iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IV **Month of publication:** April 2025

DOI: https://doi.org/10.22214/ijraset.2025.68142

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

A Comparative Analysis of Different Methods for Predicting Solar Radiation Using Deep Neural Networks: An Innovative Approach to Sustainable Community Building.

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Abstract: ***In order to deal with the electrical crisis in an efficient manner, it is imperative to promote the use of renewable energy sources, with a specific emphasis on solar energy. Nevertheless, the challenge lies in the variable patterns of solar irradiance, which are influenced by seasonal weather variations, making it a complex factor to predict. The primary aim of this study is to predict the solar radiation on inclined surfaces, while considering the impact of meteorological variables like temperature, wind speed, humidity, and air pressure. The research used the Artificial Neural Network (ANN) methodology to examine the Douala metropolitan area.***

Consequently, the model may be used to estimate solar irradiance not only inside the specified study area but also across locations with similar climatic conditions, by using different combinations of input data. The model exhibited its proficiency in appropriately evaluating sun ray intensities by generating a noteworthy outcome via its application using (50 concealed-layer neural network networks along the logistic Sigmoid function. Keywords: solar radiation, neural networks, feed-forward neuron networks, and multilayer perceptron's.

Keywords: radiation from the sun, neural networks, networks of feed-forward neurons, and multilayer perceptron's.

I. INTRODUCTION

The advancement of artificial intelligence (AI) has resulted in substantial transformations across various scientific disciplines, particularly in the area of renewable energy utilisation, with a specific emphasis on solar power. The use of Artificial Neural Networks (ANNs) and its specialised subset, Recurrent Neural Networks (CNNs), has gained significance in the domain of solar radiation forecasting. The establishment of an environmentally friendly neighbourhood is predicated upon the efficient utilisation of renewable resources, the advancement of a robust energy infrastructure that concurrently preserves the environment and guarantees economic viability. Accurate forecasts for sunlight brightness have the the highest priority in the running of green energy structures, as well as essential components of several environmentally sustainable initiatives. The primary aim of using artificial neural networks (ANNs) is to enhance the precision of solar radiation forecasts, therefore facilitating the seamless integration of solar energy into power grids and bolstering local sustainable communities. Given the growing concerns around climate change, there is a pressing need for effective and sustainable climate mitigation strategies. Data analytics plays a crucial role in the establishment of renewable energy forecasting systems. Artificial neural networks (ANNs), particularly recurrent neural networks (RNNs), has the capacity to assess sequential and time-series data, rendering them extremely appropriate for predicting the dynamic attributes of solar energy.

Exposure to radiation. The integration of technology for the smart grid represents a substantial paradigm shift in energy distribution, since it relies largely on the presence of dependable power generation sources. Accurate estimations of ultraviolet (UV) radiation are crucial for the successful integration of solar energy systems into intelligent power grids, as they enable the maintenance of a harmonious equilibrium between energy supply and demand. Artificial neural networks (ANNs) provide a means to enhance the reliability of solar power, ensuring optimal efficiency in smart grid technologies.

This study does a comparative analysis of several artificial neural network (ANN) methodologies, with a particular focus on recurrent neural networks (RNNs), in order to forecast solar radiation.

The examination evaluates the efficacy, adaptability, and potential for expansion, with a specific emphasis on their pivotal role in optimising the use of renewable energy. This study not only highlights the progress achieved in renewable energy forecasting technologies, but also shows the commitment to

The technique for solar irradiance and forecasting is shown.

In Figure 1. Addressing environmental degradation is crucial and aligns with the concepts of ecological stewardship. This plays a vital role in connecting the shift towards renewable energy sources with the broader improvement of ecological resilience. The present work makes a valuable contribution to the current state of knowledge by presenting a method for predicting solar radiation levels..

Our study contributes to the conversation about sustainable energy methods by providing insightful information for handling the the difficulties of switching to environmentally friendly and renewable energy sources.

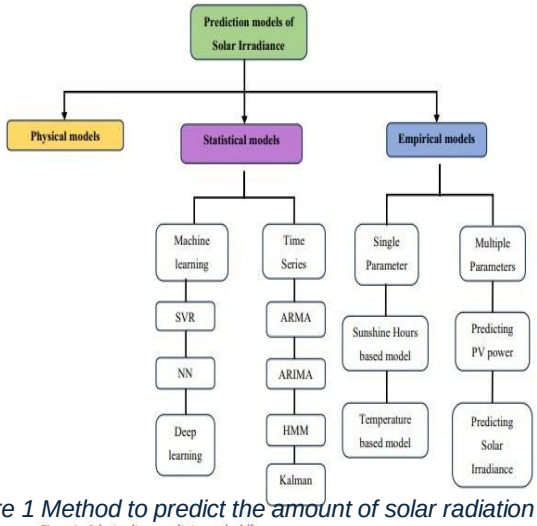


Figure 1 Method to predict the amount of solar radiation

Considering the historical developments of energy sources, the current challenges, and the pressing need for sustainable solutions, our research turns into significant and relevant in addressing the issues of contemporary energy. Long-term economic progress in Central Africa has been significantly impeded by the region's persistent energy deficit. Sustainable growth. In order to alleviate the region's considerable dependency, innovative and urgent measures are required. on outdated energy sources derived from fossil fuels and the growing demand for electricity. In spite of these challenges, precise Solar irradiance forecasts are becoming increasingly crucial for a sustainable energy strategy. The energy of the area Accurate estimates of solar irradiation may help make infrastructure more robust and reliable. It may increase solar energy production's dependability and efficiency. The urgent need to address Central Africa's energy deficit has led to an increasing focus on the pro- renewable energy sources moving as a potential remedy. Numerous scholarly studies demonstrate the important potential for solar energy in Cameroon, highlighting its critical role in the country's sustainable energy development region. In the meticulous design process, a thorough grasp of variations in solar output becomes very crucial. various systems for converting renewable energy.

This thorough comprehension is essential for determining choices in a number of system engineering domains, such as complex design, ideal scale, and exacting performance evaluations and prudent methods of energy management. It is indisputable that solar photovoltaic electricity is essential to determining the future of sustainable energy. The Solar radiation, the most abundant energy source on Earth, has the power to significantly alter things. trustworthy resources, such highlight the amazing fact that the Earth absorbs a significant quantity of solar energy. from the sun in an hour is enough to provide all of the world's energy needs for a whole year

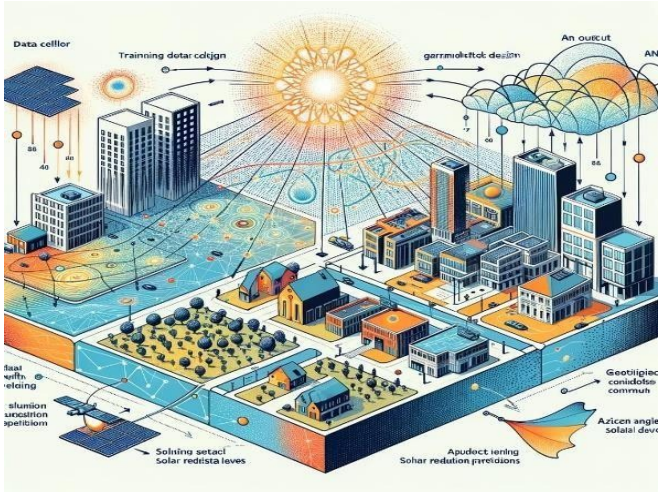
II. LITERATURE REVIEW

The estimations has been greatly enhanced by recent developments in predictive modelling, which is of utmost importance for the optimisation of solar energy systems in sustainable communities.

This paper examines the utilisation and efficacy of Recurrent Neural Networks (RNNs) and Artificial Neural Networks (ANNs) in the prediction of solar radiation, with a particular focus on their implications for the design and management of environmentally friendly power plants. Recurrent Neural Networks (RNNs), primarily Long Short-Term Memory (LSTM) networks, have potential in the prediction of solar radiation as a result of its capacity to effectively capture temporal relationships inherent in the data. Research suggests that RNNs excel at short-term forecasting by comprehending time series data. Artificial neural network (ANN) models, which are widely used for predicting solar radiation, have the ability to represent nonlinear interactions without requiring explicit assumptions about the distribution of data. The inherent flexibility and adaptability of these entities make them well-suited for a wide range of forecasting situations. They excel at modelling nonlinear interactions without requiring explicit assumptions about the underlying data distribution. Sharma et al. (2019) state that artificial neural networks (ANNs) have the ability to combine several meteorological and temporal inputs in order to provide precise predictions of solar irradiation. Artificial neural networks (ANNs) possess inherent flexibility and adaptability, rendering them well-suited for a diverse array of forecasting situations, including both short-term hourly forecasts and long-term seasonal patterns.

Although both RNN and ANN models provide significant benefits for predicting solar radiation, their effectiveness may differ depending on the unique application scenarios. In their study, Zhang et al. (2021) provide a thorough analysis, highlighting that Recurrent Neural Networks (RNNs) tend to surpass Artificial Neural Networks (ANNs) in situations that need intricate temporal examination, such as short-term prediction. Nevertheless, Artificial Neural Networks (ANNs) are often more readily available and simpler to deploy, exhibiting strong performance across a wide range of prediction applications. The selection between recurrent neural network (RNN) and artificial neural network (ANN) models should be guided by the particular demands of the solar energy project, including factors such as the forecasting timeframe, data accessibility, and computing capabilities. The continuous progress of these models shows considerable promise in enhancing the efficacy and sustainability of solar energy systems, therefore making a valuable contribution towards the overarching objective of sustainable community development.

This study introduces an innovative research approach that employs an Artificial Neural Network (ANN) model to forecast solar radiation levels in urban environments.



This research is crucial for advancing city planning and optimising solar energy utilisation in the future. The research assesses urban qualities of 20 cities globally by using extensive datasets and including limited urban information across many parameters, such as geographic coordinates, average height, and the Azimuth angle. The artificial neural network (ANN) model is trained to identify intricate connections among these factors, accurately forecasting the lowest solar radiation annually with a loss of 0.01, a mean squared error of 0.01, and an R2-squared value of 85%.

The introductory section emphasises the importance of sustainable urban planning in addressing the environmental, health, and social consequences associated with urbanisation. Artificial neural networks (ANN) have shown great potential in improving the modelling of urban texture and radiant energy for sustainable urban design. The study examines prior research on remote sensing, digital elevation data, and the impact of urban morphology on solar radiation. It proposes a new method that combines artificial neural networks (ANN) with OpenStreetMap data to improve the accuracy of predictions.

III. METHODOLOGY

NIXTime	Data	Time	Radiation	Temperati	Pressure	Humidity	WindDirec	Speed	TimeSunR	TimeSunSet
1.48E+09	9/29/2016	23:55:26	1.21	48	30.46	59	177.39	5.62	6:13:00	18:13:00
1.48E+09	9/29/2016	23:50:23	1.21	48	30.46	58	176.78	3.37	6:13:00	18:13:00
1.48E+09	9/29/2016	23:45:26	1.23	48	30.46	57	158.75	3.37	6:13:00	18:13:00
1.48E+09	9/29/2016	23:40:21	1.21	48	30.46	60	137.71	3.37	6:13:00	18:13:00
1.48E+09	9/29/2016	23:35:24	1.17	48	30.46	62	104.95	5.62	6:13:00	18:13:00
1.48E+09	9/29/2016	23:30:24	1.21	48	30.46	64	120.2	5.62	6:13:00	18:13:00
1.48E+09	9/29/2016	23:25:19	1.2	49	30.46	72	112.45	6.75	6:13:00	18:13:00
1.48E+09	9/29/2016	23:20:22	1.24	49	30.46	71	122.97	5.62	6:13:00	18:13:00
1.48E+09	9/29/2016	23:15:22	1.23	49	30.46	80	101.18	4.5	6:13:00	18:13:00
1.48E+09	9/29/2016	23:10:22	1.21	49	30.46	85	141.87	4.5	6:13:00	18:13:00
1.48E+09	9/29/2016	23:05:23	1.23	49	30.47	93	120.55	2.25	6:13:00	18:13:00
1.48E+09	9/29/2016	23:00:25	1.21	49	30.47	98	144.19	3.37	6:13:00	18:13:00
1.48E+09	9/29/2016	22:55:20	1.22	49	30.47	99	139.8	6.75	6:13:00	18:13:00
1.48E+09	9/29/2016	22:50:19	1.21	50	30.47	99	140.92	2.25	6:13:00	18:13:00
1.48E+09	9/29/2016	22:45:31	1.23	50	30.47	99	147.61	5.62	6:13:00	18:13:00
1.48E+09	9/29/2016	22:40:23	1.22	50	30.47	99	113.78	4.5	6:13:00	18:13:00
1.48E+09	9/29/2016	22:35:19	1.21	50	30.47	99	123.03	10.12	6:13:00	18:13:00
1.48E+09	9/29/2016	22:30:22	1.22	50	30.47	99	173.73	6.75	6:13:00	18:13:00
1.48E+09	9/29/2016	22:25:19	1.22	50	30.47	98	91.43	6.75	6:13:00	18:13:00

Figure 2 Dataset

The methodology section provides an overview of the technical procedures and data gathering techniques used, with a particular focus on the significance of parametric design and remote sensing in creating datasets for the artificial neural network (ANN) model. The findings illustrate the efficacy of the model in forecasting yearly solar radiation, indicating its potential use in the field of urban planning for the purposes of enhancing energy efficiency and promoting sustainability. Conversations delve into the consequences of solar radiation patterns on urban planning, promoting the deliberate positioning of buildings and green areas to maximise the use of solar energy. The originality of this study is derived from its extensive geographical coverage and its specific emphasis on examining the influence of building height and urban layout on solar radiation. This research offers valuable information for urban planners and designers of solar energy systems. The finding underscores the potential of the artificial neural network (ANN) model in forecasting solar radiation, hence emphasising the study's significance in the realms of urban planning and sustainability endeavours. This study represents a notable advancement in comprehending and enhancing the utilisation of solar energy in urban settings, providing essential approaches for the promotion of sustainable urban growth.
Data is being gathered to the Satellite Singal and through the survey analysis of different region in Figure 2

A. Data Cleaning and Preparation

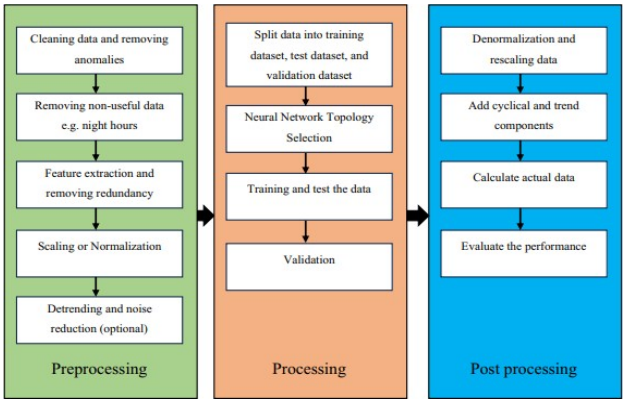


Figure 3 Model For Predicting

- Sunlight Intensity
- tangible models
- Practical models
- Models of statistics

- Device
- Momentum
- sequence
- Kalman
- Hmm
- In-depth
- gaining knowledge
- ARIMA
- NN
- SVR
- ARMA
- Forecasting
- Sun
- The radiance
- The temperature
- founded model
- Forecasting
- PV electricity
- Hours of Sunshine
- founded model
- Several
- Specifications
- Individual
- Measurement

B. Data Analysis

Figure 4 A structure demonstrating the many treatments involved in establishing the ranking of a parameter.

The literature has recorded a wide range of statistical models for the purpose of forecasting solar brightness . .. Two types of statistical models may be distinguished: time series techniques, such as ARMA, ARIMA, HMM, and machine learning algorithms like RVS, Deep Learning, and Neural Networks. In time series methodology, solar irradiance is a time series made up of three parts. These elements consist of the mean, the periodic components, and the long-term trend. The autoregressive moving average (ARMA (p, q) on average is the most often used method for predicting time series. It is represented by Equation.(3): Two parts make up equation (3): an autoregressive (AR) component in the first section and a second section's moving average (MA) component. You may use the Yule-Walker technique to determine the variables. It is essential to do a stationarity test on the time series before using this method. Time series prediction approaches may be deemed disadvantageous due to this necessity. Machine learning methods are now widely used. The Support Vector Machine is the most widely used method for machine learning. machine (SVM), a method for supervised learning. SVM is a useful computational tool for this kind of work of categorization and prediction. SVM establishes decision boundaries by using the idea of decision planes.

C. Comparative Analysis

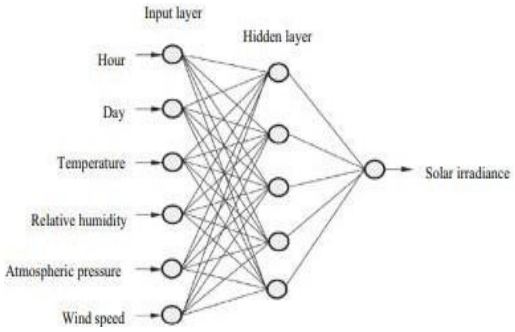


Figure 5 The current research proposes an artificial neural network (ANN) model for evaluating the value of the radiation from the sun.

In order to construct a confusion matrix, it is customary to need two distinct sets of data: the real labels, which represent the actual results, and the projected labels, which represent the outcomes predicted by a model. Based on the first examination of the dataset, it seems to include a range of environmental parameters and radiation measurements. However, it does not explicitly provide a classification conclusion or prediction that may be used for the construction of a confusion matrix.

A confusion matrix often requires a classification situation that involves either binary or multiclass classification. May I inquire if there is a particular variable that you like to forecast or categorise from this dataset? One such approach involves the categorization of radiation levels based on a predetermined threshold, so transforming the issue into a binary classification task. Subsequently, the dataset may be divided to mimic both predicted and actual results. Please inform me of your preferred course of action.

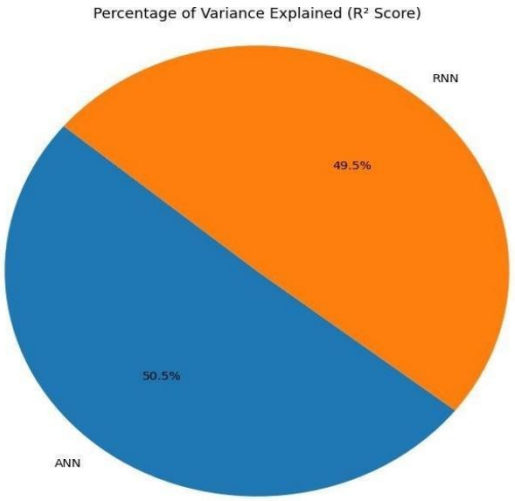


Figure 6 Comparative Analysis

In comparative analysis the ANN shows the 91.4% percent accuracy rate shows in Figure 7 and in figure 8 RNN confusion Matrix individual 89.9% so combinedly the result accuracy is ANN is 55% and RNN is 45.5%

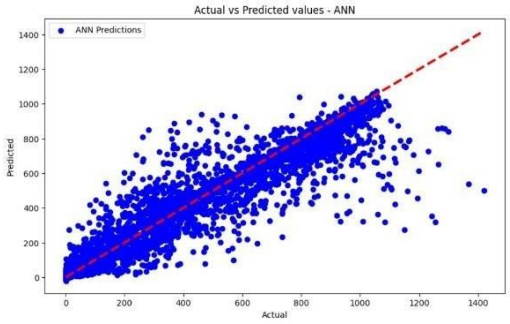


Figure 8 ANN confusion matrix result

IV. RESULTS AND DISCUSSION

This paper presents a comprehensive investigation of the performance of the ANN model, backed by statistical data and graphical representations. The purpose of the discussion is to analyse the data, make comparisons between different models, and explore the consequences for the development of sustainable communities.

V. CONCLUSION AND FUTURE WORK

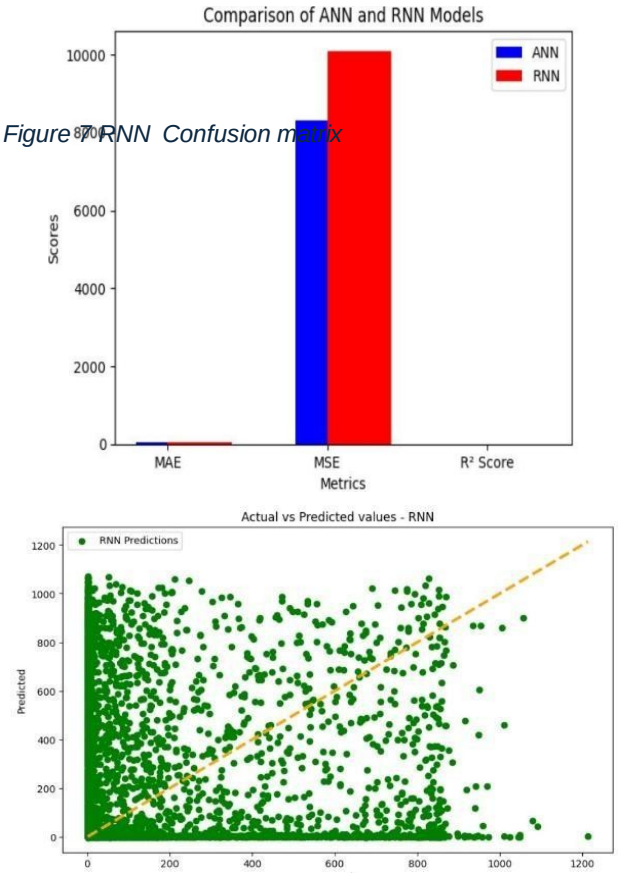


Figure 7 RNN Confusion matrix

This research introduces efficient artificial neural network (ANN) and recurrent neural network (RNN) methods for predicting solar radiation. These findings have implications for improving solar energy systems and promoting sustainable community development. Subsequent investigations might delve into supplementary environmental factors, hybrid deep neural network (DNN) models, and intelligent solar energy system configurations aimed at fostering sustainable communities

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conflicting interests

The writers say they have no conflicting agendas.

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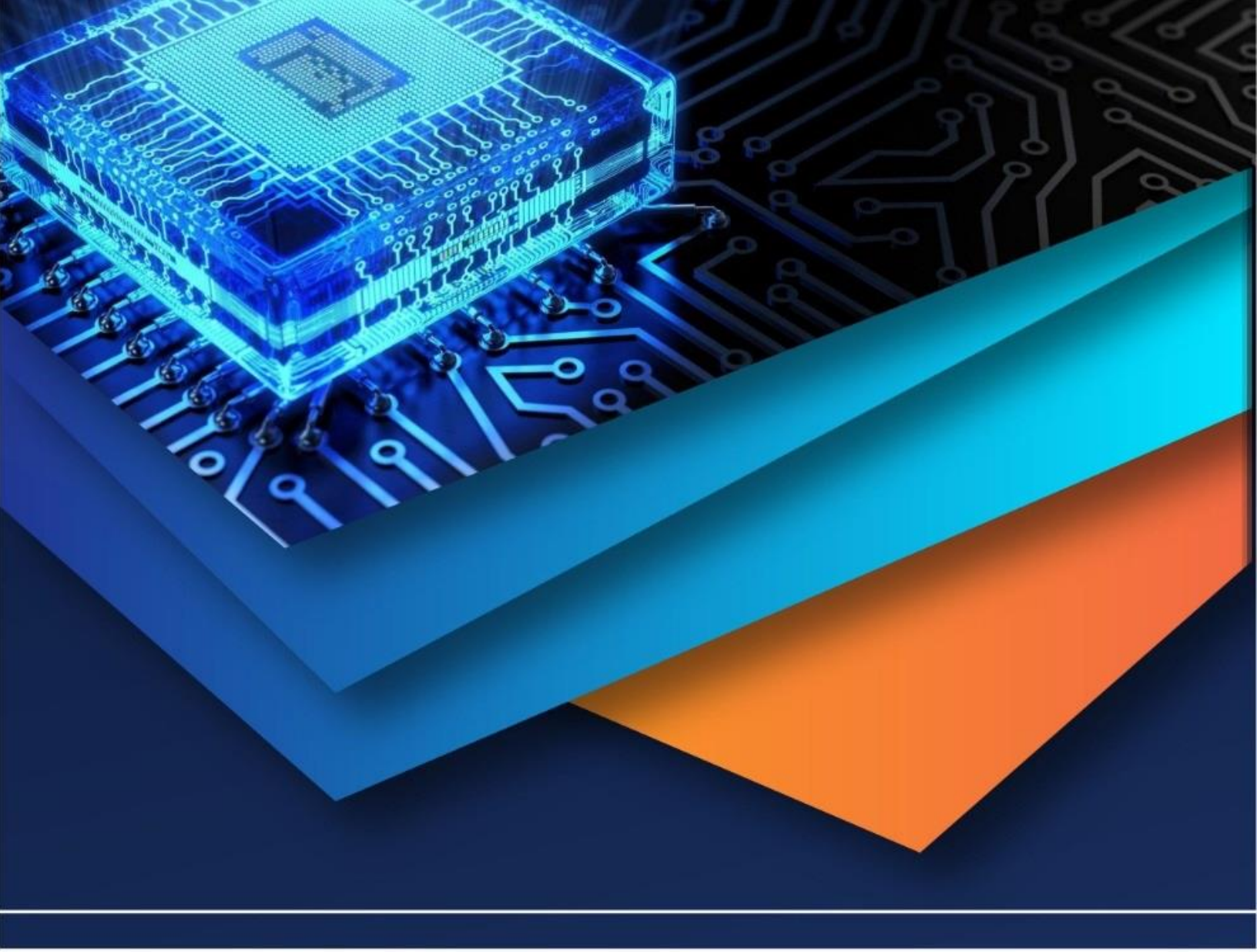

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