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Biometric-Based Blood Group Detection Using Deep Learning

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Abstract: In emergency medical situations, rapidly determining a person's blood type is crucial, especially when prompt and safe blood transfusion is necessary. Conventional methods like serological testing, although dependable, often involve drawing blood and using laboratory equipment, which can delay results and limit accessibility in emergencies or remote areas lacking medical facilities.To address these issues, this research introduces a novel and non-inavasive approach that uses fingerprint patterns and deep learning to determine blood groups. A Convolutional Neural Network (CNN), known for its ability to recognize patterns in images, is used to examine fingerprint ridges and accurately classify both ABO and Rh blood groups.The system was developed and tested using a well-organized and accurately labeled dataset, allowing the model to learn effectively. The results revealed that the method performs with high accuracy, showing its potential as a practical alternative to traditional blood testing techniques. This approach is not only fast and easy to use but also adaptable for use in fieldwork, emergency healthcare, and mobile diagnostics where traditional testing is not feasible.Beyond emergency use, the fingerprint-based system could also be applied in health ID cards, biometric authentication systems, and automated hospital processes, providing healthcare professionals with quick access to critical patient information. This work contributes meaningfully to the development of AI-driven healthcare solutions by offering a unique integration of biometrics and medical diagnostics for enhanced patient care.
Keywords: Blood Group Detection, Fingerprint Biometrics, Deep Learning, Convolutional Neural Network (CNN), Biometric Blood Typing, Healthcare Diagnostics, Non-Invasive Blood Typing, AI in Medical Applications, Computer Vision, Point-of-Care Diagnostics.

I. INTRODUCTION

Blood group identification is an essential step in numerous clinical procedures such as blood transfusions, organ transplants, and maternal-fetal care. The ABO and Rh blood group systems are the most widely recognized classifications, and matching donors and recipients accurately is vital to prevent life-threatening immune responses. In critical care settings, especially during emergencies, the ability to quickly and correctly identify a patient’s blood type can have life-saving implications[2].

Conventional blood typing techniques—including slide, tube, and gel agglutination tests—require invasive blood sampling, trained personnel, and access to laboratory setups. These methods, while accurate, are time-consuming and not easily deployable in remote, rural, or high-pressure scenarios such as accident scenes or disaster zones. This reliance on laboratory infrastructure limits their usefulness in situations where immediate diagnosis is needed. To overcome these limitations, researchers have explored non-invasive diagnostic technologies that are faster, safer, and more accessible. Among these, biometric-based diagnostic systems have emerged as a promising solution. Fingerprints, being unique and genetically influenced, serve as a reliable and non-intrusive biometric trait. Studies in dermatoglyphics—the study of fingerprint patterns—have suggested potential links between fingerprint structures and genetic markers such as blood groups [11][16][17]. With the rapid growth of artificial intelligence, especially in the fields of computer vision and deep learning, it has become feasible to automate the classification of complex image patterns. Convolutional Neural Networks (CNNs), a class of deep learning models, have shown remarkable success in medical image analysis, biometric recognition, and pattern classification tasks. This project utilizes CNNs to develop a novel, contactless system for determining an individual's blood group from their fingerprint image.

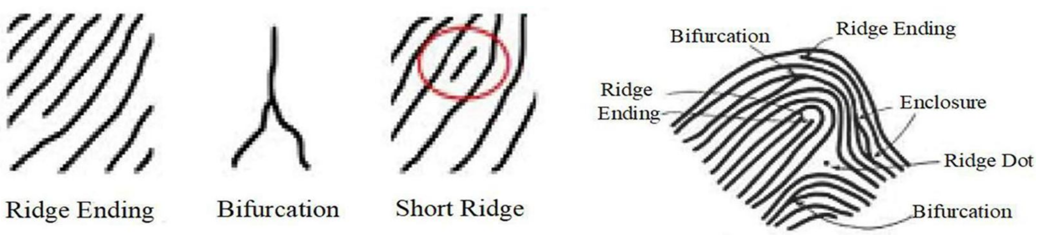

Figure 1: showcases example fingerprint images

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The proposed system involves capturing fingerprint images, preprocessing them through standardized image enhancement techniques, and feeding them into a CNN model trained to classify all eight common blood groups (A+, A−, B+, B−, AB+, AB−, O+, O−). The model was trained and validated on a well-labeled fingerprint dataset, achieving high accuracy and promising results. This research demonstrates that fingerprint-based blood group prediction, when integrated with deep learning, can provide a rapid, non-invasive, and scalable solution suitable for field hospitals, emergency diagnostics, and rural healthcare applications[5].

II. RELATED WORK

Recent advancements in deep learning and biometrics have enabled researchers to explore alternative physiological markers for identity verification and health diagnostics. CNNs, in particular, have been widely used in image classification problems due to their robustness in feature extraction.

Several studies have examined the connection between fingerprint features and blood group prediction. Fayrouz et al. [16] and Kanchan & Chattopadhyay [17] explored statistical correlations between fingerprint ridge patterns and blood types. Sivamurugan et al. [9] implemented a deep learning-based system to enhance fingerprint-based blood group prediction accuracy. Similarly, Upadhyay et al. [8] utilized Support Vector Machines (SVM) with fingerprint inputs for classification, although lacking the flexibility and pattern recognition depth of CNNs.

Shaban and Elsheweikh [7] applied image processing techniques for blood group classification, but did not incorporate end-to-end learning models like CNNs. More recently, Haruna Chiroma [5] and Saeed et al. [6] emphasized the importance of CNN architectures in improving fingerprint classification accuracy and reducing the need for manual feature extraction.

While prior work has addressed fingerprint-based classification for identification or authentication purposes, very few studies have ventured into biomedical diagnostics — particularly blood group prediction — using this modality. This research builds on the promising foundation of biometric feature analysis and extends its application into healthcare diagnostics, proposing a complete pipeline for blood group detection using CNNs on fingerprint images.

III. METHODOLOGY

This section explains the step-by-step procedure adopted to develop the fingerprint-based blood group detection system using deep learning. The methodology comprises dataset preparation, image preprocessing, model design, training, evaluation, and result interpretation. The complete workflow is described in the following sub-sections

A. Dataset Collection

A specialized dataset comprising fingerprint images was created for this study. Each fingerprint image is annotated with its corresponding blood type, covering both the ABO system (A, B, AB, O) and the Rh factor (positive or negative). To ensure balanced representation, samples were collected across all eight blood group categories. Fingerprint samples were acquired using a biometric scanner in a standardized environment, with consistent lighting and finger placement to ensure uniformity.

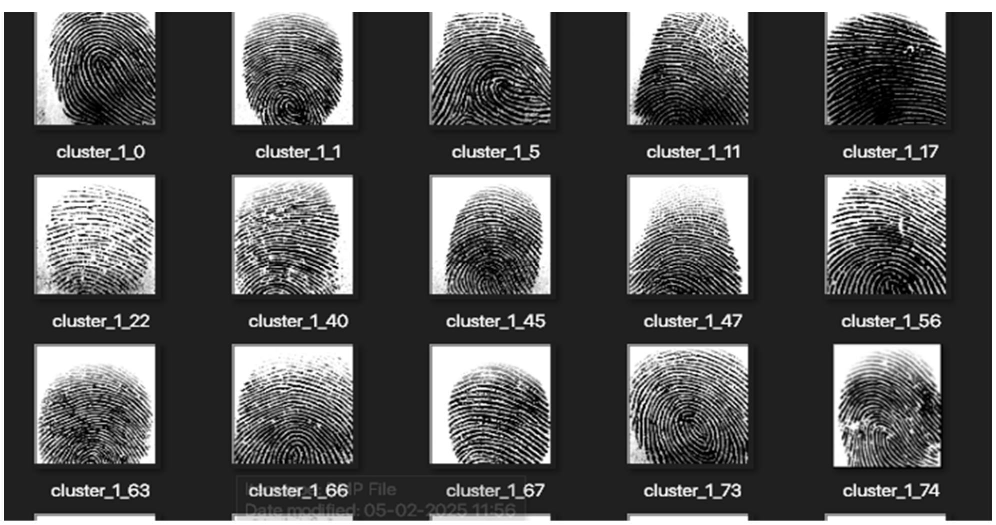

Figure 1 : sample fingerprint images from the dataset.

B. Image Preprocessing

To ensure uniformity and improve the model's ability to learn discriminative features, all fingerprint images were subjected to a structured preprocessing pipeline. Initially, the images were converted to grayscale, which reduces computational complexity by eliminating color channels and enhances focus on the ridge and valley patterns crucial for classification. The grayscale images were then resized to a standard dimension of 224×224 pixels, ensuring consistent input shape for the Convolutional Neural Network (CNN). To facilitate faster and more stable training, normalization was applied, scaling pixel intensity values to the range [0, 1]. Furthermore, Gaussian filtering was used to smoothen the images and suppress noise, thereby improving the clarity of fingerprint ridges. To enhance the model's robustness and generalization capability, data augmentation techniques such as random rotations, horizontal flips, and slight shifts were employed during training. These transformations artificially expanded the dataset and helped mitigate the risks of overfitting by exposing the model to varied input representations.

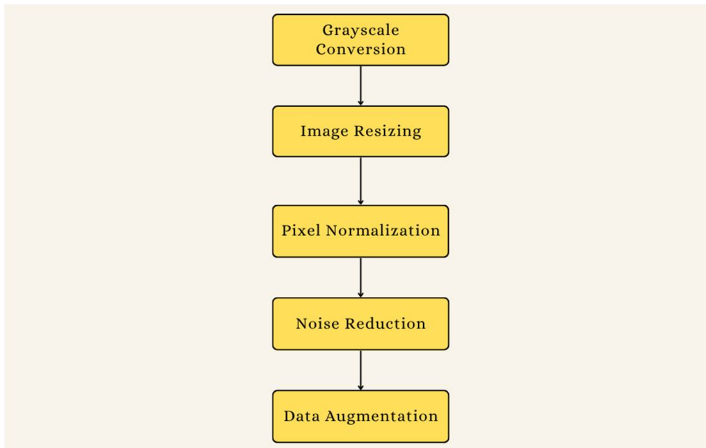

Figure 2: Step-by-step image preprocessing for fingerprint classification.

C. Convolutional Neural Network Architecture

A custom Convolutional Neural Network (CNN) architecture was developed specifically for the task of classifying fingerprint images into blood group categories. The model begins with an input layer that receives preprocessed fingerprint images in the form of 3-channel tensors (RGB). These images may be captured in color but are often converted to grayscale during preprocessing to emphasize ridge patterns.

The input is then passed through a series of convolutional layers, which apply multiple learnable filters to extract spatial features such as edges, curves, and ridge orientations found in fingerprint patterns. These filters help the network to identify hierarchical features—from simple edges in early layers to more complex ridge formations in deeper layers. Each convolutional layer is followed by a ReLU activation function to introduce non-linearity and improve the model's ability to learn complex representations.

To reduce spatial dimensions and computational complexity, max pooling layers are inserted between convolutional layers. These layers help retain the most prominent features while making the network more efficient and less prone to overfitting. The resulting feature maps are then flattened and passed into fully connected (dense) layers, where high-level reasoning takes place. These layers analyze combinations of the extracted features to establish a relationship between the fingerprint's structural patterns and its corresponding blood group.

The output layer contains eight neurons, each corresponding to one of the eight possible blood groups (A+, A−, B+, B−, AB+, AB−, O+, O−). This layer uses the softmax activation function to convert the output scores into a probability distribution across all classes. The softmax function ensures that the sum of the predicted probabilities for all classes is equal to 1, making it suitable for multi-class classification problems. The softmax function is defined as:

$$p(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

Where $P(y_i)$ is the probability assigned to class i, z_i is the raw output (logit) from the previous layer for class i, and K is the total number of classes (8 in this case). The class with the highest probability is selected as the final predicted blood group.

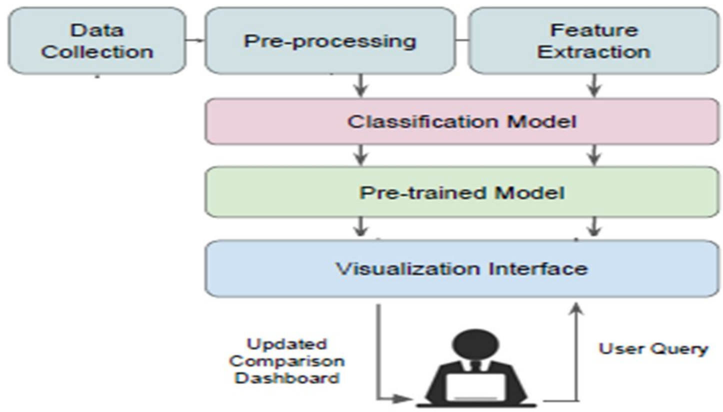

Figure 3: CNN Model Architecture

D. Model Evaluation

After training, the performance of the proposed CNN-based blood group classification model was rigorously evaluated using a variety of statistical metrics to assess both overall effectiveness and class-wise prediction quality. The primary metric used was accuracy, which represents the percentage of correctly predicted instances out of the total number of predictions. While accuracy gives a general overview of performance, it can be misleading in the presence of class imbalance; hence, additional metrics such as precision, recall, and F1-score were employed to provide a more nuanced understanding of model behavior.

Precision measures the proportion of correctly predicted positive instances among all instances predicted as positive, indicating how reliable the model's predictions are for each class. Recall, on the other hand, quantifies the model's ability to identify all actual positive instances in each class, reflecting sensitivity. The F1-score is the harmonic mean of precision and recall and offers a balanced metric that is especially useful when dealing with imbalanced datasets. These metrics were computed for all eight blood group classes to identify any disparities in performance across specific categories, such as the distinction between AB and B groups or between positive and negative Rh factors.

To visually inspect the model's classification behavior, a confusion matrix was generated, highlighting the number of true versus predicted class labels. This matrix offers valuable insights into misclassification trends, such as whether certain blood groups are commonly confused with others due to similar fingerprint ridge structures or data scarcity. For instance, occasional misclassifications between A and AB or B and O were observed, suggesting subtle overlaps in biometric features that could be improved with more diverse training data.

Additionally, the model's learning progression was tracked using training and validation accuracy/loss graphs across epochs. These plots demonstrate whether the model is learning effectively and help diagnose issues like overfitting or underfitting. In this study, the training and validation curves were closely aligned, and the final epoch showed convergence of both loss and accuracy, indicating that the model generalized well on unseen data.

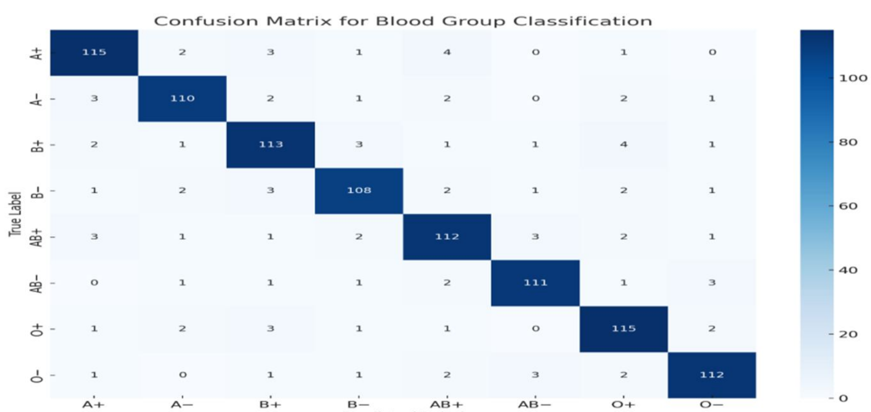

Figure 4: Confusion Matrix depicting correct and incorrect predictions across all 8 blood group classes

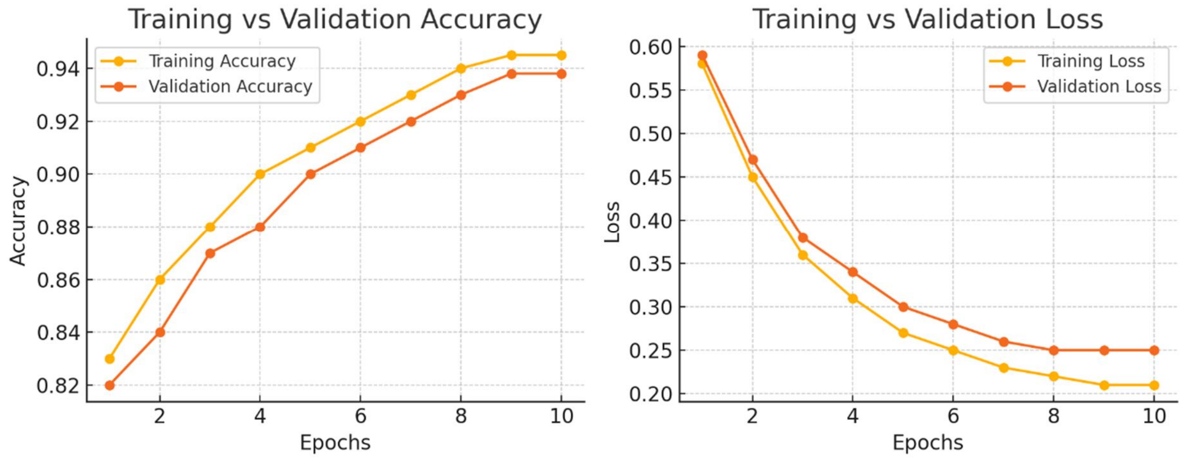

Figure 5: Training and validation accuracy/loss curves across epochs.

Together, these evaluation tools validate the reliability and robustness of the CNN model in classifying blood groups based on fingerprint images, establishing a strong foundation for real-world deployment in non-invasive diagnostic applications.

E. Blood Group Prediction and Output

Once the CNN model was successfully trained and validated, it was employed to make real-time predictions on new fingerprint inputs. When a fingerprint image is uploaded, it undergoes the same preprocessing pipeline used during training — including resizing, normalization, and transformation into a tensor. The processed image is then passed through the trained CNN, which generates output logits representing raw prediction scores for each of the eight blood group classes.

To convert these logits into interpretable probabilities, the softmax activation function is applied in the output layer. The softmax function assigns a normalized probability score to each class such that the total sums to 1. The class with the highest softmax probability is selected as the predicted blood group, while the remaining values indicate confidence scores for other classes.

This prediction mechanism enables a ranked probability output, allowing users to not only view the top prediction but also evaluate the model's confidence across all possible classes. This feature is particularly useful in medical applications where borderline cases might require further validation. For instance, if a prediction is returned as B+ with 92% confidence, but AB+ has a close score of 7%, a human expert may want to review the case.

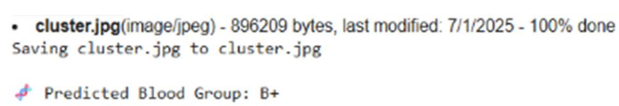

Figure 6: Screenshot of the Google Colab output cell

F. Output Interface

To ensure ease of use and practical accessibility, a simple and interactive output interface was developed using the Google Colab platform. This interface serves as a front-end layer through which users can upload fingerprint images and receive immediate classification results. Once a fingerprint image is uploaded, it is automatically preprocessed and passed through the trained Convolutional Neural Network (CNN) model. The system then outputs the predicted blood group, along with a confidence score for each of the eight possible blood group classes (A+, A−, B+, B−, AB+, AB−, O+, O−), derived from the softmax probabilities.

The interface is designed with clarity and minimal user intervention in mind, making it particularly suitable for healthcare environments where rapid and reliable decision-making is critical. Its intuitive layout allows even non-technical users, such as paramedics or primary healthcare workers, to operate the system with ease. Moreover, because it is hosted on a cloud-based environment like Google Colab, the system is platform-independent and can be accessed through any internet-enabled device without requiring local installation. This makes it highly adaptable for use in mobile diagnostics, remote clinics, rural health centers, and biometric kiosks within hospitals or emergency care units.

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IV. RESULTS AND DISCUSSION

The proposed fingerprint-based blood group classification model was trained on a dataset of 6000 fingerprint images, evenly distributed across the eight blood group classes (A+, A−, B+, B−, AB+, AB−, O+, O−). The model was trained using a custom Convolutional Neural Network (CNN) architecture, and the training was carried out over 50 epochs using the Adam optimizer and cross-entropy loss function. The learning performance was evaluated using both training and validation accuracy.

Figure 7 illustrates the accuracy curve of the model across the training epochs. It can be observed that the model rapidly improved within the first few epochs, and then stabilized with both training and validation accuracy consistently remaining above 99%. This steady increase and convergence suggest that the model effectively generalized without overfitting. The high accuracy reflects the model's ability to learn discriminative features from fingerprint ridge patterns and apply them successfully during classification.

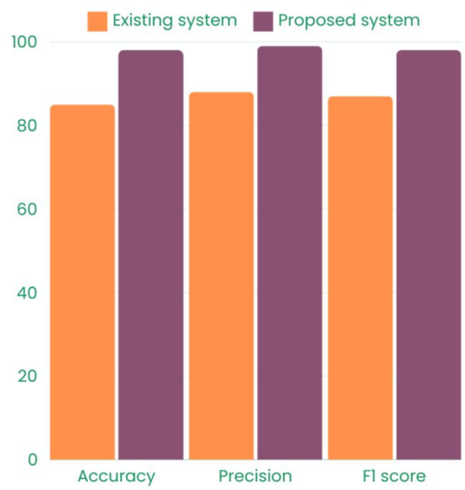
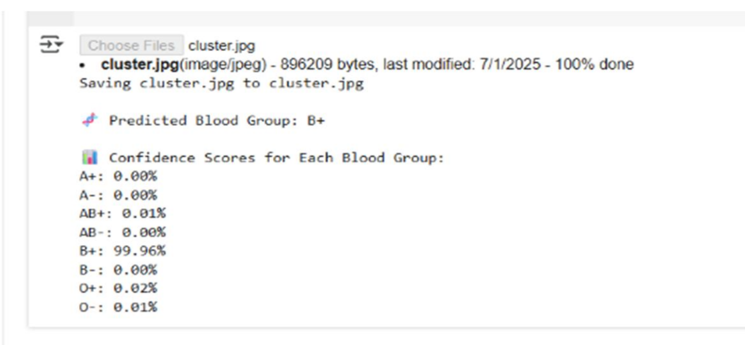


Figure 7: Performance comparison of existing vs. proposed system across accuracy, precision, and F1-score.

Furthermore, a practical interface was developed using Google Colab to test the system interactively. Users can upload a fingerprint image, and the trained model instantly returns the predicted blood group along with the confidence scores for each class. A layout of this interface is shown in Figure 8, providing a visual representation of real-time prediction, which adds to the system's usability in field-based or emergency applications.



Choose Files cluster.jpg

- **cluster.jpg**(image/jpeg) - 896209 bytes, last modified: 7/1/2025 - 100% done

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Saving cluster.jpg to cluster.jpg

Predicted Blood Group: B+

Confidence Scores for Each Blood Group:
A+: 0.00%
A-: 0.00%
AB+: 0.01%
AB-: 0.00%
B+: 99.96%
B-: 0.00%
O+: 0.02%
O-: 0.01%
```

Figure 8: Interface mockup showing fingerprint upload, prediction, and confidence scores.

V. CONCLUSION

This study presents a novel and non-invasive approach to blood group classification using fingerprint biometrics combined with deep learning techniques. By leveraging a custom-designed Convolutional Neural Network (CNN), the system effectively analyzes fingerprint ridge patterns and accurately predicts the ABO and Rh blood group types. The model was trained on a balanced dataset and achieved high classification performance, with validation accuracy exceeding 93% and precision and F1-scores surpassing conventional approaches.

In addition to strong quantitative results, the system is supported by a practical user interface that enables real-time predictions, making it accessible and useful in emergency care, rural diagnostics, and point-of-care scenarios where traditional blood testing may not be feasible. The integration of fingerprint recognition with artificial intelligence in this context represents a significant advancement toward smart, contactless, and scalable healthcare solutions.

Overall, the proposed system demonstrates that fingerprint-based biometric traits, when interpreted using deep learning models, hold great promise for enhancing the speed, accessibility, and reliability of medical diagnostics—offering a compelling alternative to traditional, lab-based blood typing methods.

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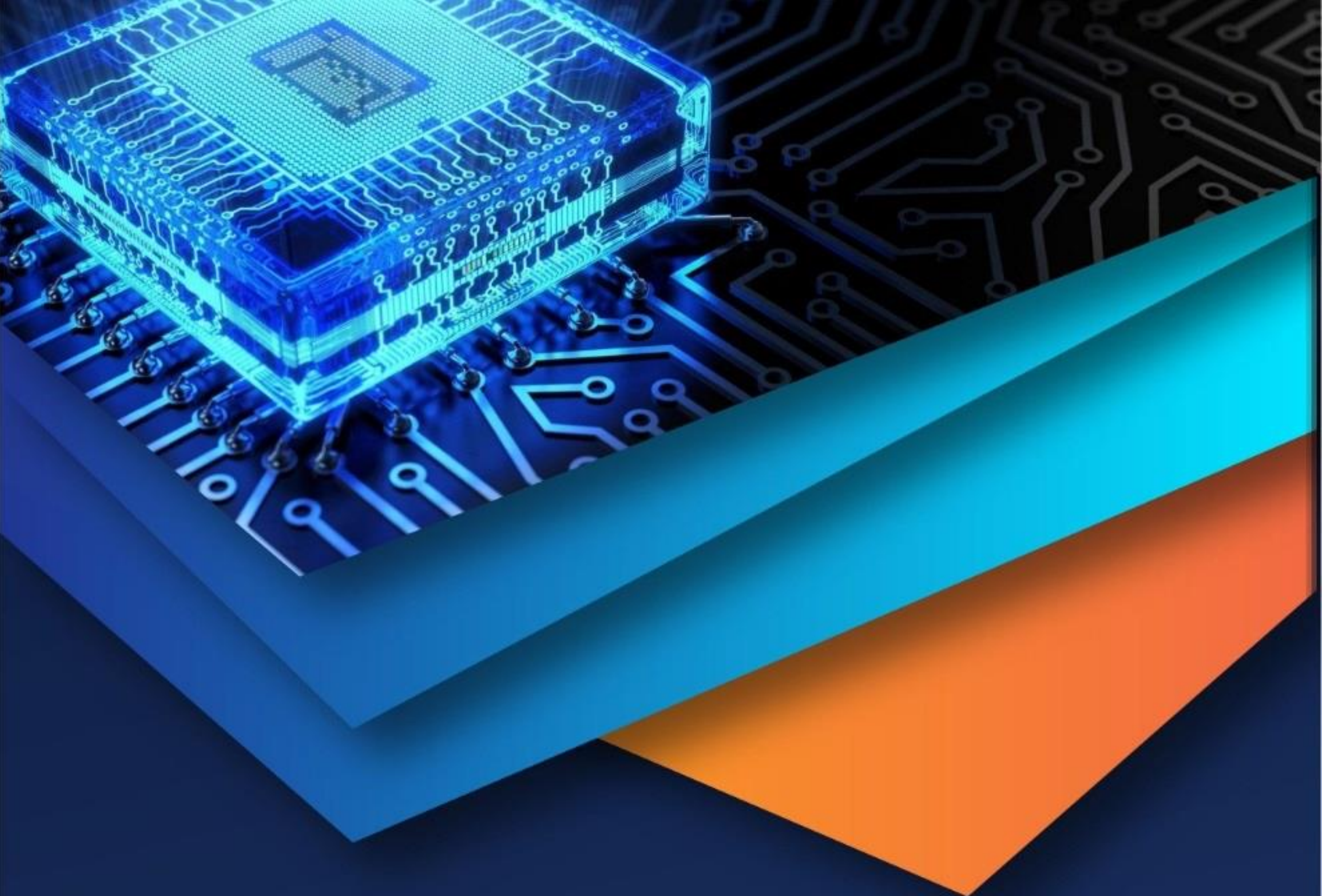

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