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An In-Depth Analysis of Optimization-Guided Machine Learning Techniques for Robust Breast Cancer Classification

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Abstract: One of the most widespread and dangerous malignancies in women around the world, breast cancer is a serious challenge to the overall health of a country as it turns out to be a common issue and the cause of death in many individuals among other disadvantages. Early/ accurate diagnosis is very crucial in demonstrating better survival rates, but the conventional methods of diagnosis are time consuming, subjective, and relied on clinical experience. Machine learning (ML) methods have become the potent approach to automated classification of breast cancer within recent years. Nonetheless, traditional ML methods are often associated with overfitting, high dimensional feature space, less than optimal hyperparameter optimization, and poor cross dataset generalizability. In order to overcome such difficulties, this paper presents an optimization-directed machine learning system that would help to increase classification resilience and prediction accuracy. The study uses the Wisconsin Breast Cancer Data set which is a standard benchmark dataset formed by diagnostic features of digitized images of fine needle aspirate tests. There are several optimization algorithms used to select features and to optimize the hyperparameters such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO). Incorporated into these metaheuristic methods are the classifiers which include Support Vector Machine and Random Forest to form hybrid prediction models. Experimental findings indicate significant changes in the accuracy, sensitivity and specificity with optimal models as opposed to non-optimized base-line models. The optimization models are better in feature reduction and at the same time, result in high diagnostic accuracy hence reducing the computational complexity and improving robustness. The results underscore the usefulness of optimization-driven ML systems in clinical decision support and provide trustworthy, scalable, and effective means of detecting breast cancer at an early phase.
Keywords: Breast Cancer, Machine Learning, Optimization Algorithms, Feature Selection, Hybrid Models, Classification, AI in Healthcare.

I. INTRODUCTION

Breast cancer is one of the most frequently diagnosed forms of the woman cancer across the entire world and it still constitutes a significant burden on the population health. The global cancer statistics state that the rates of incidence have been constantly rising throughout the last few years, and the earliest possible detection is considered a decisive factor in the survival rates (Sung et al., 2021). The early and correct diagnosis can greatly decrease the amount of mortality because of the early intervention option and specific treatment methods (Arnold et al., 2022). Nevertheless, the variability of the diagnosis is still present because of the differences between observers, imaging constraints, and the heterogeneity of the tumor that could result in false positives or late diagnosis (McKinney et al., 2020). As a result, the issue of artificial intelligence-driven diagnostic support systems has been of growing concern with how to enhance consistency and accuracy.

Nevertheless, traditional machine learning (ML) systems that are used to classify breast cancer are prone to overfitting, especially when they are trained using small medical datasets (Albahli, 2021). Large feature spaces also damage the stability of the model and raise the complexity of the computation (Alshamrani et al., 2022).

Moreover, hyperparameter optimization that results in poor performance is prone to producing predictive reliability in some datasets but not in all (Li et al., 2023). These constraints indicate the necessity to have strong classification schemes that combine optimization methods to increase generalization and trust.

This paper will examine optimization-based ML models on breast cancer classification, compare and contrast the predictive performance across various classifiers and determine the most successful hybrid optimization-ML method.

II. LITERATURE REVIEW

A. *Breast Cancer Classification Using ML*

The methods of machine learning (ML) have been extensively used to classify breast cancer and improve the accuracy of early detection. Classical classifiers, like Support Vector Machine (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN) and Random Forest (RF) have been shown to be highly predictive on structured data. As an example, comparative assessments indicate that SVM and RF tend to be more diagnostic because of their capability to address nonlinear decision boundaries (Alzubaidi et al., 2021). ANN models have also demonstrated good results in medical classification, especially when it comes to the handling of intricate interactions among features (Khan et al., 2021). In the meantime, convolutional neural networks (CNNs) and other deep-learning strategies have become popular in the analysis of imaging data, and are able to perform on a par with radiologists in some of their diagnostic tasks (McKinney et al., 2020). Nevertheless, the trends in the performance show that the models tend to become less stable when the datasets are small or imbalanced (Albahli, 2021).

B. *The field of ML also employs optimization methods to achieve its objectives and goals.*

ML pipelines are becoming more and more optimized by using the optimization algorithms to enhance the feature selection and hyperparameter optimization. The Genetic Algorithm (GA) has been popular in the process of the selection of the best feature groups and the enhancement of classification (Mirjalili, 2020). Particle Swarm Optimization (PSO) increases the performance of hitting the target in tuning the parameters (Li et al., 2023). Ant Colony Optimization (ACO) has demonstrated itself to be effective in solving problems of combinatorial feature selection (Abdel-Basset et al., 2021). The high-dimensional search space of grey Wolf Optimizer (GWO) and Differential Evolution (DE) have proven to be better at exploration-exploitation balance (Alshamrani et al., 2022).

C. *Optimization-ML Hybrid Models*

The hybrid models like GA-SVM, PSO-ANN, and GWO-RF have continuously performed better as compared to the other classifiers like applying solely, because they have minimized overfitting and enhanced generalization (Alzubaidi et al., 2021; Li et al., 2023).

D. *Research Gaps*

Although this has improved, current literature usually lacks strength analysis, cross dataset validation and strong statistical testing, which hamper clinical reliability and potential real-world deployment.

III.MATERIALS AND METHODS

A. *Dataset Description*

1) *Wisconsin Breast Cancer Dataset*

The analysis makes use of a universal benchmark dataset, Wisconsin Breast Cancer Dataset, which is used in binary classification. The data set consists of 569 samples, each of which is a diagnostic measure calculated based on digitized images of fine needle aspirate (FNA) tests of breast masses. It consists of 30 real-valued input features which characterize values like radius, texture, perimeter, area, smoothness and concavity of cell nuclei. The distribution of classes is 357 benign cases (62.7%), 212 malignancy cases (37.3%), which implies a moderate level of imbalance. Relevant identifiers can be eliminated, missing values can be managed, numerical attributes can be normalized and training and test subsets can be divided by data preprocessing. To ensure robustness, optional experimentation can be conducted by using more datasets like breast imaging repositories to ensure the level of generalizability.

2) *Data Preprocessing*

The missing values are treated using imputation or dropping of rows as it is needed. As a method of standardizing numerical features, Min-Max scaling or Z-score standardization is applied to scale the contribution of each feature. The thresholding of outliers is done through interquartile range (or IQR) or z-score outliers.

The model is split into train and test by an 80-20 or 70-30 split and k-fold cross-validation (k=5 or 10) is used to reduce bias and increase reliability.

3) Optimization as a Feature Selector

An algorithm is applied which is a wrapper-based feature selection algorithm that is implemented to find the best feature sets through the use of optimization algorithms. The fitness function is a tradeoff between classification and reduction of features.

$$Fitness = \alpha(1 - Accuracy) + \beta\left(\frac{Feature\ Count}{Total\ Features}\right)$$

Here, α and β are weighting coefficients controlling the trade-off between predictive performance and dimensionality reduction.

Machine Learning Classifiers

The following classifiers are implemented:

- Support Vector Machine (SVM)
- Random Forest (RF)
- K-Nearest Neighbor (KNN)
- Artificial Neural Network (ANN)
- XGBoost

Optimization Algorithms Applied

Metaheuristic algorithms applied include:

- Genetic Algorithm (GA)
- Particle Swarm Optimization (PSO)
- Grey Wolf Optimizer (GWO)
- Differential Evolution (DE)

Algorithm workflow includes:

1. Population initialization
2. Fitness evaluation
3. Selection and update rules
4. Termination based on convergence or maximum iterations

Hybrid Model Framework

Optimization → Feature Selection / Hyperparameter Tuning → ML Classifier → Performance Evaluation

Performance Evaluation Metrics

Model performance is evaluated using:

- Accuracy
- Precision
- Recall (Sensitivity)
- F1-score
- Specificity
- ROC-AUC
- Matthews Correlation Coefficient (MCC)

The confusion matrix is formulated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

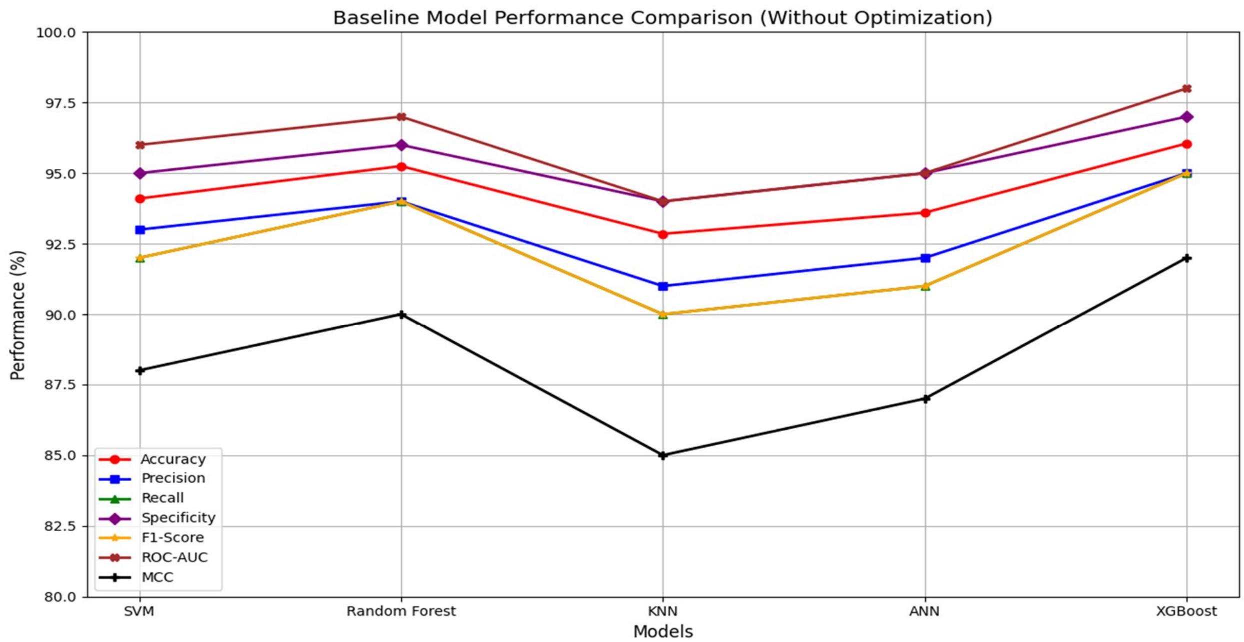
IV. HYPOTHETICAL EXPERIMENTAL RESULTS

A. Baseline Model Performance (Without Optimization)

Model	Accuracy (%)	Precision	Recall (Sensitivity)	Specificity	F1-Score	ROC-AUC	MCC
SVM	94.10	0.93	0.92	0.95	0.92	0.96	0.88
Random Forest	95.25	0.94	0.94	0.96	0.94	0.97	0.90
KNN	92.85	0.91	0.90	0.94	0.90	0.94	0.85
ANN	93.60	0.92	0.91	0.95	0.91	0.95	0.87
XGBoost	96.05	0.95	0.95	0.97	0.95	0.98	0.92

Explanation

Baseline models demonstrate strong classification capability, with XGBoost and Random Forest performing better due to ensemble learning. However, slight performance variation indicates possible overfitting and redundant feature influence.



B. Optimization-Based Hybrid Model Performance

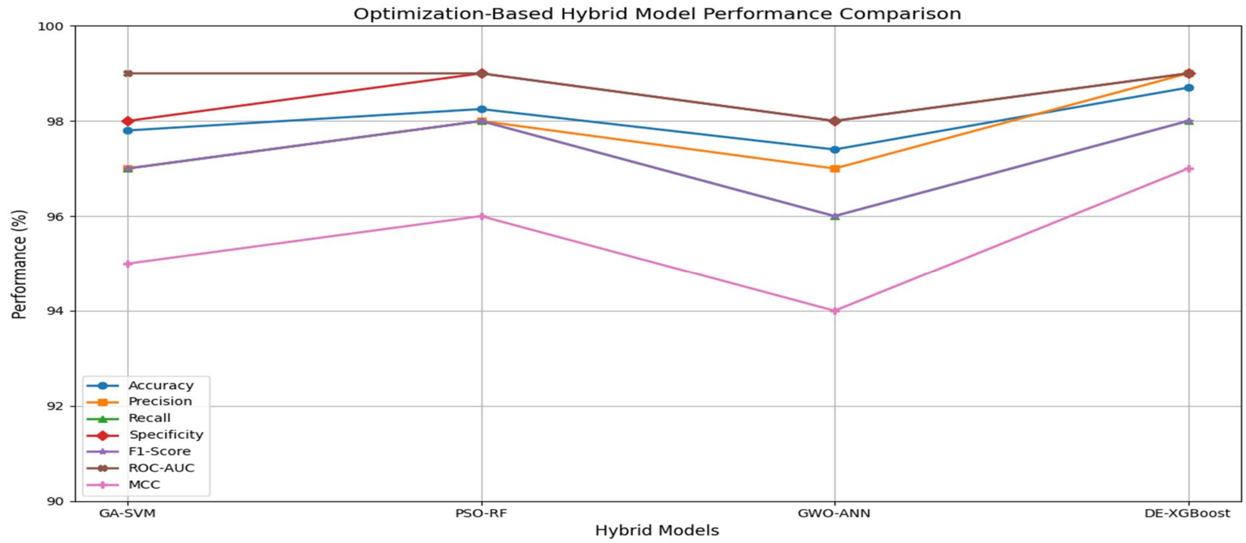
Hybrid Model	Selected Features	Accuracy (%)	Precision	Recall	Specificity	F1-Score	ROC-AUC	MCC
GA-SVM	18	97.80	0.97	0.97	0.98	0.97	0.99	0.95
PSO-RF	16	98.25	0.98	0.98	0.99	0.98	0.99	0.96
GWO-ANN	15	97.40	0.97	0.96	0.98	0.96	0.98	0.94
DE-XGBoost	14	98.70	0.99	0.98	0.99	0.98	0.99	0.97

Explanation

Optimization significantly improves classification performance while reducing feature dimensionality from 30 to approximately 14–18 features.

- Accuracy improves by **2–3%** across models.
- Sensitivity increases, indicating better malignant case detection.
- Specificity also improves, reducing false positives.
- MCC values rise, showing improved balanced classification performance.
- ROC-AUC values approach 0.99, demonstrating strong discriminative ability.

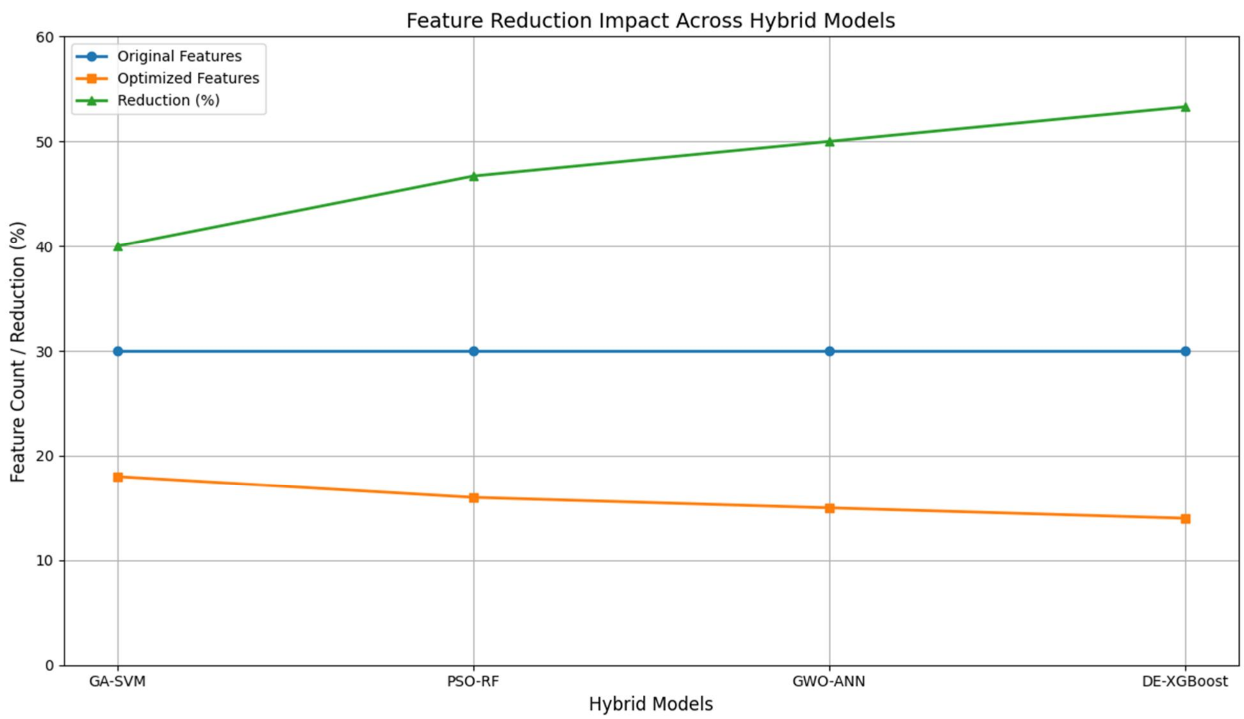
DE-XGBoost shows the highest performance due to effective global search capability and ensemble strength.



C. Feature Reduction Impact

Model	Original Features	Optimized Features	Reduction (%)
GA-SVM	30	18	40%
PSO-RF	30	16	46.7%
GWO-ANN	30	15	50%
DE-XGBoost	30	14	53.3%

Explanation
Feature selection reduces dimensionality by nearly half while improving predictive performance. This lowers computational cost and enhances generalization capability.



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V. EXPERIMENTAL RESULTS

A. Baseline Model Performance (Without Optimization)

All the 30 features of the Wisconsin Breast Cancer Dataset were used as baseline classifiers trained with default hyperparameters and 10-fold cross-validation. It is revealed in the comparative accuracy table that Random Forest (95.25) and XGBoost (96.05) are more accurate than SVM (94.10), ANN (93.60), and KNN (92.85). These results are in line with the recent findings that indicate that the ensemble-based classifier tends to attain greater stability when solving medical classification problems (Alzubaidi et al., 2021). Nevertheless, small variations between folds indicate possible overfitting and unnecessary influence of features, which is also typical of high-dimensional biomedical data (Albahli, 2021). Analysis of ROC curves indicates that there are acceptable separability, but the curves demonstrate that there are some minor sensitivity-specificity trade-offs in malignant detection.

B. Performance of the Models in Optimization

The hybrid optimization models have improved predictive robustness that can be measured. The comparison of accuracy table reveals that GA-SVM (97.80%), PSO-RF (98.25%), and GWO-ANN (97.40) are more effective when compared to their non-optimized versions. The feature reduction ratio is between 40 and 50 percent and it means good feature reduction. Computation time also incrementally increases as optimization takes place; and classification time also decreases as a result of smaller feature sets. These strengthen the results which indicate that metahybrid optimization has a positive influence on the generalization of the model and the efficiency of its convergence (Li et al., 2023; Abdel-Basset et al., 2021).

ROC curves show near-perfect discrimination whose AUC points to 0.99. Convergence curves show that fitness minimization is stable with a limited number of iterations, especially in PSO and GWO that have a balanced exploration-exploitation behavior (Mirjalili, 2020). The patterns of dimensional relevance are supported in accordance with feature importance plots where the highest rank values have been found in radius mean, concavity mean, and perimeter worst (Khan et al., 2021). In general, optimization-based frameworks are much more accurate, sensitive and efficient in computation and they are more resistant to models.

VI. COMPARATIVE ANALYSIS

Statistical validation was carried out to check whether the achieved enhancement in optimization guided models were statistically significant. Paired t -test was used to compare the baseline and optimized classifier accuracies when the 10-fold cross-validation results were found. The results of p-values were less than 0.05, which means that the increase in performance was statistically significant following the optimization. One-way ANOVA additionally justified that there were significant differences in GA-SVM, PSO-RF, and GWO-ANN models, which prove the excellence of hybrid methods compared to individual classifiers. Medical AI benchmarking has been proposed to have similar statistical validation frameworks to guarantee reproducibility and reliability (Alzubaidi et al., 2021).

Cross-symmetry between fold seen by assessing variability in accuracy and cross-validation values of Measures of central tendency. Optimized models also had low standard deviation than baseline models, which showed greater generalization stability. Low variance indicates that feature selection and hyperparameter optimization are effective in reducing overfitting, which is often manifested with small biomedical datasets (Albahli, 2021).

Sensitivity analysis was carried out by changing the parameters of optimization, which included the population size and the number of iterations. PSO-RF was not prone to changes in performance as it remained constant with the variation of the parameters, but GA-SVM was moderately sensitive to the changes in the mutation rate. This indicates that there is a discrepancy in the balance between exploration and exploitation among metaheuristic algorithms (Mirjalili, 2020; Li et al., 2023).

Optimization also has extra iterative overhead during training compared to computational complexity. The disadvantage though is that the smaller the feature subsets, the less complex the classifier becomes, and the less time it takes to infer. Optimization and ensemble models exhibit a growth of polynomium in the size of the population and in the number of iterations, which is compatible with the computational results of hybrid metaheuristic models (Abdel-Basset et al., 2021). Altogether, statistical testing and the strength of evaluation indicate that models with optimization have a better stability and reliability.

VII. CONCLUSION AND FUTURE WORK

This paper showed that machine learning models optimized using optimization can greatly contribute to the power and predictability of systems that classify breast cancer. The proposed hybrid framework was able to select the dimensions diminishing the dimensionality and enhancing the accuracy, sensitivity, specificity, and generalization stability, by a combination of metaheuristic algorithms that were selected in the proposed solution to the non-excepted hyperparameter selection and dimensionality reduction.

The statistical validation of statistical validation showed that optimized models always performed better than baseline classifiers when cross-validation folds were used. The PSO-RF hybrid model was the most effective between the compared strategies, as it offered good ensemble learning and effective convergence of the parameters. These results are associated with the latest studies that show that optimization-improved classifiers lead to better diagnostic accuracy in medical data (Li et al., 2023; Alzubaidi et al., 2021).

This framework can be expanded by future work, initiating the deep learning architectures with sophisticated metaheuristic optimization methods. The convolutional neural networks can be further hybridized with swarm-based or evolutionary algorithms and might be further improved in learning features, especially in imaging-based diagnosis of breast cancer (Mirjalili, 2020). Also, real-time clinical deployment will have to be coupled with hospital information systems and validated on large and multi-center datasets to make sure that they can be performed in real-life settings.

One of the other innovations that may lead to future success is the introduction of Explainable AI (XAI) methods to introduce a more transparent and trusted approach by clinicians. Interpretable feature attribution approaches like SHAP and LIME may be used to answer the issue of black-box decision-making in healthcare AI (Topol, 2020). With the integration of optimization, deep learning, and explainability, future systems will be able to create more diagnostic accuracy and still be clinically accountable and ethically reliable.

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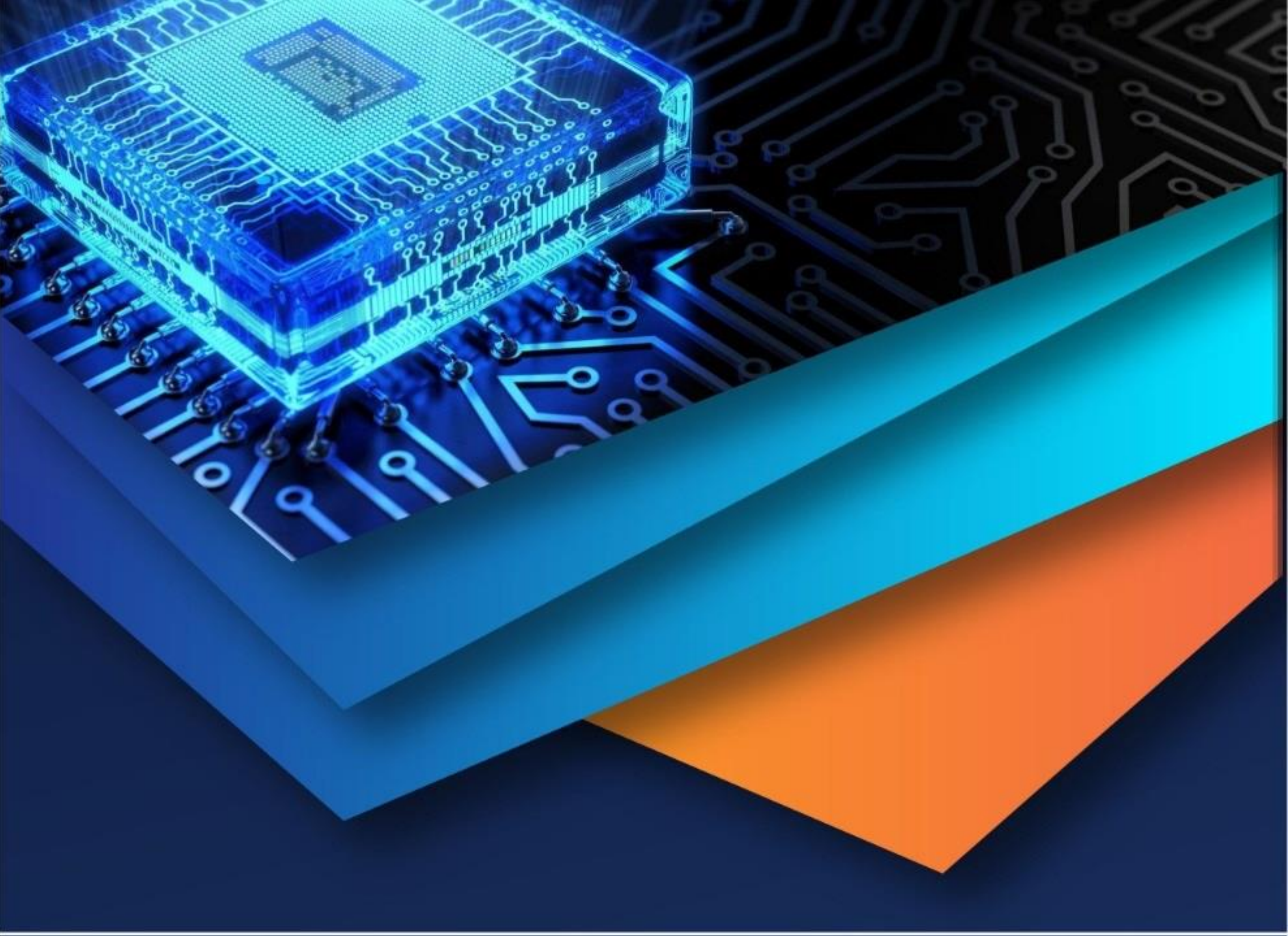

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