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A Review of Theoretical Studies and their Applications in Weak Soil Strength Enhancement using Waste Materials

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Abstract: According to an extensive evaluation of published studies, there is a shortage of research on systematic literature reviews related to machine learning prediction techniques, which includes mostly theoretical studies and methodologies in soil improvement using green waste materials. A literature review suggests that machine learning algorithms are effective at predicting various soil characteristics, including compressive strength, deformations, bearing capacity, California bearing ratio, compaction performance, and stress–strain behavior, geotextiles pullout strength behavior, and soil classification. The current study aims to comprehensively evaluate recent breakthroughs in machine learning algorithms for soil improvement using a systematic procedure known as PRISMA and meta-analysis. Relevant databases, including Web of Science, Science Direct, IEEE, and SCOPUS, were utilized, and the chosen papers were categorized based on: the approach and method employed, year of publication, authors, journals and conferences, research goals, findings and results, and solution and modeling. The review results will advance the understanding of civil and geotechnical designers and practitioners in integrating data for most geotechnical engineering problems.

Keywords: PRISMA, soil improvement; by-product; artificial intelligence; green waste materials; environmental impact.

I. INTRODUCTION

Climate change and environmental impacts are currently challenging topics for the Earth's survival; waste management became a trending issue. Reusing the waste materials in different applications is one of the solutions that help in waste management, where one of the uses is in soil improvement applications, as it is a frequently used material in this industry. Some industrial wastes have cementitious properties that could help replace traditional soil-reinforcing materials such as cement, where cement is a direct reason for climate change by a 5% of the carbon dioxide CO2 emissions through its production. Cement manufacture uses 4 Giga joules of energy and emits an equivalent amount of CO2 into the atmosphere, which accounts for 30% of all CO2 emissions worldwide from an environmental perceptive. Additionally, because limestone is essential to cement production, a severe shortage may develop over the next five years. Machine learning is a rapidly growing field that has the potential to revolutionize geotechnical engineering. In particular, it has great potential for improving soil improvement using green materials, which is a critical area of research for sustainable and environmentally friendly construction practices. Machine learning is one of the trending topics that was used in several geotechnical applications such as prediction of retaining wall deflection, excavation, soil behavior, Earth retaining structures, bearing capacity, settlement of structures liquefaction assessment, slope stability and landslide, and soil characterization. That helps geotechnical engineers to control and predict the soil properties and behavior under various loading conditions. In addition, it is used to predict the stress–strain behavior and shear resistance of the after-treatment using waste materials which helps in controlling the used ratios of waste materials. However, minimizing the error of the prediction model is one of the challenging problems which depends on the algorithm used for prediction. In this article, we will discuss some of the key applications of machine learning, in geotechnical engineering for soil improvement, including model accuracy, regression models, and performance. One of the most significant advantages of machine learning is its ability to improve model accuracy. Machine learning algorithms can use large amounts of data to identify patterns and relationships that may not be apparent to engineers. This can lead to more accurate predictions of soil behavior and the effectiveness of various soil improvement techniques. Regression models are a common tool in geotechnical engineering for predicting soil behavior based on various parameters, such as soil type, moisture content, and density. Machine learning algorithms can be used to develop more accurate regression models by identifying complex nonlinear relationships between these parameters and soil behavior.

Weak soils, such as clayey, silty, or organic soils, often exhibit low shear strength, high compressibility, and poor load-bearing capacity, making them unsuitable for construction purposes. Traditional soil improvement methods such as compaction, stabilization with lime or cement, and deep soil mixing, while effective, can be resource-intensive and environmentally harmful. As environmental concerns grow, there has been a shift towards using waste materials from industrial, agricultural, and urban sources to improve soil properties. The advent of machine learning (ML) techniques presents a promising solution to better understand the complex relationships between waste material characteristics and their effects on soil properties. ML can help optimize the usage of waste materials in soil stabilization, predict the outcomes, and minimize experimental trial-and-error approaches.
Table-1 considering a systematic review paper, merging accessible methods and recent studies is given.

Table -1
Improved soil testing research using ML

Soil Type	Materials Used	AI Models	Tests Performed
Clayey Soil	Alum	ANN(k-folded)	CBR Sieve analysis Atterberg limits Compaction test
Clay	NaOH	MFFNN CFNN RBNN ENN MLR	Sieve analysis Atterberg limits modified proctor test
Subgrade	Coal Ash Bagasse Ash Groundnut Shell Ash	ANN MRA	CBR, UCS
Cohesive Soil	Fly Ash Blast Furnace Slag	GMDH ANN	UCS
Soil	Geogrid	MLR ANN	Settlement
Sand	Peat	MARS	UCS
Various Soils	Alum Sludge	ANN	MDD, USCS OMC, SG PI, CBR
BASE	Quarry Waste	ANN	BC Deformation
Soft Soil	Fly Ash	BM	UCS

II. LITERATURE OVERVIEW

A. Paper Distribution

Since the early 1900s and up to the recent date of this article's writing, over 85,000 research papers were indexed in the field of geotechnical engineering in the Web of Science (WOS). However, when the search was limited to machine learning and soil improvement using waste or recycled materials within the field of geotechnical engineering, only eight articles were found, and the remaining titles were very limited. The number of articles on machine learning applications in soil improvement using waste or recycled materials significantly increased in the last six years, with seven of the eight articles being published during this period, and no articles detected in previous decades.

Weak soils, including clayey, silty, and organic soils, exhibit low bearing capacity and pose significant challenges for construction projects. The primary goal of soil stabilization is to enhance soil properties such as shear strength, plasticity, and compaction characteristics. There are several traditional and innovative methods to improve weak soils.

Geotechnical engineering recently showed extensive use of ELM in predicting and controlling the **bearing capacity**. Kumar and Samui [1] used the ELM model to analyze a piling foundation's reliability. The study's main goal was to determine how well an extreme learning machine model could forecast a pile's bearing capability when buried in loose soil. The evaluation and prediction of **slope stability** were also carried out by Liu et al. [18] using an extreme learning machine ELM, with significant accurate prediction. In addition,

it was demonstrated by Sahu et al. [6] that the created ANN model could explain how inputs affect outputs physically, as seen in the neural interpretation diagram NID. It was found that whereas foundation depth to width was directly related to the reduction factor, inclination angle to internal friction angle ô was inversely related to RF levels for the data conducted by Sahu et al. However, it is also possible to conclude that the appropriate pavement design technique even permits incorrect evaluation and analysis of design factors and the design process itself, which can result in uncertain, uncertain design explanations. That is supported by the weak relationships between the constructed and expected structural data.

Deformations and settlements are significant challenges for geotechnical engineers to control [6]. Therefore, using machine learning to predict and control settlements is a trending research area in both experimental work [2,8] and/or simulation [18].

That helps in better understanding the soil's behavior, especially after improvement using green, by-product, or recycled materials under various loading conditions [17]. The deformations were predicted using machine learning algorithms such as ANN, MLR, and ELM.

All derived efficient prediction models with high accuracy. ML was used to calculate the settlement of footing laid on geogrid strengthened soil using ferrochrome slag industrial waste using ANN and ELM, where the models are capable and effective at forecasting settlement [8]. That gives an advantage to ML compared to experimental methods; developed

computational models are less time- and money-consuming and considerably reproduce the findings of the experimental study.

As geotextile and geogrids are important in the geotechnical industry, new materials such as coir fibres were proposed as an eco-friendly geotextile material. The interaction among soil and geotextile and geogrids is crucial for stability and safety in the geotechnical industry. Therefore, machine learning helps predict the optimum pullout force of geogrid from soils as a proposed new eco-friendly material for soil improvement [4].

The ANN algorithm was significantly efficient in predicting the pullout force through the variables conducted from the geotechnical and engineering properties of the improved soil [4,19]. However, new data are required to enhance the performance of ANN models [4]. However, important aspects should be considered, as installation damage to geogrids should account for: used strength reduction factors and recognizing the field pullout behavior and the influence of cyclic loading on the behavior of embedded reinforcement in ISFS pulling out [4].

The efficacy of ML-based models to predict the performance of strengthened soils by geopolymer may unquestionably be improved by carrying out further trials under various conditions. In addition, this study focused on considering eco-friendly materials as a significant innovation in our understanding of soils stabilized by geopolymer in predicting unconfined compressive strength [5]. The prediction models were significantly accurate compared to traditional predict mathematical models. However, there was always a limitation in the sample number used for input datasets [6].

Therefore, including more data from various soil types and test settings allows the model to be easily retrained to consider a larger variety of data to overcome this constraint [9]. Although ANN results are more accurate, only the optimized network can be displayed. Overall lower values of MAE, RSE, MSE, and RRMSE for trained, validated, and tested dataset are approaching 0, whereas NSE values for trained, validated, and tested dataset corresponding unity show that the ANN model performs better and more efficiently [7].

B. Traditional Soil Stabilization Methods:

1) Mechanical Stabilization: Involves improving soil compaction and structure by introducing granular materials (e.g., sand, gravel).
2) Chemical Stabilization: Involves adding chemical stabilizers like cement, lime, or gypsum to induce reactions that bind soil particles.
3) Thermal Stabilization: Involves applying heat to the soil to reduce plasticity and improve compaction characteristics

C. Waste Material-Based Soil Stabilization:

Waste materials have been increasingly used for soil stabilization due to their low cost and environmental benefits. These materials include:

1) Fly Ash: A by-product of coal combustion, fly ash can improve soil strength and reduce plasticity.
2) Plastic Waste: Shredded plastics improve shear strength and decrease swelling potential in soils.
3) Recycled Concrete Aggregate (RCA): Waste concrete enhances soil bearing capacity.
4) Rubber Waste: Tire-derived rubber improves soil flexibility and shear strength.
5) Agricultural By-products: Materials like rice husk ash and coconut coir enhance soil texture and reduce plasticity.
6) Industrial By-products: Slag, silica fume, and other industrial residues are gaining attention for their stabilizing effects.

III. MACHINE LEARNING METHODOLOGY

Machine learning (ML) refers to algorithms that enable computers to learn from and make predictions based on data. In the context of soil improvement, ML can be used to model the effects of various waste materials on soil properties and optimize the stabilization process. This study conducted a systematic evaluation and illustrated the current condition of machine learning technology in predicting and controlling the strength of soil improved using green materials. This evaluation was based on the PRISMA technique as recommended by Moher et al., where the method used was the systematic literature review followed as described by both Shamseer et al. and Mardani et al. Therefore, the goals and what was written in the literature and systematic reviews explained the research topic (Machine Learning Control for Green Materials Used in Soil Improvement Applications).

A. Research Objectives

1) This paper analyzed and summarized the most recent studies on machine learning application in strengthening materials for geotechnical applications. The following are the goals of this systematic literature review:
2) To classify and categorize the related and recent research in accordance with various cases of studies;
3) To indicate the motives, challenges, and recommendations of machine learning technology with soil improvement using green materials integration to enhance this technique's efficiency;
4) To study issues relevant to machine learning incorporation in prediction and control- ling the strength of soil improved using green materials and planned solutions in the scope of this research.

B. Data Resources

Systematic exploration was achieved using four electronic databases, which were as follows: Web of Science (WOS), ScienceDirect, Scopus, and IEEE Xplore, the selection of the mentioned electronic databases was based on various articles and conferences published in English only on developing topics, including machine learning applications in soil improvement using green or/and recycled materials.

C. Study Selection

Selecting relevant studies is difficult, especially when several study areas are being considered. As a result, this step is extremely crucial and might also be the most neglected when researching a particular subject. The first stage involved filtering titles and abstracts to weed out duplicate and irrelevant studies publications. The second stage of the process involved reading the full texts of the chosen research articles.

D. Importance of Machine Learning in Geotechnical Engineering

1) Data-Driven Predictions: ML can predict how different soil properties will change after stabilization with waste materials, reducing the need for exhaustive testing.
2) Optimization of Stabilization Processes: ML can determine the optimal quantity and type of waste material to use for improving specific soil characteristics.
3) Advanced Modelling: ML can handle the complex, non-linear relationships between soil properties and stabilizing agents, leading to more accurate predictions.
4) Quality Control: Machine learning can help in monitoring the quality of stabilized soils by analyzing the relationship between various input factors (like the type and amount of waste material) and output parameters (like shear strength and plasticity index).

E. Types of Machine Learning Techniques Applied in Soil Stabilization:

1) Supervised Learning: Algorithms like linear regression, decision trees, and support vector machines (SVMs) are used when labelled datasets are available.
2) Unsupervised Learning: Clustering algorithms like k-means are used to identify patterns in unstructured data.
3) Deep Learning: Artificial neural networks (ANNs) are particularly useful for complex, multi-dimensional data and modelling non-linear relationships.
4) Reinforcement Learning: Involves learning through trial and error and could be used to continuously optimize stabilization processes in real-time.

IV. APPLICATIONS OF MACHINE LEARNING

Machine learning has been used in several studies to optimize soil stabilization and predict outcomes based on various input parameters like waste material type, percentage, and soil characteristics.

A. Data Collection and Analysis

For ML models to be effective, large datasets are needed. Data can be collected through laboratory tests, field tests, or simulation models. Important soil parameters include:

1) Shear strength
2) California Bearing Ratio
3) Compaction characteristics
4) Plasticity index
5) Permeability
6) Swelling potential

ML models are trained on these parameters, with the goal of predicting soil behaviour under different stabilization conditions.

A flow chart is given below for prediction of CBR of soil using a ML model.

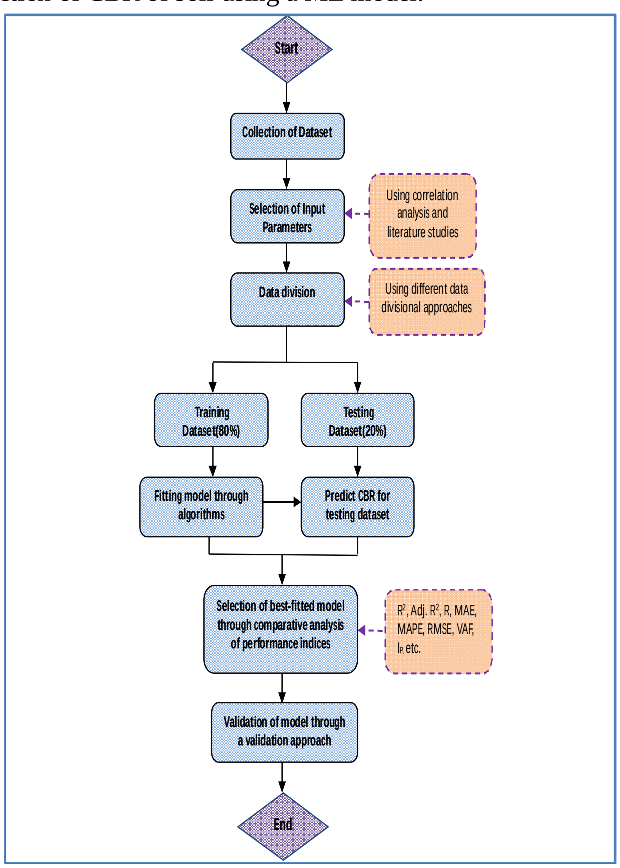

Fig. 1 Flow Chart for CBR Prediction

B. Modelling Soil Behavior with Machine Learning:

1) Regression Analysis: Used to predict continuous variables, such as shear strength or permeability, based on input features like the amount and type of waste material.
2) Multiple Linear Regression (MLR): The correlation coefficient and nature of the link between the input and output variables are often calculated in regression models. Although the least squares method is commonly used to fit linear regressions, alternative strategies may be utilized, such as lowering the “lack of fit” in various norms or the multi-objective version of the least squares loss function as in ridge regression. Basic and multiple linear regression are the two varieties of linear regression. MLR determines the degree of correlation between two or more independent variables (predictors) and a single response variable (dependent variable).
3) Artificial Neural Networks (ANNs): ANN is well known as a tool for modelling the complicated multi-criteria systems that are a part of approximation problems. Three layers comprise the ANN (artificial neural network) process: a layer of input, hidden or more layers, and a layer of output. Each hidden layer is linked to the other layers using a transfer function, weights, and biases. ANNs have been widely applied to model the complex, non-linear relationships in soil stabilization. For example, an ANN can predict the effect of fly ash and rice husk ash on soil compaction and strength.
4) Back Propagation Neural Network (BPNN): BPNN is a form of ANN algorithm evaluated within the context of supervised learning. Typically, the BPNN adjusts the weights by rerouting the output layer to the input layer. In addition, each layer of the ANN employs examples and exercises to aid learning, similar to humans. Any model could train to manipulate well using a two-layer back propagation network (BPNN) with nonlinear function as first layer’s function and linear as the second layer’s function
5) Support Vector Machines (SVM): SVMs can be used for classification tasks, such as identifying which waste materials are most effective for stabilizing particular types of weak soil.
6) Decision Trees and Random Forests: These models are used for feature selection and classifying soils based on their suitability for different stabilization techniques.
7) Genetic Algorithms (GAs): GAs have been used to optimize the parameters of soil stabilization processes, such as the quantity and type of waste material to be used.
8) K-Nearest Neighbors (KNN): KNN can classify soils based on similarities with previously tested samples, making it a valuable tool for predicting the effectiveness of waste material on a new soil sample.

C. Optimization of Stabilization Parameters

Machine learning can optimize the amount of waste material required for stabilization, minimizing cost while ensuring maximum soil improvement. Techniques like genetic algorithms (GAs) and particle swarm optimization (PSO) are used to determine the best combination of waste material and soil treatment methods.

V. LIMITATIONS

Machine learning algorithms are still limited in controlling and predicting the behavior of the eco-friendly improved soil. In addition to the trend of climate change’s effect on earth, it became essential to use ML in this trend. In addition, there are efficient algorithms not used through the conducted studies through this research, such as support vector regression (SVR), gradient boost trees (G Boost), extreme gradient boost tree (xG Boost), decision trees
(DT), adaptive neuro-fuzzy inference system (ANFIS), and others, despite their efficient prediction in other studies on deformation, stress–strain, compressive strength, and other areas of study. Therefore, more research in this area is required to understand the mathematical meaning and model architecture that would help researchers select the best algorithm application in the eco-friendly geotechnical industry. The selections of the algorithms depend on the input features used for building the models, otherwise.

While the application of machine learning in soil improvement shows great promise, there are several challenges and limitations that must be addressed:

1) Data Quality and Availability: High-quality, comprehensive datasets are essential for training ML models. However, in many cases, data may be sparse, incomplete, or not standardized.
2) Interpretability of Models: Many ML models, especially deep learning algorithms, are considered "black-box" models. This lack of interpretability can make it difficult to understand the underlying mechanisms driving the predictions.
3) Generalization of Models: Machine learning models trained on one dataset may not generalize well to different soil types or waste materials. This limits their widespread applicability.

4) Computational Complexity: Some machine learning models, particularly deep learning algorithms, require substantial computational resources, which may not be readily available in every research or practical application.

VI. FUTURE DIRECTIONS

The integration of machine learning and waste materials in soil improvement is still in its early stages. Future research could focus on the following areas:

1) Large-Scale Data Collection: A more extensive database of soil properties and waste material characteristics is necessary to build more accurate and generalized machine learning models.
2) Hybrid Models: Combining machine learning techniques with traditional geotechnical engineering methods could improve the reliability and accuracy of predictions.
3) Automation and Smart Systems: The use of ML-powered sensors and automation systems could enable real-time monitoring and optimization of soil stabilization processes in the field.
4) Sustainability Analysis: Future research should also consider the life cycle assessment (LCA) of using waste materials for soil improvement, integrating environmental impact studies with machine learning predictions.

VII. CONCLUSION

In this research, studies about machine-learning applications in green soil improvement over a 10-year period (1 January 2014 to 11 October 2024) were systematically reviewed. The research motivation of this work was the trend of machine learning and the massive environmental impact of the by-product and waste materials and, therefore, how both can be used in geotechnical applications for green soil improvement. Furthermore, there is limited research on this area (16-18 articles), the used algorithms and their limitations, the collected data from the experiments, soil types, and the targeted output. This comprehensive review focused on key aspects including the selection process for the latest articles, an analysis of the existing papers in the field using a taxonomy approach, and a discussion of previous research endeavors, challenges, and motivations. Despite the limited number of studies available in this area, the current data play a crucial role in combating future outbreaks of a similar nature and overcoming these difficulties, as geotechnical engineers and researchers. In addition, studies should consider how our respected area can be an asset in the near future. From the perspectives of geotechnical engineering, integrating other technologies, such as AI, ML, and different analysis procedures, can contribute to making a difference. Despite the outstanding potential of and vast interest in machine- learning applications, it was concluded that its impact on healthcare remains in green soil improvement applications are yet to be developed. The majority of the studies on in green soil improvement applications based on machine learning continue to remain in the form of novel concepts and in green operating by-products. The future of machine-learning applications in green soil improvement has the immense potential to exert a significant positive effect on sustainable and efficient green soil improvement.

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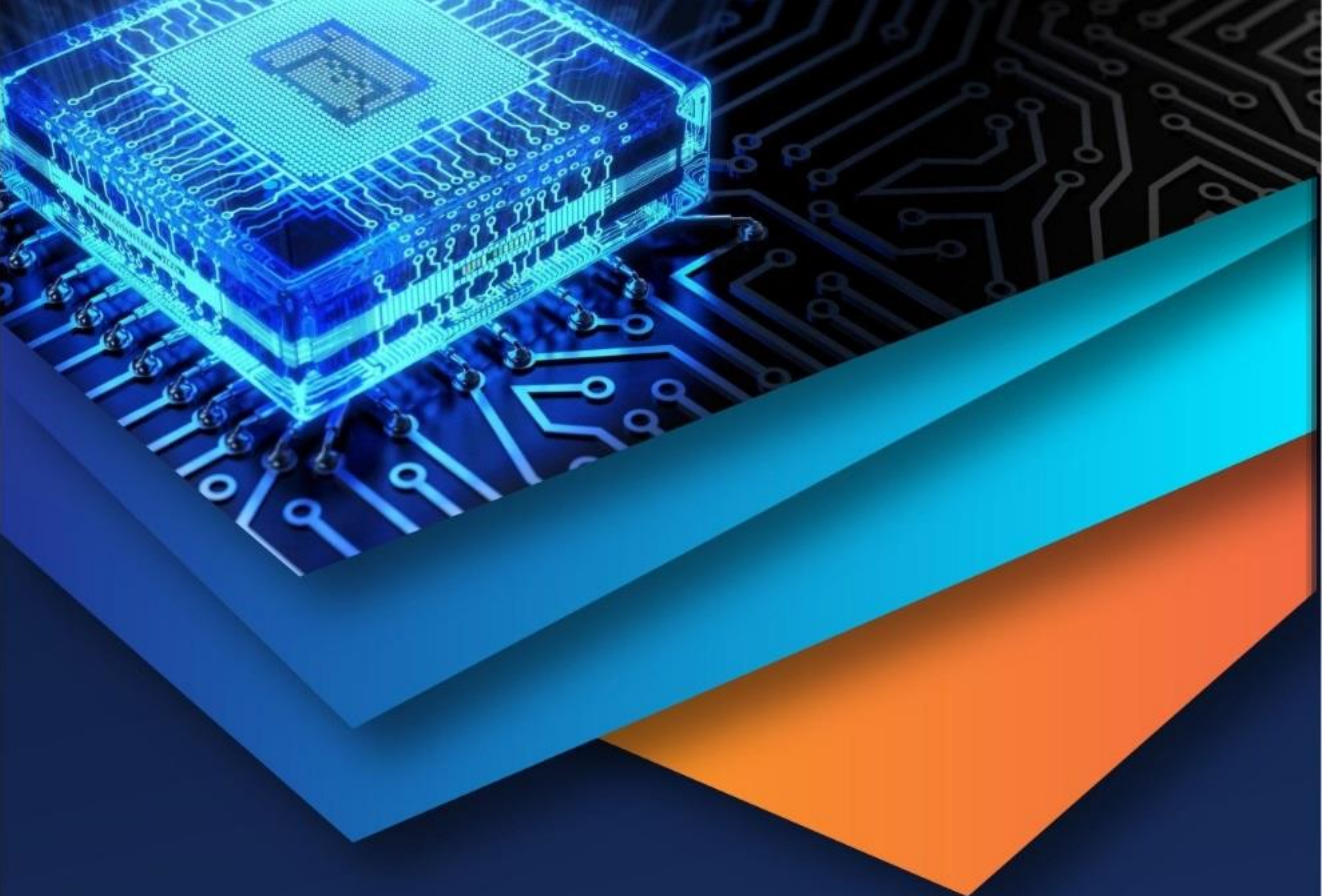

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