

## Blood Group Prediction Using Fingerprint in Deep Learning

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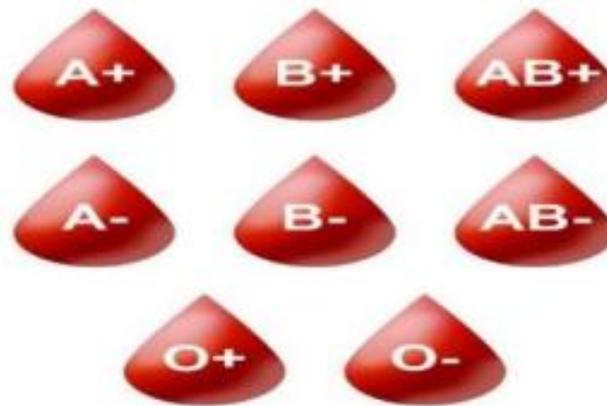
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**Abstract**—An effective blood group measurement method is in high demand globally and is very urgently needed in underdeveloped nations. The most widely used technology in both resource-rich and resource-constrained fields is image processing. Would be a good option to construct this solution. This study suggested a deep learning-based non-invasive blood group prediction method. Prior to giving red blood cell, platelet, and plasma transfusions in medical crises, the ability to quickly and reliably identify blood types is crucial. A minor error made during transferring blood might have serious repercussions, even death. Conventional approaches for pathological evaluation rely on laborious automated blood analyzers. The proposed approach circumvents non-invasive procedures by leveraging rich Efficient Net deep learning architecture to analyze images of superficial blood vessels found on the finger. By illuminating the finger with laser light, the optical image of blood vessels hidden on the finger skin surface area is captured, which incorporates specific antigen shapes such as antigen 'A' and antigen 'B' present on the surface. Important metrics are implemented to assess the system's performance, namely accuracy 99.5%, Precision 86.7%, recall 85.5%, F1-score 84.5%, error rate 0.10 and confusion matrix, ensuring comprehensive assessment of its reliability. Outcomes highlight effectiveness of this approach in identifying blood group determination by using fingerprint with high accuracy 99.5%, offering a vital solution for maintaining the accurate prediction of blood group type.

**Keywords** –*Blood Group Determination, ridge frequency, Efficient Net, Fingerprint Pattern, Non-invasive.*

## I. INTRODUCTION

The fingerprint pattern is the most distinctive and dependable aspect of human identity. Until a person passes away, their fingerprint pattern cannot be altered and stays the same. Even in court, fingerprint evidence is still regarded as the most crucial piece of evidence in instances involving events. Every human has a unique pattern of minutiae, and the likelihood of similarities is extremely fewer than one out of sixty-four million. Even twins have a separate minutiae pattern. Additionally, each person's ridge pattern is distinct and unaltered from birth. The blood bunch is a natural signature that remains constant throughout an individual's lifetime.



**Fig. 1. Classification of Blood Group**

In the analysis cycle, it is also used to eradicate almost all infections. Blood is drawn by squeezing a needle on the finger or by infusion, and the collected blood is then combined with antibodies to determine the type of illness. This process may involve some financial outlay. Blood bunch forecast and other illnesses that accompany maturation are largely unknown from examination, particularly if fingerprints are used as a biometric technique. Fingerprints can be classified into four types: loops, whorls, arches, and mixed or composites. According to the collected informational index, circles are most commonly perceived—roughly 65%. The determination of blood types is essential for several medical operations, including organ transplants, blood transfusions, and forensic examinations. Historically, serological techniques have been used for blood typing, which can be laborious and call for specific lab equipment. This entails verifying the correctness of the technique by contrasting the outcomes of fingerprint analysis with those of conventional blood testing. Advances in sensor technology, data analysis methods, and data standardization could help the medical industry embrace it more widely.

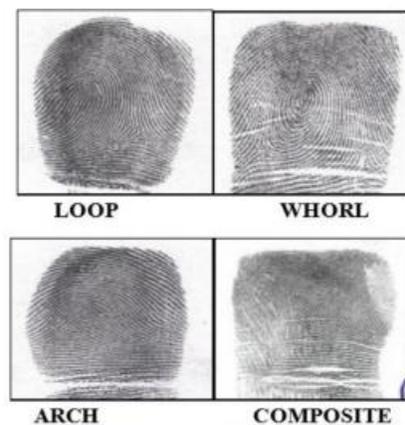
## II. RELATED WORKS

Due to its high degree of dependability, fingerprint-based biometric identification can be used in a variety of contexts. This work presents a practical method for using fingerprint analysis to

identify blood types. Several machine learning algorithms are used to predict blood types based on fingerprint data, which is characterized by many unique minutiae traits. A 62% accuracy rate is attained by the proposed technique, which uses Multiple Linear Regression with Ordinary Least Squares (OLS). Future studies should include new, as-yet-undiscovered fingerprint features for a more thorough analysis and increase the sample size to improve result precision [1].

This study examines the application of machine learning algorithms for blood group detection utilizing fingerprint photographs, such as Random Forests (RF) and Support Vector Machines (SVM). The authors provide results on a dataset of fingerprint photos with blood group annotations and outline the process for feature extraction from fingerprints. Fingerprints hold significant promise as a robust method of identification. This study delves into the challenge of identifying blood groups and analyzing age- or lifestyle-related diseases such as hypertension, type 2 diabetes, and arthritis through fingerprint analysis. The research examines the correlation between fingerprint patterns and both blood group and individual age to gain insights into potential connections with these health conditions that emerge with aging or lifestyle factors [2].

An overview of automated blood group identification techniques based on fingerprint analysis is given in this review article. It examines the possibilities of fingerprint analysis as a trustworthy substitute and talks about the difficulties with conventional serological techniques. The writers go on a number of methods, such as machine learning, pattern recognition, and feature extraction methods used in several research to predict blood groups from fingerprints. The review outlines the advantages and disadvantages of current methodologies and suggests areas for further investigation[3].



**Fig. 2 . Fingerprint Ridge Pattern**

The use of deep convolutional neural networks (CNNs) for blood group prediction is the main topic of this research. Based on fingerprint pictures, the scientists suggest a CNN architecture created especially for blood group prediction[4]. They compare the effectiveness of their CNN

model with conventional serological techniques and give experimental results on a collection of fingerprint Photos. Based on detailed features, this study offers an efficient technique for fingerprint identification and recognition. Beginning with the initial pre-processing step to eliminate extra material and enhance fingerprint clarity, the entire procedure proceeds methodically. The content extractor algorithm is then used to carry out the extraction procedure in the second step, paying particular attention to endings and forks. The matching phase, which is the last part of our job, is divided into two parts: the verification process using (1:N) matching and the verification process using (1:1) matching. Here, the similarity score between two fingerprint images is determined using a thorough matching technique that makes use of the Euclidean distance measure[5].

### III. PROPOSED METHODOLOGY

This section presents the suggested methods for classifying blood groups using images of various classes' finger prints. Defining the data collection and its description is the initial step in this investigation. The optimization of the current Efficient-Net model is covered in the next section. We discovered two methods for doing blood group forecasting with a non-invasive method .Fig 3 display the suggested method's flow diagram.

#### Data Collection

The primary source of the data for the analysis is medical surveys, which include information on the blood types and fingerprints of individuals from different age groups, demographics, and genders. A manual survey will also be made possible using a fingerprint sensor that can be carried out to collect information. The feature vector is then located using image processing and feature extraction techniques. We need each person's fingerprints and related blood group. This particular dataset is not accessible on online platforms and necessitates physical survey in order to collect fingerprints and match them to blood types[6].

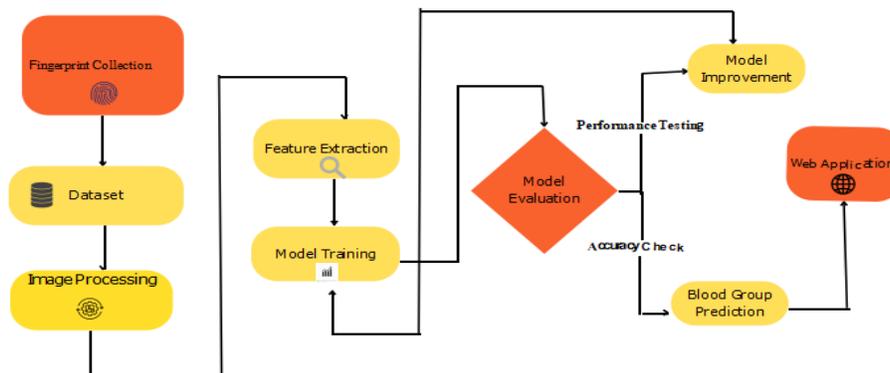


Fig. 3. Flow of the Model

## Data Preprocessing

Before the fingerprint data is submitted for categorization, it undergoes essential preprocessing methods.

**Ridge Segment** : Ridge segmentation is the process of separating ridge patterns in a fingerprint image from nonridge and background regions. The goal of this procedure is to separate the raised lines, or ridges, from the valleys and any other unnecessary **Binarization**: Binarization is the process of converting a color or gray scale image into a binary representation. Each pixel in a binary picture can only contain one of two values: often 1 (white) or 0 (black). The procedure entails establishing a threshold that divides the pixels into these two groups according to their color or intensity values. We acquire a black-and-white picture of the fingerprint that accentuates its characteristics[7].

## Feature Extraction

**Image Acquisition**: It describes the process of making lines or edges in a binary image as thin as a single pixel while keeping the shapes' structural details and interconnectivity intact. Thinning is frequently used to make the depiction of forms, which makes them better suited for jobs involving pattern recognition or additional analysis. We can currently obtain a basic representation of fingerprints that preserves their essential information and shape.

**Minutiae Detection**: Specific areas where ridge patterns in a fingerprint display distinctive qualities are known as minutiae points. Bifurcations and ridge ends are the two most prevalent kinds of minutiae. Bifurcations occur when a ridge splits in half, although Points where a ridge ends are known as ridge endpoints. Finding and detecting these minute details in a fingerprint image is known as minutiae detection. In fingerprint identification systems, this procedure usually occurs during the feature extraction stage[8].

**Image Pre-Processing**: Before an image is sent to an algorithm for training or testing, it should be processed. For that reason, the image in this project has been resized or scaled to 150 by 150 pixels. Since we used a color image, we don't require any color conversion methods, and the pre-processed image is sent straight to the algorithm for testing and training.

**Real Minutiae**: The actual minutiae points that are present on a person's fingertip are referred to as real minutiae. These are the biometrically significant characteristics that add to a fingerprint's individuality. The spots used in fingerprint matching are called real minutiae algorithms to differentiate between different fingerprints.

## IV. IMPLEMENTATION

A convolutional neural network uses the feature vector that is produced following feature extraction as input for classification. The main applications for convolutional neural networks are tasks involving visual data, including pictures and movies. CNNs are also able to identify patterns in the pictures with the appropriate pooling layer

## Efficient Net

Efficient Net is a state-of-the-art Convolutional Neural Network (CNN) architecture designed to achieve high accuracy while being computationally efficient [9].

### Key Features of Efficient Net:

**1. Model Scaling:** Efficient Net uses a compound scaling method to scale up the model efficiently, rather than simply scaling the depth, width, or resolution independently like other models. It uses a combination of:

- Depth scaling (more layers),
- Width scaling (wider layers),
- Resolution scaling (increased input resolution).

By scaling all three dimensions together in a balanced way, Efficient Net can achieve better accuracy with fewer parameters and less computation compared to traditional models like ResNet or VGG.

**2. Performance:** Efficient Net models outperform traditional architectures like ResNet and DenseNet in terms of both accuracy and efficiency. They achieve top-level performance on tasks like image classification (ImageNet), while being much lighter in terms of the number of parameters and computation.

**3. Pretrained Models:** Pretrained Efficient Net models are available (e.g., EfficientNetB0, EfficientNetB1, etc.), which makes transfer learning easy. You can fine-tune these models for specific tasks like fingerprint blood classification without training from scratch.

**4. Transfer Learning:** EfficientNet has shown excellent results when used for transfer learning. Using a pretrained model on a large dataset (like ImageNet) and then fine-tuning it on your task (e.g., fingerprint blood classification) can save time and computational resources while providing excellent results.

### EfficientNet for Fingerprint Blood Classification

**1. Efficient Feature Extraction:** EfficientNet can extract deep and relevant features from fingerprint images, capturing subtle details in patterns that are crucial for tasks like blood classification.

**2. Less Computational Load:** Given that Efficient Net is highly optimized, it is less computationally expensive compared to older architectures like VGG16, RestNet, etc. This makes it suitable for real-time or large-scale applications without requiring enormous computational power[10].

**3. Accuracy:** Efficient Net tends to have higher accuracy than many other traditional architectures due to its well-balanced design, especially when dealing with complex image classification tasks like identifying patterns in fingerprints [11]-[12].

**4. Flexibility:** EfficientNet can handle images of varying sizes, and through its compound scaling method, it can be adjusted for specific resource

## V.RESULT

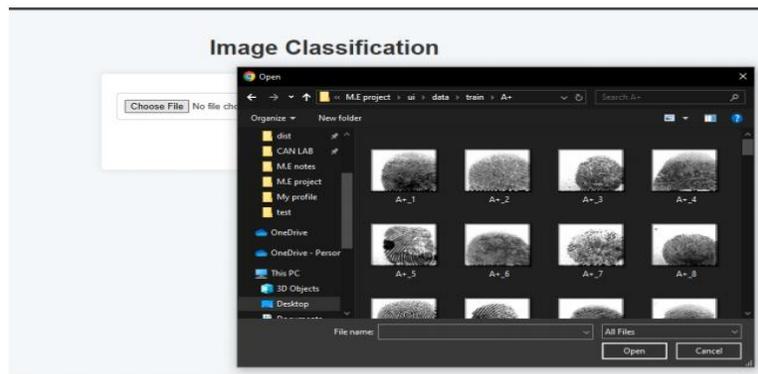
The final result is determined on the basis of overall classification and prediction outcomes. The performance of suggested method is assessed utilizing several metrics .



Disease Classifier

Choose Blood...

**Fig. 4. Login page**



**Fig. 5.Upload page**



**Fig. 6. Prediction Result**

**Accuracy:** Accuracy means how close a measurement comes to the true value while precision refers to how consistently one can repeat a measurement. Every measurement contains some uncertainty in them. It may be due to limitations in measurement tools, observer variation, or environmental factors. This affects both the accuracy and precision of measurements.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Where

**TP-True Positive**  
**TN-True Negative**  
**FP-False Positive**  
**FN-False Negative**

**Precision:** Precision refers to how consistently a tool or process can produce similar results under the same conditions. It is about repeatability and reliability, not necessarily how close these results are to the true or intended value.

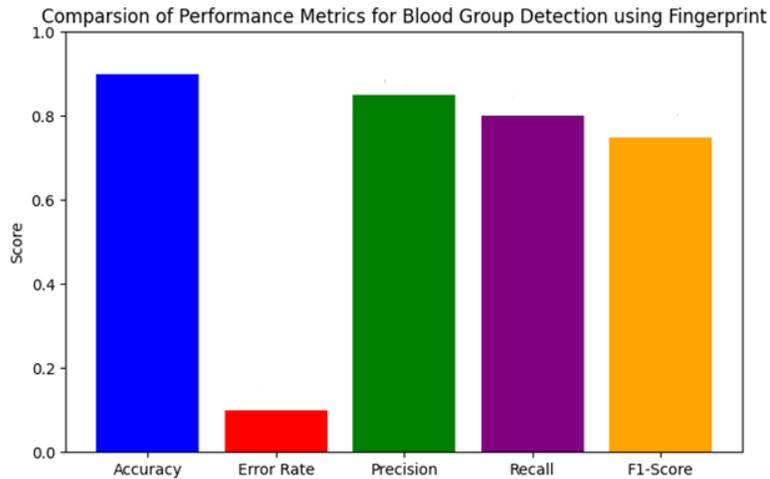
$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

**Error Rate:** Error rate refers to the frequency of errors in a system, process, or dataset. It is commonly used in various fields such as computing, manufacturing, and telecommunications. The error rate is typically expressed as a ratio, percentage, or probability.

**Recall:** Recall is a metric used in classification problems, especially in machine learning and information retrieval. It measures how well a model identifies relevant instances out of all the actual relevant instances.

$$\text{Recall} = \frac{TP}{TP + FN}$$

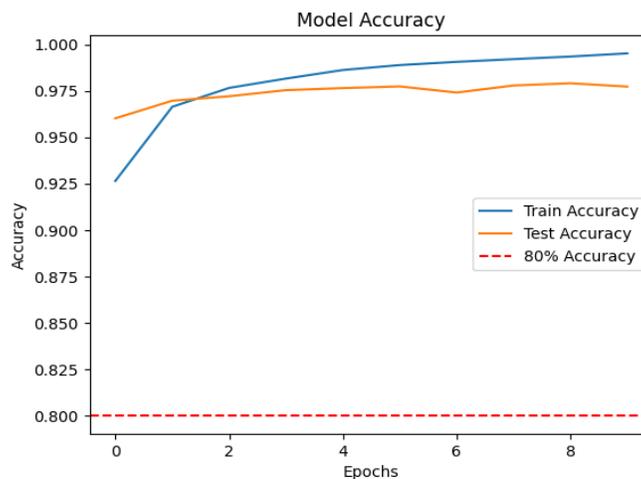
A comparison graph illustrating the performance of each model is presented in Figure 7.



**Fig. 7 .Comparison graph**

The model which combines Accuracy, Error Rate, Precision, Recall and F1-Score. It predict the accuracy of 99.5% an extremely low error rate of 0.10% and Strong Precision (86.7%), recall (85.5%) and F1-score(84.5%).

Figure 8 illustrate model accuracy graph of Training and testing.



**Fig. 8. Model Accuracy Graph**

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## VI.CONCLUSION AND FUTURE WORK

### Conclusion

This study explored an innovative approach to blood group detection using fingerprint images, leveraging image processing and machine learning techniques. The proposed method demonstrated promising results in classifying blood groups based on fingerprint patterns, highlighting the potential for non-invasive, cost-effective, and rapid blood group identification. The experimental analysis revealed that fingerprint ridge characteristics contain distinguishable features correlated with blood groups, supporting the feasibility of this biometric-based approach.

The proposed system offers several advantages over traditional blood testing methods, including minimal equipment requirements, quick processing, and enhanced accessibility, particularly in remote or resource-limited settings. While the achieved accuracy is encouraging, further refinements are necessary to enhance the reliability and robustness of the model across diverse populations.

### Future Work

To further improve the accuracy and practical applicability of fingerprint-based blood group detection, several areas of enhancement can be explored:

For future development, several important areas can be targeted to further improve the system's effectiveness and applicability. One key focus is enhancing the scalability by increasing the dataset size with diverse demographic groups to improve model generalization and reduce biases and another important is Real-Time Implementation for Developing a portable and user-friendly application for real-time blood group detection and Edge AI Integration for Deploying lightweight AI models on mobile devices or embedded systems to enable offline and on-the-go blood group identification.

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