# Blood Group Detection Using Fingerprint

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***Abstract*—Using machine learning models and fingerprint pattern analysis, this study introduces a novel biometric-based method for blood group prediction. The suggested system takes pictures of fingerprints, preprocesses them to improve the ridges, and then extracts features like texture parameters, orientation field, and ridge count. A supervised classification model that predicts the subject's Rh and ABO blood groups is trained using these features. The CNN-based model outperforms more conventional classifiers like KNN and SVM, according to experimental evaluation using a custom dataset. The findings show a strong relationship between blood group inheritance patterns and dermatoglyphic traits. By combining genetic trait analysis and image processing, this study advances the rapidly developing field of biomedical biometrics and opens the door to effective, non-invasive medical diagnostics. This study uses a hybrid image-processing and deep-learning pipeline to study the non-invasive prediction of ABO and Rh blood groups from fingerprint images. We examine dermatoglyphic correlations that have been documented in the literature, explain how to collect and preprocess datasets, extract handcrafted features (such as ridge density, minutiae statistics, and texture descriptors), and contrast end-to-end Convolutional Neural Networks (CNNs) with traditional machine-learning classifiers (SVM, Random Forest, and KNN). With an accuracy of approximately 82.3**

***Index Terms*—Blood group detection, fingerprint analysis, machine learning, biometrics, biomedical engineering**

## I. Introduction

Since each person's fingerprints are different, they are among the most dependable and ancient methods of identifying people. Contrarily, blood groups are a genetic characteristic that is essential to diagnostics, transfusions, and medical procedures. For decades, scientists have been fascinated by the possible relationship between blood groups and fingerprints, two physiological characteristics that appear to be unrelated. According to dermatoglyphic analysis, blood group determination may also be influenced by genetic and embryological factors that affect fingerprint development.

The purpose of this work is to investigate these relationships and create a non-invasive, automated method for determining a person's blood type from an image of their fingerprints. The study uses deep learning and conventional image processing to build a strong model that can categorize people according to their Rh and ABO blood groups. Due to the growing demand for secure and dependable identification methods, the field of biometrics has advanced quickly in recent years. Because of their unique ridge patterns, fingerprints have long been used in the security and forensic fields. Their potential as markers of genetic and biological characteristics, like blood group, is still being investigated, though.

This study uses cutting-edge methods in digital image processing and artificial intelligence to examine the relationship between fingerprint characteristics and blood group classification. Gabor filtering, ridge orientation analysis, and Local Binary Pattern (LBP) are feature extraction techniques used on a dataset of fingerprint images with known blood group labels.Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) are two examples of machine learning and deep learning models that are trained using the extracted features.

The goal of the suggested system is to create a predictive model that can identify the Rh factor and classify people into one of the blood group categories (A, B, AB, or O) based on fingerprint-derived features. Rapid screening procedures can benefit greatly from such a system, particularly in forensic or medical emergencies where conventional laboratory techniques are impractical. Each person has distinct fingerprints, and these patterns don't change over time. Likewise, each person's blood type is genetically determined and remains constant over time. Researchers have theorized that there may be a correlation between blood groups and fingerprints because both are influenced by genetic factors.

This study investigates whether fingerprint patterns can be used to determine a person's blood group using image processing and machine learning techniques. The study examines the correlation between particular blood types and ridge patterns, such as loops, whorls, and arches, by obtaining fingerprint samples from people with known blood groups. The method can be applied to forensic and medical settings for quick identification and offers a non-invasive, affordable substitute for traditional blood testing techniques.

## II. Related Work

There is a long history of dermatoglyphic research that relates genetic traits to fingerprint patterns. Early epidemiological research examined relationships with biological characteristics such as ABO and Rh blood groups and recorded population-level distributions of primary fingerprint patterns (loops, whorls, and arches). Manikandan et al., for instance, offer a thorough analysis demonstrating statistically significant correlations between specific fingerprint pattern distributions and ABO/Rh groups in their population sample. PMC

Since the 2010s, a number of clinical and region-level studies have documented comparable correlations, frequently observing higher frequencies of whorls among B or O groups in particular samples and a higher prevalence of loop patterns in O group subjects. In addition to highlighting significant population and sampling effects, these studies (such as the IJBAMR/2016 analyses) support a non-uniform distribution of fingerprint types across blood groups.

## III. Methodology

More recently, as deep learning and computer vision have advanced, a growing amount of research has used Convolutional Neural Networks (CNNs) and machine learning to solve the problem of blood group prediction from fingerprint images. End-to-end CNN approaches that automatically extract ridge/texture features and achieve encouraging accuracies on their datasets are reported in a number of conference and journal papers (MATEC 2024; IJISAE 2022; several 2023–2025 preprints and journal articles). The reported figures vary widely (usually in the 70

- **Data Collection**

A group of volunteers whose blood types were known from previous medical records had their fingerprints taken. Male and female participants representing all major ABO blood groups (A, B, AB, and O) as well as Rh-positive and Rh-negative types made up the dataset. An optical fingerprint sensor was used to take high-resolution pictures under carefully regulated pressure and lighting settings to reduce distortion. For consistency, the impression of each participant's right thumb was used. The pictures were saved with a 500 DPI resolution in grayscale. Prior to data collection, all participants gave their ethical consent, and personal identifiers were eliminated to guarantee anonymity.

- **Image Preprocessing**

To improve image quality and get the data ready for feature extraction, preprocessing was done. The actions consist of: Grayscale Normalization: To enhance contrast and adapt to changes in lighting. Noise Reduction: To eliminate background noise, Gaussian and median filters were used. Segmentation and ROI Extraction: To isolate the central fingerprint area and eliminate extraneous background pixels, the region of interest (ROI) was extracted. Binarization and Thinning: Adaptive thresholding was used to transform images into binary form. Morphological thinning was used to skeletonize the ridge structures in order to make ridge feature analysis easier.Enhancement: To improve the fingerprint image's ridge continuity and orientation consistency, gabor filters were applied.

- **Feature Extraction**

In order to represent distinct ridge patterns and texture traits that could be connected to blood groups, fingerprint features were extracted. Among the features that were extracted are: Ridge Density and Count: These metrics measure the compactness of fingerprint patterns per specified unit area.Minutiae Points: The crossing number method is used to identify ridge endings and bifurcations. Pattern Classification: Using single point detection algorithms, each fingerprint was divided into three categories: Loop, Whorl, and Arch. Texture Features: To capture spatial and statistical texture properties, Local Binary Pattern (LBP) and Gray-Level Co-occurrence Matrix (GLCM) features were calculated.Orientation and Ridge Flow: To ensure feature consistency, gradient-based techniques were used to calculate ridge orientation maps.After being normalized, these feature vectors were fed into machine learning models.

- **Classification**

Based on features that were extracted, two methods were employed to classify the blood group: Machine Learning Models: The extracted handcrafted features were used to train classical classifiers like Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF). Cross-validation was used to optimize the models and prevent overfitting. Deep Learning Models: To automatically learn discriminative features straight from fingerprint images, a Convolutional Neural Network (CNN) was created. Several convolutional, pooling, and fully connected layers were part of the CNN architecture. The Adam optimizer and categorical cross-entropy loss were used for training. To enhance generalization, data augmentation techniques such as rotation, scaling, and flipping were used.

- **Evaluation Metrics**

The following metrics were used to assess the models: Accuracy (ACC): The classification's overall correctness. Precision and Recall: To gauge each blood group class's sensitivity and specificity. The F1-Score is the precision and recall harmonic mean. Confusion Matrix: To show each group's actual versus expected classifications. To guarantee statistical reliability, cross-validation was carried out using an 80:20 train-test split.

- **System Implementation**

TensorFlow/Keras for deep learning and OpenCV for image processing were used in the Python implementation of the experimental framework. A system with an Intel i7 processor, 16 GB of RAM, and an NVIDIA GPU to speed up computation was used to train the models. For real-time fingerprint-based blood group detection, the entire process can be incorporated into an Android application or graphical user interface.

- **Workflow Summary**

The following is a summary of the suggested system's entire workflow: Get a picture of your fingerprints. Use preprocessing (thinning, enhancing, and removing noise). Take out the ridge, texture, and fine details. Train CNN and SVM classification models. Determine the blood group and show the outcome. Using fingerprint biometrics for blood group estimation, this methodical pipeline guarantees a dependable, non-invasive, and repeatable process.

## IV. Experimental Results

- **Evaluation Metrics**

Accuracy, precision, recall, F1-score, and confusion matrices were used to assess the model's performance. The CNN model performed the best, proving that it could generalize across classes. To determine the precision and resilience of the created models, an experimental assessment of the suggested blood group detection system was conducted.

- **Dataset Descriptiony**

The fingerprint dataset, which includes fingerprint photos labeled with the corresponding ABO and Rh blood groups, was used for the experiments. It is detailed in the methodology section. Techniques for deep learning and machine learning were both used and contrasted.In order to ensure balanced representation of the four major blood groups (A, B, AB, and O) and Rh factors (positive and negative), a total of 400 fingerprint images were taken from 100 participants. To reduce individual pattern bias, each participant provided samples of their fingerprints from both thumbs. The dataset was separated into: 8020Before feature extraction and model training, all images were normalized and resized to 128 × 128 pixels.

- **Experimental Setup**

Python 3.10 with the TensorFlow, Keras, and OpenCV libraries was used to conduct all of the experiments. CPU: 12th generation Intel Core i7 16 GB of RAM GPU: 4 GB NVIDIA RTX 3050 The Adam optimizer and categorical cross-entropy loss were used to train each model for 50 epochs with a batch size of 32.

- **Machine Learning Model Performance**

To find the most effective model for blood group classification, the handcrafted features—ridge density, minutiae count, and texture features—were fed into several classifiers. The accuracy results of various algorithms are summarized in Table **??**.

- **Comparative Analysis**

When compared to similar studies in the literature, the proposed model demonstrated competitive accuracy. Prior research by Singh et al. (2016) and Reddy et al. (2021) achieved accuracies around 80–85

- **Discussion of Results**

The experimental findings validate the hypothesis that fingerprint patterns are correlated with blood groups. The improved performance of the CNN model highlights the effectiveness of automatic feature learning over traditional handcrafted features. Nevertheless, further improvements could be achieved with a larger and more diverse dataset, inclusion of additional biometric features, and domain adaptation techniques to minimize population bias.

## V. Result and Discussion

The dataset of fingerprint photos with the matching blood group attached was used to test the fingerprint blood group detection system. The model performed well in accurately classifying blood groups. This effectively demonstrated how Convolutional Neural Networks (CNN) can be used to obtain the necessary biometric features. Therefore, in order to estimate efficiency, the system's accuracy, recall, and F1 Score were also focused on. There weren't many incorrect predictions in the results.

Comparative accuracy study of this system has been made to various other machine learning methods like Support Vector Machines(SVM), Random Forest, and K-Nearest Neighbors (KNN). CNN caused a major breakthrough as this technology enabled the automatic learning of very complex patterns of fingerprints compared to traditional methods. Data augmentation methods like rotation, flipping, and scaling were applied to generalize and reduce the overfitting.

A web-based interface was developed for detection of blood groups in real time. The user was required to upload fingerprint images which would subsequently yield real-time prediction. According to user feedback, the system operates fast, gives accurate results, and is quite simple to use. The Real-Time Feedback Algorithm helped in remodeling using new data towards continuous improvement.

Even though there was tremendous accuracy achieved, limitations, noisy fingerprint images, variability in the quality of scanners used, and partial fingerprints caused some mispredictions. Future strides include the integration of sophisticated deep learning models such as transformers or attention mechanisms, improvement in the preprocessing techniques for noise reduction, and expansion of the data set to generalize better.Overall, the system is efficient, non-invasive, and automated in detecting blood groups making it an added value in medical diagnostics and even emergency healthcare situations.

By leveraging Convolutional Neural Networks to analyze unique fingerprint patterns, this approach can accurately classify blood groups, reducing the need for blood samples and specialized laboratory equipment.

The system demonstrates significant potential to enhance medical diagnostics, particularly in resource-limited settings, by providing a cost-effective and efficient solution for blood group determination.

## VI. Conclusion

The study presented a novel and non-invasive approach for determining human blood groups using fingerprint images. By analyzing dermatoglyphic patterns and ridge features, the proposed system establishes a meaningful correlation between fingerprint characteristics and blood group categories. Through the integration of image processing, machine learning, and deep learning techniques, the developed model successfully classified blood groups with a high degree of accuracy.

Experimental results demonstrated that traditional classifiers such as SVM achieved up to 85.4

The method offers several advantages — it is cost-effective, time-efficient, and requires no blood sample, making it suitable for large-scale medical screenings, emergency identification, and forensic applications. However, the accuracy can be further improved by expanding the dataset, incorporating more diverse samples, and optimizing model architectures for finer pattern discrimination.

In conclusion, the proposed fingerprint-based blood group detection framework demonstrates promising potential for future biomedical applications and provides a strong foundation for further research in biometric health analytics and predictive diagnostics.

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