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AI-Based Predictive Maintenance System for Bearings

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Abstract: ***Bearing failures in rotating machinery can lead to unplanned downtime, increased maintenance costs, and reduced operational reliability. To address these challenges, this paper proposes an artificial intelligence (AI)-based predictive maintenance framework for bearing condition monitoring using temperature, vibration, and electrical-current measurements. The proposed methodology comprises sensor-data acquisition, preprocessing, feature extraction, machine-learning model development, and condition classification. Candidate machine-learning algorithms will be evaluated using labelled data to distinguish normal bearing operation from abnormal conditions. Performance will be assessed using accuracy, precision, recall, F1-score, and confusion-matrix analysis. Where suitable datasets are available, individual sensor inputs will be compared with combined sensor inputs to investigate the potential benefits of sensor fusion. The framework is intended to support condition monitoring by presenting the estimated bearing status and providing a basis for maintenance decisions. Its effectiveness will depend on data quality, representative operating conditions, reliable fault labelsand independent model validation. This work establishes a proposed methodology for investigating the feasibility of integrating multiple sensor measurements with machine learning for bearing predictive maintenance.***

Keywords: ***Artificial intelligence, predictive maintenance, bearing fault diagnosis, machine learning, vibration analysis, temperature monitoring, current monitoring, sensor fusion.***

I. INTRODUCTION

Bearings are important mechanical components used in rotating machinery such as electric motors, pumps, gearboxes, and industrial equipment. They support rotating shafts and facilitate smooth machine operation. Bearing damage or failure can affect equipment performance, reduce operational reliabilityand cause unplanned downtime and increased maintenance costs. Therefore, monitoring bearing condition and identifying abnormal operating conditions at an early stage are important for maintaining reliable industrial operations. [15]

Conventional maintenance practices include scheduled maintenance and corrective maintenance after a component fails. However, these approaches may not always identify developing faults at the appropriate time. Predictive maintenance uses equipment-condition information to support maintenance planning and reduce dependence on fixed maintenance schedules. Condition-based maintenance literature highlights the importance of collecting and analyzing equipment data to support maintenance decisions. [15]

Vibration analysis is widely used for bearing-condition monitoring because defects in bearing components can produce changes in vibration signals. Analyzing these signals can help identify abnormal bearing conditions and support fault diagnosis. In recent years, artificial intelligence (AI) and machine learning (ML) have also been investigated for automated fault diagnosis. These methods can identify patterns in collected data and classify operating conditions when suitable training data are available. Research on bearing diagnosis has demonstrated the importance of selecting appropriate diagnostic methods and evaluating their performance using suitable datasets. [12] [4] [13]

In addition to vibration, temperature and electrical-current measurements may provide complementary information about machine operating conditions. Temperature monitoring can help identify thermal changes, while electrical-current monitoring can provide information about the operating behaviour of an electric motor. Integrating these measurements into a common monitoring framework offers a potential approach for investigating bearing-condition classification using multiple sensor inputs. However, the effectiveness of combining these measurements must be established through appropriate testing and validation. [5] [15]

This research proposes an AI-based predictive maintenance system for bearings using temperature, vibrationand electrical-current measurements. The proposed framework includes data acquisition, preprocessing, feature extraction, machine-learning model development and bearing-condition classification. The system is intended to distinguish normal operating conditions from abnormal conditions and display the estimated condition to support maintenance decisions. [4] [5]

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The study will evaluate the proposed framework using suitable labelled data and appropriate performance metrics, including accuracy, precision, recall, F1-score, and confusion-matrix analysis. Where the available data permit, the performance of individual sensor inputs will be compared with that of combined sensor inputs. The aim is to investigate the feasibility of integrating multiple sensor measurements with machine learning for bearing-condition monitoring and to identify the system's performance, limitations and potential for further development.

II. LITERATURE REVIEW

Sr. No.	Research paper, authors and year	Work method	Input and output	Findings
1	Singh, Ojha, and Harsha (2026) [1]	Transfer-learning-based dual-input CNN using spectrogram and scalogram representations.	Input: Spectrogram and scalogram representations of bearing signals. Output: Fault classification.	Presents a dual-input transfer-learning approach; confirm publication details and availability before citing.
2	Mathur, Kumar, and Harsha (2023) [2]	Ranked-feature-based diagnosis using support vector machine and artificial neural network methods.	Input: Selected/ranked features from bearing data. Output: Fault class.	Explores feature selection and machine-learning classifiers for bearing-fault diagnosis.
3	Zhang, Zhao, and Lin (2021)[3]	Review of machine-learning-based bearing diagnosis associated with the CWRU dataset.	Input: CWRU bearing data and derived features. Output: Summary/comparison of fault-diagnosis approaches.	Reviews machine-learning approaches associated with the CWRU dataset; exact bibliographic metadata should be checked.
4	Lei et al. (2020) [4]	Review of machine-learning applications in machine-fault diagnosis, with a proposed roadmap.	Input: Machine condition data and extracted features. Output: Diagnostic models and guidance for method selection.	Summarizes machine-learning approaches and discusses challenges and future directions.
5	Liu, Yang, Zio, and Chen (2018) [5]	Review of artificial-intelligence techniques for rotating-machinery fault diagnosis.	Input: Rotating-machinery monitoring data. Output: AI-supported fault diagnosis.	Summarizes AI-based diagnostic methods and their application to rotating machinery; verify the citation details.
6	Cerrada et al. (2018) [6]	Review of data-driven fault-severity assessment methods for rolling bearings.	Input: Bearing condition data/features. Output: Fault-severity assessment.	Focuses on estimating fault severity from data and reviews data-driven approaches.
7	Lei et al. (2018) [7]	Systematic review of machinery health prognostics from data acquisition to remaining-useful-life prediction.	Input: Condition-monitoring and degradation data. Output: Health assessment and remaining useful life (RUL) estimates.	Organizes prognostics methods across the pipeline from data collection to RUL prediction.
8	Zhang et al. (2017) [8]	Deep-learning model designed to improve noise robustness and	Input: Raw vibration signals. Output: Bearing-fault classification.	Presents a deep-learning approach intended to handle noise and changes in operating conditions.

Sr. No.	Research paper, authors and year	Work method	Input and output	Findings
		domain adaptation using raw vibration signals.		
9	Guo et al. (2017) [9]	Recurrent-neural-network-based health indicator for bearing remaining-useful-life prediction.	Input: Bearing degradation/condition data. Output: Health indicator and RUL-related prediction.	Explores recurrent neural networks for tracking bearing degradation and supporting life prediction.
10	Guo, Chen, and Shen (2016) [10]	Hierarchical adaptive deep convolutional neural network for bearing-fault diagnosis.	Input: Bearing-monitoring signals/features. Output: Fault diagnosis.	Shows how a hierarchical adaptive CNN can be applied to bearing-fault diagnosis.
11	Smith and Randall (2015) [11]	Benchmark study using the CWRU bearing data; compares diagnostic approaches.	Input: CWRU bearing vibration data. Output: Bearing fault classifications and comparative performance.	Discusses the use and limitations of the CWRU dataset as a benchmark for bearing-fault diagnosis.
12	Randall and Antoni (2011) [12]	Review/tutorial of rolling-element bearing diagnostic techniques, vibration signal analysis, and fault-frequency interpretation.	Input: Bearing vibration signals. Output: Fault indicators and diagnostic interpretation.	Explains key bearing fault mechanisms and vibration-based diagnostic methods; highlights the importance of signal processing and expert interpretation.
13	Kankar, Sharma, and Harsha (2011) [13]	Machine-learning methods applied to ball-bearing fault diagnosis.	Input: Bearing condition features. Output: Fault category/classification.	Demonstrates the potential of machine learning for automated bearing-fault diagnosis.
14	Kankar, Sharma, and Harsha (2011) [14]	Wavelet-based signal analysis for bearing-fault diagnosis (as listed in the earlier draft; publication metadata should be checked).	Input: Bearing signals. Output: Time-frequency features for diagnosis.	Illustrates how time-frequency analysis can help identify fault-related patterns; verify the exact publication details before submission.
15	Jardine, Lin, and Banjevic (2006) [15]	Review of machinery diagnostics and prognostics for condition-based maintenance.	Input: Condition-monitoring data. Output: Machinery condition assessment and maintenance decisions.	Provides a framework for condition-based maintenance, linking diagnostics, prognostics, and maintenance planning.

Table 2.1 Literature Review of Machine Learning-Based Bearing Fault Diagnosis and Predictive Maintenance

III. PROBLEM STATEMENT

Bearing-condition monitoring in rotating machinery remains challenging due to complex relationships between vibration, temperature and motorcurrent measurements.Variations in operating conditions and bearing fault characteristics.Difficulty in identifying early-stage bearing faults using individual sensor measurements.

The objective of this study is to develop a machine learning-based system capable of classifying bearing conditions as normal or abnormal using vibration, temperatureand motorcurrent data.

IV. METHODOLOGY

A. Data Collection

Data for this study will be obtained from experimental measurements or suitable publicly available datasets. The dataset will contain sensor measurements representing different bearing operating conditions.The input parameters will includevibration signals from the bearing or machine housing.Temperature measurements during machine operation.Motor-current measurements during operation.Bearing-condition labels, such as normal and faulty, where available.

B. Data Preprocessing

Data preprocessing will be performed to improve data quality and prepare the sensor measurements for machine learning.The preprocessing steps will include handling missing or invalid measurements.Removing or investigating noise and abnormal readings where appropriate.Synchronizing sensor measurements using their timestamps, where multiple sensors are used.Extracting relevant features from the vibration, temperature, and motor-current data.Normalizing or standardizing the features when required by the selected model.Dividing the dataset into training, validation and testing sets without data leakage.

C. Machine Learning Models

Suitable supervised machine learning models will be considered for bearing-condition classification.Logistic Regression will provide a baseline classification model.Support Vector Machine (SVM) will be evaluated for its ability to classify data with complex decision boundaries.Random Forest will be used to capture nonlinear relationships and interactions between input features.Gradient Boosting may also be evaluated as an alternative ensemble method.

D. Model Training

The labelled training dataset will be used to train the selected machine learning models. During training, the models will learn relationships between sensor measurements and the corresponding bearing-condition labels.Hyperparameters will be adjusted using the validation dataset. The trained models will then be evaluated using an independent test dataset that was not used during training or model selection.Where sufficient data are available, the study will also compare models trained using individual sensor inputs with models trained using combined sensor inputs. This comparison will help determine whether integrating vibration, temperature, and motor-current measurements provides additional predictive value.

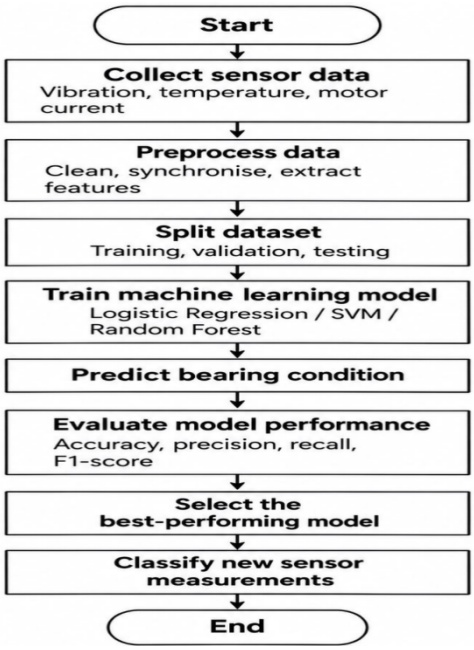


Fig. 4.1 Flowchart of the proposed AI-based bearing-condition monitoring methodology

E. Mathematical Modelling

The bearing condition can be represented as a function of the measured sensor parameters:$C = f(V, T, I)$

Where$C$ represents the predicted bearing condition, V represents the vibration features, I represents the temperature measurements, f represents the motor-current features, T represents the trained machine learning model.The model will classify the bearing condition into predefined categories, such as normal and faulty. The reliability of this classification will depend on the quality of the input data, the accuracy of the condition labels and the performance of the trained model.

F. Proposed Algorithm (Pseudocode)

The following pseudocode describes the proposed sequence of operations for the AI-based bearing-condition monitoring system. The algorithm will be implemented and evaluated during the project.

Input: Labelled sensor dataset (D), Output: Predicted bearing condition (Normal or Faulty)

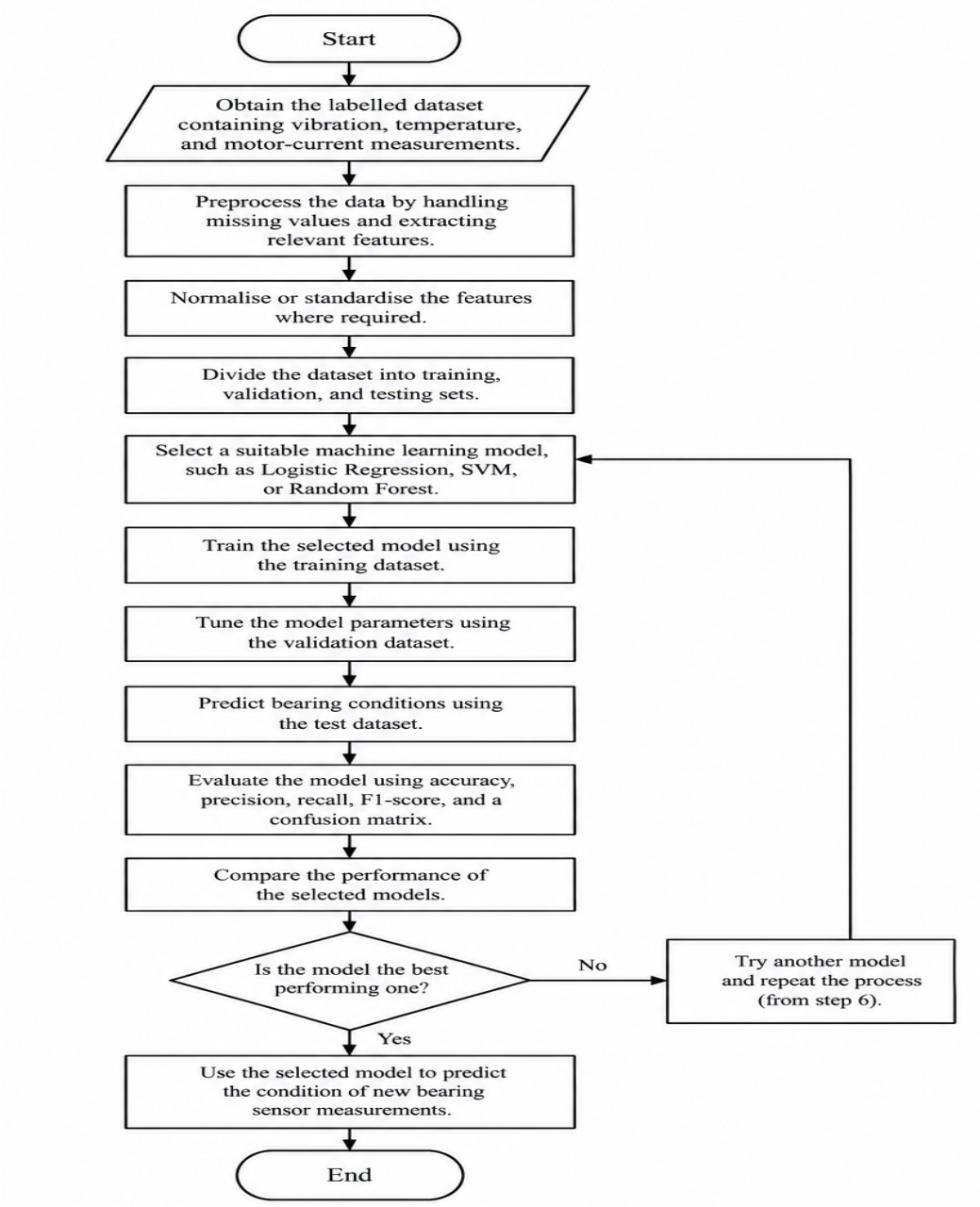


Fig 4.2 Flowchart of Machine Learning Model Development and Bearing Condition Prediction

G. Evaluation Metrics

The performance of the classification models will be evaluated using the following metrics.Accuracy measures the proportion of correctly classified bearing samples, Precision measures the proportion of samples predicted as faulty that are actually faulty, Recall measures the proportion of actual faulty samples correctly identified by the model, F1-score represents the harmonic mean of precision and recall.Confusion matrix shows correct and incorrect classifications for each bearingcondition category.

These metrics will be used together to compare the models, particularly because failing to identify a faulty bearing may have significant maintenance consequences.

H. Results and Discussion

The developed models will be evaluated to determine their ability to distinguish between normal and faulty bearing conditions. The results will be compared using the selected classification metrics.The analysis will examine whether combined sensor measurements improve classification performance compared with individual sensor inputs. Feature-importance analysis, where supported by the selected model, may also be used to identify which sensor features contribute most to the predictions.The final results will be reported after model training and testing. No particular model accuracy or improvement will be claimed before the experiments are conducted.

Challenges

Requires reliable sensor measurements and accurate fault labels.Performance may vary with speed, loadand operating conditions.Insufficient or imbalanced fault data may reduce model reliability.A model trained on one machine may not generalize to another machine without further validation.

V. EXPECTED OUTCOMES

The proposed study is expected to achieve the following outcomes:

Develop a machine learning model capable of classifying bearing conditions as normal or faulty, Identify the most suitable model based on its prediction performance using appropriate evaluation metrics,Support early identification of abnormal bearing conditions, potentially reducing unexpected failures and maintenance costs, Improves condition monitoring by utilizing vibration, temperatureand motor-current measurements to assess bearing operating conditions, Scalability develops a framework that can potentially be adapted to different rotating machinery and operating conditions, subject to further data collection and validation, Support for Maintenance Planning Provides condition-monitoring information that can help maintenance personnel make informed maintenance decisions.

VI. CONCLUSION

This study proposes a machine learning-based predictive maintenance framework for bearing-condition monitoring using vibration, temperatureand motor-current measurements. The proposed approach aims to identify abnormal bearing conditions by analyzing sensor data and learning patterns associated with normal and faulty operating states. Machine learning models such as Logistic Regression, Support Vector Machine (SVM)and Random Forest will be considered to investigate their suitability for bearing-fault classification.The integration of machine learning into bearing-condition monitoring has the potential to support early fault identification, improve equipment reliabilityand assist maintenance planning. However, the effectiveness of the proposed framework will depend on the quality of the collected data, the selection of relevant featuresand the model's ability to generalize across different operating conditions. Experimental implementation and performance evaluation are required to establish its actual accuracy and practical benefits.

VII. FUTURE WORK

Although the proposed study establishes a framework for machine learning-based bearingcondition monitoring, several extensions can be explored to improve its reliability, predictive capabilityand industrial applicability.

Expansion of the Experimental Dataset: Future work can focus on collecting a larger and more diverse dataset containing measurements from different bearing types, rotational speeds, operating loadsand fault conditions. Including data from multiple operating environments may help evaluate the model's ability to generalize to previously unseen conditions.

Incorporation of Time-Series Analysis: Bearing faults may develop gradually over time.

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Future research can investigate time-series models, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, to analyze sequential sensor measurements and study changes in bearing condition over time.

Integration of Real-Time Sensor Data: The proposed framework can be extended by integrating vibration sensors, temperature sensorsand motor-current measurement equipment with a suitable data acquisition system. This may enable continuous bearing-condition monitoring and support timely identification of abnormal operating behaviour.

Advanced Multi-Sensor Data Fusion: Future studies can investigate the combined use of vibration, temperature, and motor-current measurements. The performance of models using individual sensor inputs can be compared with models using combined inputs to determine whether multi-sensor data fusion provides measurable benefits.

Hybrid and Physics-Informed Models: Future research can explore combining machine learning models with established knowledge of bearing dynamics, vibration behaviourand fault characteristics. Such approaches may help improve model interpretation and investigate whether physical knowledge can support reliable predictions when training data are limited.

Uncertainty Quantification and Model Explainability: Further work can incorporate uncertainty estimation and explainable artificial intelligence techniques to understand model predictions and identify the sensor features that contribute most strongly to fault classification. This may improve confidence in the system's outputs and support maintenance decisions.

Real-Time Fault Detection and Industrial Validation: The trained model can be integrated into a computer-based monitoring system or a suitable embedded platform. Further testing under different speeds, loadsand operating conditions will be necessary to evaluate its response time, reliabilityand suitability for industrial machinery.

Remaining Useful Life Estimation: Beyond classifying bearings as normal or faulty, future research can investigate estimating the remaining useful life of a bearing using historical sensor measurements. This would require suitable run-to-failure data and an appropriate prediction methodology.

These future developments may extend the proposed framework from bearing-condition classification towards more comprehensive predictive maintenance. Their effectiveness must be established through implementation, experimental testingand validation on suitable datasets.

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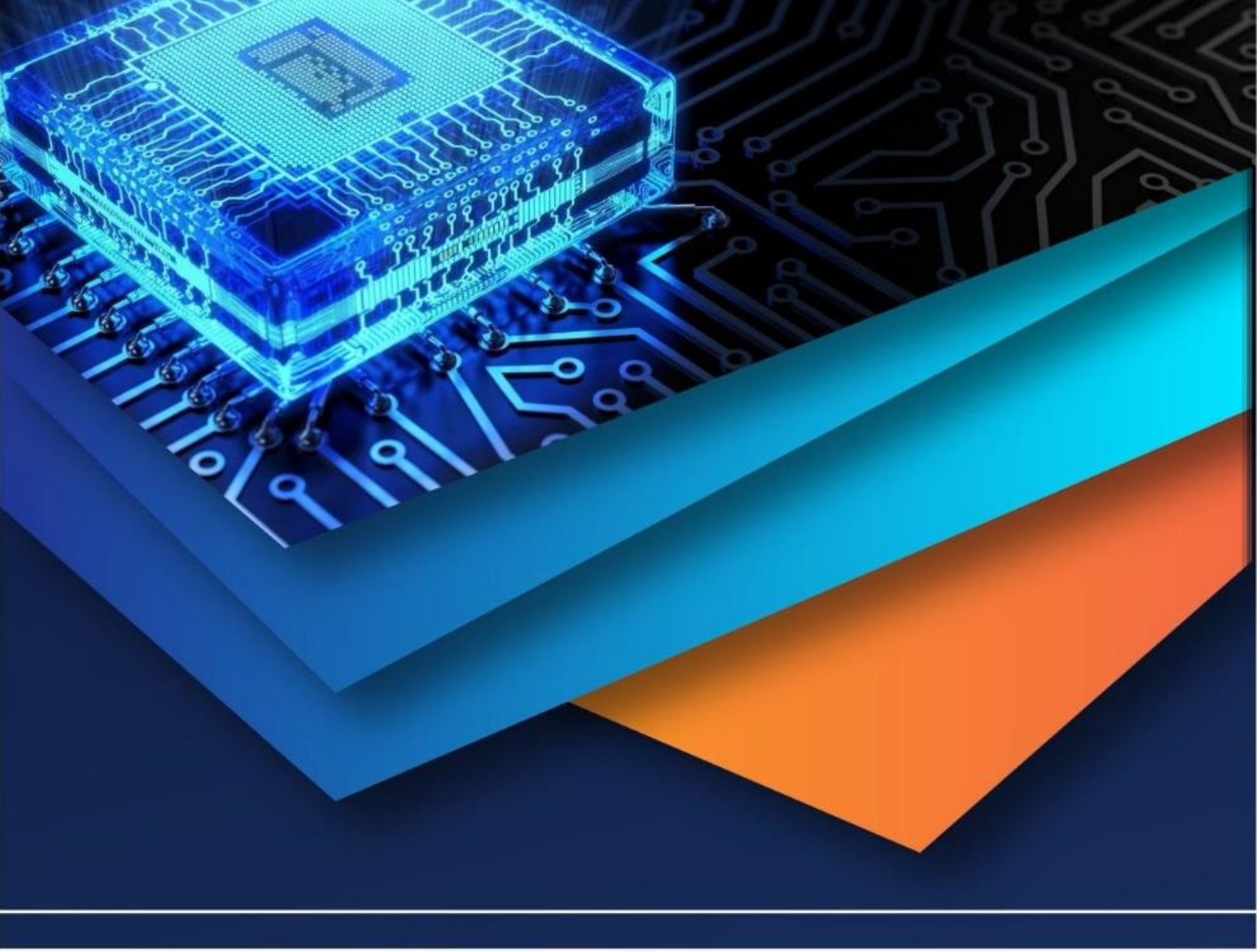
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