iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: V Month of publication: May 2026

DOI: https://doi.org/10.22214/ijraset.2026.78753

Deep Learning-Based Automated Skin Disease Detection and Classification from Dermoscopic Images

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Abstract: Skin conditions cause health problems for a large number of people worldwide [11],[12]. However, a considerable percentage of people suffering from skin problems remain undetected due to limited access to dermatologists [12] and also because of the unreliable nature of online information. This paper introduces an intelligent web-based platform that can automatically detect and classify skin diseases through a deep learning approach. The system uses an EfficientNet-B3 model for precise categorization of images and is capable of producing results as high as 90.2% accuracy in recognizing different types of skin disorders [2],[5],[15]. In addition, the platform offers lesion segmentation through U-Net DeepLabV3 method [4], explainable AI visualization by Grad-CAM heatmaps [3] and a healthcare system that not only detects disease but also provides PDF reports helps users find location-based dermatologists and pairs them with AI powered chatbots for assistance.

Developed using secure PHP, MySQL backend combined with responsive HTML, CSS and JavaScript frontend this platform makes it feasible for users to carry out preliminary dermoscopic evaluation of various skin lesions using a standard camera or smartphone in real time. In fact, the system solutions the issue of healthcare accessibility in several ways by offering instantaneous AI supported diagnosis by making the time gap for diagnosis lesser, and by making the dermatological screening process available to people who don't have direct contact with specialists.

Keywords: Artificial Intelligence, Deep Learning, EfficientNet-B3, Dermatology, Medical Image Classification, Lesion Segmentation, Healthcare Technology, Web Platform, Explainable AI, Skin Disease Detection

I. INTRODUCTION

Skin diseases pose a major health issue worldwide as a lot of people are being affected by them. Early detection of skin problems particularly cancerous ones is very important for effective treatment and improved patient outcomes [1],[13]. Yet, there is still a shortage of qualified dermatologists in areas other than big cities [12]. People living in rural or deprived regions have limited access to healthcare due to factors such as distance, long waiting times for appointments and high costs. In addition, a lot of them depend on faulty internet resources for their self-diagnosis that leads to incorrect diagnoses and postponement of seeking professional help.

Our system is based on deep learning technology that helps to provide instant AI powered preliminary skin disease diagnosis through dermoscopic images [1],[6],[7]. The users can upload images and get results with confidence scores indicating the level of certainty of the model. Besides, the system generates clinical grade PDFs of the reports for the users, providing features such as location-based dermatologist recommendations, an AI powered chatbot for medical advice and secure detailed history tracking all these features could be accessed through a responsive website [5], [8].

By harnessing advanced architectures like EfficientNet-B3 to extract features [2],[15],[16] and utilizing explanation methods like Grad-CAM [3] the system promotes clarity and builds user confidence. It empowers not only the specialists but everyone to benefit from dermoscopic examination through the availability of this diagnostic tool online at any time without the constraints of one physical location. The present investigation has demonstrated the great value of linking sophisticated artificial intelligence with the design oriented towards the users to effectively solve major issues related to healthcare accessibility over time.

II. LITERATURE REVIEW

One of the major impacts of computer vision and deep learning in healthcare is the significant improvement of medical image analysis [1],[6]. This is particularly true for skin disease detection with the use of textural analysis. Automated classification of dermoscopic images based on Convolutional Neural Networks (CNNs) has becomes a standard practice [6],[8]. Their performance in identifying skin diseases has been so good that for example, a deep neural network was able to classify skin cancer at the level of a dermatologist [1],[13] which opens up the possibility of AI assisted medical diagnosis.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

Various deep learning architectures have been tried for skin lesion classification. For instance, ResNet , VGG and DenseNet are quite popular [8],[9]. But these models tend to be very demanding in terms of computational resources. So, there was a need for more efficient architectures and thus Efficient-Net was launched [2],[16]. It adopts a novel approach compound scaling that evenly scales all dimensions of depth, width and resolution together, thereby improving performance without increasing computational cost.

On the other side, segmentation methods are very helpful and are indeed a key factor in boosting the performance of classification models. Among others U-Net is the most popular architecture for image segmentation of dermoscopic lesions [4]. Segmenting the lesion from the surrounding skin allows classification models to only focus on features responsible for the disease. Moreover, lesion segmentation also helps to eliminate any confounding factors in the background.

Additionally, explainable artificial intelligence techniques like Grad-CAM have been developed to enhance the transparency of deep learning systems [3]. Grad-CAM produces pictorial heatmaps which point out the parts of an image that led to the model prediction, thus assisting medical experts in comprehending and placing their trust in AI driven diagnostic systems.

Even though these technologies have been developed a large number of existing works are primarily targeted towards classification models only and therefore do not get integrated with practical healthcare systems [5],[9]. Hence, there is an emphasis on the design of the systems which incorporate powerful deep learning models, lesion segmentation and explainable AI methods along with being a user-friendly software aimed at real world skin ailment detection.

III. METHODOLOGY

A. System Architecture

Behind the scenes, it runs on three layers. One shows what users see. Another handles the requests. The third pulls data from storage. Each works alone but stays linked through strong connections below.

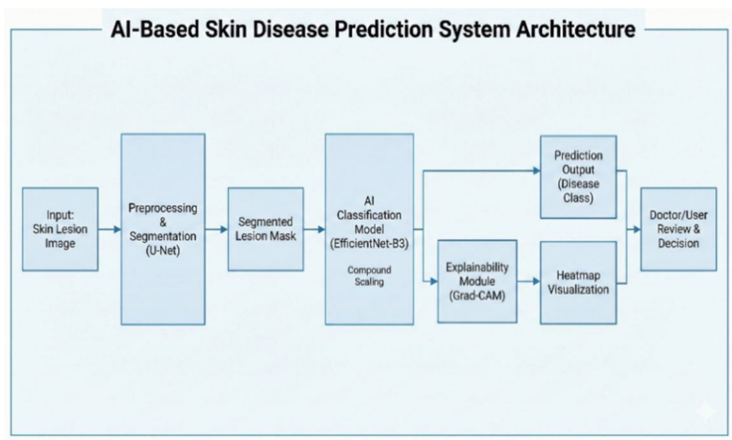

Fig. 1 System Architecture

Fig. 1 shows how the skin disease system works, from raw image to final diagnosis. The flow splits into three parts: Preprocessing & Segmentation, Classification, and Explainability.

1) Preprocessing & Segmentation Module

At the beginning of the process, the system gets a raw Skin Lesion Image. Background artifacts (e.g., hair, skin pores, or ruler markings) can be present in medical imaging. As a result, the system performance in classification might decrease. A U-Net architecture is employed for semantic segmentation in order to counter this issue [4].

Method: U-Net processes the input image and creates a Segmented Lesion Mask, which is a binary image describing the ROI and background [4].

Result: Thus, the classification model is able to focus only on the lesion area which is of interest to it. Consequently, the noise gets reduced and the feature extraction is improved.

2) Classification Module

The segmented data enters the heart of the AI Classification Model, which is built on EfficientNet-B3 [2],[16]. The main feature of this model is Compound

Study / Paper	Model Used	Segmentation	Explainable AI	Limitation
Esteva et al. (2017)	CNN	No	No	High computational cost and no explainability
Manole et al. (2024)	EfficientNet	No	No	Only classification, no lesion segmentation
Rezvantalab et al. (2018)	CNN	No	No	Limited interpretability
Chaturvedi et al. (2019)	MobileNet	No	No	Lower performance for complex lesions
Akter et al. (2023)	CNN	No	No	Lack of explainable AI
Proposed System	EfficientNet + U-Net	Yes	Grad-CAM	Limited disease categories

Scaling, which allows network depth, width, and resolution to be adjusted in a balanced manner [2].
Architecture: In a nutshell, this harmony allows the model to identify complex textural patterns and subtle details with very high accuracy, while at the same time, the computational cost is kept low, a typical problem with bigger traditional networks [2],[15].
Output: After examining the features of the lesion, the model produces a Prediction Output which is the categorization of the disease into appropriate classes (e.g., Melanoma, Benign, etc.).

3) Explainability & Decision Support

In order to foster clinical trust and make the process clear to everybody the system architecture has been equipped with an Explainability Module implemented with Grad-CAM (Gradient weighted Class Activation Mapping) [3].
Mechanics: At the same time as the system generates the prediction output Grad-CAM takes into consideration the gradients of the final convolutional layer to figure out the parts of the image which were the main factors of the decision [3].
Outputs: Based on this, it creates a Heatmap Visualization which marks the exact parts of a lesion that the model considered suspicious [3].
Doctor/User Final Decision: Hence, both the predicted disease class and the visual heatmap are submitted to the
Doctor/User to verify, thus enabling them to make a more informed and confident decision.

B. Image Processing Pipeline

The users are able to upload images of dermoscopic through a very simple and user-friendly web interface that even supports drag and drop functionality and file preview. On the server-side standardized preprocessing is carried out where an image is resized to 224x224 pixels are normalized 0 to 1 range and histogram equalization is done to clarify the diagnostic features.
The images are thus preprocessed to be perfectly compatible with deep learning model inference [6],[7].

C. Feature Extraction using Efficient Net-B3

The system uses EfficientNet-B3 which is a very advanced convolutional neural network picked out for its outstanding performance on medical imaging tasks [2],[15]. Efficient-Net gets close to bigger models' accuracy at the same time it only has a few parameters which makes it easy to put on regular server infrastructure [2],[16].
The model handles images after preprocessing by passing them through several convolutional layers which extract features of increasing abstraction at each layer. Starting from simple characteristics such as edges and textures it moves on to complex ones like morphology and color of lesions. Such a feature extraction at different levels results in a vector representation of the image in a very high dimensional space. This representation is informative enough for the classification of the disease [5],[8].

D. Lesion Segmentation using U-Net DeepLabV3

Accurate isolation of lesions facilitates classification accuracy as well by limiting the model's attention solely to the affected regions and thus, avoiding the healthy tissue nearby. U-Net DeepLabV3 architecture is a combination of an encoder, decoder structure with skip connections that help retain spatial information [4].

The encoder consecutively down samples and extracts the features from the input image, whereas the decoder restores the spatial resolution through transposed convolutions. The inclusion of the DeepLabV3 feature is the use of atrous spatial pyramid pooling that enables the capturing of a multiscale contextual information. The result is a binary segmentation mask that distinguishes lesion pixels from healthy tissue pixels and serves as a classification model's focus area refiner [4],[10].

E. Disease Classification and Confidence Scoring

After segmentation, the cropped lesion area was classified into the following types of skin disease: Melanoma, Benign Nevi, Basal Cell Carcinoma, Actinic Keratosis, Seborrheic Keratosis, Dermatofibroma, and Vascular Lesions [7]. A classification head processed the features extracted by the fully connected neural network layers, resulting in a probability distribution over the disease categories [6],[8]. The model's output is the disease with the highest probability as the first diagnosis, and the maximum probability expresses the confidence in the prediction. High confidence scores (>85%) signify that the model is making a very certain prediction and thus only a limited consultation with the specialist is needed, whereas low confidence (60, 70%) indicates that the model is uncertain and the predictions should be checked by a professional.

F. Explainability through Grad-CAM Visualization

A major drawback of deep learning models is that they are usually 'black boxes' regarding their decision, making rationale. The system uses Grad, CAM (Gradient, weighted Class Activation Mapping) to provide visual explanations [3]. Grad-CAM generates color, coded heatmap overlays on the original images where red areas are the ones that have contributed most to the classification. Looking at these heatmaps, doctors may be able to check whether the model has concentrated on the correct clinical features and therefore, their trust in AI recommendations will be increased [3],[8].

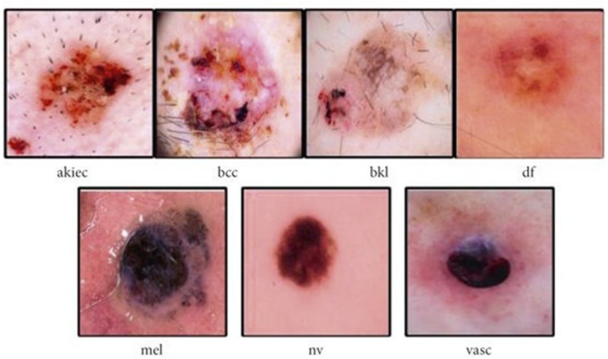

Fig.2

The fig.2 is of HAM10000 dataset which consists of the following seven diagnostic categories:

- akiec (Actinic Keratoses and Intraepithelial Carcinoma): These are precancer or very early-stage cancers of the skin caused by the sun. They usually look like rough, scaly patches.
- bcc (Basal Cell Carcinoma): This type of cancer is the most common cancer of the skin. It grows very slowly almost never spreading but if not treated it can cause damage to the tissue around it.
- bkl (Benign Keratosis, like Lesions): Non- cancerous growths that are grouped together, including seborrheic keratoses ("senile warts") and solar lentigines ("liver spots").
- df (Dermatofibroma): A flesh, coloured raised bump formed by overproduction of fibrous tissue of the skin that is usually confused with a firm scar like nodule.
- mel (Melanoma): It is the deadliest type of skin cancer developing from the pigment producing cells (melanocytes) which has the characteristic of spreading rapidly to other organs.
- nv (Melanocytic Nevi): These are typical benign moles. This is the most frequent class in the dataset and it corresponds to normal non-cancerous pigment accumulations.
- vasc (Vascular Lesions): These are non, cancerous red- or purple-coloured growths, for instance, angiomas, which are made up of a collection of blood vessels located near the skin's surface.

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ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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G. Backend Infrastructure

The server side in general uses PHP to handle coming requests, apply the logic of the business and deliver APIs. MySQL is used for keeping user profiles, diagnostic reports, Lists of Dermatologists and audit logs. Two factor authentication through OTP email adds an additional layer of security. All database queries are done through prepared statements so as to not allow SQL injection. HTTPS encryption gives protection to data while it is being transferred.

H. Fronted Implementation

The responsive interface uses HTML, CSS, and JavaScript technologies and adjusts flawlessly on mobile, tablet, and desktop devices. Its features are easy to use dashboard drag and drop image upload instant display of results with confidence metrics and Grad-CAM heatmaps, PDF report generation, location-based dermatologist search, AI chatbot integration, and full history tracking.

I. Tools and Technologies.

Supporting Libraries: PHP Mailer for OTP delivery, Google Gemini API for chatbot functionality, PDF generation libraries.
Model Architecture: EfficientNet-B3 for feature extraction, U-Net DeepLabV3 for segmentation, Grad-CAM for explainability.

IV. RESULT AND DISCUSSION

The proposed deep learning model effectiveness was assessed by employing classification metrics such as precision, recall and F1-score for each disease category. The entire system attained a classification accuracy of 90.2% highlighting the potential of the proposed method for automated skin disease detection.

Fig. 3 presents the confusion matrix

The confusion matrix in Fig. 3 illustrates the efficiency of the model in differentiating the seven types of skin diseases. It is a comparison between the actual disease labels and the ones predicted by the model. The figures on the diagonal of the matrix indicate the number of cases that were successfully identified.
The other figures (off-diagonal) are those cases where the model went wrong in predicting the disease.
The findings reveal that the model is capable of identifying melanocytic nevi (nv) very accurately since almost all predictions for this class are correct. Identification of basal cell carcinoma (bcc) and benign keratosis (bkl) is also done well by the model. On the other hand, the model is sometimes confounded when two diseases have very similar images for example, melanoma (mel) and benign keratosis (bkl). This is due to the fact that their visual features are very similar. Nevertheless segmentation and feature extraction steps help to limit these errors and increase the general classification accuracy even further.

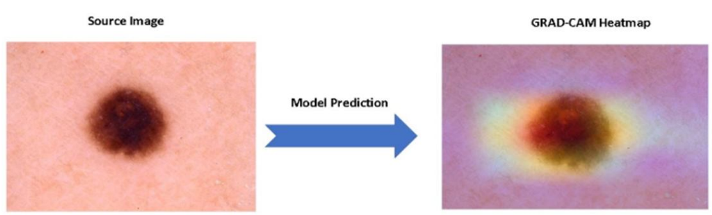

Fig. 4 GRAD-CAM Heatmap

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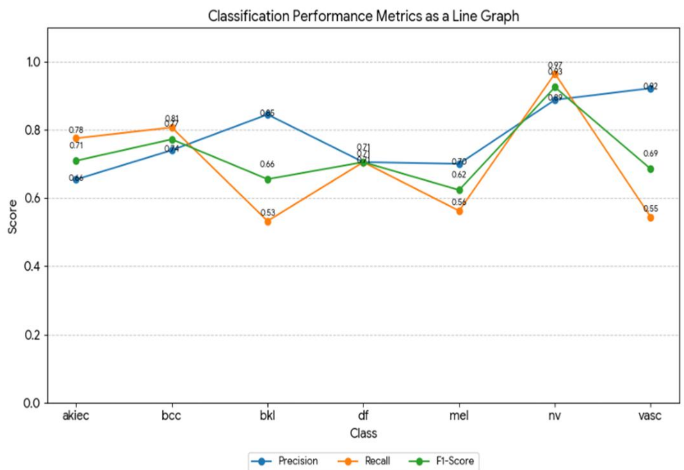

Fig. 5: Precision, recall, and F1-score comparison for different skin disease classes.

Figure 5 shows the model's capability to classify different types of skin diseases. Here the precision, recall and F1-score metrics were used. Precision measures what percentage of the cases predicted are actually correct. on the other hand, tells us how well a model is able to find all the real positive cases while F1-score is a balanced average of precision and recall. The results reveal that the model was able to maintain a good balance between precision and recall for several types of diseases especially nevus and basal cell carcinoma. The similar F1-scores for various diseases mean that the model is consistently well-working in several disease categories.

In a nutshell, these findings demonstrate that the proposed deep learning system classifies skin diseases in a dependable manner and provides accurate predictions. The integration of lesion segmentation, feature extraction and explainable AI contributes towards enhancing the model's accuracy as well as the interpretability of its predictions.

V. CONCULSION AND FUTURE SCOPE

This piece of research indicates how deep learning and intelligent healthcare platforms can enhance the availability of dermatological diagnosis. The system at hand employs recent deep learning methods including EfficientNet-B3 for the classification task U-Net based segmentation and Grad- CAM for explainable AI visualization. The developed model got 90.2% as the overall classification accuracy which means that AI can support skin disease detection at an early stage through dermoscopic images.

The platform is a comprehensive solution that merges automatic disease identification, report generation, dermatologists' search and patient support aspects. Such a system can be a big step forward in decreasing diagnosis time and preliminary skin disease screening can be made accessible to people living in remote and underserved areas where dermatologists are hardly available. Besides, a transparent and explainable AI based approach allows the establishment of trust between technology and healthcare professionals.

The system can be enhanced in many ways in the future. For instance, more types of skin diseases can be added if the system has the capability to diagnose up to 7 types at present only. Besides, access of doctors to patient history can be made easy by integrating the system with hospital records. Moreover, patients and dermatologists can get in touch remotely through the use of telemedicine tools such as live chat.

Another way to enhance the system would be the development of mobile applications thereby providing easier access to users. Incorporating multiple languages support will allow people from various ethnic backgrounds to be able to use the system.

Lastly, the system needs to undergo testing with more diverse datasets before it can be utilized in the real world. Ongoing research and development can enable this system to become a dependable AI assistant for skin disease identification and also aid in making healthcare more accessible to the global community.

VI. ACKNOWLEDGEMENT

The authors greatly appreciate their invaluable guidance and mentorship, which was a great support throughout this research project. Authors are thankful, especially to the Department of Information Technology at the Vishwakarma Institute of Technology for letting us use the required computation and laboratories facilities.

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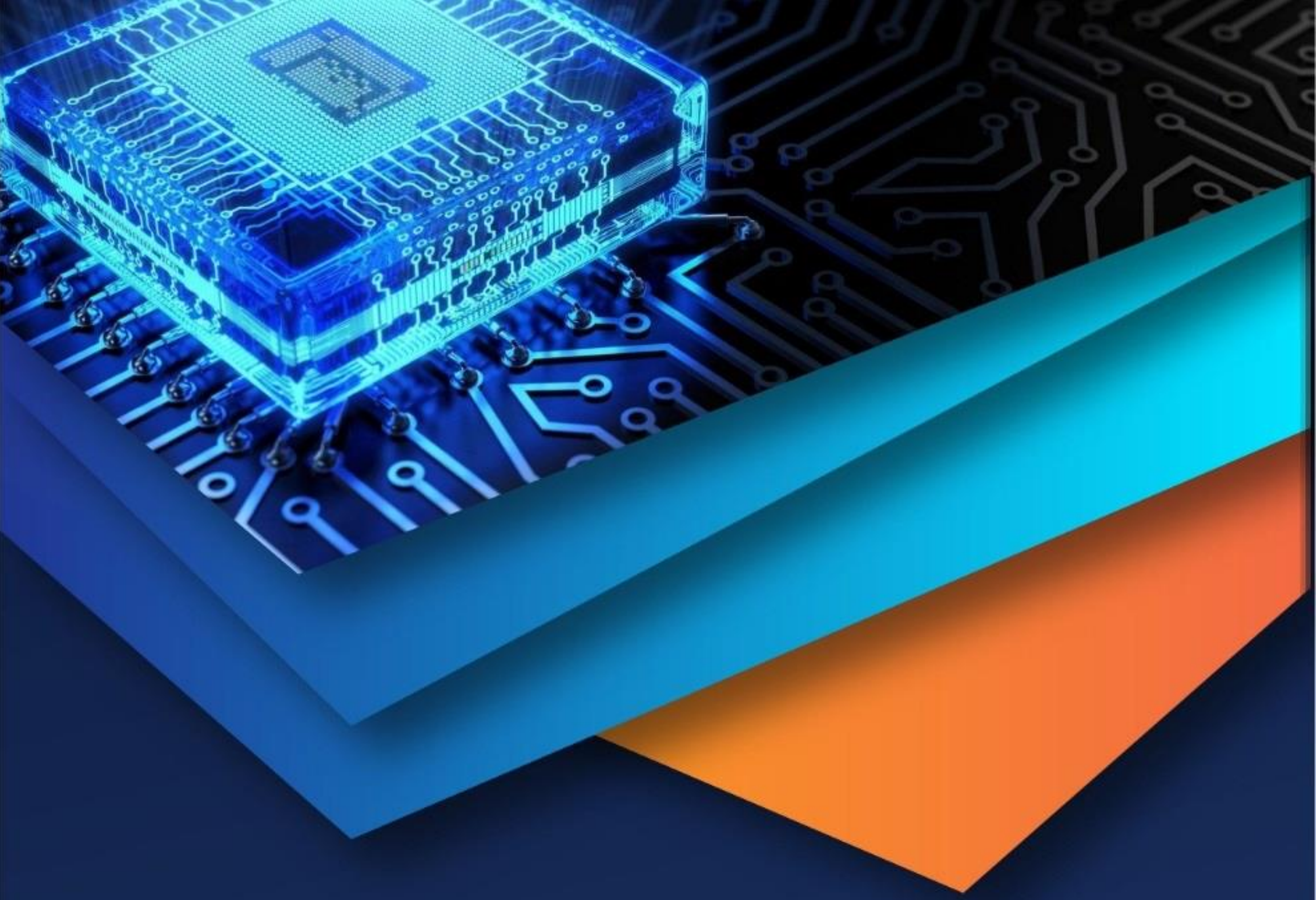

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