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Smart Water Quality Monitoring System

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Abstract: Among the largest global health, environmental, and industrial issues is water pollution.The newest technologies, such as machine learning and the Internet of Things, are being studied to meet the growing demand for water monitoring solutions. In order to determine the factors of water quality, including temperature, turbidity, dissolved oxygen (DO), and pH level, and electrical conductivity in real-time and predict them, this study proposes a Smart Water System for Monitoring Quality, which combines of IoT sensors, cloud storage, and machine learning algorithms. To predict the degree of contamination and issue automatic alerts to the concerned parties through which necessary action can be taken, The gathered sensor data isArtificial Neural Network analysis(ANN) to enable prompt action in the urban and industrial water bodies as well as agricultural waters.
Keywords: Artificial Neural Networks (ANN), cloud computing, sensors, IoT, the quality of the water, and real-time monitoring.

I. INTRODUCTION

Low water quality can result in degradation of the environment, severe health issues and financial losses. In both developed and developing nations, Monitoring of water quality has make it a top goal to ensure that everyone can access potable water that is suitable for drinking, farming, and industry. IoT sensors can continuously measure key Water factors include pH level, turbidity, temperature, dissolved oxygen (DO), and electrical conductivity (EC) furnish stakeholders with fast, real-time information.

However, there are obstacles to IoT adoption in water quality monitoring, including scalability problems, resource constraints, and high data transmission latency. Fog computing, which processes data closer to the source, lowers latency, and ensures effective real-time analysis, can help to overcome these issues. Water quality data may be easily tracked, analyzed, and saved by combining cloud-based platforms, fog computing, and Internet of Things sensors.

To predict and analyse the water quality, this paper proposes Intelligent Water Quality Surveillance System, which combines IoT and machine learning. The levels of water contamination are predicted Using Artificial Neural Networks (ANN) and can be promptly notified and a decision taken.

II. RELATED WORKS

The development of Internet of Things (IoT)-based systems to track and evaluate environmental conditions, especially water quality, has been the subject of some research.

A wireless sensor network (WSN) that tracked water quality metrics in real-time was put into place by the authors in [1]. The system locally pre-processed data through edge computing and then transmitted the information to the cloud to be stored and further analysed. This architecture ensured faster reaction times and reduced latency when there were marked variations in the quality of water.

In the study in [2], the monitoring of remote water quality using Technology related to the Internet of Things in agricultural environments was investigated. A network of sensors measured temperature, turbidity, and pH and sent the measurements to the cloud to be analyzed in detail.

A cloud-based smart water management technology was described by the authors of [3] that could judge water quality based machine learning and predictive analytics. The system predicted occurrences of contamination based on both historical and real-time data which made proactive intervention possible.

To make sure the security of information transmission between sensors and monitoring systems, the authors of [4] used a blockchain-based model. Such an approach enhanced integrity and transparency which is a critical factor in sustaining trust in systems for monitoring water quality. An Internet of Things-based fog computing strategy for decentralized Water quality monitoring was first implemented in [5].

To reduce the dependency of centralized cloud services, the fog nodes analysed data at the closest point to the source and dispatched real-time alerts about water quality anomalies.

In [6], a study proposed a combined Internet of Things system that constantly measured multiple variables, such as electrical conductivity, pH and dissolved oxygen, through energy-efficient sensors. The algorithms of machine learning deployed to a cloud platform were utilized to discover patterns of contamination by analysing the collected data.

An edge and cloud computing hybrid architecture was used in [7] to monitor water quality in smart cities. Preemptive maintenance procedures were made possible by the use of Long Short-Term Memory (LSTM) networks to forecast future patterns in water quality data. The authors of [8] implemented a low-cost Internet of Things system to track the water resources in the rural environment. In the case of regions with insufficient infrastructure, the system provides reliable and sustainable answers by using solar-powered sensors and mobile communication.

In [9], field-programmable gate arrays (FPGAs) were used to preprocess sensor data prior to transmission in a modular water quality monitoring system. This method increased the deployed sensors' lifespan and reduced energy consumption.

Lastly, the study in [10] showed how well a cloud-based architecture works for extensive water quality monitoring. Quick response times and safe data handling were ensured by the system's integration of XML Web services, which allowed for smooth data transmission between sensors and the monitoring platform.

III. PROPOSED FRAMEWORK

The suggested solution, known as the Smart Water Quality Monitoring solution, makes use of Internet of Things technology to ensure effective and instantaneous water quality parameter monitoring. Through constant monitoring and analysis of the water quality in a variety of areas, including rivers, lakes, reservoirs, and industrial wastes, this system is intended to satisfy the urgent need for safe and clean water.

1) Overview of the Framework

Three layers make up the construction of the framework: the cloud layer, fog layer, and sensing layer.

2) Layer of Sensing

IoT-enabled water quality sensors placed across the bodies of water make up this layer. These sensors are in charge of monitoring important aspects of water quality, including turbidity, temperature, and pH level.

3) Smart Gateway Fog Layer

In order to lower latency and improve data processing efficiency, the fog layer serves as a local processing hub. It fulfills the following functions:

Data Aggregation: Gathers information in the form of several IoT devices.

Edge processing: carries out initial analysis, such as identifying deviations in water quality indicators and sending out prompt notifications.

4) Layer of the Cloud

Advanced analytics features and centralized data storage are offered by the cloud layer. Important roles include:

Analyzing historical data helps with research and policymaking by monitoring long-term patterns in water quality.

AI-Driven Insights: Predicts possible contamination occurrences using machine learning algorithms.

5) Advantages and Uses

Real-time monitoring guarantees prompt identification of deterioration in water quality.

Cost-effective: Minimizes the requirement for laboratory analysis and hand sampling.

The system will offer a long-term water quality monitoring approach in both urban and rural areas and demonstrate the innovative power of IoT and fog computing to control such a critical resource as water.

This system offers in a both urban and rural settings, showcasing the revolutionary potential of IoT and fog computing in managing vital resources like water.

6) Layer of Fog Processing

Between the Sensor Layer and the Cloud Layer, the Fog Processing Layer acts as a mediator. This layer is essential for improving processing efficiency, lowering latency, and providing real-time warnings. Important features include of:

Cleaning and standardizing sensor data in preparation for analysis is known as data preprocessing.

Finding abrupt alterations in water quality, like contamination incidents, is known as anomaly detection.

Instant Alerts: Alerting interested parties of possible dangers, such as water management organizations and local authorities.

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The layer processes and interprets the data in real time with the use of complex algorithms. For instance, utilizing historical records, the Artificial Neural Network (ANN) approach can be modified to identify abnormalities in water quality.

7) Fog Processing Layer

The Fog Processing Layer serves as a mediator between the Sensor Layer and the Cloud Layer. This layer is crucial for reducing latency, increasing processing efficiency, and delivering real-time alerts. Among the salient characteristics are:

Data preprocessing is the process of cleaning and standardizing sensor data before analysis.

The procedure of detecting anomalies is identifying sudden changes in water quality, such as contamination events.

Instant Alerts: Notifying local government agencies and water management groups of potential threats.

The layer uses complex algorithms to process and understand the information in real time. For instance, using data from the past, the Artificial Neural Network (ANN) approach can be modified to identify abnormalities in water quality.

Fig1.Proposed Model

A. Algorithm

1) Step 1: Standardize all of the water quality measures collected (such as temperature, turbidity, dissolved oxygen, and pH) in the water quality dataset (D1) to ensure uniformity across the dataset.
2) Step 2: Use a Feed-Forward Techniquefor Neural Networks with Back Propagation to feed the normalized dataset into the training procedure.
3) Step 3: Create network restrictions by defining thresholds for each parameter and including the neural network's structure (number of layers, neurons per layer, and activation functions).
4) Step 4: Simulate the interplay between layers by calculating the neuronal outputs using the input information and the defined restrictions.
5) Step 5: Determine the output layer, which represents the expected classification of water quality (safe or hazardous) based on the sum of the findings from the layers that before it.
6) Step 6: Determine the error rate for every neuron kkk by contrasting the expected and actual outcomes. To reduce error, use the backpropagation technique to modify weights and biases.

   Step 7: Until the network converges and a trained model with low error and high prediction accuracy is created, repeat Steps 3 through 6 iteratively.

B. Cloud Layer

The Cloud Layer offers a powerful analytics and storage that has sensor-collected water quality data. Water management authorities, environmental agencies, and other stakeholders can use the centralized processing and long-term archiving of water quality data made possible by this layer. Important features include of:

1) Data Storage: The cloud provides a large amount of storage space for keeping detailed information about water quality, such as While predictive models predict changes in water quality, models can detect possible sources of contamination.
2) Visualization and Reporting: Stakeholders can view historical using of intuitive visualization tools and dashboards. Keep an eye on patterns and trends. Produce comprehensive reports for regulatory compliance and policymaking.
3) DecisionSupport: Well-informed decisions that has got the data analysis. For instance: Sending out warnings about tainted water sources. Determining which regions need further monitoring or intervention.

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Assisting with resource management and sustainability projects.

The Smart Water Quality Monitoring System's foundation is the Cloud Layer, which facilitates effective data management and gives stakeholders useful insights for preserving environmental health and water safety.

IV. EXPERIMENT AND RESULTS

Software designed to mimic some of the system's essential features was used in specialized simulation applications. One technique for examining several AI prototypes that mimic actual medical applications is system simulation. This study utilizes Microsoft's ML.NET Cross-Platform's open source technologies and machine learning techniques. Deep learning algorithms were created and applied to several applications using this technique. Additionally, by creating well-trained healthcare applications, it integrates artificial inelegancy with any application.

A. Parameters that got the Experiment

The parameters will going show assessing how well artificial intelligence systems monitor water quality. The algorithms' ability to evaluate and categorize water quality metrics under various circumstances is gauged by these indicators. In order to comprehend the model's behavior and make the required adjustments to guarantee precise monitoring and forecasts, choosing the appropriate metric is essential. Below is a description of the mathematical models utilized in this investigation.

1) Accuracy

The percentage of accurate predictions the algorithm makes over all classification scheme categories is known as accuracy. It represents the predictions and metric used to assess classification models. The formula for accuracy is:

\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}Accuracy=TP+TNTP+FP+FN+TN TP+FP+FN+TNTP+TN = Accuracy

Where:

TP (True Positives): Accurately detected problems with water quality.

TN (True Negatives): Accurately determined the quality of a water normal.

False Positives (FP): When normal water quality is mistakenly reported as a problem.

FN (False Negatives): Did not detect real problems with water quality.

2) Precision

By calculating the percentage of accurately detected water quality issues among all flagged cases, Precision assesses the caliber of the categorization results. It is provided by: \text{Precision} = \frac{TP}{TP + FP} Precision=TPTP+FP TP+FPTP = Precision

Reducing false alerts is ensured by this statistic, which is essential for prompt and efficient replies.

3) Sensitivity Recall

Recall quantifies the percentage of real water quality problems that the model accurately detects. It is computed as follows: Text{Recall} = \frac{TP}{TP + FN} Recall=TPTP+FN TP+FNTP = Recall

Even while it may result in some false positives, a high recall guarantees that the majority of contamination incidents are identified.

4) F1 Rating

The F1 Score provides a balance between precision and recall by combining the two into a single score. F1 Score is computed as follows: 2×Precision×Recall \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = Precision+Recall\text{F1 Score} Precision + Recall2×Precision×Recall = F1 Score In the event that there is an unequal distribution of classes (for example, more normal water quality samples than contaminated ones), the F1 Score is especially helpful.

V. OUTCOMES AND CONVERSATION

This study suggested an Internet of Things (IoT)-based smart water quality monitoring system that makes use of state-of-the-art technologies such as artificial neural networks (ANN). to immediately identify and forecast issues with water quality. Among the key conclusions are: Minimal Data Acquisition Error: The water quality indicators that were measured included dissolved oxygen, temperature, turbidity, conductivity, and pH.

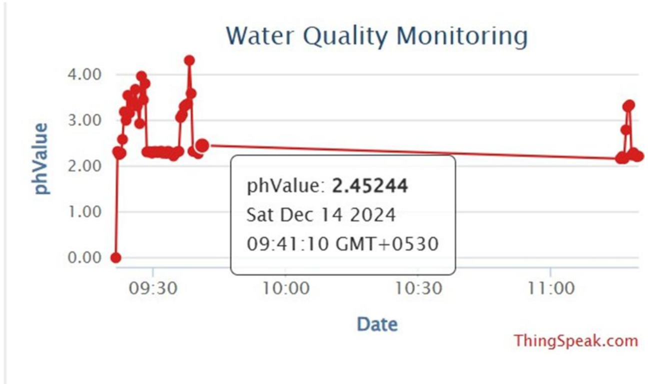

Fig.1.Turbidity Value Detection

sensors powered by IoT. The data obtained was preprocessed to provide high quality inputs to ANN analysis. Its incredibly low rate of data collection errors was discovered to provide a reliable anomaly diagnosis.

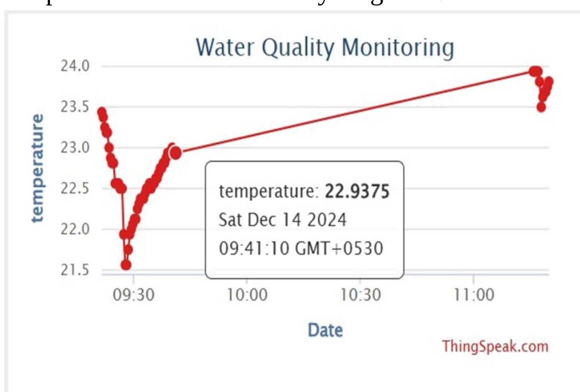

Fig.2 Temprature Value Detection

A. *Accuracy of predictions*

Several machine learning techniques, such as Multi-layer Perception (MLP), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), are compared with the suggested model in order to determine the level of precision and efficacy of smart water quality monitoring system prediction. The Artificial Neural Network (ANN) model outperforms the other models, as the findings show, with the maximum accuracy of 93.21.

The study states that ANN algorithm is superior to CNN, MLP, and RNN and is appropriate to predict water quality features. Simulations indicated the accuracy of CNN, MLP and RNN is 72.13, 90.04 and 87.21 respectively. Accuracy results based on model selection are presented in Figure 4 since the results indicate the performance of each algorithm across the trials.

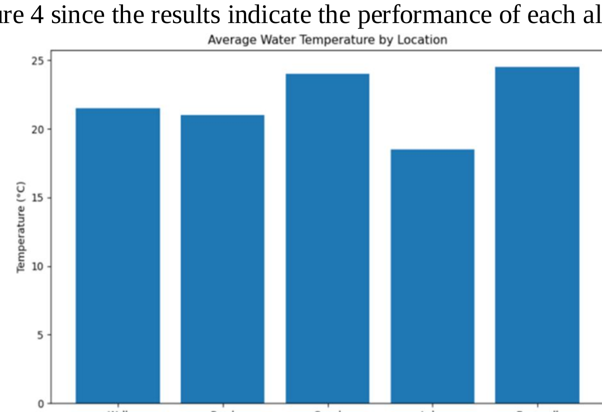

Fig.3.Accuracy of Deep Learning algorithms

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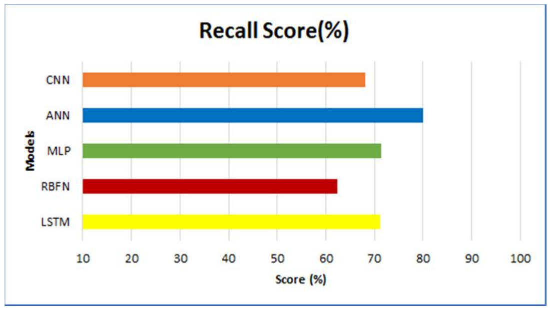

Fig.4.F1Score

The F1 Score and Recall Score Figures 4 and 5 below illustrate the chosen learning models. Simulation shows shows ANN models outperform all other models in terms of efficiency currently in use, depending on the parameter selections.

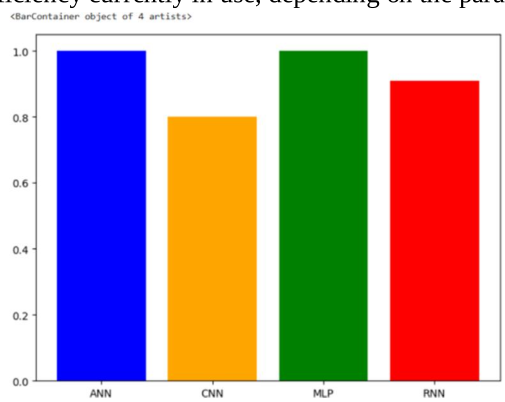

Fig.5Recall Score

B. *Training Dataset Selection*

Results from using different dataset sizes, ranging from 45 percent to 90 percent, are shown in Figure 5. The researchers came to the conclusion that, across all techniques used, training datasets with 75–80% accuracy produced the best outcomes. The only model that showed increases in water quality indicator prediction accuracy as the amount of the training dataset increased was the artificial neural network (ANN) model.

In contrast, precision Poor performance resulted from the other methods' scores being below 80% on the broader training data ranges. According to this experiment, the optimal training dataset to use in order to get precise predictions about the water quality—which includes factors like turbidity, dissolved oxygen, pH, and pcontaminants. Additionally, this range guarantees the best results for performance metrics including accuracy, recall, precision, and F1 score. Furthermore, it was discovered that underfitting was more likely to occur in a dataset where 50% of the data was used for training; however, when training was finished, 90% of the data was used. Overfitting, in which the model would perform exceptionally well with the training data but fall short in its predictions with the 90% of the water quality data that was not visible, was more likely to occur. In order to ensure that water quality monitoring systems are intelligent enough to predict and track water quality without overfitting or underfitting the data, it is advised that the size of a training dataset be between 75 and 80 percent model.

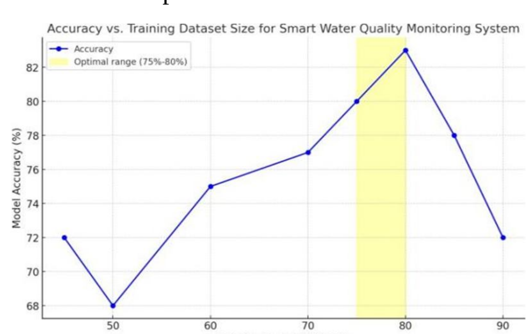

Fig. 6 Selection of Training Datasets

This graph demonstrates the connection between model accuracy and training data set size of intelligent water quality monitoring system. Yellow shows the ideal range (75%-80%), the accuracy is maximum. Training sizes smaller or larger than this range, e.g. 50% or 90, will lead to underfitting or overfitting respectively since the model is optimal within the range.

VI. CONCLUSION

One of the biggest risks to world health is safe water quality. As a result, early monitoring of water quality indicators is necessary to prevent waterborne diseases. This essay suggests An intelligent water quality monitoring device that analyzes water parameters in real time using a Wireless Sensor Network (WSN) made possible by the Internet of Things (IoT). Using IoT-based sensors placed in water bodies, the system first gathers important water quality metrics (such as temperature, turbidity, dissolved oxygen, pH, and chemical pollutants).

When comparing the proposed system In contrast to existing water quality monitoring techniques, the proposed system may detect pollutants early and anticipate the dangers that could result in contaminated water or other hazardous situations. The Artificial Neural Network (ANN) model used in this study has an incredibly high accuracy of 94.58.

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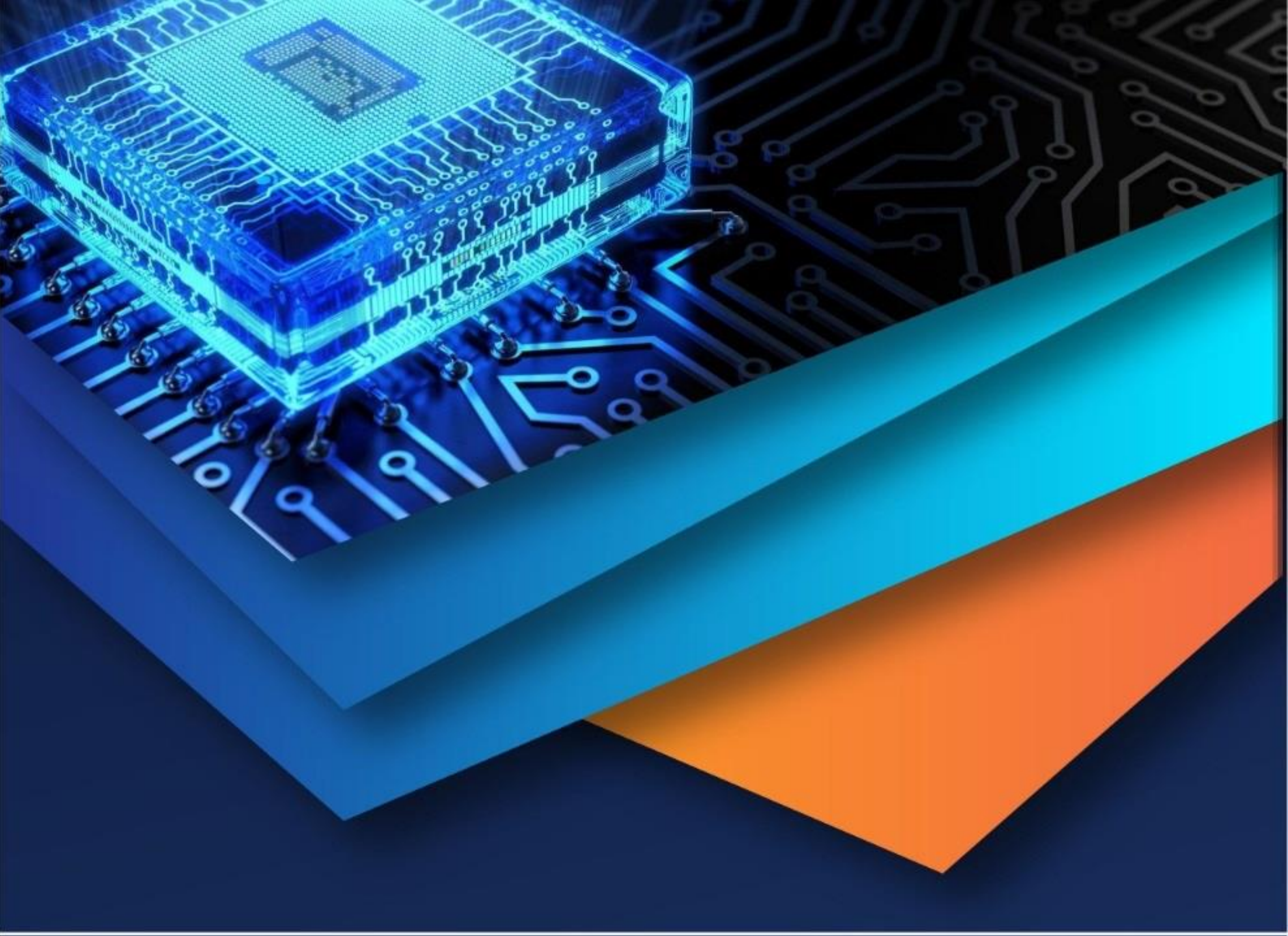

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