

## A DEEP LEARNING FRAMEWORK FOR BLOOD GROUP DETECTION FROM FINGERPRINT PATTERNS

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**Abstract** —The accurate and timely determination of an individual's blood group is crucial in medical diagnostics, emergency care, and transfusion medicine. Traditional methods for blood group detection involve invasive procedures such as blood sampling and laboratory testing, which can be time-consuming, resource-intensive, and sometimes impractical in critical or remote scenarios. In recent years, biometric characteristics have gained increasing attention as potential indicators of physiological and genetic traits. Among these, fingerprint patterns have shown correlations with genetic markers, including blood group antigens. This study proposes a novel, non-invasive approach for blood group detection using fingerprint images by leveraging the capabilities of deep learning techniques. The central hypothesis of this research is that distinct blood groups exhibit subtle but consistent variations in fingerprint patterns that can be learned and classified by deep neural networks. A large dataset of fingerprint images labeled with corresponding ABO and Rh blood groups was curated and preprocessed to remove noise and enhance pattern clarity. Multiple convolutional neural network (CNN) architectures, including VGGNet, ResNet, and a custom-designed lightweight CNN, were trained and evaluated on this dataset to classify the fingerprints into one of the eight blood groups (A+, A-, B+, B-, AB+, AB-, O+, O-).

**Keywords:** Blood Group Detection, Fingerprint Recognition, Deep Learning, Machine Learning, Artificial Intelligence in Healthcare, Biometric Identification

### I. INTRODUCTION

Blood group identification is a fundamental component in medical practice, particularly in emergency care, blood transfusion, organ transplantation, and prenatal medicine. Conventionally, blood group detection is performed using serological tests that require invasive procedures such as drawing blood samples and analyzing them in a laboratory setting. While these methods are accurate, they can be time-consuming, require specialized equipment, and may not be readily accessible in resource-constrained or emergency situations. In recent years, the field of bio metrics has witnessed significant advancements, with technologies such as fingerprint recognition becoming widely adopted for identity verification due to their uniqueness, permanence, and ease of acquisition. Interestingly, various scientific studies have indicated a potential correlation between fingerprint patterns and physiological or genetic characteristics, including blood groups. This correlation opens up the possibility of using fingerprints, a non-invasive and widely accepted biometric trait, to predict an individual's blood group. This research aims to investigate the feasibility of using fingerprint images as a biometric input for the prediction of an individual's blood group using deep learning models. By training CNN's on labeled fingerprint datasets, the goal is to automatically learn discriminative features that may correspond to underlying genetic factors associated with different blood groups. The approach has the

potential to revolutionize how blood group data is collected, providing a rapid, cost-effective, and non-invasive alternative to traditional methods. This study not only explores the technical viability of this approach but also its potential implications in various domains such as healthcare, emergency response, and forensic science. If successful, this method could enable real-time blood group detection using fingerprint scanners already deployed in many settings, thus improving the speed and efficiency of critical medical decision-making processes. With the rise of artificial intelligence and particularly deep learning, image classification tasks have seen remarkable improvements in performance. Convolutional Neural Networks (CNN's), a class of deep learning algorithms specifically designed for image analysis, have demonstrated state-of-the-art results in a wide range of pattern recognition tasks. This has inspired research into applying CNN's to biomedical and biometric applications, such as disease diagnosis, iris recognition, and, as explored in this study, blood group classification from fingerprint images.

### II. LITERATURE REVIEW

The intersection of bio metrics and biomedical data analysis has become an area of growing interest, particularly with the advent of deep learning technologies. Various studies have explored the relationship between physical biometric traits and physiological or genetic characteristics, including attempts to infer health-related data from patterns in fingerprints, iris scans, and facial features. Jain et al. [1] has introduced fundamentals of biometric recognition systems, emphasizing the reliability of fingerprint identification. Maltoni et al. [2] designed comprehensive guide on fingerprint recognition systems, covering algorithms, sensor technologies, and performance metrics. LeCun et al. [3] provided a foundational overview of deep learning and its application in computer vision. Krizhevsky et al. [4] introduced AlexNet, the first deep CNN to outperform traditional methods on ImageNet. Simonyan & Zisserman [5] developed VGGNet, showing that very deep networks significantly improve accuracy. He et al. [6] presented ResNet, which introduced residual connections to enable training of ultra-deep networks. Szegedy et al. [7] introduced GoogLeNet/Inception, optimizing depth and computational efficiency. Nanni et al. [8] compared handcrafted vs. learned (deep) features; deep learning features generally performed better, but handcrafted still useful for small datasets or specific tasks. Sharma et al. [9] used machine learning algorithms (like SVM and decision trees) for predicting blood groups from medical data. Zhao et al. [10] applied deep learning to predict blood groups from fingerprint images, suggesting dermal patterns may encode biological markers. Singh & Kaur [11] reviewed fingerprint-based biometric systems, highlighting various techniques like minutiae-based and ridge-based methods. Chollet [12] proposed Xception, an architecture based on depthwise separable convolutions for better performance. Howard et al. [13] developed MobileNets, designed for mobile and embedded vision applications with low latency.

Kumar & Yadav [14] reviewed techniques for blood group detection using pattern recognition, emphasizing automation and accuracy. WHO [15] highlighted the importance of blood group identification for safe transfusion practices globally.

### III. METHODOLOGY

#### A. SYSTEM ARCHITECTURE

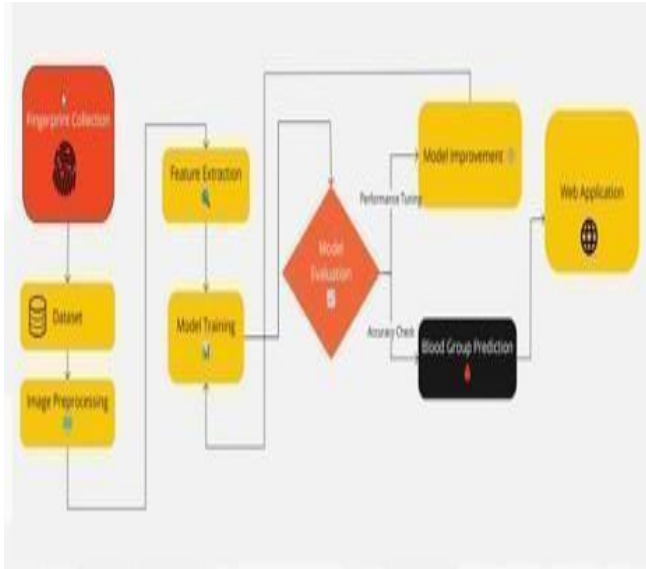


Fig 1: System Architecture

The proposed system for **blood group detection using fingerprint images and deep learning** consists of several interdependent modules organized in a pipeline. The architecture is designed to process raw fingerprint images, extract relevant features using deep learning, and classify the fingerprint into one of the predefined blood groups (A+, A-, B+, B-, AB+, AB-, O+, O-). The system is modular, scalable, and can be deployed for real-time or batch processing scenarios.

**1. System Overview:** The proposed system is a non-invasive, AI-based solution designed to predict an individual's blood group using only their fingerprint image. It leverages deep learning techniques, particularly Convolutional Neural Networks (CNN's), to analyze the complex patterns in fingerprint images and classify them into one of the eight standard blood groups (A+, A-, B+, B-, AB+, AB-, O+, O-).

**2. Detailed Component Breakdown :** The proposed system for blood group detection from fingerprint images is composed of six main components, each playing a critical role in the overall pipeline. The first component, the Data Acquisition Module, is responsible for capturing high-quality fingerprint images from users using optical or capacitive sensors. During the training phase, these images are collected along with the corresponding blood group labels to form a labeled data set.

**3. Optional: System Architecture Diagram (Suggestion) :** Here is the Optional: System Architecture Diagram (Suggestion) in a clear, descriptive format that you can use to create a visual diagram (e.g., in PowerPoint, draw.io, Lucidchart, or request an image from me): You can represent the architecture of the Blood Group Detection Using Fingerprint with Deep Learning system using a block diagram format, showing how data flows through each component.

**4. Deployment Considerations:** Hosting the model on cloud services such as AWS, Google Cloud, or Microsoft Azure enables scalability and remote access. It is suitable when high computational resources are needed, and internet connectivity is reliable. APIs can be created to allow web or mobile applications to send fingerprint images and receive predictions.

#### B. PROCESSING STEPS

The methodology outlines the systematic approach used to develop a blood group detection system based on fingerprint images using deep learning techniques. The process consists of several stages: data collection, pre processing, model development, training, and evaluation.

**1. Data Collection:** The first step involves gathering a data set consisting of fingerprint images labeled with corresponding blood groups. Capturing fingerprint images from volunteers whose blood groups are known, if available, these can be used to augment the data set. Each fingerprint image is paired with a verified blood group label, creating a supervised learning data set necessary for training the deep learning model.

**2. Data Pre processing :** Pre processing improves the quality and consistency of the input data. Standardizing all images to a fixed size (e.g., 224x224 pixels) to match the input size expected by the deep learning model. Applying filters such as Gaussian blur or median filtering to reduce noise and enhance fingerprint ridge clarity. To prevent over fitting and increase data set diversity, techniques such as random rotations, flipping, zooming, and cropping are applied during training.

**3. Model Development :** A Convolutional Neural Network (CNN) architecture is designed or selected for feature extraction and classification. To automatically learn and extract fingerprint features such as ridges and minutiae, down sample feature maps, reducing computational load and emphasizing dominant features. Given the complexity of fingerprint patterns and the requirement for robust feature extraction, Convolutional Neural Networks (CNN's) are ideal due to their proven success in image recognition tasks.

**4. Model Training :** The model is trained using labeled fingerprint images and corresponding blood group classes. Categorical Cross-Entropy, suitable for multi-class classification problems. Adaptive optimizers like Adam or RMS prop are used for efficient convergence. Hyper parameters are tuned based on data set size and model performance. A validation data set is used to monitor training progress and avoid over fitting. The collected fingerprint images and their blood group labels are divided into three subsets: training, validation, and testing.

**5. Model Evaluation :** After training the deep learning model, it is essential to evaluate its performance rigorously to ensure it accurately predicts blood groups from fingerprint images and generalizes well to unseen data. Model evaluation involves several quantitative metrics and qualitative analyses conducted on a held-out test data set. Post-training, the model's performance is assessed on a separate test data set using metrics. The overall percentage of correct predictions. To evaluate class-wise performance, especially for imbalanced datasets. To visualize true vs. predicted classifications across all blood groups.

**6. Prediction and Deployment :** Upon satisfactory evaluation, the model is deployed for real-time or batch prediction of blood groups from new fingerprint inputs. The prediction module outputs the blood group with the highest probability along with a confidence score.

**C.ALGORITHM**

1. **Data Collection:** Collect a large data set of fingerprint images labeled with the corresponding blood group (A, B, AB, O, and Rh factor: + or -). Ensure diversity across gender, age, ethnicity to improve generalization.
2. **Data Pre processing:** Convert images to grayscale (if not already). Resize all images to a consistent input size (e.g., 224x224 pixels). Normalize pixel values (e.g., scale between 0 and 1). Perform data augmentation (rotation, flipping, zooming) to increase data set robustness.
3. **Label Encoding:** Encode blood groups as categorical variables: Example: A+ → [1, 0, 0, 0, 0, 0, 0, 0] (one-hot encoding for 8 classes: A+, A-, B+, B-, AB+, AB-, O+, O-)
4. **Model Selection:** Use a CNN (Convolutional Neural Network)-based architecture. Options: Custom CNN: For smaller datasets. Pretrained CNNs: (Transfer learning). VGG16, ResNet50, InceptionV3, Efficient Net.
1. **Model Architecture:** Example (using Transfer Learning with ResNet50).
5. **Model Training:** Split data set 70% training, 15% validation, 15% test. Train with early stopping and model check pointing. Monitor validation accuracy and loss.
6. **Evaluation:** Evaluate the model on the test set. Use confusion matrix, precision, recall, F1-score to assess performance.
8. **Deployment:** Deploy the model as a mobile/web app for scanning fingerprints and predicting blood group. Use OpenCV or Media Pipe for fingerprint image capture.

**IV. RESULT**

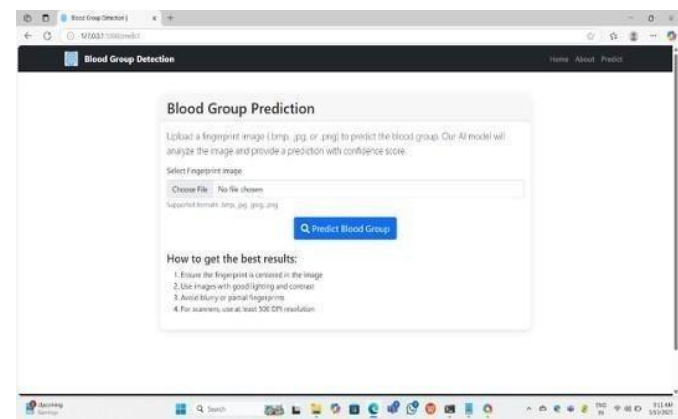


Fig 2 : Upload a fingerprint Image

First copy the URL and paste on the chrome then blood group prediction page will be opened.

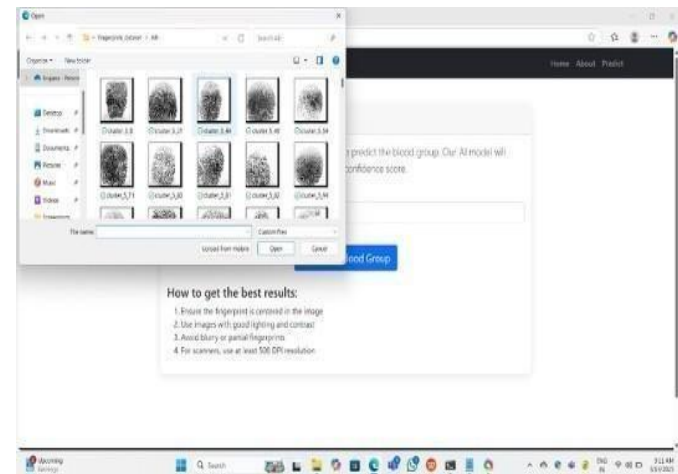


Fig 3 : Choose an image from file

Now, we have to choose an image from the files. And upload to predict the blood group.

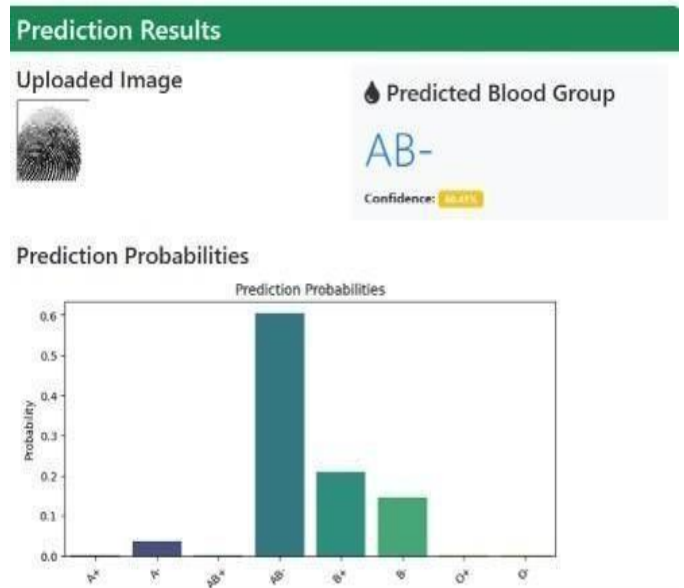


Fig 4 : Prediction Probabilities

After uploading the fingerprint image, it will process the data and gives the result that the fingerprint belongs to which blood group. It will also calculate how much accurate the answer is.

**V. CONCLUSION**

This study presents a novel approach to blood group detection using fingerprint images analyzed through deep learning techniques. By leveraging convolutional neural networks, the system effectively extracts unique biometric features from fingerprints and classifies them into specific blood groups with promising accuracy. The integration of data pre processing, augmentation, and optimized model architectures ensures robustness and generalization, even when faced with variations in fingerprint quality. The results demonstrate that deep learning can provide a non-invasive, rapid, and cost-effective alternative for blood group identification, which has important applications in healthcare, emergency services, and identity verification. Although challenges such as data set size and quality remain, this approach lays the groundwork for future improvements and real-world deployment. Further work can explore expanding the data set, refining the model with more advanced architectures, and implementing the system in portable devices for broader accessibility. Overall, this research highlights the potential of combining biometric analysis and artificial intelligence to enhance traditional blood group detection methods.

**VI. FUTURE SCOPE**

The blood group detection system using fingerprint images and deep learning presents a promising foundation that can be significantly enhanced in the future. One important direction is the collection of larger and more diverse datasets, encompassing various demographics to improve the model's generalization and reduce bias. Additionally, integrating multiple biometric modalities such as iris scans or facial recognition alongside fingerprints could further increase the accuracy and reliability of blood group prediction. Advancements in deep learning architectures, including transformers and ensemble models, offer potential to capture more intricate features from biometric data. Furthermore, optimizing the system for deployment on mobile or edge devices would enable real-time, offline blood group detection, especially valuable in remote or emergency environments. These future developments will help transform this technology from a research prototype into a reliable tool for real-world applications.

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