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Performance Evaluation of Oral Cancer Detection Using Deep Learning

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Abstract: Oral cancer remains a major public health challenge, especially in developing regions where access to early screening facilities is limited. Conventional diagnosis depends heavily on clinical inspection and biopsy, which are time-consuming, invasive, and require expert evaluation. With recent advancements, deep learning has become a promising tool for automated medical image analysis, enabling faster and more reliable identification of cancer-related abnormalities. This study compares the performance of four deep learning models—CNN, ResNet152V2, EfficientNetB0, and VGG19—using an open-source oral cancer image dataset. After applying preprocessing, augmentation, and transfer learning, each model was evaluated using accuracy, precision, recall, and F1-score. Among the tested architectures, VGG19 achieved the highest performance with 95% accuracy and strong sensitivity for malignant lesion detection. The outcomes highlight the growing potential of deep learning as a supportive diagnostic tool for early oral cancer detection.
Keywords: Oral Cancer Classification, Deep Learning, VGG19, ResNet152V2, EfficientNetB0, Convolutional Neural Networks, Transfer Learning

I. INTRODUCTION

Oral cancer is one of the most prevalent cancers worldwide, with India experiencing particularly high incidence due to factors such as tobacco consumption, betel-nut chewing, alcohol use, and poor oral hygiene. Early identification is crucial as it improves survival chances and lowers treatment costs. However, initial visual symptoms often appear as subtle discolorations or lesions that are easily missed during clinical examination. Traditional diagnosis relies on biopsy and histopathology, which demand specialized resources and are not always accessible. The rapid evolution of Artificial Intelligence (AI), especially deep learning, has paved the way for automated medical image analysis. Convolutional Neural Networks (CNNs) are capable of learning subtle visual patterns, making them suitable for distinguishing between cancerous and non-cancerous lesions. This paper aims to evaluate and compare several deep learning models to determine the most effective approach for oral cancer detection.

II. LITERATURE SURVEY

Lopez-Cortés et al. (2022) demonstrated that machine learning techniques are effective in differentiating malignant and benign oral lesions. Patel Kumar (2024) highlighted that AI-driven systems improve diagnostic sensitivity and specificity compared to manual screening. Kavyashree et al. (2023) observed that deep learning models outperform conventional ML classifiers such as SVM and Random Forest for medical image interpretation. Studies involving ResNet, DenseNet, VGG19, and EfficientNet consistently report strong performance in cancer-related image classification due to their depth, feature extraction efficiency, and transfer learning capabilities. Despite this progress, challenges such as limited datasets, image variability, and generalization issues persist. This work addresses these limitations by comparing four widely used deep learning architectures using a common dataset.

TABLE I
REFERRED PAPERS AND BOOKS

Aspect	Research Paper 1 (2022)	Research Paper 2 (2024)	Research Paper 3 (2023)	Research Paper 4 (2021)
Publishing Dates	04-06-2022	04-12-2024	22-01-2024	05-04-2023
Problem statement	Review of ML in oral cancer	Traditional methods	Oral cancer aggressive;	Late diagnosis drives

	(diagnosis, prognosis, pre-cancer).	invasive/subjective → apply AI/ML for early detection.	biopsy limited; DL for non-invasive detection.	mortality; ML/CV for automated detection.
Models used	SVM, ANN, Logistic Reg., CNN, RF, KNN, etc.	CNN, SVM, RF.	CNN, Transfer learning (ResNet, VGG, DenseNet, Inception), hybrid CNN+SVM.	CNN, SVM, RF, ensemble classifiers.
Preprocessing methods	Spectral preprocessing, feature extraction, cleaning.	Missing value imputation, outlier detection, normalization, feature extraction (GLCM, shape, color).	Resizing, normalization, noise reduction, augmentation.	Image enhancement (CLAHE, hist. eq.), resizing, denoising, augmentation.
Evaluation metrics	Accuracy, Sensitivity, Specificity, AUC.	Accuracy, MSE.	Accuracy, Precision, Recall, F1, AUC.	Accuracy, Precision, Recall, Specificity, F1, AUC.
CNN accuracy (%)	>85 (varies)	89-94 (normalization)	85-95	92-95
SVM accuracy (%)	85-90	85-91	80-88	88-91
RF accuracy (%)	80-90	87-92	78-85	85-89
Key findings	SVM strongest; CNN adoption growing	Normalization boosts all models; CNN best.	CNN > ML; transfer learning improves; explainability important.	CNN > SVM/RF; hybrid improves; augmentation crucial.

III.METHODOLOGY

A. System Overview

The proposed model processes oral lesion images and categorizes them as cancerous or non-cancerous using deep learning. The system workflow includes:

- Dataset collection
- Preprocessing
- Augmentation
- Feature extraction using CNN/Transfer Learning
- Model training
- Model evaluation

B. Dataset Description

The dataset used in this study was obtained from Kaggle, containing labeled images grouped into two classes:

- Cancerous
- Non-Cancerous

Key challenges in the dataset include class imbalance, variations in lighting conditions, noise, and inconsistent image sizes.

C. Data Preprocessing

To enhance model performance, the following preprocessing steps were applied:

- Resizing all images to 224 × 224 px
- Normalization (pixel values scaled between 0 and 1)
- Gaussian noise reduction
- Brightness correction
- Augmentation (rotation, zooming, flipping, shifting)

D. Deep Learning Models Evaluated

- Custom CNN – Baseline model with convolution, ReLU activation, pooling, flattening, and fully connected layers.
- ResNet152V2 – A deep residual architecture that addresses vanishing gradient issues; fine-tuned using ImageNet weights.
- EfficientNetB0 – Lightweight but powerful network optimized through compound scaling.
- VGG19 – A deep convolutional architecture known for strong texture-based feature extraction.

E. Transfer Learning

ImageNet weights were used for all models except the baseline CNN. Fine tuning included:
Unfreezing final layers
Adding dropout
Using Adam optimizer (LR 0.0001)

F. Training Setup

Environment: VS Code + TensorFlow/Keras
Batch size: 32.
Epochs: 25
Loss function: Categorical Crossentropy
Metrics: Accuracy, Precision, Recall, F1-score

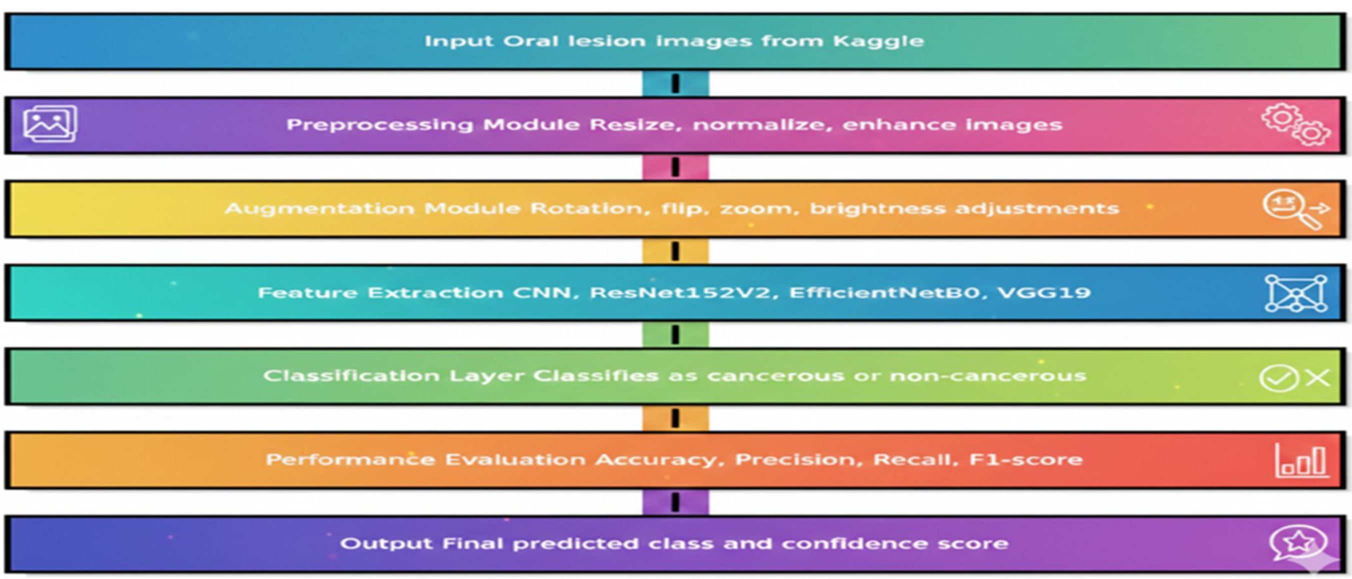

Fig. 1 Flow diagram

IV. RESULTS AND DISCUSSION

A. Quantitative Results

TABLE II
PERFORMANCE COMPARISON OF ALL MODELS

Model	Accuracy	Precision	Recall	F1-Score
CNN	84%	82%	80%	81%
ResNet152V2	89%	87%	88%	87%
EfficientNetB0	90%	89%	90%	89%
VGG19	95%	94%	95%	94%

B. Qualitative Results

1) CNN Results

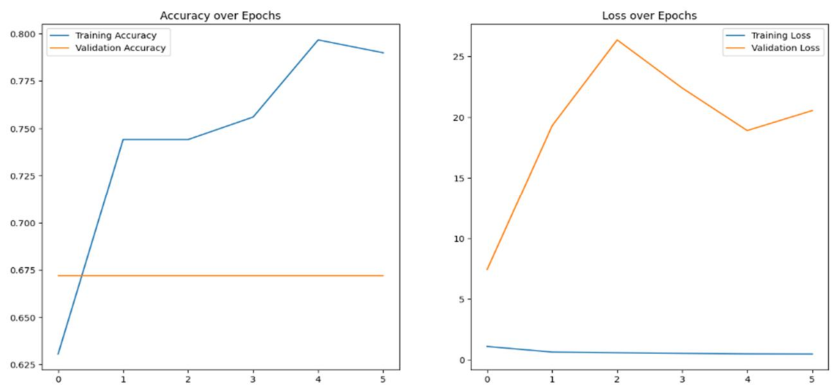

Fig. 2 Results obtained for CNN

2) ResNet152V2 Results

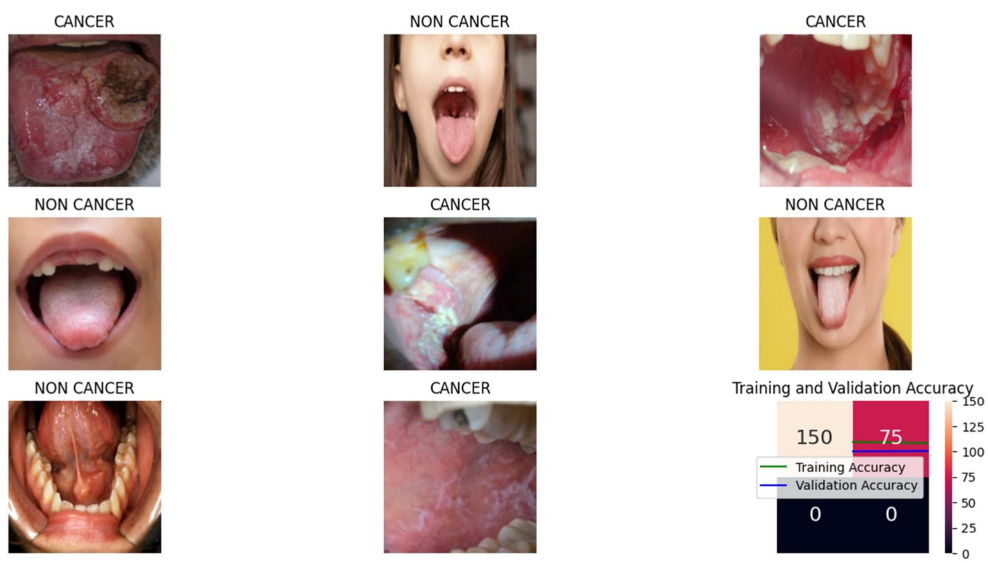

Fig. 3 ResNet152V2 Output

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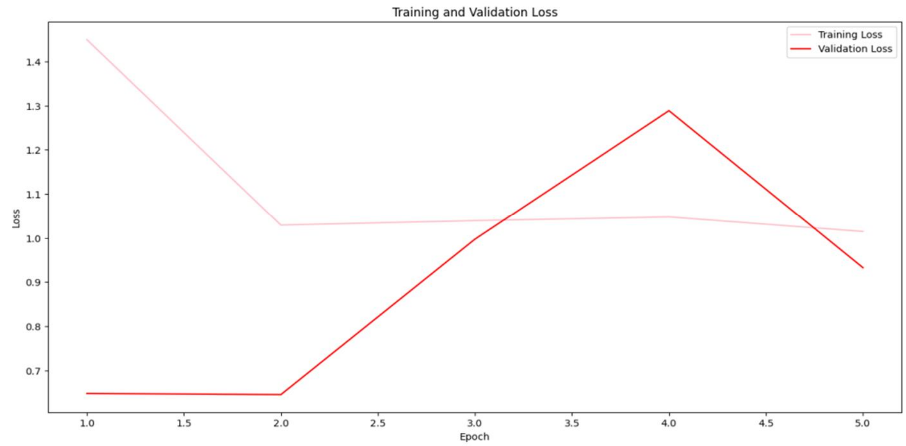

Fig. 4 Training and Validation Loss using ResNet152V2

3) EfficientNetB0 Results

Fig. 5 EfficientNetB0 output

4) VGG_19 Results

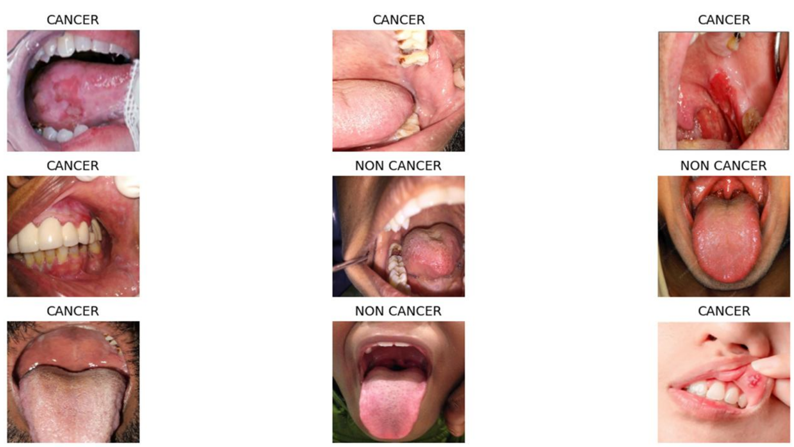

Fig. 6 VGG_19 Output

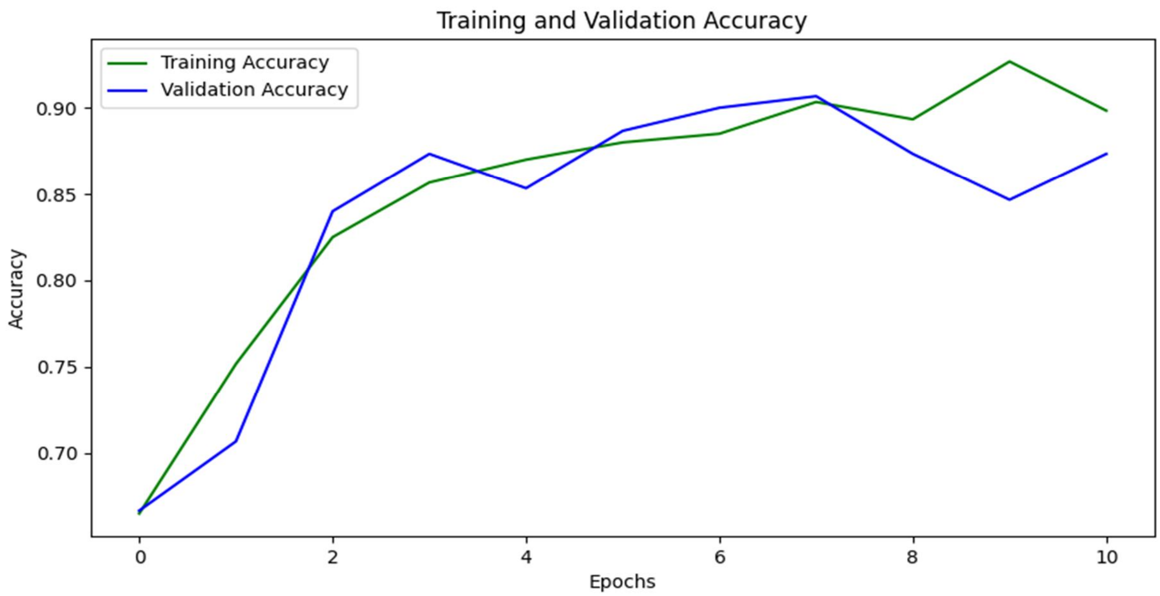

Fig. 7 Training and Validation Accuracy using VGG_19

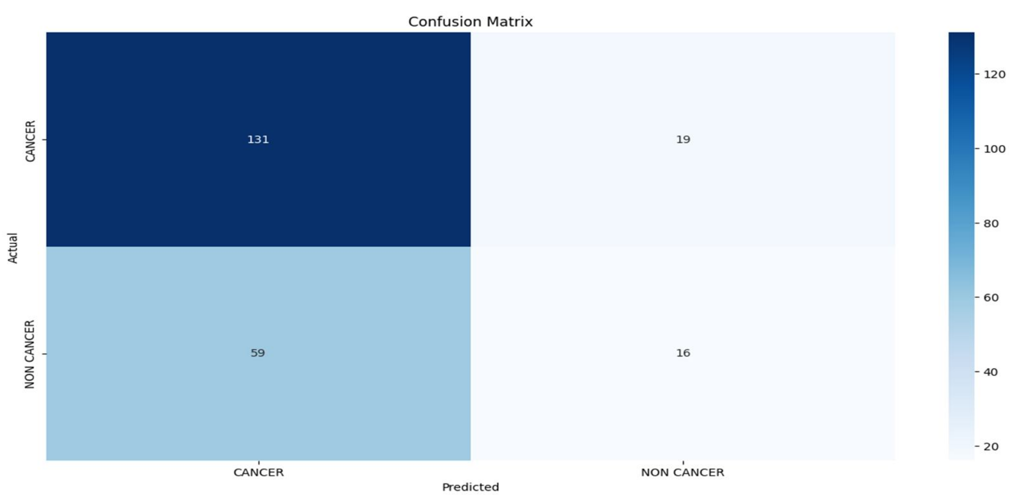

Fig. 8 Confusion Matrix

VGG19 achieved the lowest false negatives and false positives as shown in fig. 8

C. Analysis

VGG19 produced the lowest false-positive and false-negative rates, indicating highly reliable classification. The baseline CNN performed the weakest due to its limited depth and feature extraction capability.

V. CONCLUSION

The comparative study confirms that deep learning is a promising approach for oral cancer detection. Among the evaluated models, VGG19 achieved the best results with 95% accuracy, surpassing CNN, ResNet152V2, and EfficientNetB0. The system’s strong performance demonstrates its feasibility as a supportive diagnostic tool in clinical environments such as hospitals and dental screening centers.

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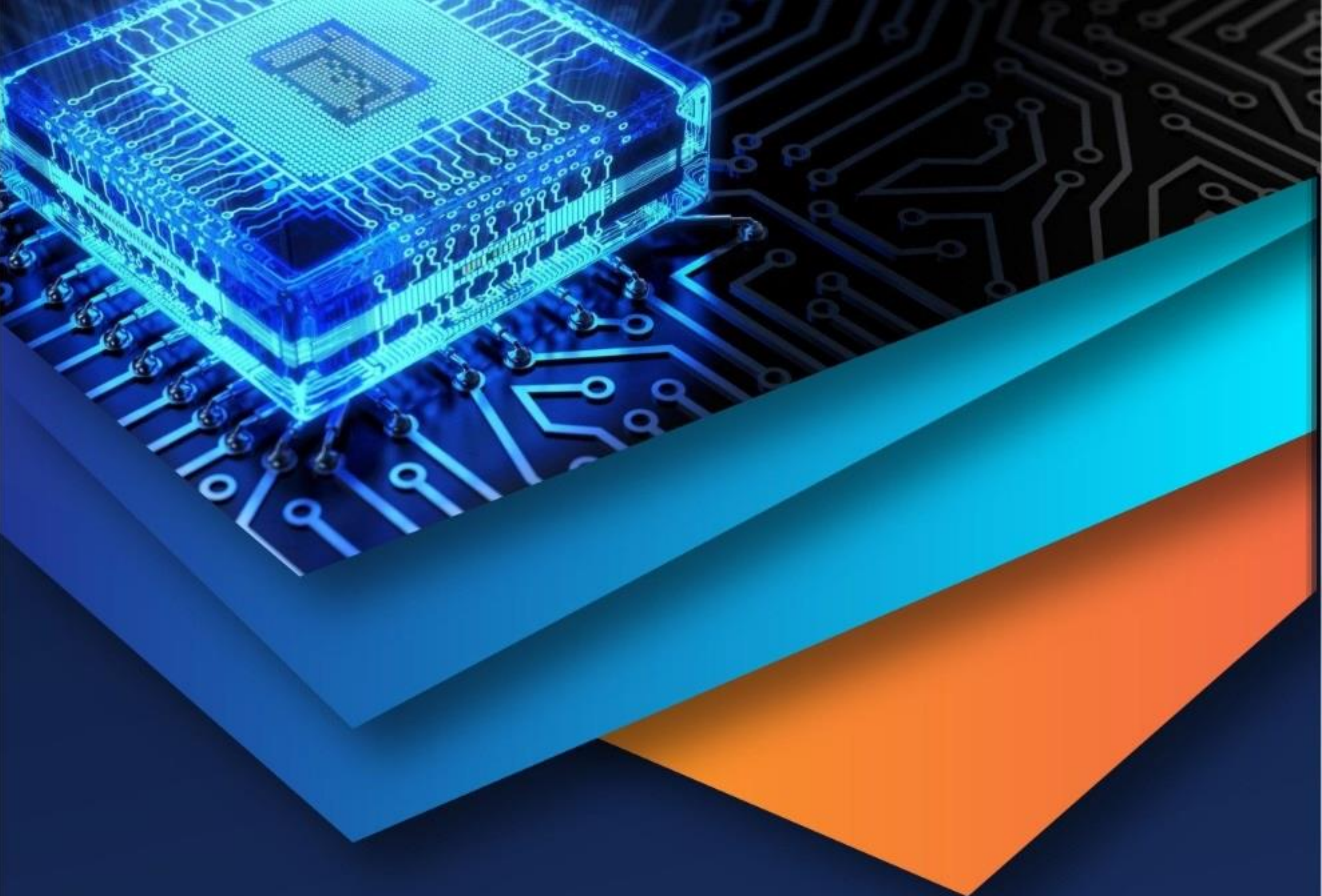

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