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Computer-Aided Detection of Skin Cancer Detection from Lesion Images Via Deep Learning Techniques: A Review

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Abstract: ***Skin cancer is a widespread disease in many countries, with melanoma being the leading cause of skin cancer-related deaths worldwide. To detect skin cancers, including malignant melanoma and other types, deep learning-based algorithms have been developed for image classification. Early recognition of skin cancer signs is essential due to the increasing incidence of the disease, its high fatality rate, and expensive medical treatments. This study presents a literature review of various techniques used to identify skin cancer.***

These systems utilize image processing techniques such as feature extraction, segmentation, and classification to distinguish melanoma and other skin conditions. The article also provides information on skin cancer types, stages, and treatments, and highlights the various deep learning techniques employed in diagnosis. Although researchers have developed advanced machine learning methods to detect each stage of melanoma cancer, there is still a need for more accurate, faster, and affordable detection methods. The article emphasizes the importance of continued research in this field to address future directions for skin cancer detection.

I. INTRODUCTION

Skin cancer is defined by abnormal skin cell proliferation and frequently develops in regions exposed to sunshine and UV radiation [1]. it can also occur in locations that do not usually receive sunlight. The three main types of skin cancer are basal cell carcinoma, squamous cell carcinoma, and melanoma. Around 3.5 million instances are diagnosed annually in the United States alone, which is more than the total number of cases for colon, breast, and lung cancers. A person is diagnosed with skin cancer every 57 seconds. Melanoma and non-melanoma are the 2 basic classifications of skin cancer, according to the type of cell that has formed the cancer [2].

As with all types of cancer, early detection and screening are crucial for successful treatment.

Some of the machine learning (ML) and deep learning (DL) methods developed for recognizing, classifying, and sectioning skin cancer includes support vector machines (SVM), fuzzy C-means, recurrent neural networks, and deep neural networks. Compiling and analysing the findings, classifying them, and describing the findings of the existing research is essential. We developed search strings to gather pertinent data in order to carry out a major, systematic review of skin cancer detection methods utilizing deep neural network-based categorization. Only publications published in respectable journals and conference proceedings were included in our search.

A complete diagnostic imaging assessment is required to detect irregularities in a variety of physiological locations, including skin cancer, breast cancer, brain tumours, lung cancer, and stomach cancer [3]. Based on the GLOBOCAN survey, 9.9 million cancer-related mortality and 19.2 million new cancer detection are anticipated in 2020. Skin cancer, which claimed 18.2% of fatalities, was the most common type of cancer. Moreover, 20% of cancer-related deaths that occur in Europe and over 50% in Asia, according to the poll. Figure 1 also shows the geographical areas most commonly afflicted by skin cancer, with over half of all occurrences occurring in North America.

There are 4 major parts to this article. The introduction part included in part 1,The evaluation of deep learning techniques for detecting skin cancer (SC) is described in part 2 of this article. It includes information about the reviewing area, search parameters, search standards, etc In part 3, a thorough analysis of SC detection methods is offered after the evaluation of a few chosen research papers. Part 4 provides a concise summary of the entire investigation and its findings.

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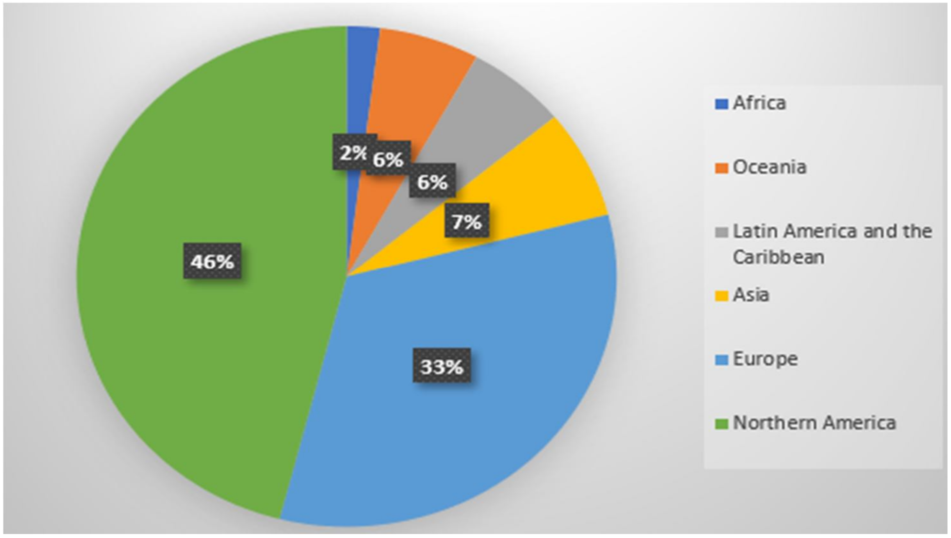

Fig. 1. Skin cancer cases globally

A. Steps for skin cancer detection

The approaches for detecting and predicting skin cancer have significantly improved as a result of the introduction of machine learning techniques to computer vision [4]. Figure 2 displays the categorization of lesion images in addition to the recognition and diagnosis of malignancy.

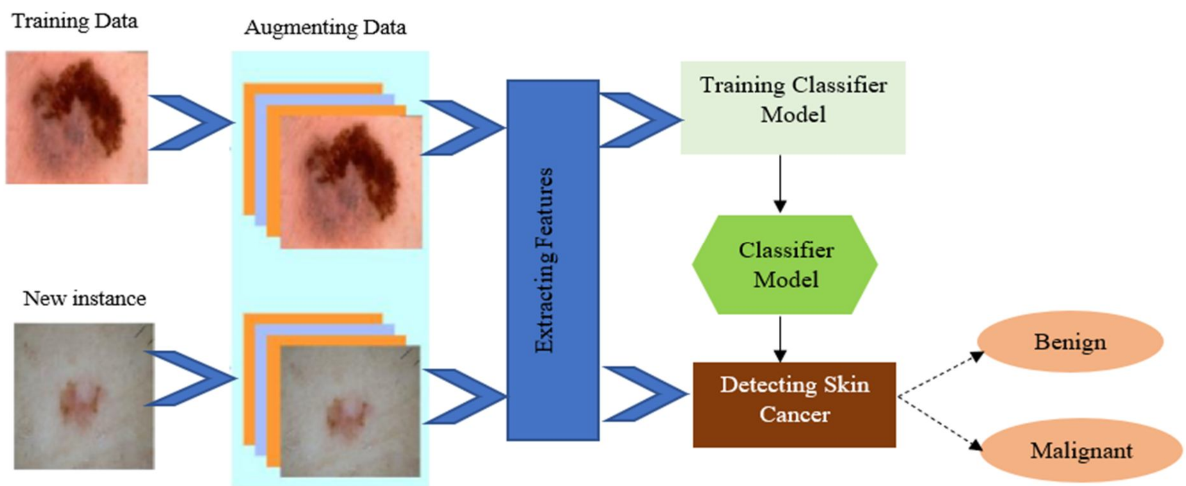

Fig. 2. Skin cancer diagnosis procedure.

The following describes various forms of skin cancer. Basal cell carcinoma or basalioma (BCC): In roughly 80% of instances, basal cell carcinomas (BCC) constitute the major prevalent kind of skin cancer. BCCs arise from basal cells in the epidermis' lowest layer. BCC normally has a modest rate of growth, making it curable with little harm if caught early.

Squamous cell carcinoma or cutaneous spinocellular carcinoma (SCC) : Squamous cells, which are found in the top layer of the epidermis, are the source of squamous cell carcinoma (SCC), which accounts for roughly 16% of skin cancer cases. Although it is easily treatable if caught early, ignoring it might cause it to spread to other places of the body and penetrate deeper layers of skin.

Malignant Melanoma (MM): The melanocytic cells of the epidermis are the origin of this aggressively malignant skin tumour. As it metastasizes early on, it spreads quickly, has a high death rate, and is challenging to treat. Just 4% of skin malignancies are caused by it, but in 80% of cases, it results in death. Only 14% of melanoma patients who have metastasized survive for five years. As it can be cured in 95% of cases if detected early, early diagnosis can significantly improve survival rates. Systems for detecting skin cancer use a variety of learning methods, including ANN, CNN, KNN, and GAN. In the following section, specific research on each of these deep neural networks is covered.

II. LITERATURE REVIEW

Gouda et al. used the 3533 skin lesions from the ISIC2018 datasets and a convolutional neural network (CNN) to categorize benign and malignant tumors [5]. The enriched super-resolution generative adversarial network (ESRGAN) was employed in the study as a preprocessing phase to repair and boost the images. The researchers tested with several to fine-tune their models, including Resnet50, InceptionV3, and Inception Resnet. According to the results of the research, the accuracy rate of the CNN model was 83.2%, and that of the other models was comparable. The study's originality and contribution lay in the preprocessing stage that used ESRGAN to improve the model's classification accuracy. The study's findings have important implications for skin cancer diagnosis and treatment, particularly in regions with high skin cancer incidence rates.

A deep learning-based computer-aided diagnostics technology is proposed by Kim et al. to differentiate between benign and malignant skin cancers utilizing RGB channel skin images [6]. The proposed approach comprises a classification method for malignant melanoma and a segmented framework for tumor lesions. Dermoscopy images were analyzed using U-Net to identify skin lesions, and a convolutional neural network was utilized to analyze the findings of expert identification. The accuracy of classifying malignant melanoma was 80.06%, whereas the U-Net models were able to achieve a dice similarity coefficient of 81.1%. This suggests that the proposed AI algorithm has the potential to be used as a computer-aided diagnostic tool for the early detection of malignant melanoma.

Arshad et al. recommend a brand-new automated framework [7] for categorizing multiclass skin lesions. The framework consists of several procedures, including extraction of features and fusion, deep model optimization, transfer learning, feature augmentation, and feature selection using a skewness-controlled support vector regression technique. Using the HAM10000 dataset, the suggested system is evaluated and outperforms the original imbalanced dataset with an accuracy of 91.7%. The study shows that utilizing deep learning techniques within the suggested framework can enhance the accuracy of identifying skin lesions in classification tasks.

Malibari et al. have presented a novel technique for detecting and categorizing skin cancer, named the Optimal Deep Neural Network Driven Computer Assisted Diagnostic Model (ODNN-CADSCC). This approach employs a deep neural network to achieve its objectives. The proposed approach divides data into sections using U-Net and prepares data using Wiener Filtering (WF). Feature vectors are generated using SqueezeNet, while skin tumors are identified and categorized using the Improved Whale Optimization Algorithm (IWOA)[8]. A maximum accuracy of 99.90% is achieved by the suggested model, outperforming more contemporary methods.

For several kinds of skin lesions, Saleh et al. suggests an automated diagnosis approach employing dermoscopic images [9]. The framework consists of four basic steps: pre-processing, feature extraction using six deep learning algorithms that have already been trained, concatenation of characteristics, and classification/diagnosis using machine learning methods. A review of the suggested system reveals that it performs well, with average values of 99.94% accuracy, 91.48% sensitivity, 98.82% specificity, precision, and disc similarity coefficient (DSC) of 97.01%, 97.01%, and 94.00%, correspondingly. The disorders include melanocytic nevi, basal cell carcinoma, dermatofibroma, melanoma, and vascular skin lesions. Actinic keratoses and benign keratoses are also covered.

For the identification and categorization of skin lesions in dermoscopic images, Adla et al. suggests a deep-learning model termed DLCAL-SLDC[10]. The model involves image pre-processing using techniques such as hair removal and noise removal, followed by segmentation using a Tsallis entropy-based technique. The SSO-CSAE model is employed for categorization, and the segmented lesions are used to extract class-specific characteristics from the DLCAL layer of the Capsule Network (CapsNet). When evaluated on a benchmark ISIC dataset, the suggested structure showed promise with excellent accuracy, sensitivity, and specificity. In comparison to other methodologies, the suggested scheme has achieved encouraging outputs with 98.50% accuracy, 94.5% sensitivity, and 99.1% specificity.

A computer-aided automated technique was developed by Fatima and her colleagues [11] for the detection of skin cancer in dermoscopy images. The procedure involves categorizing the malignant spots using CNN, denoising the input image using a median filter, and optimizing the SBO algorithms. They proposed an ideal feature selection method based on the SBO algorithm, which is used to extract features from the segmented images and simplify the classification process. The final classification is then performed using an improved SVM classifier that employs the SBO method. The methodology is used to analyze data from the ACS database and is then compared to eleven other cutting-edge techniques. The results demonstrate improved performance in terms of accuracy, specificity, NPV, sensitivity, and PPV.

Shoieb et al. [12] offer an improved model for skin assessment Utilizing skin lesion images captured by a common camera. The model employs CNN as a feature extractor for automated skin disease diagnosis, which can decrease diagnostic errors and provide remote patients with assistance at a reduced cost while eliminating an overreliance on medical specialists.

With regard to sensitivity, specificity, and accuracy, experimental results show that CNN characteristics perform better than manually-engineered characteristics. Comparing the suggested model to the most advanced computer-aided skin diagnostics techniques, the diagnostic accuracy was significantly improved by about 11%.

Kaler et al. [13] proposed an approach to categorizing dermoscopic images using a CNN structure with ResNet-50 modules. The method involves attaching a smartphone to a lens in order to capture the images, and the dataset utilized in the study was obtained from a Kaggle repository.

When compared to earlier work utilizing a Visual Geometry Group model, the new approach had a skin cancer detection accuracy of 93% as opposed to that 73%. The dataset consisted of 25,000 images of skin lesions.

Kanimoshi et al[14] propose a computerized method for analyzing medical images using Neural Networks. In order to analyze skin cancer photos and assess parameters including asymmetry, border, color, and diameter (ABCD), cost-effective emergency assistance systems are being developed. These systems will be used to create diagnostic algorithms that will enhance emergency department triage procedures. In the classification phase of the suggested technique, Back Propagation Algorithm is combined with Artificial Neural Networks (ANN). The network achieves 96.9% accuracy. It is then determined whether the unidentified values are more effective at classifying cancers, particularly skin cancers.

Ameri [15] suggests using a deep learning algorithm to identify skin blemishes in images as skin cancer. Instead of relying on expensive procedures for lesion segmentation and feature extraction, the proposed approach employs a deep convolutional neural network to categorize images into benign and malignant groups. By setting a confidence score threshold of 0.5 and utilizing the model's area under the receiver operating characteristic (ROC) curve of 0.91, the classification accuracy reached 84%, sensitivity was 81%, and specificity was 88%. This technique can be applied to smartphones, allowing users to self-diagnose skin cancer and support dermatologists in identifying malignant skin lesions.

The computer-aided categorization system proposed by Birkenfield[16] et al. aims to aid in the early identification of melanoma by assisting in the recognition of questionable pigmented lesions. 133 participants were enrolled in the study, and a clinical database was built by capturing wide-field images of all the body's major organs in settings with natural lighting. An optimized computer-aided classification approach was used to binary classify each lesion based on its suspiciousness score. The approach achieved a sensitivity of 100% for suspected pigmented lesions and 83.2% for presumed but unconfirmed pigmented lesions in a testing set. For non-suspicious lesions, the sensitivity was 72.1% and the overall accuracy rate was 75.9%. Wide-field images and computer-assisted classification methods may distinguish between worrisome and non-suspect pigmented lesions, according to the results, and may be useful for enabling population-level skin screenings.

Using dermoscopy images from the HAM10000 dataset, Pila et al suggested a model for identifying and categorizing skin cancer[17]. 10 different pre-trained Convolutional Neural Networks (CNNs) were employed to features extracted after image classification, and Support Vector Machine (SVM) was utilized to classify the information.

The findings demonstrated that, in comparison to models without image segmentation, those with segmentation had accuracy levels between 80.67% and 90% higher.

The AlexNet plus SVM model identified and classified the seven types of cutaneous lesions with the best accuracy rate (90.34%) and the shortest processing time.

To use a Convolutional Neural Network, Pratiwi et al intended to automatically distinguish between skin cancer and benign tumor lesions. The proposed model utilized three hidden layers and employed various optimizers, such as SGD, RMSprop, Adam, and Nadam, with a learning rate of 0.001. By using the Adam optimizer, the model achieved a remarkable accuracy rate of 99% in categorizing skin lesions in the ISIC datasets, including dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma.

This model may enable the development of a computer-aided detection method for early and precise melanoma detection, as its performance surpassed the existing techniques for skin cancer classification. The system utilizes ML and DL-based transfer learning models for categorizing pigmented skin lesions, covering preprocessing, segmentation, feature extraction, and classification stages. The system's evaluation is based on dermoscopic images from publicly available datasets, such as PH2 and ISIC-16, with and without image enhancements.

Among all the deep learning-based transfer learning models, the VGG-16 model outperformed others with an accuracy of 99.1% on the PH2 dataset. The performance metrics of the CAD-MD system include accuracy, sensitivity, specificity, dice coefficient, and Jacquard Index.

TABLE I
COMPARISON OF DIFFERENT ARCHITECTURES

Ref	Dataset	CNN Architecture	Highlights	Limitations	Performance
(20)	Self-collected dataset	ResNet-34, ResNet-50, ResNet-101 and ResNet-152	suggested ways to enhance the classification of dermoscopy data using deep learning.	Data from additional sources are not taken into account, including information on additional symptoms and the patient's medical history.	Accuracy: 0.89
(21)	ISIC-2017, IAD	Inception-v2	improving the sensitivity of the model by incorporating sonification into the diagnosis of skin cancer lesions.	The model's prediction outcomes can be impacted by variations in pathologists' diagnoses.	AUC: 0.976 Sensitivity: 0.86 Specificity: 0.91
(22)	ISIC-2017	DensNet, Dual Path Nets Inception-v4, Inception-ResNet-v2MobileNetV2, PNASNet, ResNet SENet, Xception	They thoroughly assessed the parameters impacting the selection of CNN structure by examining 13 factors from 9 different models.	The dataset used in this study is overly small and concentrates solely on the melanoma classification problem.	Top accuracy: 0.827
(23)	IAD	VGG-19	VGG-19 network was used for the first time to measure melanoma thickness.	Predicting melanoma thickness precisely would be more therapeutically meaningful because pre-training procedures for comparison are no longer used.	Accuracy: 0.872 Specificity: 0.840
(24)	Derm7pt	Inception-v3	The seven-point checklist and skin disease diagnosis were categorized using a multi-task network. As well as handling various input modalities, such as clinical and dermoscopic images and patient diagnostic data, several loss functions were also developed.	There are several criteria on the seven-point checklist that cannot be distinguished.	Accuracy: 0.737
(25)	HAM 10000	Deep CNN models	proposed a technique for classifying skin diseases using one-versus-all (OVA) and CNN.	The model may have a significant amount of variance since it has not been tested on datasets from other domains.	Accuracy: 0.929
(26)	HAM 10000 ISIC-2019	ResNeXt, SeResNeXt, DenseNet Xception, and ResNet	Adopted a grid search methodology to identify the top ensemble learning techniques for classifying skin cancer	The majority of the models used in ensemble learning come from the same network architecture, and there is still a lack of training data.	Accuracy: 0.88 F1 score:0.89

III. CONCLUSION

For the purpose of identifying and categorizing skin cancer, a variety of non-invasive neural network algorithms have been studied in the systematic review research. The process of identifying skin cancer involves a series of steps such as preprocessing, image segmentation, extracting features, and performing classifications. The classification of lesion images using artificial neural networks (ANNs), convolutional neural networks (CNNs), k-nearest neighbors (KNNs), and radial basis function networks (RBFNs) has especially been examined in this research. Choosing the best categorization strategy is essential for achieving the best results because each algorithm has unique strengths and weaknesses. However, when it comes to classifying image data, CNNs tend to perform better than other types of neural networks due to their close relationship with computer vision.

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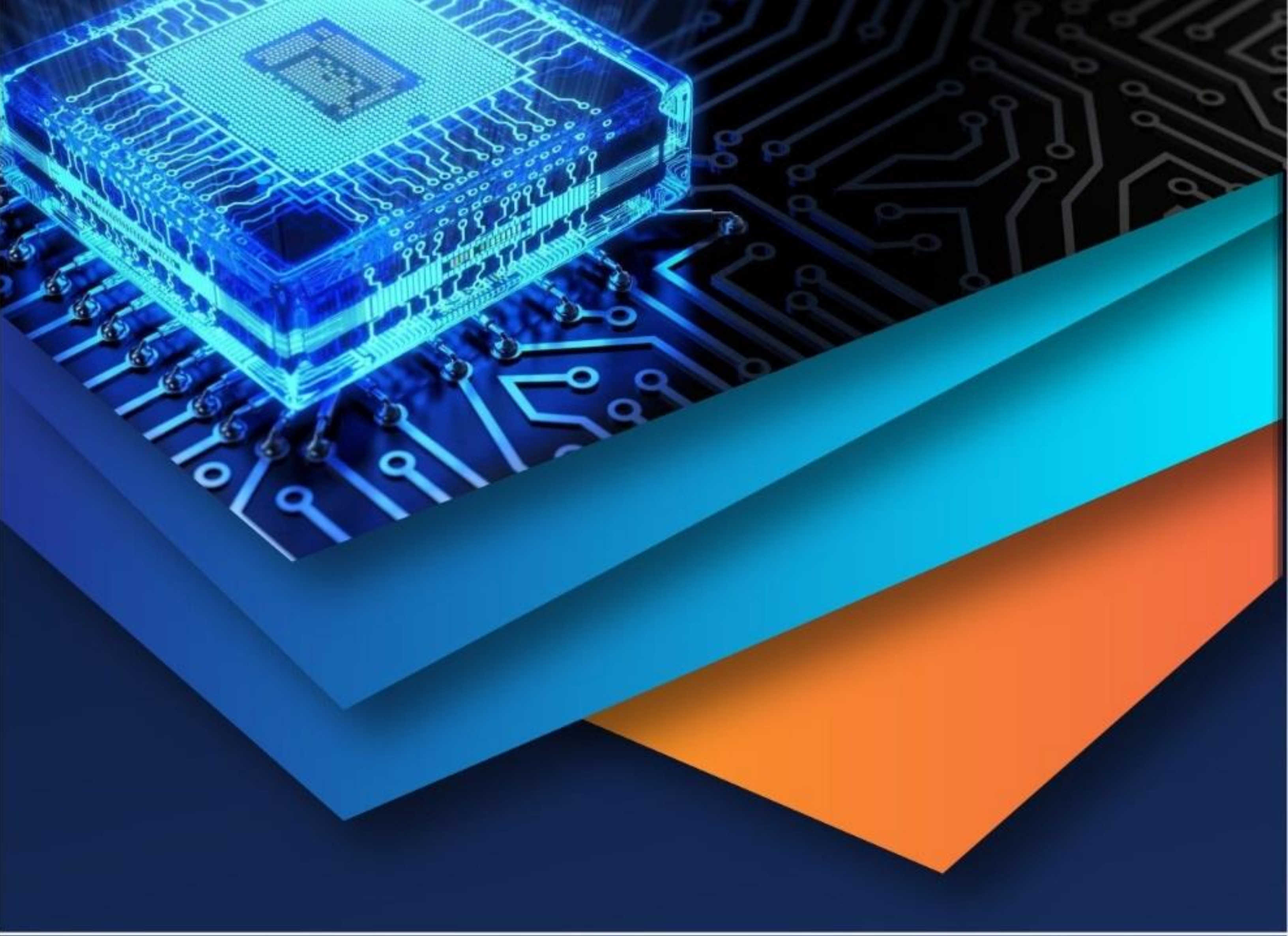

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