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A Review on Prostate Cancer Detection using CNN

Merlyn Koonamparampath[1], Raj Shah[2], Mahipal Sundvesha[3], Meena Ugale[4]
[1, 2, 3, 4]*Department of Information Technology, Xavier Institute of Engineering, University of Mumbai, Maharashtra*

Abstract: ***Prostate cancer is the second biggest cause of mortality in men, according to statistics. It's said to be a slow-growing malignancy that doesn't exhibit symptoms until it's advanced. Over the last few years, numerous studies on AI algorithms processing various medical imaging such as CT, MRI, and Ultrasound have been conducted. Using AI to manage prostate cancer would have a significant influence on healthcare. With almost 1.3 million new cases identified each year around the world, cancer experts would have a better grasp of the disease and be able to generate more accurate cancer detection forecasts. We give a review of the usage of CNN applied to several automatic processing tasks of prostate cancer detection and diagnosis, to provide an overview of the progress in this field, based on the increased interest of CNN in recent years. We've noticed that the use of CNN has skyrocketed, with outstanding results obtained either with fresh models or employing pre-trained networks for transfer learning. According to the results of the survey, deep learning-based research outperforms traditional patient prognosis techniques in terms of accuracy.***

Keywords: Convolutional Neural Network, Deep Learning, Prostate Cancer Detection, Artificial Intelligence, Survey.

I. INTRODUCTION

Prostate cancer is a type of cancer that arises in the prostate gland. The prostate, a small walnut-shaped gland in males, produces seminal fluid, which nourishes and transports sperm. It is found to be one of the most common kinds of cancer. Often, prostate cancer grows slowly and is conned to the prostate gland, where it's unlikely to cause significant harm. Some prostate cancers are slow-growing and require little treatment, while others are more aggressive and rapidly spread.

In the case of prostate cancer, AI has been proven to help assist with a standardized pathological grading to determine prostate cancer stratification and treatment. Additionally, AI shows promise in automating image-based tasks such as histopathologic, MRI, and biomarker diagnosis to assess the characterization and severity of cancer.

Furthermore, unless they experience any physiological side effects, certain patients diagnosed with prostate cancer, which is thought to be more indolent, can continue to have prostate biopsies, PSA, and other forms of digital testing through Rectal examinations or MRI. As technology advances and helps patient prognosis over time, AI can help improve these forms of surveillance and can be one of the most valuable tools for Urological Pathologists and the Field of Urology at large.

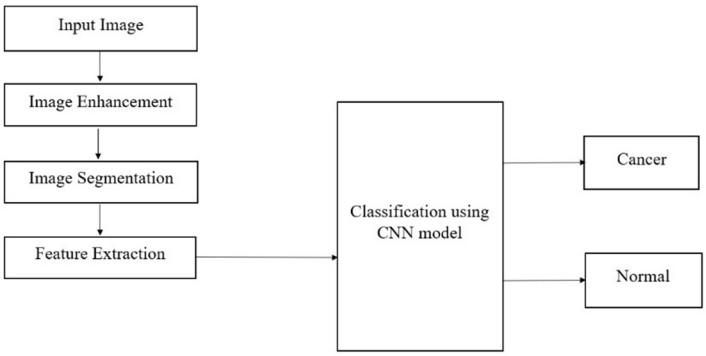


Fig. 1 Block Diagram of Cancer Detection

The block diagram shows the elements used in the system. The medical images are fed as input into the system. Enhancement of the images can be done to reduce blurring and to remove noise from the images, to decrease the color redundancy, making it appropriate for the Neural Network model. Image segmentation will be done on the images to extract the boundaries of the tumors present. Features can be extracted from the enhanced images which should be given as input to the Neural Network model. Training and testing will be done on the extracted features using Convolutional Neural Network (CNN). Predictions can be made from the resultant output if the person has cancer or not.

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II. CONVOLUTION NEURAL NETWORK CONCEPT

A Convolutional Neural Network (CNN) is a Deep Learning technique that assigns priority to various objects within an image process using learnable weights and biases results with the ability to distinguish one from the other. The architecture of a CNN is inspired by the organization of the visual area and is akin to the connectivity pattern of Neurons within the Human Brain.

The two main parts of a CNN architecture are Feature Extraction and Fully Connected Layer. Feature Extraction is a convolution tool that separates and identifies the distinct characteristics of an image for study. A fully connected layer that uses the output of the convolution process to predict the image's class using the information acquired in previous stages. Convolutional layers, pooling layers, and fully-connected (FC) layers are the three types of layers that make up the CNN. A CNN architecture will be constructed when these layers are stacked. There are two more significant factors, the dropout layer, and the activation function, in addition to these three layers.

The Convolutional Layer is the initial layer that extracts the different features from the input photos. The convolution mathematical operation is done between the input image and a filter of a specific size in this layer. The Feature map is the result, and it contains information about the image such as its corners and edges. This feature map is then supplied to further layers, which learn a variety of other features from the input image. After a Convolutional Layer, a Pooling Layer is usually applied. This layer's major goal is to lower the size of the convolved feature map to reduce computational expenses. This is achieved by reducing the number of connections between layers and operating on each feature map independently. The Pooling Layer is commonly used to link the Convolutional and FC Layers. The weights and biases, as well as the neurons, make up the Fully Connected (FC) layer, which is used to connect the neurons between two layers. The previous layers' input images are flattened and supplied to the FC layer in this step. When all of the characteristics are connected to the FC layer, the training dataset is prone to overfitting. To address this issue, a dropout layer is employed, in which a few neurons are removed from the neural network during the training process, resulting in a smaller model. Finally, the activation function is one of the most crucial elements in the CNN model. They're used to learn and approximate any type of continuous and complex network variable-to-variable relationship.

When compared to other classification methods, CNN requires significantly less pre-processing. While in primitive methods filters are hand-engineered, with enough training, CNN has the power to find out these characteristics. Due to the reduction in the number of parameters involved and the reusability of weights, the architecture performs considerably better fitting to the picture dataset.

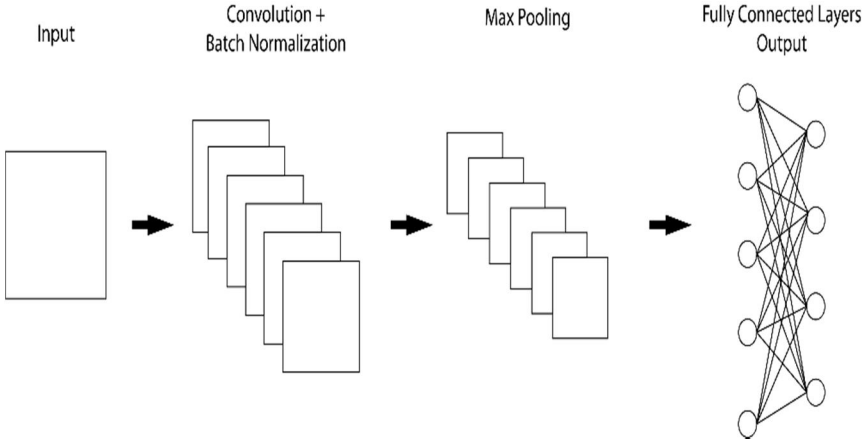


Fig. 2 Convolutional Neural Network Architecture.

CNN must first specify some super parameters, such as the number and size of filters, the pooling step size of the pooling layer, the zero filling quantities, the batch size, and the learning rate, before beginning the training. The super parameters do not alter during the training once they are set. Batches of training photos can be fed into CNN for training. After the training, CNN is given a new image to work with. The network then repeats the forward propagation procedure, calculating the likelihood that each image belongs to each category.

Image datasets available for prostate cancer are in an early stage of research. Due to the raw image dataset available for prostate cancer, CNN can prove to be a boon for detecting cancer from the images. Another reason for using CNN is the ability of the neural network to self-identify and extract the labels which are useful for the image classification or detection of cancer. Results help to classify the deep learning methods and the use of convolutional neural networks are amongst the best for detecting cancer from medical images.

Transfer learning is the process of applying a previously learned model to a new problem. Transfer learning is when a model that has already been trained is used to solve a separate but related problem. The concept is leveraged by what has been learned in one task to improve generalization in another via transfer learning. The weights that a network has learned are transferred from "task A" to a new "task B." Transfer learning provides many advantages, the most important of which are reduced training time, improved neural network performance, and the absence of a large amount of data.

III. CNN-BASED APPROACHES FOR PROSTATE CANCER IDENTIFICATION TASKS

G. Litjens, et al. proposed a model where prostate cancer identification was done using biopsy specimens using CNN. The result of performing histogram analysis on the CLMs can be best represented quantitatively using ROC analysis. The average bootstrapped area under the ROC curve (AUC) for the median analysis was 99% and 98% for the 90th-percentile analysis. However, the 90th-percentile analysis has higher specificity at a sensitivity level of 99.9% compared to the median analysis [1].

For the classification of prostate cancer lesions, S. Liu, H. Zheng, Y. Feng, and W. Li developed a deep learning architecture called XmasNet based on Convolutional neural networks. The system made use of the 3D multiparametric MRI data provided by the PROSTATEx challenge.

To include the 3D information of the lesion, data augmentation was done using 3D rotation and slicing [2].

E. Arvaniti, et al. designed an Automated Gleason grading of prostate cancer tissue microarrays via deep learning using CNN. The model used TMA H&E staining image patches. Mobile-net CNN architecture was used and they found that transfer learning, strong regularization, and balanced mini-batches were crucial for successfully training the classifier. Two trained Uropathologists were tested against the model and the performance accuracy was 71% and 75% respectively [3].

Z. Hu, et al. conducted a survey for image-based cancer detection using DL. 6 papers reviewed CNN architecture using different modalities such as MRI, 3D Magnetic resonance volume, Computed tomography slices, and histopathology. Different applications were mentioned such as Segmentation, Lumen based cancer detection, and Gleason Grading. All models except for one used end-to-end training while the remaining used Transfer learning [4].

K. Nagpal, et al. suggested a Deep Learning system for enhancing prostate cancer Gleason scoring. The system consisted of two stages. In the first, the images from the dataset were fed into a CNN, which classified the images into four categories: non-tumor, Gleason pattern 3, 4, or 5. The KNN classifier was utilized in the second stage to determine the grade of each Gleason pattern. An accuracy of 70% was achieved [5].

S. Goldenberg, G. Nir, and S. Salcudean mentioned in their review paper about D. Karimi, et al.'s [6] CNN-based model for prostate segmentation in MRI. The network was first trained to predict cancer and added modules for predicting the parameters of the shape model. A data augmentation method was proposed by training the images and their prostate surface key points are deformed according to the displacements computed based on the shape model and employed various regularization techniques. The model was developed using Elastic Net architecture spectral dropout for regularization and it yielded an accuracy of 88% [7].

D. Nguyen, et al. proposed a CNN model using U-net by modifying the architecture to accurately predict the dose of intensity-modulated radiation therapy (IMRT) for prostate cancer patients along with the average mean and max dose differences of all structures within 5.1% of the prescription dose. The patient image contours of the planning target volume (PTV) and organs at risk (OAR) were the parameters considered for prediction and the model achieved an accuracy of 91% [8].

W. Bulten, et al. produced an automated Deep learning system for Gleason grading using prostate biopsies. The model used U-net architecture to delineate individual glands, assign Gleason growth patterns, and determine the biopsy-level grade. The model yielded an accuracy of 91%. In an observer experiment, the model outperformed a panel of pathologists by scoring 85% while the latter achieved 81% [9].

P. Ström, et al. conducted a diagnostic study on AI for the diagnosis and grading of prostate cancer using needle core biopsies. They trained a CNN-based ImageNet architecture for the biopsy assessment. Predicting the existence, extent, and Gleason grade of cancerous tissue was used to assess the networks.

They also analysed grading performance and discriminatory performance using receiver operating characteristics, as well as tumour extent predictions using projected cancer length correlations. The area under the receiver operating characteristics curve for the model was 99.7%.

The correlation between cancer length predicted by the AI and assigned by the reporting pathologist was 96% for the independent test dataset and 87% for the external validation dataset [10].

TABLE I
Summary of State-of-the-Art CNN-Based Approaches Applied for Prostate Cancer Identification

Year	Study	Application	Dataset	Algorithm/ architecture	Performance Results
2016	G. Litjens, et al. [1]	Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis	H&E-stained biopsy specimens were used for developing the system.	CNN	The system was able to diagnose the biopsy specimens at an accuracy of 99%.
2017	S. Liu, et al. [2]	Prostate Cancer Diagnosis using Deep Learning with 3D Multiparametric MRI	The dataset was provided by PROSTATEx Challenge which contains 3D multiparametric MRI data. The labels of the lesions (clinically significant or non-significant) were supplied in 341 cases, including 204 training cases. Diffusion Weighted Images (DWI), Apparent Diffusion Coefficient (ADC) maps, Ktrans, and T2 Weighted Images (T2WI) were all utilized in each case.	CNN	The model achieved an accuracy of 84% which was the second-highest in the challenge
2018	E. Arvaniti, et al. [3]	Automated Gleason grading of prostate cancer tissue microarrays via deep learning	Prostate cancer - tissue microarray with Hematoxylin and Eosin (H&E) staining dataset was used for training the system. On a discovery cohort of 641 patients, the system was trained using detailed Gleason annotations.	CNN MobileNet	The model had a 75% accuracy rate in automating the Gleason grading of tissues microarrays.
2018	Z. Hu, et al. [4]	Deep learning for image-based cancer detection and diagnosis – A survey	PROMISE12 was used for various projects.	CNN	-
2019	K. Nagpal, et al. [5]	Development and validation of a deep learning algorithm for improving Gleason scoring of prostate cancer	The Camelyon16 dataset, which included 112 million pathologist-annotated picture patches from 1226 slides, was used.	2stages: D-CNN k-NN	In correlations to clinical follow-up data, the system achieved a much higher diagnostic accuracy of 70% and trended towards better patient risk classification.
2019	S. Goldenberg, et al. [7]	A new era: artificial intelligence and machine learning in prostate cancer	There were 49 T2-weighted axial MR images in the training dataset. An endorectal coil was not visible in these photos. As a result, 26 of the training photos from the PROMISE-12 challenge that did not include an endorectal coil were used to evaluate the approach.	CNN Elastic-net	By employing both elastic-net and spectral dropout for regularization, the proposed technique yields a Dice score of 88%.

2019	D. Nguyen, et al. [8]	A feasibility study for predicting optimal radiation therapy dose distributions of prostate cancer patients from patient anatomy using deep learning	The patient image contours of the planning target volume (PTV) and organs at risk (OAR) were used for the dataset.	C-DNN U-net	The system had a 91% accuracy rate in predicting the estimated dose of radiation therapy.
2020	W. Bulten, et al. [9]	Automated deep-learning system for Gleason grading of prostate cancer using biopsies: a diagnostic study	The system was developed using samples from patients at Radboud University Medical Center that were randomly selected and sampled based on the biopsy Gleason score. A total of 5759 biopsies were taken from 1243 patients.	U-net	The developed system scored an accuracy of 99% for grading the biopsies.
2020	P. Ström, et al. [10]	Artificial intelligence for diagnosis and grading of prostate cancer in biopsies: a population-based, diagnostic study	An independent test dataset of 1631 biopsies from 246 men from STHLM3 and an external validation dataset of 330 biopsies from 73 men were used to assess the system's ability to predict the presence, extent, and Gleason grade of malignant tissue.	C-DNN ImageNet	The model distinguished between benign and malignant biopsy cores with 99% accuracy.

IV. ANALYSIS & DISCUSSION

In the present, we found that CNN-based models can be an efficient approach to address ways to assess prostate cancer identification. However, applying CNN-based techniques in real-world circumstances will pose significant problems. The scarcity of large training datasets was one of the biggest challenges in developing deep learning models for medical image analysis. However, the widespread use of picture archiving and communication systems (PACS) in hospitals has aided in the collection of millions of medical photos, the vast majority of these include personal patient information and are preserved in hospitals. More work on the data, such as de-identification and data transfer, is required to make such datasets available for research purposes. To test and evaluate deep learning models, many of the reviewed articles included data from hospitals or cancer research institutes. Furthermore, comparing the performance of CNN models across various studies is challenging [4].

The precise labelling of digitized slides is required for the development of AI systems and the training of classifiers. Because of disparities in pathologists' training, experience, institutional rules, and protocols, prostate cancer grading is well documented to be subject to observer dynamics [7].

By focusing the pathologist's attention on regions of interest, an AI system could improve sensitivity and patient safety, reduce pathology workload by automating the removal of benign biopsies, and reduce the high intra-observer variability in prostate histopathology reporting by producing reproducible decision support for grading. Another advantage of AI is that it can provide diagnostic knowledge in areas where it is currently missing [10]. Data Augmentation and regularization techniques were applied to increase the amount of data by using filters or adding slightly modified copies of already existing data. This helps in avoiding overfitting when the model is being trained. These techniques were often used when the dataset wasn’t large enough to train the model [2] [7] [4].

When presenting a CNN architecture for a specific problem, defining the number of layers and filters, as well as the model's parameters and hyperparameters, remains a crucial challenge. Using trial-and-error tuning until the best settings are found is a common way to solve this but it can be time-consuming for complex models.

The CNN Architectures reviewed can be categorized into two general categories: Pre-trained Networks and self-developed networks. A similar problem has already been taught to a pre-trained model. Instead of starting from scratch to solve a similar problem, you start with a model that has already been trained on another problem. We can directly use the weights and architecture obtained and apply the learning to our problem statement by employing pre-trained models that have been previously trained on huge datasets. Few studies adopted a pre-trained deep learning model as the feature extractor to extract high-level characteristics for training a classifier, while others fine-tuned pre-trained models by modifying the last layer and trained models on new medical datasets [4]. A Self-Developed model network is usually developed from scratch and is specially made to address the specific needs of the experiment. The training period of this model will be time-consuming as it has to learn and fine-tuning will be a tedious task.

V. CONCLUSIONS

Multiple forms of applications are used to detect cancer. In this paper, we reviewed the most recent applications of detecting prostate cancer from images using Convolutional Neural Networks. Different architectures were explored to analyse the input and predict the outcome of the same. In some studies, CNN has been used not only for detection but to improve the treatment parameters of cancer. AI has massively contributed to this field and it's quite evident that in the future it can play a huge role in assessing medical diagnosis. Systems with higher accuracy can be developed for advancing new technologies of image detection via deep learning.

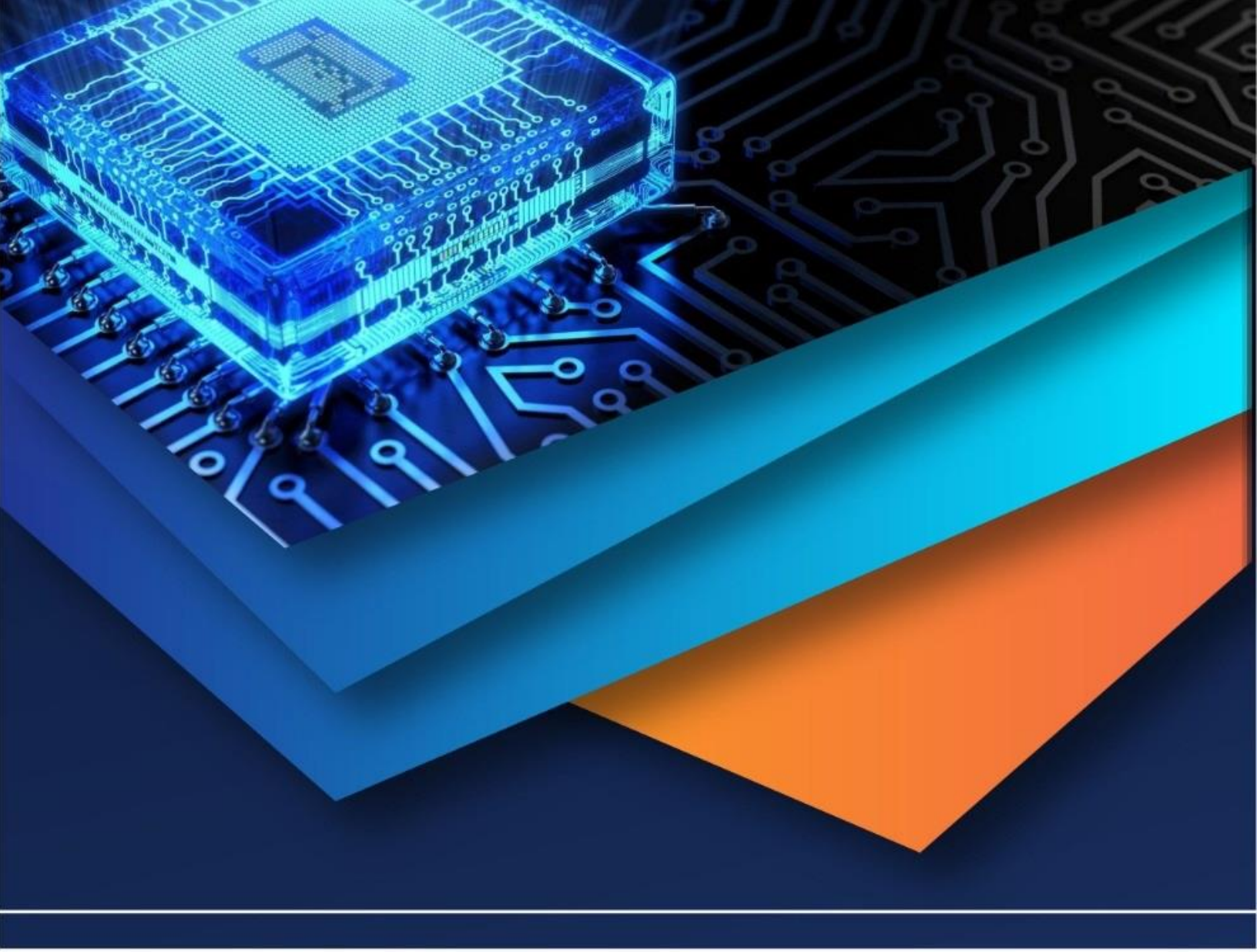
VI. ACKNOWLEDGMENT

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