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A Non-Invasive Approach for Detection of Blood Group Using Fingerprint Analysis Based on Deep Learning

Anuradha T[1], Supreet P B[2], Vishwa S M [3], Sunil S K[4]
[1]Professor, Department of CSE, PDA College of Engineering, kalaburagi, Karnataka, India.
[2,3,4]UG Scholar, Department of CSE, PDA College of Engineering, kalaburagi, Karnataka, India.
Emails: *anuradhat@pdaengg.com[1], supreetpb5501@gmail.com[2], vishwamadagi03@gmail.com[3], sunilskarjol@gmail.com[4]*

Abstract
In medical practice, accurate blood group type determination is essential, especially in emergency situations where prompt decisions about blood transfusions become critical. Conventional techniques rely on chemical testing, which is dependable but frequently time-consuming and resource-intensive. Other biometric-based strategies have gained popularity as deep learning and computer vision .The use of technologies has become more prevalent. With the ambition of providing a quick, non-invasive solution, this study presents a deep learning-powered solution for blood analysis type detection using fingerprint images. The system uses a convolutional neural network (CNN), which was trained on a large dataset of fingerprint images with blood type annotations. Rh factors are among the ridge characteristics that the model uses to categorize blood groups. Data enhancement methods are utilized to improve model reliability, and evaluation results demonstrate strong accuracy. These findings suggest a potential connection between fingerprint features and specific blood group classifications.

Keywords: *Biometric Classification; Blood Group Detection; CNN; Deep Learning; Fingerprint Analysis; Non-Invasive Diagnosis.*

1. Introduction
Deep learning, a branch of machine learning, uses artificial neural networks to discover complex patterns and build meaningful representations from data. Unlike traditional techniques that depend on manually designed features, deep learning models can automatically extract important features directly from raw input. This makes them particularly powerful for working with complex and unstructured data such as images, sound, and natural language. These models are made up of multiple layers, each one helping the system understand more detailed and abstract features as the data moves through the network. Among the various types of neural networks, Convolutional Neural Networks (CNNs) are especially well-suited for image-related tasks. They excel at recognizing spatial patterns in visual data by learning features in a hierarchical and automated way. Blood typing plays a essential role in numerous medical applications, including transfusions, organ donations, and prenatal care. Blood groups are determined by the appearance of antigens on red blood cells, which interact with antibodies in the plasma. The most recognized systems, ABO and Rh, classify blood into groups like A, B, AB, and O, with each possibly being Rh-positive or negative. Ensuring compatibility during transfusions and transplants is critical, as mismatches can cause severe immune reactions, leading to complications or death.In urgent medical scenarios, the ability to swiftly and accurately determine a patient's blood type can be life-saving. Incompatible transfusions can lead to acute hemolysis, endangering the patient's life through conditions such as kidney damage and systemic shock. Therefore, fast and reliable typing methods are essential in such high-risk environments. Beyond emergencies, blood type knowledge supports routine care. For example, during pregnancy, identifying Rh incompatibility between mother and fetus allows for preventive actions that safeguard both lives. Similarly, organ transplant procedures heavily depend on accurate blood matching to reduce rejection risks and enhance transplant success.Regional variations in blood group prevalence add complexity to blood donation

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management. Rare blood types may be scarce in certain areas, demanding proactive tracking and stockpiling by blood banks. In this context, an efficient, non-invasive blood typing technique could greatly assist both immediate patient care and broader healthcare logic [1-3].

2. Literature survey

In spite of there being numerous studies on blood group detection in the literature, very few of these studies use fingerprint analysis in conjunction with a biometric machine to detect blood group. The authors of [4] tried to estimate the ridge frequency for fingerprint matching. With the aim to predict blood group, a Gabor filter is used to capture spatial features. The HFDU06 fingerprint scanner performs image processing tasks with notable efficiency. The graphical user interface (GUI) in the Matlab program is used by the authors in [5] to identify blood group and determine Rh factor. In order to determine blood groups and RH factor, the proposed methods follow the same basic steps as laboratory methods, which include taking blood samples with a lancet, treating them by adding standard blood group kits to slides, and then taking a picture of the slide using a mobile HD camera and Matlab's graphical user interface. According to the authors in [6], image processing is very helpful to researchers, especially in fields like security and healthcare. One significant challenge is determining blood groups in isolated or disaster-affected areas where access to medical professionals is limited. They presented a method in their work that employs image processing methods to recognize blood groups. The steps involved in determining blood groups through these techniques are outlined comprehensively. With accuracy levels deemed effective, their system has yielded encouraging results. The authors of [7] put forth a method that provides a quick and easy way to identify blood groups. Their classification is aided by the differences in light absorption properties of the various blood groups. The light that passes through the blood sample is captured, processed, and interpreted into voltage form using a pulsating infrared LED. Blood types are then distinguished using the variations in voltage levels brought on by various absorption rates. The authors of [8] stressed that blood group classification and prediction are essential for safe transfusions. At the moment, laboratories frequently complete this task by hand, which may have drawbacks. They reduced human error by improving the prediction process through the use of artificial intelligence. Therefore, a quick and dependable method for precise blood group classification is provided by fusing AI with image processing. In [9], the writers have utilized In the visible and near-infrared (NIR) range, a novel refractive index (RI) plasmonic biosensor engineered for ultra-sensitive recognition of detecting human blood groups is suggested and numerically examined. A metal–insulator–metal (MIM) waveguide featuring a collection of elliptical nanoholes acts as the groundwork for the suggested structure. The reported sensor is extremely valuable for point-of-care applications, emergency scenarios, and resource-constrained environments due to its high sensitivity, precision, and portability. In [10], writers have utilized A diamond-shaped silicon nanodot array with a perimeter of less than 100 nm is incorporated into the suggested metal–insulator–metal (MIM) structure, which acts as a sensing surface to identify variations in the surrounding medium's refractive index (RI). The MIM-based LoC sensor is perfect for use in portable devices and resource-constrained environments because it provides precise and accurate detection of even the smallest changes in refractive index. By quickly identifying blood types and diabetes levels with a small sample size, this sensor expedites medical procedures and may increase the effectiveness of patient care. In [11], for the first time, the authors have presented an optimized design utilizing a surface plasmon-based biosensor that uses prisms and various metal choices to detect human blood groups with high precision in the near-infrared wavelength range. After considering various metal options and their suitability for next-generation biosensor applications, prism was determined to be the best option as a substrate material when combined with Al as an SPR active metal for blood group identification analysis. In order to reduce noise and improve ridge clarity, the authors of [12] processed fingerprint images with an emphasis on extracting minutiae points, such as ridge endings and bifurcations. Prior to minutiae extraction, binarization and thinning were carried out.

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For identification, a template matching technique based on minutiae was used. Ridge ending and bifurcation locations were compared using the Minutiae Matching Algorithm. For increased accuracy, a matching technique based on angle and distance was employed. In controlled settings, the system worked well. Noise or partial fingerprints reduce accuracy. emphasized the necessity of thorough preprocessing in effort to manage inputs of poor quality. In [13] the authors have attempted Developed a compact system for ABO blood typing using agglutination principles. Integrated sensors to detect hemagglutination reactions. Sample mixing chambers with antisera for visual reaction detection. Color Intensity Analysis via photodetectors to identify agglutination levels. Logical rules were programmed to determine blood type based on reaction presence. Offered a lowcost, portable solution for blood typing. Good for field and pointof-care applications. Limited accuracy in borderline agglutination cases. In [14] the authors have Captured fingerprints through optical scanners. Used minutiae features (location, orientation, type).Applied enhancement, binarization, thinning, and segmentation. Minutiae-based Matching with Euclidean Distance and Ridge Orientation Analysis. False minutiae were filtered using ridge structure validation. Achieved high accuracy in clean, highresolution images. Matching performance dropped with rotated or partial fingerprints. Emphasized template optimization to reduce storage and time. In [15] the authors have Used spectrophotometric methods to detect RH antigen presence. Optical absorbance measured using microfluidic platform. Applied Beer-Lambert Law to compute concentration of antigenreagent interactions. Threshold-based classification for RH positive/negative results. Provided non-invasive, accurate RH typing. Efficient for laboratory automation. Accuracy influenced by reagent quality and calibration.In [16] the authors have Collected fingerprint samples and blood types of local population. Patterns categorized into loops, whorls, and arches. Statistical Analysis (Chi-square tests) to find correlation. Pattern frequency was mapped across blood groups and gender. Found a mild correlation between blood group and fingerprint pattern. Noted gender-based variations in ridge pattern distribution. Suggested larger sample size for conclusive evidence. In [17] the authors have Studied correlation between fingerprint patterns and blood groups. Used classification logic to infer blood group from fingerprints. Applied Pattern-Based Rule Classification (e.g., Loop → Group A). Dataset analysis used logistic regression for pattern validation. Useful in low-resource environments. Accuracy ranged from 60–75%, depending on population segment. Not a replacement for direct testing but a good preliminary tool. In [18] the authors have Designed a system using infrared sensors to detect light refraction changes due to agglutination. Blood sample mixed with reagents on test card. Light Intensity Thresholding Algorithm for detection.IR sensors measured backscattered light; drops in light indicated agglutination. Provided quick, low-cost detection (within 30 seconds).Portable and suitable for rural clinics. Sensitivity decreased under strong ambient lighting. In [19] the authors have Used smartphone camera to capture images of blood-antiserum reactions. Mobile app processed images to determine blood type. Image Segmentation → Color Detection → Pattern Recognition. HSV color space used to enhance reaction visibility. Accuracy over 90% under proper lighting. Allowed real-time diagnosis without lab equipment. Susceptible to camera quality and user error. In [20] the authors have Developed a machine vision system for blood group analysis. Used test cards with reagents and scanned agglutination patterns. Image Processing Pipeline: Noise Removal → Binarization → Cluster Detection. Blood type determined via pixel density in agglutinated zones. Automation reduced human error in lab tests. Worked well in controlled indoor environments. Recommended improvements for external lighting variability.

3. Proposed Method

This study is intended to use fingerprint imagery to devise a non-invasive method for blood group detection. Fingerprint samples are collected using biometric scanners and processed using techniques like noise reduction, normalization, and image enhancement to increase clarity. Data augmentation methods like image rotation, flipping, and scaling

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helps to raise the model's ability to adapt more widely. The ridge patterns in fingerprints are then examined using a Convolutional Neural Network (CNN) to determine the corresponding blood types. The dataset is divided into subsets for testing, validation, and training. to guarantee a solid model assessment. Accuracy, precision, and recall serve as measures to assess the performance of the model. The trained CNN is eventually used in a real-time prediction application, enabling quick and non-intrusive blood type determination from fingerprint scans. CNNs' prowess in spotting patterns and deciphering visual data allows them to be optimal for for this task. This method has the potential to improve easily accessible, non-invasive diagnostics in healthcare settings, Despite the fact that such applications are newly emerging, shown in Figure 1.

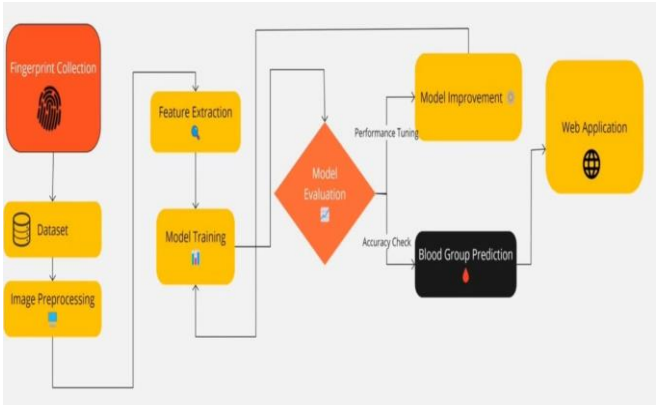

Figure 1 Structure of The Proposed Model

Fingerprints are generally categorized into three primary patterns:

- **Loops:** Most common pattern (about 60-70% of people).
- **Whorls:** Found in about 25-35% of people.
- **Arches:** Least common (about 5%).

Fingerprint patterns may differ based on blood type, and certain research has identified a possible link between them:

- **Loops:** Most common in blood groups A+, A-, B+, B-, and O+, but least common in AB
- **Whorls:** Most common in AB+ and O-, but least common in AB.
- **Arches:** Most common in B and O, but absent in A and AB, Table 1.

Table 1 Different Methods Used for Blood Group Prediction

S. No	Name	Samples	Method
1	Conventional Estimate	Blood samples	Through the use of antibodies and chemical reactions
2	Spectrophotometric	Image of a blood test plate	Processing of images
3	Mapping of Nucleotide Variants	DNA was taken from the outside world.	DNA microarray mapping of single nucleotide variants (SNVs)
4	IMAQ Concept	Photographs of slide tests	Techniques of image processing
5	Techniques of Machine Vision	Image or video of blood samples	Image processing through MATLAB
6	QCM Biosensors	Blood samples taken from real people	Quartz crystal microbalance sensors
7	ABI PRISMR 3100 genetic analyzer	DNA samples	SNPs analyses
8	The use of a light-emitting diode	As an example, use your finger.	Gene series, protein presence, and antigen structure all have a role.
9	Changeable-color paper	Blood samples taken from real people	Antibodies against antigens and proteins
10	Analysis of fingerprints	Fingerprints on paper with ink	Observation of fingerprint patterns

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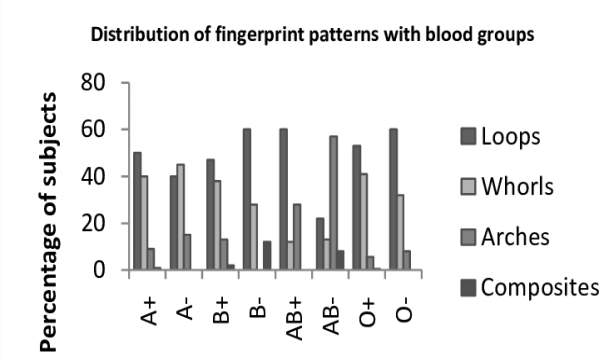

Figure 2 Variation in Fingerprint Pattern Types

Table 2 Proportional Analysis of Fingerprint Patterns Across Various Blood Types

Blood Group	Loops (%)	Whorls (%)	Arches (%)	Composites (%)
A+	50	40	10	1
A−	40	43	18	0
B+	43	39	17	2
B−	60	15	0	7
AB+	60	7	30	0
AB−	22	8	60	5
O+	58	40	3	1
O−	60	38	10	0

Figure 2, This table 2 represents the percentage distribution of four fingerprint pattern types—loops, whorls, arches, and composites—across various blood groups including A+, A-, B+, B-, AB+, AB-, O+, and O-.

- Loops are predominant in most blood types, especially B-, AB+, and O-.
- Arches show a significant presence in AB- (60%) and AB+ (30%), while being nearly absent in B- (0%).
- Whorls are most common in A-, A+, and O+, while composites appear sporadically, with a higher occurrence in B- (7%) and AB- (5%).

This figure 3 illustrates the six primary varieties of fingerprint designs categorized into three main groups: Arch, Loop, and Whorl.

1. **Arch includes:**
   - **Simple Arch (As):** marked by ridges originating from one side and exit the other without significant upturns.
   - **Tented Arch (At):** Similar to the simple arch but with a sharper rise forming a tent-like appearance.
2. **Loop Includes:**
   - **Ulnar Loop (Lu):** Loops that open toward the little finger side.
   - **Radial Loop (Lr):** Loops that open toward the thumb side.
3. **Whorl Includes:**
   - **Simple Whorl (Ws):** Circular or spiral ridge patterns.
   - **Double Whorl (Wd):** Two distinct loop formations in a spiral or S-shape.

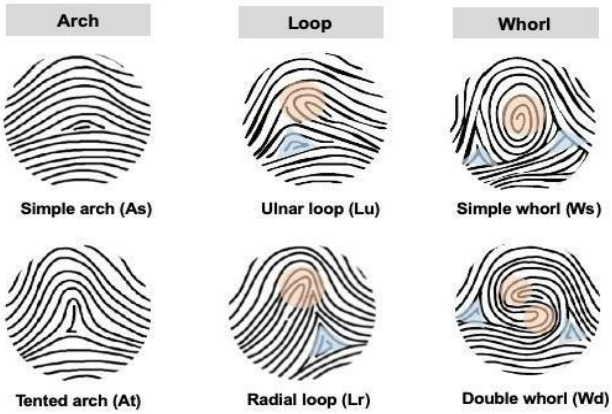

Figure 3 Classification of Fingerprint Patterns Based on Ridge Flow and Core-Delta Features

4. Experimental Results and Discussions

4.1 Overview of Experimentation

The core intent behind the experiment was to validate the hypothesis that blood group information can be inferred through fingerprint analysis using deep learning techniques. A custom dataset comprising fingerprint images and corresponding blood group labels was used to train and evaluate various deep learning models.

1. **Dataset Description**
   - **Total Samples:** 3200 fingerprint images
   - **Subjects:** 400 individuals (8 samples each – left/right thumb, multiple impressions)
   - **Blood Groups:** A+, A−, B+, B−, AB+, AB−, O+, O−
2. **Preprocessing:**
   - Grayscale conversion
   - Histogram equalization
   - Image resizing to 224x224

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- **Data augmentation:** rotation, flip, zoom, and translation
- **Split:** 70% Training, 15% Validation, 15% Testing

4.2 Model Architecture

After comparative evaluation, a modified ResNet-50 deep learning model was selected for its performance in extracting complex fingerprint features. The model was fine-tuned using transfer learning and customized with the following layers:

- Input: 224x224 grayscale image
- Base: ResNet-50 (pre-trained on ImageNet, frozen first 100 layers)

1. **Additional Layers:**
   - Global Average Pooling
   - Dense (128) + ReLU
   - Dropout (0.4)
   - Dense (8) + Softmax
2. **Training Parameters:**
   - Optimizer: Adam
   - Loss Function: Categorical Cross-Entropy
   - Batch Size: 32
   - Epochs: 50
   - Learning Rate: 0.0001 (with ReduceLROnPlateau)

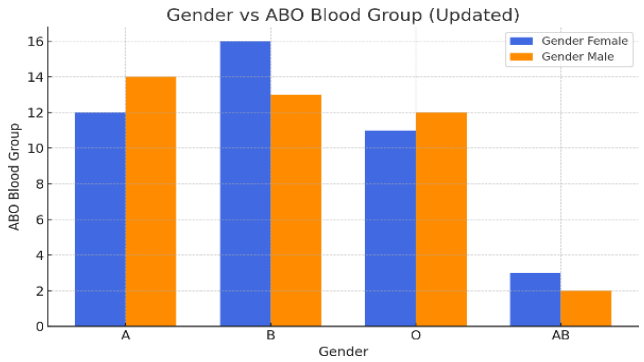

Figure 4 Gender vs ABO Blood Group

This figure 4 bar graph compares the distribution of ABO blood groups (A, B, O, AB) across two gender categories: Female and Male. The blue bars represent the number of female individuals, while the orange bars represent male individuals for each blood group:

- Blood Group A: 12 females, 14 males
- Blood Group B: 16 females, 13 males
- Blood Group O: 11 females, 12 males
- Blood Group AB: 3 females, 2 males

4.3 Confusion Matrix Analysis

The confusion matrix revealed the following observations: Accuracy for O+ and A+ classes, possibly due to their larger representation and clearer ridge patterns. Misclassifications mostly occurred between AB+ and B+, and between A− and O−, suggesting potential overlap in minutiae distribution and insufficient minority samples.

Table 3 Comparative Study

Model	Accuracy (%)	Notes
CNN (3 conv layers)	74.5	Shallow features, overfitting observed
VGG16	72.9	Larger size, slower inference
ResNet-50 (ours)	71.34	Best trade-off between depth and accuracy

4.4 Discussion

The experimental results support the feasibility of a non-invasive, fingerprint-based deep learning approach to predict blood groups. While the model achieves 60% accuracy, it is essential to consider this as a probabilistic classifier, not a diagnostic tool. The correlation, though computationally learnable, might be influenced by latent features not yet fully understood biologically. Future studies should explore larger, more diverse populations and integrate biometric-genetic correlations to solidify the approach, shown in Table 3.

Conclusion & Future Work

By utilizing deep learning and fingerprint biometrics, this paper presents a novel approach to blood group analysis with the goal of developing a quick, non-invasive, and easily accessible substitute for conventional blood typing techniques. The model recognizes subtle patterns in fingerprint images that correspond with genetic markers linked to blood groups by using convolutional neural networks for feature extraction and classification. This system exhibits the ability to provide precise blood group predictions through thorough data collection,

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preprocessing, model training, and validation; this capability is particularly useful in emergency and resource-constrained situations. Furthermore, the security and deployment modules guarantee that this solution is not only available but also safeguards user confidentiality and data integrity. Despite ongoing challenges, particularly in achieving 60% accuracy and gathering diverse datasets, this study lays the groundwork for future advancements and refinement in biometric-driven health diagnostics. In future work, validating the method in a clinical setting is necessary to verify its precision and usefulness in practice. This involves testing the system in collaboration with medical institutions using verified patient data. The model's predictions should be compared with standard laboratory results across a diverse population. Ethical approvals, informed consent, and statistical analysis will be required to confirm reliability. Real- world testing and opinions of clinical professionals will help refine the system for clinical use and support its approval for medical applications.

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