Type
ShapeNet	2015	55	51.3K models	Synthetic	CAD Models
ModelNet	2015	40	12K models	Synthetic	CAD Models
S3DIS	2016	13	6 scenes, 271 rooms	Real	Point Cloud
SceneNN	2016	22	100 scenes	Real	RGB-D
SunCG	2017	84	45K scenes	Synthetic	RGB-D
Matteport3D	2017	20	90 scans; 194K images	Real	RGB-D
ScanNet	2017	20	1513 scenes	Real	RGB-D
House3D	2018	80	45K scenes	Synthetic	RGB-D
ScanObjectNN	2019	15	2.9K objects	Real	Point Cloud
PartNet	2019	24	26K models; 573K parts	Synthetic	CAD Models
Replica	2019	88	18 scenes	Synthetic	3D Mesh
Structured3D	2020	40	3.5K scenes	Synthetic	RGB-D
3D-FUTURE	2020	34	5K scenes; 20K images	Synthetic	CAD Models
HM3D	2021	NA	1K scenes	Real	RGB-D
BuildingNet	2021	31	2K models; 292K parts	Synthetic	CAD Models
IFCNet	2021	65	19K models	Synthetic	CAD Models
ScanNet200	2022	200	1.5K scenes	Real	RGB-D
SQA3D	2022	20	650 scenes; 20K descriptions	Real	RGB-D
HPointLoc	2022	41	49 scenes; 76K frames	Real	RGB-D
FEE Corridor	2023	NA	2 sequences; 75 static poses	Real	Point Cloud



A. ShapeNet (2015) [11]

ShapeNet is a massive library of 3D models covering many different types of objects, including furniture, cars, home goods, and more. These models are richly varied in form, scale, and structure, demonstrating their diversity. The dataset offers fine-grained part annotations for 3D mesh models, which facilitates the creation of algorithms for tasks such as item recognition, shape retrieval, and semantic segmentation in 3D scenarios.

B. ModelNet (2015) [12]

ModelNet comprises a substantial collection of 3D CAD models, primarily focused on common object categories, such as chairs, tables, and desks. The 10-class version of ModelNet consists of 10 object categories, each containing almost 4000 3D models for training and more than 900 models for testing. The 40-class variation further extends the dataset to include a broader range of object categories, with each class having a minimum of 100 models. Researchers have also created point clouds from the 3D models provided in ModelNet to study point cloud classification.

C. S3DIS (2016) [13]

Stanford University has compiled a substantial dataset comprising colored 3D scans of indoor spaces within large buildings, featuring a variety of architectural styles. These scans predominantly encompass office, educational, and exhibition areas. Within this dataset, thirteen semantic elements are detected, including structural components like beams, walls, and doors, as well as commonly encountered objects such as chairs, tables, and sofas.

D. SceneNN (2016) [14]

SceneNN focuses on indoor environments and offers a comprehensive collection of 3D reconstructions of real indoor spaces capturing actual real-world scenes using depth sensors and RGB cameras. It includes over 100 scenes, each equipped with dense 3D point clouds and aligned RGB images, providing rich and detailed information about indoor spaces. Every scene is transformed into triangular meshes with annotation at the per-vertex and per-pixel levels. In 2018, [15] introduced 76 scenes re-annotated with the 40 classes identified in [16], of which 56 scenes were used for training and 20 scenes were set aside for validation.

E. SUNCG (2017) [17]

The SUN Computer Graphics dataset encompasses various room types, architectural styles, and furnishing configurations, providing diverse and realistic indoor scenes for research and development. It is a synthetic dataset primarily meant for semantic scene completion. The dataset is no longer publicly available.

F. Matterport3D (2017) [18]

Matterport3D comprises a substantial collection of 3D reconstructions of real-world indoor environments, primarily focused on residential and commercial spaces. It offers highly detailed and textured 3D models, point cloud data, and RGB-D images captured using a Matterport Pro Camera. It contains almost 11,000 panoramic views constructed from 194,400 RGB-D images.

G. ScanNet (2017) [19]

ScanNet stands as a crucial 3D dataset primarily focusing on indoor spaces, containing 2.5 million views distributed across 1513 scans. Distinguished by its dense 3D point cloud data, RGB-D images, and detailed semantic and instance-level annotations, ScanNet was expanded in 2022 to encompass 200 annotated classes, enhancing its versatility and utility across diverse research fields.

H. House3D (2018) [20]

House3D is a sophisticated environment, with over 45 thousand meticulously crafted 3D scenes showcasing realistic houses. These scenes have a wide variety of accurately annotated 3D textures, objects, and scene layouts that are taken from the SUNCG dataset. The environment provides agents with observations across multiple modalities, which makes House3D an ideal platform for reinforcement learning in navigation and scene understanding in complex indoor settings.

I. ScanObjectNN (2019) [21]
ScanObjectNN is a point cloud dataset developed to showcase the common occurrence of partial obstructions or background clutter in real-world object scans, which significantly reduces the accuracy of current classification techniques. The authors stress the importance of real-world scans by comparing techniques on synthetic data like ModelNet40. Additionally, they propose a resilient network architecture capable of managing imperfect data obtained from real-world scans.

J. PartNet (2019) [22]
PartNet was created for the task of Part Segmentation of 3D objects. PartNet offers intricate annotations for object parts, providing a more detailed understanding of the composition of 3D objects. It makes use of the ShapeNet dataset along with more than half a million part annotations for over 26 thousand shapes and introduces a hierarchical structure for object parts.

K. Replica (2019) [23]
The Replica dataset comprises 18 meticulously reconstructed interior layouts ranging from individual rooms to entire buildings. Its annotation adopts a hierarchical data structure resembling a forest, with individual mesh primitives forming the bottom level and object entities at the top level. Thanks to its exceptional scan quality, it proves to be ideal for evaluating 3D perception systems, including SLAM (Simultaneous Localization and Mapping) and dense reconstruction systems.

L. Structured3D (2020) [24]
Structured3D is a synthetic dataset containing over 3000 house designs created by professional designers under varying lighting and furniture layouts. The authors also introduce a “Primitive + Relationship” unified representation for structures that minimizes redundancy and preserves relationships between entities for 3d modeling. Structured3D emphasizes geometric primitives like lines, planes, and cuboids more than categorizing objects. As such, they follow the 40 label ids used in [16] to annotate objects encountered.

M. 3D-FUTURE (2020) [25]
3D-FUTURE is a dataset comprising more than 20,000 high-resolution synthetic images captured within scenes meticulously crafted by experienced designers. These scenes are constructed using CAD models typically utilized in industrial production settings. Unlike relying on online open-source repositories, 3D-FUTURE offers quality 3D furniture shapes with intricate details, providing a valuable resource for various applications requiring high-fidelity virtual environments.

N. Habitat-Matterport 3D (2021) [26]
HM3D comprises 1,000 3D scan reconstructions representing various real-world locations, with each scan accompanied by a 3D mesh detailing the interior. Notably, HM3D surpasses previous datasets by up to 3.7 times in size and up to 85\% in image quality. This enhanced size and quality have demonstrated its superiority in indoor navigation tasks, as agents trained on HM3D consistently outperform those trained on previous datasets, regardless of the evaluation environment. HM3D prioritizes precise 3D scans of entire scenes over individual objects, and thus does not provide a report on encountered object classes.

O. BuildingNet (2021) [27]
BuildingNet is a consistently labeled dataset of CAD models comprising structures such as houses, skyscrapers, castles, and more. It boasts over half a million annotated mesh primitives arranged in part components. A graph neural network is used to analyze the relationship between the primitives and labels the building exterior accordingly.

P. IFCNet (2021) [28]
The IFCNet dataset encompasses 19,000 CAD models, categorized into 65 classes following the Industry Foundation Classes (IFC) standard taxonomy.
Specifically tailored for the Architecture, Engineering, and Construction (AEC) domain, the IFC standard facilitates open data exchange in projects.
To address disparities in object counts among classes, a subset of 8,000 objects spanning 20 classes is curated, forming the more equitably distributed IFCNetCore dataset.

Q. ScanNet200 (2022) [29]

ScanNet200 is an extension of the original ScanNet dataset, incorporating 200 distinct annotated classes without introducing any new scene data. Notably, this dataset features a natural class imbalance due to its expanded vocabulary. The ScanNet200 benchmark serves as a prominent benchmark widely utilized by researchers in the fields of 3D Indoor Modeling and BIM (Building Information Modeling).

R. SQA3D (2022) [30]

SQA3D is a dataset based on 650 scenes from ScanNet for smart scene understanding, where an agent attempts to grasp a first-person perspective of a scene and answer questions. The agent has access to three different modalities: 3D scan, egocentric video, and BEV picture. The questions cover a broad range of reasoning skills, including sequential inference, commonsense reasoning, navigation, and spatial comprehension.

S. HPointLoc (2022) [31]

HPointLoc originates from scenes within the Matterport3D dataset, utilizing the Habitat simulator. It is primarily designed to explore visual scene recognition within indoor environments and closure detection as essential components of simultaneous localization and mapping (SLAM) systems.

T. FEE Corridor (2023) [32]

The FEE Corridor dataset contains highly accurate point cloud data captured within indoor environments, along with precise localization and ground truth mapping details. To ensure data quality, the capturing methodology minimizes errors induced by sensor movement during lidar scans. Notably, the dataset prioritizes detailed 3D scans of complete scenes over individual objects, omitting information regarding encountered object classes.

V. DISCUSSION

The paper extensively examines the domain of 3D indoor modeling, addressing challenges related to data collection, annotation, processing, and modeling. It surveys over twenty relevant datasets in this field, providing a comparative table that facilitates accessibility to key dataset attributes for both researchers and practitioners.

The applications of 3D modeling in fields like architecture, urban planning, virtual reality, and augmented reality are constantly advancing. The capacity to generate lifelike digital renderings of indoor spaces streamlines design and planning processes. Moreover, the broad accessibility of 3D models and datasets across different sectors presents opportunities for the automated generation of shapes, structures, and scenes.

The future scope of 3D modeling lies in addressing current challenges, advancing techniques for more efficient data collection, and refining modeling algorithms to enhance accuracy and speed.

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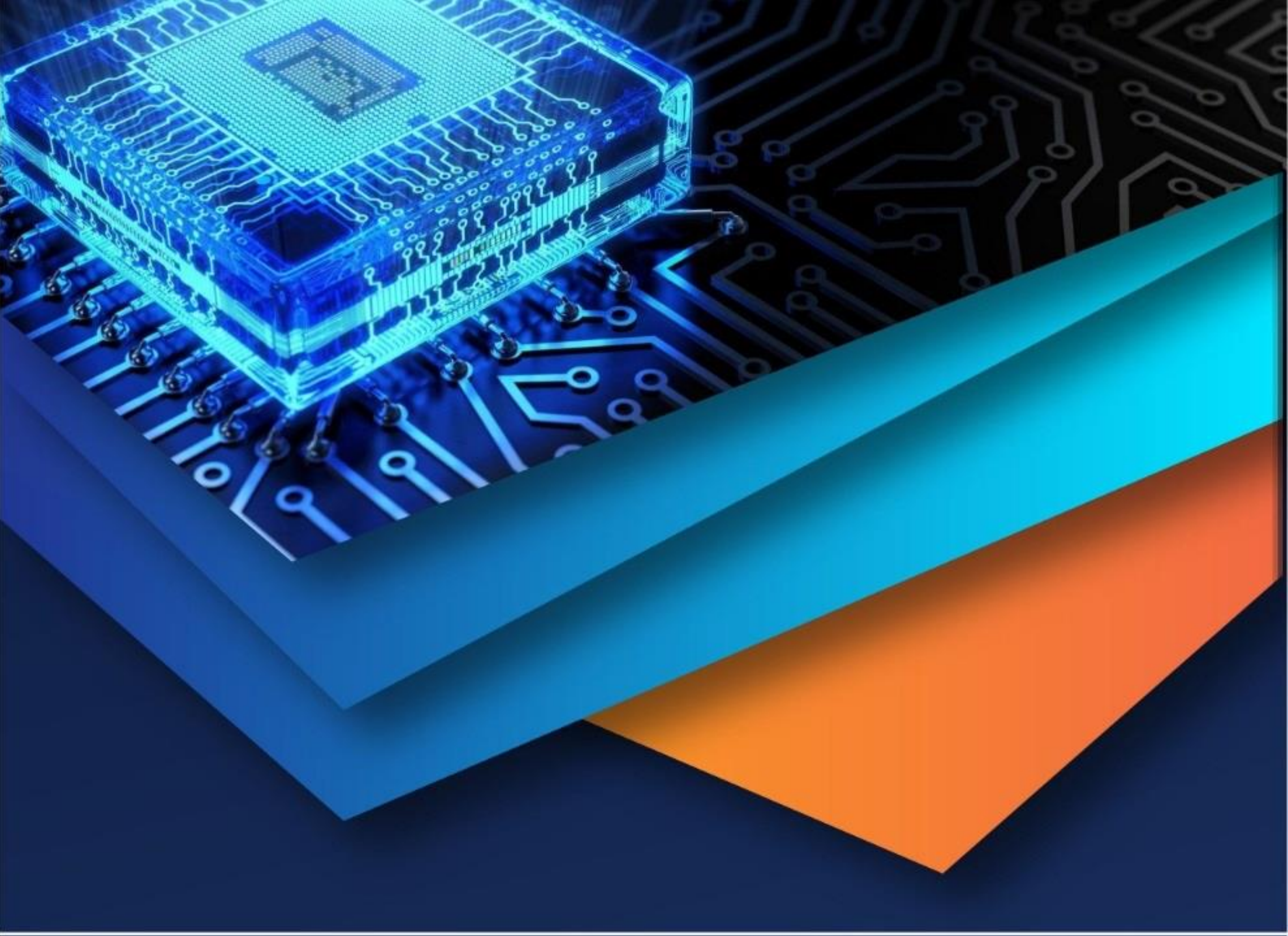

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