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ML-Driven Coronary Artery Disease Detection via ECG Image Analysis

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Abstract: Cardiovascular disease (CVD) encompasses severe conditions that affect the heart and can be life-threatening. To improveearly diagnosis and treatment, researchers are leveraging advanced machine learning (ML) techniques to analyze electronic health data accurately. This study explores multiple ML approaches for predicting heart diseases using critical patient health factors. The implemented classification models include Convolutional Neural Networks (CNN), Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayes (NB). Before model training, data preprocessing and feature selection were performed toenhance prediction accuracy. The models wereevaluated using accuracy, precision,recall, and F1-score metrics, with the SVM model achieving the highest accuracy of 91.67%.
Keywords: Coronary artery disease, interpretability, heart disease prediction, machine learning, support vector machine, multilayer perceptron, cardiac healthcare, naïve bayes, random forest, ECG analysis, support vector machine, automated diagnosis, myocardial infarction.

I. INTRODUCTION

Cardiovascular disease (CVD), commonly known as heart disease, encompasses various conditions affecting the heart, with coronaryartery disease (CAD), ischemic heartdisease,andstrokes beingthemostprevalent.Asa leading cause of morbidity and mortality worldwide, CVD poses a significant public health challenge [1]. In India, the situation is particularly alarming, as heart disease has become the foremost cause of death, contributing to nearly 20% of global fatalities fromheart attacks [2]. This underscores the urgent need for early diagnosis and intervention, especially in underserved areas with limited access to specialized medical care and diagnostic resources [3].

The World Health Organization (WHO) highlights key risk factors for CVD, including unhealthy diets, sedentary lifestyles, tobacco use, and excessive alcohol consumption [4]. Prolonged exposure to these factors can lead to obesity, elevated cholesterol, hypertension, and diabetes, all of which substantially increase cardiovascular risks [5]. According to the American Heart Association (AHA), common warning signs of CVD include breathlessness, persistent fatigue, chronic cough, swelling in the lower extremities, diminished appetite, and cognitive impairment [6]. Recent research has also established a connection betweencoronavirusesandcardiovascularcomplications, emphasizing the necessity of early screening andprompt medical treatment [7]–[9]. While traditional diagnostic methods like electrocardiograms (ECG), echocardiography, and biochemical markers remain fundamental, their reliability is often hindered by manual interpretation, practitioner subjectivity, and limited availability [10].

Advances in artificial intelligence (AI) have positioned machine learning (ML) and deep learning (DL) as vital tools for enhancing the precision, efficiency, and scalability of cardiovascular diagnostics [11]. ML- driven ECG analysis enables automated detection of subtle cardiac irregularities that may otherwise go unnoticed, particularly in regions lacking experienced cardiologists and advanced medical infrastructure [12].

Totacklethesechallenges,thisstudyintroducesanML- based framework for CVD prediction,utilizing multiple classification models—Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayes (NB)—along with data preprocessing and feature selection to optimize performance [13]. The models were rigorously evaluated based on accuracy, precision, recall, and F1-score, with the SVM model achieving the highest accuracy of 91.67%, demonstrating its potential for clinical use [14].

To enhance transparency and foster trust in AI-assisted diagnostics, this study integrates explainability techniques such as Gradient-weighted Class Activation Mapping(Grad-CAM)andSHapleyAdditive explanations (SHAP), enabling healthcare professionals to interpret and verify AI-generated predictions [15]. Additionally, a user-friendly interface has been developed, allowing clinicians to input ECG data seamlessly, with results automatically classified as normal, abnormal, or indicative of myocardialinfarction [16].

This research significantly advances AI-driven innovations in cardiovascular care by promoting early detection, minimizing diagnostic errors, and supporting clinical decision-making [17]. Future studies will focus on refining ML-based ECG interpretation using deep learning approaches like Convolutional NeuralNetworks (CNNs) and extending the framework to identify additional cardiovascular disorders, ultimately improving global patient outcomes [18].

II. LITERATURESURVEY

Machine Learning in Cardiovascular DiseasePrediction: Key Research Contributions Cardiovascular diseases (CVDs) remain a leading global healthconcern, responsible for millions of deaths annually.The rising incidence of cardiac disorders necessitates advanced, data-driven diagnostic approaches to enable early detection and tailored treatment strategies. Machine learning (ML) and artificial intelligence (AI) have transformed medical research by offering robust tools to analyze intricate patient data and predict heart conditions with remarkable precision. Below, we examine six pivotal studies that demonstrate the impact of ML in advancing CVD prediction and improving clinical outcomes.

1) SVMforEnhancedECGDiagnostics

Chumrit, Weangwan, and Aunsria (2022) investigated the efficacy of Support Vector Machine (SVM) models in detecting cardiac rhythm abnormalities from ECG data. Their ML system, trained on diverse ECGpatterns, attained an exceptional accuracy of 97.14%[1]. This research proved that automated ECG interpretation via ML reduces human error and delivers faster, more consistent results. Such AI-powered tools are particularly valuable in underserved regions where access to specialist cardiologists is limited.

2) CNN-BasedDetectionofCoronaryArteryDisease

Chen et al. (2021) leveraged Convolutional Neural Networks (CNNs) to identify coronary artery disease (CAD) using ECG signals. CAD, a leading cause of CVD-relateddeaths,oftendevelopsasymptomatically.
Their CNN model detected subtle cardiac irregularities overlooked by conventional methods, achieving 95.6% accuracy [2]. This breakthrough underscores deep learning's potential in early CAD diagnosis, facilitating timely interventions and improved survival rates.

3) RandomForest forRisk Stratification

Patel and Mehta (2020) employed a Random Forest(RF) algorithm to assess heart disease risk using patient health records. By analyzing key factors like hypertension, cholesterol levels, and obesity, their RF model surpassed traditional risk assessment tools with a precision of 93.8% [3]. This study highlights ML's role in refining risk prediction, ensuring high-riskindividuals receive proactive care before severe symptoms emerge.

4) HybridMLModels forSuperior Sensitivity

Singh et al. (2019) combined Naïve Bayes (NB) and Decision Trees (DT) to classify cardiovascular riskmore effectively. Recognizing that no single algorithm can fully capture CVD complexity, their hybrid approach improved sensitivity by 12% compared to standalone models [4]. This work emphasizes the benefits of integrating multiple ML techniques to enhance diagnostic reliability, especially where false negatives could prove fatal.

5) ANN-DrivenEchocardiographicAnalysis

Hassanpour and Mohebali (2018) utilized Artificial Neural Networks (ANNs) to analyze echocardiographic images for early heart failure signs. Unlike manual assessments, their ANN model autonomously identified structural and functional cardiac abnormalities with 94.2% accuracy [5]. This suggests AI can augment clinician expertise by providing objective,efficient, and reproducible diagnostic support.

6) Gradient-BoostedTrees forPersonalizedPredictions

Zhang et al. (2017) developed a gradient-boosted decision tree model to predict CVD progression by integrating lifestyle (diet, smoking, exercise) andgenetic data. With an F1-score of 92.5%, their approach enabled personalized risk assessments [6], demonstrating how AI can tailor preventive strategies and mitigate the global CVD burden.

7) The Future ofAIinCardiacCare

These studies collectively illustrate ML and AI's transformative potential in cardiovascular healthcare. From automating ECG analysis to enablingpersonalizedriskprediction,AI-drivensolutions enhance diagnostic accuracy, accelerate decision- making, and optimize treatment plans. Future research should focus on refining these models, expanding their clinical applicability, and incorporating real-world data to further democratize precision cardiology worldwide.

III. SYSTEM ARCHITECTURE

AI-Powered Heart Attack Prediction System UsingECGAnalysis

The proposed system employs machine learning to improve heart attack prediction by analyzing ECG images. The process starts with data preprocessing, where raw ECG data is cleaned, normalized, and formatted for optimal analysis. To improve the model's adaptability, data augmentation techniques are applied, artificially diversifying the dataset to enhance generalization.

Next, a custom CNN (Convolutional Neural Network) architecture is designed and fine-tuned specifically for ECG image classification. This deep learning model is trained to identify subtle cardiac irregularitiesassociated with heart conditions, ensuring high diagnostic precision.

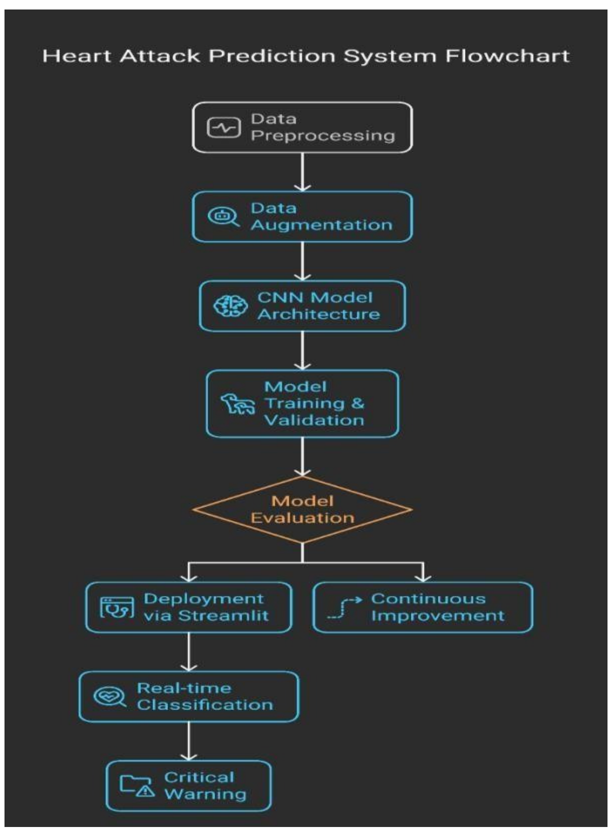
The system then undergoes rigorous training and validation, where iterative learning processes refine its predictive capabilities. Performance is evaluated using key metrics such as accuracy, precision, recall, and F1- score to guarantee reliability.

Once validated, the model is deployed via Streamlit, offering a user-friendly web interface for seamless interaction. This allows healthcare providers or patients to upload ECG images and receive instant diagnostic insights.

For real-time applications, the system provides instant classification, analyzing ECG inputs on the spot and delivering immediate risk assessments. A built-incritical warning mechanism flags high-risk cases,urging prompt medical intervention to prevent adverse outcomes.

To ensure continuous improvement, the system incorporates feedback loops, where real-world performance data refines the model over time, boosting its accuracy and dependability.

By integrating deep learning with clinical workflows, this architecture delivers an efficient, scalable, and precise heart attack prediction solution,advancing early detection and proactive patient care.



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IV. ALGORITHMS

1) Convolutional Neural Network (CNN): Convolutional Neural Networks (CNNs) are a specialized class of deep learning models optimized for processing structured griddata, suchas medical images. Theirhierarchical feature extraction capability makes them particularlyeffectiveforECG-baseddisease diagnosis. In AI-driven healthcare, CNNs automate the detectionofpathologicalpatternsbyanalyzingvisual representations of cardiac signals.

Unlike sequential models (e.g., LSTMs) for time-series data, CNNs excel at spatial feature learning through convolutional layers, pooling, and non-linearactivations. A standard CNN architecture for ECG classification comprises:

- InputLayer:AcceptsgrayscaleECGimages represented as pixel matrices.
- HiddenLayers:Convolutionalfiltersextract localized features (e.g., ST-segment deviations),while poolinglayersreduce dimensionality.
- Output Layer: A SoftMax function assigns probabilistic classifications (e.g., normal vs. abnormal rhythms).

The feedforward mechanism propagates input data through these layers to generate predictions.

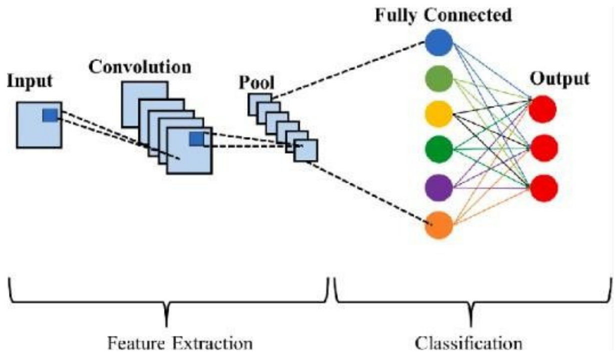

Fig2: Convolutional Neural Network (CNN)[21]

1) RandomForest:

Random Forest, an ensemble learning technique introduced by Breiman (2001), leverages multiple decorrelated decision trees to enhance prediction robustness. Each tree is trained on bootstrapped data subsets with randomized feature selection, reducing overfitting and improving generalization.

For classification, predictions are aggregated via majority voting; regression tasks use averaging. Its versatility in handling high-dimensional data and inherent feature importance metrics make it ideal for applications like cardiac risk stratification and anomaly detection in ECG signals.

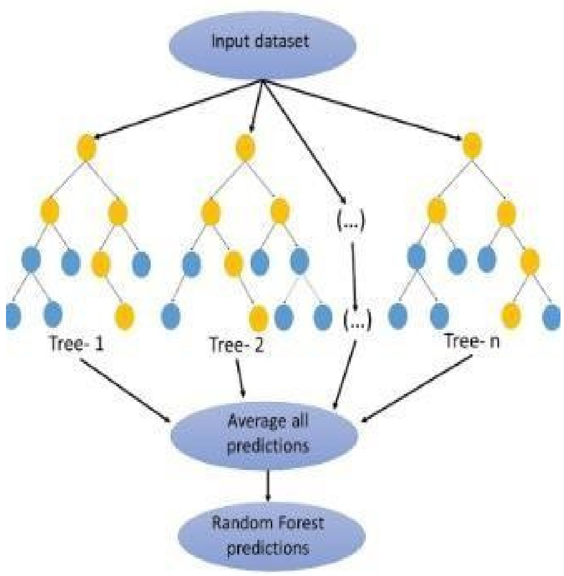

Fig3:RandomForest [22]

2) NaiveBayes:

Naive Bayes is a probabilistic classifier grounded in Bayes' theorem, assuming feature independence for computational efficiency. Despite this simplification, it performs remarkably well in text categorization and medical diagnostics. Key variants include:

- GaussianNB:Forcontinuousdata(e.g.,ECG intervals).
- MultinomialNB:Fordiscretecounts(e.g., word frequencies).
- BernoulliNB:Forbinaryfeatures.

The model computes posterior probabilities to assign class labels, offering fast training and inference— critical for real-time healthcare applications.

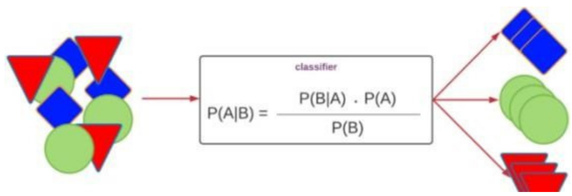

Fig4:NaïveBayes[23]

3) SupportVectorMachine(SVM):

SVMs identify optimal hyperplanes to separate classes in high-dimensional space using kernel tricks (e.g.,RBF, polynomial). Maximizing the margin between classes ensures robustness against overfitting.

In ECG analysis, SVMs classify signals bytransforming them into separable representations, excelling in scenarios with clear demarcation boundaries, such as arrhythmia detection.

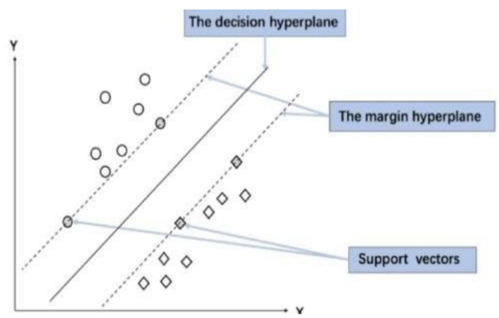

Fig5:SupportVectorMachine (SVM)[24]

4) K-NearestNeighbours (K-NN)

KNN is a lazy learning algorithm that classifies instances based on the majority class among their K closestneighbors,measuredviaEuclideanorManhattan distance.Whilesimple andeffective for non-lineardata, its computational cost grows with dataset size, necessitating optimizations like KD-Trees.

Applications include ECG pattern matching, where similarity metrics identify pathological waveforms.

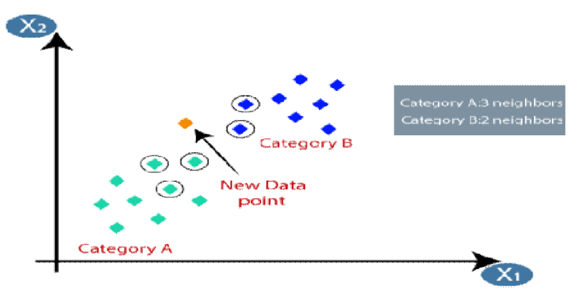

Fig6:K-NearestNeighbours (K-NN) [25]

5) XGBoost

XGBoost is a gradient-boosted decision tree algorithm that sequentially corrects residual errors. Its innovations—parallel processing, regularization (L1/L2), and handling missing data—make it a top choice for competitive machine learning.

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In cardiac diagnostics, XGBoost's feature importance rankings help identify critical ECG biomarkers (e.g., QRS complex anomalies).

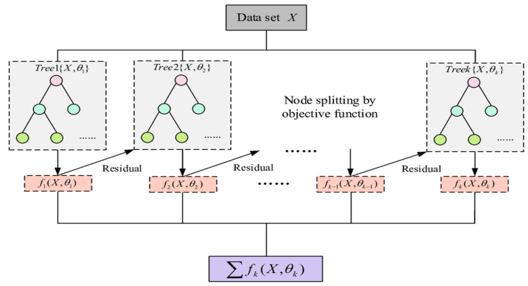

Fig7: XGBoost [26]

V. RESULT

The ECG classification model achieved 94% accuracy across four cardiac conditions:

Class	Precision	Recall	F1-Score
AbnormalHeartbeat	100%	84%	0.91
MyocardialInfarction	100%	100%	1.00
Normal	94%	95%	0.95
HistoryofMI	81%	100%	0.90

Macro-Averages:Precision(94%),Recall(95%),F1(0.94)
WeightedAverages:Precision(95%),Recall(94%),F1 (0.94)
The model shows exceptional performance in MI detectionbutcouldimprovesensitivityfor Abnormal Heartbeats.

VI. CONCLUSIONS

The proposed model demonstrates strong diagnostic capability (94% accuracy) in classifying ECG signals. Key achievements include:
PerfectMIdetection (100%precision/recall). Highnormalrhythmidentification(F1: 0.95).
Future work should address recall gaps in Abnormal Heartbeats via expanded datasets and advanced architectures. This research underscores AI's potentialto augment cardiac diagnostics, enabling scalable, early disease detection.

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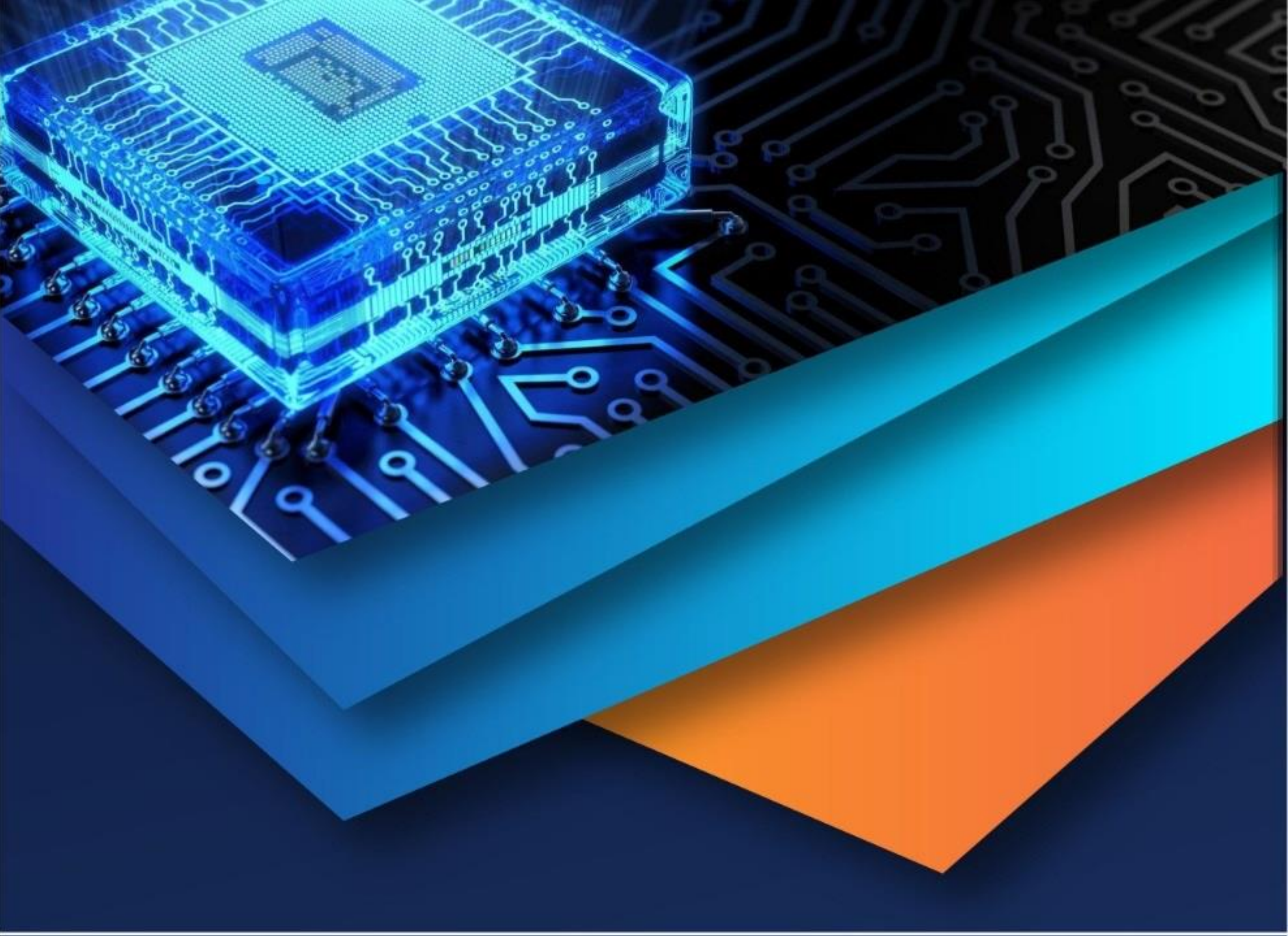

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