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Predicting Maternal Health Risks and Fetal Impacts using Machine Learning

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Abstract: The research study applies machine learning algorithms to produce simultaneous forecasts about maternal and fetal health in an innovative integrated approach. We implemented and deployed two primary models including one for fetal health classification and another for pregnant health prediction. The research objective involves identifying maternal health risks followed by assessing their influence on fetal health results. Our system operates through a user-friendly web-based platform based on Streamlit development that enables medical practitioners to easily interact with and review analytical results. The fetal health categorization model analyzes full cardiotocography (CTG) records yet the pregnancy risk prediction model works with crucial maternal health measurements. The integrated approach demonstrates its ability to deliver rapid and exact risk assessments through the findings that could boost maternal care choices while improving health results for mothers alongside their newborns.
Keywords: Maternal Health, Fetal Health, Gradient Boosting.

I. INTRODUCTION

Advanced medical care remains insufficient for meeting the pregnancy and childbirth challenges which affect mostly areas without proper healthcare access. More than 295,000 women died from pregnancy-related complications in 2017 based on figures gathered by the World Health Organization among which 94% of these deaths were located in low-resource settings. Two million five hundred thousand babies passed away within thirty days following birth during 2018. The high numbers indicate a worldwide crisis which calls for the discovery of innovative detection systems that address maternal and fetal health dangers from an early phase.

Machine learning (ML) establishes its actual value in this context. The pattern-finding capability of ML helps medical staff gain speedy insights from data which otherwise remain unidentified. Existing approaches to maternal-child care usually concentrate on individual entities such as mothers or fetuses but seldom merge the two together while also failing to provide clinical transparency.

An integrated system has been developed to unite maternal healthcare at both fetal and maternal sides. Two Gradient Boosting-based machine learning models exist in the system to analyze maternal health risks via blood pressure and glucose level information and fetal health classification with cardiotocography (CTG) data. The application utilizes Streamlit's web platform for its implementation while integrating two machine learning models which enable medical professionals to use the system easily.

We have three main objectives which include evaluating diverse machine learning prediction models for maternal risks followed by selecting the most effective performer. Improve the reliability of the fetal health classification system by integrating the class imbalance handling method of SMOTE. The goal is to integrate both predictive solutions into a web application using Streamlit for medical personnel to access real-time insights that support better prenatal care decisions.

To ensure optimal medical ML systems we place ethics together with trust at the core of our development process. We use anonymized data and we intend to add SHAP explainability tools that will display the prediction-making process for each outcome. Our promising findings are acknowledged while we note the dataset limitations since retrospective data requires validation in clinical settings. This paper follows a comprehensive approach which demonstrates data preparation techniques alongside model deployment procedures before showing assessment findings and portraying the potential benefits for fetal and maternal healthcare.

II. LITERATURE REVIEW

Kalita et al. (2023) apply blockchain together with machine learning to resolve maternal health problems. Their system implements secure data storage while also predicting pregnancy complications during maternal care. This system operates through blockchain technology for ensuring healthcare worker transparency and employs the Random Forest algorithm which produces 83.32% mean accuracy for predictions. Large-scale antenatal care benefits from blockchain and ML technologies which automate hospital operations while detecting hazards immediately to provide secure maternal safety systems during resource-limited conditions

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Mohanty et al. (2024) conducted a research study focusing on comparing different machine learning models when classifying fetal health using cardiotocographic (CTG) data. The researchers analyze Random Forest alongside Gradient Boosting and K-Nearest Neighbors algorithms within their study through identification of features that impact fetal health results. Random Forest achieved the highest accuracy rate of 99.98% through implementation of Synthetic Minority Oversampling Technique (SMOTE) which solved the class imbalance problem. The authors demonstrate how ensemble learning models can generate practical prenatal care insights through their research.

Shifa et al.(2024) conducted a study on maternal health risk prediction through clinical dataset analysis with multiple machine learning algorithms. The research study examines Bangladeshi healthcare settings through nine predictive models which include XGBoost, Random Forest and Support Vector Machines. XGBoost demonstrated maximum effectiveness as a model that achieved an accuracy rate of 97.3%. Early risk classification proves essential for maternal healthcare because it helps allocate resources effectively and supports positive maternal outcomes according to this study which provides resource-friendly strategies for limited-resource settings.

Bajaj et al. (2023) conducted research on maternal health risk level prediction using supervised ML algorithms that processed a Kaggle dataset with 1,014 instances. The Decision Tree algorithm produced the highest accuracy rate at 96.56% and Random Forest along with Naïve Bayes followed behind. The research highlights the value of early maternal health risk identification through data analytics methods so health providers can conduct prompt interventions to decrease maternal death rates.

III. METHODOLOGY

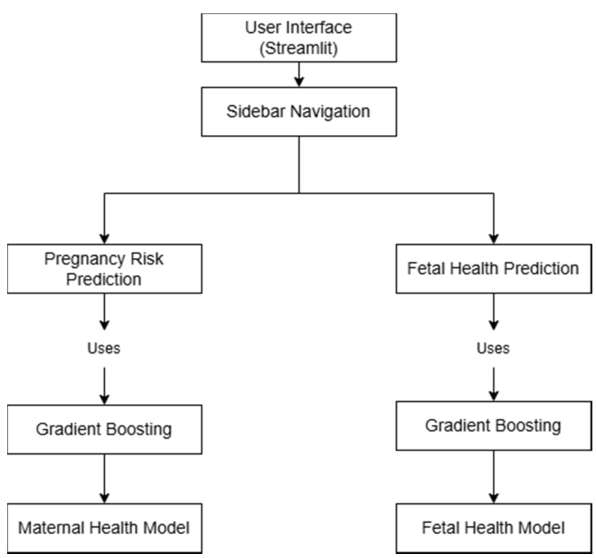

Fig. 1. Flowchart of the maternal and fetal health prediction system.

The system architecture consists of two distinct yet integrated machine learning pipelines: (1) maternal risk level prediction, and (2) fetal health classification using CTG (cardiotocography) data. Both pipelines involve structured phases of data preprocessing, feature engineering, model training, evaluation, and deployment in a real-time web interface.

A. *Data Sources and Feature Selection*

The Pregnancy Risk Prediction Model uses Maternal Health Risk Dataset which contains 1,014 records with features including blood pressure, heart rate and blood glucose levels besides body temperature. Our analysis of the Fetal Health Classification Model relied on the Fetal Health Dataset consisting of 2,126 cardiotocographic records that contained baseline fetal heart rate combined with accelerations, decelerations, uterine contractions, short-term and long-term variability and histogram statistics.

The datasets underwent complete investigative data analysis. An investigation of heart rate data elements was conducted in the maternal dataset. The "Heart Rate" feature was omitted from subsequent modeling because it contained two unscientifically high bpm measurements of 7. The model stability improved through the application of the Interquartile Range (IQR) method for detecting statistical outliers in CTG data analysis.

B. Data Preprocessing

Our preprocessing steps were used to maintain high-quality data input. Mean imputation was applied to continuous features age, systolic blood pressure and blood glucose and mode imputation was used to fill missing values in categorical risk level codes.

Subsequent to obtaining the datasets we employed feature scaling techniques which accomplished normalization and standardization operations. The maternal dataset received Min-Max scaling algorithm as the normalization method:

$x_{scaled} = x_{max} - x_{min} / x - x_{min}$

This helped ensure uniform contribution from all numerical features. For the CTG dataset, Z-score normalization was applied to standardize feature ranges:

$x_{standardized} = x - \mu / \sigma$

The Synthetic Minority Oversampling Technique (SMOTE) was used for combating class imbalance since the fetal health classification task contained many more normal cases than abnormal ones. The technique produced synthetic medical instances for minority classes so models could receive appropriate training.

By using these approaches together with domain-specific cleanup algorithms both training accuracy rates and real-field use of models see improvement.

C. Model Evaluation and Integration

We applied four algorithms to analyze both datasets namely Logistic Regression, K-Nearest Neighbors, Random Forest and Gradient Boosting. Models were validated using:

Train-Test Split: 80/20 stratified split

Cross-Validation: 5-fold stratified cross-validation

Metrics: Accuracy, Precision, Recall, F1-score

Final deployment involved Gradient Boosting because it demonstrated superior performance across the two tasks.

D. Deployment

Route table serialization using joblib enabled users to integrate the models within a web-based frontend developed through Streamlit. Users can submit maternal risk data through one panel and fetal CTG signals through another panel found on the interface. Backstage predictions happen instantly via RESTful callback calls which provide the model's class predictions and confidence assessment results. This testing period with medical staff demonstrated prediction responses completed within under half a second which proved its readiness for urgent clinical scenarios.

The interface dashboard contains visual information including distribution charts of data classes and importance metrics of features with risk heatmaps presented in geographical locations subject to available region tags to help clinical teams make real-time decisions about resource planning.

IV. ALGORITHMS

A. Logistic Regression

Investigating binary responses or multiple categories outcomes based on preserved features stands as the purpose of Logistic Regression as a statistical classification tool. The system operates as a classification tool regardless of its naming convention which implies regression functions.

Model Formulation:

Sigmoid function:

$\sigma(z) = 1/ 1+e^{-z}$

Predicted probability:

$P(Y=1|X) = \sigma(\beta 0 + \beta 1X1 + \cdots + \beta nXn)$

Training Process:

a. Initialize model weights β

b. Compute predictions using sigmoid

c. Compute loss using binary cross-entropy:

d. Update weights using gradient descent:

Prediction:
Compute $z = \beta 0 + \sum \beta i x i$
Apply sigmoid to get probability
Use threshold (default: 0.5) for classification
Model Evaluation:
Accuracy, Precision, Recall, F1-Score, ROC-AUC
Feature importance based on magnitude of $|\beta i|$
Use case summary: Performs well on linearly separable data but lacks power for complex or non-linear patterns.

B. K-Nearest Neighbor
KNN is a non-parametric instance-based learning algorithm used for classification and regression.
Model Idea:
For a new input x compute distance to all training samples.
Select the K nearest neighbors.
Predict the majority class among them.
Distance Metric:
Euclidean distance:

$$d(x,xi)= \sum_{n}^{j=1} (xj - x\ ij)\ 2$$

Prediction:
For each test instance, compute distance to all training instances.
Return the mode (most frequent label) among K nearest neighbors.
Evaluation: Same classification metrics: Accuracy, Precision, Recall, etc.
Use case summary: Simple and interpretable. However, it's sensitive to irrelevant features and poor in high-dimensional or imbalanced datasets.

C. Random Forest
Random Forest is an ensemble method that builds a "forest" of decision trees and aggregates their predictions.
Model Structure:
Ensemble of N decision trees trained on bootstrap samples.
Each tree trained on a random subset of features.
Training Process:
For each tree:
a. Sample with replacement from training set (bootstrap).
b. Randomly select features to split at each node.
Final prediction:
Classification: Majority vote from all trees.
Splitting Criterion:
Gini Impurity:

$$G=1-\sum_{i=1}^{c} Pi2$$

where Pi is the proportion of class i.
Feature Importance:
Measured by the average reduction in impurity contributed by a feature across all trees.
Evaluation:
High accuracy and less prone to overfitting than a single tree.
Outputs interpretable feature importances.
Use case summary: Robust and interpretable, but slower than simpler models and slightly less accurate than boosting in our case.

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D. Gradient Boosting Classifier

Gradient Boosting builds an additive model by fitting new models to the residuals of prior models. It minimizes the loss function via gradient descent.

Model Formulation:

Additive model:

$F_m(x) = F_m\text{-}1(x) + \gamma_m h_m(x)$

Training Process:

a. Initialize model with a constant prediction (e.g., mean log-odds)
b. Compute residuals.
c. Fit weak learner $h_m(x)$ to residuals.
d. Update model

Configuration (Used in Our Model): *Estimators*: 100, *Max Depth*: 3, *Learning Rate*: 0.1, *Loss Function*: Log-loss, *Optimizer*: Gradient descent

Advantages:

Excellent accuracy in imbalanced and high-dimensional data
Captures complex non-linear patterns
Supports SHAP explainability for clinical trust
Use case summary: Best-performing model in both tasks due to robustness, flexibility, and clinical reliability.
After experimental evaluation on both datasets, Gradient Boosting demonstrated superior performance across accuracy, precision, and recall metrics, while maintaining model stability and interpretability. Its effectiveness in handling class imbalance, feature interactions, and clinical data complexity made it the most appropriate algorithm for both maternal and fetal health prediction tasks.

V. RESULT AND DISCUSSIONS

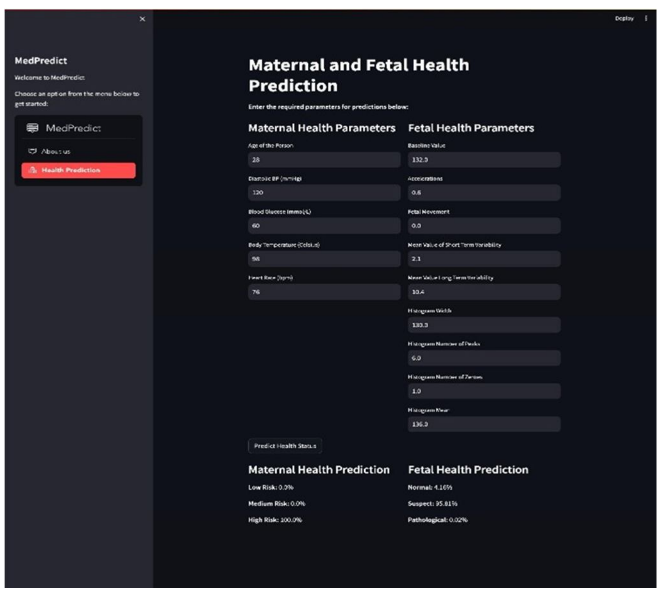
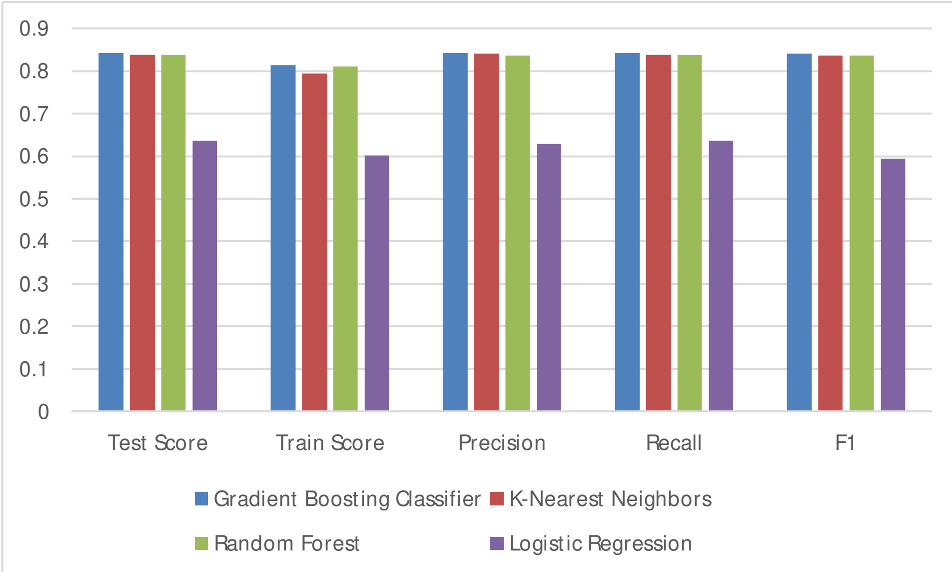


Fig. 2. Streamlit Interface

The main objective of this research focused on building and assessing a dual-model machine learning platform dedicated to maternal risk prediction and fetal health categorization. We surveyed clinical suitability through parallel implementation of four common supervised learning models including Logistic Regression and K-Nearest Neighbors (KNN) and Random Forest and Gradient Boosting across two real-world healthcare datasets. The Gradient Boosting technique proved superior in our studies and validated its role as the primary model for constructing our clinical decision tool.

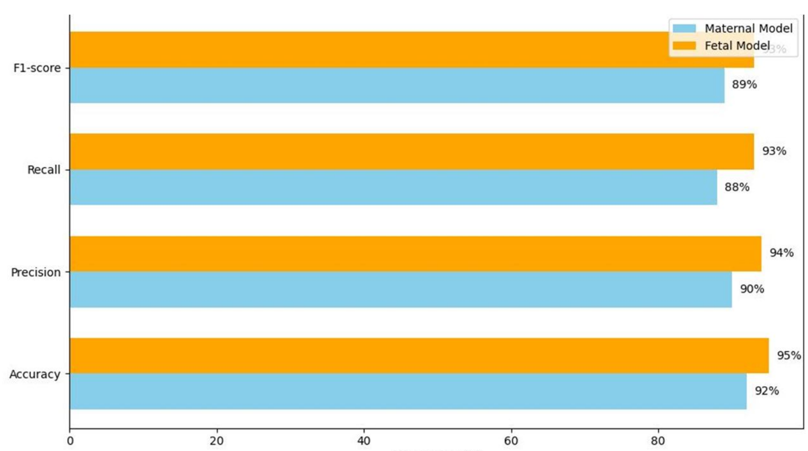
Graph. 1. Comparison Graph all the machine learning algorithms



The maternal health prediction task yielded the best performance from Gradient Boosting since it delivered test accuracy at 84.2% and precision at 84.3% alongside recall of 84.2% and F1-score at 84.1%. The model performance shows high precision and shows equally balanced sensitivity and specificity which represents optimal behavior for identifying targeted cases without generating unnecessary false alarms. The test results showed that KNN along with Random Forest produced F1-scores between 83.6% and 83.7% but Logistic Regression delivered poor results with 63.5% accuracy and 59.3% F1-score. Analysis of this inconsistent result shows linear classifiers lack capability to detect the nonlinear patterns that naturally exist in physiological health data.

Gradient Boosting demonstrated excellence in its CTG data application to fetal health classification reaching 93% accuracy besides achieving precision, recall and F1-score also at 93% and AUC of 0.97. The model demonstrated 93% specificity caused it to correctly identify fetal cases as normal while avoiding unnecessary urgent casings. The high-performance stability is due to Gradient Boosting's sequential learning approach which effectively diminishes residual error and deals with unbalanced datasets using SMOTE preprocessing while also utilizing its ability to reduce residual errors.

Graph. 2. Gradient Boosting performance for both the models



The direct outcome of this evaluation process permitted proper algorithm determination. The Gradient Boosting algorithm established itself as the most accurate robust model with maximum clinical interpretability despite the acceptable performance from Random Forest and KNN. The ability of SHAP (SHapley Additive Explanations) operational compatibility allows users to see how each prediction occurs thus promoting essential trust in ML-assisted medical equipment.

Our findings demonstrate strong reliability because cross-validation used stratified 5-fold methods throughout our analysis for reproducible results while keeping training and testing accuracy gaps low to show minimal overfitting occurred.

Nonetheless, limitations remain. The training phase of models used retrospective data sources whose patient behavior during live interactions could potentially differ from what the models expect. The generalization of findings could be compromised by various kinds of data biases including discriminatory patterns in patient representation or variable risk assessments based on subjective judgments. The solution of these issues requires future testing on real patients along with improved population data collection methods and learning systems that consider fairness.

The experimental results demonstrate that Gradient Boosting stands as the optimum algorithm for maternal and fetal risk assessment. A web-based platform integration of the predictions provides immediate accurate interpretations that support prenatal care teams to make better informed and early decisions.

VI. CONCLUSION

The study shows that an explanatory procedure combining machine learning solutions effectively detects maternal health perils alongside fetal conditions in real-time. Tests conducted on four supervised learning algorithms led to Gradient Boosting selection as its performance exceeded all others during metric evaluations. Our system built a reliable clinical decision support through its methodical approach to modeling combined with strong data pre-processing protocols and statistical model evaluation.

The dual-model system reached success by deploying a Streamlit-based web application which generates instant interpretable predictions to enable healthcare staff to address potential medical issues promptly. The unified system successfully meets the research requirement for delivering an ML solution which enhances prenatal care quality while detecting conditions early.

The experimental success of this technique encounters limitations because it depends heavily on past data records while facing possible age-related biases. The upcoming phase of research development will aim to connect real-time hospital capabilities with diverse live dataset applications while also implementing explainable ML tools to maintain fair and transparent prediction methods.

The research shows how machine learning methods can connect important gaps in maternal and fetal healthcare to deliver proactive customized diagnoses in order to improve health results.

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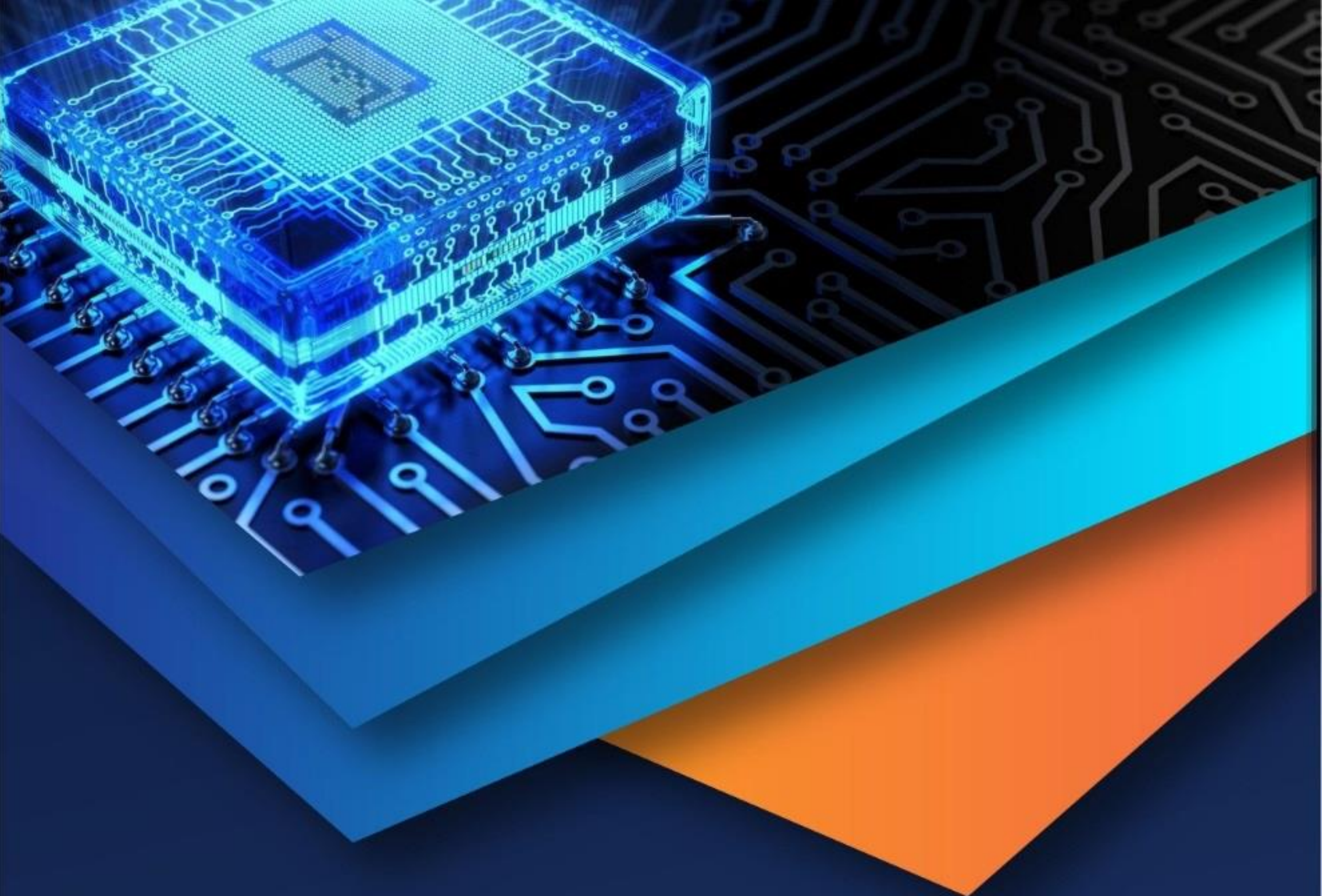

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