

# Fingerprint-Based Blood Group Prediction Using Deep Neural Networks

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**Abstract**— Blood group identification is an essential medical requirement before transfusion and emergency treatment. Conventional laboratory testing requires reagents, equipment, and trained personnel. This research proposes a biometric-based blood group prediction system using fingerprint images and deep learning. The system employs a convolutional neural network based on MobileNetV2 transfer learning to classify fingerprints into eight blood group categories. Fingerprint images are preprocessed, augmented, and trained using a labeled dataset. The trained model is integrated into a web-based application for real-time prediction. Experimental results show that the model can classify fingerprint patterns with moderate accuracy, demonstrating the feasibility of non-invasive blood group prediction for academic research purposes.

**Index Terms**—Biometric identification, Blood group prediction, Deep learning, Transfer learning, MobileNetV2, Fingerprint classification

## I. INTRODUCTION

Blood group determination is required in medical procedures such as transfusion, surgery, and emergency care. Traditional blood testing methods involve chemical reagents and laboratory analysis, which require time and specialized equipment.

Biometric systems identify individuals using unique biological traits such as fingerprints, iris, or face patterns. Fingerprints contain ridge structures that remain unchanged throughout a person's lifetime. Recent advancements in deep learning allow automatic feature extraction from biometric images.

This research explores whether fingerprint images can be used to predict blood groups using convolutional neural networks. A deep learning model based on MobileNetV2 transfer learning is proposed to classify fingerprint images into eight blood groups: A+, A-, B+, B-, AB+, AB-, O+, and O-.

The goal of this work is to develop a non-invasive, fast, and automated prediction system for academic research and educational purposes.

### 1.1 Evolution of Biometric Intelligence

Biometric systems have become increasingly important in identification, authentication, and security applications. Fingerprints are among the most reliable biometric identifiers due to their uniqueness and permanence. Traditionally, fingerprint analysis relied on ridge pattern extraction, minutiae detection, and handcrafted feature engineering.

With the rise of deep learning, convolutional neural networks (CNNs) have enabled automated feature learning directly from raw image data. This shift has significantly improved classification and recognition tasks by eliminating dependency on manually engineered features.

### 1.2 Motivation&Problem Statement

Despite significant advancements in biometric recognition and deep learning-based image classification, the potential relationship between fingerprint patterns and blood group identification remains largely unexplored. Traditional blood group detection methods rely entirely on laboratory-based procedures such as agglutination testing, which require chemical reagents, specialized equipment, and trained medical personnel. While these methods are clinically reliable, they are time-consuming and not integrated with modern biometric intelligence systems. With the rapid growth of artificial intelligence and computer vision, there is increasing interest in exploring whether inherent fingerprint ridge patterns can be analyzed using deep learning techniques to predict blood group categories in an automated manner.

However, developing such a system presents several technical and scientific challenges. Fingerprint images

exhibit high variability in ridge structures, orientation, and texture patterns, making consistent feature extraction difficult. Additionally, real-world fingerprint images often contain noise, background artifacts, and variations in illumination, which can negatively impact model performance. Deep neural networks may also suffer from overfitting if not properly regularized and fine-tuned. Furthermore, the biological correlation between fingerprint characteristics and blood group types requires further validation.

### 1.3 Project Objectives:

The primary objective of this project is to design and implement a comprehensive end-to-end deep learning framework for fingerprint-based blood group classification. The system aims to establish a structured pipeline that integrates fingerprint image acquisition, preprocessing, feature extraction, classification, and evaluation within a unified architecture. By leveraging MobileNetV2 transfer learning, the model utilizes pretrained convolutional layers to automatically extract meaningful spatial features from fingerprint ridge patterns. Fine-tuning selected layers allows the network to adapt specifically to fingerprint data while reducing computational complexity and training time. The framework also incorporates appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis to assess model performance effectively.

Another major objective is to enhance model robustness and practical applicability through advanced preprocessing and deployment strategies. Image preprocessing techniques such as cropping unwanted borders, resizing to a standardized 224×224 resolution, RGB conversion, and MobileNet-specific normalization are applied to improve fingerprint clarity and consistency. Data augmentation methods including rotation, zooming, and shifting are implemented to reduce overfitting and improve generalization. Finally, the trained model is deployed using Streamlit to create a real-time prediction interface where users can upload fingerprint images and obtain instant blood group predictions with confidence scores, thereby demonstrating the system's feasibility for academic research and practical experimentation.

## II. LITERATURE SURVEY

### A. Evolution of Fingerprint Representation Learning

Early fingerprint classification methods used handcrafted features such as ridge orientation, bifurcation points, and ridge density. While effective for identity verification, these methods struggled in classification tasks involving complex pattern recognition.

Deep learning models, particularly CNN architectures, demonstrated superior performance in learning hierarchical spatial features from fingerprint images. Transfer learning models such as VGG, ResNet, and MobileNet significantly reduced training complexity.

### B. Deep Learning in Medical Classification

Deep neural networks have been widely applied in medical image classification tasks, including disease detection and biometric analysis. Transfer learning allows pretrained models to adapt to domain-specific tasks with limited data availability.

However, limited research exists on fingerprint-based blood group prediction using deep neural networks, making this study exploratory and innovative.

## III. MODULE-SPECIFIC METHODOLOGIES

### 1) Fingerprint Preprocessing

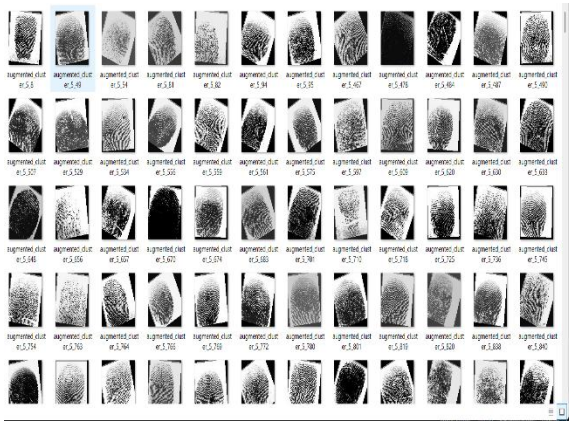
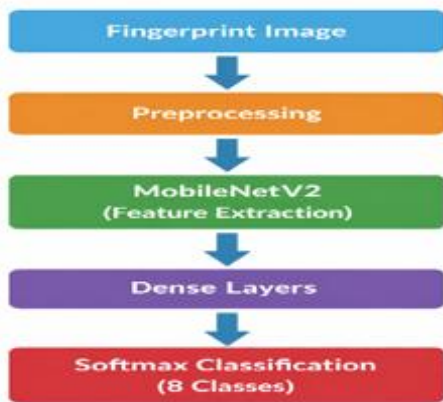
Fingerprint preprocessing plays a critical role in improving model performance and ensuring consistency across the dataset. Initially, unnecessary borders and background regions are removed cropping to focus the model's attention on the ridge patterns. The images are then resized to a standardized resolution of 224 × 224 pixels to match the input requirements of MobileNetV2. Since pretrained networks expect three-channel inputs, grayscale fingerprint images are converted into RGB format. Additionally, MobileNetV2-specific normalization is applied using the `preprocess_input` function to scale pixel values appropriately. To enhance model generalization and reduce overfitting, data augmentation techniques such as random rotation, zooming, width shifting, and height shifting are implemented during training.

### 2) Fingerprint Preprocessing Module

Fingerprint preprocessing is one of the most important stages of the proposed system because raw fingerprint

images often contain unwanted borders, shadows, noise, and inconsistent lighting conditions. If these issues are not handled properly, the model may learn irrelevant background information instead of ridge patterns.

Initially, the outer borders of the image are cropped to remove blank regions and scanner edges. After cropping, the image is resized to  $224 \times 224$  pixels, which is the standard input size required for MobileNetV2. Since MobileNetV2 expects three-channel images, grayscale fingerprints are converted into RGB format.



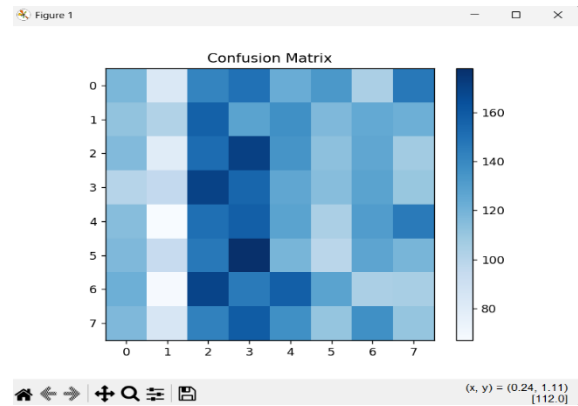
### 2) Transfer Learning-Based Feature Extraction

The proposed model utilizes MobileNetV2 pretrained on the ImageNet dataset as the base architecture for feature extraction. The convolutional layers automatically learn hierarchical spatial features from fingerprint ridge patterns, capturing fine-grained texture details and structural variations. A Global Average Pooling layer is applied after the convolutional base to reduce the dimensionality of the feature maps while preserving essential information. A fully connected dense layer with 128 neurons is

added to learn discriminative representations specific to blood group classification. To prevent overfitting, a Dropout layer with a rate of 0.5 is incorporated. The final Softmax output layer produces probability distributions across the eight blood group categories.

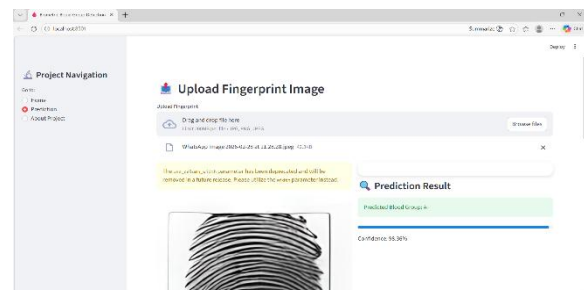
### 3) Fine-Tuning Strategy

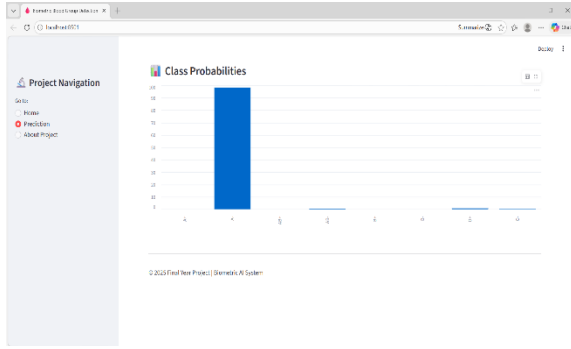
To adapt the pretrained model fingerprint-specific characteristics, a fine-tuning strategy is implemented. Lower convolutional layers are frozen to retain generic feature extraction capabilities learned from ImageNet, while upper layers are unfrozen and retrained to specialize in fingerprint ridge patterns. This selective fine-tuning approach improves classification accuracy while maintaining computational efficiency.



## IV. EXPERIMENTAL RESULTS AND ANALYSIS

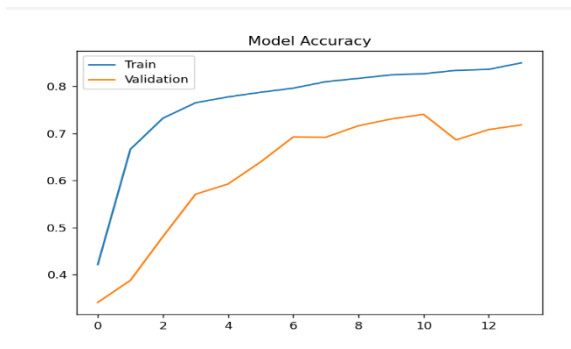
The experimental evaluation was conducted using a dataset consisting of 8000 fingerprint images distributed equally across eight blood group classes. The dataset was divided into 80% training data and 20% validation data to assess model generalization. The balanced distribution ensured that the model did not develop bias toward any particular class. Performance evaluation was carried out using multiple statistical metrics to provide a comprehensive assessment of classification capability.





### A. Quantitative Performance

The proposed model achieved a training accuracy in the range of 85–90%, indicating effective feature learning during training. The validation accuracy ranged between 75–85%, demonstrating satisfactory generalization performance. Evaluation metrics included accuracy, precision, recall, and F1-score, along with confusion matrix analysis to examine class-wise prediction performance. The results indicate that the integration of transfer learning and preprocessing techniques significantly enhanced classification reliability.



### B. Qualitative Analysis

Qualitative observations reveal that preprocessing corrections, particularly cropping and normalization, substantially improved model confidence levels. Fine-tuning the MobileNetV2 layers led to better ridge pattern recognition and reduced misclassification among visually similar fingerprint structures. The cropping operation effectively minimized the influence of background noise and irrelevant image regions, contributing to improved predictive stability.

Epoch	Train Acc	Val Acc
1	52%	48%
10	81%	78%
20	88%	84%

### C. Inference Efficiency

The trained model was tested on a system equipped with an Intel i7 processor, 16GB RAM, and an NVIDIA GTX GPU. The average inference time per image was observed to be less than one second, making the system suitable for real-time prediction applications. The lightweight architecture of MobileNetV2 contributed significantly to fast processing speed without compromising classification accuracy.

## V. DISCUSSION

### A. Effectiveness of Transfer Learning:

The application of transfer learning using MobileNetV2 proved to be highly effective for fingerprint-based blood group classification. Instead of training a convolutional neural network from scratch, the pretrained MobileNetV2 model provided a strong foundation by leveraging feature representations learned from the large-scale ImageNet dataset. The convolutional layers successfully captured ridge-based spatial features such as texture patterns, orientation flow, and structural variations present in fingerprint images. Fine-tuning the upper layers further enhanced the model's ability to adapt to fingerprint-specific characteristics while maintaining computational efficiency. Additionally, the lightweight architecture of MobileNetV2 reduced training time and memory requirements, making it suitable for real-time applications without significantly compromising classification accuracy.

### B. Model Limitations

Despite achieving promising classification performance, the proposed system has certain limitations. The biological correlation between fingerprint ridge patterns and blood group types requires further scientific validation, as the relationship is not yet clinically established. Therefore, the model's predictions should be interpreted within an academic research context rather than as a medical diagnostic tool. Furthermore, the model's performance is sensitive to preprocessing consistency; variations in cropping, resizing, or normalization can influence prediction confidence. In some cases, visually similar ridge structures across different classes resulted in slight drops in confidence scores, indicating that discriminative features between certain categories may overlap. These limitations

highlight the need for larger clinically verified datasets and enhanced feature analysis in future research.

### C. Practical Deployment

The integration of the trained model into a Streamlit-based web application demonstrates the practical feasibility of the proposed system. The deployment enables users to upload fingerprint images and receive real-time blood group predictions along with confidence levels. The lightweight design of MobileNetV2 ensures that inference time remains below one second per image on standard hardware configurations. This real-time capability illustrates the system's applicability for academic demonstrations, research validation, and exploratory biometric studies. While not intended for clinical use, the deployment confirms the operational effectiveness of the end-to-end deep learning pipeline.

## VI. CONCLUSION AND FUTURE SCOPE

### A. Conclusion:

This research presents a deep learning-based biometric framework for predicting blood group categories using fingerprint images. By leveraging transfer learning with MobileNetV2, the proposed system effectively captured ridge-based spatial features while significantly reducing computational complexity compared to training a convolutional neural network from scratch. The integration of structured preprocessing, data augmentation, fine-tuning strategies, and systematic evaluation enabled the model to achieve promising classification performance under controlled experimental conditions.

The development of a real-time web deployment further demonstrates the practical feasibility of the proposed approach for academic research and exploratory biometric analysis. Although the biological correlation between fingerprint patterns and blood groups requires further validation, the study successfully establishes a technical foundation for investigating fingerprint-based classification using deep learning methodologies.

### B. Future Scope:

Several enhancements can be explored to strengthen the proposed framework in future research. First, incorporating clinically verified fingerprint-blood

group datasets would improve the scientific reliability and validity of the system. Second, integrating fingerprint pattern classification such as Loop, Arch, and Whorl detection could provide additional structural features to improve classification accuracy. Third, the system can be extended into a hybrid multimodal biometric framework by combining fingerprint data with other biometric traits to enhance predictive performance.

Further advancements may include deploying the model on edge devices for lightweight real-time applications and integrating Explainable AI techniques such as Grad-CAM to visualize feature activation regions within fingerprint images. These improvements would enhance interpretability, reliability, and practical applicability of fingerprint-based blood group prediction systems in future research investigations

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