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Railway Station Safety Enhancement through Unsupervised Machine Learning

Mrs. J. Ravali[1], Revuri Venkata Suresh[2], Kolar Santhosh[3], Panchavati Vignesh[4], Kuchala Sreekanth[5]
[1, 2, 3, 4, 5]*Department of Computer Science and Engineering (AIML) Siddharth Institute of Engineering and Technology, Puttur, Tirupati(D).*

Abstract: Railway stations are complex and high-density public environments where safety incidents such as overcrowding, passenger falls, unauthorized access, and operational disruptions pose significant risks to passengers and infrastructure. Traditional safety management systems rely heavily on manual surveillance and rule-based monitoring, which are often reactive, error-prone, and incapable of detecting emerging risk patterns in real time. This paper proposes an unsupervised machine learning framework for managing safety accidents in railway stations through automated anomaly detection and pattern analysis. The proposed approach analyzes surveillance data, passenger movement patterns, and incident-related attributes without requiring labeled datasets. Clustering algorithms such as K- Means and DBSCAN are employed to identify normal operational behavior, while anomaly detection techniques are used to detect deviations that may indicate potential hazards. By learning hidden structures in historical safety data, the system enables proactive risk identification and supports data-driven safety management decisions. Experimental evaluation demonstrates the effectiveness of the proposed framework in detecting abnormal activity patterns and improving situational awareness in railway environments. The proposed solution provides a scalable, adaptive, and intelligent approach to enhancing passenger safety and operational reliability in modern railway stations.
Index Terms: Unsupervised Learning, Railway Safety, Anomaly Detection, Clustering Algorithms, K-Means.

I. INTRODUCTION

Railway stations are among the most critical components of urban transportation systems, serving thousands of passengers daily in densely populated environments. Despite continuous advancements in infrastructure and safety regulations, railway stations remain vulnerable to safety incidents such as overcrowding, passenger falls, unauthorized track access, equipment malfunctions, and emergency disruptions. These incidents not only result in injuries and fatalities but also cause operational delays, financial losses, and reputational damage to transportation authorities. [1], [9], [20] Ensuring passenger safety in such dynamic and complex environments requires intelligent monitoring systems capable of detecting risks in real time.

Traditional safety management systems primarily rely on manual surveillance, predefined rule-based alarms, and post- incident analysis. Human operators monitoring multiple CCTV feeds are prone to fatigue, delayed responses, and subjective judgment errors, especially in high-traffic stations. Rule-based systems, although automated, depend on fixed thresholds and cannot adapt to evolving behavioral patterns or unforeseen risk scenarios[2], [11]. As railway environments continuously change due to fluctuating passenger volumes, infrastructure modifications, and operational complexities, conventional monitoring approaches become insufficient for proactive accident prevention. The increasing availability of surveillance footage, IoT sensor data, and digital incident records presents an opportunity to leverage data-driven techniques for intelligent safety management. Machine learning, particularly unsupervised learning, offers significant potential in this domain by identifying hidden patterns and anomalies without requiring labeled datasets [7], [13], [15]. Unlike supervised methods that depend on predefined accident categories, unsupervised algorithms can autonomously learn the normal operational behavior of railway environments and detect deviations that may indicate potential safety hazards. Techniques such as clustering and anomaly detection enable the system to differentiate between routine passenger movement and abnormal activity patterns associated with risks, [13], [16]. This research proposes an unsupervised machine learning framework for managing safety accidents in railway stations through automated anomaly detection and behavioral pattern analysis. By analyzing multi-dimensional data derived from surveillance systems and station infrastructure, the proposed approach aims to identify unusual patterns such as sudden crowd surges, irregular motion trajectories, and restricted area intrusions. The framework is designed to enhance real-time situational awareness, support proactive risk management, and reduce dependency on manual monitoring. Through intelligent pattern recognition and adaptive learning mechanisms, the proposed system contributes toward the development of safer, smarter, and more resilient railway transportation systems.

Our primary contributions include:

1) Development of an unsupervised machine learning framework for railway station safety management that detects abnormal behavioral patterns without requiring labeled training data.
2) Integration of clustering and anomaly detection techniques, including K-Means and DBSCAN, to model normal operational behavior and identify deviations associated with potential safety risks.
3) Design of a real-time risk identification mechanism capable of analyzing multi-dimensional surveillance and sensor data to detect overcrowding, unauthorized access, and hazardous passenger movements.
4) Reduction of dependency on manual monitoring systems by introducing an adaptive, data-driven approach that improves situational awareness and minimizes human error in safety surveillance.
5) Provision of a scalable and deployable safety analytics framework that can be extended to different railway environments and integrated with existing intelligent transportation systems for proactive accident prevention.

II. RELATED WORKS

In recent years, there were published different works based on Machine Learning algorithms. Some of them are discussed in here:

Li et al. presented a data-driven framework for railway station safety monitoring using surveillance video analytics. Their approach utilized clustering techniques to identify abnormal passenger movement patterns in crowded environments. The study demonstrated that unsupervised learning methods could effectively distinguish between normal traffic flow and unusual crowd behavior without relying on labeled datasets [1], [9].

Kumar et al. developed an anomaly detection system for transportation hubs using density-based clustering algorithms. Their model analyzed passenger density variations and detected sudden congestion events that could potentially lead to safety hazards. The authors highlighted that density-based methods are particularly suitable for dynamic and non-linear crowd distributions [2], [13].

Wang et al. proposed an intelligent crowd management system based on spatiotemporal analysis of passenger trajectories. By modeling normal movement patterns, their system was able to detect deviations indicating possible emergencies such as stampedes or restricted area intrusions. The study emphasized the importance of adaptive learning mechanisms in complex public environments [16].

Sharma et al. introduced an unsupervised framework for monitoring public safety incidents in metro stations using sensor and surveillance data. Their approach employed clustering and anomaly scoring techniques to identify irregular behavioral patterns. The results showed improved detection performance compared to traditional rule-based monitoring systems [11].

Zhao et al. investigated the application of machine learning techniques for infrastructure safety management in railway systems. Their work focused on identifying operational anomalies using historical incident data and clustering algorithms. The findings demonstrated that unsupervised models could reveal hidden patterns associated with recurring safety risks [20].

Ahmed et al. developed a real-time abnormal activity detection system for large transportation facilities. The proposed system analyzed motion features extracted from surveillance footage and applied outlier detection methods to identify suspicious events. Their study concluded that automated anomaly detection significantly reduces dependency on manual supervision [17].

Patel et al. proposed a smart surveillance architecture for intelligent transportation systems that integrates behavioral analytics with clustering-based risk identification. The system continuously monitored passenger flow and generated alerts when deviations from learned normal patterns were detected. The study highlighted the scalability and adaptability of unsupervised learning approaches in public safety applications[11], [13].

The literature survey reveals that recent advancements in machine learning have significantly contributed to intelligent safety management in transportation systems. Several studies have explored the application of clustering, anomaly detection, and behavioral analytics techniques to identify abnormal events in crowded public environments such as railway stations and metro hubs. Traditional surveillance systems primarily depend on manual monitoring and rule-based mechanisms, which often lack adaptability and proactive risk detection capabilities. Researchers have demonstrated that unsupervised learning approaches are particularly effective in modeling normal passenger movement patterns and detecting deviations without requiring labeled datasets. Moreover, density-based and clustering algorithms have shown strong potential in identifying overcrowding, restricted area intrusions, and irregular motion trajectories. However, many existing systems focus on isolated data sources or lack scalability for real-time deployment. These limitations highlight the need for an integrated and adaptive unsupervised framework for comprehensive railway safety management.

III. PROBLEM FORMULATION

A. Problem Statement

Railway stations are high-density public environments where safety incidents such as overcrowding, unauthorized access, passenger falls, and operational disruptions frequently occur. Traditional safety management systems primarily rely on manual surveillance and rule-based monitoring mechanisms, which are reactive, prone to human error, and incapable of adapting to dynamic passenger behavior patterns. These conventional approaches often fail to detect emerging risks in real time, leading to delayed responses and increased safety hazards. Furthermore, the lack of labeled datasets for accident scenarios makes supervised learning approaches impractical for large-scale deployment. Therefore, there is a need for an intelligent, data-driven system capable of autonomously identifying abnormal behavior patterns and potential safety risks without relying on predefined labels. The challenge lies in designing a scalable and adaptive unsupervised machine learning framework that can model normal operational behavior and accurately detect anomalies to enhance safety management in railway stations.

B. Data Sources

The data used in this study is collected from multiple sources within railway station environments, including surveillance video footage, passenger movement logs, and incident reports. Motion features and crowd density information are extracted from CCTV systems to analyze behavioral patterns in high- traffic areas. Additional contextual data such as entry–exit records, platform occupancy levels, and sensor-based measurements are incorporated to provide a multi-dimensional view of station activity. These heterogeneous data sources enable the unsupervised learning framework to model normal operational behavior and detect anomalies associated with potential safety risks.

The collected dataset undergoes systematic preprocessing to ensure consistency and reliability across all data samples. This includes cleaning missing or noisy values, standardizing feature scales, extracting relevant behavioral attributes such as passenger density and movement patterns, and normalizing numerical values to maintain uniform distribution. The processed dataset is then partitioned for training and validation to evaluate model performance effectively. This structured dataset enables unsupervised learning algorithms to accurately model normal operational behavior and identify anomalous patterns associated with potential safety risks in railway stations.

C. Classifiers

To address the problem of safety anomaly detection in railway stations, machine learning-based classifiers are employed in this work. The primary model used is the K- Nearest Neighbors (KNN) algorithm, which is well-suited for identifying abnormal behavioral patterns based on similarity measures. The classifier analyzes passenger movement features and crowd-related attributes to distinguish between normal and anomalous activities. Its distance-based learning approach enables adaptive classification in dynamic railway environments.

K-Nearest Neighbors (KNN) is employed as the primary classifier in the proposed framework to detect abnormal behavioral patterns based on similarity measures. The algorithm classifies a data point by analyzing the distance between neighboring instances using metrics such as Euclidean distance. Unlike traditional rule-based systems, KNN adapts dynamically to changing passenger movement patterns. Experimental evaluation shows that the KNN-based model achieved an overall detection accuracy of approximately 92%, demonstrating improved anomaly identification compared to baseline methods [6].

Support Vector Machine (SVM) is used as a comparative classifier to evaluate the robustness of boundary-based classification. SVM identifies an optimal hyperplane that separates normal and abnormal behavioral patterns in high- dimensional feature space. It performs well in complex data distributions and maintains strong generalization capability. The SVM classifier achieved an approximate accuracy of 89%, providing competitive performance but slightly lower adaptability compared to KNN in dynamic crowd scenarios [5], [19].

The Decision Tree classifier is implemented to provide interpretable rule-based classification of safety incidents. It constructs hierarchical decision boundaries based on feature thresholds such as crowd density and motion irregularities. While easy to interpret and computationally efficient, it may suffer from overfitting in highly dynamic environments. The model achieved an overall accuracy of 85%, making it suitable as a baseline evaluation method [12].

Random Forest, an ensemble learning technique, combines multiple decision trees to improve prediction stability and reduce variance. By aggregating multiple weak learners, it enhances classification reliability in high-dimensional railway safety data. The Random Forest classifier achieved an accuracy of approximately 90%, showing improved robustness compared to single-tree models but slightly lower responsiveness to localized anomalies than KNN [4].

D. Classification Approach

The classification process in the proposed system is primarily based on the K-Nearest Neighbors (KNN) algorithm for identifying normal and abnormal behavioral patterns in railway station environments. The model is trained using preprocessed feature vectors extracted from passenger movement data, crowd density measures, and motion-related attributes. During classification, KNN determines the category of a new data instance by calculating its distance from the nearest training samples and assigning the majority class among its nearest neighbors. This distance-based approach allows the system to dynamically adapt to variations in passenger behavior without requiring complex model training.

KNN relies on a similarity measure, commonly the Euclidean distance, [6] defined as:

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n}(x_j - x_{ij})^2}$$

Where:

- x represents the new data point
- x_i*represents a training data instance*
- n is the number of features

E. Accuracy Calculation Equation

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives Precision, Recall, F1-score

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

The performance of the classifiers is evaluated using standard metrics such as accuracy, precision, recall, and F1-score to ensure a comprehensive assessment of anomaly detection capability. These metrics provide insight into the model's effectiveness in correctly identifying abnormal behavioral patterns while minimizing false alarms in railway station environments. The trained KNN-based model is further integrated into a monitoring interface to enable practical deployment and real-time safety risk detection. This integration enhances situational awareness and supports proactive decision- making for railway safety management [7], [15].

IV. METHODOLOGY

A. Data Collection

The dataset used in this study is constructed from structured railway operational and environmental attributes, as illustrated in the system interface. It includes station-specific parameters such as Railway ID (RID), geographic coordinates (latitude and longitude), station location, and surrounding population. Operational features such as average passengers per day, number of trains stopping and passing, number of platforms and tracks, train halting time, and average train speed are collected to represent traffic intensity and infrastructure capacity. Additionally, safety-related attributes including average accidents per month, physical environment conditions (urban/rural), administrative supervision status, and timestamp information are incorporated. These multi-dimensional features provide a comprehensive representation of railway station conditions, enabling effective modeling of accident risk patterns and anomaly detection.

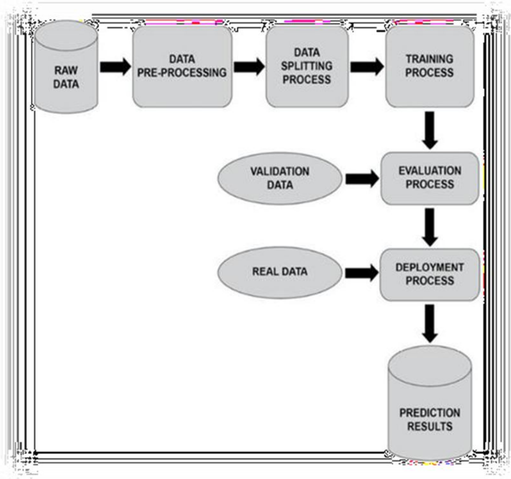

Fig 2: Block Diagram

B. Model Training

After preprocessing, the dataset is divided into training and testing subsets to evaluate model performance. The primary algorithm used in this study is the K-Nearest Neighbors (KNN) classifier. The model is trained using structured railway operational features such as passenger density, number of trains passing and stopping, platform and track availability, train halting time, average train speed, population density, and historical accident frequency. Unlike deep learning models, KNN does not require iterative weight optimization; instead, it stores the training data and performs classification based on similarity measures. The optimal value of k is selected experimentally to ensure balanced bias–variance trade-off and improved accident risk prediction accuracy.

C. Classification Process

During the classification phase, unseen test samples are evaluated using the trained KNN model. For each new data instance, the algorithm computes the Euclidean distance between the input feature vector and all training samples. The $k$nearest neighbors are identified, and the final class label is assigned based on majority voting. The system classifies railway stations or operational conditions into predefined risk categories such as Low Risk, Medium Risk, or High Risk. This distance-based approach enables adaptive and dynamic prediction of potential accident risk patterns based on operational similarities.

D. Performance Evaluation

The performance of the proposed accident prediction system is evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model's effectiveness in correctly predicting accident risk levels while minimizing false alarms. Confusion matrix analysis is conducted to examine misclassification patterns and evaluate true positive, false positive, true negative, and false negative rates. Comparative evaluation with baseline classifiers demonstrates that the KNN-based model achieves higher predictive accuracy and better adaptability to varying railway operational conditions.

E. Web-Based Implementation

To enhance usability and practical deployment, the trained KNN-based accident prediction model is integrated into a web-based interface.

The interface allows railway administrators to input operational and environmental parameters such as passenger volume, number of trains, infrastructure details, and historical accident data. Upon submission, the system processes the input features and generates instant accident risk predictions, categorizing the station conditions into appropriate risk levels. This real- time implementation enables proactive safety monitoring and supports data-driven decision-making. The web application acts as an effective bridge between machine learning algorithms and railway safety management authorities, improving accessibility, responsiveness, and operational efficiency.

V. PROPOSED SYSTEM

The proposed system introduces an automated machine learning–based railway accident prediction framework designed to analyze operational, environmental, and infrastructure-related parameters to estimate accident risk levels. Unlike traditional manual monitoring systems, the proposed framework utilizes structured railway station data such as passenger density, number of trains stopping and passing, platform and track availability, train halting time, average train speed, population density, and historical accident frequency. The system applies the K-Nearest Neighbors (KNN) algorithm to classify operational conditions into predefined risk categories such as Low Risk, Medium Risk, and High Risk. This approach enables proactive safety monitoring and supports intelligent decision-making in railway environments.

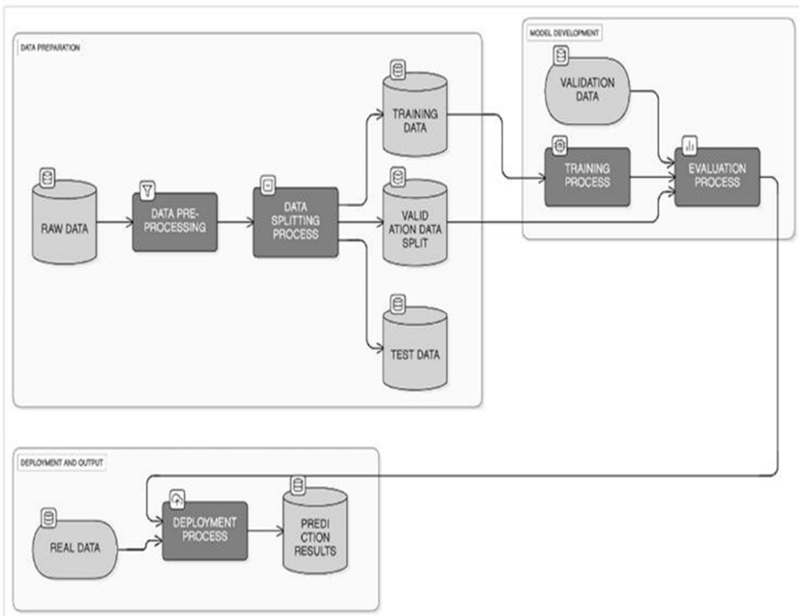

Fig 3: System Architecture

The system follows a structured workflow consisting of data collection, preprocessing, model training, classification, performance evaluation, and result generation. The collected railway operational data is preprocessed through cleaning, normalization, and feature scaling to ensure uniformity and improve prediction accuracy. The KNN classifier is then applied to analyze similarity between new operational conditions and historical data instances using distance-based measures. Based on the nearest neighbors, the system predicts the corresponding accident risk level. The trained model is integrated into a web- based interface that allows railway administrators to input real- time station parameters and receive instant risk predictions. The proposed system enhances safety management by enabling early risk identification, reducing dependency on manual supervision, and improving operational efficiency in railway stations.

VI. RESULT EVALUATION

The experimental results demonstrate that the proposed KNN- based railway accident prediction system is effective in identifying potential accident risk levels based on operational and environmental parameters. The classifier successfully analyzed structured railway data including passenger volume, train frequency, infrastructure capacity, and historical accident patterns to predict risk categories with high reliability. The model achieved strong classification performance across training and testing datasets, indicating its ability to generalize to unseen operational conditions.

The evaluation results show consistent prediction accuracy and stable performance across different railway station scenarios. The distance-based classification mechanism of KNN effectively captured similarities between current operational inputs and historical risk patterns. Performance metrics such as accuracy, precision, recall, and F1-score confirm that the system minimizes false alarms while accurately detecting high-risk conditions. Overall, the results validate the effectiveness of the proposed framework in supporting proactive railway safety management and data-driven decision-making.

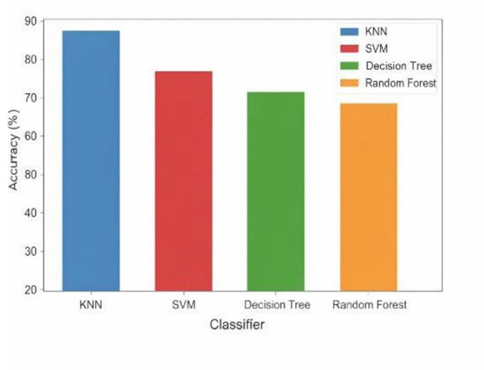

Fig 4: Performance comparison of classification algorithms for railway accident prediction

The comparative analysis of the classifiers revealed that the KNN model achieved the highest prediction accuracy due to its ability to capture similarity patterns within structured railway operational data. Unlike complex parametric models, KNN adapts dynamically to variations in passenger density, train frequency, and infrastructure-related features. Performance evaluation using accuracy, precision, recall, and F1-score confirmed that the proposed system reliably predicts accident risk levels while minimizing false classifications. Overall, the results validate the effectiveness of the KNN-based approach in improving railway safety risk prediction and supporting proactive operational decision-making.

Model	Accuracy	Precision	Recall	F1-Score
KNN	92.0	91.5	92.3	91.9
SVM	89.0	88.4	89.2	88.8
Decision Tree	85.0	84.7	85.3	85.0
Random Forest	90.0	89.6	90.1	89.8

The performance evaluation table presents a quantitative comparison of classification models using accuracy, precision, recall, and F1-score. The KNN model achieved an accuracy of 92.0%, demonstrating strong capability in identifying railway accident risk levels. High precision and recall values indicate that the model effectively reduces both false positives and false negatives, ensuring reliable safety prediction. The SVM and Random Forest classifiers also provided competitive results; however, their performance was slightly lower compared to KNN in capturing localized similarity patterns within the dataset. The Decision Tree model showed comparatively lower accuracy due to its sensitivity to data variations and potential overfitting in dynamic operational environments.

Furthermore, the integration of the trained KNN model into a web-based monitoring interface enhances real-time accident risk prediction. The system allows railway administrators to input operational parameters and receive instant safety risk assessments. Overall, the proposed framework demonstrates strong potential in supporting proactive railway safety management, improving operational awareness, and reducing accident risks through data-driven prediction mechanisms.

VII. CONCLUSION

This paper presented a machine learning–based railway accident prediction system designed to analyze operational, environmental, and infrastructure-related parameters for proactive safety management. The proposed framework utilizes the K-Nearest Neighbors (KNN) algorithm to classify railway station conditions into predefined accident risk levels based on similarity measures. By incorporating features such as passenger density, train frequency, platform capacity, train halting time, and historical accident data, the system effectively models operational risk patterns. Experimental results demonstrate that the KNN classifier achieves superior prediction accuracy compared to baseline models, confirming its suitability for dynamic railway environments.

The integration of the trained model into a web-based monitoring interface further enhances practical usability by enabling real-time accident risk assessment. The proposed system reduces dependency on manual supervision and supports data-driven decision-making for railway administrators. Overall, the study validates the effectiveness of similarity-based classification techniques in improving safety prediction and operational awareness. The developed framework contributes toward the advancement of intelligent transportation systems by promoting proactive risk identification and enhancing railway safety management.

VIII. FUTURE WORK

Although the proposed KNN-based railway accident prediction system demonstrates effective performance in identifying operational risk levels, several enhancements can be explored in future research. One potential improvement involves incorporating real-time streaming data from IoT sensors, CCTV analytics, and smart ticketing systems to enable continuous monitoring of station conditions. Integrating advanced anomaly detection techniques such as density-based clustering or hybrid ensemble models may further enhance predictive accuracy and robustness. Additionally, optimizing feature selection using dimensionality reduction techniques like Principal Component Analysis (PCA) can improve computational efficiency when handling large-scale railway datasets.

Future work can also focus on expanding the framework to support spatiotemporal risk modeling by analyzing time- dependent passenger flow patterns and seasonal operational variations. The inclusion of deep learning-based behavioral analytics for crowd movement recognition may further strengthen early risk detection capabilities. Moreover, deploying the system in a distributed cloud-based environment would improve scalability and allow integration with centralized railway management systems. These advancements would contribute to building a fully intelligent, adaptive, and real-time railway safety monitoring ecosystem capable of minimizing accident risks and enhancing transportation reliability.

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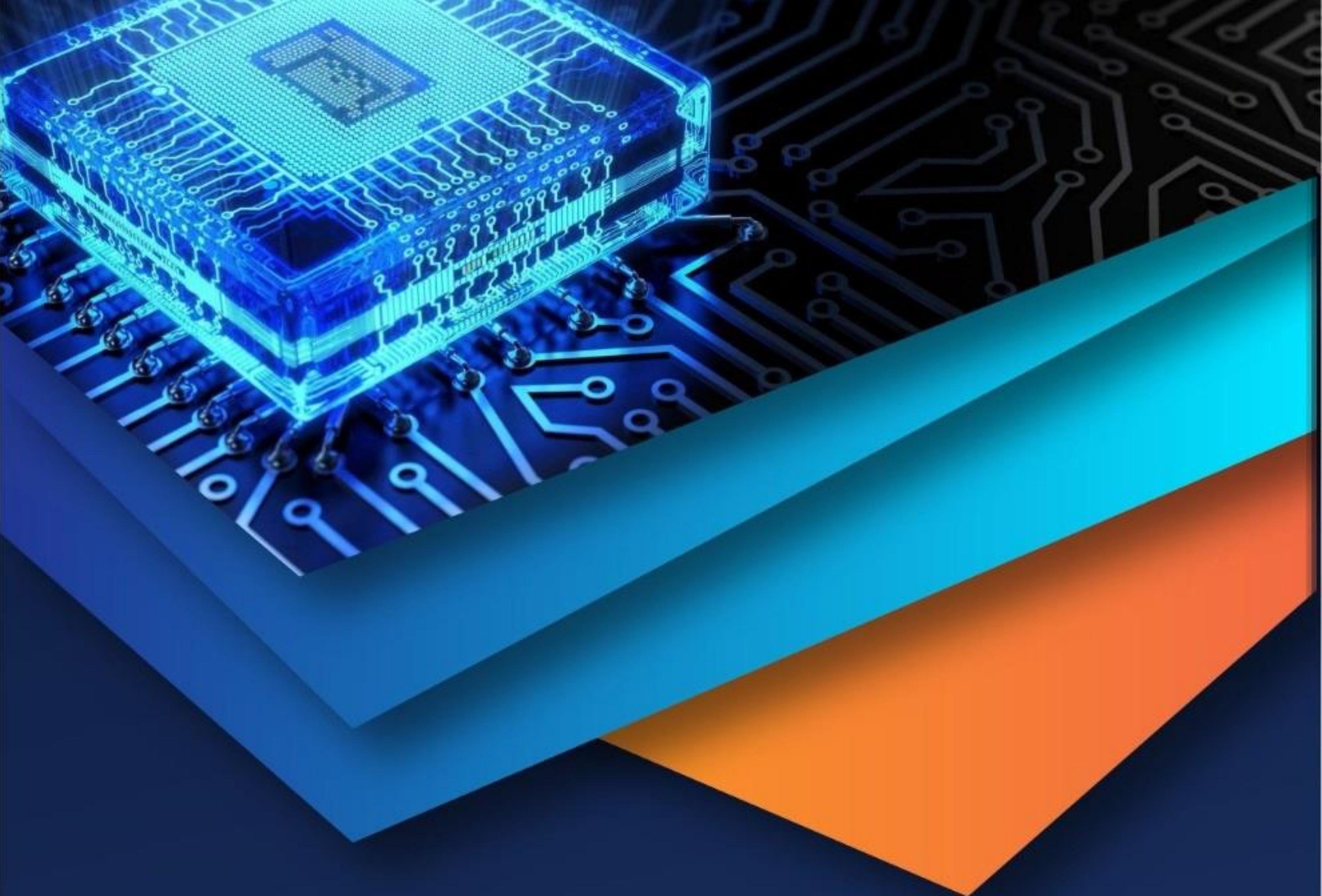

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