iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.83141

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

Integrated Multi Component Prognostics for EV Systems Using GRU and LSTM

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Abstract: The Integrated Multi Component Prognostics is a key technology for electric vehicle (EV) systems, and can be applied to improve reliability, reduce maintenance expenses and prevent sudden failures. In the present study, the focus is placed on the prediction of Remaining Useful Life (RUL) of EV motors and other components by deep learning models like Deep Learning based LSTM, GRU networks. It analyzes sensor data such as current, voltage, temperature, brake pressure and pad wear to find patterns of component degradation. The methodology is based on the time-series preprocessing, normalization, sequence generation and training of a recurrent neural network. Implementation and evaluation is performed using Python, TensorFlow/Keras, NumPy, Pandas and Scikit-learn. The experimental results show that both models are able to predict the degradation trends effectively while the GRU is more computationally efficient. The system can realize real-time monitoring and early fault detection, which provides strong foundation for future intelligent EV maintenance system.
Keywords: predictive maintenance, electric vehicles, LSTM, GRU, remaining useful life, deep learning, fault detection, time-series forecasting.

I. INTRODUCTION

Electric Vehicles are revolutionizing the transport industry owing to their environmental benefits as well as their lower emissions and energy efficiencies. However, the reliability and operational safety of EV systems largely depend on the condition of critical components such as electric motors, braking systems and battery units. Conventional maintenance techniques such as reactive maintenance and periodic scheduled maintenance are inefficient as they either react after failure occurs or replace components unnecessarily. Predictive maintenance addresses such issues through constant monitoring of system parameters and prediction of any possible failure before it happens. Due to advancements in artificial intelligence (AI), machine learning (ML), and deep learning (DL), predictive maintenance is able to process a lot of data produced by sensors to diagnose wear and tear. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, have become highly effective for time-series forecasting applications because they can learn temporal dependencies from sequential sensor data. These capabilities make them suitable for EV motor health monitoring and Remaining Useful Life (RUL) prediction.

A. Research Problem

The electric motors and brakes used by electric vehicles (EVs) experience varied conditions that result in slow degradation. This unexpected breakage may lead to hazards, reduce performance levels, and increase maintenance costs. Traditional techniques are often ineffective at detecting initial stages of degradation.

The following is the research problem:

Developing an intelligent Integrated Multi Component Prognostics system that will be able to monitor the operational parameters of EVs in real-time, predict the degradation paths of the parts, estimate the remaining useful life, and detect any possible faults before system breakage occurs.

B. Motivation

The increased popularity of electric vehicles (EVs) is resulting in the need for smart maintenance solutions, which improve reliability and minimize downtime. The application of deep learning techniques can contribute to developing a fault prediction solution based on sensor data.

The motivations for this research are:

- Prevention of surprise faults in EVs.
- Passenger safety improvement.
- Longer component lifetime.
- Cost-effective maintenance.
- Development of intelligent transport systems.

C. Objectives

The main objectives are:

- To devise a system for integrated multi component prognostics of electric vehicle (EV) parts.
- To utilize LSTM and GRU neural networks to predict the remaining useful life (RUL).
- To pre-process and analyze time series data obtained from sensors.
- To perform prediction and forecasting in real-time.
- To evaluate the performance of different deep learning algorithms.
- To make intelligent maintenance suggestions

II. LITERATURE REVIEW

A. Prior Art in Predictive Maintenance

A substantial amount of research has been conducted in the area of predictive maintenance in the context of industrial automation, manufacturing, aviation, and automotive fields. The current techniques used include statistical approaches, threshold-based monitoring, and rule-based expert systems. Even though these techniques are computationally less intensive, they tend to be inadequate when it comes to dealing with complex non-linear degradation processes.

Moreover, the application of Machine Learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), Decision Trees (DTs) and Artificial Neural Networks (ANNs) in the fault detection and condition monitoring processes have been used. This approach boosts prediction performance while having a problem with temporal relationships.

B. Deep Learning for Time-Series Analysis

There have been some deep learning models which show significant success in the field of predictive maintenance due to the ability to learn features from raw data automatically. Some of these models include Recurrent Neural Networks (RNN).

LSTM networks tackle the problem of vanishing gradients in conventional RNNs through the implementation of memory units and gates. They prove highly effective in predicting long sequences and are widely applied in:

- Fault diagnosis
- Remaining Useful Life analysis
- Battery condition assessment
- Industrial system prediction

On the other hand, the LSTM networks usually require more computing power and longer training periods.

GRU is a simplified version of the LSTM model, where the gates used are merged to create a single unit referred to as update gate. GRU-based predictions usually provide:

- Fast training
- Less computing power requirement
- Comparable accuracy
- Improved performance in real-time scenarios.

C. Research Gap

Despite having many predictive maintenance models proposed, there is a considerable amount of previous research focusing on industrial machines instead of electric vehicle (EV) subsystems. Also,

- Predictive maintenance for EV motors in real time is largely overlooked.
- Frameworks for multiple component predictive maintenance are still narrow.
- Lightweight deep learning models suitable for EV systems require more attention.
- Several previous studies have failed to combine multi-step prediction with real-time prediction capability.

This research intends to fill the gap by creating predictive maintenance models using GRU and LSTM for EV motors and brakes, which also involve real-time prediction capability.

III. DATASET

A. Motor Dataset

The dataset defines the health condition of an EV motor and forecasts the number of years before the motor fails. The motor degradation is modelled based on the High Current and High Temperature. Exceeding these parameters from safe limits increases the rate of degradation, thus reducing the motor's Remaining Useful Life (RUL).

These are Utilized for Motor health monitoring,Predictive maintenance,RUL prediction

Table I. Motor Dataset with RUL

Feature	Description
Current	Motor current consumption (Amps)
Voltage	Motor operating voltage (volts)
Temperature	Motor temperature (in degrees)
Time-to-failure	Remaining operational cycles before failure
Years-to-failure	Estimated remaining life in years

B. *Battery Dataset*

The database models battery degradation in electric vehicles (EV) and predicts the time period that a battery can maintain its efficiency before needing to be replaced.

Degradation of batteries increases when the following factors come into play:

- Increased temperature
- Increased current
- Decrease in voltage
- State of charge being too high or too low

Such factors reduce the life span of the battery gradually.

The main Applications of this dataset are

Battery Health Monitoring (BHM), Battery Management System (BMS), Maintenance Prediction in EVs

Table II. Battery Dataset with RUL

Feature	Description
Battery Voltage	Battery cells voltage
Battery Current	Charging/discharging currents
Battery Temperature	Battery temperature
Time to failure	Remaining battery life cycles
Years to failure	Estimated battery life in years

C. *Braking Dataset*

This dataset predicts the life span of the EV brakepads and other braking system parts.

The main working principle is the degradation of the brakes results from the following:

- Increased temperature of the brakes
- Low brake force
- High pad wear rate
- Fast moving vehicle

The main aim for using this dataset is to Monitoring brake wear,Safety Assessment,Planning preventive maintenance.

All this speeds up the wear rate.

TABLE III. Braking Dataset with RUL

Feature	Description
Brake pressure	Hydraulic brake pressure
Brake temperature	Brake system temperature
Pad wear	Brake pad wear percentage
Speed	Vehicle speed
Time to failure	Remaining braking life cycles
Years to failure	Estimated remaining brake life in years

IV. METHODOLGY

The Integrated Multi Component Prognostics framework uses deep learning techniques to estimate the Remaining Useful Life (RUL) of EV motors and braking components. The system processes sequential sensor data and predicts degradation patterns using LSTM and GRU architectures.

The Overall workflow includes:

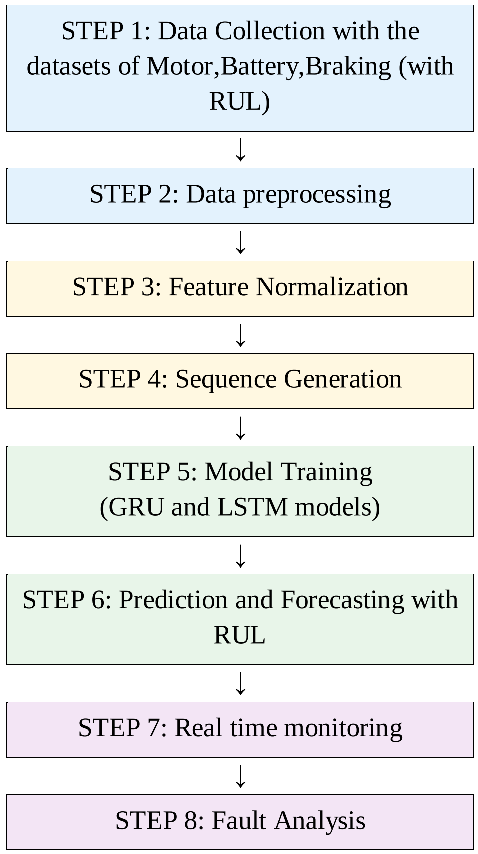

Fig. 1. End-to-end system architecture

A. Data Acquisition & Software Tools

The implementation stack is pointed in Table I.

Table IV. Implementation tools and libraries

Tool / Library	Role
Python	Primary programming language
TensorFlow/Keras	Deep learning model development
NumPy	Numerical computations
Pandas	Data manipulation and preprocessing
Matplotlib	Data visualization
Scikit-learn	Preprocessing and evaluation
Jupyter Notebook	Development environment

B. Implementation Modules

The system has been designed to have five major components:

1) Data Loading Component: The sensor data files are loaded using Pandas, along with the choice of relevant features and target variable.
2) Data Preprocessing Component: This part is responsible for missing data, feature normalization, creating sequences, and splitting the dataset.
3) Model Training Component: Sequential sensor data is used to create and train the LSTM and GRU models.
4) Prediction Component: This component provides predictions for remaining useful life (RUL), predicted deterioration trend and failure probability score.
5) Visualization Component: Graphs are generated to show comparison between actual and predicted RUL values, sensor data in real-time, and deterio ration trend.

C. Fault Detection Algorithm

Fault detection follows a threshold-based decision rule:

If the predicted RUL< threshold value then Potential fault detected

Else the system operates normally

The system allows for preventive maintenance suggestions before critical faults occur.

V. SYSTEM IMPLEMENTATION

The implementation process starts with data pre-processing where the data missing values are dealt with, feature normalization is performed, and time series sequences are constructed. The pre-processed data is split into training and test data sets. LSTM and GRU, both being RNN architectures, are used to train their networks to capture the patterns of temporal degradation in the sensor data.

Therefore, this explains training output of prognostics of EV motor of TABLE V, TABLE VI, TABLE VII

Table V. Training Prognostics of EV Motor

Sl.No	Current	Voltage	Temp	Time To failure	Years to failure
0	10.9934	210.460	34.429	100	5.0
1	9.7234	215.698	36.845	100	5.0
2	11.2953	217.931	35.289	100	5.0
3	13.046.	229.438	37.260	98	4.9
4	9.5316	222.782	38.929	98	4.9

Table VI. Training Prognostics of EV Breakinpads

	PRESSURE	TEMP	PAD WEAR	TIME TO FAIL	YEARS TO FAIL
0	81.74	77.84	34.82	149	3.90
1	51.21	79..51	18.27	149	3.80
2	66.72	80.96	40.37	135	2.90
3	69.58	94.20	21.14	149	3.11
4	70.15	68.79	41.24	149	3.90

Table VII. Training Prognostics of EV Battery

	VOLTAGE	CURRENT	TEMP	TIME TO FAIL	YEAR TO FAIL
0	3.7496	1.0460	24.429	120	6.0
1	3.6861	1.5698	26.845	120	5.4
2	3.7647	1.7931	25.289	120	5.0
3	3.8523	2.9438	27.260	120	5.7
4	3.6765	2.2782	28.929	120	5.2

VI. EXPERIMENTAL RESULTS

A. Evaluation Metrics

Model performance is assessed using Mean Squared Error (MSE), Mean Absolute Error (MAE), accuracy analysis, and visual comparison of predicted versus actual RUL trajectories. Fig 1 explains about the graph represents real-time sensor monitoring and prognostics analysis for an EV motor system. And Fig 2. The graph represents real-time sensor monitoring and prognostics analysis for an EV Breaking pads system. And Fig 3. The graph represents real-time sensor monitoring and prognostics analysis for an EV Battery system and Fig 4. Real-Time EV Motor Sensor Monitoring and Fault Prediction and Fig5. Real-Time EV Braking pads Sensor Monitoring and Fault Prediction and Fig6. Real-Time Battery Sensor Monitoring and Fault Prediction

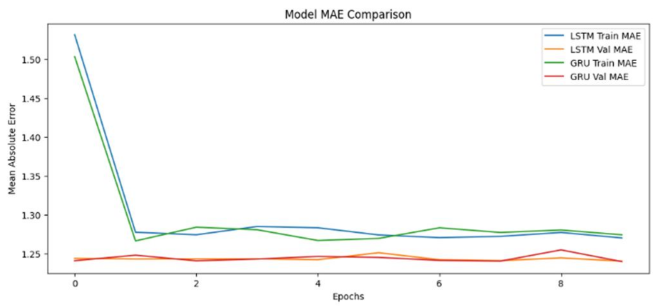

Fig 1. The graph represents real time sensor monitoring and prognostics analysis for an EV motor system.

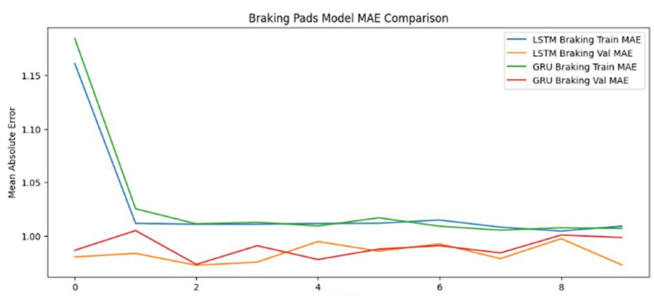

Fig 2. The graph represents real time sensor monitoring and prognostics analysis for an EV Braking pads system.

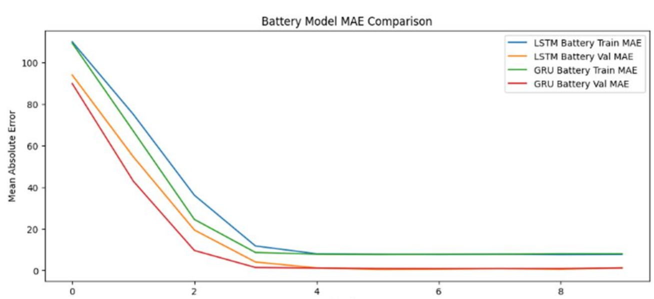

Fig 3. The graph represents real time sensor monitoring and prognostics analysis for an EV Battery system.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

B. RUL Prediction Performance

Scatter plot analysis comparing actual and estimated RUL values for both LSTM and GRU models yields the following findings:

1) The trends in the degradation predictions are very similar to the observed trends.
2) GRU is able to perform with competitive accuracy at lesser model complexity.
3) LSTM has good performance in long range dependency.
4) Both models are able to describe non-linear degradation dynamics well.

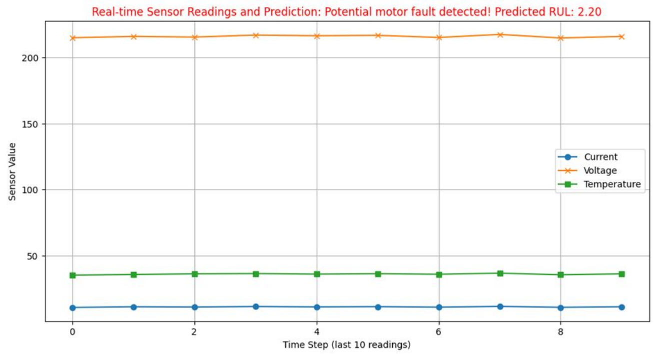

Fig 4. Real Time EV Motor Sensor Monitoring and Fault Prediction

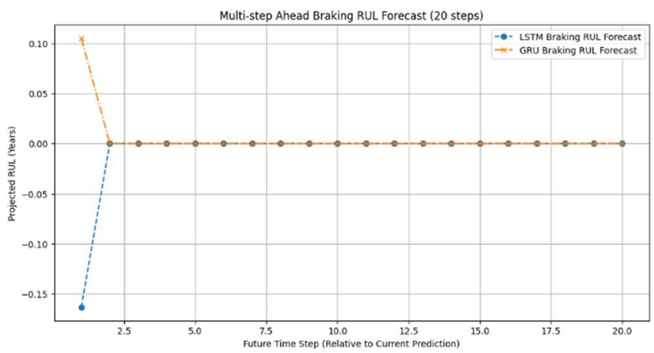

Fig5. Real Time EV Braking pads Sensor Monitoring and Fault Prediction

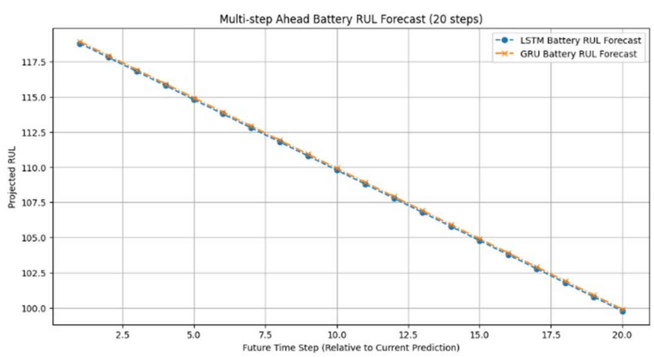

Fig6. Real Time Battery Sensor Monitoring and Fault Prediction

C. Real-Time and Multi-Step Forecasting Results

The real-time prediction module correctly categorizes the health state of its components based on the live sensor readings, providing the RUL estimates, fault indicators and maintenance suggestions. The multi-step forecasting module is able to accurately reflect the slow degradation trend over long periods of time, which helps to plan long-term maintenance and identify problems in advance.

The trained LSTM and GRU algorithms predict the future degradation patterns for several time intervals ahead in the multi-stage forecast method. It will offer insight on the potential future prediction of the motor/battery/brakingpads, helping to support long-range motor maintenance planning.

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Based on experiments Fig 7,Fig 8 and Fig 9 both LSTM and GRU have proven capable of capturing temporal information within the sensor readings, whereas GRU has an advantage of fast computation speed and equivalent forecast accuracy compared to LSTM.

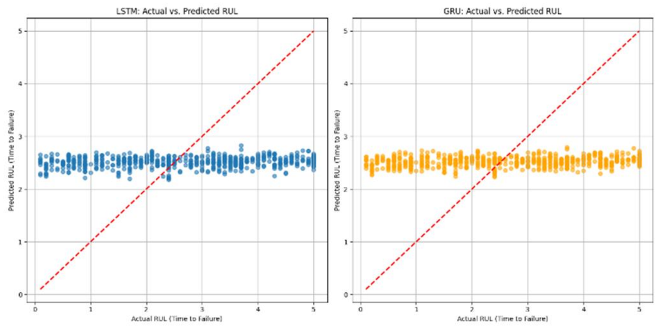

Fig 7. Actual vs Predicted RUL Visualization of EV motor by using LSTM and GRU models

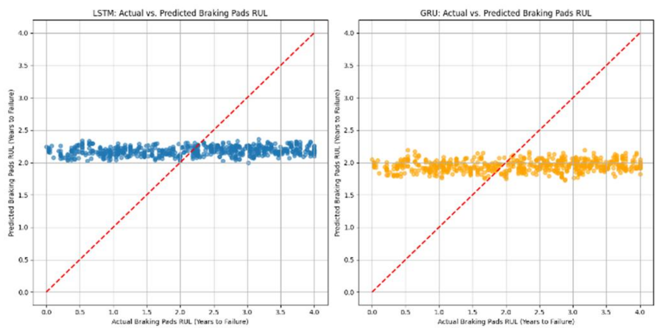

Fig 8. Actual VS Predicted RUL Visualization of EV Braking pads by using LSTM and GRU models

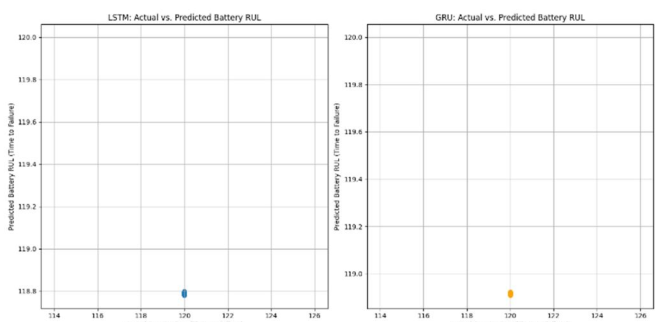

Fig 9. Actual vs Predicted RUL Visualization of EV Battery by using LSTM and GRU models

D. Summary of Findings

Experimental results showed that deep learning models can accurately determine the health of EVs' components by analyzing data from their sensors, across a range of different scenarios. The proposed framework shows promise to decrease vehicle downtime, minimize safety concerns, enhance maintenance responsiveness, and lengthen component service life.

VII. LIMITATIONS AND FUTURE WORK

A. Limitations

Acknowledgements are made to the following limitations:

1) Simulated datasets are used; broader real-world EV datasets would improve generalizability.
2) Fault detection relies on threshold-based rules; advanced anomaly detection models could improve diagnostic performance.
3) Deep learning methods impose substantial computational demands on large-scale datasets.
4) Environmental factors (temperature, humidity, road conditions, driving patterns) are not currently modeled.
5) Multi-step forecasting assumes linear degradation trajectories.

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Volume 14 Issue V May 2026- Available at www.ijraset.com

B. Future Work

Such a system could be extended to facilitate real-time monitoring in the cloud and IoT platforms, thereby supporting the smart management of fleets and self-driving cars. In future research, another possible area that could be studied is using the technique of explainable AI to interpret the prediction outputs more effectively. Moreover, using the proposed approach in embedded systems could help in improving real-time processing.

Planned future enhancements include:

1) Integration with real EV hardware and onboard diagnostic systems
2) Development of CNN-LSTM hybrid and transformer-based architectures
3) IoT integration for cloud-connected real-time monitoring
4) Advanced fault classification and root cause analysis
5) Edge AI deployment of lightweight GRU models
6) Extension to battery, suspension, steering, and power electronics subsystems

VIII. CONCLUSION

Integrated Multi-Component Prognostics for EV system presents a deep learning framework for predictive maintenance of electric vehicle systems using LSTM and GRU recurrent neural networks. The system processes sequential sensor data to estimate remaining useful life and predict fault occurrence.

Experimental results show that RNNs can be used to learn time-series degradation patterns from EV sensor data. Both LSTM and GRU models provide accurate predictions, GRU having lower computational complexity and better real-time deployment capabilities. The real-time inference, multi-step forecasting and visualization further boosts the framework's practicality for intelligent transportation systems.

The experimental results indicated that LSTM and GRU algorithms both achieved good performance for real-time and multi-step ahead predictions of wear and tear of components. In terms of performance, the GRU model was able to match the level of accuracy as the LSTM algorithm but with less computation and faster performance. This system will enhance the reliability of the vehicle and prevent failures, as well as allow proper scheduling of maintenance.

The increasing significance of AI driven maintenance systems in improving the reliability, safety, and efficiency of EVs highlights their role in the future of automotive technology.

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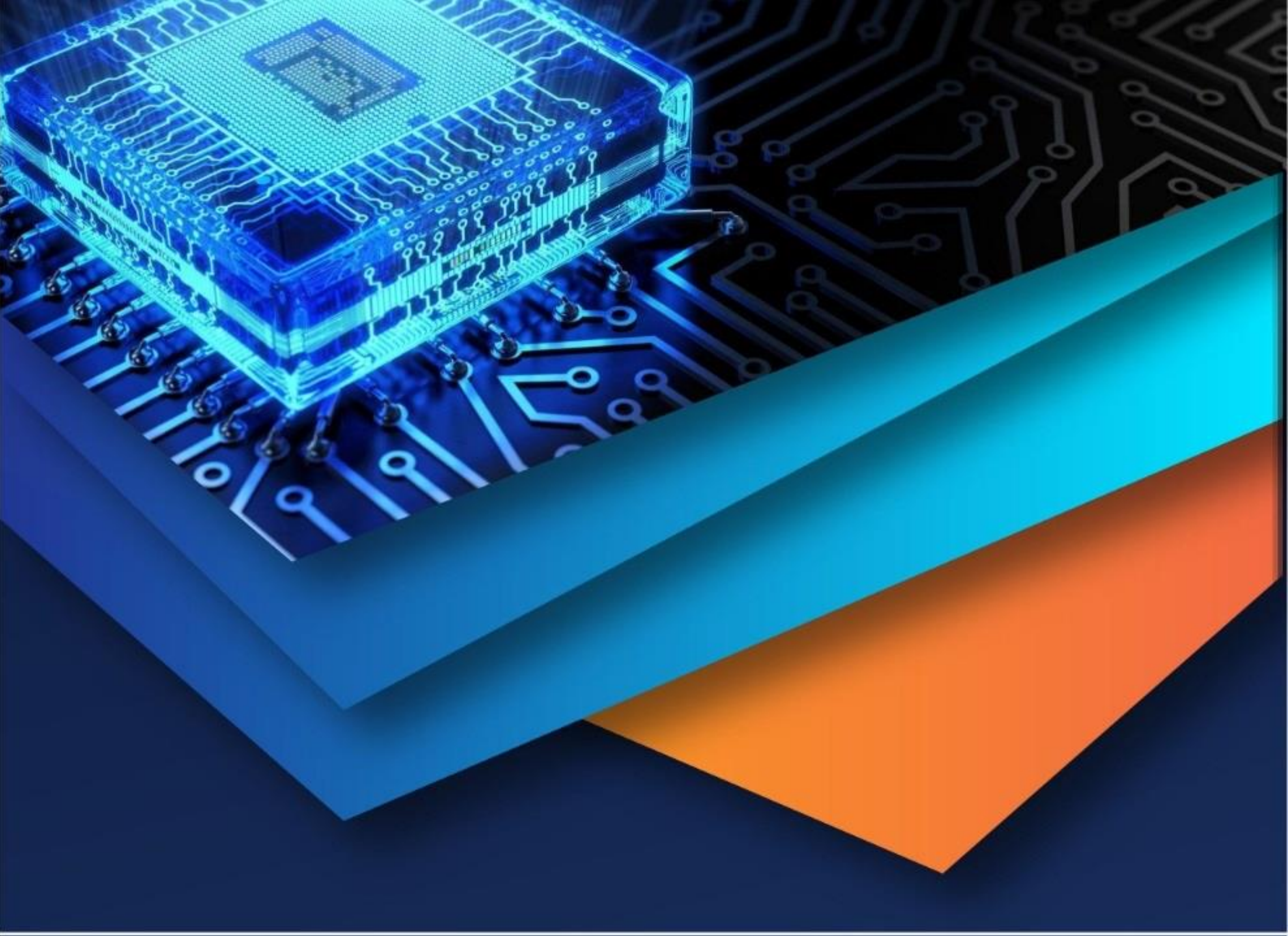

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