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Wind Power Analysis Using Machine Learning in Wind Turbines

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Abstract: In order to effectively estimate how energy production and consumption will develop and change, this research suggests a new neural network prediction method. The authors concentrate on well-known techniques that can manage a vast volume of data and utilize machine learning to combine results from numerical weather prediction models with local observations. The importance of accurate energy consumption prediction in promoting energy conservation is highlighted, along with the nonlinear correlation between lighting energy usage and its influencing factors. Support vector regression with radial basis function is shown to outperform neural networks in terms of forecasting accuracy for lighting energy consumption. In summary, accurate energy consumption prediction is crucial for energy conservation and SV regression with radial basis function is a more effective tool for achieving this compared to neural networks. The study offers a thorough method for projecting energy production and consumption that can assist in addressing the escalating conflict between energy and the environment.
Index-Terms: Machine Learning, SVM, Random Forest Regression

I. INTRODUCTION

The development of data-driven models for predicting wind farm power has attracted due to the growing amount of data available from simulations and experiments. Although the data-driven models can accurately predict the power of a wind farm with characteristics like those in the training ensemble, they typically lack a high degree of flexibility for extrapolating to an untested case. The demand for energy production and consumption has consistently increased in alignment with economic growth. This research paper establishes a novel prediction approach using neural networks by integrating energy production and consumption. By leveraging statistical data from the energy industry, the proposed method accurately forecasts the evolution and fluctuations of energy production and consumption. This prediction system addresses the challenges posed by global energy supply pressures and the escalating concerns surrounding energy and environmental issues.

To combine results from numerical weather prediction models with local observations, we use machine learning. While the latter gives the model more recent and site-specific data, the former offers useful information on higher-scale dynamics. We focus on well-established techniques that can handle a large amount of data to make the results practical for practitioners. We investigate first-variable selection using a nonlinear approach as well as a linear approach. The accuracy of neural networks' prediction method is shown by numerical results. The important task is that energy conservation is the prediction for energy consumption. Support vector regression has been frequently used to forecast building energy consumption in recent years due to its success in addressing non-linear data regression issues.

II. EXISTING SYSTEM

Wind turbines play a vital role as a sustainable and efficient source of renewable energy, offering numerous advantages such as zero carbon emissions. However, effectively monitoring wind farms and accurately predicting their electricity generation poses challenges due to the unpredictable nature of wind speed. Consequently, the management team faces difficulties in efficiently planning energy consumption. To tackle this issue, our proposed solution leverages a cloud-based architecture of digital twins, coupled with the G-Next Generation Radio Access Network (G-NG-RAN), to enable virtual monitoring of wind turbines. By developing a predictive model, we aim to anticipate wind speed and forecast the power generated, providing valuable insights for effective energy planning. The developed model utilizes Microsoft Azure's platform for the creation of three-dimensional digital twins. Our predictive model incorporates a non-parametric k-nearest neighbors (KNN) regression method combined with a deep learning approach called a temporal convolution network (TCN). The predictive modeling process is divided into two main components. Firstly, it analyzes the univariate time series data of wind speed to forecast its future values. Secondly, it predicts the power generation for each quarter of the year, ranging from weekly to monthly intervals. To evaluate the effectiveness of our framework, we conducted tests using publicly available datasets specifically designed for onshore wind turbines. The results obtained demonstrate the applicability and effectiveness of our proposed framework, outperforming traditional prediction models.

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III. PROPOSED SYSTEM

Due to the emergence of the energy crisis and growing environmental concerns, there has been a significant transformation in the landscape of energy consumption over the past few years. With the rising share of renewable energy sources and a decline in non-renewable resources, accurate estimation of the energy structure has become crucial for cities to formulate effective development strategies. In this paper, a novel approach is proposed to enhance the prediction model for energy structure using machine learning (ML) techniques. By incorporating additional constraints derived from energy demand projections and future energy plans, the model aims to provide more accurate predictions. The relationship between the energy structure and the influencing variables is intricate and challenging to establish accurately. To address this complexity, machine learning (ML) techniques are employed to analyze historical data on energy consumption structure and extract trends. By leveraging ML theory, the study aims to unravel the intricate connections between the influencing factors and the energy structure. This research suggests a model-based approach to forecasting electrical energy consumption. Energy consumption prediction is an important task for energy trading organizations. Because the accuracy of the prediction is directly related to the business's success, it should be as precise as possible. In this study, we compare an evolving ML model to an adaptive linear model for predicting energy usage. The support vector machine (SVM) approach involves utilizing a kernel function to establish a non-linear association between the input and output variables, thereby transforming the input space into a higher-dimensional feature space. This enables SVM to effectively model complex relationships between the input and output variables. By reducing structural risk, the model's generalization ability can be improved to produce sound statistical laws even when there are fewer input samples. Support vector regression is useful because it can find the best overall solution to a non-linear situation. While the support vector regression (SVR) model is capable of modeling complex relationships between input and output variables, its performance is heavily influenced by hyperparameters such as the variance of the kernel function and the penalty factor C. Thus, a crucial challenge is to determine these hyperparameters in a reliable and scientifically sound manner to optimize the performance of the SVR model. As a result, the optimization algorithm must be added to the hyper-parameter search process.

IV. ARCHITECTURE DIAGRAM

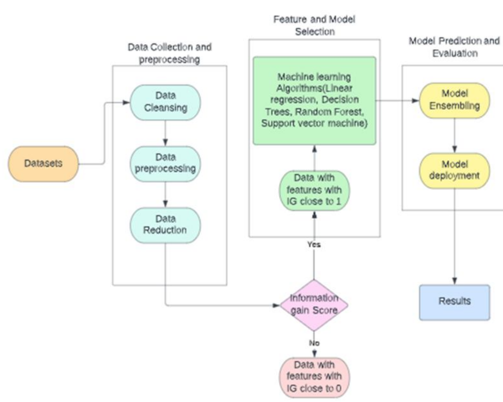

Fig 1. Architecture Diagram

V. MODULE DESCRIPTION

A. Data Preprocessing

Machine learning model validation processes are critical for determining their error rate, which is critical in ensuring that the model's performance is as close to the real error rate of the dataset as possible. Validation processes may not be required if the dataset is large enough to be representative of the population. Working with data samples that are not totally typical of the dataset's population is prevalent in real-world circumstances.

To overcome this problem, data subsets are utilized to modify the hyperparameters of the model while providing a neutral evaluation of the model's fit on the training dataset. These subsets are used to find duplicate values, missing values, and data types like integers and floats. The model's hyperparameters can be modified to increase its accuracy and overall performance by carefully picking the proper subset of data.

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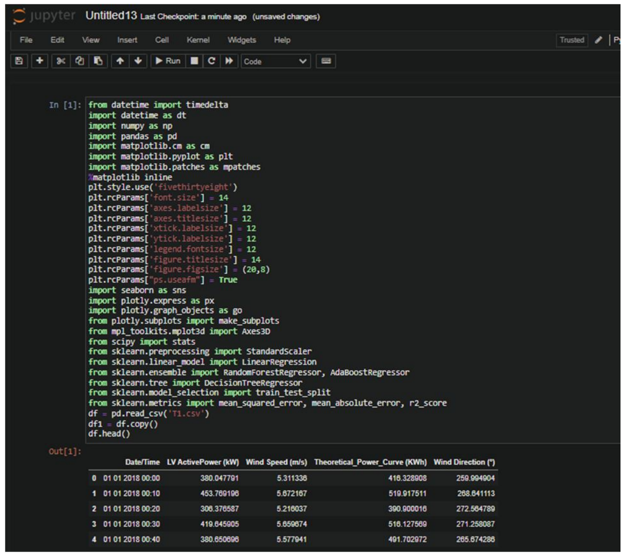
We began by importing the necessary libraries and the dataset. We made use of panda library to read the data from a csv file. After reading the data, we checked for missing values and duplicates, and then converted the "Date/Time" column to a datetime data type. We also added a "Month" column to the data frame.



jupyter Untitled13 Last Checkpoint: a minute ago (unsaved changes)

In [1]:

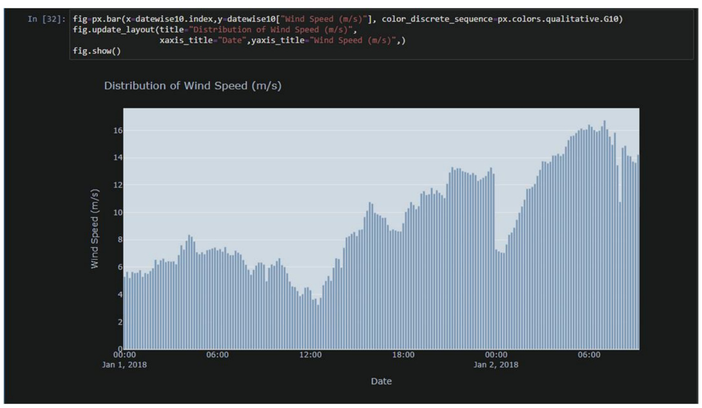
```
from datetime import timedelta
import datetime as dt
import numpy as np
import pandas as pd
import matplotlib.cm as cm
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
%matplotlib inline
plt.style.use('fivethirtyeight')
plt.rcParams['font.size'] = 14
plt.rcParams['axes.labelsize'] = 12
plt.rcParams['axes.titlesize'] = 12
plt.rcParams['xtick.labelsize'] = 12
plt.rcParams['ytick.labelsize'] = 12
plt.rcParams['legend.fontsize'] = 12
plt.rcParams['figure.titlesize'] = 14
plt.rcParams['figure.figsize'] = (20,8)
plt.rcParams["ps.useafm"] = True
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from mpl_toolkits.mplot3d import Axes3D
from scipy import stats
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
df = pd.read_csv('T1.csv')
df1 = df.copy()
df.head()
```

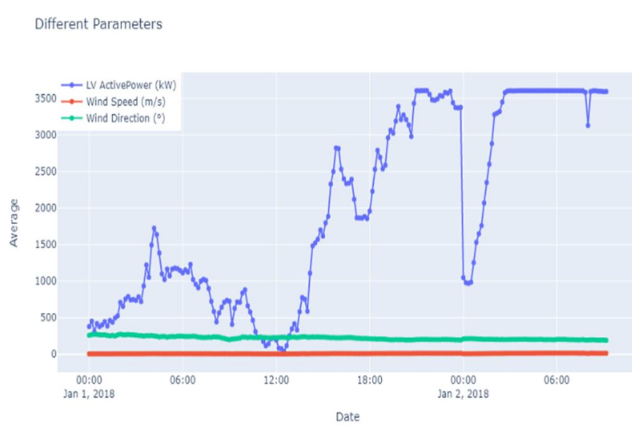
Out[1]:

	Date/Time	LV ActivePower (kW)	Wind Speed (m/s)	Theoretical_Power_Curve (KWh)	Wind Direction (°)
0	01 01 2018 00:00	380.047791	5.311336	416.328908	259.994904
1	01 01 2018 00:10	453.769196	5.672167	519.917511	268.641113
2	01 01 2018 00:20	306.376587	5.216037	390.900016	272.564789
3	01 01 2018 00:30	419.645905	5.659674	516.127569	271.258087
4	01 01 2018 00:40	380.650696	5.577941	491.702972	265.674286

1) Exploratory Data Analysis

EDA is carried out for the gain insights into the dataset. We used various visualization techniques to explore the relationships between different features of the data. We plotted histograms, scatter plots, box plots, and heat maps. We used seaborn and matplotlib libraries for data visualization.





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B. Feature and Model Selection

The technique of picking a subset of the variables being used that are most relevant to the variable in question (that we desire to predict) is known as feature selection. The variable we want to forecast is referred to as the target variable. We shall assume for the sake of this essay that we only have numerical variables as inputs and a numerical target using regression predictive modelling. We can readily estimate the connection between every input variable and the target variable if we assume this. Correlation measures how two variables evolve in tandem. Pearson's correlation is the most used correlation measure, which assumes a distribution that is Gaussian for each variable and discovers a linear relationship among numerical variables.

You can specify the characteristics (or predictors) to include in the model in Regression Learner. Examine whether you can enhance models by eliminating features with low predictive power. If data gathering is costly or difficult, you may prefer a model that performs well with fewer predictors.

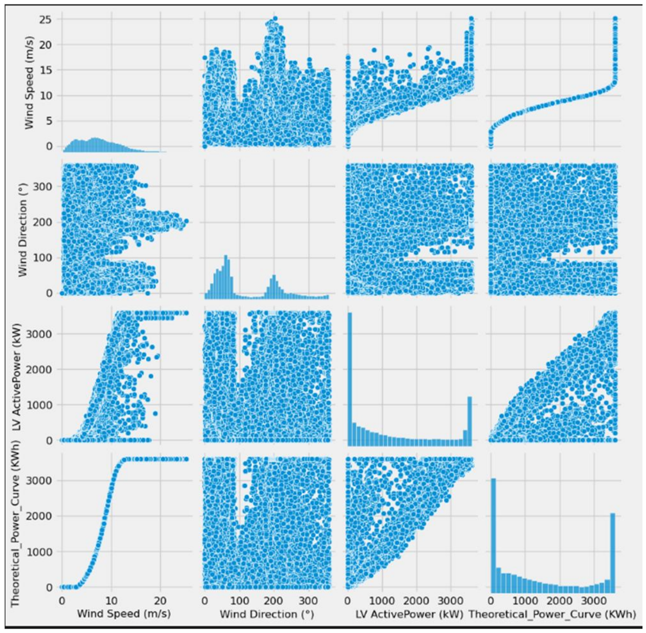
C. Model Prediction & Evaluation

1) Random Forest Regression

Bootstrapping is a resampling technique that involves selecting subsets of a dataset randomly and repeatedly, which is then used to derive a more robust outcome through averaging. This approach exemplifies the concept of ensemble modeling, where multiple models are combined to improve accuracy. One such example is the bootstrapping Random Forest, which utilizes the decision tree framework to generate multiple randomized decision trees from the data, and then aggregates the outcomes to obtain a more reliable prediction. In supervised learning, RF Regression is an ensemble learning method that employs multiple machine learning algorithms to generate a more accurate prediction compared to a single model. It is important to note that when using information from external sources, it is essential to avoid plagiarism and properly cite the original source.

```
In [43]: X = df[['Wind Speed (m/s)', 'Wind Direction (°)', 'Theoretical_Power_Curve (KWh)']]

In [44]: y = df['LV ActivePower (kW)']

In [45]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

In [46]: regr = RandomForestRegressor(max_depth=10, random_state=0)

In [47]: regr.fit(X_train, y_train)
Out[47]: RandomForestRegressor(max_depth=10, random_state=0)

In [48]: pred_train_rf= regr.predict(X_train)

In [49]: print("Training RMSE and R2 score:")
         print(np.sqrt(mean_squared_error(y_train,pred_train_rf)))
         print(r2_score(y_train, pred_train_rf))

         Training RMSE and R2 score:
         327.03193792693526
         0.937774292696154

In [50]: pred_test_rf= regr.predict(X_test)

In [51]: print("Testing RMSE and R2 score:")
         print(np.sqrt(mean_squared_error(y_test,pred_test_rf)))
         print(r2_score(y_test, pred_test_rf))

         Testing RMSE and R2 score:
         384.1973279505062
         0.9150499920792354

In [52]: df['y_hat_rf'] = regr.predict(X)

In [53]: plt.scatter(pred_test_rf,y_test)
         plt.xlabel('Predicted')
         plt.ylabel('Actual')
         plt.title("RF Predicted vs. Actual Plot")
```

VI. RESULTS AND OBSERVATIONS



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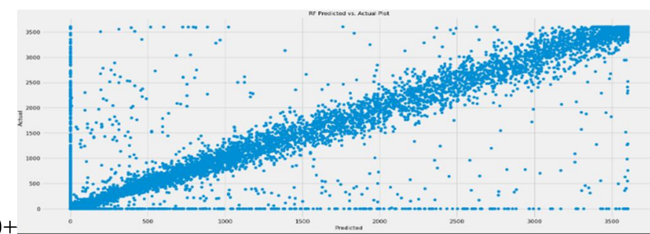
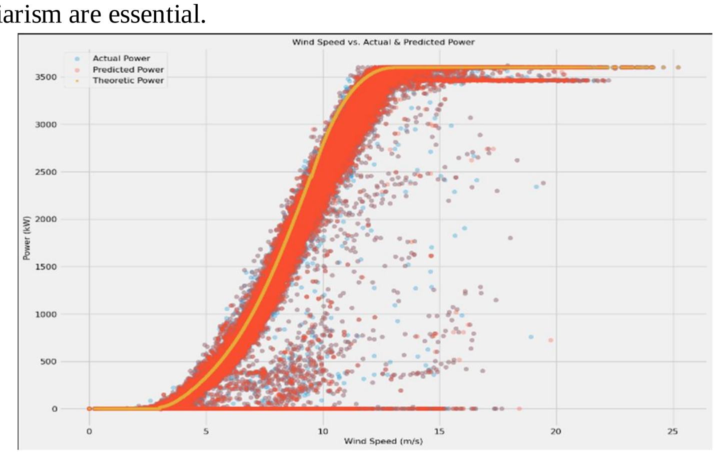


VII. CONCLUSION

To address the shortcomings of current models in terms of prediction accuracy and generalization ability, as well as to take into consideration the volatility of wind power, this study offers an integrated learning model for wind power prediction. The suggested model uses a two-step process that starts with forecasting energy demand and moves on to residual correction and enhanced energy structure prediction based on an examination of the energy supply system and the no aftereffect property of NN. Then, while considering the technique energy plans, the enhanced energy structure prediction model is produced by combining limitations based on the power projection for demand and the future energy plan. The work also offers a fresh approach to calculating the transition matrix chance. It is essential for the analysis of time series of energy consumption and production. Additionally, the study shows how effectively artificial neural networks perform in separating related components of estimates and complexities as well as operational precision estimations. It is crucial to remember that when using outside sources, correct citation and prevention of plagiarism are essential.



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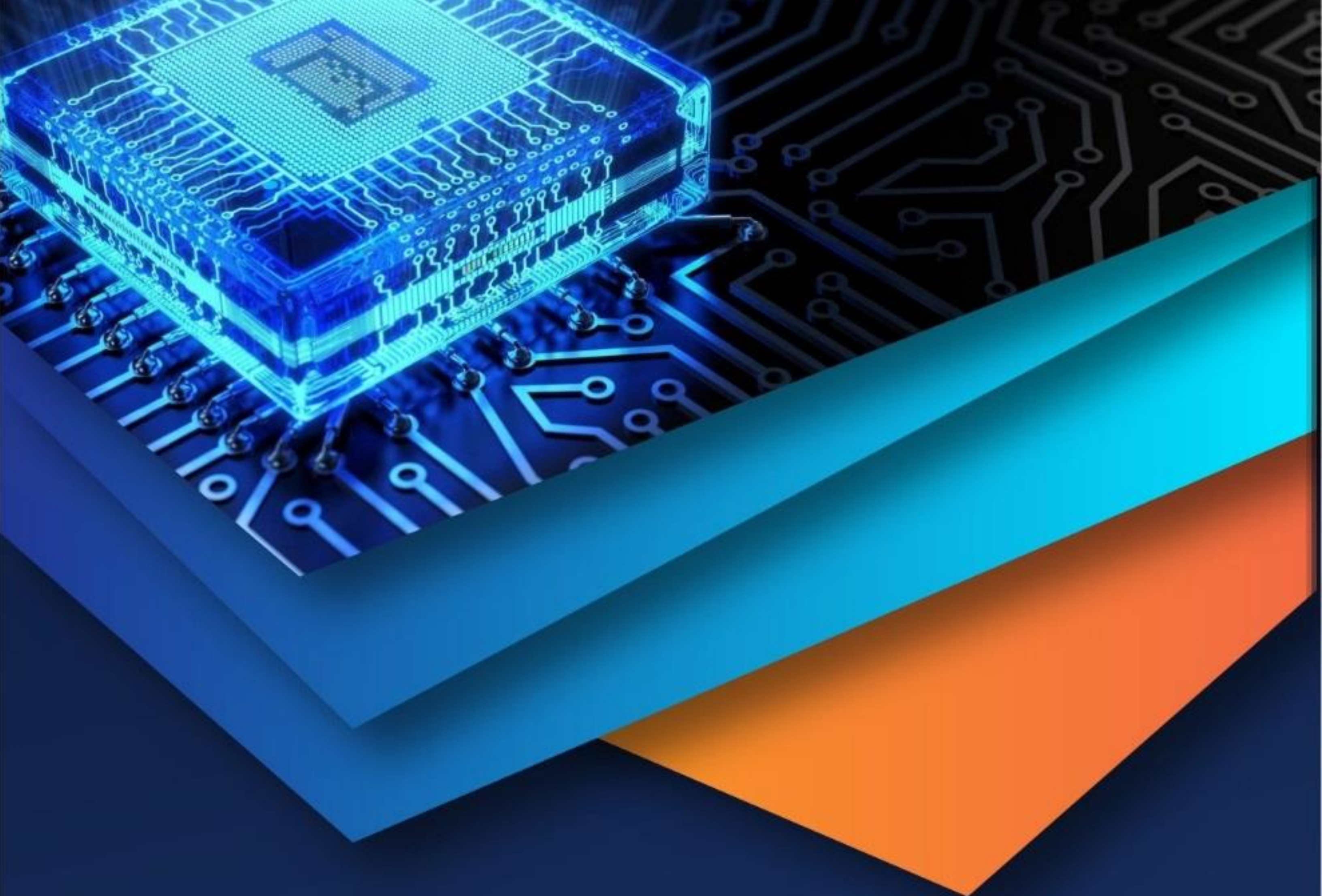

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