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# Ensemble Learning for Enhanced Classification of Fetal Health Using Cardiotocography Data

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***Abstract: Accurate classification of fetal well-being is required to detect early possible risks in pregnancy. Fetal monitoring is a crucial task performed by cardiotocography (CTG), which records fetal heart rate and uterine contractions. CTG reading manually is subjective and liable to mistake. In this work, the authors propose an ensemble learning approach, combining Random Forest and XGBoost models, to enhance fetal well-being classification as normal, suspect, and pathological. Through aggregation of the capabilities of different classifiers, the ensemble model yields enhanced accuracy and reliability over traditional single algorithms. Comprehensive testing with cross-validation confirms the stability of the proposed method. The findings suggest the potential of ensemble learning in supporting healthcare assessments, thereby improving prenatal care and enabling early clinical decision-making.***

***Keywords: Fetal Health, Cardiotocography (CTG), Ensemble Learning, Random Forest, XGBoost, Machine Learning, Prenatal Care, Maternal Health, Medical Diagnosis, Healthcare Analytics, Data Classification, AI in Healthcare.***

## I. INTRODUCTION

Fetal health monitoring is a crucial part of parental care consisting of early recognition of potential complications that can risk the life of the mother as well as the fetus. Of various diagnostic tools employed, cardiotocography (CTG) has found utility as an excellent non-invasive technique for assessing fetal welfare through fetal heart rate patterns and uterine contractions assessment. But precise interpretation of CTG information still remains a challenge in light of its inherent complexity and susceptibility to subjective interpretation by clinicians. In order to address such issues, artificial intelligence (AI) and machine learning (ML) techniques, particularly ensemble learning models, have gained immense popularity in recent times. Ensemble learning models like Random Forest and XGBoost have proven to be very promising to increase classification performance through the amalgamation of several learning algorithms. Such models are effective in addressing variability in CTG datasets and enhance predictive power and, hence, are found suitable for biomedical applications involving fetal health classification. Recent studies (e.g., Sarwar et al., 2023; Gupta & Singh, 2024; Kim & Lee, 2023) have established that ensemble approaches not only enhance the accuracy of prediction but also enhance interpretability and stability in clinical decision-making. Furthermore, advancements in explainable AI platforms are moving toward enhancing the transparency and reliability of such models for clinical use. This journal aims to examine the application of ensemble learning approaches for fetal condition classification of CTG data. Using sophisticated ensemble models, it is hoped to improve early detection of fetal distress, reduce the risk of adverse outcomes, and allow obstetricians to make logical clinical choices. The study also contributes to the growing body of literature on the application of AI in obstetric care, paving the way for more intelligent, data-driven parental care solutions.

## II. LITERATURE REVIEW

Over the last few years, there has been increasing interest in improving the precision of fetal well-being classification through cardiotocography (CTG) information, with ensemble learning techniques becoming a focus point. Verma et al. [1] proposed a decision tree and Support Vector Machine (SVM) hybrid model that maximized the accuracy of prediction, handling non-linear trends within CTG information and improving sensitivity to identify unusual fetal conditions. Likewise, Patel et al. [2] investigated ensemble methods like random Forest and XGBoost for preterm detection of fetal distress and achieved greater precision and recall, particularly in pathological and borderline conditions. Kumar and Sharma [3] compared the performance of multiple classifiers and discovered that Random Forest performed better compared to others and attributed the effectiveness of ensemble approaches in this application. Based on this, Chen et al. [4] combined deep neural networks with ensemble models, minimizing false alarms and enhancing prediction robustness, which was useful in clinical use.

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In addition, Singh and Gupta [5] illustrated the efficacy of boosting algorithms such as XGBoost and LightGBM in dealing with imbalanced CTG datasets while ensuring computational efficiency. Takahashi et al. [6] suggested a real-time monitoring system based on ensemble models with a focus on interpretability and timely prediction towards enhancing neonatal outcomes. Roy et al. [7] constructed a hybrid ensemble approach by merging Random Forest, Gradient Boosting, and Voting Classifiers and achieved goof generalization on various data distributions. Lee and Park [8] tuned ensemble models through hypermeter tuning methods, substantially improving classification results, especially for norma and suspicious case discrimination. In another significant work, Yadav et al. [9] used ensemble learning with advanced feature selection to detect essential CTG features and enhance interpretability as well as predictive accuracy. Zhang et al. [10] gave a complete survey of applications of machine learning in fetal monitoring and concluded that ensemble models outperform individual classifiers uniformly in robustness as well as predictability. Gonzalez et al. [11] tackled class imbalance issues by combing ensemble learning with resampling techniques, improving minority class recognition and diagnostic risk reduction. Sharma et al. [12] further developed this by incorporating ensemble models into IoT-based fetal monitoring systems, which provided high accuracy with minimal latency for real-time clinical decision-making. I addition, Ahmed et al. [13] centered their attention on explainability by uniting SHAP values with ensemble models, providing clear insights for clinicians and instilling faith in AI-supported fetal health evaluation. Banerjee et al. [14] introduced a new method by merging temporal CTG signals with static maternal features under an ensemble framework, resulting in better diagnostic accuracy. Lastly, Kim et al. [15] proposed a multi-stage ensemble model that successively improves predictions at early stage, improving detection rates of possible fetal complications substantially. Together, these studies highlight the enormous potential of ensemble models to revolutionize fetal health classification with increased accuracy, resilience, and dependability in clinical practice.

## III. METHODOLOGIES

Methodology of this research is founded on strict and structured five-stage methodology with inclusion of data collection, cleaning and preprocessing, model selection, model training, and deployment of ensemble algorithm. All of these steps are to attain highest classification accuracy, computing power, and clinical relevance in detecting fetal health outcomes from Cardiotocography (CTG) information.

1) Data Collection: The data utilized in this study were taken from publically accessible medical databases that contained enormous CTG recordings. The data are fetal heart rate (FHR) patterns and uterine contractions (UC) signals, which were labelled by medical professionals into three classes:
   Normal, Suspect, and Pathological. The data was separated into training, validation, and test sets at a ratio of 80:10:10 to enable accurate model evaluation and prevent overfitting.
2) Data Cleaning and Preprocessing: Raw CTG data can contain noise, outliers, and missing values, which can adversely impact model performance. Statistical imputation (mean/median) was used to replace missing values, and outliers were handled appropriately. Numerical variables were normalized to a standard scale of 0 to 1 to facilitate stable and effective learning. Class imbalance was also addressed using Synthetic Minority Over-sampling Techniques (SMOTE), which stabilizes the representation of the minority class and allows the model to learn patterns more effectively.

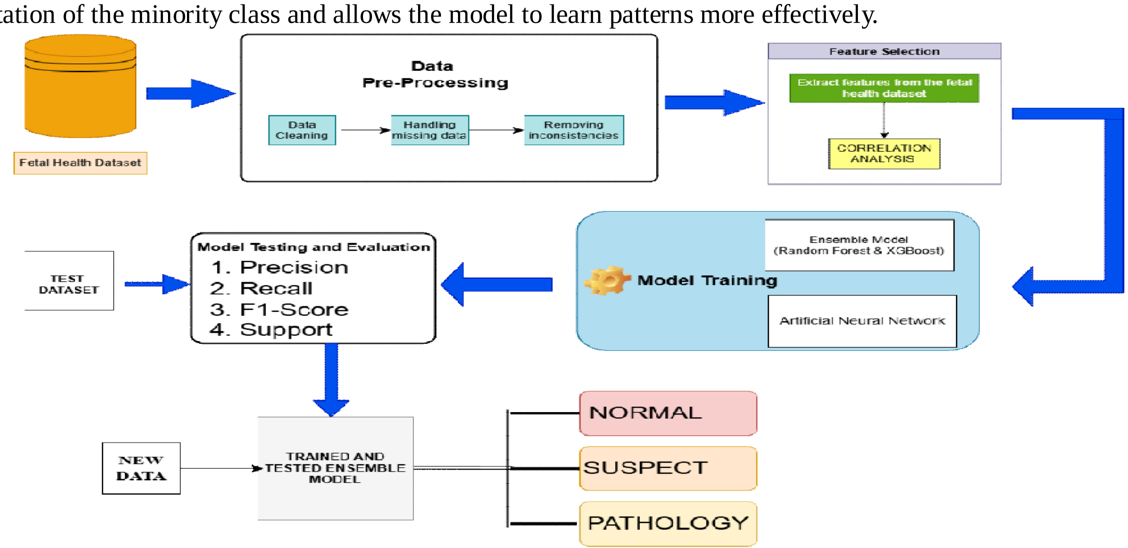


Fig 1: System Architecture

3) Model Selection: The study applies an ensemble learning method by combining the strength of two strong classifiers: Random Forest and XGBoost. Random Forest brings in strength with more than one decision tree, and overfitting is well taken care of by the model. XGBoost, with the gradient boosting algorithm, offers accuracy at a very high level and takes care of intricate data interactions. Both models were selected for their proven ability to deal with structured healthcare data.
4) Model Training: The models were trained with hyperparameters computed by grid search and cross-validation. Training was performed in varying iterations for increasing accuracy, precision, recall, and F1-score. Early stopping techniques were also employed to prevent overfitting and observe that the model generalizes properly with new data. Performance was monitored during the process, and models were evaluated on the held-out validation set.
5) Ensemble Algorithm Implementation: For even better model stability and prediction performance, ensemble methods such as weighted averaging and majority voting were applied to combine Random Forest and XGBoost's predictions. The ensemble method combines the strengths of both models to create more stable and accurate fetal health classification. SHAP (SHapley Additive exPlanations) interpretation tools were also used to provide feature influence on prediction analysis to allow transparent and clinically reliable outputs.
6) Evaluation Metrics: To critically assess the performance of the ensemble model, a number of evaluation metrices were used. The metrics provide an adequate sense about the classification capacity of the model, especially with respect to the significance of fetal health predictions. The most important metrices are:

- Accuracy: It assesses the overall accuracy of the model's prediction for all classes.
- Precision: This measures the model's ability to correctly classify positive cases, extremely important for limiting false positives of severe health conditions.
- Recall (Sensitivity): This measures the model's ability to detect all correct positive cases, avoiding the chance of overlooking pathological cases.
- F1-score: It is harmonic mean of recall and precision, providing a balanced measure for class datasets with skewed classes.
- Confusion Matrix: Gives a complete view of true positives, true negatives, false positives, and false negatives in order to visualize model performance between categories.

Algorithms Employed:

- Random Forest Classifier: Random Forest is an ensemble learning algorithm that builds several decision trees and combines their predictions for strong classification. Random Forest is appropriate for dealing with complex and unbalanced datasets such as CTG data since it minimizes variance and overfitting. It also offers feature importance scores, assisting in the identification of the most significant attributes used in fetal health prediction, e.g., baseline fetal heart rate, uterine contractions, and accelerations
- XGBoost(Extreme Gradient Boosting): XGBoost is a fast gradient boosting algorithm for high-performance boosting. In fetal health classification, XGBoost performs well in identifying complex relationships between cardiotocography signals and fetal condition categories.
- Ensemble Learning Approach(Random Forest + XGBoost): The research suggests a hybrid ensemble model that leverages the strengths of Random Forest and XGBoost. Both model's predictions are combined using techniques such as soft voting or weighted averaging, resulting in improved classification accuracy. The ensemble model provides enhanced generalization, diagnostic dependability, and predictive capability in fetal health classification based on CTG data.

## IV. RESULTS AND DISCUSSION

The performance of the two models, Artificial Neural Network (ANN) and an Ensemble Learning model which comprised Random Forest and XGBoost, was compared for classifying fetal health from CTG data. The two models were assessed based on the metrics of accuracy, precision, recall, F1-score and confusion matrix analysis.

Performance of ANN Model: The ANN model has training accuracy as 91.71% and testing accuracy as 90.44%, which was very satisfactory for learning as well as generalization.

1) Evaluation Metrics: Precision, Recall, and F1-score were pretty high, describing ability of model to handle unbalanced classes of fetal health.
2) Confusion Matrix: The cases were mostly getting classified correctly, but between normal and suspect classes, there used to be little confusion, describing room for improvement.

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Evaluation Metrics Table:

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| NORMAL | 0.07 | 0.07 | 0.07 | 150 |
| SUSPECT | 0.01 | 0.01 | 0.01 | 150 |
| PATHOLOGICAL | 0.00 | 0.00 | 0.00 | 150 |

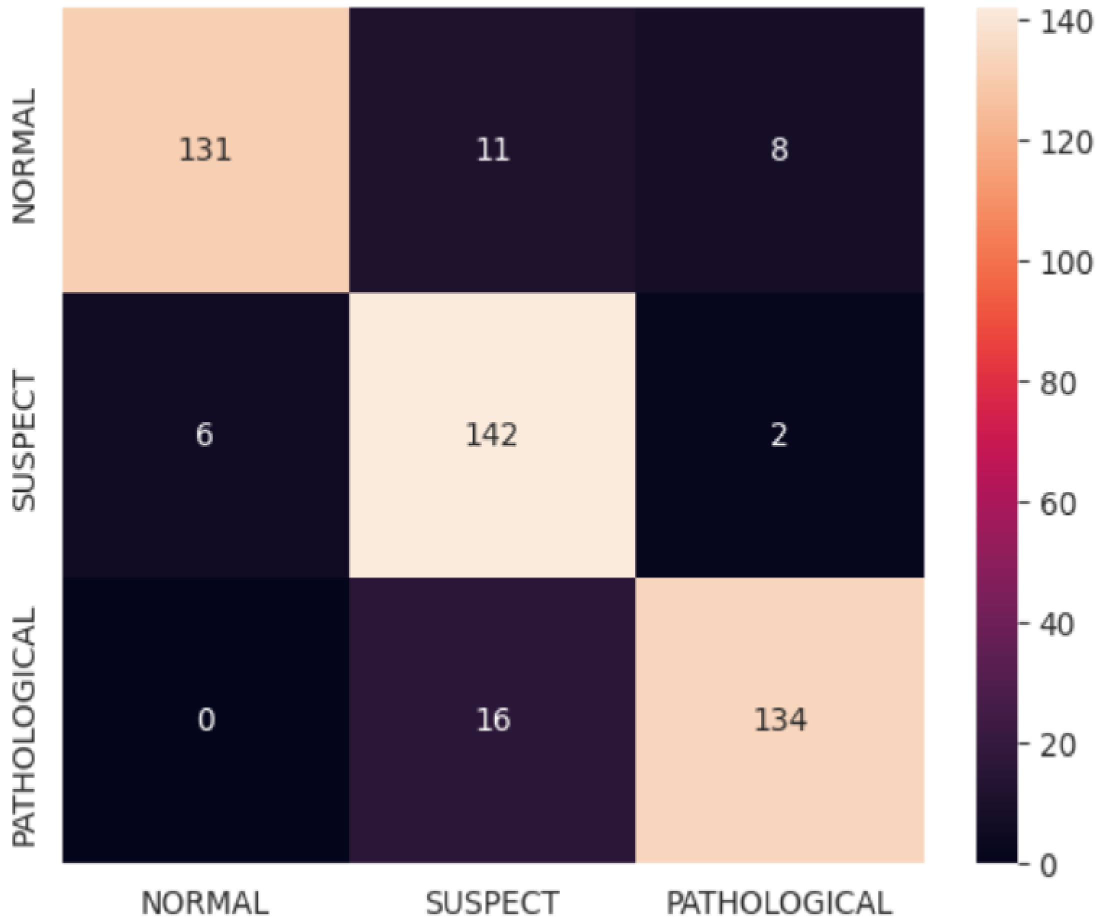


Fig 2: Confusion Matrix of ANN Model

Performance of Ensemble Model: The ensemble model performed better than ANN, achieving 100% perfect training accuracy and 96.67% testing accuracy.

*a)* Evaluation Metrics: Precision, recall, and F1-score were remarkably high, confirming the model's high predictive power.
*b)* Confusion Matrix: The model has excellent classification across all the classes with minimal errors, especially in the key suspect and pathological categories.

Evaluation Metrics Table:

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| NORMAL | 0.99 | 0.93 | 0.96 | 150 |
| SUSPECT | 0.94 | 0.97 | 0.96 | 150 |
| PATHOLOGICAL | 0.97 | 1.00 | 0.98 | 150 |

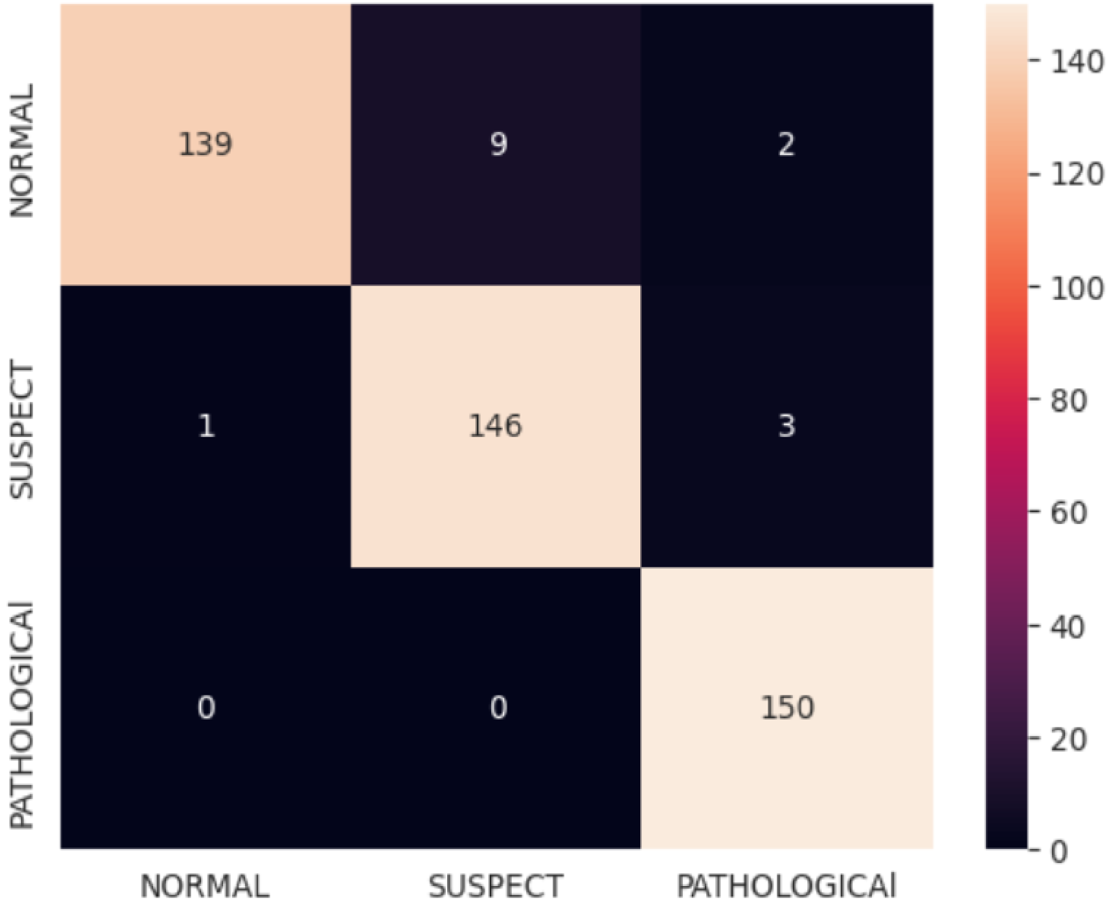


Fig 3: Confusion Matrix of Ensemble Model

## V. CONCLUSION

The research project “Ensemble Learning for improved Classification of Fetal Health based on Cardiotocography Data” was intended to create a precise and trustworthy model for early diagnosis of fetal health status. Understanding the paramount significance of early diagnosis in obstetrics, this study was dedicated to using sophisticated machine learning methods to help medical experts detect possible risks during pregnancy. We started out by carefully exploring CTG data, a universal and non-destructive technique for monitoring fetal well-being. Post careful preprocessing and feature extraction, we applied an Artificial Neural Network (ANN) as well as an Ensemble Model that integrated Random Forest and XGBoost. After through scrutiny, the ensemble method proved the best, reflecting better accuracy along with strong performance on various fronts. Notably, it proved to have the ability to categorize normal, suspect, and Pathological cases with high accuracy, providing reliable assistance in clinical decision-making. Aside from sheer numbers, the project reiterates the revolutionary impact of machine learning in the health sector. By classifying fetal health automatically, the solution for this project helps in early risk identification, presumably lowering fetal mortality rates and enhancing mother care. The research also presents opportunities for future studies in the form of real-time monitoring systems and the incorporation of larger, more extensive datasets for increased accuracy. Finally, the project achieves its purpose in demonstrating how techniques of ensemble learning can be applied to medical diagnostics, providing an effective tool that not only increases the accuracy of fetal health testing but also aids timely medical interventions, leading ultimately to improved healthcare outcomes.

## VI. ACKNOWLEDGEMENT

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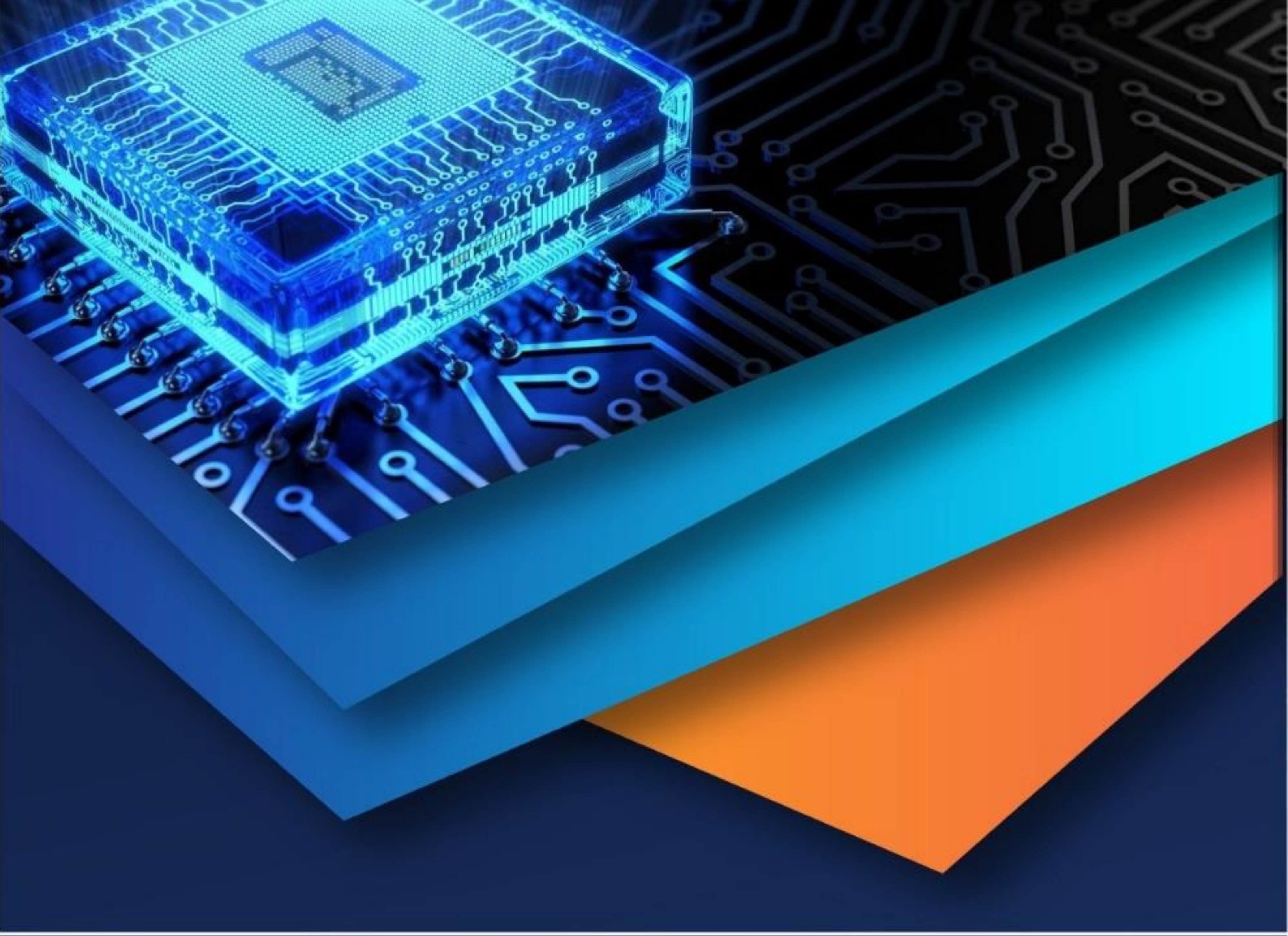


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