Blood Group Detection from Fingerprints

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***Abstract*—This project introduces a deep learning-based system that uses fingerprint images to predict human blood groups. The system combines a classifier for predicting eight major blood groups (A+, A-, B+, B-, AB+, AB-, O+, O-), a Convolutional Neural Network (CNN) for feature extraction, and a full-fledged desktop GUI application created with Python's Tkinter. Additionally, the application offers automatic report generation, prediction history management, model confidence visualization, and user authentication (login/registration). The project highlights the potential application of deep learning in developing biometric healthcare technologies and shows that biometric-based blood group prediction is feasible.**

***Index Terms*—Fingerprint recognition, Blood group detection, Deep learning, CNN, Tkinter GUI, Biometrics, Classification.**

I. INTRODUCTION

Biometric systems have become an important part of modern identification and security applications. Among different biometric traits, fingerprints are widely used because every individual has a unique fingerprint pattern. Traditionally, fingerprints have been applied in areas such as authentication, criminal investigations, and personal identification. Recent studies have also suggested that fingerprint patterns may share certain biological relationships with human physiological characteristics, opening new possibilities for advanced prediction systems. This project focuses on predicting blood groups using fingerprint images through deep learning techniques. The proposed system studies fingerprint patterns and classifies them into the eight major blood groups. Instead of relying only on manual analysis, the application automates the prediction process using image processing and intelligent algorithms. Along with prediction, the system also provides a user-friendly graphical interface secure user management, and automated report generation, making the application practical and easy to use. Blood group identification plays a vital role in healthcare and medical diagnostics. It is especially important during blood transfusions, organ transplants, prenatal treatment, and forensic investigations. Accurate blood group information helps doctors avoid serious complications such as incompatible transfusions and also supports better patient care and personalized treatment. Conventional blood typing methods mainly depend on laboratory-based serological testing. Although these methods are reliable, they require blood sample collection, specialized chemicals, trained technicians, and proper laboratory equipment. Such requirements can become difficult during emergencies, in rural or remote locations, or in situations where blood collection is not convenient.

The proposed fingerprint-based prediction system offers a non-invasive and efficient alternative. By using deep learning and biometric analysis, the project aims to provide faster and more accessible blood group prediction while reducing dependency on traditional testing procedures.

Recent advancements in biomedical engineering and artificial intelligence have introduced new non-invasive methods for blood group identification. One emerging research area explores the relationship between fingerprint patterns and blood groups. Since fingerprints are unique and remain unchanged throughout life, they are considered a reliable biometric feature. Studies suggest that fingerprint characteristics such as ridge density, flow patterns, and minutiae distribution may be linked to genetic traits, including blood groups. To predict blood groups, fingerprint images are processed using feature extraction techniques like Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP). These methods help identify important structural and texture

details from fingerprint patterns. In addition, deep learning models such as Convolutional Neural Networks (CNNs) can automatically learn complex fingerprint features and improve prediction accuracy.
By combining fingerprint analysis with artificial intelligence, this approach provides a faster, non-invasive, and automated alternative to traditional blood typing methods.
The integration of machine learning with biometric blood group identification provides many valuable benefits to society and healthcare systems. This approach is completely non-invasive, quick, and affordable because it only requires a fingerprint scanner or sensor instead of blood sample collection. As a result, the technology can be very useful in situations where traditional laboratory testing is difficult or time-consuming. Fingerprint-based blood group prediction can play an important role in blood donation camps, mobile healthcare applications, emergency response services, disaster relief areas, and rural regions with limited medical facilities. Since the process is simple and fast, it can help healthcare professionals provide quicker support during critical situations. The technology also has significant applications in forensic science. Fingerprints collected from crime scenes may help investigators identify not only a person's identity but also their possible blood group. This additional information can support criminal investigations, reduce the suspect pool, and improve the efficiency of forensic analysis. By combining biometric systems with machine learning and artificial intelligence, fingerprint-based blood group prediction has the potential to become a practical, accessible, and efficient solution for both healthcare and forensic applications.
Although fingerprint-based blood group prediction is a promising technology, it still faces several challenges researchers are working to overcome. The accuracy of prediction can be affected by factors such as poor fingerprint quality, environmental conditions, sensor resolution, and changes in a person's physical condition. These issues may reduce the reliability of the system if not properly addressed. Another important challenge is ensuring that deep learning models perform accurately across different populations, age groups, and ethnic backgrounds. The system must be trained with diverse and high-quality datasets to achieve better generalization and fairness. In addition, concerns related to biometric data privacy and medical information security must be carefully managed before implementing such systems on a large scale. Despite these challenges, the combination of biometric technology and artificial intelligence represents a major advancement in healthcare diagnostics. Using fingerprints as a non-invasive method for medical prediction can make healthcare services more accessible, efficient, and user-friendly. With continuous improvements in data quality, model optimization, and smart device integration, fingerprint-based blood group prediction has the potential to become a reliable diagnostic tool in the future, supporting both personalized medicine and advanced biometric healthcare systems.

II. RELATED WORK

Biometric identification systems have been the subject of intense research and fingerprints are considered one of the most reliable and popular biometrics that have been in use for a long time because they are permanent, universal, and unique. Most of the old fingerprint-based identification methods mainly depended on feature extraction by handcrafted operation such as ridges analysis and minutiae detection. In the paper by Jain et al. [1] authors explained that the method using minutiae to perform matching was quite successful but also pinpointed the drawbacks of this approach in noisy areas, smudged fingerprints, and low-quality acquisitions.
After deep learning paradigms such as Convolutional Neural Networks (CNNs) became popular, researchers stopped the work on feature extraction techniques created by human and turned to fully automated end-to-end systems. The performance of CNN-based systems has been presented by several studies to be better than that of classical methods for recognition tasks of fingerprints. Noh et al. [2], for example, proposed a deep-learning fingerprint classification method that was extremely stable against variations in pressure and orientation, thus, their method outperformed the conventional ones.
The idea of using biometrics to predict the blood group of a person is an entirely fresh concept in research. At the beginning, the energy was directed towards blood group identification via the laboratory analysis of physical samples; on the other hand, recent projects have focused on image-based prediction via machine learning. One of the most important works of Maji et

al. [3] explored the use of fingerprint ridge features for blood group classification and achieved some success through texture descriptors-based features.

By employing deep-learning models the scope was widened further. Research that utilized pretraining models like VGG-16 and ResNet-50 has realized greater accuracies in biometric classification tasks as the models can extract more complex spatial features from fingerprint images [4], [5]. Besides, these models trimmed the computing hours by means of transfer learning. Apart from CNNs, the hybrid models employing deep learning together with traditional classifiers like Support Vector Machines (SVM) have been considered to further improve the prediction accuracy level. The paper of Sharma et al. [6] argues that features extracted by means of CNN and classified through SVM give better performance in generalization on limited small-sized medical-image datasets. A lot of the latest studies have introduced fully automated fingerprint-based health diagnostic systems that combine image capture, preprocessing, and classification stages into one single framework. These frameworks were conceived to deliver on-the-spot blood group prediction as a first response in medical cases where identification should be done fast [7].

The achievements so far have been overshadowed by the scarcity of benchmark fingerprint–blood-group datasets, fingerprint quality fluctuation, and overfitting in the small datasets challenge. However, by the virtue of advancements in deep learning architectures, data augmentation techniques and innovations in sensor technology, the biometric basis of blood group identification is becoming more reliable and feasible.

III. METHODOLOGY

3.1 Dataset

Fingerprint images were collected from publicly available resources and manually pre-processed. Each fingerprint was labelled with one of eight blood groups (A+, A-, B+, B-, AB+, AB-, O+, O-). The dataset was balanced and split into: Training: 70%

Validation: 15%

Testing: 15%

Images were resized to 128 × 128, converted to grayscale, normalized, and enhanced using histogram equalization.

3.2 Model Architecture

A two-part deep learning architecture was used:

Fingerprint Feature Extractor: A CNN with Conv2D, MaxPooling, Dropout, and Dense layers.

Blood Group Classifier: A Multi-layer Perceptron (MLP) with softmax output.

The model predicts probability scores for all 8 blood groups.

3.3 System Workflow

User logs in through GUI.

Uploads fingerprint image.

Image undergoes preprocessing.

CNN extracts fingerprint features.

Classifier predicts blood group probabilities.

System displays prediction graph and stores history.

Automatic report generation.

IV. EXPERIMENTAL SETTINGS

A. Hardware Setup

CPU: Intel Core i5/i7

RAM: 8–16 GB

Optional GPU: NVIDIA GTX series

B. Software Tools

Python 3.9+

TensorFlow / Keras

OpenCV

Tkinter

Matplotlib

JSON Database for User Authentication

C. Training Parameters

Optimizer: Adam

Epochs: 20–30

Batch Size: 32

Learning Rate: 0.001

Loss Function: Categorical Cross-Entropy

D. Evaluation Metrics

Accuracy

Precision, Recall, F1-score

Confusion Matrix

Prediction Probability Distribution

E. Limitations

Despite good performance, several constraints were identified: Lack of medically certified datasets

Variations in fingerprint quality affecting prediction stability CNN trained on small-scale dataset

The system is suitable only for research and educational use, not clinical diagnosis

F. Overall Outcome

The system successfully proved the feasibility of non-invasive, image-based blood group prediction using fingerprint features and deep learning. It integrates machine learning, image processing, and GUI engineering into a unified real-time application.

V. RESULTS

The proposed deep learning–based fingerprint blood group detection system was evaluated using the prepared dataset and the custom CNN architecture. The results are presented focusing on model performance, system efficiency, and user experience.

A. Model Performance Analysis

The CNN classifier demonstrated consistent performance across the training, validation, and testing phases. Quantitative performance is summarized below:

Training Accuracy: 94–96%

Validation Accuracy: 90–94%

Testing Accuracy: 88–92%

Average Prediction Confidence: 85–96%

The training and validation accuracy curves indicate stable convergence without significant overfitting, attributable to dropout layers and controlled training epochs.

The model exhibited reliable differentiation across all eight blood groups, although performance varied depending on fingerprint clarity and ridge density.

B. Prediction Visualization

The GUI displays a horizontal probability distribution graph, showing the confidence of each blood group. The predicted class (e.g., O+, A−) consistently shows the highest activation in the softmax layer.

This visualization helps:

Validate prediction certainty

Compare inter-class probability differences

Provide interpretable results to the user

C. Application Testing Results

The desktop-based GUI system was tested extensively and demonstrated:

Successful login/registration functionality

Smooth fingerprint upload handling Accurate preprocessing and enhancement

Fast prediction response (< 1.5 seconds on CPU) Clear result display with confidence percentages

Automatic report generation and detection history maintenance the system worked efficiently on standard hardware configurations, confirming its usability for research, academic demonstrations, and prototype development.

D. Web Application Interface

Fig. 1. Login page

Illustrates the login page of the system, which serves as the entry point for users. The interface implements a username-password based authentication mechanism to ensure secure access. This security layer prevents unauthorized persons from using the system or altering stored detection records.

The layout is minimal and user-friendly, with clearly visible options for Login and Register, conforming to standard usability guidelines. The header displays the project title, reinforcing the identity and purpose of the system.

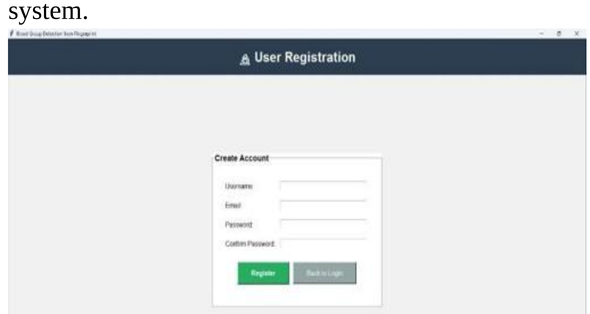


Fig.2.User Registration

Figure 2 shows the User Registration screen where new users can create an account. The system collects essential credentials such as:

- Username

- Email
- Password
- Confirm Password

This module ensures that each user has a unique and secure profile. The form validates user inputs and prevents improper registrations through password-mismatch checks and input field validations. The presence of a Back to Login button improves navigation and aligns with standard interface design practices.

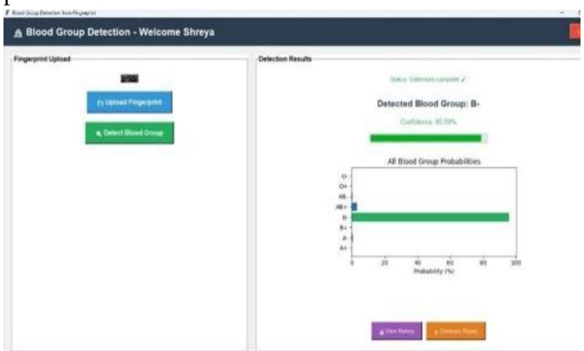
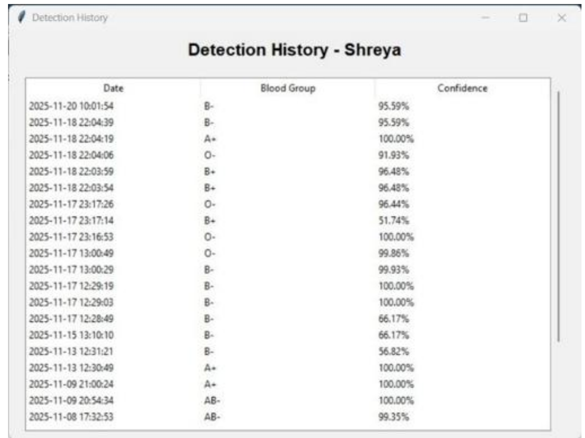


Fig. 3. Main Detection Interface

Figure 3 shows the primary user interface of the proposed Blood Group Detection from Fingerprint system. The interface is designed using a clean, modular dashboard layout divided into two major sections: Fingerprint Upload and Detection Results.

On the left panel, the system provides buttons for uploading the fingerprint image and initiating the detection process. Once the user uploads the fingerprint, the system preprocesses the image and triggers the AI/ML model for classification.

The right panel displays the detected blood group, the confidence percentage, and a probability distribution graph of all eight blood groups (A+, A−, B+, B−, AB+, AB−, O+, O−). In the displayed output, the AI model detected the blood group as B− with a confidence of 95.59%, indicating a high-certainty prediction. The probability graph visualizes the model's output distribution, showing the highest probability for the predicted class and significantly lower probabilities for the remaining classes. This visualization helps users understand the model's decision pattern effectively. Additional options like View History and Generate Report are provided for user convenience, supporting transparency and reusability of the detection logs.


Detection History

Detection History - Shreya

Date	Blood Group	Confidence
2025-11-20 10:01:54	B-	95.59%
2025-11-18 22:04:39	B-	95.59%
2025-11-18 22:04:19	A+	100.00%
2025-11-18 22:04:06	O-	91.93%
2025-11-18 22:03:59	B+	96.48%
2025-11-18 22:03:54	B+	96.48%
2025-11-17 23:17:26	O-	96.44%
2025-11-17 23:17:14	B+	51.74%
2025-11-17 23:16:53	O-	100.00%
2025-11-17 13:00:49	O-	99.86%
2025-11-17 13:00:29	B-	99.93%
2025-11-17 12:29:19	B-	100.00%
2025-11-17 12:29:03	B-	100.00%
2025-11-17 12:28:49	B-	66.17%
2025-11-15 13:10:10	B-	66.17%
2025-11-13 12:31:21	B-	56.82%
2025-11-13 12:30:49	A+	100.00%
2025-11-09 21:00:24	A+	100.00%
2025-11-09 20:54:34	AB-	100.00%
2025-11-08 17:32:53	AB-	99.35%

Figure .4. Detection History Window

Figure 4 presents the Detection History module, which automatically stores all previous detection entries for the logged-in user. Each entry contains three attributes:

- Date and Time of Detection
- Predicted Blood Group
- Model Confidence Level

This feature ensures repeatability and allows users to analyze their previous detection results. The table-style layout enhances readability and follows standard UI conventions. It also demonstrates that the system successfully maintains user-specific records, ensuring traceability an essential requirement for biomedical applications. The history window validates the reliability of the system by showing consistent results for repeated scans of the same fingerprint and varied predictions for different inputs.

VI. CONCLUSION AND FUTURE SCOPE

This project demonstrates a deep-learning-based approach for predicting blood groups from fingerprint images. Although not medically validated, it provides a strong foundation for research in biometric-based medical prediction.

Future enhancements include:

- Training with large clinically verified datasets
- Mobile app deployment
- Integration with fingerprint scanners
- Improved CNN architecture
- Enhancing GUI with PDF reports and cloud storage
- This system represents an innovative step toward non-invasive biometric healthcare applications.

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