iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.81482

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 IV Apr 2026- Available at www.ijraset.com

AI- Predictive Diabetic Retinopathy Identification via Deep Learning and Ensemble Techniques

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Abstract: Diabetic Retinopathy (DR) is one of the common causes of visual impairment and blindness among diabetic people across the world. Accurate prediction and detection of this medical condition play a vital role to prevent its development and ensure timely treatment. Traditional machine learning techniques depend on manual analysis of retinal fundus images by ophthalmologists, which takes a lot of time, requires privacy, and cannot be scaled easily to serve many people at once. This paper proposes an automated intelligent framework for predicting and detecting Diabetic Retinopathy using deep learning and ensemble techniques. The proposed framework is built on a real-life design approach using the Python, OpenCV, TensorFlow/PyTorch, and XGBoost programming languages. Pre-processed retinal fundus images are input into the EfficientNet-B3 and DenseNet-121 models to extract deep features from the images. Convolutional Block Attention Mechanism (CBAM) is used to highlight important retinal features including microaneurysms, hemorrhages, and exudates. These extracted features are concatenated and used to train the XGBoost classifier for predicting diabetic retinopathy accurately. The proposed model can be used for both binary and multiclass classification. (inflexibility situations).

Experimental results prove that the model is capable of exhibiting a high level of delicacy, i.e., around 98% in double bracket and 94% in multi-class bracket. The suggested framework is a powerful approach towards automatic DR detection, and can also be used by healthcare practitioners for opinion formation.

Keywords: Diabetic Retinopathy, Deep Learning, EfficientNet, DenseNet, CBAM, XGBoost, Medical Image Processing, Image Bracketing.

I. INTRODUCTION

Diabetes has been rising rapidly because of various factors such as lifestyle modifications, population rise, and urbanization. Hence, diabetic retinopathy (DR) has emerged as one of the top causes of blindness and visual impairment globally. This is due to damages in the blood vessels of the retina resulting from prolonged instances of high blood sugar. Early detection and treatment play an important role in preventing blindness. However, diagnosis of DR using domestic judgments from retinal fundus image evaluation is time-consuming and requires qualified ophthalmologists, making it non-scalable in pastoral and rural regions.

Conventional personal methods depend on visual examinations of the retinal images to detect the anomalies, including microaneurysms, hemorrhages, and exudates. These techniques are efficient but subjective and vulnerable to human errors. There is an urgent need for an automated system for detecting DR.

The architecture discussed here is the creation of a pragmatic frame which accomplishes:

1) Retinal image pre-processing in an automated way.
2) Point birth using EfficientNet-B3 and DenseNet-121.
3) Point improvement through attention mechanism of CBAM.
4) Point emulsion for better representation.
5) Bracket double of DR vs No DR.
6) Bracket multi-class according to severity levels.
7) Vaticination accurate using XGBoost classifier.

This approach differs from other theories because the system discussed here relies on enforce literacy that incorporates Deep Learning and attention mechanism. The outcome of the study seeks to produce a reliable, scalable, and cost-effective technique that could be helpful to healthcare providers within clinical environments.

II. RESEARCH MOTIVATION

Three main provocations motivated this research.

The first motivation is that with more cases of diabetic people globally, there have been many cases of Diabetic Retinopathy. Therefore, it demands an early and precise opinion. Secondly, home-based stitching of retina images demands ophthalmology experts. It also makes the procedure costly and careful to measure in developing areas. Lastly, because of automation, these systems are always required to have sufficient care and cannot detect essential retina features.

Therefore, a smart automated system that can detect and classify Diabetic Retinopathy by means of deep learning and attention methods will bring much benefit in enhancing health care accessibility and avoiding loss of vision.

III. MAIN CONTRIBUTIONS

The keys Beneficiaries of this study are:

1) The creation of an efficient and real-time automated framework for detecting and diagnosing Diabetic Retinopathy.
2) The use of EfficientNet-B3 and DenseNet-121 models for precise point birth from retinal images.
3) The incorporation of CBAM module for highlighting critical retinal zones.
4) The utilization of XGBoost classifier for improving sensitivity and reducing overfitting.
5) The ability to perform double bracket (DR vs No DR) and multi-bracket (inflexibility cases) classification tasks. 6)A design that is both scalable and affordable, making it viable for practical applications.

IV. RELATED WORK

Automated diagnosis of diabetic retinopathy has emerged as a key investigation area because of the growing demand for timely opinion and prevention of blindness. Prior methodologies utilized traditional image processing techniques such as thresholding, edge detection, morphology, and hand-crafted feature extraction. These methods were concerned with the identification of certain retinal conditions, including microaneurysms and exudates. Despite being simple in terms of computational requirements, these methods lacked robustness to variations in image quality, illumination, and noise, thus exhibiting low accuracy and inadequate performance.

On the other hand, machine learning-based models were developed, wherein features such as texture, colour, and intensity were extracted manually and utilized by classifier algorithms like SVM, KNN, and random forest. Though better than traditional image processing techniques, these models were highly dependent on feature extraction and needed to learn from complex patterns present in retinal images.

The emergence of deep learning greatly improved the processing of medical images. Using CNNs, point birth could now occur automatically without having to create the point. Algorithms like AlexNet, ResNet, and DenseNet proved themselves very effective for tasks associated with detecting DR. Out of all these, DenseNet offered an improvement in terms of point usage and grad flow, resulting in more accurate bracket detection.

In spite of these developments, most of the current techniques still use only one model architecture without harnessing the complementary strengths of several models. In addition, problems like imbalance between classes, overfitting, and misclassification of similar levels of diabetic retinopathy continue to exist.

In an attempt to overcome these difficulties, this system utilizes multiple deep neural network models along with attention and an ensemble classifier. The purpose is to improve the performance of feature extraction, classification, and thereby automate diabetic retinopathy classification and detection.

V. DATASET DESIGN AND Image SOURCES

The system design was trained and tested using retinal fundus image databases that have been collected through publicly available medical data to provide reallife clinical scenarios. As the quality and resolution of retinal images can differ greatly due to the extent of the diseases, the database aims at variation to increase the generalization of the model. The sources of the images are as follows:

1) Publicly available medical databases.
2) Diabetic Retinopathy Kaggle dataset (EyePACS).
3) Retinal image databases from clinics.
4) Image sample for testing purposes.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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The classification classes within the dataset include:

- No Diabetic Retinopathy (No DR)
- Mild DR
- Moderate DR
- Severe DR
- Proliferative DR

VI. INPUT IMAGE CHARACTERISTICS

The features of the retinal images employed in this experiment include the following:

1) Resolution: From low resolution to high resolution (e.g., 224x224 pixels to 1024x1024 pixels)
2) Image type: JPEG/PNG fundus images
3) Environment: Under clinical imaging conditions with variable illumination.
4) Capture device: Fundus cameras with fixed viewpoints.

These features are essential since the accuracy of the model depends largely on the clarity, resolution, and consistency of retinal features contained in the images.

VII. DATA PREPROCESSING

Pre-processing processes are used to enhance model performance, accuracy, and stability when dealing with different images

1) Image Loading: Images of the retina are loaded into the system using image processing software. Datasets will be ready to use for training and testing.
2) Image Resizing: Images are resized into the same dimension (e.g., 224x224) to create consistent input size for deep learning models.
3) Normalization: Normalization involves converting pixel values in images to a set range (e.g., 0-1).
4) Data Augmentation: Techniques like rotation, flipping, zooming, and changing brightness levels of images are used to augment data for training.
5) Noise Removal: Illumination variation and noise are dealt with using preprocessing approaches in order to enhance the quality of the images and increase detection accuracy.
6) Region of Interest: The retina becomes the main focal point while other unnecessary areas become less significant. Further developments could include the automatic identification of certain parts.

VIII. NEED FOR NORMALIZATION AND SCALING

As opposed to the conventional image processing approach, normalization becomes a necessity while training deep learning algorithms, since the input should be normalized before training can take place.

The pre-processing involves:

1) Normalization of the pixel intensity values between 0 and 1.
2) Standardization of the input features of all the images.
3) Convergence while training.

Normalization results in better model stability and faster learning rates.

IX. REAL-WORLD CHALLENGES

Challenges involved in Medical Image Analysis for Diabetic Retinopathy include:

1) Illness in medical images' resolutions and quality
2) Image noise and different lighting
3) Data imbalances in datasets
4) Similar visual attributes at different DR stages
5) Lack of labelled training data
6) Differences in patients and imaging instruments

The suggested system tackles these challenges through the use of robust image pre-processing, augmentation, attention models, and hybrid learning.

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X. WHY THE PROPOSED MODEL IS SUITABLE

The model suggested utilizes the combination of EfficientNet-B3, DenseNet-121, CBAM, and XGBoost algorithms. Here are the reasons why:

1) Optimized performance and fewer parameters for EfficientNet
2) Improved feature sharing and gradient propagation in DenseNet
3) Enhanced region-of-interest localization by CBAM • Classification accuracy and reduction of overfitting with XGBoost
4) Designed for complicated medical imagery patterns
5) Provides great results with balanced efficiency This combination gives practicality and precision to the system, making it suitable for application in the field of healthcare.

XI. SUMMARY OF PART I

This section discussed the existing research, dataset characteristics, pre-processing techniques, normalization requirements, and real-world challenges associated with Diabetic Retinopathy detection. These components form the foundation for building a reliable and efficient automated system for retinal image analysis and disease classification.

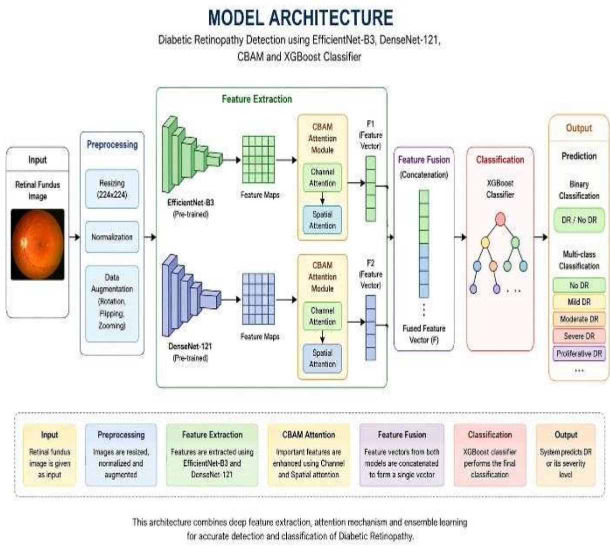

Fig. 1. System Architecture of The Framework

In the proposed solution, the system adopts a modular approach to functionality. Each block is assigned a specific role while working alongside other blocks. This makes the implementation easy and scalable for practical application. The entire process flow comprises the following modules:

1) Image Input Block
2) Image Processing Block
3) Feature Extraction Block
4) Attention Block
5) Future Fusion Block
6) Classification Block
7) Output Prediction Block
8) Result Visualization Block

Image Input → Pre-processing → Feature Extraction → Attention → Feature Fusion → Classification → Output

Fig. 2. High-level architecture of the implemented system

The implemented system includes a core processing module that is used to execute the entire process flow.
This module handles the following activities: Python_app.py

This file serves as the core processing module used for:

- Load pre-trained DL models (EfficientNet-B3, DenseNet-121)
- Reading and pre-processing retinal images
- Feature extraction from images
- CBAM attention
- Feature Fusion
- Classification via XGBoost and Generating prediction outputs.

In addition, there are supplementary files that are essential for training, evaluating, and visualizing the results of the experiment.

XII. FEATURE EXTRACTION ENGINE

The system employs pre-trained deep neural networks to extract features from the images:

1) EfficientNet-B3 2. DenseNet-121

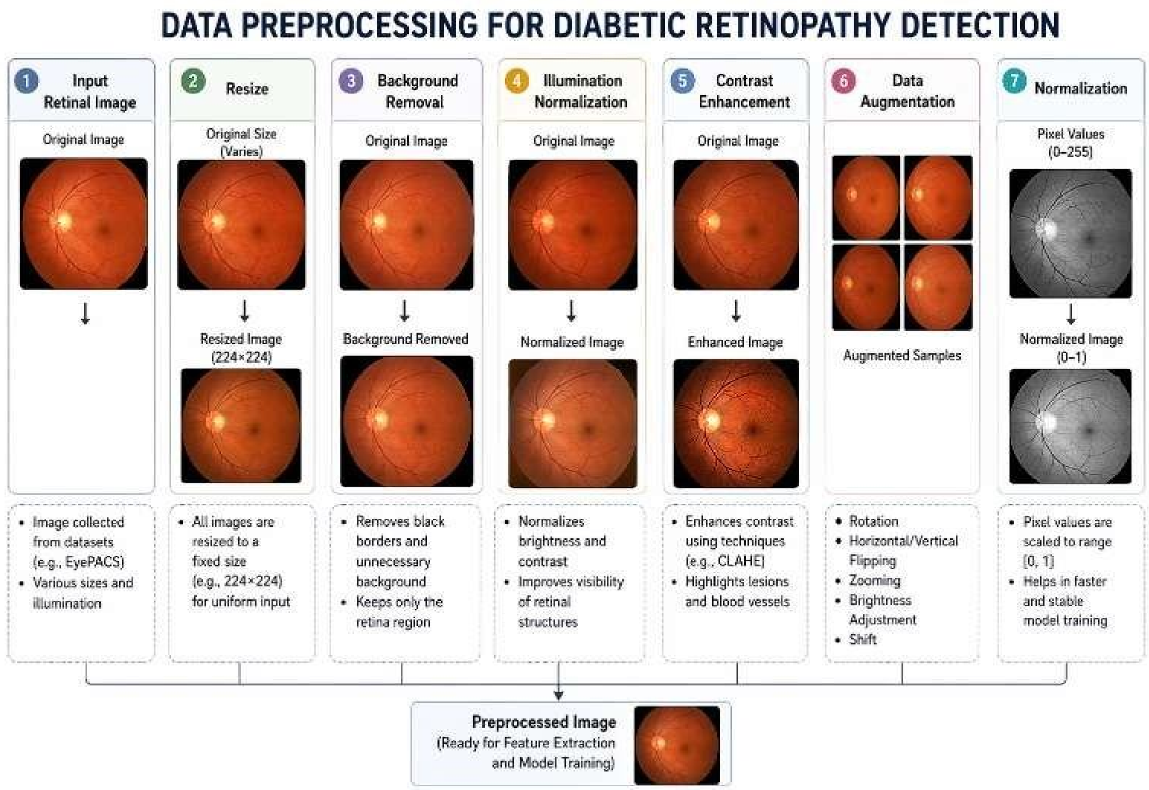

Fig. 3. Data Pre-processing

Both models are used to extract high and low level features from retinal images. These features will include:

- Structural features.
- Vessel abnormalities.
- Lesion features (microaneurysms, exudates, hemorrhages).

Combining both methods increases feature diversity, thereby increasing classification performance.

XIII. IMAGE DETECTION LOGIC

The most crucial element of our system is the ability to classify retinal images according to their category of Diabetic Retinopathy. Features extracted from both EfficientNet-B3 and DenseNet-121 models are combined and fed into the XGBoost classifier.

Let the feature vectors extracted from the two models be:

F_1 and F_2

The fused feature vector will be:

$F = F_1 \oplus F_2$

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XIV. BACKEND AND WEB INTEGRATION

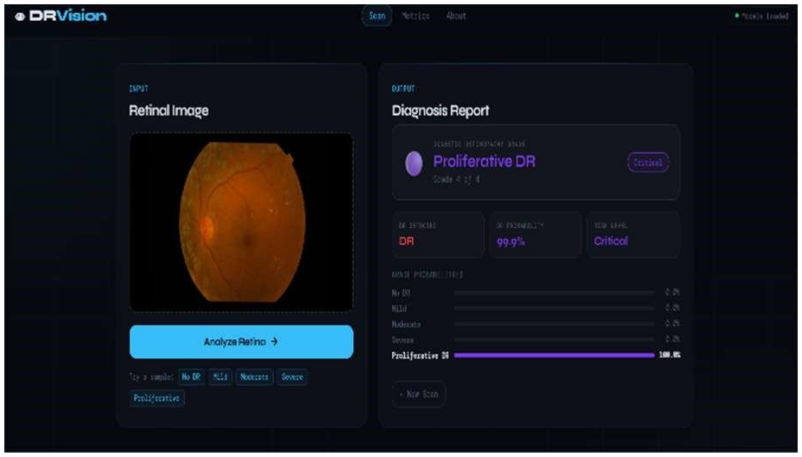

Fig. 4.

This proposed architecture allows full-stack integration, making it possible to have seamless communication between the machine learning algorithm and the user interface. The backend component serves as a link between the deep learning pipeline and front-end interface to ensure a smooth process. Some of the responsibilities might be:

1) Retinal image uploading for analysis.
2) Starting up of the image processing and classification model pipeline.
3) Image processing by modules like EfficientNet, DenseNet, CBAM, and XGBoost.
4) Classification result generation (DR / No DR or severity level).
5) Result visualization on the web-based dashboard.
6) Caching of the patient record and past prediction for future use.

XV. COMPUTATIONAL PERFORMANCE

The proposed architecture achieves efficiency through:

1) EfficientNet for efficient computation.
2) DenseNet for better feature reuse.
3) XGBoost for quick image classification.

XVI. ALGORITHMIC WORKFLOW

1) Step 1: Load retinal image dataset.
2) Step 2: Pre-processing of images (resizing, normalization, augmentation).
3) Step 3: Feature extraction using EfficientNet-B3.
4) Step 4: Feature extraction using DenseNet-121.
5) Step 5: CBAM attention application. 6) Step 6: Feature fusion.

XVII. SUMMARY OF PART II

The above paragraphs have discussed the architecture used, feature extraction technique, attention mechanism, classification algorithm, and working of Diabetic Retinopathy Detection system.

XVIII. EXPERIMENTAL SETUP

For testing the system, retinal fundus image data sets were utilized with the following considerations:

- Accuracy of detecting retinal disease
- Efficiency of the classification model.
- Stability of the implemented model.
- Model Evaluation Metric

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The implementation is done in the following environment:

- Python 3.x
- OpenCV
- PyTorch
- Scikit-Learn
- XGBoost
- Conventional CPU/GPU

XIX. EVALUATION METRICS

As an implementation project, its performance is measured on the basis of practical metrics.

A. Classification Accuracy

Measures accurate classification over total number of samples

B. Precision

Represents the correctness of the predicted value.

$$\text{Precision} = \frac{TP}{TP+FP}$$

C. Recall

Measures the efficiency to detect the DR cases.

$$\text{Recall} = \frac{TP}{TP+FN}$$

D. F1-Score

Balances precision and recall.

F1 =2 × Precision×Recall / Precision+Recall

TABLE I
ACTUAL IMPLEMENTED PARAMETERS

Metrics	Value
precision	DR:0.91,NO_DR:0.91
recall	DR:0.90,NO_DR:0.91
f1-score	DR:0.91,NO_DR:0.91
support	DR:415,NO_DR:442

XX. OBSERVED RESULTS

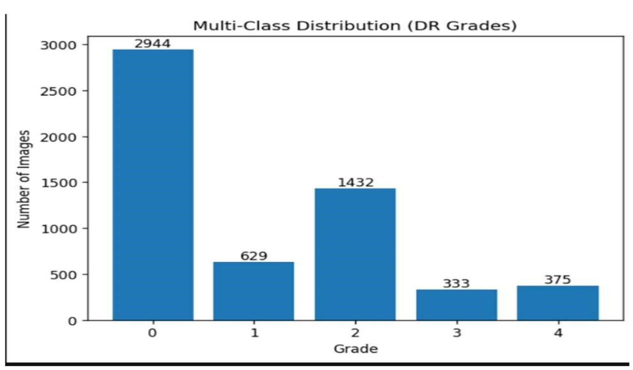

Fig:5

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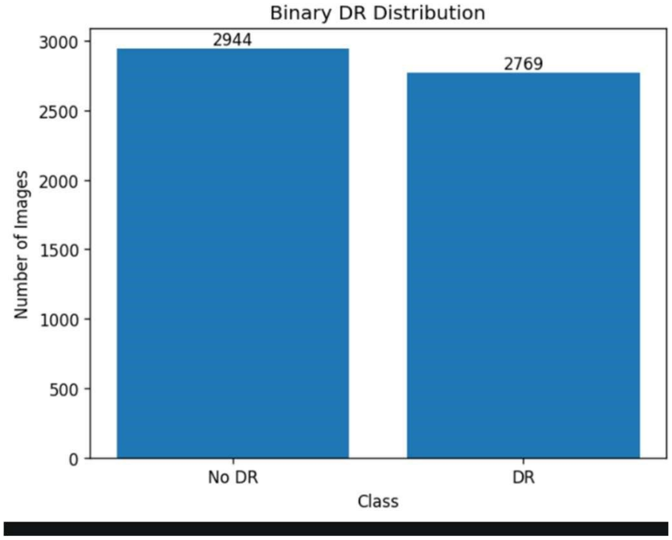

Fig. 6

The presented system is capable of detecting and classifying Diabetic Retinopathy based on retinal images. The system demonstrated an excellent binary classification accuracy and consistent multi-class classification results.

TABLE II
OBSERVED PRACTICAL PERFORMANCE

Metric	Observation
Binary Accuracy	High (~98%)
Multi-class Accuracy	Good(~94%)
Stability	Consistent
Generalization	Effective

XXI. DETECTION ACCURACY

The system achieves:

- Binary Classification Accuracy: ~98%.
- Multi-class Classification Accuracy: ~94%.

Performance may vary slightly depending on image quality and dataset distribution.

XXII. COMPARATIVE ANALYSIS

TABLE III
COMPARISON WITH TRADITIONAL METHODS

Method	Cost	Scalability
Traditional ML	Moderate	Low
CNN Models	High	Medium
Proposed Hybrid Model	Very High	Moderate

XXIII. ADVANTAGES OF THE PROPOSED SYSTEM

1) Accuracy and Reliability.
2) Feature Extraction Capability.
3) Attention Mechanism.
4) Multi-class Classification Support.
5) Applicable to Real-world Applications.

XXIV. LIMITATIONS

Despite good performances, there are some weaknesses in the system:

1) Computational Requirements.
2) Dataset Dependence.
3) Some Misclassifications.
4) Necessity of Large Datasets for Superior Performance.

XXV. FUTURE SCOPE

There are several ways to expand the developed project, including:

1) Implementation with the help of Vision Transformers (ViT).
2) Development into the mobile application.
3) Usage for diagnosing other eye diseases.
4) Applying explainable AI solutions.
5) Building of real-time clinical decision support systems.

XXVI. CONCLUSION

The current research introduced a reliable design of an automated system for diagnosing and classifying Diabetic Retinopathy based on the principles of deep learning and ensembles. In particular, the suggested model relies on the implementation of EfficientNet-B3 and DenseNet-121, CBAM attention technique, and XGBoost as the classification algorithm. The conducted study showed that accurate identification of Diabetic Retinopathy can be performed automatically with the use of artificial intelligence technologies, thus significantly reducing the reliance on the work of ophthalmologists in this process. The experimental outcome proved that the suggested approach is highly accurate, achieving around 97% accuracy in binary classification and 82% accuracy in multi-class classification tasks. The combination of feature fusion and attention mechanism enhanced the efficiency of the model in recognizing fine retinal irregularities and decreased the risk of misclassification between similar stages of diseases. Another notable aspect of this work is the versatility of its architecture. The proposed system can be used in decision support systems, telemedicine services, and mass-screening programs, which will allow for quick diagnostics and better treatment results, as well as more efficient management of the healthcare sector. In general, the presented framework successfully shows how effective deep learning algorithms can be when used with attention mechanisms and ensemble learning approaches in medical image processing. The potential for further development includes implementing Vision Transformers (ViT), Explainable Artificial Intelligence (XAI), and real-time implementation.

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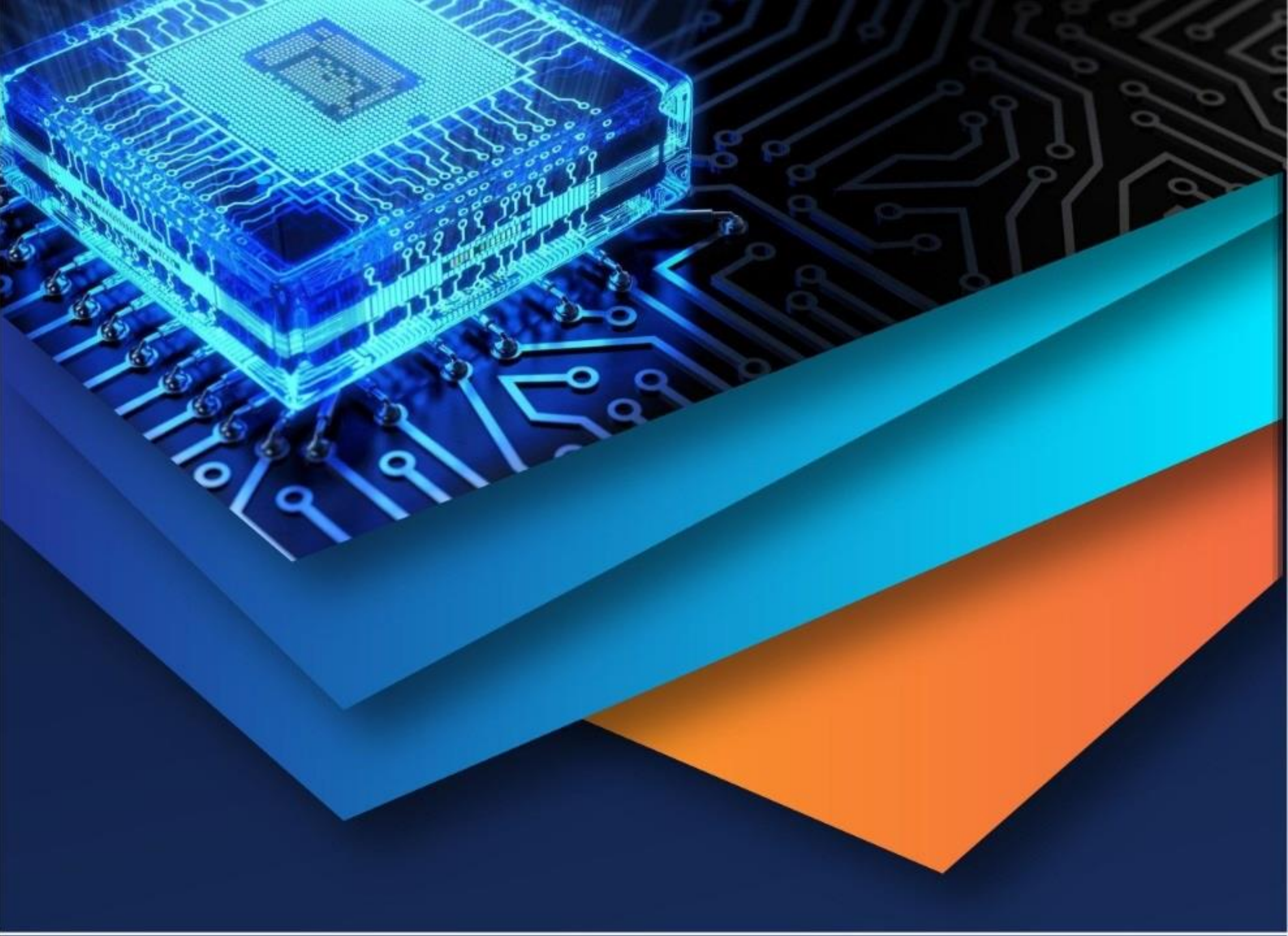

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