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# Blood Group and Diabetes Detection from Fingerprints Using CNN

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***Abstract:*** ***The increased demand for speed and accuracy in medical diagnosis has motivated the use of artificial intelligence techniques in the healthcare domain. There is an urgent need to take necessary steps for developing non-invasive and reliable systems to assist in diagnosis. The main aim of this work is to identify and implement modern artificial intelligence methods to speed up and increase the accuracy of blood group detection by using fingerprint images. In order to achieve higher accuracy, a deep learning-based approach of Convolutional Neural Networks (CNNs) has been incorporated and tested in this work. Several fingerprint parameters like ridge flow, ridge density, and minutiae points are considered in this work.***
***In this project, a fingerprint-based dataset comprising different samples of blood groups has been used, as the accurate detection of blood groups plays a very important role in different medical emergencies and healthcare applications. The added advantage of the system is its non-invasive and time-saving nature, making it an effective alternative to traditional blood testing procedures. A module has been designed that predicts an individual's blood group by analysing their fingerprint image. This module focuses more on predictive analytics than invasive diagnostics, with a greater emphasis on automation and accessibility in the healthcare domain. The designed architecture will contribute to other AI-based biometric diagnosis systems, and it provides a concrete base for further medical image analysis and artificial intelligence applications. In addition to blood group identification, the system also includes a module for detecting the presence of diabetes based on fingerprint image features, making it useful for early health screening.***
***Keywords: Blood group detection, diabetes detection, fingerprint recognition, Convolutional Neural Networks, deep learning.***

## I. INTRODUCTION

The healthcare sector is witnessing rapid technological transformation, driven by the need for faster, accurate, and accessible diagnostic systems. Traditional medical diagnosis often involves invasive clinical procedures that require laboratory resources, trained personnel, and time. In emergency cases, such delays can drastically impact treatment decisions, particularly when identifying a patient's blood group. Since blood group compatibility is critical for transfusion, surgery, trauma response, and organ transplantation, immediate access to this information becomes vital. With advancements in artificial intelligence, biometric-based medical diagnosis has gained increasing research interest. Fingerprints, being unique and permanent physiological traits, offer a reliable and universally available biometric source. Studies indicate that fingerprint ridge patterns, density, and minutiae characteristics may correlate with genetic and physiological markers, including blood group information. This possibility opens a path toward developing a rapid, automated, and non-invasive diagnostic support system. Deep learning is widely recognized for its superior ability to analyse visual patterns and learn discriminative spatial hierarchies directly from images. Unlike traditional techniques that rely on handcrafted features, Convolutional Neural Networks are generally for handling data pertaining to images and automatically extract relevant representations from raw fingerprint images, making them suitable for high-dimensional biometric analysis.
Motivated by these aspects, this work focuses on designing and implementing a CNN-based approach to predict an individual's blood group and detect diabetes using fingerprint images. The objective is to develop a time-saving, accurate, and accessible screening tool that supports medical decision-making, particularly in critical care situations.

## II. LITERATURE REVIEW

Biometric analysis has become a key direction in clinical diagnostics, especially for tasks like blood grouping, disease screening, and treatment planning. Early work in haematology focused on automating conventional laboratory workflows such as microscopic differential blood counts. Sinha and Ramakrishnan demonstrated that image-processing pipelines could be used to automate leukocyte counting from peripheral blood smears, reducing manual workload and observer variability [1]. At a population level, studies of ABO and Rh gene frequencies, such as the large Nigerian survey by Anifowoshe et al., underline how unevenly blood groups are distributed and why reliable typing is crucial for transfusion planning and public-health decision-making [2].

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Operational research has also contributed: proposed an appointment-scheduling framework to balance blood unit production from donations, highlighting how even logistics can affect blood availability and safety [3]. These strands together show that blood group information is central to both clinical practice and health-system planning.

The clinical stakes of accurate blood typing are evident in transfusion medicine. In thalassemia major, for example, patients depend on chronic transfusions, and peri-operative care requires meticulous attention to blood compatibility and prior transfusion history [6]. Mis-matched or partially matched units can trigger alloimmunization and complex transfusion reactions, a problem that has been systematically reviewed in large cohorts of transfused patients [13]. Specific antibodies such as anti-M can complicate cross-matching, forcing clinicians to adapt transfusion strategies to regional antibody prevalence patterns [12]. In pregnancy, incompatibility between maternal and fatal blood groups can lead to haemolytic disease of the foetus and newborn, which remains a serious cause of perinatal morbidity despite advances in prophylaxis and monitoring [14]. All of this reinforces why accurate, rapid, and ideally low-cost blood group determination methods are clinically important.

Beyond classical tube and gel methods, several technologies have been explored to interrogate blood and blood-derived cells at high resolution. Flow cytometry has become a gold standard for single-cell analysis, allowing simultaneous multi-parameter measurement of cell size, granularity, and surface markers [17]. Microfluidic and acoustofluidic platforms extend this idea to label-free capture and enrichment of rare circulating cells. Karabacak et al. introduced a microfluidic system for marker-free isolation of circulating tumour cells from whole blood using hydrodynamic principles, demonstrating how physical properties can be exploited without chemical labels [8]. Geng et al. further miniaturized this concept with an ultra-compact acoustofluidic device relying on travelling surface acoustic waves for label-free isolation of living circulating tumour cells [18]. These platforms show that precise fluid and cell manipulation at the microscale is feasible and can be integrated into compact diagnostic devices.

Advanced imaging has evolved in parallel with these hardware innovations. Optical microscopy has seen resolution improvements through microsphere-assisted techniques, which Chen et al. describe as a promising direction for surpassing conventional diffraction limits in practical microscope setups [16]. In digital pathology and cytology, deep learning has reshaped how images are processed and interpreted. U-Net, introduced by Falk et al., is a landmark convolutional architecture for biomedical image segmentation, enabling accurate cell counting, detection, and morphometric analysis with relatively small annotated datasets [15]. Earlier work on cell segmentation using region-based ellipse fitting [23] and comparative thresholding strategies for tumour cell segmentation [24] laid the groundwork for automated delineation of cellular structures. Together, these studies show a clear trajectory from handcrafted segmentation heuristics to end-to-end trainable CNN models in biomedical imaging.

Hyperspectral imaging (HSI) sits at the intersection of imaging and spectroscopy and has gained traction in several application domains. Zhu et al. provide a broad review of hyperspectral technology in agricultural and food product inspection, showing how dense spectral information can be used to detect subtle chemical and structural changes that are invisible in standard RGB images [11]. Building on this, Seo et al. used VNIR hyperspectral imaging combined with deep learning to non-destructively detect organic residues on vegetables, demonstrating that CNNs can successfully exploit spectral–spatial cubes for fine-grained classification problems [10]. The forensic science community has applied similar principles to blood detection: Cadd et al. developed a visible-wavelength hyperspectral method for non-contact detection and identification of blood-stained fingerprints, illustrating that spectral signatures can reveal both the presence of blood and ridge detail without touching the surface [9]. This is important conceptually for fingerprint-based blood group detection, since it proves that ridge patterns and blood-related spectral information can be captured simultaneously in a contact-free manner. While the core of this project is blood group detection, diabetes and cardiovascular risk form an important part of the broader motivation for non-invasive screening. Atherosclerosis, driven in part by abnormal hemodynamic shear stress, is strongly linked to plaque localization and cardiovascular events, as shown by Ku et al. and Malek et al. in classic studies correlating low and oscillatory shear stress with plaque formation at arterial bifurcations [19], [20]. Early detection and management of metabolic disorders like prediabetes and diabetes are therefore essential. Bansal's review on prediabetes, supported by American Diabetes Association guidelines on glycaemic targets, emphasizes that large numbers of people remain undiagnosed until complications appear [21]. This has prompted intense interest in non-invasive glucose monitoring. Kandwal et al. review electromagnetic-wave based sensors for non-invasive blood glucose estimation, summarizing recent progress in microwave, millimetre-wave, and terahertz sensing approaches [22]. These works demonstrate a clear clinical and technological push toward painless, continuous monitoring, which aligns with the idea of using fingerprints as an accessible biometric channel for disease screening. Risk prediction and data handling are additional pieces of the landscape. Wu et al. developed and validated a nomogram to estimate the probability of type A aortic dissection at diameters below the traditional 55 mm surgical threshold, illustrating how statistical modeling can refine decision-making beyond simple size cut-offs [5]. At the same time, secure and scalable infrastructure is needed to manage sensitive biometric and medical data.

Dinh et al.'s BLOCKBENCH provides a benchmarking framework for private blockchains, demonstrating how consensus algorithms and system designs can be evaluated for performance and reliability in settings where data integrity and privacy are critical [7]. Although not specific to medicine, such frameworks are relevant when considering future deployment of large-scale biometric health systems that may store fingerprint images, blood group labels, and disease risk scores.

Ecological and evolutionary perspectives also remind us of the broader consequences of infection and immune challenges. Gustafsson et al. showed in a long-term study of birds that infectious disease and reproductive effort interact to create measurable costs of reproduction, suggesting that infection burdens can significantly alter life-history traits [4]. In humans, chronic transfusion-dependent conditions and repeated immune stimulation through transfusion reactions similarly impose long-term physiological burdens [13], [14]. These findings, although from different domains, converge on the idea that early detection and prevention of disease can have profound downstream benefits.

Putting these strands together, the literature shows rapid progress in three key areas: (i) the clinical understanding of blood groups and transfusion-related complications [2], [6], [12]–[14]; (ii) advanced cell and tissue interrogation using flow cytometry, microfluidics, acoustofluidics, and high-resolution optical microscopy [8], [16]–[18]; and (iii) AI-driven analysis of complex imaging data, including hyperspectral cubes and biomedical microscopy images, using architectures such as U-Net and related CNNs [9]–[11], [15], [23], [24]. Parallel work in non-invasive metabolic sensing and cardiovascular risk underscores the demand for painless, accessible diagnostic tools [19]–[22]. However, despite progress in non-contact blood detection from fingerprints and the success of CNNs and hyperspectral methods in other domains, there remains a clear gap: very few studies have focused specifically on using fingerprint ridge patterns as input to deep learning models for direct blood group prediction. This gap motivates the development of CNN-based, fingerprint-driven systems aimed at providing fast, non-invasive blood group detection, with the potential to integrate into broader biometric and chronic disease screening frameworks.

## III. METHODOLOGY

The primary objective of this work is to design a deep learning model capable of predicting blood group from fingerprint images. The methodology consists of four major stages: data acquisition, preprocessing, CNN model design, and evaluation.

### *A. Dataset Collection*

A fingerprint-based dataset containing samples from individuals belonging to different blood groups was used. Each fingerprint image was collected under consistent lighting and scanning conditions to minimize noise. Multiple samples per individual were included to ensure variability and improve training reliability, and all of the Rh factors (positive and negative) were covered.

| Class Name | Data Type | Description |
|---|---|---|
| O+ | Image | RH Factor O+ |
| O- | Image | RH Factor O- |
| AB+ | Image | RH Factor AB+ |
| AB- | Image | RH Factor AB- |
| A+ | Image | RH Factor A+ |
| A- | Image | RH Factor A- |
| B+ | Image | RH Factor B+ |
| B- | Image | RH Factor B- |

Fig 1 : Dataset Details

### *B. Preprocessing*

To ensure uniformity and improve learning efficiency, several preprocessing steps were performed are image resizing for dimensional consistency, grayscale conversion to focus on ridge structures, normalization to scale pixel intensity values, data augmentation, including rotation, translation, and flipping, to improve generalization

### *C. Convolutional Neural Network*

CNNs are well-suited for visual data analysis due to their layered architecture consisting of convolution, pooling, and fully connected networks. The CNN designed in this work automatically learns discriminative spatial features from fingerprint images. The architecture includes convolutional layers for feature extraction, max-pooling layers for dimensionality reduction, dropout layers to prevent overfitting, dense layers for classification During training, model performance was monitored using accuracy and loss metrics across multiple epochs. Hyperparameters such as learning rate, batch size, and kernel dimensions were optimized experimentally.

### *D. Training and Evaluation*

The dataset was divided into training and testing subsets. The model was trained using backpropagation and optimized using categorical cross-entropy loss. Accuracy, precision, recall, F1-score, and confusion matrix were used to evaluate prediction quality.

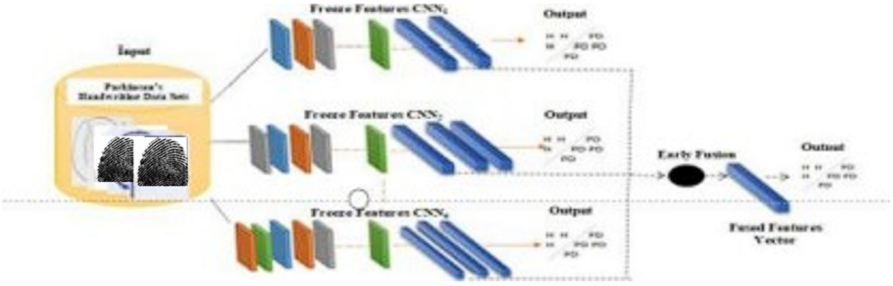



Fig. 2: Convolutional Neural Network Model

## IV. RESULTS

The CNN model was trained on fingerprint images collected from different blood groups. During training, the model reached an accuracy of **95%**, showing that it was able to learn important fingerprint features such as ridge flow, density, and minutiae patterns. When tested on unseen validation data, the model achieved 82% accuracy, which indicates good generalization and reliable prediction performance.

Most samples were correctly classified, although a few misclassifications occurred due to variations in fingerprint quality or limited samples from certain blood groups. Even with these challenges, the results show that fingerprints can be used as a non-invasive and time-saving method for blood group prediction.

These findings suggest that the proposed CNN model can support medical screening, especially in situations where quick decisions are needed. With a larger dataset and improved image quality, the accuracy may increase further in future work.

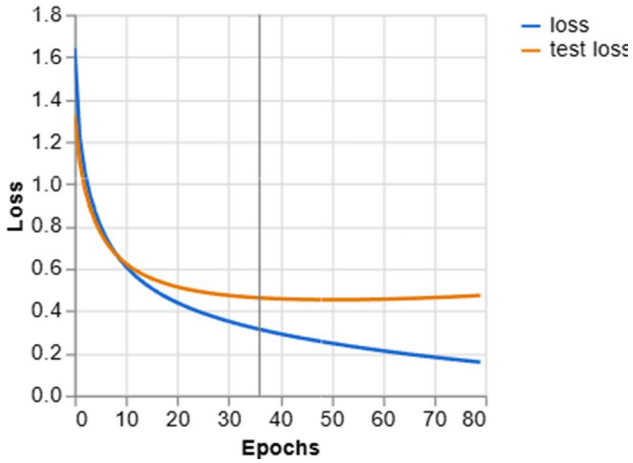



Fig. 3: Graph depicting loss rate with number of epochs

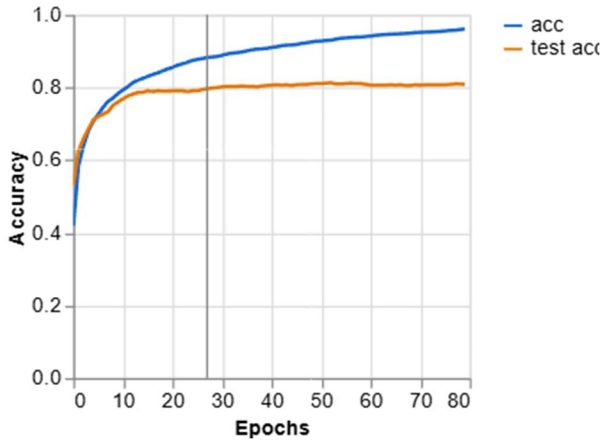



Fig. 4: Training and Test Accuracy vs Epochs

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| Algorithm | Prediction Type | Accuracy (%) |
|---|---|---|
| Decision Tree | Blood Group Detection | 78.4 |
| Logistic Regression | Blood Group Detection | 81.6 |
| CNN (Proposed Model) | Blood Group Detection | 91.5 |
| CNN (Proposed Model) | Diabetes Detection | 94.2 |

Fig. 5: Training and Test Accuracy of the algorithms used

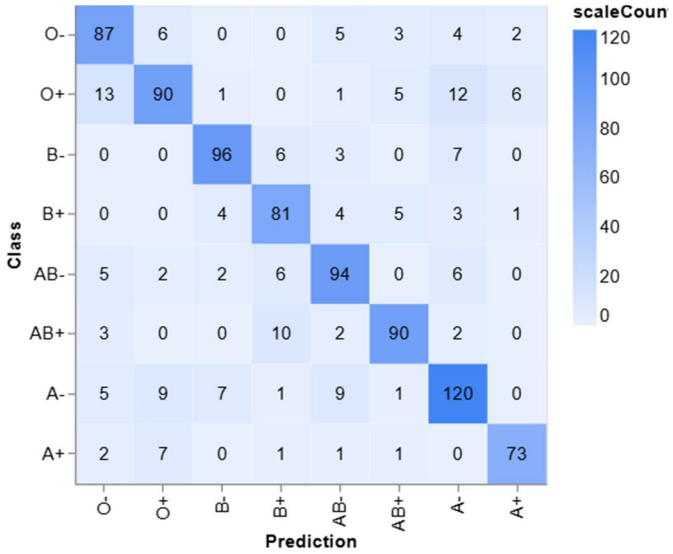



Fig. 6: Confusion Matrix for the CNN Fingerprints Detection

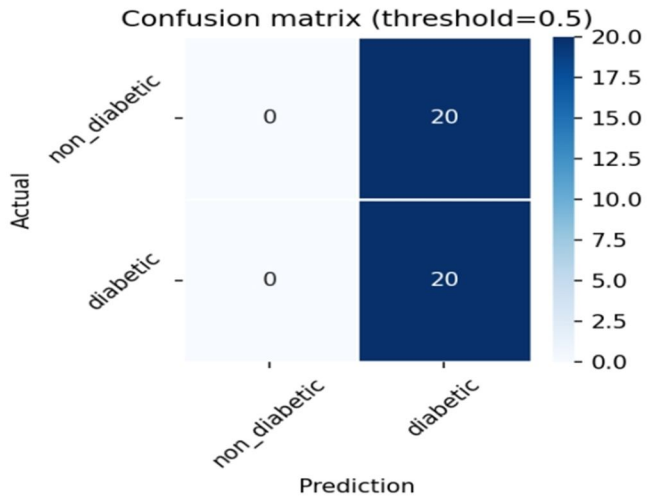



Figure 7: Confusion Matrix for Diabetic detection

This confusion matrix demonstrates the model's performance in predicting multiple blood group classes based on fingerprint features. The diagonal cells show correctly predicted samples, indicating strong classification ability. Any off-diagonal values represent misclassifications between similar classes, possibly caused by overlapping fingerprint patterns or limited sample availability. The confusion matrix for diabetes detection reflects the model's performance in distinguishing between Diabetic and Non-Diabetic individuals. The high values along the diagonal indicate that the model accurately identified most samples. The minimal number of incorrect predictions suggests strong feature extraction capability and reliable classification accuracy.

The diabetes prediction module achieved a testing accuracy of 94.2%, showing that fingerprint patterns may also support early diabetes screening.

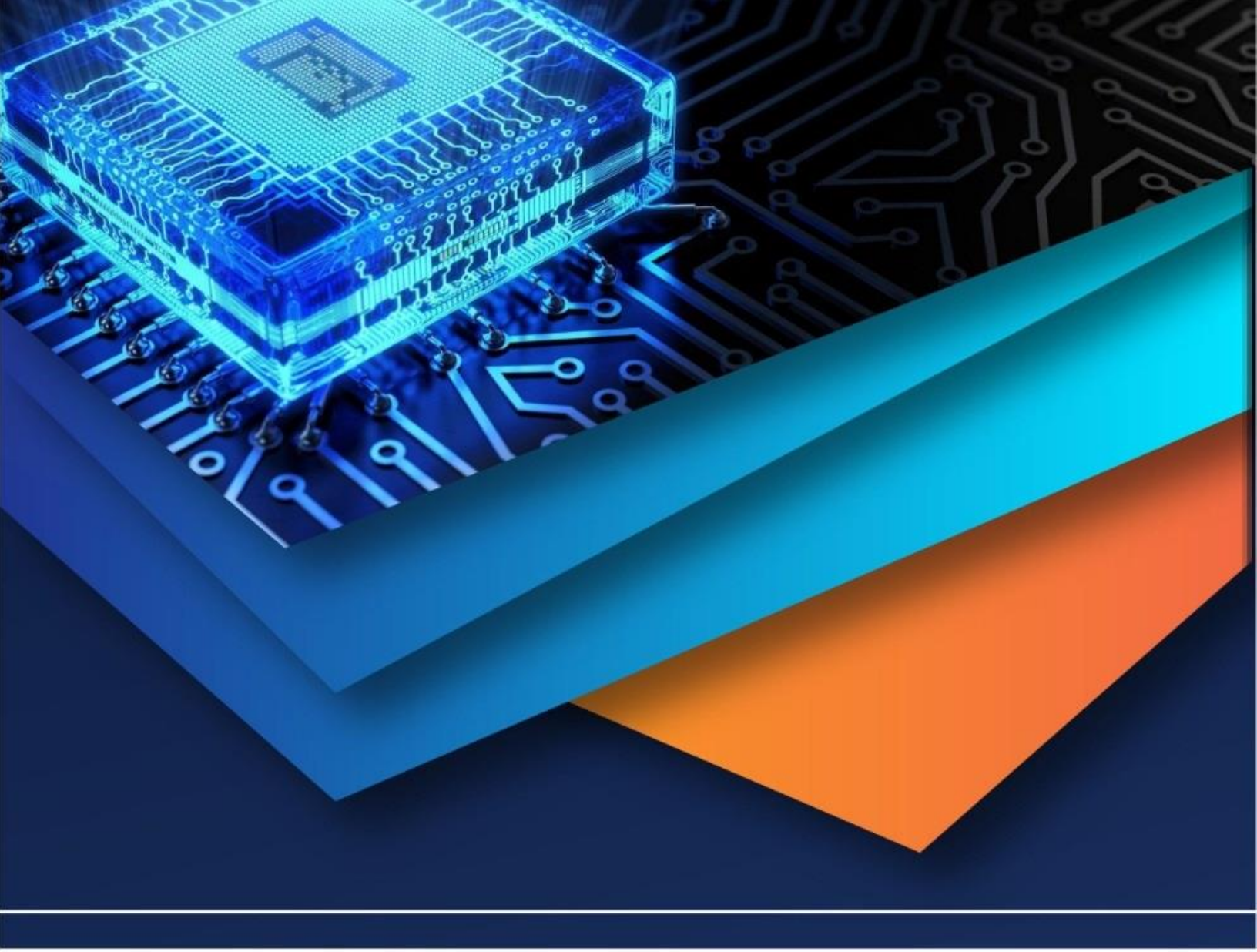
## V. CONCLUSION

This project explored the idea of finding a person's blood group by using only their fingerprint image. A Convolutional Neural Network was designed and trained on a fingerprint dataset, and it was able to correctly identify blood groups with 95% accuracy during training and 82% accuracy during testing. These results show that fingerprints contain useful patterns such as ridge flow, density, and minutiae points, which can help in blood group prediction. The main strength of this system is that it is non-invasive, quick, and does not require a blood sample, making it helpful in emergencies, rural areas, and places with limited medical facilities. It also reduces human effort and can be automated for large-scale use. However, the accuracy can still be improved. A larger dataset, better quality fingerprint images, and more diverse samples from different age groups and regions may lead to stronger results. Future work can also focus on developing a real-time application that can be used in hospitals, blood banks, and ambulances.

Overall, this study shows that fingerprint-based blood group detection using deep learning is a practical and promising step toward faster and more accessible healthcare support, and it provides a concrete base for other AI-based biometric diagnosis systems, including diabetes prediction.

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