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Real-Time Handwritten Digit, Character and Mathematical Symbol Recognition Using Deep Learning

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Abstract: Handwritten recognition of mathematical content is a challenging task due to diverse writing styles and the coexistence of digits, alphabets, and mathematical symbols. This project presents a unified deep learning–based system for handwritten digit, character, and mathematical symbol recognition using a multi-model architecture. The proposed framework employs Convolutional Neural Networks (CNNs) trained on standard benchmark datasets, including MNIST for digit recognition, EMNIST for handwritten character recognition, and the CROHME handwritten mathematical symbol dataset for mathematical symbol classification. The architecture combines TensorFlow/Keras-based models for digit and character recognition with a PyTorch-based optimized CNN for mathematical symbol recognition.

A robust image preprocessing pipeline is designed to normalize handwritten inputs, enhance contrast, and preserve structural features critical for accurate recognition. To improve adaptability and robustness, the system incorporates a user FEEDBACK–driven correction mechanism, where misclassified samples are stored in custom datasets and matched using deep feature similarity measures during inference. This feedback-driven approach allows the system to improve recognition accuracy over time without full retraining. The system further incorporates ensemble prediction strategies and cosine similarity–based feature matching to enhance robustness.

Keywords: Convolutional Neural Networks (CNNs), *Deep learning,* ***EMNIST, MNIST, CROHME***

I. INTRODUCTION

Handwritten recognition represents a transformative technology that bridges the gap between the organic, freeform nature of human writing and the structured precision of digital systems, enabling machines to interpret and process one of humanity's oldest forms of communication. This project introduces an advanced handwritten recognition system meticulously designed to identify numerical digits (0– 9), alphabetic characters (A–Z, a–z), and individual mathematical symbols, harnessing the power of deep learning to tackle a wide array of real-world challenges. At its core, the system employs multiple specialized neural network architectures: Convolutional Neural Networks (CNNs) for digit recognition, Residual Convolutional Neural Networks (ResNets) for character recognition, and a dedicated convolutional model for mathematical symbol classification.

A. *Methodology*

The methodology of this project adopts a modular and systematic approach to develop a unified handwritten recognition system capable of identifying handwritten digits, alphabetic characters, and individual mathematical symbols. Separate deep learning models are designed and trained for each recognition category to ensure high accuracy and robustness.

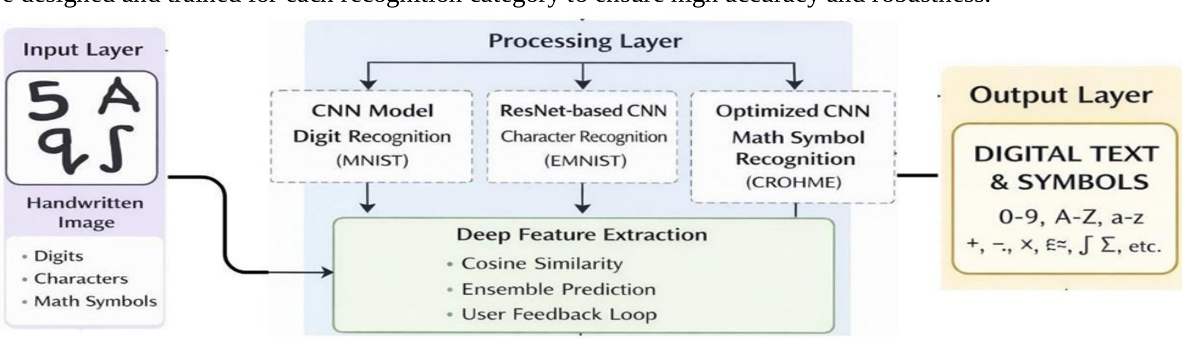

Figure. 1. Handwritten Recognition System Workflow

II. EXISTING SYSTEM

The existing system focuses on recognizing handwritten digits (0–9) using Artificial Neural Networks (ANNs) trained with a back-propagation algorithm. The input images are preprocessed through binarization, resizing to 16×16 pixels, and thinning to obtain skeletonized forms. Feature extraction is performed using horizontal, vertical, and diagonal histograms, which are concatenated to form a feature vector. This vector is provided as input to a three-layer neural network consisting of 94 input units, 15 hidden units, and 10 output units. Experimental results show that the system can achieve high accuracy, reaching up to 99% under controlled conditions.

III. PROPOSED SYSTEM

The proposed system is a robust and intelligent framework designed for real-time handwritten recognition of digits, alphabetic characters, and individual mathematical symbols using deep learning techniques. The system employs multiple convolutional neural network–based models trained on standard datasets. A CNN trained on the MNIST dataset is used for handwritten digit recognition and achieves an accuracy of 99.64%, while a deeper CNN with residual connections trained on the EMNIST ByMerge dataset enables accurate recognition of alphabetic characters (A–Z, a–z). In addition, a dedicated CNN trained on samples derived from the CROHME dataset is used for handwritten mathematical symbol recognition.

IV. LITERATURE REVIEW

The experimental results confirmed the superior performance of the CNN-based model, achieving an accuracy rate exceeding 98.5% on the test dataset. Compared to traditional machine learning models like Decision Trees, Naive Bayes, and k-Nearest Neighbors (k-NN), the CNN outperformed in terms of both accuracy and computational efficiency. The authors noted that the deep hierarchical structure of CNNs enabled the extraction of abstract and invariant features from raw pixel data, which classical models failed to generalize effectively. Furthermore, the study suggested that integrating advanced data augmentation techniques such as rotation, scaling, and shifting could enhance the model's robustness against diverse handwriting patterns. The paper concludes by highlighting the relevance of CNNs in real-world applications including cheque processing, automated banking, digital form recognition, and postal address digitization. Future work includes expanding the system to multilingual digit datasets and hybridizing CNNs with Recurrent Neural Networks (RNNs) to handle continuous handwriting streams, thereby broadening its applicability to cursive script recognition.

V. SYSTEM DESIGN

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases.

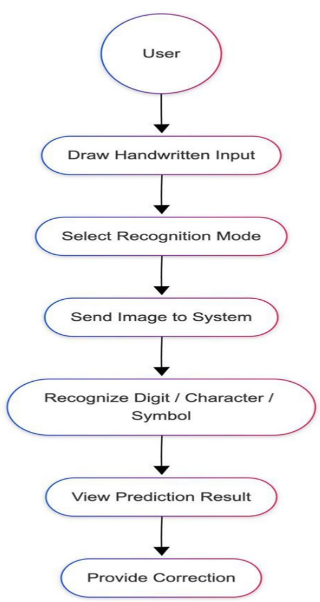

Fig. 2. Use case diagram

A collaboration diagram groups together the interactions between different objects. The interactions are listed as numbered interactions that help to trace the sequence of the interactions. The collaboration diagram helps to identify all the possible interactions that each object has with other objects

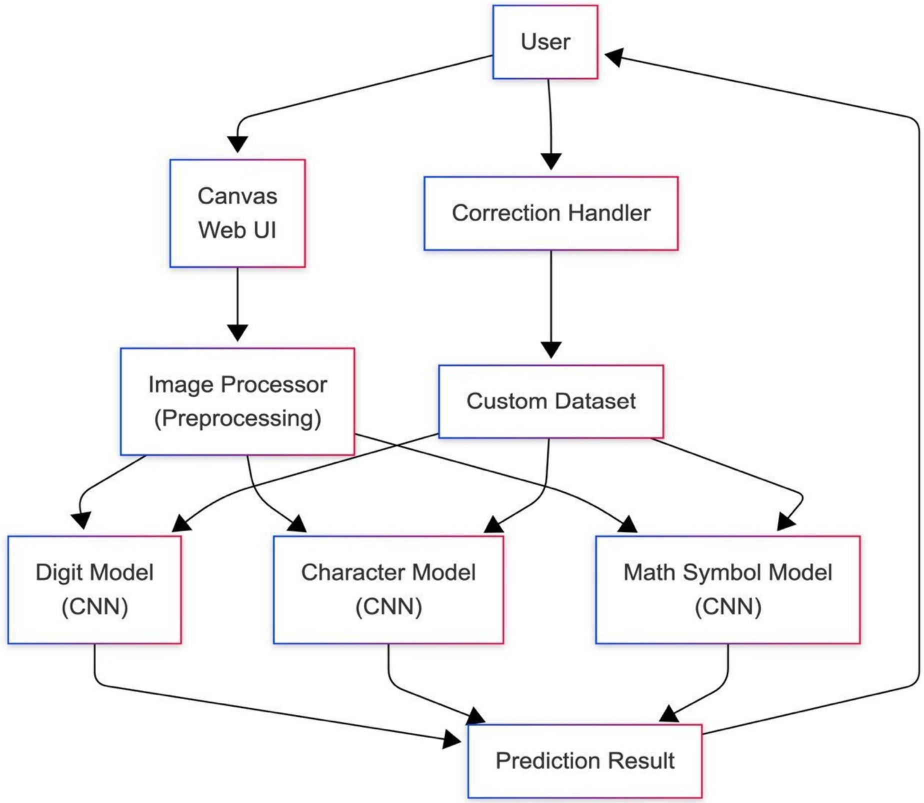

Figure. 3. Collaboration diagram

A sequence diagram represents the interaction between different objects in the system. The important aspect of a sequence diagram is that it is time-ordered

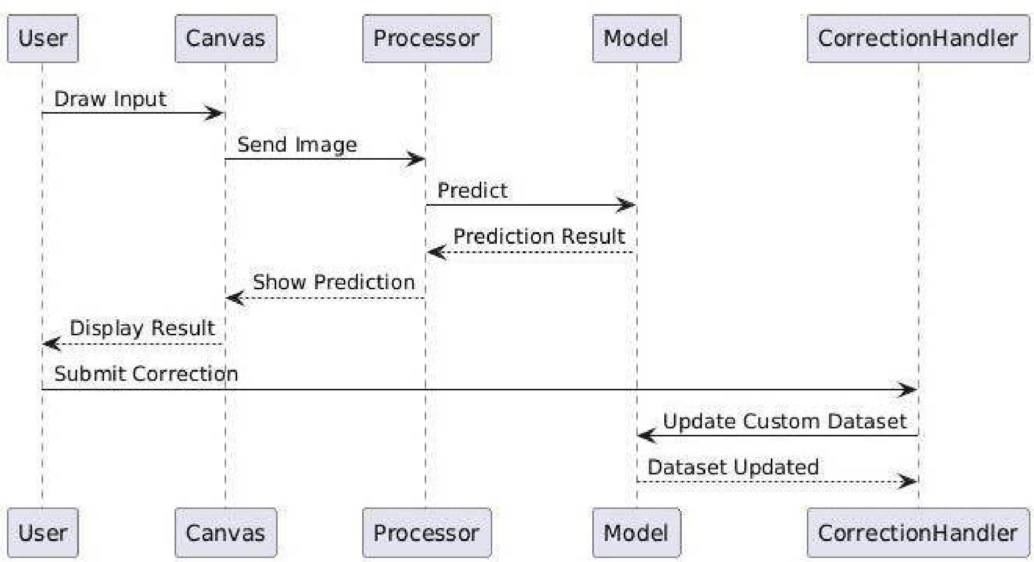

Fig. 4. Sequence diagram

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VI. TESTING

A. *Testing Strategy*

Testing plays a crucial role in the success of any intelligent recognition system, particularly when it involves user input and real-time prediction. In this handwritten digit and character recognition system, various layers of testing were conducted to ensure the system performs reliably, efficiently, and accurately under different conditions. The system's predictive core, data handling pipeline, correction logic, and user interface were all rigorously validated through structured testing strategies. Both component-level and system-level testing were performed to ensure smooth integration of handwritten digit, character, and mathematical symbol recognition.

1) Unit testing
2) Integration testing
3) Performance testing
4) Robustness testing
5) Stress testing
6) Functional testing
7) Error handling testing

B. *Test Cases*

Test Case ID	Test Case Description	Input	Expected Output	Status
TC_01	Load digit model successfully	Load improved1.weights.h5	Model loads successfully	Pass
TC_02	Load character model successfully	Load checkpoint. Weights .h5	Character model initialized correctly	Pass
TC_03	Load math model successfully	optimized. pth	Math model loads without error	Pass
TC_04	Base64 image preprocessing	se64 PNG string	Normalized grayscale image	Pass
TC_05	Predict digit from user sketch	Drawn digit '5'	Prediction = 5 with confidence > 90%	Pass
TC_06	Predict character from user sketch	Drawn character 'B'	Prediction = B with high confidence	Pass
TC_07	edict math symbol	Drawn ‘+’	Prediction = ‘+’	Pass
TC_08	Save corrected digit to custom dataset	Label = 8, image = drawn 8	Custom entry saved to custom_digits.h5	Pass
TC_09	Save corrected character to custom dataset	Label = 'G', image = drawn G	Custom entry saved to custom_characters.h5	Pass
TC_10	Predict from custom dataset	Image previously saved	Custom label returned if similarity is high	Pass
TC_11	Handle invalid base64 input	Invalid string	Error message returned, no crash	Pass
TC_12	Handle empty input image	Empty canvas	Error: "Image processing failed"	Pass
TC_13	isplay prediction instantly on UI	Canvas sketch	Result and confidence shown within 0.5 seconds	Pass
TC_14	witch modes (digit/character) on frontend	User clicks mode toggle	Model switch confirmed, mode updates on UI	Pass

TC_15	Exceed custom dataset size (stress test)	200+ saved images	System handles with no major lag	Pass
TC_16	Correct misclassified digit with retraining logic	Image = 3, model says 8, label = 3	Prediction improves to 3 after correction	Pass
TC_17	Feature similarity threshold evaluation	Similar custom entry exists	Prediction from custom if similarity > model	Pass

Table. 1. Test Cases

VII. EXPERIMENTAL RESULTS

A. Screenshots of execution

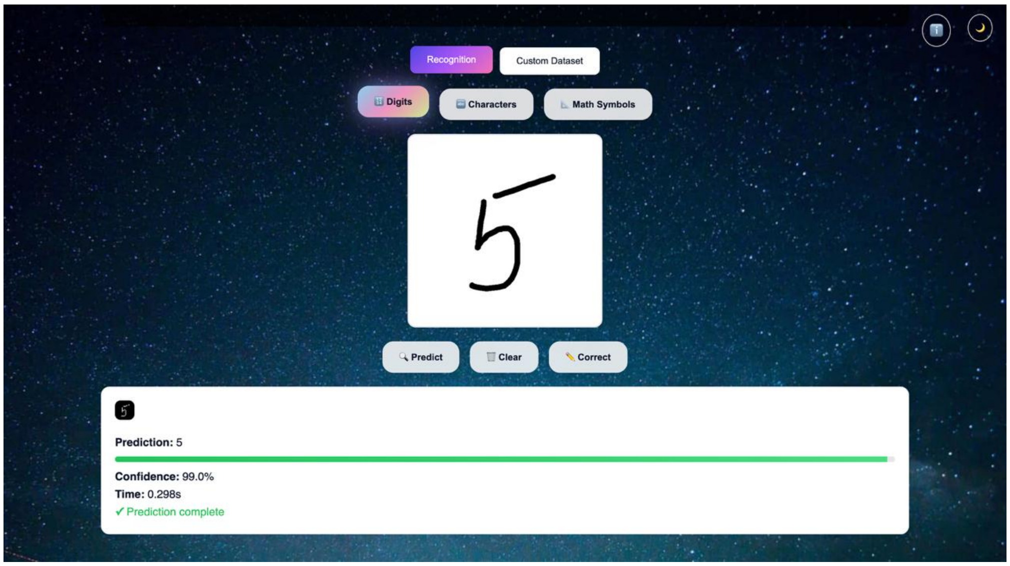

Fig. 5. Incomplete digit

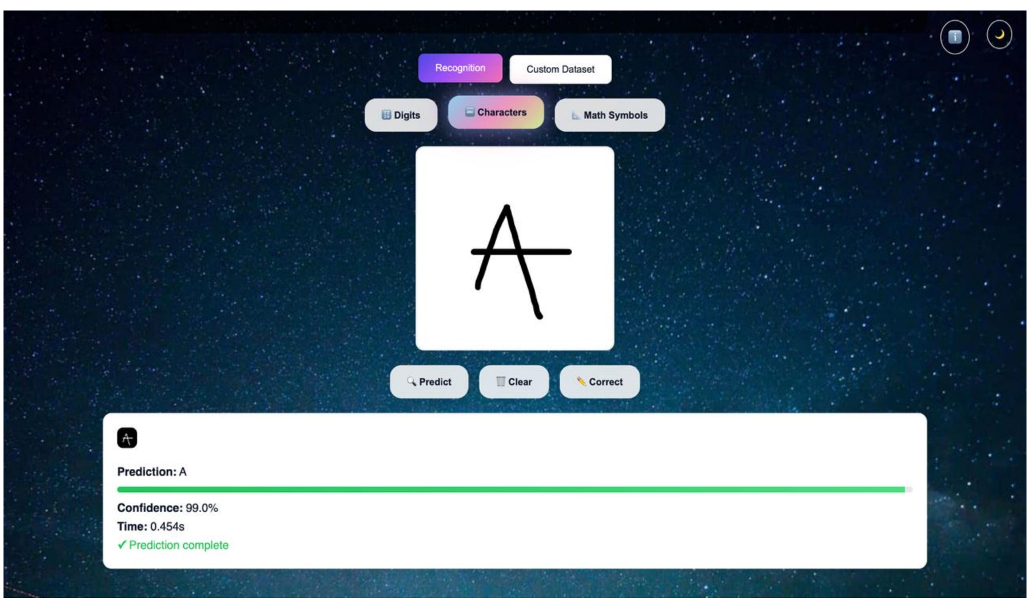

Fig. 6. Character with Uppercase

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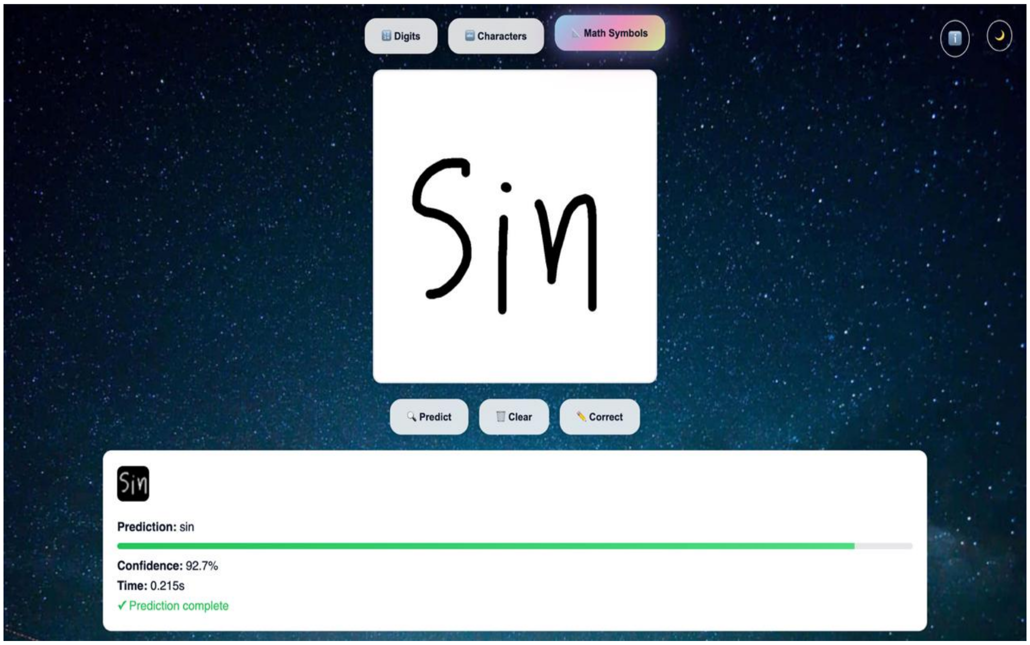

Fig. 7. Mathematical function

VIII. CONCLUSION AND FUTURE SCOPE

A. Conclusion

The handwritten recognition system successfully delivers an accurate, efficient, and adaptive solution for recognizing handwritten digits, alphabetic characters, and mathematical symbols using deep learning techniques. By integrating a Convolutional Neural Network (CNN) trained on the MNIST dataset for digit recognition, a Residual CNN (ResNet) trained on the EMNIST ByMerge dataset for character recognition, and a dedicated CNN trained on the CROHME dataset for mathematical symbol recognition, the system effectively handles diverse handwriting styles. The real-time web-based interface enables users to draw inputs and receive instant predictions with confidence scores, while the modular backend architecture ensures scalability and maintainability.

B. Future scope

The proposed system can be further enhanced by extending symbol-level recognition to full handwritten mathematical expression recognition, incorporating spatial relationship analysis, structural parsing, and expression evaluation. Future work may also include multilingual handwriting recognition by training models on additional scripts such as Devanagari or Chinese. The system can be deployed as a mobile or cloud-based application to improve accessibility and scalability, while advanced deep learning architectures such as attention mechanisms and transformer-based vision models can be explored to improve accuracy for complex handwriting patterns. Personalized handwriting adaptation using incremental or few-shot learning can enable the system to better adapt to individual users.

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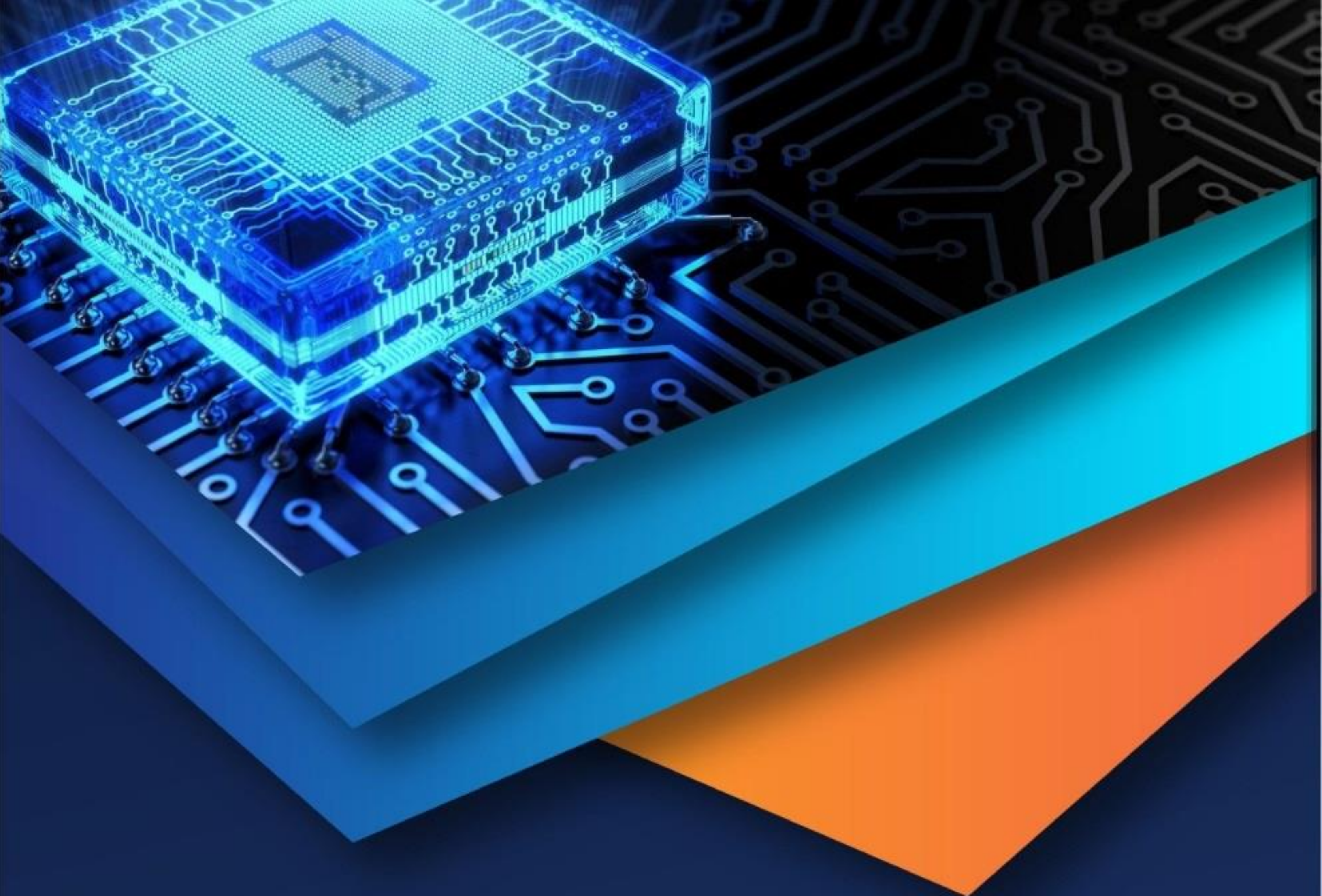

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