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Cloudy Weather Prediction Using CNN Models and Satellite Images

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Abstract: Cloudy weather classification is a vital task in meteorology and remote sensing, facilitating various applications such as weather forecasting, climate monitoring, and environmental analysis. In this study, we explore the application of convolutional neural network (CNN) techniques for classifying cloudy weather conditions using the Cloudy Weather Dataset sourced from Kaggle. The primary CNN architectures investigated include AlexNet, LeNet, and ResNet.
The dataset undergoes preprocessing steps, including resizing and normalization to floating-point representation. Additionally, for calculating cloud cover percentage, the images are processed through grayscaling followed by thresholding. The performance of each CNN model is evaluated based on metrics of accuracy, that is providing insights into their effectiveness for cloudy weather classification.
Keywords: Satellite Image Processing, Image Processing, Weather prediction, Natural language processing, Flask, Machine Learning, Deep Learning, Thresholding, Classifier, Grayscale, Matplotlib, tensorlfow and Convolutional Neural Network (CNN).

I. INTRODUCTION

Cloudy weather classification is a fundamental task in meteorology, environmental science, and remote sensing, with wide-ranging applications across various domains. Accurate classification of cloud cover conditions plays a crucial role in weather forecasting, climate modeling, agriculture, and disaster management. Traditional methods for cloud classification often rely on manual interpretation of satellite imagery or meteorological observations, which can be time-consuming and subjective.

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have revolutionized the field of image classification. CNNs have demonstrated remarkable performance in various image recognition tasks, including object detection, facial recognition, and medical image analysis. Leveraging CNNs for cloudy weather classification offers the potential for automated and accurate identification of cloud cover conditions from satellite or ground-based imagery.

In this study, we investigate the effectiveness of different CNN techniques for classifying cloudy weather conditions using the Cloudy Weather Dataset obtained from Kaggle. The dataset comprises a diverse collection of images capturing various cloud formations and weather patterns. We employ popular CNN architectures, including AlexNet, LeNet, and ResNet, to train and evaluate models for cloudy weather classification.

Prior to model training, the dataset undergoes preprocessing steps to ensure compatibility with CNN architectures. This includes resizing the images to a standardized dimension and normalization to float representation, enhancing the convergence and stability of the training process. Additionally, for calculating cloud cover percentage, the images are processed through gray-scaling followed by thresholding to segment cloud pixels from the background.

Through extensive experimentation and evaluation, we assess the performance of each CNN model in terms of classification accuracy. The findings of this study provide valuable insights into the suitability of different CNN techniques for cloudy weather classification tasks, contributing to advancements in automated meteorological analysis and weather prediction systems.

II. LITERATURE SURVEY

1) A Flexible and Lightweight Deep Learning Weather Forecasting Model (2023). In this review examines a novel approach to weather forecasting presented in the paper "A Flexible and Lightweight Deep Learning Weather Forecasting Model (2023)." The study explores a hybrid model combining Long Short-Term Memory (LSTM) networks and Generative Adversarial Networks (GANs) to address data scarcity and achieve short-term weather forecasting.
2) Weather prediction using cnn and image processing (2023). In this review it investigates the use of Convolutional Neural Networks (CNNs) for classifying cloud cover from satellite images.

The study emphasizes the importance of image preprocessing techniques for feature extraction and demonstrates the effectiveness of CNNs in extracting weather-related information from visual data.

3) Cloud Type Classification for Prediction of Rain Fall using CNN (2020). In this review the study utilizes a CNN-based model (CNN-CLP) to classify different cloud types from satellite images. While not directly predicting cloudiness, these classifications are intended as valuable input for further rainfall prediction models, highlighting the potential of CNNs for understanding cloudiness and its impact on weather.
4) Weather Classification Model Performance: Using CNN, Keras-Tensor Flow (2022). In this review it evaluates the performance of a CNN for classifying weather conditions, including cloudy skies. The study demonstrates the effectiveness of CNNs in identifying cloudy conditions within a broader weather classification framework using Keras and TensorFlow frameworks. However, further investigation is needed for specific cloudiness prediction in real-world applications.
5) Deep learning-based effective fine-grained weather forecasting model (2020).In this review it explores a deep learning model using CNNs and LSTMs for general weather forecasting. While not specifically focused on cloudy weather prediction, the study examines MIMO and MISO models for various weather elements, offering insights into the potential application of these techniques for further research and development in cloudy weather prediction.

III. ALGORITMIC SURVEY

A. Pre-Processing Techniques for Cloudy Weather Classification using CNNs

Convolutional Neural Networks (CNNs) have emerged as powerful tools for classifying cloud cover in satellite images, offering valuable insights for weather prediction. However, their effectiveness heavily relies on the quality of pre-processed image data. This section explores common pre-processing techniques employed in CNN-based cloudy weather classification:

1) Resizing

Purpose: Standardizes image dimensions, ensuring consistent input for the CNN model.
Benefits: Facilitates efficient computation. Improves model performance by enabling consistent processing of images.

2) Normalization (Floating)

Purpose: Scales pixel values to a specific range (typically 0-1) for improved model convergence and stability.
Benefits: Enhances the convergence process of the CNN model during training. Enables better generalization on unseen data.

3) Grayscaling

Purpose: Converts color images to grayscale, reducing computational complexity and preserving relevant features.
Benefits: Improves model efficiency by reducing the number of input channels (from 3 RGB channels to 1 grayscale channel). Maintains essential information for cloud cover classification.

4) Thresholding

Purpose: Separates foreground objects (clouds) from the background using a predefined intensity threshold.
Benefits: Isolates cloud regions in grayscale images. Facilitates accurate cloud cover percentage calculation and classification.

B. Main Algorithms for CNN-based Cloudy Weather Classification

CNNs are the backbone of modern deep learning approaches for cloudy weather classification due to their ability to automatically learn discriminative features from image data. Here, we explore prominent CNN architectures employed in this domain:

1) Convolutional Neural Network (CNN):

For the project, Convolutional Neural Network or CNN have been used. CNN, or also called as ConvNet is a Deep Learning Algorithm used extensively in image processing applications. The algorithm requires very less amount of pre-processing as compared to the other image processing deep learning algorithms.

There are 4 important layers of CNN –

- Convolution Layer – The first layer of CNN Model is called the convolutional layer. Its main purpose is to perform convolutional operations on the image by passing it through several filters. All the images that passes through this layer are considered as a matrix of pixel values.

- ReLU Layer – The second layer is the Rectifier Layer Unit, or commonly called as the ReLU Layer. It performs element wise operations by setting all the inputted negative values to 0.
- Pooling Layer – Pooling Layer or the third layer of CNN identifies edges, corners, bodies, etc. on the input image after multiple filters are applied to the image. It is a down-sampling operation that reduces the dimensionality of the feature map.
- Fully Connected Layer – The fourth and the final layer of CNN is the Fully Connected Layer, which is nothing but a simple ANN or Artificial Neural Network, where all the nodes of the first layer is/are connected to all the nodes of the following layer.
- Strengths: Automatically learns discriminative features from raw image data. Highly effective for various image classification tasks, including cloudy weather classification.

2) AlexNet

Pioneering CNN architecture: Comprises multiple convolutional layers with ReLU activations, followed by pooling layers and fully connected layers.
Contribution: Demonstrated the effectiveness of deep CNNs in large-scale image recognition, paving the way for advancements in cloudy weather classification.

3) ResNet (Residual Neural Network):

Addresses vanishing gradient problem: Introduces residual connections to facilitate training of extremely deep networks.
Benefits: Enables training of deeper and more accurate models. Achieved state-of-the-art performance in various image classification tasks, including cloudy weather classification.

4) LeNet:

Early CNN architecture: Comprises convolutional layers, average pooling layers, and fully connected layers.
Significance: Laid the foundation for modern CNNs, inspiring further research in image classification, including cloudy weather classification.
By effectively pre-processing image data and utilizing optimized CNN architectures, researchers can develop robust and accurate models for classifying cloud cover, contributing to improved weather prediction systems.

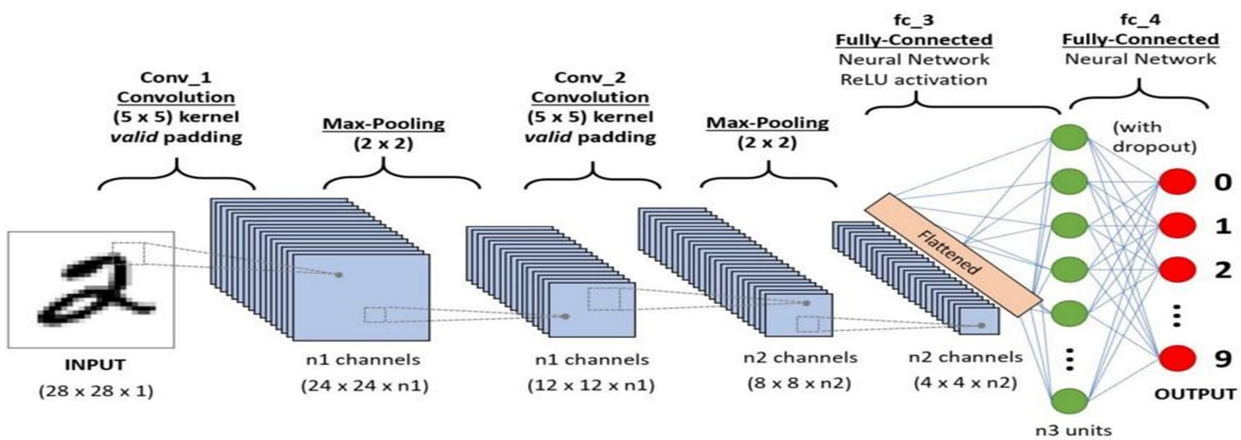


Fig 1: CNN Architecture

IV. COMPARATIVE STUDY

Paper Title	Model	Application	Strengths	Weaknesses
A Flexible and Lightweight Deep Learning Weather Forecasting Model	Hybrid LSTM/GAN	Weather forecasting (flexible and lightweight)	- Addresses data scarcity with GAN-generated data	- May not be specifically optimized for cloudy weather prediction

(2023)				
WETHER PREDECTION USING CNN AND IMAGE PROCESSING (2023)	CNN	Cloud cover classification	- Effective feature extraction from satellite images	- Not directly focused on cloudy weather prediction
Cloud Type Classification for Prediction of Rain Fall using CNN (2020)	CNN-CLP	Cloud type classification for rainfall prediction	- Contributes to cloudy weather prediction by classifying cloud types	- May not be directly applicable to real-time forecasting
Weather Classification Model Performance: Using CNN, Keras-Tensor Flow (2022)	CNN	Weather classification (cloudy, rainy, sunny, sunrise)	- Demonstrates CNN effectiveness for classifying weather types	- Limited to four weather categories, may not capture nuances of cloudiness
Deep learning-based effective fine-grained weather forecasting model (2020)	CNN, LSTM	Weather forecasting (fine-grained)	- Explores CNNs and LSTMs for weather forecasting	- Limited details on specific application to cloudy weather prediction

Table 1: Comparative Study of Existing Work

V. FLOW OF WORK & RESULTS

A. *Data Acquisition*

Source: Use images from Kaggle focusing on cloudy weather prediction.

B. *User Interface*

1) Input: Allow users to upload an image of the sky or capture an image using the device camera.
2) Model Selection: Provide options for users to choose a pre-trained model for prediction (e.g., ResNet, AlexNet, LeNet).

C. *Preprocessing*

1) Resize: Resize the uploaded image to a fixed size suitable for the chosen model. This ensures consistency in the input data for the model.
2) Normalization: Normalize the pixel values of the resized image to a specific range (e.g., 0-1 or -1 to 1) based on the model's requirements. This improves model convergence and stability.

D. *Cloud Detection*

1) Grayscale Conversion: Convert the normalized image to grayscale to focus on brightness variations and reduce computational complexity.
2) Thresholding: Apply a pre-defined threshold value (i.e., 140) to the grayscale image. Pixels above the threshold are considered "white" (potentially cloud), while pixels below are considered "black" (background).

E. *Cloud Pixel Counting*

Count the number of white pixels in the image.

F. *Cloud Cover Estimation*

1) *Percentage Calculation:* Here, the total number of calculated white pixels is divided by the total number of image pixels. The result is then multiplied by 100 to obtain the percentage of cloud cover in the image.

TERMINOLOGY	PERCENT SKY COVER	OKTA SKY COVER
Cloudy	90 - 100%	8/8
Mostly Cloudy	70 - 90%	¾ - ⅞
Partly Cloudy/Partly Sunny	30 - 70%	⅜ - ⅝
Mostly Sunny/Mostly Clear	10 - 30%	⅛ - ¼
Clear	0 - 10%	0/8
Fair	Less than 40% with no precipitation or extreme weather	Less than ⅜, used at night, with no precipitation or extreme weather

Table 2: OKTA Sky Cover Percentage Data

Image	Cloud Percentage	Classification
0	99.62921143	Cloudy
1	100	Cloudy
2	100	Cloudy
3	100	Cloudy
4	100	Cloudy
5	60.887146	Partly Cloudy
6	0.007629395	Clear
7	100	Cloudy
8	0	Clear
9	100	Cloudy
10	42.41790771	Partly Cloudy
11	99.57885742	Cloudy
12	99.52545166	Cloudy
13	0	Clear
14	100	Cloudy
15	38.89007568	Partly Cloudy
16	76.99432373	Mostly Cloudy

Table 3: Sample Cloud Percentages and Classification

G. *Prediction*

1) Model Inference: Based on the user's chosen model, pass the preprocessed image through the pre-trained model for prediction.
2) Output: The model predicts the cloud cover category, which could be:

- Clear: If the percentage is below a pre-defined threshold (i.e., 30%).
- Partly Cloudy: If the percentage falls within a specific range (i.e., 30% to 70%).
- Mostly Cloudy: If the percentage is above another threshold (i.e., 70% to 90%).
- Cloudy: If the Percentage is above 90%.

H. *Display*

- Display the predicted cloud cover category (e.g., "Mostly Cloudy") on the application interface.
- Optionally, display the calculated cloud cover percentage and the chosen model used for prediction.

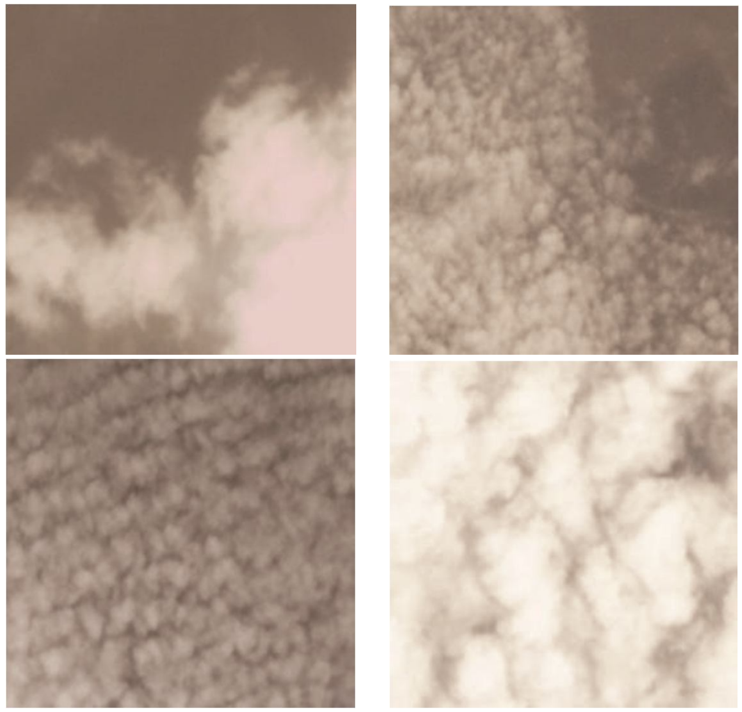
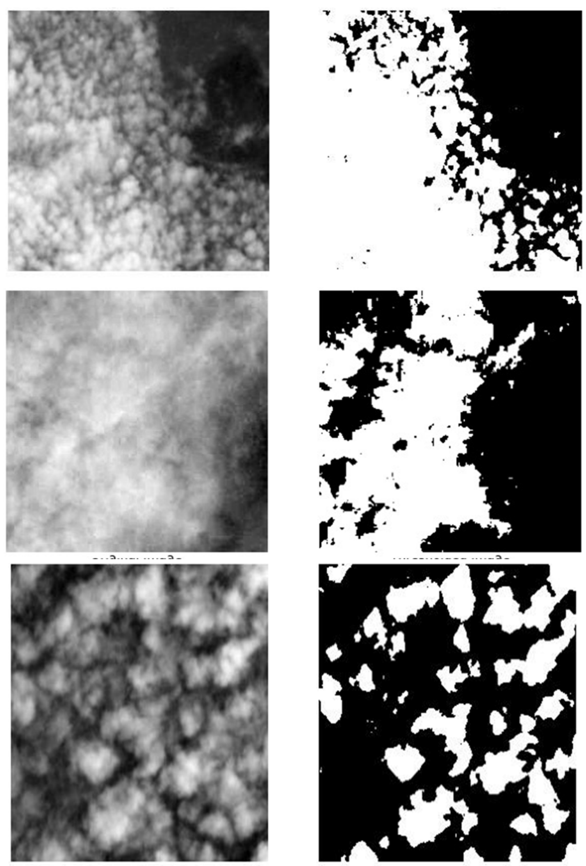


Fig 2: Dataset Images



(a) (b)

Fig 3: Prep-rocessed Images (a) Grey Scale Images (b) Thresholding Images

VI. RESULTS & DISCUSSION

After performing extensive training and testing of each model using our dataset, Calculation of Accuracy Score of each predictive model was done.

We observed that the accuracy achieved by the ResNet CNN Model, gave the best result by giving the accuracy of 89%.

MODEL	ACCURACY (100%)
ResNet	89
AlexNet	86
LeNet	83

Table 4: Accuracy Score

Original_Label	Predicted_Label
Cloudy	Cloudy
Partly Cloudy	Partly Cloudy
Mostly Cloudy	Partly Cloudy
Cloudy	Cloudy
Cloudy	Cloudy
Cloudy	Cloudy
Cloudy	Cloudy
Cloudy	Cloudy
Cloudy	Cloudy

Table 5: Sample Predicted Data using AlexNet

VII. APPLICATIONS

Cloudy skies hold the key to clearer futures with the potential of CNN-based weather prediction:

1) *Weather:* More accurate forecasts, thanks to detailed cloud cover and type information, empower better preparation for precipitation, temperature changes, and other weather elements influenced by cloudiness. Earlier detection also allows for issuing timely alerts and warnings.
2) *Aviation:* Imagine safer skies with airlines leveraging CNN models to avoid turbulence, icing, and Optimize flight routes for fuel efficiency and quicker travel times.
3) *Agriculture:* Farmers can predict crop yields and manage water resources effectively by integrating cloud cover data with agricultural models. This empowers informed decisions regarding pest control, harvesting, and resource allocation.
4) *Renewable Energy:* Solar and wind power producers can optimize their generation by utilizing CNN models to predict cloud cover, leading to improved grid management and efficiency.
5) *Disaster Management:* Communities can prepare for potential hazards like floods and landslides with early warnings triggered by timely predictions of cloudy weather. Additionally, information on cloud cover and potential weather events can be used for better emergency response planning and ensuring the safety of disaster relief personnel.

The potential of this technology extends beyond these examples, impacting various sectors like logistics, construction, and tourism. As the technology evolves, we can expect even more accurate and reliable cloudy weather prediction, paving the way for a future with clearer skies and a better prepared world

VIII. CONCLUSION

The paper delves into the utilization of Convolutional Neural Networks (CNNs) to forecast cloudy weather conditions through satellite imagery analysis. Notably, CNNs demonstrate efficacy in categorizing cloud cover and exhibit promise in delineating various cloud types. These findings underscore their pivotal role in augmenting weather forecasting capabilities, offering valuable insights into cloud behavior and its implications for weather patterns. However, the research also identifies certain constraints, such as an overarching emphasis on classification tasks and the complexity arising from limited data availability and model intricacy.

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Despite these limitations, CNNs remain a potent tool for cloudy weather prediction. To further advance the field, future studies should focus on refining models tailored specifically for cloudy weather forecasting. Additionally, there is a pressing need to explore sophisticated classification techniques, incorporating temporal data to address challenges associated with data scarcity. Moreover, integrating CNNs with existing weather prediction models could enhance the comprehensiveness and reliability of forecasting endeavors. By addressing these research gaps and leveraging the strengths of CNNs, the field can propel towards the development of robust and accurate cloudy weather prediction systems, facilitating informed decision-making across diverse sectors.

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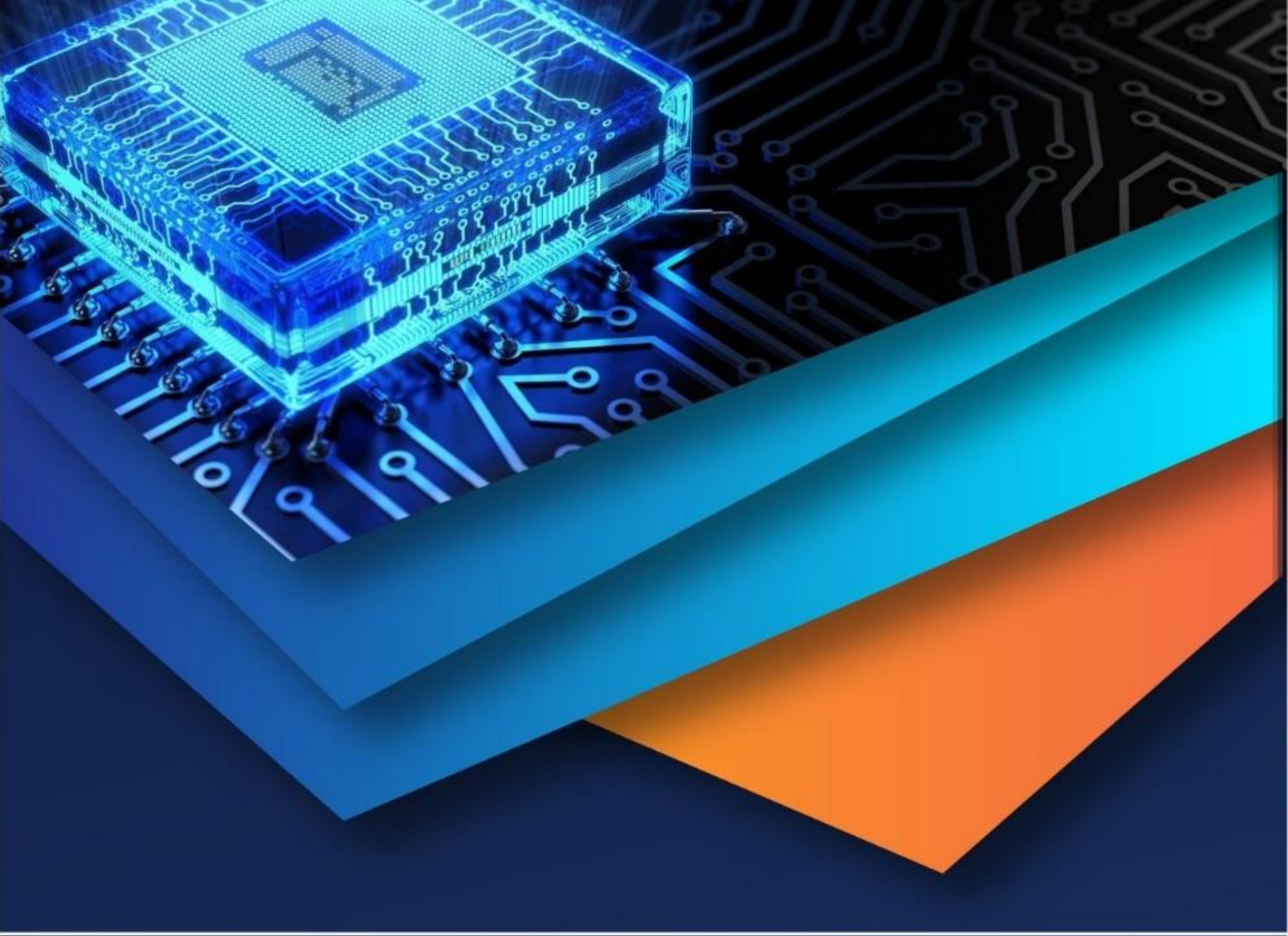

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