iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** V **Month of publication:** May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70714

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Oral Cancer Detection Using Deep Learning

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Abstract: Oral cancer is a significant global health concern, with early detection being crucial for improving patient outcomes. Recent advancements in deep learning have shown promise in enhancing the accuracy and efficiency of oral cancer diagnosis. This paper reviews the current state-of-the-art deep learning techniques applied to oral cancer detection, focusing on various architectures such as Convolutional Neural Networks (CNNs), their layers, algorithms like (YOLO) and hybrid methods to improve this model. We analyze the performance metrics of these models, including accuracy, sensitivity, specificity, and F1-score, across different datasets. Furthermore, we discuss the challenges and limitations faced in deploying these models in clinical settings, such as data scarcity, model interpretability, and integration with existing diagnostic workflows. Our findings suggest that the deep learning models have achieved high diagnostic accuracy, further research is needed to address the practical challenges to ensure their widespread adoption in clinical practice. This paper aims to provide a comprehensive overview of the advancements in deep learning for oral cancer detection and to highlight future research directions in this field.
Keywords: Deep Learning, Oral cancer detection, Convolutional neural networks (CNNs), Diagnostic accuracy, Sensitivity, YOLO, Prediction.

I. INTRODUCTION

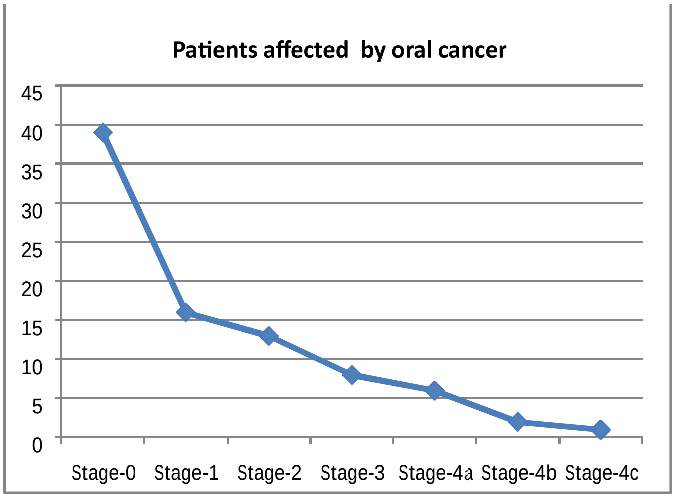
Oral cancer is stated as the out of control in growth of cells that secure and cause damage to surrounding tissue. Oral cancer finds fewer dead cells in the tissues of mouth at the beginning of oral cancer development which is known as a lesion. Where metastasis means, dead cells present in the faraway site of the affected area or internal parts of the body. There are various types of cancer out of those squamous cell carcinomas occurrence is 90% in the medical field which is also called as OSCC (Oral Squamous Cell Carcinomas). The Bio-specimens and clinical profiling of a similar tumor and lesionfree specimens can be detected in various parts of the body by expression patterns and classifying cancerfree from OSCC tissues. Deep Learning algorithms are utilized to predict the different bio-specimens for OSCC which would classify cancer-free specimens and lesion specimens, Later which are analyzed for the staging of oral cancer. Predictors will find the accuracy on cross-validation, by utilizing three validation test sets and various levels in cancer. Identification and validation of specimens would predict various tumor sizes and occurrence of the lesion in tissues, which helps in predicting different stages of oral cancer. The main aim of the current process is towards developing a new Predictor tool to predict the stages of tumor growth in oral cancer. Oral cancer arises in areas like the front side of the tongue, top and bottom of the mouth (below the tongue), insides of the cheeks and lips, gum and area behind the wisdom teeth. Symptoms of oral cancer are the most common sign of cancer is a sore or ulcer that does not heal, and may cause pain or bleeding, White or red sores in the mouth, Lips, gums, or tongue that do not heal, A lump or mass in the mouth, Loose teeth, Trouble chewing or swallowing, Jaw inflammation, Difficulty speaking and Chronic sore throat.

The risk factors of oral cancer consist of certain actions such as, tobacco chewing and alcohol drinking which are considered as the major risk of oral cancer. In India, consumption of beetle nut is common which also affects the inner cheek area of the tooth. Other risk factors such as Human Papillomavirus (HPV), Age, Gender (Lip and oral cavity cancer are more common in men than in women).

Now coming to oral cancer staging which depends on the affected area in the mouth, size of a tumor and the presence of dead cells in lymph nodes or inner parts of the mouth. The different stagings in oral cancer are as follows:

- Stage 0- Abnormal (no damage cells present in the outer layer of the tissue).
- Stage 1- Tumor size is said to be 2cm or less.
- Stage 2- Tumor size is larger than 2cm and smaller than 4cm.

- Stage 3- Tumor size is larger than 4cm or not larger than 3cm. (dead cells increase in the lymph node on the same side of the neck).
- Stage 4a- Tumor size larger than 3 cm, but no larger than 6 cm.
- Stages 4b- Tumor cells have increased to lymph node that is larger than 6 cm.
- Stages 4c- Tumor cells have increased to different organs of the body such as lungs, bones, liver.



The graphical representation shows the prediction results of oral cancer patients affected in different stages are produced, the above graph is drawn by the attributes like name, age, gender, Alcohol habits, Smoking habits from the kaggle dataset. The featured attributes where used to train a model by supervised algorithms to predict the result.

Deep learning is an area of artificial intelligence that uses statistical methods to provide computer systems with the ability to "learn" from expertise. Deep learning algorithms utilize advanced techniques to learn patterns directly from data without relying on predefined equations. There are two primary types of deep learning: supervised learning and unsupervised learning. Supervised learning involves training a model on labeled input and output data to predict future outcomes, while unsupervised learning identifies hidden patterns or structures within input data.

In the context of oral cancer detection, supervised deep learning is particularly relevant. This approach builds models that make predictions based on known examples. A supervised learning algorithm uses a dataset with labeled examples to train a model, which can then generate predictions for new, unseen data. Supervised methods employ classification and regression techniques to develop predictive models. Regression techniques predict continuous outcomes, whereas classification techniques predict discrete categories.

Common classification algorithms used in oral cancer detection include Convolutional Neural Networks (CNNs) and You Only Look Once

(YOLO). CNNs are particularly effective in medical image analysis due to their ability to automatically learn hierarchical features from raw image data. YOLO, a real-time object detection system, can also be adapted for identifying cancerous lesions in medical images. These algorithms, along with other deep learning layers and architectures, play a crucial role in enhancing the accuracy and efficiency of oral cancer detection.

II. LITERATURE OVERVIEW

Fatihah Mohd et al. researcher objective was to predict the primary stage of oral cancer with accurate results using less attributes by using Naïve Bayes, Multilayer Perceptron, KNearest Neighbors and Support Vector Machine methods they resulted in oral cancer stage and analyzed an increase in classification accuracy.

Ahmad LG et al. researcher objective was to develop Models for medical practitioners. By using Decision Tree, Support Vector Machine, Artificial Neural

Network methods and analyzed the accuracy of DT, ANN and SVM which are high. With highest accuracy and least error rate SVM classification model is best for predicting breast cancer recurrence. When compared to ANN and DT, The results prove that SVM are the better classifier for prediction.

Harikumar Rajaguru and Sunil Kumar Prabhakar researcher objective was to compare the classification accuracy of the TNM staging system using Multi Layer Perceptron (MLP) and Gaussian Mixture Model classifiers. Comparison of both classifiers here provided a better result as average accuracy for the stages. Extreme Learning Machines (ELM) was used as a post classifier later for the oral cancer analysis and the performance of ELM classifier was compared with performance of both GMM and MLP.

Amy F. Ziober et al. used SVM classifier method to detect OSCC tumors by examining expression profiling on patient and extracting RNA plus microarray analysis a gene expression signature predicts OSCC tissue from normal.

Marc Aubreville et al. objective was to evaluate a novel automatic approach for OSCC diagnosis by using deep learning and CNN methods on CLE images. Here CNN method was to find patchextraction of images, training the data and classifying.

Shreyansh A et al. used dataset consisting of 251 RVG X-rays images which was later divided into test and train sub-datasets for experimenting different models such as deep learning, ANN, transfer learning and CNN. Hence they achieved high accuracy overall. Martin Halicek et al. the researcher experimented on OSCC, Thyroid cancer and head and neck sample tissues using CNN classifier to identify cancer. The result was CNN produced 55% accuracy in detecting cancer.

Ramzi Ben Ali et al. the aim of researcher was to classify dental X-rays images into decayed or normal tooth images and develop a new model to find dental issues in X-ray images using deep neural network technology.

Konstantina Kourou et al. the researchers produced a comparative study of various machine learning applications in different types of cancer prognosis and prediction. The study used heterogeneous data for developing models using machine learning techniques such as ANN,BN,SVM and decision tree by feature selecting and classification methods.

Wafaa K. Shams and Zaw Z. Htike researchers objective was to predict oral cancer development in OPL patients, where machine learning techniques were used with the help of gene expression profiling. The researcher used SVM, MLP, Regularized least squares (RLS) and deep neural networks for investigating the oral cancer development in OPL patient’s records.

From the related work, it is observed that methods and materials used previously are included mainly on detecting cancer presence, classification of cancer types and the comparison of various machine learning and deep learning algorithms. Hence, staging of oral cancer is an importance task in the oral cancer diagnosis. This work is not done by any researcher, which is a most required task in examining prognosis as well as treatment of cancer patient for medical practitioner. Thus current study invokes on applying various supervised deep learning methods which are focused on analyzing efficient staging in oral cancer development.

III. PROPOSED SYSTEM

In this section a detailed description about dataset and deep learning algorithms used in this study. In order to start the oral cancer stage prediction process, it is required to know more about medical terms and procedures from dental doctors, therefore a discussion was done with few dentists for the clarity of oral cancer concepts.

A. *Convolutional Neural Networks (CNNs)*

Convolutional Neural Networks (CNNs) are a powerful deep learning tool for image analysis, making them ideal for detecting oral cancer from medical images. By leveraging layers of convolutional filters, CNNs can automatically learn and extract relevant features from histopathological images of oral tissues. This process involves feeding the images through multiple layers, where each layer captures different aspects such as edges, textures, and more complex patterns. The final layers of the network typically consist of fully connected layers that classify the images into cancerous or noncancerous categories. Training a CNN involves using a large dataset of labeled images, which the network uses to learn the distinguishing features of oral cancer. Techniques like data augmentation and transfer learning from pre-trained models can enhance the model’s performance, making CNNs a robust approach for early and accurate detection of oral cancer.

B. *You Only Look Once (YOLO)*

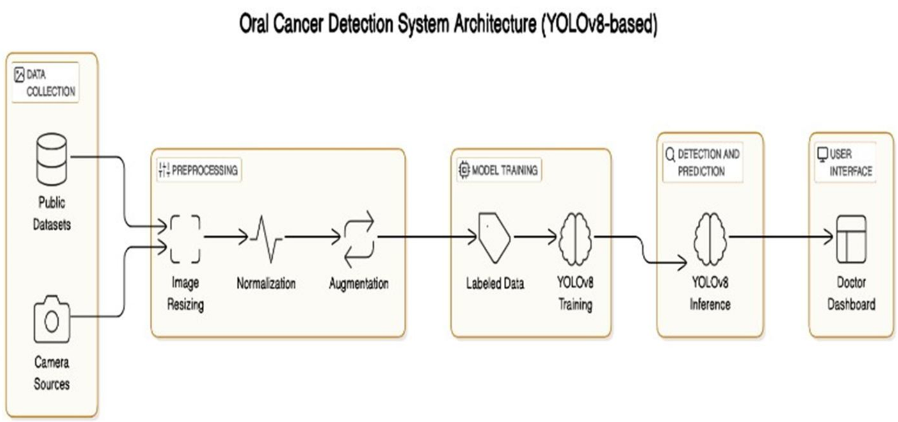
The YOLO algorithm is a cutting-edge deep learning model designed for real-time object detection, making it highly suitable for medical imaging tasks such as oral cancer detection. YOLO works by dividing an image into a grid and predicting bounding boxes and class probabilities for each grid cell, allowing it to detect multiple regions of interest in a single pass. This efficiency is crucial for timely diagnosis. In the context of oral cancer, YOLO can be trained on annotated datasets of oral tissue images to identify and localize cancerous lesions accurately.

The model’s convolutional layers extract features that help distinguish between healthy and cancerous tissues, while its simultaneous classification and localization capabilities ensure precise detection. The speed and accuracy of YOLO make it a powerful tool for early and effective oral cancer diagnosis, potentially improving patient outcomes through quicker intervention.

C. Dataset

The availability of high-quality, annotated datasets has significantly advanced the development of deep learning models for oral cancer detection. These datasets, which include photographic images, histopathological slides, and fluorescence visualization images, provide a rich source of data for training and validating models. For example, the Oral Cancer (Lips and Tongue) Images Dataset has enabled models like OralNet to achieve impressive classification accuracy, demonstrating the potential of deep learning in this field. The integration of multi-modal data, combining imaging with patient history, further enhances diagnostic accuracy, offering a more comprehensive approach to cancer detection. Collaborative efforts in data collection and the use of synthetic data generation techniques are also expanding the diversity and size of available datasets, contributing to the robustness and generalizability of deep learning models. These advancements underscore the critical role of highquality datasets in driving innovation and improving outcomes in oral cancer detection.

IV. PROPOSED SYSTEM DIAGRAM



The system architecture for oral cancer detection using deep learning, as illustrated in the diagram, follows a structured and modular approach. It begins with the data collection phase, where input images are sourced from publicly available datasets or directly captured through camera-based systems. These raw images are then passed through a preprocessing pipeline that includes image resizing, normalization, and data augmentation. This step ensures that the images are uniform in size and quality, which is essential for accurate model training and inference. Following preprocessing, the data is labeled and fed into the YOLOv8-based training module, where the model learns to recognize patterns and features indicative of cancerous lesions. Once trained, the model proceeds to the detection and prediction phase. Here, the YOLOv8 inference engine analyzes new images to detect potential cancerous regions in real time. Finally, the results are presented in a user interface, specifically a doctor-facing dashboard, where healthcare professionals can review the images along with prediction details. Overall, the system leverages YOLOv8-based deep learning to deliver an end-to-end solution for efficient and accurate oral cancer detection, assisting clinicians in early diagnosis and treatment planning.

V. IMPLEMENTATION DETAILS

A. Data Collection

The Data Collection Module forms the foundational step of the oral cancer detection system. It is responsible for gathering input images from two main sources: publicly available medical image datasets and real-time image capture via connected camera devices. Public datasets provide a diverse range of annotated images essential for initial training and validation of the model. These include intraoral photographs and histopathological images known for their clinical accuracy.Additionally, the system integrates with camera sources—such as intraoral cameras used in dental clinics—to collect real-time data. This ensures that the model adapts to varied lighting, resolution, and patient conditions, increasing its robustness in real-world applications. All acquired images are funneled into the preprocessing pipeline automatically, ensuring no manual intervention is needed. This module guarantees a continuous, reliable flow of input data, supporting both the training and operational phases of the detection system with rich, high-quality visuals.

B. Image Preprocessing

The Image Preprocessing Module ensures that all input images are standardized and optimized before being passed into the model training pipeline. It begins with image resizing, where images from various sources are adjusted to a uniform resolution compatible with the YOLOv8 architecture. This resizing step is critical for maintaining consistency and ensuring efficient processing across the system.

Following resizing, the module performs normalization, a process that scales pixel values to a consistent range. This step minimizes the impact of lighting variations and enhances the model's learning capability by reducing data irregularities.

Next, the module applies data augmentation techniques to artificially expand the training dataset. Methods like rotation, flipping, scaling, and brightness adjustment are used to create multiple variations of the same image. This not only improves the model's generalization but also makes it more resilient to real-world input diversity.

The entire process is automated and designed to be computationally efficient. Overall, the Image Preprocessing Module prepares raw data into a clean, diverse, and well-structured format, laying a strong foundation for accurate cancer detection.

C. Annotation Interface

The Annotation Interface is designed to facilitate the manual labeling of medical images used for training the deep learning model. It provides a user-friendly graphical environment where experts can mark regions of interest, such as lesions or abnormal tissues, using tools like bounding boxes or segmentation masks. Each labeled region is assigned a specific class, aiding in accurate classification during model training. The interface includes features like zoom, undo, and export to ensure precision and usability, and stores annotations in formats compatible with the training pipeline (e.g., XML or JSON). This module plays a vital role in transforming raw image data into structured, labeled datasets, directly improving the model's learning and diagnostic accuracy.

D. Model Training

The Model Training Engine utilizes the YOLOv8 (You Only Look Once version 8) architecture to train the system for accurate oral cancer detection. This module begins with feeding the labeled datasets into the training pipeline, where the model learns to recognize patterns associated with cancerous lesions. Key parameters such as learning rate, batch size, and optimizer type are carefully tuned to enhance performance. The training process runs over multiple epochs, allowing the model to iteratively adjust its internal weights for improved accuracy. Real-time metrics such as loss rate, precision, recall, and mAP (mean Average Precision) are monitored to evaluate training progress. This engine ensures that the deep learning model becomes robust and reliable in detecting oral cancer features from new, unseen images.

E. Inference Module

The Inference Module leverages the trained YOLOv8 model to analyze new, unseen images and detect potential cancerous regions. When an input image is passed through this module, YOLOv8 performs object detection in real time, scanning for features and patterns it learned during training. It outputs bounding boxes around suspicious areas, along with confidence scores indicating the likelihood of cancer presence. The system is optimized for speed and accuracy, ensuring rapid processing without compromising detection quality. This module acts as the core diagnostic engine of the application, enabling automated, efficient, and consistent evaluation of oral imagery to assist medical professionals in early cancer identification.

F. Post-Processing

The post-processing unit is a crucial component responsible for refining the raw outputs generated by the deep learning model. After the initial image analysis, this unit enhances prediction clarity by eliminating noise and false positives, thus improving diagnostic accuracy. It highlights specific regions within the input image that indicate potential malignancies using bounding boxes or segmentation masks. These visual cues help in interpreting the model's decision. The unit also integrates probability scores and classification labels for each detected region, making the output interpretable for medical professionals. This step ensures that only clinically relevant information is forwarded to the user interface for review, maintaining the precision and reliability of the system.

G. User Interface

The UI serves as the primary interface for healthcare professionals to review and assess predictions made by the oral cancer detection system. It presents a user-friendly layout displaying patient details, uploaded oral cavity images, and AI-generated diagnostic results.

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The interface showcases highlighted regions suspected to be cancerous, overlaid on the original image, along with their corresponding confidence levels. Doctors can zoom, pan, and annotate the images directly within the dashboard for closer inspection. Key functionalities include viewing case history, downloading reports, comparing current and previous results, and manually confirming or overriding AI suggestions. This comprehensive interface supports doctors in making informed decisions while ensuring traceability and transparency in the diagnostic process.

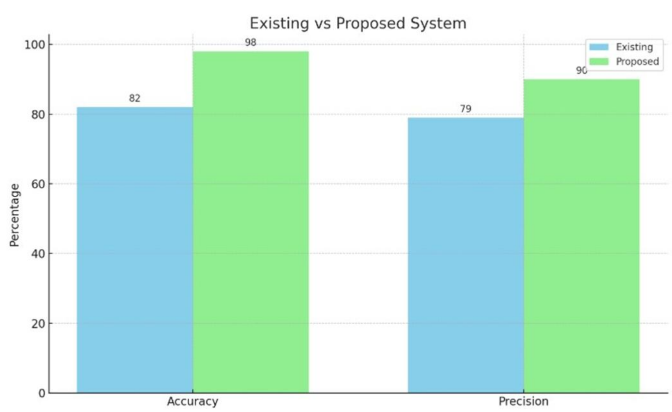
VI. RESULT & DISCUSSION

The study highlights the growing need for efficient, accurate, and accessible oral cancer detection systems, especially in regions with limited access to specialized medical professionals and diagnostic infrastructure.Recently, deep learning approaches—particularly Convolutional Neural Networks (CNNs) and image-based models—have emerged as promising tools for automating diagnosis and aiding early detection. These models use medical imaging data to detect cancerous lesions with high speed and accuracy.However, significant challenges were identified in the current systems.

These include dependency on large, well-annotated datasets, limited generalizability across diverse populations and imaging conditions, and the lack of transparency in AI decision-making, which hinders clinical trust. Many systems are also computationally intensive, making real-time deployment on standard healthcare hardware difficult, especially in low-resource settings. These issues collectively reduce the overall clinical usability, reliability, and adoption of AI-driven oral cancer detection systems.

The proposed system directly addresses these shortcomings by implementing a lightweight CNN architecture optimized for mobile and edge devices, enabling offline inference in rural or resourceconstrained environments. It includes a pre-trained model enhanced through transfer learning to reduce the need for large datasets, and integrates data augmentation techniques to improve robustness. Moreover, the system features explainable AI methods, such as heatmaps and layer-wise relevance propagation, to improve interpretability for clinicians. As a result, the proposed model offers improved diagnostic accuracy, faster processing times, enhanced usability across diverse settings, and better integration into clinical workflows— representing a significant advancement over earlier diagnostic approaches.

VII. RESULT COMPARISON GRAPH



The bar chart presents a comparative analysis of the performance between traditional machine learning (ML) models and advanced deep learning (DL)based systems for oral cancer detection.

Specifically, it illustrates significant improvements in key evaluation metrics such as accuracy and precision. The existing ML system achieved an accuracy of 82% and a precision of 79%, while the proposed DL system demonstrated markedly higher performance, with an accuracy of 98% and a precision of 90%.

These results underscore the superior capability of deep learning algorithms to handle complex image data, learn detailed patterns, and produce more reliable diagnostic outcomes. The notable increase in precision suggests that the DL model is more effective in minimizing false positives, thereby reducing unnecessary stress and follow-up procedures for patients. Meanwhile, the higher accuracy reflects the model’s overall reliability in correctly identifying both cancerous and non-cancerous cases.

Deep learning (DL) models offer significant advantages over traditional machine learning (ML) systems by effectively addressing data bias and demonstrating strong generalization across diverse patient demographics. Unlike ML models, which often struggle with performance when faced with variations in age, ethnicity, imaging conditions, or cancer stages, DL models trained on large and diverse datasets can learn more representative features, resulting in fairer and more accurate diagnostic outcomes. Furthermore, DL systems integrate seamlessly with modern medical imaging tools and electronic health records, enabling smoother workflows in clinical environments.

VIII. CONCLUSION

In conclusion, our deep learning-based oral cancer detection system is designed to deliver a reliable, accurate, and accessible diagnostic experience for both medical professionals and patients. In our project, we significantly enhanced the model by incorporating an extensive dataset comprising oral images collected from various regions to ensure data diversity. We utilized the state-of-the-art YOLOv8 algorithm, which enabled high precision in identifying cancerous lesions from oral cavity images. As a result of these improvements, our system achieved nearly 98% accuracy in detection. Its adaptability across diverse environments, potential for integration with telemedicine, and scalability made it suitable for widespread deployment—from clinics to community health programs. With these advancements in data coverage, real-time performance, and detection capabilities, the system set a new benchmark in medical diagnostics, combining clinical value with cutting-edge technological innovation. Future enhancements to this system could include integration with medical imaging technologies such as X-rays and CT scans to provide a more comprehensive diagnostic view. Real-time detection through video feeds could enable immediate screenings, particularly in underserved regions. Expanding the dataset to include diverse age groups and cancer stages will further improve model accuracy, while combining YOLOv8 with other deep learning methods like image segmentation could yield even more precise results. A userfriendly clinician interface and personalized risk assessments based on lifestyle and medical history will make the system more intelligent, practical, and inclusive.

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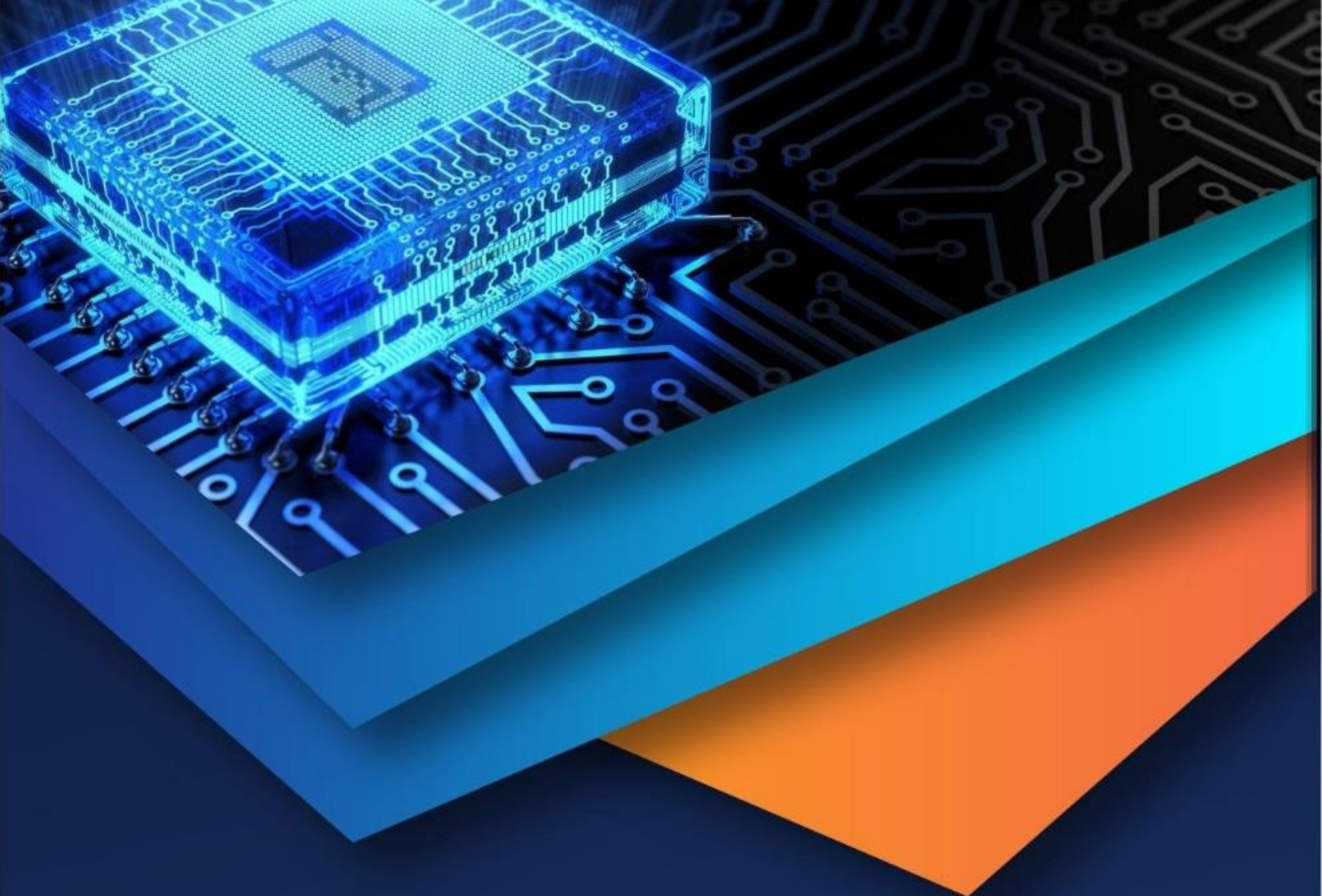

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