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Skin Cancer Detection Using CNN

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Abstract: Skin cancer disease is recognized as one of the most perilous types of cancer & an increasing rate of mortality is attributed to insufficient awareness of symptoms and preventive measures. Consequently, it is of very importance to detect skin-cancer at the beginning of stage to prevent its spread. Various types of skin cancer exist, with some posing significant risks. Detecting malignant skin lesions, particularly those with pigmentation, necessitates advanced image detection techniques and computer classification capabilities. In the proposed model, we have used the HAM10000 dataset, comprising 10,015 images, for enhancing the accuracy of skin cancer detection. We have carefully selected a subset of this dataset and implemented augmentation techniques to improve the model's precision. Our analysis focuses on the CNN- based model. Our proposed system achieved an outstanding validation accuracy of 97.92 % with the CNN model. This research contributes to the early identification of specific categories of skin diseases, empowering medical practitioners to validate and administer appropriate treatments.

Keywords: Skin Cancer, CNN, Image Processing, Machine Learning, Deep Learning, Detection.

I. INTRODUCTION

The skin-cancer is characterized by an uncontrolled growth in the abnormal cells of the skin, triggered by DNA damage and mutations [2]. It poses a significant health risk, with an estimated 13.1 million people projected to be affected by 2030. The primary diagnosis of skin cancer relies on visual examination, often supported by dermoscopic analysis, biopsies, and histopathological examination. Dermatologists use various characteristics, such as body irregularity, symmetry, color variation, diameter & evolution (ABCDEF rule), to identify melanoma [1]. However, early detection remains challenging as many melanomas are initially diagnosed without specific indications. Ultraviolet radiation exposure is one of the key factors in the development of these cancers, primarily affecting sun-exposed areas like the lips, ears, hands, scalp, and face. The American Cancer Society [3] reports an estimated death rate of 7990 for melanoma skin cancer, with approximately 97610 new cases each year. Male individuals face a higher mortality risk compared to females. Visual analysis by dermatologists includes the examination of pigmented lesions, considering changes in size, shape, and color. Histopathological diagnosis by experienced dermatopathologists plays a crucial role in confirming melanoma. Prior studies have extensively explored machine learning techniques to facilitate the automated detection of melanoma, thereby making significant contributions to the advancement of research in this field. However, accurate prediction of skin cancer types and determination of malignancy or benignity require robust systems. The differentiation between lesions that are non-pigmented, can present challenges due to their similar visual characteristics. However, automated systems offer valuable benefits in this context. These systems provide faster and easier identification and classification of such lesions, complementing visual analysis and enhancing the overall diagnostic process. Besides visual analysis, automated systems offer faster and easier identification, reducing risks to patients. Various classification algorithms, including deep learning [4], K-nearest neighbor, decision tree algorithm, logistic regression, and SVM, have been employed to analyze dermoscopic images. In prior research [5], the K- means clustering was utilized for skin cancer segmentation, followed by the process of extracting features using a co-occurrence matrix & classification with a support vector machine. Utilizing classification techniques can significantly impact patient outcomes, thus motivating the adoption of the deep-learning approaches, such as CNN, for an accurate identification of different skin-cancer types [7] [8] [6]. This research paper presents a proposed CNN model designed to detect and classify skin cancers automatically.

II. RELATED WORK

A. Learning-based Approaches

In the study conducted by Garg et al. [9] which focuses on the detection of melanoma skin cancer, where they presented a methodology leveraging diverse image-processing techniques. As part of their approach, they introduced the ABCD rule, which encompassed the assessment of skin lesions based on color, diameter, border irregularity, and asymmetry. Before performing the segmentation of skin lesions, an illumination correction technique was applied. Their proposed methodology achieved a noteworthy accuracy of 91.6%.

In a study conducted by Tammineni et al. [10] around melanoma segmentation for the purpose of early detection of skin-cancer. In their research, they employed the Gradient and Feature Adaptive Contour (GFAC) model specifically designed for the melanoma segmentation. The experimentation phase was carried out on the PH2 dataset that consisting of 200 images. Notably, their proposed segmentation technique demonstrated an impressive accuracy of 98.64%. However, it is crucial to acknowledge that this high accuracy was achieved on a relatively small-sized dataset.

These studies highlight the advancements made in the field of melanoma detection and segmentation techniques. Garg et al. demonstrated promising results by incorporating the ABCD rule and illumination correction, while Tammineni et al. showcased how effective is the GFAC model on smaller datasets.

B. CNN-based Approaches

In their investigation, Pham et al. [11] undertook a study focused on the skin lesion classification using a Deep CNN approach coupled with techniques of data augmentation. They compiled a comprehensive dataset by combining images from various sources, including the ISBI Challenge, ISIC Archive, and PH2 dataset. For their classification model, they opted for the InceptionV4 architecture.

The model's performance was evaluated using three different classifiers: SVM, Neural Network, and Random Forest. Despite leveraging the advanced InceptionV4 architecture, the overall accuracy achieved was 89%, which the researchers considered below the desired level of performance.

In another investigation conducted by Jordan et al. [12], a novel approach was proposed for classifying multimodal skin lesions using deep learning techniques. The researchers curated a dataset consisting of 2917 cases from five distinct classes. To tackle the classification task, a modified version of the ResNet-50 architecture was employed. The traditional soft max and fully connected layers were removed, and instead, a 2048-dimensional image feature vector, known as the image feature extraction network, was utilized as the flattened output.

The single-image classification achieved an average accuracy of 85.8%, while the multimodal network's highest accuracy reached 86.6%. Despite these promising results, the multimodal network faced challenges in achieving higher accuracy, indicating the existence of limitations in its performance.

In their research, Serban et al. [13] proposed a model of CNN for the automated diagnosis of the skin-cancer. Their dataset consisted of 1000 images sourced from the International Skin Imaging Collaboration & PH2 databases. The dataset includes total of two classes of skin lesions: benign tumors & malignant tumors, containing 500 images each. A proposed CNN model achieved an accuracy of 80.52% when evaluated on this dataset. Although the dataset was limited to two classes, there is potential for further enhancements to enhance the model.

Hosny et al. [14] focused on the classification of three distinct types of skin cancer: common nevus, atypical nevus, and melanoma. Modifications to the existing AlexNet architecture have been done by the authors and the authors have achieved 80% accuracy when trained with original images.

After using augmented images, the accuracy improved to 98.61%. The dataset consists of the 200 images from the PH2 dataset, which has been expanded to 11,000 images after augmentation. However, it should be noted that the original dataset had only three classes with a total of 200 images.

Ensaf et al. [15] employed transfer learning in deep convolutional networks for classifying enhanced skin lesions. For this, the HAM10000 dataset has been used, which underwent data pre- processing steps such as cleaning, down sampling, splitting, and augmentation. DenseNet-121 and MobileNet architectures were utilized as CNN models, both of which were pre-trained. The testing accuracy achieved on the unbalanced dataset was 71.9% for DenseNet-121 and 82.6% for MobileNet. On the balanced dataset, the accuracies improved to 92.7% and 91.2% for DenseNet-121 and MobileNet, respectively.

In their study, Ulzii et al. [17] introduced a classification approach for skin cancer utilizing the ECOC SVM classifier combined with a pre-trained AlexNet architecture. The dataset from multiple online search engines, which consisted of 3753images categorized into four distinctclasses.

III. METHODOLOGY

The process of skin lesion detection involves several distinct phases, as depicted in Figure 1, which collectively contribute to the accurate identification and classification of skin lesions.

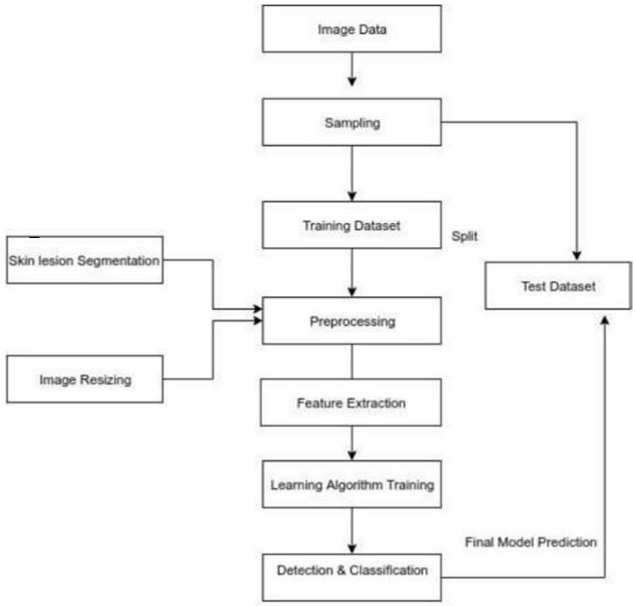

Figure 1. Flowchart of Proposed Model

1) The dataset used in the proposed model is HAM10000 and can be accessed publicly on the web through the following URL: https://www.kaggle.com/datasets/kmader/skin- cancer-mnist- ham10000.
2) The proposed model utilizes HAM10000 dataset, which has 10,015 dermoscopic images of the skin lesions which are pigmented and collected from various sources. The images in the HAM10000 dataset are saved in JPEG format and havea resolution of 600 × 450 pixels.
3) Each image and patient record in the dataset encompassed seven distinct features. These features include the patient's age, gender, image ID, lexicon ID, DX type (used for technical validation), the geospatial location of the skin- lesion, and the diagnostic skin lesion category employed for classification and diagnosis purposes.

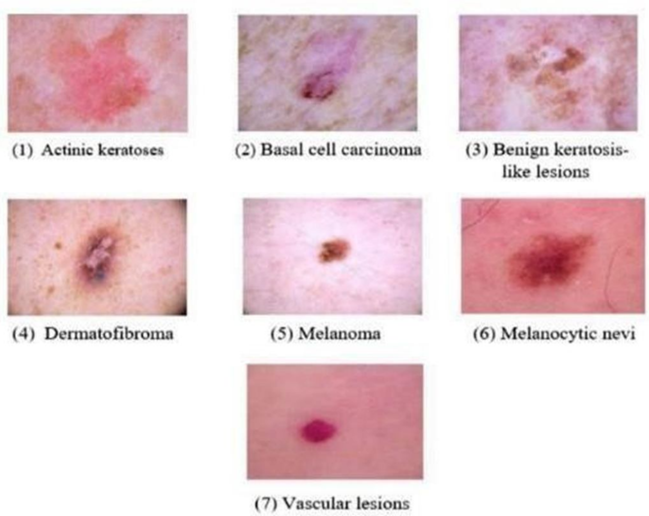

Figure 2. Different types of the skin cancer lesions in HAM10000 dataset.

To organize the dataset effectively, it is necessary to sort each image within its respective folder according to the seven different diseases. In this scenario, the key parameters used for organizing the images in the dataset are the 'Image id' and 'dx'(disease) labels.

A. Image Resizing

1) Prior to processing in various machine learning models, resizing all images in the folder to dimensions 220 x 220 was done. This resizing step ensures uniformity in image size across the dataset.
2) In the case of the trained CNN model, the images were initially scaled down to dimensions of 96 x 96with a depth of 3 (representing the RGB channels) to expedite the processing time. Subsequently, the images were converted into NumPy array, enabling access to a pixel value of the each and every image. To facilitate effective training, the value of pixels was normalized to a range [0,1]. Class of LabelBinarizer was utilized for handling the conversion of class labels from string form in the dataset to one-hot encoded vectors. This conversion enables the model to predict integer class labels using Keras CNN and subsequently made them human- readable.

B. Data Augmentation

1) Data augmentation involves the generation of new data to enhance machine learning model training. In this study, Horizontal Flip augmentation was used, horizontally shifting image pixels. When data augmentation techniques are applied during training, models tend to learn more distinct features compared to models trained without augmentation.
2) After augmentation, each class had 200 images, resulting in a dataset of 200*7 images. To address the limited data points, random transformations (rotations, shearing, etc.) were applied during CNN model training. To mitigate overfitting, we employed data augmentation techniques while ensuring that each and every epoch had the exact same number of images as before in the original dataset.

C. Feature Extraction

To measure the entirety of an image without relying on specific interest points global feature descriptors are exploited. These descriptors, such as Color Histogram, Hu Moments, and Haralick Texture, color quantification, shape,& texture of the skin lesions. The selection of this features was based on the prominence within the lesion area. In the feature extraction experiment, each image was processed individually to extract three global features. The extracted features, along with their corresponding labels, were saved in HDF5 format for further analysis and utilization.

D. Image Classification

In the proposed work, we employed a CNN model for training & evaluating the image dataset. To evaluate model performance, various model evaluation metrics like f1- score, recall, precision, and accuracy. These metrics evaluate necessary effectiveness and reliability of the model based on CNN for classifying & analyzing theimage dataset.

E. CNN and its Architecture

CNN is specifically designed to capture intricate details with the help of filters that are applied to the image's pixel data. This approach allows the CNN to effectively extract meaningful features and hierarchies of representations from the input data. By leveraging convolutional operations, pooling layers, and specialized architectures, CNNs excel object & image recognition, image classification & object detection, etc. The CNN architecture is depicted in Figure 3, providing a high-level overview of its structure. Please refer to Figure4 for a comprehensive overview of the specific layers and corresponding hyperparameters employed in our CNN model. This diagram provides a detailed summary of the network configuration, including the kernel size, stride, number of filters, poolsize, and dropout rate for each layer.

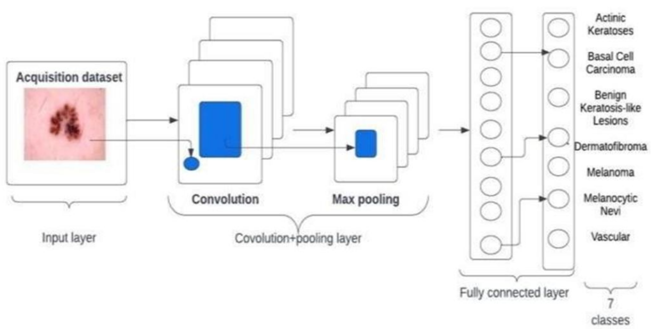

Figure 3. The High level architecture of CNN

Layer	Hyperparameters
Conv2D	32 filters, 3 × 3 filter size, ReLU activation, same padding, followed by batch normalization
MaxPool2D	3 × 3 pool size to reduce image spatial dimensions quickly from 96 × 96 to 32 × 32
Dropout (Core Layer)	0.25 Neurons
Conv2D	64 filters, 3 × 3 filter size, ReLU activation, same padding
Conv2D	64 filters, 3 × 3 filter size, ReLU activation, following the same padding, batch normalization is perform
MaxPool2D	2 × 2 pool size
Dropout (Core Layer)	0.25 Neurons
Conv2D	128 filters, 3 × 3 filter, ReLU activation, following the same padding, batch normalization is performed
Conv2D	128 filters, 3 × 3 filter size, ReLU activation, same padding followed by batch normalization
MaxPool2D	2 × 2 pool size
Dropout (Core Layer)	0.25 Neurons
Flatten (Core Layer)	–
Dense	1024 Units, ReLU sctivation, and batch normalization
Dropout (Core Layer)	0.5 Neurons
Dense	7 Units, softmax activation

Figure 4. Layers & Hyperparameters of CNN

F. Model hyperparameters

To ensure a comprehensive evaluation of the model, specific hyperparameter values were chosen in the CNN implementation. Figure 4 highlights the hyperparameter values used in the proposed work. The reasoning behind selecting these values is explained below:

1) *Optimizer:* Adam, a widely used optimization method, was chosen due to its simplicity, computational efficiency, and effectiveness in handling parameters and large datasets.
2) *Loss-Function:* To implement the loss function *of* multi- class, we employed "categorical cross-entropy" approach, which is specifically designed for multi-class classification tasks. This loss function effectively measures the discrepancy between the predicted class probabilities and the actual class labels.
3) *Epochs:* The model was trained for 50 epochs. To avoid overfitting of model the number of epochs was determined.
4) *Batch Size:* After conducting experiments, we found that a batch size of 64 yielded the optimal results in terms of model performance.
5) *Learning Rate:* Learning rate of 0.001 has been set. Learning rate controls the step and sizes taken along the gradient during training. A smaller learning rate takes smaller steps, while a larger learning rate takes larger steps.

By carefully selecting these hyper parameter values, the CNN model was optimized to achieve optimal performance in the proposed work.

IV. EXPERIMENTAL RESULTS

We conducted the development of the models using Python 3.7.9, making use of the Keras library and the cv2numpydependency. Figure 5 and Figure 6 show graphs of loss & accuracy with and without augmentation. Figure 7 and Figure8 depict experimental results for the CNN which include model evaluation metrics like recall, accuracy f1-score, and precision.

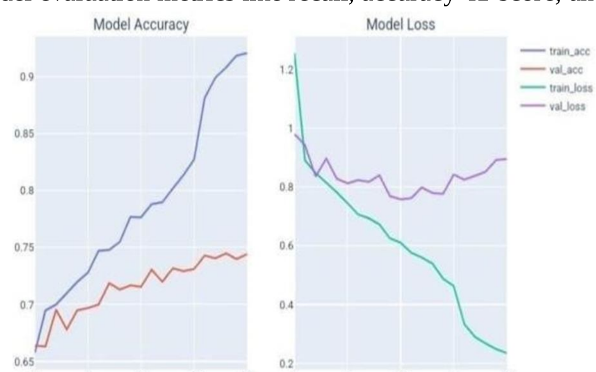

Figure 5. Graphs of Loss & Accuracy after using Augmentation

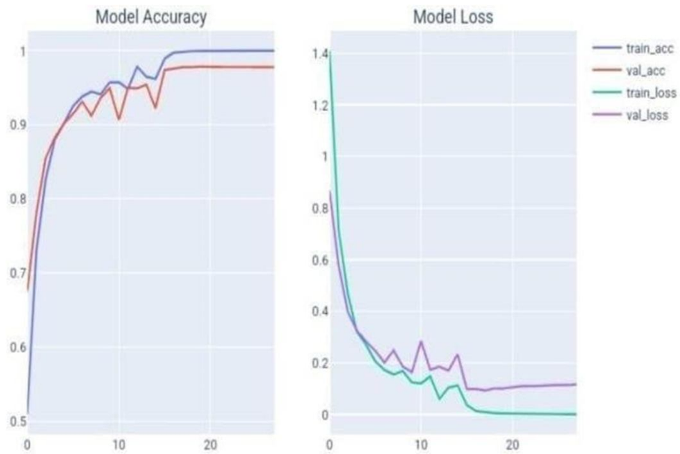

Figure 6. Graphs of Loss & Accuracy with Augmentation

Test Accuracy: 75.337%

	precision	recall	f1-score	support
nv	0.85	0.93	0.89	1374
mel	0.64	0.22	0.33	205
bkl	0.45	0.41	0.43	227
bcc	0.39	0.73	0.51	94
akiec	0.41	0.27	0.33	55
vasc	0.93	0.50	0.65	28
df	0.00	0.00	0.00	20
accuracy			0.75	2003
macro avg	0.52	0.44	0.45	2003
weighted avg	0.74	0.75	0.73	2003

Figure 7. Model Performance metrics without augmentation.

Test Accuracy: 97.924%

	precision	recall	f1-score	support
nv	0.99	0.87	0.93	1385
mel	0.94	0.99	0.97	1328
bkl	0.95	1.00	0.97	1294
bcc	0.99	1.00	0.99	1325
akiec	1.00	1.00	1.00	1270
vasc	1.00	1.00	1.00	1293
df	1.00	1.00	1.00	1257
accuracy			0.98	9152
macro avg	0.98	0.98	0.98	9152
weighted avg	0.98	0.98	0.98	9152

Figure 8. Model Performance metrics after using augmentation

V. CONCLUSION

In this research paper, we employed a dataset comprising seven distinct varieties of skin-cancer and employed data augmentation techniques to expand its size. The primary objective was to propose a machine- learning-based method for skin-cancer detection. To mitigate overfitting, we incorporated data regularization techniques like batch normalization. Our proposed model demonstrated a remarkable accuracy rate of 97.92% while detecting the types of skin-cancer. In terms of model accuracy metrics such as accuracy, recall, precision, etc. our proposed model has performed well. Furthermore, our model stands out for its simplicity and lightweight architecture, distinguishing it from more complex models. Moving forward, our future work involves designing even lighter architectures that maintain accuracy, thereby reducing computational complexity in skin-cancer detection.

VI. FUTURE SCOPE

Diagnosing skin-cancer is a critical medical application, and optimizing the training process can improve accuracy. Instead of scaling down the original image size, training the network with the original size as input can allow for better preservation of details. Additionally, using a larger batch size during training enables the network to learn general features as well as region-specific features from the lesions. These parameter scan be assigned values and incorporated into the network to enhance its performance. By introducing a stochastic model that considers these parameters, they can be combined with the network, further improving the model's accuracy.

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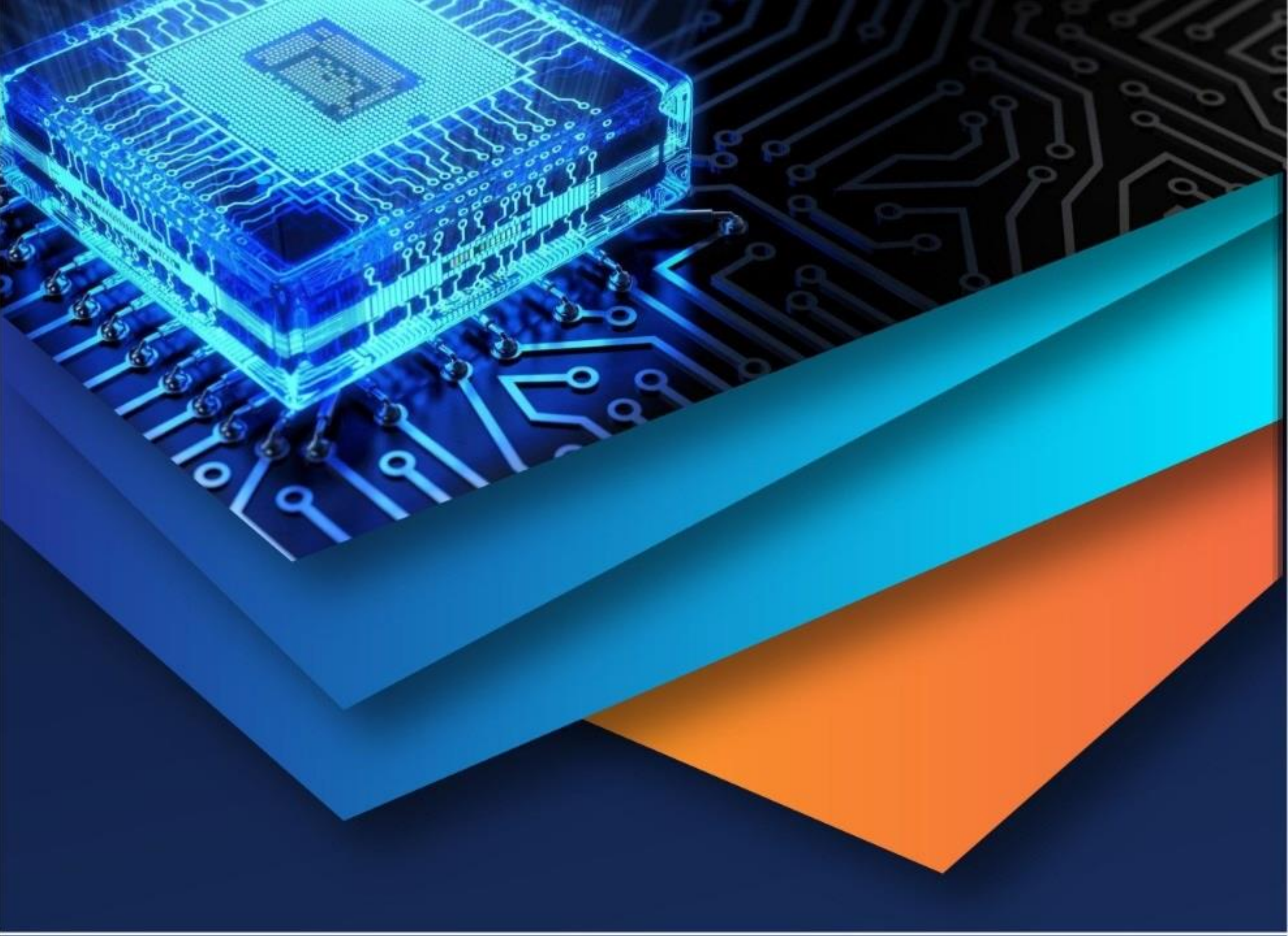

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