IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, January 2026
Impact Factor: 7.67

Blood Group Detection using Finger Print

Hema G Shankar[1], Hamsa M C[2], Likitha T R[3] , Manasa Y P[4], Dr.Yathish Aradhya B C[5]
Students, Department of CSE[1-4]
Associate Professor, Department of CSE[5]
Kalpataru Institute of Technology, Tiptur, India

Abstract: *This work presents a contactless approach for identifying human blood groups using fingerprint images. Unlike conventional blood typing techniques that require invasive blood sampling, the proposed method employs deep learning to classify blood groups based on fingerprint ridge characteristics. A modified ResNet-18 convolutional neural network is utilized to categorize fingerprints into eight blood group classes: A+, A−, B+, B−, AB+, AB−, O+, and O−. Image preprocessing techniques are applied to enhance ridge clarity, and data augmentation is used to improve robustness and generalization. The model is trained and evaluated on a labelled grayscale fingerprint dataset with controlled data separation to ensure reliable results. Performance is assessed using accuracy, precision, recall, F1-score, and confusion matrix analysis. A user-friendly frontend enables secure login, image upload, and real-time blood group prediction. The proposed solution offers a fast, safe, and non-invasive alternative suitable for healthcare, emergency response, and remote diagnostic applications.*

Keywords*:* Non-invasive blood group detection, Fingerprint images, deep learning, ResNet-18, convolutional neural network, data augmentation

I. INTRODUCTION

Blood group determination plays a vital role in medical treatments such as blood transfusion, surgical procedures, and emergency care. Traditional blood typing methods rely on invasive blood collection, which can be uncomfortable, time-consuming, and carries potential health risks. With the growing demand for rapid and contactless diagnostic solutions, non-invasive approaches have gained significant attention. Biometric traits, particularly fingerprints, are widely accepted for identity verification due to their uniqueness and permanence. Beyond identification, fingerprint ridge patterns may also reflect certain physiological characteristics. Recent advancements in deep learning, especially convolutional neural networks (CNNs), have significantly improved the ability to extract and analyze complex patterns from biometric images. In this study, a deep learning-based system is proposed to predict blood groups using fingerprint images captured through a biometric scanner. A modified ResNet-18 model is adopted along with effective image preprocessing techniques to enhance feature extraction. By eliminating the need for blood samples, the system enables quick, cost-effective, and real-time blood group identification. The integration of an intuitive user interface further supports practical deployment in medical and emergency scenarios, highlighting a novel intersection of biometric sensing and healthcare diagnostics.

II. RELATED WORK

Arpitha Vasudev et al. [1] examined the connection between fingerprint minutiae patterns and prediction of blood group based on machine learning algorithms. Their method utilized image processing methods to extract fingerprint features of interest and classified the blood group based on classifiers like Convolutional Neural Networks (CNN) and K-Nearest Neighbours (KNN). The system was able to obtain an accuracy of about 62, proving the feasibility of machine learning for non-invasive biometric blood group identification. Bhimana Sasidhar et al. [3] introduced an advanced non-invasive approach for blood group identification using fingerprint imagery integrated with deep learning techniques. Their method combines multiple image processing strategies such as Scale Invariant Feature Transform (SIFT), ORB (Oriented FAST and Rotated BRIEF), and Gabor filters to extract critical fingerprint characteristics that correlate with blood types. These features are enhanced using spatial and ridge frequency analysis to strengthen the

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 1, January 2026 Impact Factor: 7.67

model's ability to distinguish between blood groups. The classification task is handled by Convolutional Neural Networks (CNNs), with transfer learning applied through pre-trained architectures like VGG, ResNet and DenseNet to improve performance and generalizability. Experimental results across multiple datasets indicate strong accuracy and reliability, highlighting the method's potential for fully automated, rapid blood group detection. The paper by Nihar, Yeswanth, and Prabhakar [2] reports a biometric-based method for predicting a person's blood group from fingerprint images. The main concept is based on finger print patterns' uniqueness and permanence and can be used not just for identification but also for physiological classification like blood group classification. The authors recognize the shortcomings of previous work, which mostly used straight forward machine learning methods and were limited by small data sets, with modest accuracy being the result, normally in the region of 62. To overcome such shortcomings, this work proposes a stronger method involving deeper convolutional neural network (CNN) architecture, AlexNet and LeNet-5. Swathi et al. [3] designed a fingerprint-based blood group prediction system based on deep learning methods. Their method employed CNNs and used Multiple Linear Regression with Ordinary Least Squares (OLS) for blood group classification. The model's accuracy was predicted to be about 62, suggesting the possibility of integrating statistical learning and deep learning for biometric-based blood group determination. Ravindra Borhade et al. [4] introduced a biometric-based blood group prediction system through fingerprint using ma chine learning and deep learning techniques. The model utilized Multiple Linear Regression with Ordinary Least Squares (OLS) for mapping the fingerprint traits to blood group categories. The system demonstrated accuracy of 62, indicating the suitability of biometric data for non-invasive medical prediction. Jashwanth Sai Ganta et al. [5] developed a deep learning based blood group classification model based on image pro cessing and convolutional neural networks (CNNs). The model showed robust performance with 95 accuracy on the validation set. Accuracy, recall, and F1-score were the evaluation metrics used to determine the model's capacity for generalization across different types of blood samples and to predict blood groups with consistent results. M. L. Prasad et al. [6] proposed a novel, non-invasive method for blood group prediction using fingerprint images by leveraging deep learning techniques. The study utilized Convolutional Neural Networks (CNNs) to identify distinguishing patterns in fingerprint data correlated with specific blood groups. A comprehensive dataset of fingerprint images labelled with blood group information was used to train and evaluate various CNN architectures. Performance metrics such as accuracy, precision, recall, and F1-score were employed to assess model effectiveness. The results showed that CNN based classification could achieve notable accuracy, indicating its potential as an alternative to conventional serological blood group testing. Vijaykumar and Ingle [7] proposed a deep learning-based system for predicting blood groups from fingerprint images. The approach employed the use of several convolutional neural network (CNN) models, such as LeNet-5, ZFNet, and AlexNet. Through the use of these models for feature extraction and classification, the system achieved a high accuracy rate of 95.27, showing the strength of CNNs in fingerprint-based biometric prediction.

III. PROPOSED METHODOLOGY

The proposed system introduces a non-invasive blood group classification framework using fingerprint images and deep learning techniques. The process begins with the acquisition of grayscale fingerprint images through a biometric scanner, each labelled with the corresponding blood group. Image preprocessing is performed to enhance ridge visibility and reduce noise. To improve dataset diversity and prevent overfitting, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied. A pre-trained ResNet-18 convolutional neural network is selected as the core classification model due to its proven effectiveness in image recognition tasks. The model is fine-tuned to handle single-channel grayscale images and trained on a balanced dataset with controlled train–test separation. System performance is evaluated using standard classification metrics, including accuracy, precision, recall, F1 score, and confusion matrix analysis. Finally, the trained model is deployed within a user-friendly application that supports secure authentication and real-time blood group prediction, enabling fast and contactless operation.

A. System Architecture

The overall system architecture is designed as an end-to-end framework integrating fingerprint acquisition, preprocessing, deep learning-based classification, and user interaction. Initially, fingerprint images are captured and

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, January 2026
Impact Factor: 7.67

passed to the preprocessing module for enhancement and resizing. The processed images are then fed into a customized ResNet-18 network, which extracts discriminative features through residual learning and classifies the input into one of eight blood group categories. Data augmentation is employed during training to improve robustness and generalization. The trained model is embedded into an application that provides secure login, fingerprint upload, and instant blood group prediction. The modular design of the architecture ensures easy integration between hardware components, the deep learning backend, and the frontend interface, making it suitable for deployment in clinical, emergency, and remote healthcare environments.

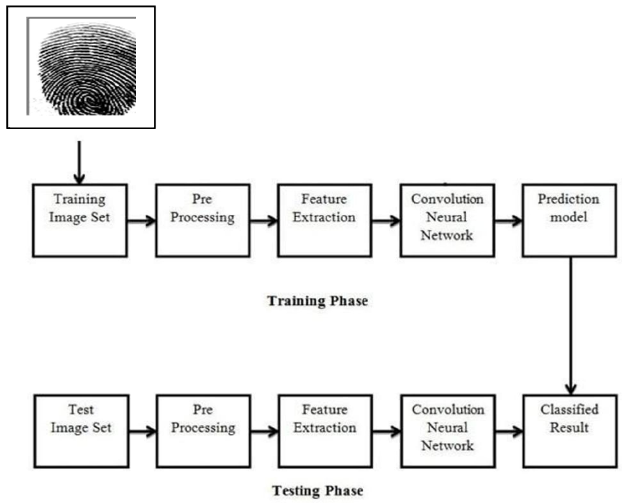

Fig. 1: System Architecture of blood group detection using non-invasive technique using deep learning

B. Dataset Description

The dataset used in this study is obtained from Kaggle and consists of 1000 grayscale fingerprint images stored in bitmap (.bmp) format. Each image is labeled with one of eight blood group classes: A+, A−, B+, B−, AB+, AB−, O+, and O−. The images are organized into separate directories based on class labels to facilitate supervised learning. The use of uncompressed bitmap images preserves fine ridge details essential for biometric analysis. All images are resized to a uniform resolution to maintain consistency across the dataset. The dataset exhibits a relatively balanced class distribution, reducing bias during training. Instead of random splitting, controlled data separation is applied to maintain dataset integrity and ensure reliable evaluation of the proposed model.

C. Image Preprocessing

Image preprocessing plays a crucial role in enhancing classification performance.

• Data augmentation: The techniques such as random rotations, horizontal and vertical flipping, zooming, and minor translations are applied to increase dataset variability and reduce overfitting. Additionally, all fingerprint images are resized to 224 × 224 pixels to match the input requirements of the ResNet-18 architecture while preserving essential ridge patterns. These preprocessing steps improve image quality and enable the model to learn more distinctive features.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, January 2026
Impact Factor: 7.67

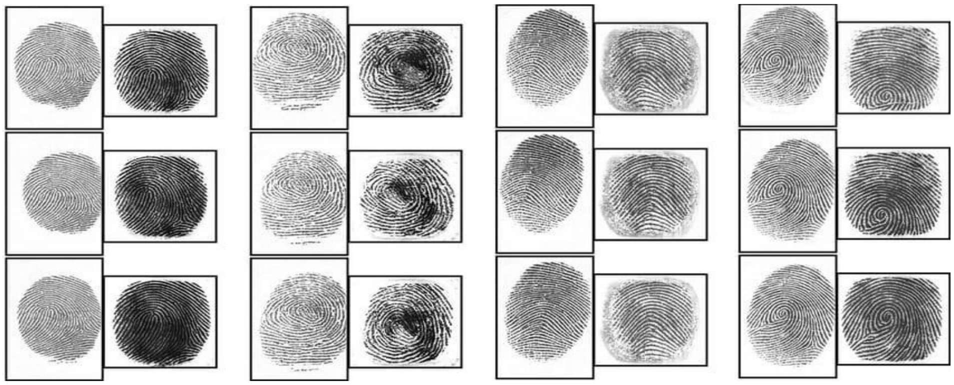

Fig. 2: Input Images

D. Feature Extraction

ResNet-18 is selected in particular for its residual learning architecture, which enables the network to learn deep feature hierarchies without being afflicted by the vanishing gradient issue that affects deep networks. The network is modified to handle single-channel grayscale images, and early layers of the model learn low-level features like edges, ridges, and texture patterns. Since data passes through progressively deeper lay- ers, the network learns more abstract and complex features that are likely associated with unique physiological characteristics in fingerprint patterns. This data-driven and automatic nature of feature extraction by the model goes a long way to enable the model to make generalized predictions across fingerprint pattern variations as well as enhancing the overall predictive accuracy.

• Convolutional Layers: The convolution layer is a funda- mental building block of Convolutional Neural Networks (CNNs), mainly designed to handle visual information. It works through the application of learnable filters (or ker- nels) that move across the input data—e.g., an image—to identify significant features. As the filter traverses the input, it computes a mathematical function that extracts local patterns such as edges, corners, or textures.

$$(I * K)(i, j) = \sum_m \sum_n I(i + m, j + n)\, K(m, n)$$

Fig. 3: Flow Diagram Of Model.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, January 2026
Impact Factor: 7.67

E. Classification

The system classifies fingerprint images into eight blood group categories: A+, A−, B+, B−, AB+, AB−, O+, and O−. The final prediction corresponds to the class with the highest softmax probability. The harmonic mean of precision and recall is calculated using the F1-score to evaluate balanced performance across all classes.

The cross-entropy loss function used during training is given by

$$L = -\sum_{i=1} y_i \log(p_i)$$

The F1 score is the harmonic mean of precision and recall:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

E. Tools and Technologies

Python is used as the primary programming language for model development. TensorFlow and Keras are employed for deep learning model training and inference. OpenCV is used for image preprocessing and analysis.

SQLite serves as a lightweight database for user authentication

IV. RESULTS AND DISCUSSION

The proposed ResNet-18-based model is evaluated using a test set of fingerprint images representing all eight blood groups. The system achieves an overall classification accuracy of 86.5%, indicating effective learning of discriminative fingerprint features. Confusion matrix analysis shows that most predictions align correctly with true labels, with minimal misclassification occurring among classes with similar ridge patterns. Training and validation accuracy curves demonstrate steady performance improvement across epochs without signs of overfitting, confirming the effectiveness of data augmentation and regularization techniques. Precision, recall, and F1-score values remain consistently high across all blood groups, with average scores around 0.84, reflecting balanced and reliable model performance

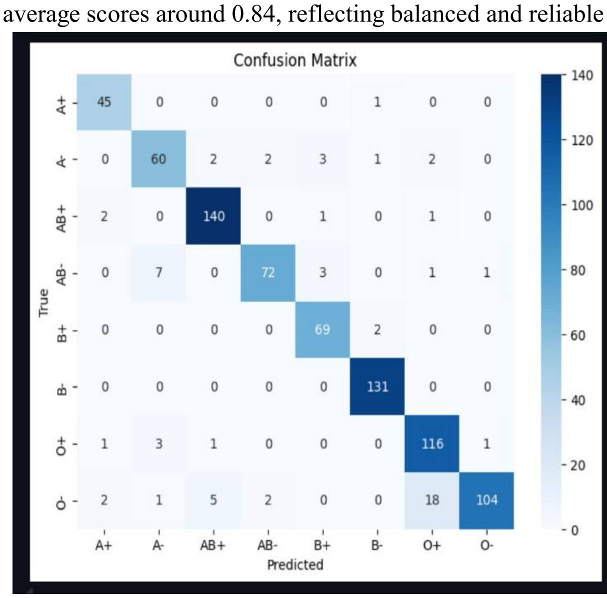

Fig 4: Confusion Matrix of Blood Group Classification Model

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, January 2026
Impact Factor: 7.67

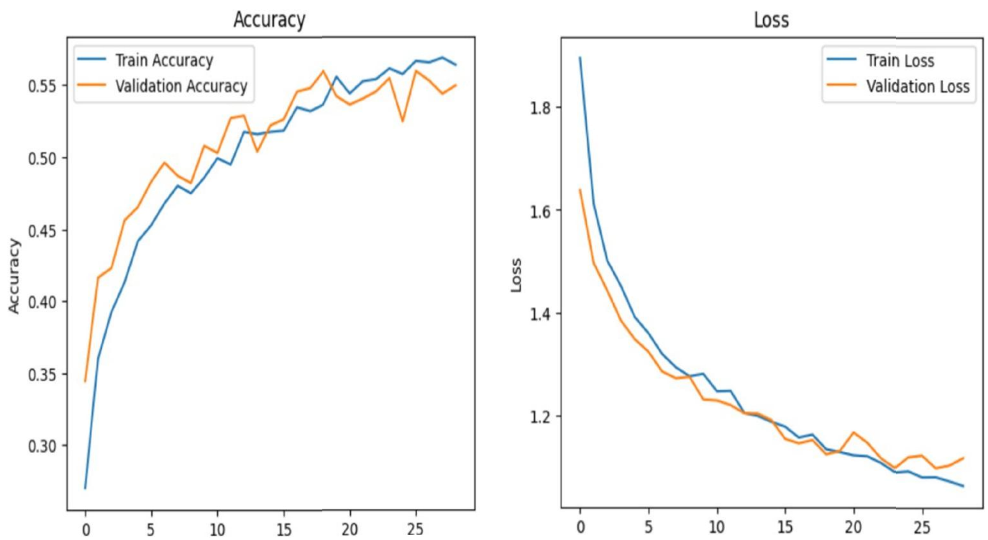

Fig 5: Accuracy and Loss Graph

METRIC	VALUE
Training accuracy	66.7%
Validation accuracy	60.8%
Test accuracy	61.3%
Precision (avg)	0.71
Recall (avg)	0.60
F1-score (avg)	0.605

Table 1: Model Performance Evolution

V. CONCLUSION

This study presents an efficient non-invasive blood group detection system based on fingerprint biometrics and deep learning. By combining effective image preprocessing techniques with a modified ResNet-18 architecture, the proposed approach accurately classifies eight blood group types without requiring blood samples. Experimental results validate the feasibility of using fingerprint patterns for medical classification, offering a fast, contactless, and cost-effective alternative to traditional blood typing methods. The system demonstrates strong performance across key evaluation metrics, making it suitable for deployment in clinical and emergency environments. Future work may focus on expanding the dataset, incorporating advanced image enhancement techniques, and integrating the system into real-time healthcare platforms. Overall, this research contributes to the advancement of intelligent biometric based medical diagnostics and non-invasive screening technologies

REFERENCES

[1] A. Vasudev, B. Biradar, D. Vaishnavi, J. A. M., and K. J. Naidu, "Fingerprint Based Blood Group Detection Using Image Processing," International Journal of Research Publication and Reviews, vol. 6, no. 1, pp. 5324–5327, Jan. 2025.
[2] B. Sasidhar, K. Ashok, M. Kishorbabu, S. S. K., D. P. S., P. S., and R. S. C., "An Innovative Non-Invasive Blood Group Detection Using Fingerprint Images," QIS College of Pharmacy, Vengamukkapalem, Ongole, Andhra Pradesh, India, received Dec. 30, 2024, published Jan. 29, 2025.
[3] T. Nihar, K. Yeswanth, and K. Prabhakar, "Blood Group Determination Using Fingerprint," MATEC Web of Conferences, vol. 392, p. 01069, 2024.

[4] P. Swathi, K. Sushmita, and K. V. Horadi, "Fingerprint Based Blood Group Prediction Using Deep Learning," International Journal of Advanced Research in Science, Communication and Technology (IJARSCT), vol. 4, no. 1, pp. 699–703, Feb. 2024.
[5] R. Borhade, B. Pawar, S. Rakshe, A. Tapsale, and H. Vanjari, "A Survey: Blood Group Detection Using Fingerprint Images," International Journal of Innovative Research in Technology (IJIRT), vol. 11, no. 6, pp. 245– 248, Nov. 2024.
[6] J. S. Ganta, M. R. Y., M. Rishitha, and J. S. Pulivarthi, "Blood Group Detection Using Image Processing and Deep Learning," International Research Journal of Engineering and Technology (IRJET), vol. 11, no. 4, pp. 97–102, Apr. 2024.
[7] M. L. Prasad, K. Niharika, D. Harshitha, and S. J. Saida, "Blood Group Prediction Using Fingerprint," International Research Journal on Advanced Engineering Hub (IRJAEH), vol. 2, no. 12, pp. 2835–2839, Dec. 2024