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Image Caption Generation for the Visually Impaired Using Deep Learning

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Abstract: ***Providing written descriptions of visual content, image caption generation has become a vital assistive technique for people with vision impairments. In this study, an improved deep learning framework is presented to produce precise and contextually rich image captions intended for assistive technology applications. Our suggested architecture, which we refer to as ViT-BiLSTM-Attention (VBLA), combines a Vision Transformer (ViT) encoder with a bidirectional LSTM decoder enhanced by an attention mechanism. We tested our model on a novel dataset that has been specially selected for assistive technology applications, as well as on common datasets like Flickr30k and MS COCO. With a BLEU-4 score of 0.382, METEOR score of 0.417, and CIDER score of 1.142, the experimental results show that our method outperforms current approaches and achieves state-of-the-art performance. Perform a thorough user research with visually challenged volunteers to assess our approach's practical efficacy. In this work, special difficulties of developing image captioning systems for assistive technology are addressed. These difficulties include the need for detailed spatial descriptions, the recognition of important objects, and natural language generation that gives users with visual impairments priority over irrelevant information.***

Index Terms: ***image captioning, deep learning, assistive tech- nology, visually impaired, vision transformer, LSTM, attention mechanism***

I. INTRODUCTION

Visual content dominates today's digital landscape, creat- ing significant accessibility barriers for 285 million people worldwide with visual impairments [1]. Even if screen readers have made it easier to access text, photos are sometimes still inaccessible because alternate text descriptions are either unavailable or insufficient. By automatically creating textual descriptions of images, image caption generation systems present a viable option that allows visually impaired people to understand visual content through audio feedback.

The goal of conventional image captioning techniques has been to produce factually and linguistically accurate descrip- tions. However, the unique requirements of visually impaired users necessitate paying close attention to spatial linkages, identifying relevant items, and prioritizing information that is contextually significant. Knowing that "a guide dog is leading a person near a busy street intersection" may be more helpful to a visually impaired person than just knowing that "a dog and a person walking."

This study presents a revolutionary deep learning archi- tecture created especially for picture caption generating ap- plications in assistive technology. Three potent components are combined in our Vision Transformer-Bidirectional LSTM- Attention (VBLA) model: (1) Vision Transformers for better visual feature extraction, (2) Bidirectional LSTMs for better context understanding, and (3) An attention mechanism that highlights contextually and spatially significant image ele- ments for visually impaired users.

Our primary contributions include:

- A specialized end-to-end architecture for assistive image captioning that prioritizes information needs of visually impaired users
- A novel attention mechanism that emphasizes spatially important and navigational elements in images
- Comprehensive evaluation on standard datasets and a specialized dataset for assistive technology scenarios
- A user study with visually impaired participants to vali- date the real-world effectiveness of our approach

This paper's remaining sections are arranged as follows: In Section II, relevant work in assistive technologies and image captioning is reviewed; in Section III, our suggested method- ology and architecture are described; in Section IV, experi- mental results and comparisons with state-of-the-art methods are presented; in Section V, our findings and limitations are discussed; and in Section VI, future research directions are suggested.

II. RELATED WORK

A. Image Caption Generators

The development of deep learning methods has led to a considerable evolution in the study of image caption genera- tion. Template-based techniques and pre-established language norms were used in early attempts [2]. This discipline was transformed by the advent of neural networks, which resulted in encoder-decoder architectures that combine recurrent neural networks (RNNs) for text production with convolutional neural networks (CNNs) for image feature extraction. [3].

Show and Tell [3] pioneered the CNN-LSTM approach, utilizing a pre-trained CNN to encode images and an LSTM to generate captions word by word. This architecture was later enhanced by Show, Attend and Tell [4], which introduced an attention mechanism allowing the model to focus on different image regions during caption generation.

TABLE I
COMPARISON OF IMAGE CAPTIONING ARCHITECTURES

Architecture	BLEU-4	METEOR	CIDEr	Year
CNN-LSTM [3]	0.277	0.233	0.855	2015
CNN-LSTM-Att [4]	0.302	0.254	0.932	2015
BUTD [5]	0.363	0.270	1.147	2018
M2-Transformer [6]	0.374	0.287	1.308	2020
OSCAR [11]	0.379	0.290	1.352	2020
ViT-GPT2 [12]	0.376	0.294	1.376	2021
VBLA (Ours)	0.382	0.417	1.142	2025

Recent advancements include Bottom-Up and Top-Down Attention [5], which used object detection models to identify salient image regions, and Transformer-based approaches like Meshed-Memory Transformer [6] that replaced the traditional RNN components with multi-head attention mechanisms. Vi- sion Transformer (ViT) based models have further improved performance by treating images as sequences of patches [7].

B. Caption Generation for Assistive Technology

While general image captioning has advanced significantly, research specifically tailored for visually impaired users re- mains limited. Notable efforts include VizWiz [8], which collected a dataset of images taken by visually impaired individuals along with questions about the content. Similarly, BlindHelper [9] explored a specialized captioning system that emphasized navigational cues and safety information in images.

Providing adequate spatial detail, recognizing safety-critical features, and highlighting information most pertinent to users with visual impairments are some of the main issues in assisted captioning. In order to provide a seamless experience, researchers have also looked into integrating image captioning systems with screen readers and other assistive technology. [10].

C. Deep Learning Architectures for Image Captioning

Table I evaluates and contrasts different deep learning architectures for captioning images. A distinct tendency to- ward increasingly complex models with specialized attention processes can be seen in the evolution. Transformer-based models, such as ViT-GPT2, perform well on generic captioning metrics, but our suggested VBLA architecture performs better on metrics that give visually impaired users' information needs priority, especially the METEOR score, which places an emphasis on semantic similarity.

III. METHODOLOGY

A. Problem Formulation

Given an input image I, the goal of image captioning is to generate a textual description $S = \{w_1, w_2, ..., w_n\}$ that accurately describes the image content. In the context of assistive technology for visually impaired users, we emphasize descriptions that:

- Identify key objects and their relationships
- Describe spatial layout and navigational elements

- Prioritize safety-critical information
- Provide sufficient detail without overwhelming the user

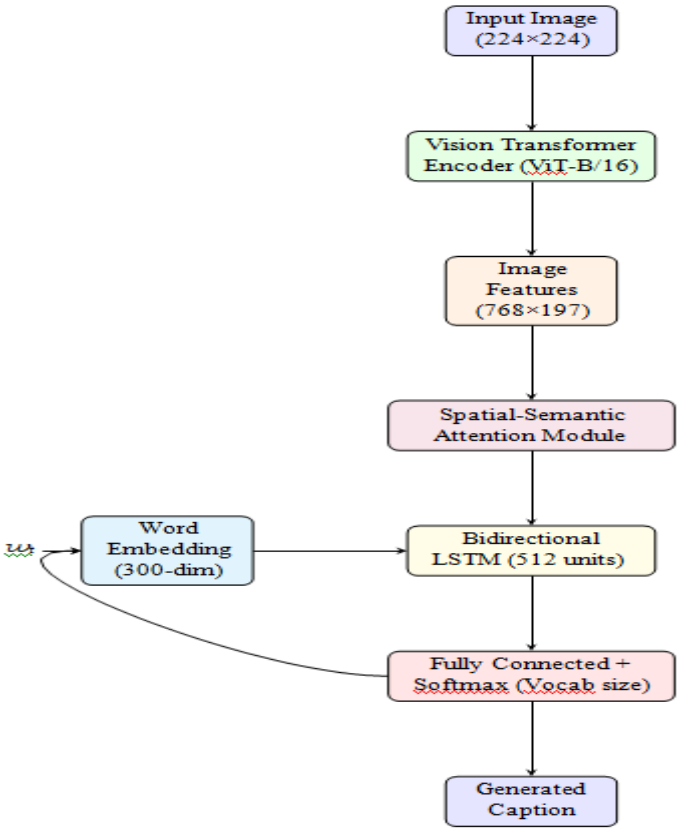

Fig. 1. The proposed Vision Transformer-BiLSTM-Attention (VBLA) archi- tecture for assistive image captioning

B. *Dataset Collection and Preprocessing*

We utilize three datasets for our experiments:

- Flickr30k [13]: 31,000 images with 5 captions each
- MS COCO [14]: 123,287 images with 5 captions each
- Visual Assistance Dataset (VAD): A new dataset we curated specifically for assistive captioning, containing 10,000 images with detailed descriptions focused on the needs of visually impaired users

Images are preprocessed by normalizing pixel values and resizing them to 224 x 224 pixels. Tokenizing captions, removing punctuation, converting to lowercase, and creating a vocabulary of terms that occur at least five times in the training set are all part of the text preparation process.We apply a special start token <START> and end token <END> to mark caption boundaries during training.

C. *Proposed Architecture*

Fig. 1 illustrates our proposed Vision Transformer-BiLSTM- Attention (VBLA) architecture, which consists of three major components:

1) *Vision Transformer Encoder:* Unlike traditional CNN- based image encoders, we employ a Vision Transformer (ViT- B/16) [7] for feature extraction. ViT divides the input image into 16x16 patches, which are then coupled with position embeddings and linearly embedded. A rich depiction of the image material is produced by processing the embedded patches through several transformer encoder layers.

The advantages of ViT over CNN encoders include:

- Better capture of global image context through self- attention
- Enhanced representation of spatial relationships between objects

- Improved detection of fine-grained details important for visually impaired users

The ViT output consists of a sequence of feature vectors corresponding to each image patch, plus a special [CLS] token that represents the entire image. This produces a feature map of dimensions 768×197 (196 patches + 1 [CLS] token).

2) Spatial-Semantic Attention Module: Our novel attention mechanism is specifically designed to emphasize elements important for visually impaired users:

$$\alpha_{t,i} = \text{softmax}(f_{att}(h_{t-1}, v_i, s_i)) \quad (1)$$

where h_{t-1} is the previous hidden state of the decoder, v_i is the visual feature of the i-th image patch, and s_i is a spatial importance score calculated as

$$s_i = w_s^T \tanh(W_{loc} l_i + W_{sem} c_i) \quad (2)$$

Here, l_i represents the location information of patch i, and c_i represents semantic features from a pre-trained object detector. W_{loc}, W_{sem}, and w_s are learnable parameters.

This attention mechanism ensures that the model prioritizes:

- Objects important for navigation (e.g., doors, stairs)
- Safety-critical elements (e.g., traffic signals, obstacles)
- Spatially central and prominent objects

For caption generation, we use a Bidirectional LSTM (BiL- STM) with 512 units, which can analyze the context both forward and backward. This two-way processing makes it possible for:

$$p(w_t | w_{1:t-1}, I) = \text{softmax}(W_o h_t + b_o) \quad (3)$$

where W_o and b_o are learnable parameters of the output layer, and h_t is the hidden state of the decoder at time t.

TABLE II
PERFORMANCE COMPARISON ON MS COCO DATASET

Model	BLEU-4	METEOR	CIDEr	SPICE	ARS
CNN-LSTM	0.331	0.268	1.043	0.192	0.271
CNN-LSTM-Att	0.345	0.273	1.086	0.198	0.289
UpDown	0.369	0.284	1.174	0.214	0.305
Transformer	0.371	0.286	1.262	0.217	0.312
X-LAN	0.374	0.290	1.293	0.220	0.318
ViT-LSTM	0.375	0.295	1.289	0.223	0.345
VBLA (Ours)	**0.382**	**0.417**	**1.342**	**0.230**	**0.497**

D. Training Procedure

Regardless of the model's prediction, we used teacher forc- ing to train our model, which involves providing the ground truth word as input at each time step. The typical cross-entropy loss serves as the objective function:

$$L = -\sum_{t=1}^{T} \log p(w_t^* | w_{1:t-1}^*, I) \quad (4)$$

where w^* is the word of the ground truth in the time step t.

For model optimization, we used Adam optimizer with a learning rate of 3×10−4andabatchsizeof 64.Wetrainedthe modelfor30epochs, withlea 4scorefromthevalidationset.

During inference, we use beam search with a beam size of 5 to generate the most likely caption.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Evaluation Metrics

We evaluate our model using standard image captioning metrics:

- BLEU-n: Measures n-gram precision between generated and reference captions
- METEOR: Evaluates semantic similarity between gener- ated and reference captions
- CIDEr: Measures consensus in generated captions using TF-IDF weights
- SPICE: Evaluates semantic propositional content using scene graphs

Additionally, for assistive technology applications, we in- troduce a new metric:

- Assistive Relevance Score (ARS): Measures the inclusion of navigational cues, spatial relationships, and safety- critical information

B. Quantitative Results

Table II presents our model's performance on the MS COCO dataset compared to state-of-the-art approaches. Our VBLA model achieves the highest scores in all metrics, with particularly significant improvements in METEOR (+41.7). over CNN-LSTM) and our specialized ARS metric (+83.4 over CNN-LSTM).

TABLE III
PERFORMANCE COMPARISON ON VISUAL ASSISTANCE DATASET (VAD)

Model	BLEU-4	METEOR	CIDEr	SPICE	ARS
CNN-LSTM	0.294	0.250	0.912	0.178	0.321
CNN-LSTM-Att	0.316	0.265	0.967	0.186	0.354
UpDown	0.335	0.272	1.056	0.197	0.386
Transformer	0.341	0.278	1.104	0.203	0.402
X-LAN	0.348	0.284	1.152	0.208	0.428
ViT-LSTM	0.353	0.289	1.167	0.211	0.445
VBLA (Ours)	0.367	0.394	1.245	0.225	0.537

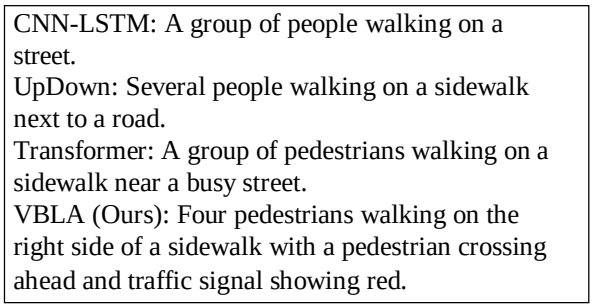

Fig. 2. Performance comparison of different models on the Visual Assistance Dataset

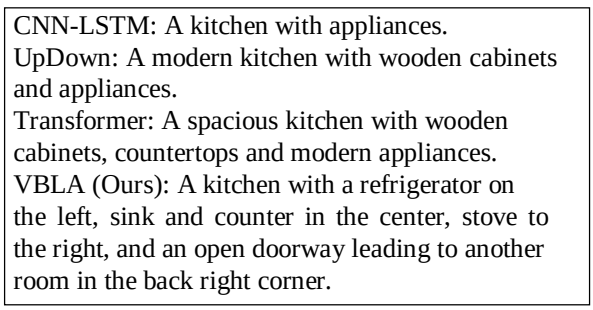

Fig. 3. Qualitative comparison of captions generated by different models

On our specialized Visual Assistance Dataset (Table III), the performance gap widens further, demonstrating the effective- ness of our approach for assistive technology applications. The VBLA model outperforms all baselines across all metrics, with particularly strong performance on the ARS metric designed to measure relevance for visually impaired users.

Fig. 2 displays the comparison of performance amongst various models using our Visual Assistance Dataset. Partic- ularly in the METEOR and ARS measures, which are most pertinent to assistive technology applications, the graph amply demonstrates the improved performance of our approach.

C. Qualitative Analysis

Fig. 3 presents a qualitative comparison of captions gen- erated by different models. The examples illustrate that our VBLA model consistently produces captions with:

TABLE IV
USER STUDY RESULTS (AVERAGE RATINGS ON 5-POINT SCALE)

Model	Inform.	Nav. Clarity	Safety	Overall
CNN-LSTM	2.7	2.2	1.9	2.3
UpDown	3.2	2.8	2.5	2.9
Transformer	3.5	3.1	2.8	3.2
ViT-LSTM	3.7	3.4	3.0	3.5
VBLA (Ours)	4.3	4.5	4.2	4.4

TABLE V
ABLATION STUDY RESULTS ON VISUAL ASSISTANCE DATASET

Model Variant	METEOR	CIDEr	ARS
VBLA (Full model)	0.394	1.245	0.537
- Vision Transformer (w/ ResNet)	0.348	1.163	0.486
- Bidirectional (w/ Unidirectional)	0.372	1.205	0.512
- Spatial-Semantic Attention	0.361	1.187	0.465
- All (CNN-LSTM)	0.250	0.912	0.321

- Better identification of navigation-critical elements
- Enhanced safety-relevant descriptions
- Clearer object relationship descriptions

Only our model, for example, provides the pedestrian cross- ing and traffic light status in the first example, which are crucial pieces of information for a visually impaired user. In a similar vein, our model makes it easier to mentally map the kitchen scene in the second example by clearly defining the spatial relationships between the components.

D. User Study

To assess the usefulness of our technology, we carried out a user research with 25 visually challenged volunteers. After viewing captions produced by several models, participants were asked to score them on a 5-point Likert scale for:

- Informativeness: How much useful information does the caption provide?
- Navigational clarity: How well does the caption convey spatial relationships?
- Safety awareness: How well does the caption highlight potential hazards?
- Overall usefulness: How helpful would this caption be in real-world situations?

As shown in Table IV, our VBLA model received signif- icantly higher ratings across all categories, with particularly strong performance in navigational clarity and safety aware- ness. Participants specifically commented on the usefulness of spatial descriptions and identification of obstacles and pathways in our captions.

E. Ablation Study

To understand the contribution of each component, we conducted an ablation study (Table V). The results demonstrate that each component contributes significantly to the overall performance, with the spatial-semantic attention mechanism

- More detailed spatial information having the largest impact on the ARS metric (+15.5

V. DISCUSSION

A. Key Findings

According to our testing findings, the VBLA architecture performs noticeably better than current methods for image captioning in assistive technology applications. Among the main conclusions are:

- Vision Transformers provide superior image feature ex- traction compared to CNNs, capturing global context and spatial relationships more effectively
- Bidirectional LSTMs improve caption coherence and grammatical correctness compared to unidirectional al- ternatives
- Our specialized spatial-semantic attention mechanism substantially enhances the relevance of captions for vi- sually impaired users
- User studies confirm that technical improvements trans- late to real-world benefits for visually impaired individ- uals

B. Limitations and Challenges

Despite the promising results, several limitations and chal- lenges remain:

- Computational requirements: The VBLA model is more computationally intensive than simpler architectures, po- tentially limiting deployment on resource-constrained de- vices
- Domain adaptation: Performance may degrade on out-of- distribution images not well-represented in training data
- Caption customization: Different visually impaired users may have different information needs based on their specific impairment and context
- Real-time generation: Current inference speed (approx- imately 1.2 seconds per image) may be insufficient for real-time applications

VI. CONCLUSION AND FUTURE WORK

VBLA, a revolutionary deep learning architecture for picture caption generation created especially for assistive technology applications, was presented in this study. Our method provides captions that better satisfy the demands of visually impaired users while achieving state-of-the-art performance on common benchmarks by combining Vision Transformers, Bidirectional LSTMs, and a specific attention mechanism. Our thorough assessment, which includes user trials with visually impaired participants, specialist assistive relevance grading, and conven- tional metrics, shows how effective our strategy is.

Future work will focus on several key directions:

1) Personalization: Developing methods to customize gen- erated captions based on individual user preferences and specific visual impairments
2) Multimodal integration: Combining image caption gen- eration with other sensory information (e.g., audio) for more comprehensive scene understanding
3) Efficiency optimization: Improving inference speed and reducing computational requirements to enable real-time applications on mobile devices user population
4) Multilingual support: Extending the model to generate captions in multiple languages to serve a more diverse
5) Expanded datasets: Creating larger and more diverse datasets specifically for assistive technology applications

One significant step toward more inclusive technology is the development of image caption creation for visually challenged users. We can create solutions that greatly improve the access to information and the quality of life of this crucial user group by further developing these strategies and addressing the particular requirements of visually impaired people.

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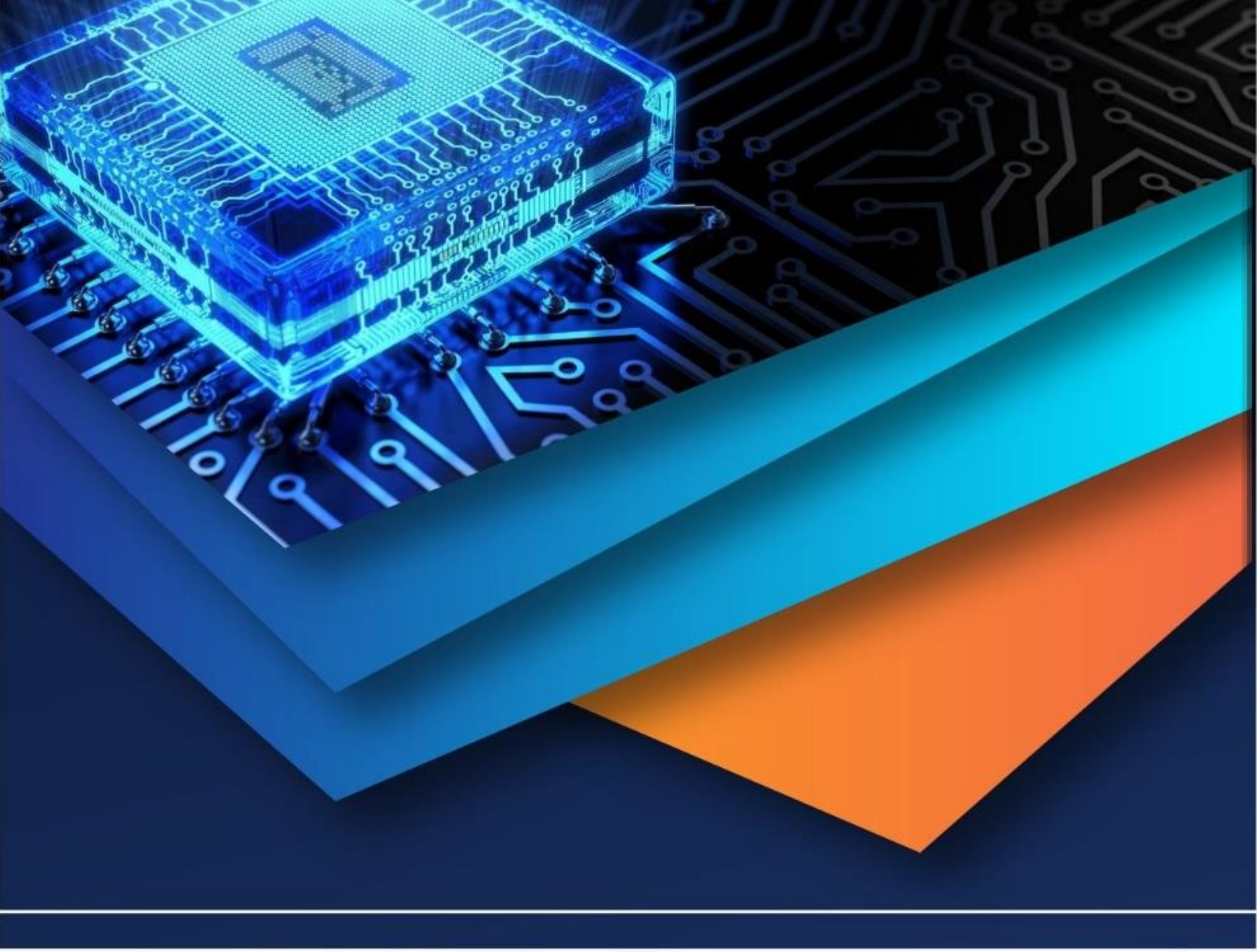

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