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A Review of Image-Based Monument Identification Using Deep Learning Techniques.

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Abstract: Image-based monument identification is very much demanding task due to the variability of lighting conditions, viewpoints, and occlusions. Deep learning-based methods have significantly improved in classifying and recognizing images, and they are now more frequently employed to identify monuments. The current development in deep learning-based monument recognition is given in this literature study paper. The many methods for feature extraction, categorization, and model fine-tuning are described. We also discuss the field's limitations and potential developments, including the need for larger, more diversified datasets and the investigation of more sophisticated deep learning methods. Overall, this work offers a thorough summary of the state-of-the-art for deep learning-based image-based monument recognition and provide sustainable growth towards identifying and understanding about ancient historical monument identification.
Keywords: Monument Identification, Deep Learning, Feature Extraction.

I. INTRODUCTION

Utilizing photos to identify monuments Deep learning has received a lot of attention recently. The use of deep learning algorithms, which are becoming more and more common, to precisely identify monuments from pictures has been studied in a variety of ways. In a number of industries, including tourism, history, and cultural heritage, monument identification is crucial. However, identifying monuments manually is a time-consuming task that requires human expertise. Therefore, developing an automated system to identify monuments from images can significantly aid in reducing manual efforts and improving accuracy.

Convolution neural networks (CNNs) have demonstrated outstanding performance in a range of picture recognition tasks, including the recognition of monuments. These deep learning algorithms can identify the aspects of monuments because they can extract fine information from images. Models can also adjust to changing image conditions including lighting, occlusion, and viewpoint adjustments. In this literature survey, we will discuss the various approaches proposed in recent years to identify monuments using deep learning techniques. We will also explore the challenges and limitations of the existing methods and discuss future research directions.

II. LITERATURE SURVEY

Authors	Technique/ Algorithm employed	Findings	Remarks
Varsha Singh *et.al.*,[1]	Feature extraction: • CNNs (Xception) • Object Detection (SSD on MS COCO) Classifiers/Models: • LSTM • Encoder Decoder with attention	29.75% improvement in METEOR score.	Emphasizes the need for human-like image captioning and enhanced caption coherence.
Preeti S *et.al.*,[2]	• Encoder-decoder architecture, VGG16 (CNN) for encoding, LSTM (RNN) for decoding. • Classifiers: VGG16, LSTM	The model is trained on the Flickr8k Captions dataset and evaluated using the BLEU score.	The model uses VGG16 for image analysis and LSTM for natural language processing to generate captions

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Arunkumar Gopu *et.al.,*[3]	• Multilayer CNN for image analysis and LSTM for sentence construction. • Classifiers: VGG16, XceptionV3	Used the BLEU metric for evaluation on the Flickr 8k dataset.	Emphasized challenges in accessing non-visible data in images and the importance of semantic understanding.
Yukta Nagpal *et.al.,*[4]	Classifying the 8 heritage monuments, the whole dataset is divided into 8 classes and successfully developed a CNN algorithm for the multiclassification of these heritage monuments.	The best detection accuracy recorded over this multiclassification of heritage monuments is 97.97%. The macro average recorded while performing this experiment was 89.59%.	Further used over the hybrid model to achieve better detection accuracy. In future, this study can be extended to develop a mobile app and embed this CNN model into it.
Satish Kumar Satti *et.al.,*[5]	The system leverages the ResNet-50 model, a deep convo-lutional neural network (CNN), for image feature extraction. ResNet-50	The ResNet-50 model provides a high-level representation of the image.	Empirical results unequivocally demonstrate that model surpasses existing methods in terms of caption quality and semantic coherence.
Chandradeep Bhatt, *et.al.,*[6]	The architecture of image caption generators includes two parts: an encoder and a decoder , The encoder is a CNN which draws out the characteristics from the image, while the decoder is an LSTM that generates the textual description of the image.	Used the BLEU-1, BLEU-2, BLEU-3, BLEU-4, and METEOR assessment metrics.	Future research in this field should focus on creating models which will be capable of generating various diverse and relevant captions.
Himanshu *et.al.,*[7]	Investigate on Multimodal decoders, and Deep sequential modeling architectures, such as RNN,LSTM,GRU.	Deep learning based bottom-up decoders outperforms, machine-learning based top-down decoders.	Forthcoming methods may combine transfer learning techniques with large datasets and cutting edge deep learning algorithms to produce better models.
Anoopa S *et.al.,*[8]	Analysis of faster RCNN and YOLO V3 for anomaly localization.	Evaluated based on FPS, mAP, Precision, Recall, and F1 Score.	Provides insights into the effectiveness of Faster RCNN vs. YOLO V3 for video anomaly detection
Fatma Nur Ortatas *et.al.,*[9]	Utilized Mask RCNN and Faster RCNN for lane detection and tracking in a Gazebo environment.	Developed software successfully tested in a simulation environment for lane detection and tracking.	Demonstrates Mask RCNN and Faster RCNN's efficacy in real-time image analysis, hinting at their utility for dynamic captioning.
Padmashree Desai *et.al.,*[10]	GLCM and morphological operators	To evaluate the proposed method, the authors conduct experiments on their dataset, measuring the classification accuracy for each art form.	Limited scope of the dataset used for evaluation
Aradhya Saini *et.al.,*[11]	State-of-the-art Deep CNN	Carried out on the manually acquired dataset that is composed of images of different monuments where each monument has images from different angular views.	Comprises of low dataset and also to include more variations on terms of structure and illumination.
Siddhanth Gada *et.al.,*[12]	Inception V3 Architecture classification. CNN, ReLU is an activation function	User can train model without the requirement of Graphic Processing Unit(GPU)	Size of data-set to be increased by adding monuments and structure from all over the Globe.

Jaimala Jha *et.al.*,[13]	Used k-means clustering.	Scope of this is to reduce the semantic gap of features vectors	Still improvements are required, to reduce gap and also to use Deep Learning in-place of machine learning techniques.
RonakGupta *et.al.*,[14]	Semantic hierarchy preserving retrieval scheme	Semantic embeddings with different convolutional neural network architectures and compare its performance with pre-trained CNN architecture	Efficiency to be increased in order to identify the exact images and also further improvement is to be done by increasing the size of dataset.
Shahd Hesham *et.al.*,[15]	VGG16 and ResNet50 represent deep learning and the KNN	Proposed the difference in monument identification using DL and ML.	Future work is to extend the experiment to cover more than three classes of monuments.
V. Palma *et.al.*,[16]	CNN algorithm is based on the MobileNet model	Mobile app based monument recognition.	Interface and functionalities could enhance the interaction with 3D digital models by implementing Augmented Reality (AR) functions.
Ravi Devesh *et.al.*,[17]	CBIR system which is used to retrieve the images of the monuments based on low level features.	Used morphological operator along with invariant moment in extracting shape, features.	Morphological methods can be applied on image with distinct structuring element. Such operations are Erosion, Dilation, Open, and Close
M. Trivedia *et.al.*,[18]	This study has used InceptionV3, MobileNet, ResNet50, VGG16 and AlexNet Deep Learning architectures for classification	Accuracy evaluation in all five different algorithms	To improve the performance further suitable preprocessing techniques can be applied to the dataset,
Sowjanya Jindam *et.al.*,[19]	Convoluted neural network(CN N). Along with some preprocessor techniques	Heritage identification of monuments is an important task in the field of cultural heritage preservation.	Future developments are required in enhanced accuracy, greater resolution satellite imagery.
Neha Himesh *et.al.*,[20]	Convolutional Neural Network (CNN) Architecture using a GPU unit.	Convolutional Neural Networks to detect and classify different types of monuments	Increase the dataset and improve the scope of the model
Malay S.Bhatt *et.al.*,[21]	GCMs as input to GP system. Other popular feature descriptors like Harris, HoG, SIFT, Local Binary Pattern (LBP)	Preprocessing, Genetic programming evolution and Classification.	Further extended by adding other international and national monuments.
Tanvi Sahay *et.al.*,[22]	kNN, logistic regression, support vector machines and random forests	Descriptor-wise image classification performs much better than the image-wise classification,	More discriminative features is required to increase efficiency.
Pushkar Shukla *et.al.*,[23]	Framework that relies on Deep Convolutional NeuralNetwor ks (DCNN)	Framework on four attributes Class, Architecture, era, Purpose.	Little more efficiency is required to identify the architectural style.

III. CHARACTERISTICS OF DEEP LEARNING

A kind of machine learning called deep learning teaches artificial neural networks how to understand and extrapolate information from complicated data structures. It is different from conventional machine learning techniques in a few ways, such as:

1) Representation Learning: Hierarchical data representations may be automatically found and extracted using deep learning algorithms. Instead of relying on manually constructed features, deep learning models may be able to learn abstract and high-level characteristics directly from the raw input data.

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2) Neural Networks: Neural networks, which consist of numerous layers of interconnected nodes (neurons), are the foundation for most of the models. These networks can process and analyze complex patterns and relationships in the data because they are built to resemble the structure and operation of the human brain.
3) End-to-End Learning: Models are capable of learning end-to-end mappings from input to output, without the need of explicit feature engineering or intermediate representations. This allows models to automate complex tasks and handle raw, unprocessed data directly.
4) Non-Linear Transformations: Models can capture complex non-linear relationships between input and output data. This is achieved through the use of non-linear activation functions within the neural network layers, enabling the model to learn intricate patterns and dependencies.
5) Scalability: Models can scale to handle large and complex datasets. With advancements in hardware and parallel processing techniques, deep learning models can be trained on powerful computing systems, leveraging distributed computing or specialized hardware (such as GPUs or TPUs) to speed up training and inference processes.
6) Transfer Learning: Deep learning models can leverage pre-trained models on large benchmark datasets and transfer the learned knowledge to new, related tasks or datasets. Transfer learning enables faster training, better generalization, and improved performance on limited data.
7) Interpretability Challenges: Deep learning models often exhibit a black-box nature, making it challenging to interpret their decisions and understand the underlying reasoning behind their predictions. This has led to ongoing research on interpretability and explainability methods for deep learning models.

IV. APPLICATIONS

It has many uses in many different fields as shown in Fig 1, because of its capacity to automatically discover and extract intricate patterns and representations from data. Deep learning has some prominent uses, like:
1) Computer Vision: Computer vision tasks like picture categorization, object recognition, segmentation, and image production have been transformed by deep learning. It has made advancements possible in fields including surveillance systems, facial recognition, driverless vehicles, and medical image analysis.
2) Natural Language Processing (NLP): It has made significant advancements in NLP tasks, with sentiment analysis, language translation, text generation, speech recognition, and question answering systems. It has improved machine translation, chatbots, voice assistants, and automated text summarization.
3) Speech and Audio Processing: These methods have been used for speaker identification, voice synthesis, emotion recognition from speech, and speech recognition. Real-time speech translation, automatic speech recognition, and voice-controlled technology have all been made possible.

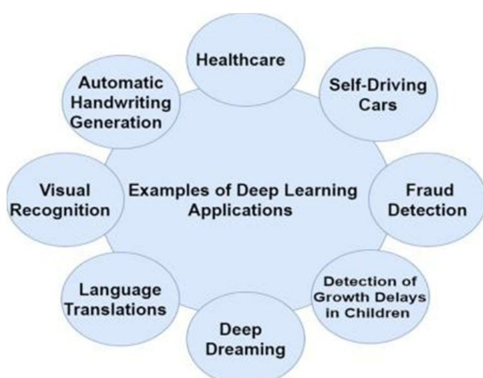

Fig 1. Examples of Deep learning Applications

4) Recommender Systems: It has enhanced recommender systems, enabling more accurate and personalized recommendations in areas like e-commerce, streaming services, and content platforms. It can learn user preferences and make predictions based on their historical data and behaviors.
5) Healthcare: It has been used for illness diagnosis, medication development, and personalized medicine as well as medical picture analysis. It has improved the accuracy and efficiency of medical imaging interpretation, early detection of diseases, and prediction of treatment outcomes.

6) Finance and Trading: Deep learning has been utilized for financial forecasting, fraud detection, algorithmic trading, and risk assessment. It can analyze complex financial data, identify patterns, and make predictions for investment decisions and risk management.
7) Autonomous Systems: Deep learning is crucial in the development of autonomous systems, including self-driving cars, drones, and robotics. It enables perception, decision-making, and control based on real-time sensory data, allowing these systems to navigate and interact with their environment.
8) Gaming and Simulation: It has advanced gaming and simulation by creating intelligent agents that can learn and improve their performance in complex virtual environments. It's been used to train agents in games like chess, Go, and Dota 2, and in simulated environments for training autonomous systems.
9) Manufacturing and Quality Control: Deep learning has been applied to manufacturing processes, quality control, and anomaly detection. It can analyze sensor data, monitor production lines, and detect defects or deviations from normal operation.
10) Environmental Monitoring: Deep learning is used in analyzing satellite imagery, weather forecasting, climate modeling, and environmental monitoring. It aids in monitoring deforestation, natural disaster prediction, land cover classification, and pollution detection.

These are just a few applications that deep learning can be used for. New applications and scientific advances are anticipated in fields including robotics, genetics, energy, cybersecurity, and others as the discipline develops.

V. AVAILABLE TECHNOLOGIES IN DEEP LEARNING

1) TensorFlow: TensorFlow, an open-source deep learning framework, was developed by Google. It provides a full environment for the creation and function of machine learning models, including deep neural networks. TensorFlow provides a high-level API (Keras) that supports distributed computation.
2) PyTorch: PyTorch is an open-source deep learning library developed by Facebook's AI Research Lab. It is widely used for research and development in deep learning due to its dynamic computation graph, which enables flexible and efficient model building. PyTorch also has a rich set of tools and utilities for training and deploying models.
3) Keras: TensorFlow, CNTK, or Theano can all be combined with Keras, a high-level deep learning API. It provides a simple and user-friendly interface for building and improving deep learning models. With Keras, which also supports convolutional and recurrent neural networks, rapid prototyping is feasible.
4) Caffe: Caffe is a framework developed by Berkeley AI Research (BAIR). It is known for its efficiency and speed, especially for convolutional neural networks. Caffe offers a command-line interface and a Python API for model training and deployment.
5) MXNet: Apache created the open-source deep learning framework MXNet. It offers a high-level API for simple model construction and allows flexible programming approaches. Python, R, and Scala are just a few of the programming languages supported by MXNet, which is renowned for its effective distributed training capabilities.
6) Theano: Theano is a library that enables effective evaluation and optimization of mathematical expressions. It supports GPU acceleration, frequently used for creating and training deep neural networks. Theano is renowned for its symbolic computation capabilities and tight NumPy integration.
7) ONNX: It is deep learning model can be represented in an open format called ONNX (Open Neural Network Exchange). It makes it possible for models developed in one deep learning framework to be applied to another, enabling interoperability between several deep learning frameworks. A standard interface for model sharing and deployment is offered by ONNX.

Deep Learning Frameworks for Particular Domains: These frameworks created expressly for domains, such as DeepChem for cheminformatics and drug discovery, TensorFlow.js for web-based applications, and OpenCV for computer vision tasks.

These are but a handful of the many deep learning-related technologies that are now available. Because each technology has a distinct set of capabilities, features, and community support, developers and researchers may choose the one that best meets their needs and expectations.

VI. ISSUES IN DEEP LEARNING

Deep learning has made significant advancements in various domains, but it is not without its challenges and limitations. Some of the key issues in deep learning include:

1) Data requirements: In order to perform well, models need a lot of labelled training data. Such datasets may not always be accessible for some fields and can be difficult to find and annotate.
2) Computational resources: Training a model is often requires substantial computational resources, including powerful GPUs or specialized hardware like TPUs. This can be a limitation for individuals or organizations with limited access to such resources.

3) Overfitting: These algorithms are susceptible to overfitting, which occurs when they memorize the training data rather than understanding the underlying patterns. This problem can be reduced by regularization methods like dropout and weight decay, but careful model construction and hyperparameter optimization are required.
4) Interpretability: Deep learning models are often considered as black boxes, making it challenging to interpret and understand their decisions. Explaining why a model made a particular prediction can be difficult, limiting their use in domains where interpretability is crucial, such as healthcare or legal systems.
5) Lack of transparency: Understanding and debugging deep learning models is difficult due to their complexity. It might be challenging to comprehend how decisions are made within the model and see any biases or mistakes, which undermines confidence and responsibility.
6) Adversarial attacks: Deep learning models are susceptible to adversarial attacks, where intentionally crafted inputs can cause the model to misclassify or make incorrect predictions. This poses security concerns in applications like autonomous vehicles or cybersecurity.
7) Transferability: Deep learning models may not generalize successfully to new or diverse datasets if they were trained on a single dataset or domain. Transfer learning approaches can help to some extent, but for best results, domain adaptation and fine-tuning may still be needed.
8) Ethical considerations: Deep learning raises ethical concerns regarding privacy, bias, and fairness. Biased training data or biased decision-making algorithms can perpetuate societal biases and discrimination.
9) Researchers and practitioners are actively working on addressing these issues through advancements in model architectures, regularization techniques, explainability methods, and ethical frameworks to ensure the responsible and effective use of deep learning technology.

VII. PERFORMANCE EVALUATION

Performance evaluation in monument identification typically involves measuring the efficiency of the model in correctly recognizing and classifying monuments in images. Here are some common evaluation metrics used:
1) Accuracy: It measures the overall correctness of the model's predictions by comparing the predicted labels with the ground truth labels. It is described as the proportion of accurately categorized samples to all samples.
2) Precision, Recall, and F1-score: These measures are often used in multi-class classification problems. Precision is the proportion of correctly predicted positive samples out of all samples that are expected to be positive. Recall measures the percentage of genuine positive samples among all true positive samples that were accurately anticipated. Recall and precision are combined to create the F1-score, a single statistic that strikes a balance between the two.
3) Confusion Matrix: It provides a detailed breakdown of the model's predictions, showing the number of samples classified correctly and incorrectly for each class. It helps identify specific classes where the model may have higher confusion or misclassification.
4) ROC curve and AUC: These metrics are used in most of binary classification issues. The area under the curve (AUC) demonstrates how well the model performs overall at discriminating between positive and negative data. The genuine positive rate is displayed against the false positive rate on the Receiver Operating Characteristic (ROC) curve.

VIII. AVAILABLE DATASETS IN MONUMENT IDENTIFICATION

Table 1: Available datasets

Si.No	Name	Description
1	Google Landmarks Dataset	Consists of over one million images of famous landmarks from around the world.
2	UNESCO World Heritage Sites Dataset:	Which comprise both natural and man-made features, are included in this dataset
3	Flickr Landmark Dataset	Consists of images from various landmarks worldwide, collected from the Flickr platform
4	Aachen Day-Night Dataset	Contains images of landmarks in Aachen, Germany, captured during the day and at night
5	Rome16K Dataset	Contains high-resolution images of landmarks in Rome, Italy
6	Tokyo 24/7 Dataset	Consists of images of landmarks in Tokyo, Japan, captured at different times of the day and night
7	Landmarks in Context (LinC) Dataset	contains images of landmarks with their surrounding context

Several publicly accessible databases are used to identify monuments from images. In this field, some of the frequently used datasets are as follows:

IX. CONCLUSION

In conclusion, the survey paper on monument identification from an image using deep learning presents a comprehensive overview of the advancements, methodologies, and challenges in this field. Through an extensive review of relevant literature, several key findings and insights have emerged. Despite the significant progress, there are still challenges and limitations in monument identification from images using deep learning. Overall, the survey article shows the potential of deep learning for identifying monuments from photos and lays the groundwork for more investigation and advancement in this fascinating area. For scholars, practitioners, and stakeholders interested in using deep learning techniques for automated monument recognition and categorization, it is an invaluable resource.

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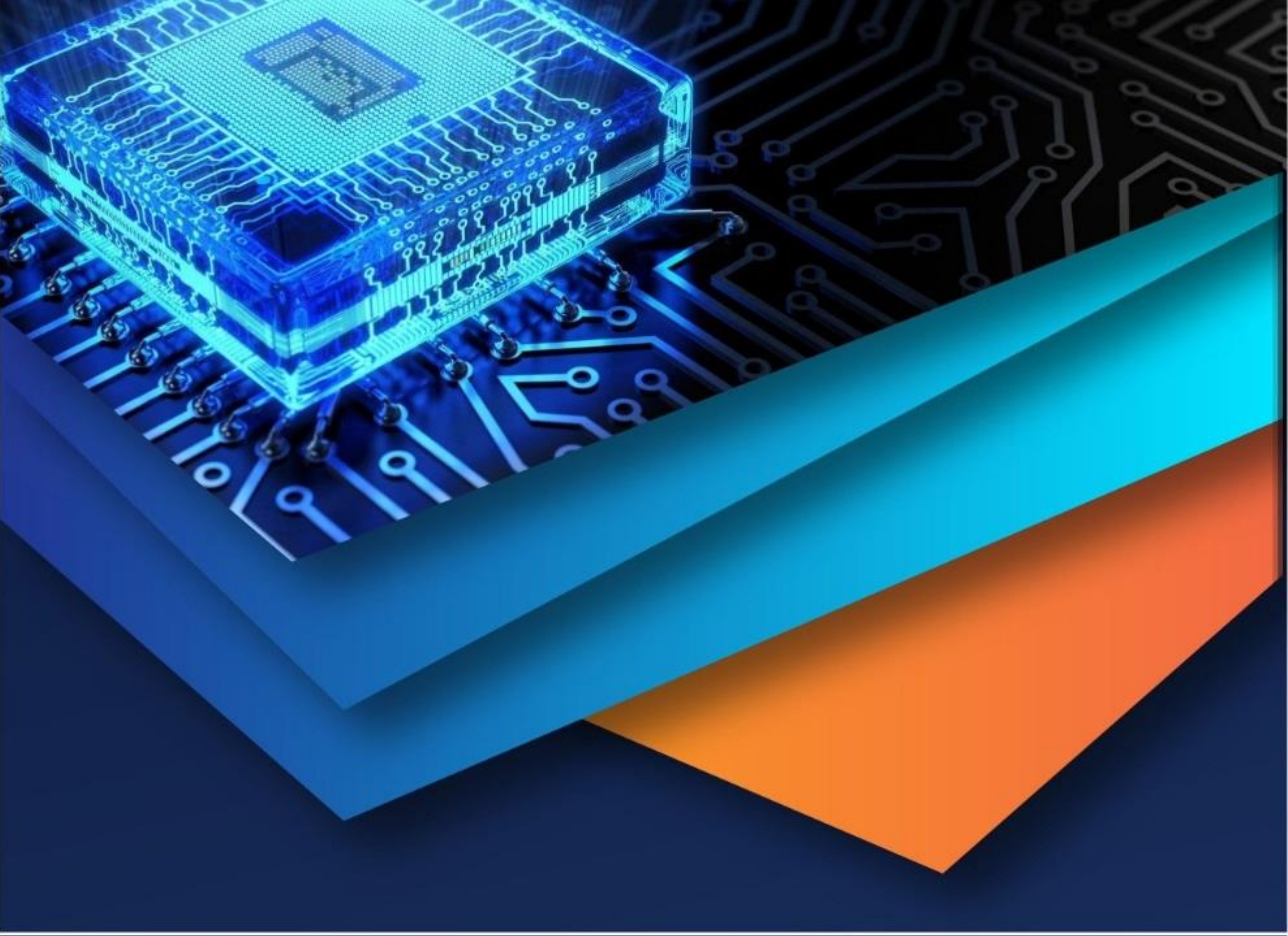

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