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Failure Detection of Aircraft Engine using Machine Learning Techniques

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Abstract: Predictive maintenance lets you estimate when machine failure will occur. This way, you can plan maintenance in advance, better manage inventory, eliminate unplanned downtime, and maximize equipment lifetime Knowing the predicted failure time helps you find the optimum time to schedule maintenance for the equipment. Predictive maintenance not only predicts a future failure, but also pinpoints problems in your complex machinery and helps you identify what parts need to be fixed. This type of maintenance uses various machine learning algorithms to predict the failure. In this paper a study has been done using various machine learning algorithms the existing dataset of aircraft engine were obtained from C-MAPSST (Commercial Modular Aero propulsion System Simulation). With the data obtained MATLAB was used to classify the data into four labels and to train and verify with the test data. Accuracy and RMSE of various algorithms were predicted. Comparison was done to obtain maximum accuracy and minimum RMSE values.
Keywords: RMSE; Machine Learning algorithms;MATLAB

I. INTRODUCTION

Aircraft engines are the most complex systems in the world. An aircraft engine is a component of the propulsion system for an aircraft that generates mechanical power. Aircraft engines are almost always either lightweight piston engines or turbines engines in use on today's turbine-powered with fuel and combustion are very reliable.

Aircraft engines in the current days operate efficiently with regularly scheduled inspections and maintenance. These units can have lives ranging in the thousands of hours of operation. However, engine malfunctions or failures occasionally occur that require an engine to be shut down in flight. Since multi-engine airplanes are designed to fly with one engine inoperative and flight crews are trained to fly with one engine inoperative, the in-flight shutdown of an engine typically constitutes a serious safety of flight issue. The failure of these engines leads to catastrophic disasters hence the maintenance of these engines is basic step for the safety. There are different types of maintenance reactive maintenance, preventive maintenance, predictive maintenance. Reactive maintenance mainly describes maintenance and repairs are done only after machine fails. Preventive maintenance tries to prevent failure by performing regular checks. Predictive maintenance helps to estimate remaining useful time. In this paper the data obtained from various sensors are classified into four labels according to the remaining useful time that is very short, short, medium, long. The model is trained with various machine learning algorithms and the accuracy of prediction of the various described time cycles of four labels is done.

II. METHODOLGY

The methodology describes the model flow with various steps involved each step-in detail starting from the acquisition to processing of data. This section also explains in detail about different machine learning algorithms used for the prediction

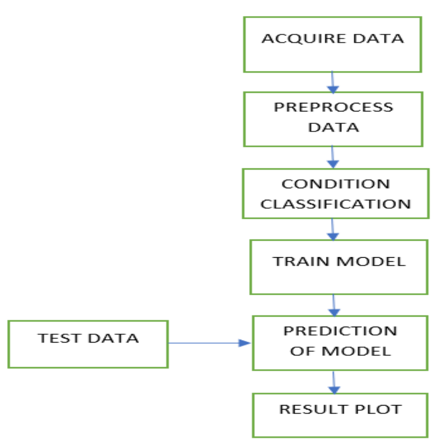

Fig. 1. Flowchart of the model

A. Data

The dataset is obtained from the C-MAPSST (Commercial Modular Aero-Propulsion System Simulation). This dataset includes various sensor data from aircraft engines throughout their usage cycle. The data is divided into training and test set. The training set has trajectories that ends at the cycle in which the failure occurs for each engine. The test set also has trajectories but ends at the cycle prior to the failure. The number of additional cycles till failure occurs for each engine in the test set is given by a separate file.

Sl no	Description
1.	LPressure Outlet Temp
2.	HPressure Outlet Temp
3.	Phys Fan Speed
4.	Phys Core Speed
5.	Fuel Flow Ratio
6.	Core Fan Speed
7.	Static HPC Outlet Pressure

Table 1. Sensor data

B. Preprocess of the data

In the data preprocess the various sensor data is extracted and the and the variable names are set in the raw data according to the sensors. The classification is done on the dataset considering the remaining useful time. The classified labels are very short, short, medium, long.

Label	No of cycles
Very short	0-50
Short	50-100
Medium	100-200
Long	>200

Table 2. Classification

C. Simulation Setup

MATLAB was used as the tool for training the model. The dataset file was accumulated into the workspace and read through the inbuilt functions. In MATLAB it is easy to apply different algorithms and generate the result.

D. Machine Learning Algorithms

The following machine learning algorithms were used for prediction. The various classifier type models of decision tree has fast prediction speed, small memory usage and interpretability as easy.

1) *Decision Tree*: A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements

a) *Fine Tree*: It is a different classifier type model under decision tree, the model flexibility is high . It has many leaves to make fine distinctions between classes. It has maximum number of splits of 100. It has easy interpretability style.

b) *Medium Tree*: It is a different classifier type model under decision tree, model flexibility is medium. It has medium number of leaves for finer distinction between classes. It has maximum number of splits of 20.

c) *Coarse Tree*: It is a different classifier model under decision tree with model flexibility small. It has few leaves to make coarse distinction between classes. It has maximum number of splits is 4.

2) *Support Vector Machine:* The SVM's are the learning models with associated learning algorithms that are very much used to analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier.

a) *Linear SVM:* It is a classifier type of SVM with prediction speed of multi class and memory usage is medium. It has a very less model flexibility, uses simple linear separation between classes.

b) *Quadratic SVM:* It is a classifer type of SVM with slow multi class prediction speed and large memory usage.It has medium model flexibility.

c) *Fine Guassian SVM: It is a classifier type of SVM with slow multi class prediction speed and medium memory usage. It has high model flexibility.*

3) *KNN:* It is a non-parametric method and instance based learning used for classification and regression. In both the cases input consists of the k closest training examples in the feature space. The output depends on whether the k-NN used for classification or regression. In this paper it is used for classification.

a) *Fine KNN:* It has finely detailed distinctions between classes. The number of neighbors is set to 1.

b) *Medium KNN:* It has medium distinctions between classes. The number of neighbors is set to 10.

c) *Coarse KNN*: It has Coarse distinctions between classes. The number of neighbors is set to 100.

III. RESULT

Training and evaluation of the Machine Learning Model was done for algorithms described in methodology section. The scatter plot has been plotted for KNN algorithm for each of the sensor values. The Decision tree and Support Vector Machine algorithms are used to plot actual vs predicted and Response plot for each of the sensor values. The data consists of a single aircraft engine. The plotted sensor data are standardized irrespective of their units.

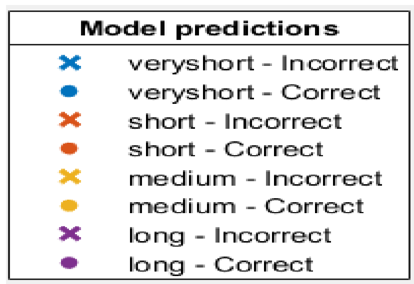

Fig. 2. Model predictions

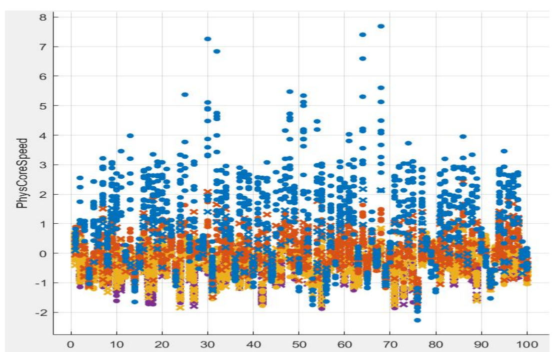

Fig. 3. PhysCoreSpeed vs unit

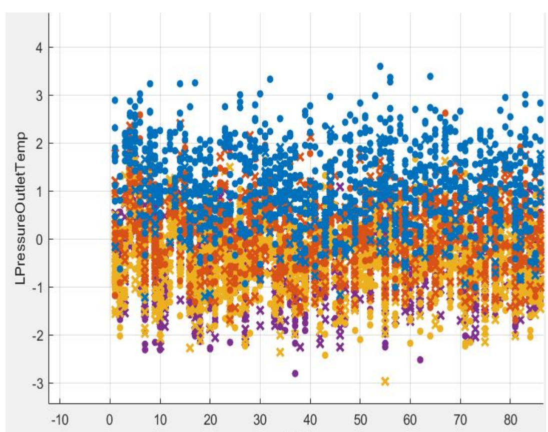

Fig. 4. LPressureOutletTemp vs unit

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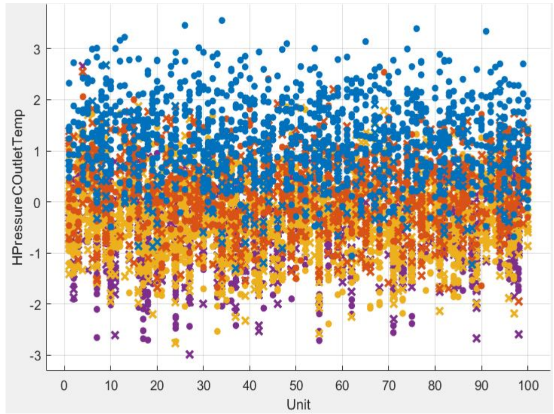

Fig. 5. HPressureOutletTemp vs unit

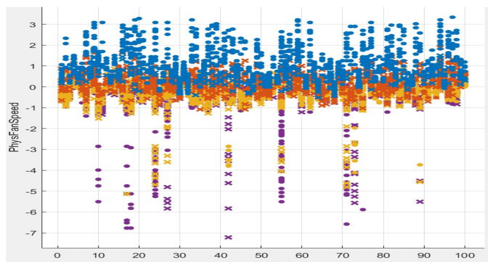

Fig. 6. PhysFanSpeed vs unit

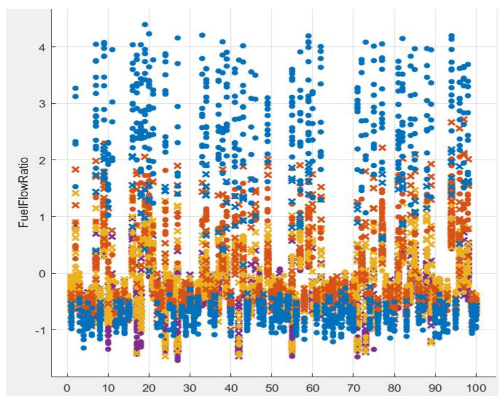

Fig. 7. FuelFlowRatio vs unit

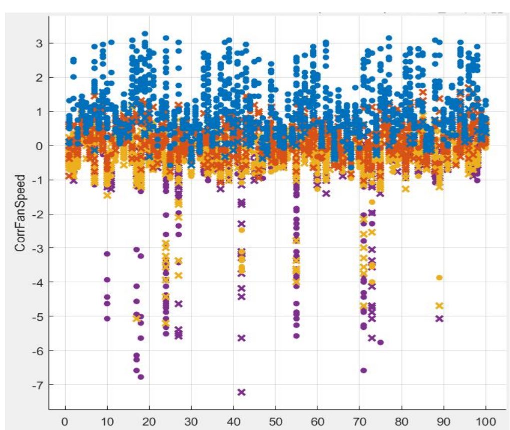

Fig. 8. CoreFanSpeed vs unit

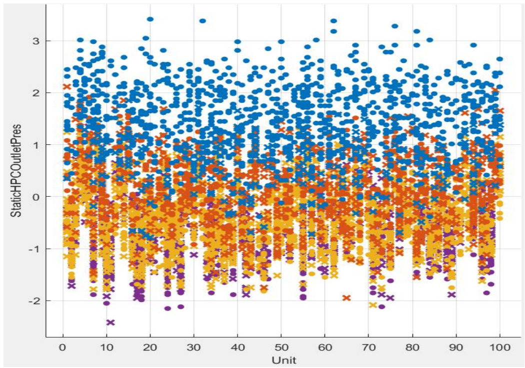

Fig. 9. StaticHPCOutletPres vs unit

The various sensors are prediction scatter plots of fine KNN algorithm on test data. All the sensor data is standardized.

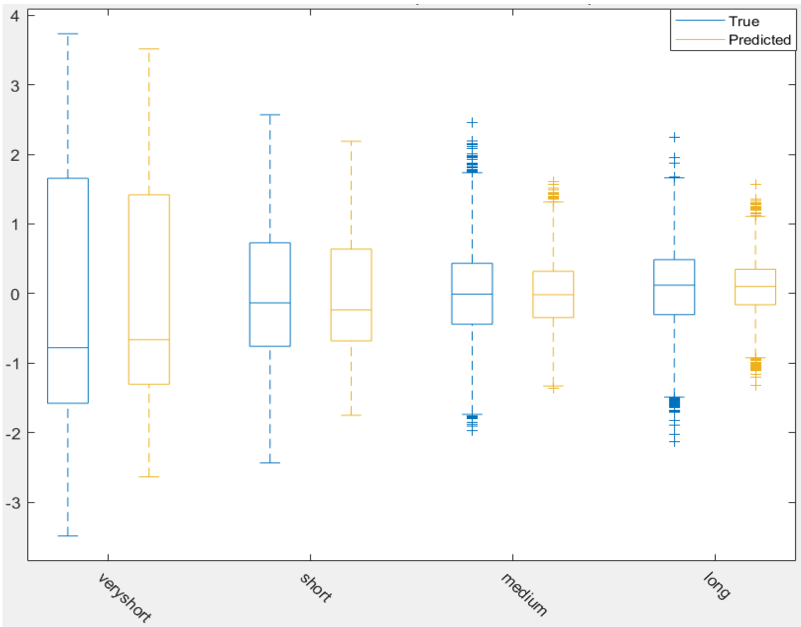

Fig 12 Response vs Label (Fine Gaussian SVM)

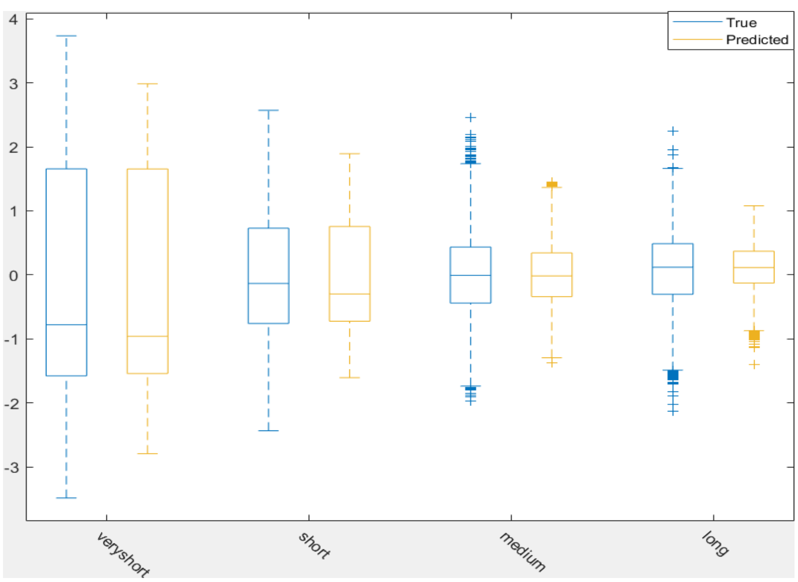

Fig 13 Response vs Label (Quadratic SVM)

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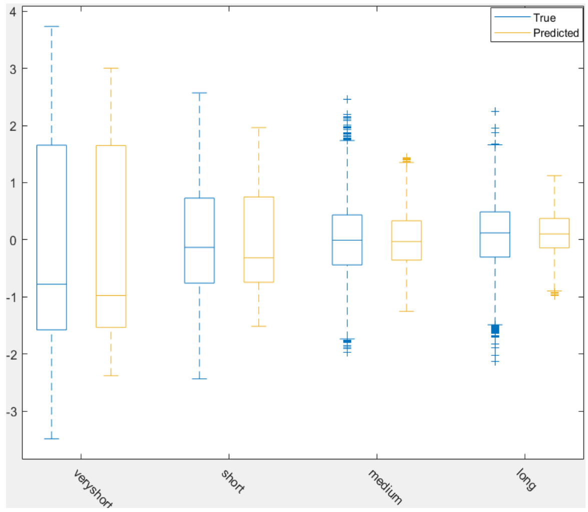

Fig 14 Response vs Label (Linear SVM)

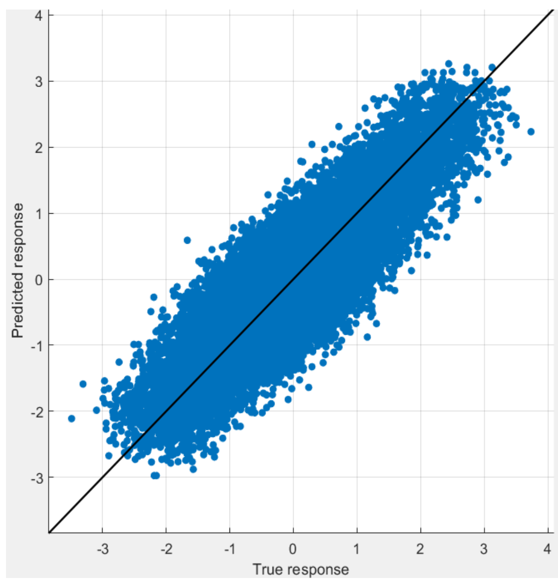

Fig. 15. Predicted vs Actual response (Fine Tree)

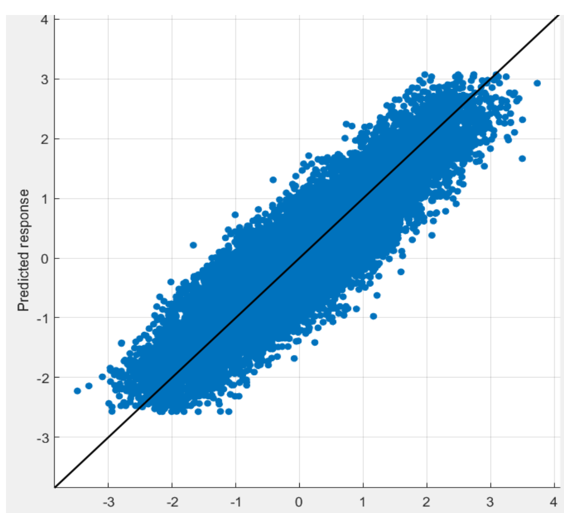

Fig. 16. Predicted vs Actual response (Medium Tree)

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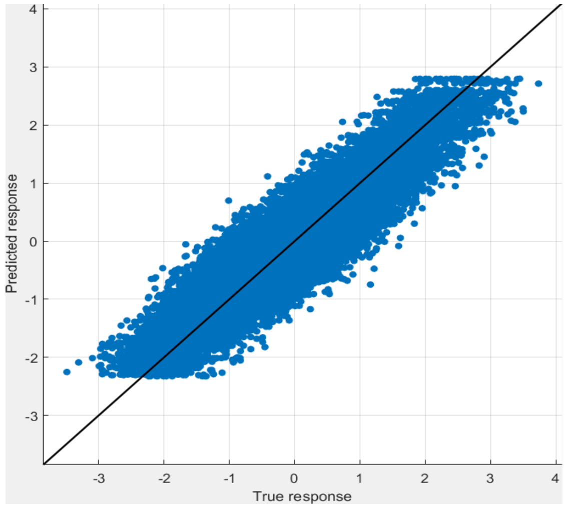

Fig. 17. Predicted vs Actual response (Coarse Tree)

The scatter plots help us to identify how good the model predicts for various labels and the accuracy depicts its performance factor. A perfect regression model has a predicted response equal tSo the true response, so all the points lie on a diagonal line. The vertical distance from the line to any point is the error of the prediction for that point. A good model has small errors, and so the predictions are scattered near the line. Predicted vs actual response is plotted different for Tree algorithms. In SVM algorithms a box plot is made as model predictions. A box plot displays the typical values of the response and any possible outliers. The central mark indicates the median, and the bottom and top edges of the box are the 25th and 75th percentiles, respectively. Vertical lines, called whiskers, extend from the boxes to the most extreme data points that are not considered outliers. The outliers are plotted individually using the '+' symbol.

Algorithms	Accuracy (%)
Fine Tree	66.3
Medium Tree	62.6
Coarse Tree	54.7
Linear SVM	65.0
Quadratic SVM	66.4
Fine Gaussian SVM	65.0
Fine KNN	60.6
Medium KNN	66.7
Coarse KNN	67.5

Table 3. Accuracy of Algorithms

Algorithms	RMSE (0-1)
Fine Tree	0.53173
Medium Tree	0.47249
Coarse Tree	0.43332
Linear SVM	0.41251
Quadratic SVM	0.41301
Fine Gaussian SVM	0.50524

Table 4. Root Mean Square Error Values

IV. DISCUSSION

The main objective was to handle big dataset and train the model with different machine learning algorithms and also to check their performance, two factors were considered accuracy and RMSE. The performance was almost constant with slight variation. This reduces great deal of loss and improves the efficiency and cost.

V. CONCLUSION AND FUTURE SCOPE

Predictive analytics solutions analyze historical and current data to understand various objectives and identify potential opportunities and risks. This results in analyzing patterns and providing meaningful insights, helping organizations in adding more value to their offerings and ensuring safety experience. Predictive maintenance can mine critical asset data and identify anomalies or deviations from their standard performance. Such insights can help discover and proactively fix issues days, weeks or even months before they lead to failures. This can help avoid unplanned downtime, reduce industrial maintenance overspend, and mitigate safety and environmental risks.

It uses predictive analytics and machine-learning algorithms based on historical and real-time data to identify specific issues on the horizon. Often these issues won't be showing any physical signs of degradation – even a sharp human eye or an intuitive and well-trained maintenance technician wouldn't be able to catch them. In near future predictive maintenance would be very useful for big data and safety driven industries

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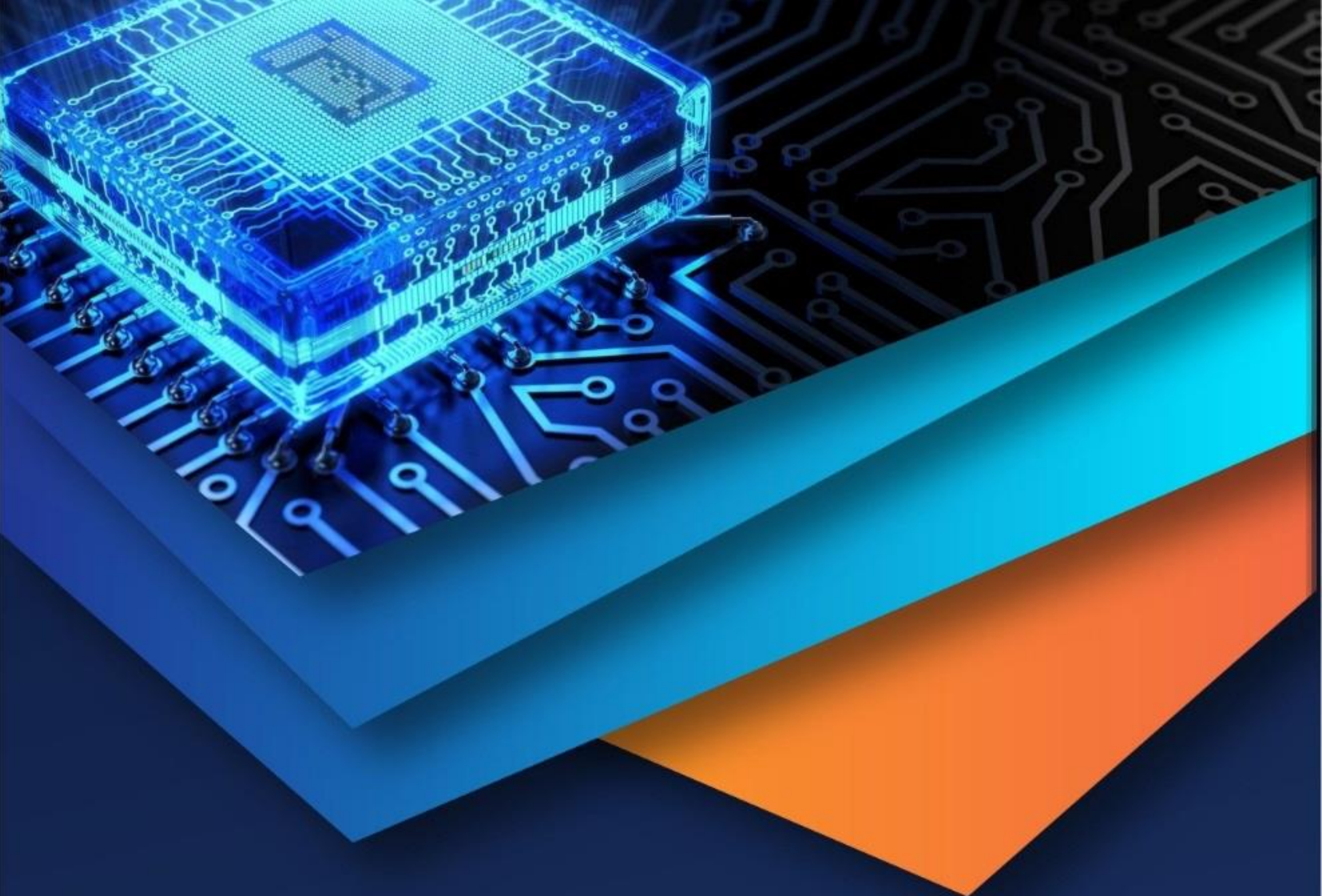

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