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.2026.82788

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

AI-Enhanced Breast Tumor Classification Using Medical Imaging and Dense Neural Networks

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Abstract: Breast cancer remains one of the leading causes of mortality among women worldwide, making early and accurate diagnosis essential for improving treatment outcomes. Conventional image interpretation is time-consuming and depends heavily on radiologist expertise, which may lead to diagnostic variability. This research paper presents an AI-enhanced breast tumor classification framework using medical imaging and a Dense Neural Network (DNN) architecture for classifying benign and malignant tumors. The proposed framework uses publicly available breast tumor imaging datasets and applies preprocessing techniques such as resizing, normalization, and feature enhancement to improve learning efficiency. The DNN model includes multiple dense layers, dropout regularization, and early stopping to reduce overfitting and improve generalization. The system is implemented using Python, TensorFlow, and Keras in Google Colab. Performance is evaluated using accuracy, precision, recall, F1-score, confusion matrix analysis, and training-validation convergence behavior. Experimental results show an overall classification accuracy of 95.61%, indicating strong potential for reliable AI-assisted breast tumor diagnosis. The study highlights the importance of deep learning-based diagnostic support systems in modern healthcare and demonstrates the usefulness of automated medical image analysis for early breast cancer screening.
Keywords: Breast Cancer, Medical Imaging, Deep Learning, Dense Neural Network, Artificial Intelligence, Tumor Classification, Healthcare Analytics, Medical Diagnosis.

I. INTRODUCTION

Breast cancer is one of the most commonly diagnosed cancers among women worldwide and remains a major public health concern because delayed diagnosis increases treatment complexity and reduces survival probability. Early detection and accurate classification of breast tumors into benign and malignant categories are therefore essential for improving treatment outcomes, reducing healthcare costs, and supporting timely clinical decisions [1].

Conventional breast cancer diagnosis relies on mammography, ultrasound, MRI, and histopathological examination. Radiologists manually analyze tumor shape, density, texture, and structural irregularities, but manual interpretation is time-consuming, subjective, and dependent on clinical expertise, which may lead to false-positive or false-negative outcomes [2]. Artificial Intelligence, Machine Learning, and Deep Learning have significantly improved medical image analysis by enabling automated pattern recognition and decision support. Traditional ML algorithms such as SVM, Random Forest, Decision Trees, and k-NN have been used for breast tumor classification, but they depend heavily on handcrafted features and domain expertise [3].

Deep learning techniques overcome many feature-engineering limitations by learning hierarchical and non-linear representations directly from image data. Dense Neural Networks can capture complex relationships among imaging features and support accurate benign-malignant classification when combined with suitable preprocessing and regularization strategies [4]. The availability of public medical imaging datasets, GPU-enabled platforms, TensorFlow, Keras, and Google Colab has accelerated AI-assisted healthcare research and made deep learning implementation more scalable and reproducible [5]. Despite these advancements, medical imaging datasets may contain noise, class imbalance, inconsistent quality, and limited labeled samples. Interpretability, patient privacy, clinical accountability, and model reliability also remain important concerns for real-world AI deployment in healthcare [7].

This research paper proposes an AI-enhanced breast tumor classification framework using medical imaging and a Dense Neural Network architecture. The model integrates image preprocessing, feature enhancement, dropout regularization, early stopping, and multi-metric evaluation including accuracy, precision, recall, F1-score, confusion matrix, and convergence analysis.

II. REVIEW OF LITERATURE

Breast cancer remains a major global health challenge, and early diagnosis is central to improving survival rates and reducing treatment complexity. Conventional diagnostic methods such as mammography, ultrasound, MRI, and biopsy analysis are widely used, but manual interpretation can be subjective and time-consuming. AI, ML, and DL techniques have therefore become important tools for automated breast tumor classification and clinical decision support [1]. Traditional machine learning approaches rely on handcrafted texture, shape, edge, and statistical features. Algorithms such as SVM, Random Forest, Decision Trees, and k-NN have improved diagnostic consistency, but their performance is limited by manual feature engineering and reduced generalization on complex medical images [2], [3].

Deep learning introduced major improvements by learning hierarchical image representations directly from raw data. Surveys on medical image analysis confirm that deep learning frameworks generally outperform conventional ML methods in disease detection, segmentation, and classification tasks [4], [5]. CNN-based systems have been widely adopted for breast cancer classification because they automatically learn texture, shape, edge irregularity, and density features from mammogram and ultrasound images. Prior studies report improved diagnostic accuracy and reduced false-positive rates using deep convolutional models [6], [7].

Transfer learning using architectures such as VGGNet, ResNet, AlexNet, and DenseNet has also been explored to improve performance on limited medical datasets and reduce training cost [8], [9]. Medical image segmentation is also important in AI-based breast tumor analysis because accurate localization of tumor regions improves feature extraction, classification accuracy, and diagnostic reliability. U-Net and related segmentation frameworks have shown strong capability in biomedical image localization and mammographic mass detection [10], [11].

AI-enabled Computer-Aided Diagnosis systems assist radiologists by improving diagnostic consistency, reducing workload, and supporting early detection. International studies have shown that AI-assisted screening systems can achieve performance comparable to expert radiologists while reducing false positives and false negatives [12], [13]. Dense Neural Networks and hybrid deep learning architectures have shown promising results for breast tumor classification because they learn non-linear feature interactions across multiple hidden layers. Regularization techniques such as dropout, batch normalization, and early stopping improve generalization and reduce overfitting [14].

Dropout regularization and early stopping are widely used in medical imaging models to reduce overfitting and improve stability on limited datasets. These techniques help the model maintain generalized diagnostic performance instead of memorizing specific training samples [15]. Explainable AI has become important in healthcare because clinicians require transparent diagnostic support. Saliency mapping, attention mechanisms, and visualization methods can improve trust and interpretability of AI-based breast cancer diagnosis [16]. Key challenges include limited sample size, class imbalance, image noise, imaging-device variability, overfitting, computational complexity, lack of interpretability, and ethical concerns related to patient privacy and accountability [18].

Overall, the literature shows that AI-enhanced deep learning frameworks, supported by transfer learning, explainable AI, and robust validation, provide effective solutions for automated breast tumor classification using medical imaging.

III. RESEARCH METHODOLOGY

The methodology evaluates an AI-enhanced Dense Neural Network framework for breast tumor classification using medical imaging data. The study follows a quantitative experimental approach in which diagnosis is formulated as a supervised binary classification task involving benign and malignant tumor categories.

A. Dataset Used and Algorithm

The dataset used in this research consists of labeled breast tumor medical images collected from publicly available breast cancer imaging repositories commonly utilized in AI-assisted healthcare research. The dataset contains two major tumor categories: benign and malignant. Each medical image represents breast tissue characteristics that are important for tumor identification and classification. The dataset includes sufficient image samples to support supervised deep learning training and unbiased performance evaluation. Before training, images are resized, normalized, and enhanced to improve quality and learning stability. These preprocessing steps help the model learn tumor texture, density variation, tissue patterns, and structural abnormalities more effectively. The proposed algorithm is based on a Dense Neural Network architecture specifically designed for medical image classification tasks. The network consists of an input layer followed by multiple hidden dense layers capable of learning hierarchical and non-linear feature representations from medical imaging data. Rectified Linear Unit (ReLU) activation functions are utilized within hidden layers to introduce non-linearity and improve convergence performance during training. Dropout regularization and early stopping are used to reduce overfitting and improve model generalization under unseen data conditions.

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The final output layer uses a sigmoid activation function to perform binary classification between benign and malignant breast tumors. The model is implemented using Python programming language with TensorFlow and Keras deep learning libraries in the Google Colab environment. GPU acceleration is utilized to improve computational efficiency and reduce model training time.

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	3,968
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 1)	65

Figure 1: Dense Neural Network model architecture summary used for breast tumor classification.

B. *Performance Evaluation Metrics*

The model is evaluated using accuracy, precision, recall, F1-score, confusion matrix analysis, and training-validation accuracy-loss curves. These metrics provide a reliable assessment of diagnostic performance beyond overall accuracy. Precision measures the reliability of malignant predictions, recall measures the ability to identify actual malignant cases, and F1-score balances both. Confusion matrix analysis is used to inspect false-positive and false-negative outcomes. Confusion matrix analysis is additionally utilized to examine detailed classification behavior and identify misclassification patterns between benign and malignant tumor classes. This analysis provides important insights regarding false-positive and false-negative predictions, which are highly critical in healthcare diagnostic systems.

IV. RESULTS AND DISCUSSION

A. *Overall Performance Analysis*

The proposed AI-enhanced Dense Neural Network model achieved an overall classification accuracy of 95.61%, confirming its ability to distinguish benign and malignant breast tumors from medical imaging data. Balanced performance across both tumor categories is important because missed malignant cases may delay treatment, while false positives may cause unnecessary clinical procedures.

Classification Report:

	precision	recall	f1-score	support
0	0.9111	0.9762	0.9425	42
1	0.9855	0.9444	0.9645	72
accuracy			0.9561	114
macro avg	0.9483	0.9603	0.9535	114
weighted avg	0.9581	0.9561	0.9564	114

Figure 2: Classification report showing precision, recall, F1-score, and support for the proposed model.

B. *Confusion Matrix Analysis*

The confusion matrix shows strong diagonal dominance, indicating that most benign and malignant samples are correctly classified. Only limited misclassification is observed, confirming effective feature learning and class separability. The balanced distribution of errors suggests that the model does not show strong bias toward either benign or malignant prediction, which is essential for reliable medical diagnosis.

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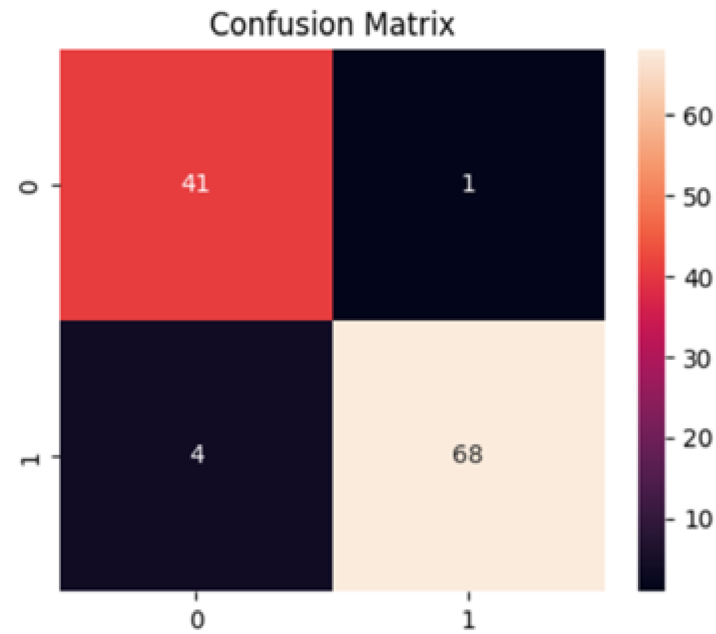

Figure 3: Confusion matrix showing class-wise prediction outcomes for benign and malignant tumor classification.

C. Training and Validation Analysis

Training and validation curves show stable convergence, with validation performance closely following training performance. This confirms effective learning and good generalization on unseen medical images. The loss curves decrease consistently with only minor fluctuations, showing stable optimization. Dropout and early stopping help reduce overfitting and improve model robustness.

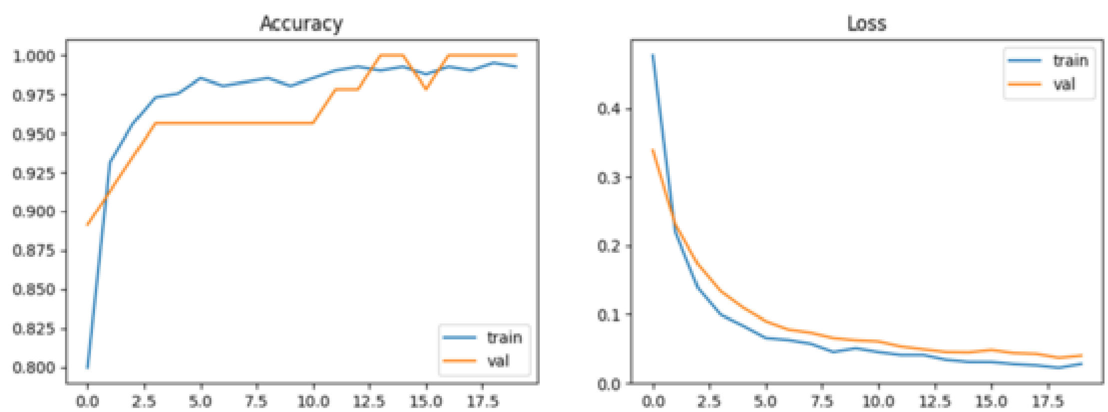

Figure 4: Training and validation accuracy-loss convergence curves of the proposed Dense Neural Network model.

D. Performance Table Description

The performance table summarizes accuracy, precision, recall, and F1-score values, confirming strong and balanced diagnostic performance across tumor classes.

Table 1: Performance Evaluation Metrics of Proposed Breast Tumor Classification Model

Metric	Value
Accuracy	95.61%
Precision	95.81%
Recall	95.61%
F1-Score	95.64%

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E. Discussion

The experimental findings show that Dense Neural Network architectures provide an effective solution for automated breast tumor classification using medical images. The achieved accuracy of 95.61% with balanced precision, recall, and F1-score confirms reliable diagnostic performance.

The model successfully learns non-linear tumor features such as texture irregularity, tissue density variation, structural abnormality, and edge characteristics without extensive handcrafted feature engineering. From a healthcare perspective, AI-assisted tumor classification can support radiologists, reduce workload, improve diagnostic consistency, minimize interpretation errors, and promote early-stage cancer detection.

V. CONCLUSION

This research presented an AI-enhanced breast tumor classification framework using medical imaging and a Dense Neural Network architecture for classifying benign and malignant tumors. The study aimed to reduce limitations of manual diagnosis and traditional machine learning by developing an automated, reliable, and efficient diagnostic support system. The framework integrated image preprocessing, feature enhancement, Dense Neural Network model development, dropout regularization, early stopping, and comprehensive evaluation using publicly available breast cancer imaging datasets.

Experimental evaluation showed that the proposed model achieved 95.61% accuracy with balanced precision, recall, and F1-score values. Confusion matrix analysis confirmed strong class separability with limited misclassification, while convergence curves demonstrated stable learning and minimal overfitting. The study highlights the importance of AI and deep learning in healthcare, where automated diagnostic systems can support radiologists, reduce workload, improve consistency, and enable early disease detection.

From a technical perspective, the proposed Dense Neural Network demonstrates strong capability for learning non-linear feature representations directly from medical imaging data without extensive handcrafted feature engineering. The findings of this study additionally highlight the growing importance of Artificial Intelligence and Deep Learning technologies in modern healthcare systems. AI-assisted diagnostic frameworks can support radiologists by reducing manual workload, improving diagnostic consistency, minimizing interpretation errors, and enabling early-stage cancer detection. Early and accurate breast tumor diagnosis plays a critical role in improving treatment effectiveness, increasing patient survival rates, and reducing healthcare costs associated with delayed diagnosis and advanced-stage cancer treatment. The study has limitations, including reliance on structured datasets, binary classification, and the need for larger diverse clinical data. Future research may explore CNN, ResNet, Vision Transformer, hybrid CNN-DNN, explainable AI, federated learning, and multi-modal imaging approaches to improve accuracy, transparency, privacy preservation, and clinical deployment.

Future research can strengthen this work by using larger multi-institutional datasets, advanced architectures such as CNN, ResNet, Vision Transformer, and hybrid CNN-DNN models, and explainable AI methods such as Grad-CAM and saliency mapping. Multi-modal approaches integrating mammography, ultrasound, MRI, histopathology, and genomic information may further improve diagnostic reliability and personalized treatment planning. Federated learning, cloud-based AI, and privacy-preserving deployment can also support collaborative medical analytics across healthcare institutions while protecting patient data.

Overall, the research establishes that AI-enhanced Dense Neural Network frameworks provide an effective, scalable, and intelligent solution for automated breast tumor classification and next-generation AI-assisted medical diagnosis.

VI. FUTURE SCOPE

Future research in AI-enhanced breast tumor classification can focus on the integration of more advanced deep learning architectures such as Convolutional Neural Networks (CNNs), Residual Networks (ResNet), Vision Transformers, and hybrid CNN-DNN frameworks to improve feature extraction capability and classification performance. Although the proposed Dense Neural Network achieved strong diagnostic accuracy, advanced architectures specifically designed for image analysis may further enhance tumor localization, texture learning, and fine-grained abnormality detection in complex medical imaging datasets. The incorporation of Explainable Artificial Intelligence (XAI) techniques represents another important future research direction. Deep learning models are often considered black-box systems because clinicians cannot easily interpret how classification decisions are generated. Future frameworks may therefore integrate saliency mapping, Grad-CAM visualization, attention mechanisms, and interpretable learning models to improve transparency, trustworthiness, and clinical acceptance of AI-assisted diagnostic systems.

Future studies may also explore multi-class breast cancer classification frameworks involving additional tumor categories, disease stages, and pathological conditions rather than only binary benign-malignant classification. Integration of histopathological imaging, ultrasound scans, mammography, MRI data, and genomic information within multi-modal AI frameworks may further improve diagnostic reliability and personalized treatment planning capability. Another promising research direction involves real-time deployment of AI-based breast cancer diagnostic systems within clinical environments and edge healthcare devices. Cloud computing, edge AI, and federated learning technologies may enable scalable and privacy-preserving medical analytics across hospitals and healthcare institutions without directly sharing sensitive patient data. Such frameworks can support collaborative learning while maintaining medical data confidentiality.

Future research may additionally focus on improving dataset diversity and generalization capability by incorporating larger multi-institutional clinical datasets collected under varying imaging conditions and patient demographics. Data augmentation, transfer learning, and synthetic image generation techniques using Generative Adversarial Networks (GANs) may help address limitations associated with small or imbalanced medical imaging datasets. Integration of AI-assisted breast tumor classification systems with clinical decision support systems and hospital management platforms may further enhance healthcare efficiency and reduce radiologist workload. Intelligent diagnostic systems capable of automated report generation, risk assessment, and treatment recommendation may significantly improve early-stage cancer detection and patient management processes. Cybersecurity and ethical considerations also represent important future research areas in AI-assisted healthcare systems. Ensuring patient privacy, secure data sharing, algorithm fairness, and unbiased diagnostic decision-making will remain critical for safe and responsible deployment of intelligent medical diagnostic technologies.

Overall, continuous advancements in Artificial Intelligence, deep learning, explainable AI, cloud computing, and intelligent healthcare analytics are expected to significantly improve automated breast cancer diagnosis systems in the future. AI-enhanced medical imaging frameworks have strong potential to support accurate, scalable, and accessible healthcare diagnostics while improving clinical efficiency, patient survival rates, and global healthcare outcomes.

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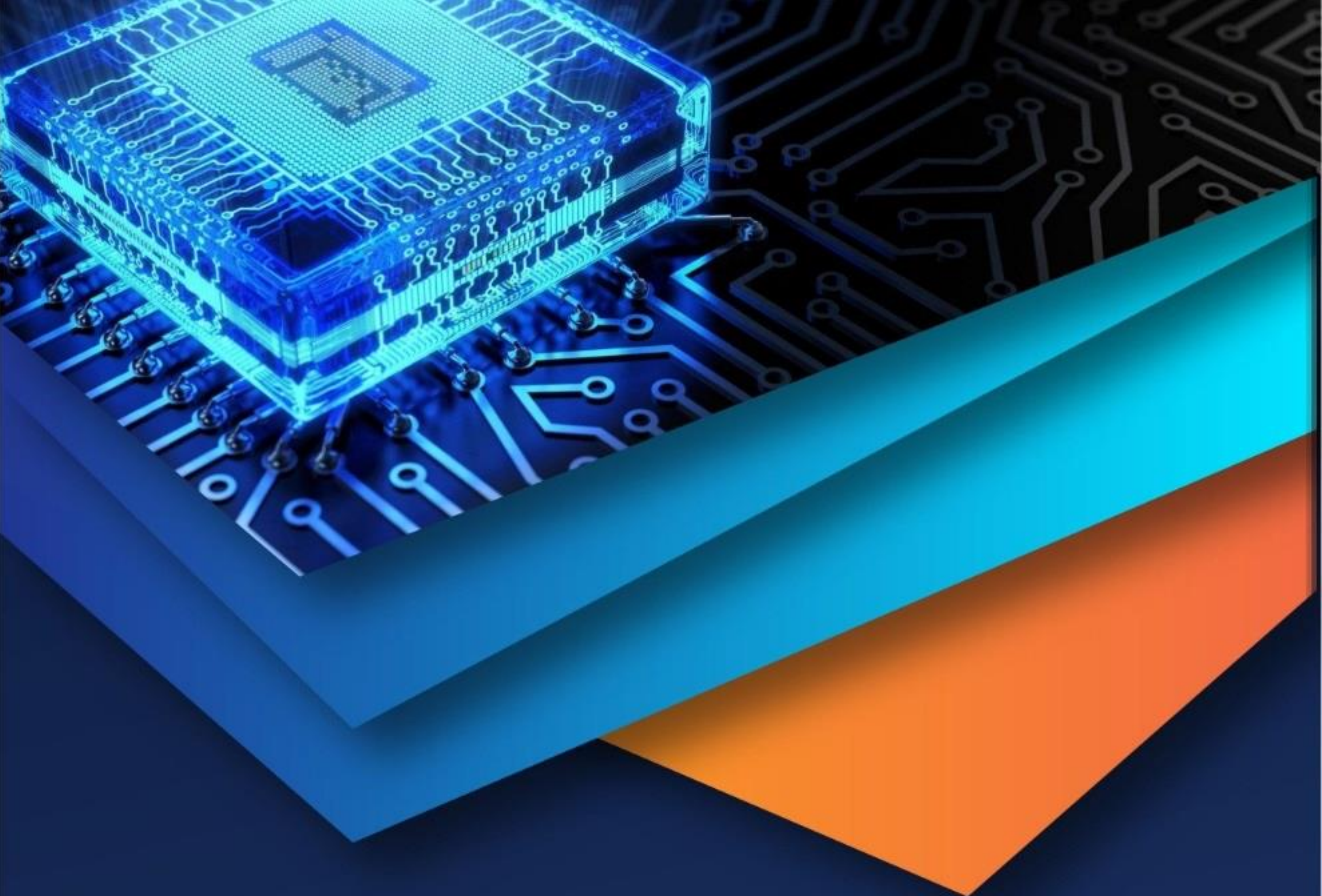

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