

AI-Assisted Blood Group Prediction from Fingerprint Images An Explainable Multi-Finger Deep Learning Framework for ABO Blood Group Screening

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Abstract: Blood-group information is normally obtained through laboratory testing of blood samples. This project investigates whether fingerprint images can provide a useful non-invasive signal for AI-assisted prediction of the ABO blood group. Earlier dermatoglyphic studies have reported statistical associations between fingerprint-pattern distributions and ABO groups, while other studies have reported no significant association, indicating that the relationship is population-dependent and should not be treated as a direct biological diagnostic rule.

The proposed system therefore frames fingerprint-based blood-group identification as a machine-learning screening problem rather than a replacement for clinical typing. The method combines standardized fingerprint acquisition, image-quality assessment, segmentation, enhancement, multi-finger feature learning, and an explainable classifier. A subject-level split is used to prevent leakage between training and test impressions.

The system will compare a convolutional neural network with conventional classifiers and evaluate accuracy, macro-F1, balanced accuracy, confusion matrix, calibration, and uncertainty. A confidence threshold will allow the system to return an “uncertain” outcome when evidence is insufficient.

The main research contribution is an end-to-end, multi-finger and uncertainty-aware framework designed for controlled experimental validation on a locally collected dataset. The system is intended for academic research and preliminary screening only; laboratory ABO typing remains necessary for clinical decisions.

Keywords: Fingerprint biometrics; dermatoglyphics; ABO blood group; convolutional neural network; deep learning; explainable AI; image classification; uncertainty estimation.

I. INTRODUCTION

Fingerprints are persistent biometric patterns formed by friction ridges. Their use in automated recognition has produced extensive research infrastructure, datasets, quality measures, and standards. NIST, for example, provides fingerprint databases and evaluation resources for automated fingerprint research [1]–[3]. Separately, dermatoglyphic research has investigated relationships between fingerprint patterns and inherited traits, including ABO blood groups. A study of 800 participants in eastern India reported a statistically significant difference in primary fingerprint-pattern distributions across ABO groups, while Rh-group differences were not statistically significant [4]. A 2025 Indian study



with 50 participants also reported an ABO association but emphasized the need for larger validation [5]. In contrast, a 700-participant study from Nepal reported no significant association and concluded that fingerprints should not be used for blood grouping [6].

These conflicting findings establish a meaningful research problem: can modern image-based learning discover repeatable predictive information that is not captured by simple loop, whorl, and arch counts, and can that prediction be measured honestly across subjects and acquisition conditions?

II. RESEARCH PROBLEM AND MOTIVATION

The proposed engineering problem is to design and evaluate an AI system that receives one or more fingerprint images and estimates the most probable ABO blood group. The project is motivated by the low-cost acquisition of fingerprint images, the availability of embedded and mobile imaging hardware, and the possibility of rapid preliminary screening in research or educational settings.

The central scientific question is not whether a fingerprint contains a deterministic blood-group label, but whether statistically useful information exists in the image and whether a model can generalize beyond the people and devices used during training.

III. RESEARCH GAP AND NOVEL CONTRIBUTION

A 2025 IEEE conference paper has already reported machine-learning-based blood-group detection from fingerprints using CNN, Random Forest, and SVM models [7]. Therefore, simply repeating “CNN for fingerprint blood-group detection” would not constitute a strong novelty claim.

This project instead emphasizes:

1. multi-finger fusion at the subject level;
2. explicit fingerprint-quality gating;
3. subject-disjoint evaluation;
4. comparison of image-only deep features with handcrafted dermatoglyphic features;
5. calibrated confidence and an abstention/uncertain class; and
6. explainability analysis to identify which fingerprint regions influence predictions.

These design choices create a clearer experimental research contribution while keeping the project feasible for a final-year engineering team.

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed pipeline is organized as follows.

Fingerprint acquisition: Capture standardized images of selected fingers using a fingerprint sensor or controlled optical camera.

Quality control: Reject or flag samples with excessive blur, dry or wet ridge regions, incomplete area, low contrast, or severe rotation.

Pre-processing: Perform grayscale conversion, region-of-interest extraction, ridge enhancement, normalization, resizing, and optional orientation correction.

Feature learning: Extract deep representations using a lightweight CNN or transfer-learning backbone.

Multi-finger fusion: Combine representations from multiple fingers using concatenation, attention, or weighted aggregation.

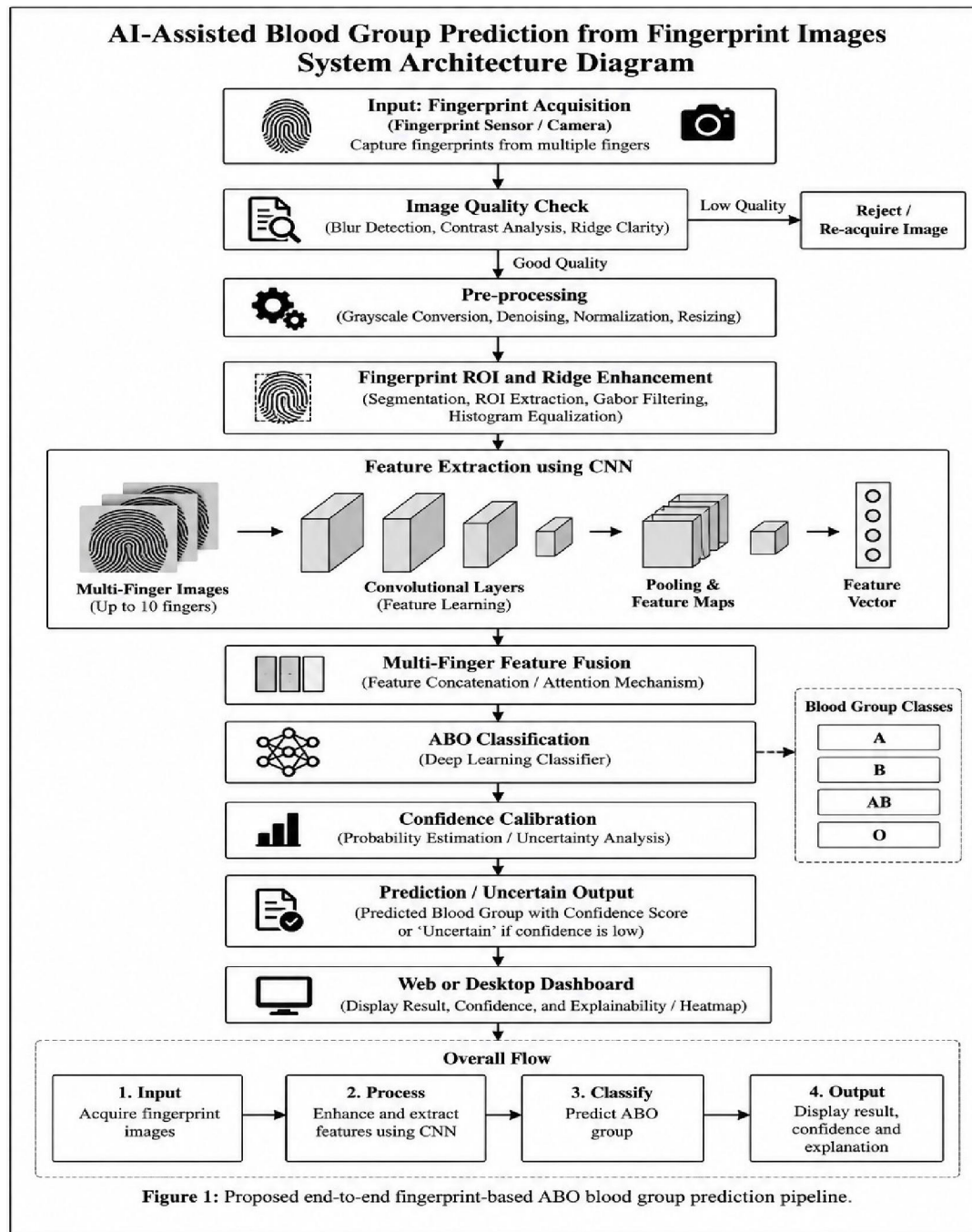
Prediction: Classify the subject into A, B, AB, or O using a softmax classifier. An optional Rh-positive/Rh-negative model may be trained if sufficient data are available.

Uncertainty estimation: Use probability calibration and a confidence threshold so low-confidence samples are reported as uncertain rather than forced into a blood-group class.



Output: Display the predicted group, confidence, quality score, and an explanation or heatmap for research interpretation.

V. SYSTEM BLOCK DIAGRAM



VI. DATASET DESIGN

A new subject-level dataset should be created because public fingerprint datasets generally do not contain verified ABO labels. Each participant should provide informed consent and a laboratory-confirmed blood-group label, together with fingerprint images captured under a fixed protocol.

The recommended target is at least 800–1,200 participants for the engineering study, with balanced representation of A, B, AB and O as far as recruitment permits. Multiple impressions from the same finger may be captured, but all images from a person must remain in the same train, validation, or test partition. This is essential because placing different impressions from one person in different partitions can create identity leakage and unrealistically high performance.

Table 1: Recommended Dataset Design

Field	Recommended Design
Participant ID	Anonymous random identifier
Ground truth	Laboratory-confirmed ABO result
Fingerprint data	3–10 fingers per participant; repeated impressions optional
Acquisition	Same sensor/camera where possible; record device and session
Quality meta data	Blur, contrast, ridge coverage, orientation, missing area
Split	Subject-disjoint train/validation/test split
Privacy	Consent, coded IDs, restricted access, encrypted storage

VII. CIRCUIT DIAGRAM

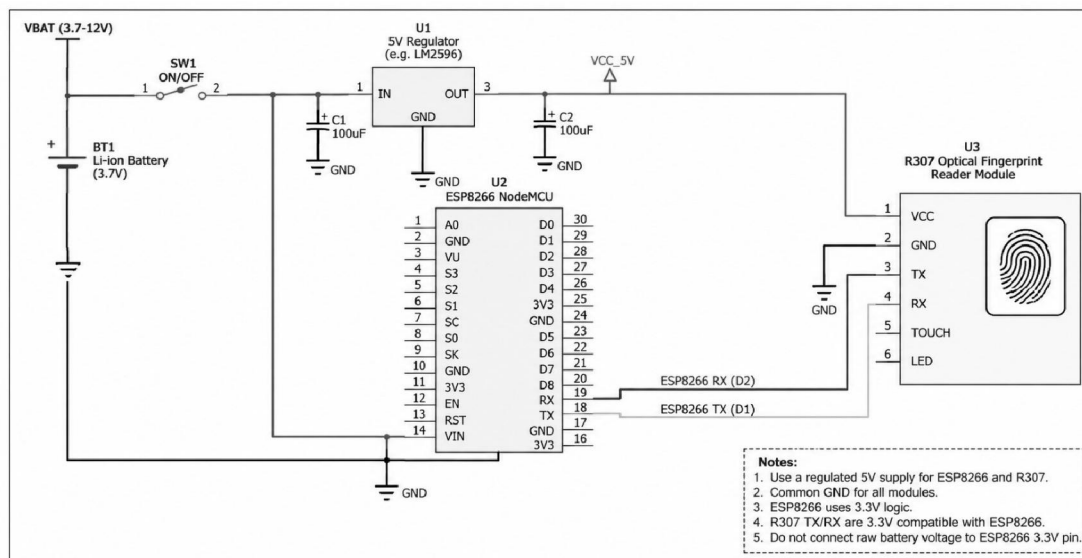


Figure 1 Circuit Diagram of the Web3-Based Digital Portfolio Verification Platform

VIII. CIRCUIT DIAGRAM EXPLANATION

The circuit consists of a Li-ion battery, ON/OFF switch, voltage regulator, ESP8266 NodeMCU, and R307 fingerprint sensor.



The battery provides power to the circuit, while the regulator provides the required regulated voltage. The ESP8266 acts as the main controller. The R307 sensor captures the fingerprint and sends the data to the ESP8266 using UART communication.

The TX and RX pins of the R307 are connected to the RX and TX pins of the ESP8266. A common ground is provided for all components. The ESP8266 receives the fingerprint data and sends it to the software system for further processing.

IX. GROUND TRUTH AND ETHICAL CONSIDERATIONS

ABO labels must be obtained independently from fingerprint images. WHO guidance describes ABO interpretation using cell and serum typing and requires discrepancies to be resolved before a patient's or donor's ABO group is interpreted [8]. Accordingly, the project must never generate its labels from the same fingerprint-derived prediction that it is trying to learn.

Participant consent, anonymization, controlled access, and secure storage are required because fingerprints are biometric identifiers and blood-group information is sensitive personal data. The student project should obtain institutional approval where required before collecting human-subject data.

X. PRE-PROCESSING AND FEATURE ENGINEERING

Fingerprint images should first be converted to a consistent grayscale representation and normalized for illumination. A region-of-interest mask can remove irrelevant background. Ridge enhancement may use oriented filters or other validated enhancement techniques. Images can then be resized to a fixed CNN input such as 224×224 pixels.

Data augmentation should be limited to transformations that preserve fingerprint structure, such as small rotations, translations, contrast changes, and mild noise. In parallel, a handcrafted feature branch can encode ridge-pattern class, orientation statistics, ridge density, minutiae counts, and other measurable dermatoglyphic descriptors. The final study can compare handcrafted features, CNN features, and their fusion.

XI. MACHINE-LEARNING METHODOLOGY

The primary model should be a compact CNN or transfer-learning network selected according to available computing resources. A practical baseline is a pretrained MobileNetV3 or EfficientNet-type backbone followed by global average pooling and a four-class ABO head. A second model can use a custom lightweight CNN trained from scratch.

Classical baselines should include Random Forest and Support Vector Machine using handcrafted or CNN-extracted features. The purpose of these baselines is not only comparison but also to determine whether deep image representations provide measurable improvement over simpler feature engineering.

XII. MULTI-FINGER FUSION STRATEGY

Instead of predicting blood group from one arbitrary finger, the proposed system treats the participant as the prediction unit. For each selected finger, the model generates an embedding vector. These embeddings are fused by concatenation followed by a fully connected layer, or by an attention-based weighted average.

Missing or low-quality fingers are masked so that the model does not treat unusable samples as valid evidence. The study should compare single-finger, two-finger, five-finger, and multi-finger configurations. This experiment directly tests whether combining independent fingerprint observations improves generalization.

XIII. TRAINING PROTOCOL

The training protocol is defined as follows:

1. Use a subject-disjoint split such as 70% training, 15% validation, and 15% test, with stratification by ABO group where feasible.
2. Use class-weighted cross-entropy or balanced sampling when the four blood groups are imbalanced.



3. Apply early stopping using validation macro-F1 or validation loss.
4. Do not use test images for hyperparameter tuning, augmentation selection, or threshold selection.
5. Repeat training with several random seeds and report mean and standard deviation where computationally feasible.
6. Store the model version, preprocessing configuration, sensor/device information, and dataset version for reproducibility.

XIV. EVALUATION METRICS

Table 2 Evaluation Metrics

Metric	Purpose
Accuracy	Overall proportion of correctly classified subjects
Macro-F1	Balances performance across A, B, AB and O classes
Balanced Accuracy	Useful when class frequencies are unequal
Precision / Recall	Class-specific error analysis
Confusion Matrix	Shows which ABO classes are confused
ROC-AUC	Optional one-vs-rest discrimination measure
Expected Calibration Error	Measures whether confidence reflects correctness
Abstention Rate	Fraction returned as uncertain at a chosen threshold

XV. EXPERIMENTAL PLAN

The experiments should be organized around five questions. E1 measures the performance of classical fingerprint-pattern features. E2 evaluates the CNN image model. E3 tests multi-finger fusion. E4 evaluates robustness to controlled changes in image quality and acquisition session. E5 measures confidence calibration and the effect of an uncertain-output threshold.

Statistical confidence intervals should be reported for the final test metrics. A subgroup analysis can examine performance by sex, age band, device, and acquisition session only when the sample size is sufficient. These analyses are intended to detect dataset bias rather than to infer biological causation.

XVI. EXPECTED ENGINEERING DELIVERABLES

The expected deliverables are:

- Fingerprint acquisition and quality-control module.
- Pre-processing and fingerprint feature-extraction pipeline.
- Trained CNN and classical baseline models.
- Multi-finger fusion and confidence/uncertainty module.
- Local web or desktop dashboard showing image quality, predicted ABO group, confidence, and model explanation.
- Dataset documentation, experiment log, model configuration, and reproducible evaluation scripts.

XVII. DISCUSSION

The central value of this project is methodological rather than the assumption that fingerprints deterministically reveal blood type. Existing literature is mixed: several studies have reported significant associations between fingerprint patterns and ABO groups, while at least one relatively large study reported no significant association [4], [6]. Population, sampling, fingerprint classification method, and sample size can therefore affect observed relationships.



A deep-learning model may discover image features that are not represented by the traditional four pattern categories, but high test accuracy alone would not establish a causal biological relationship. Subject-disjoint testing, independent laboratory labels, calibration, and external validation are therefore essential.

The project also has an important reproducibility challenge. A model can unintentionally learn acquisition artifacts, scanner-specific characteristics, image backgrounds, or demographic correlations rather than fingerprint structure. Recording device and session metadata, using controlled acquisition, and testing on a second acquisition session can help identify this problem. Explainability maps should be treated as diagnostic evidence about model behavior, not proof of a biological mechanism.

XVIII. LIMITATIONS

- The project predicts a blood-group label statistically; it does not directly measure ABO antigens or antibodies.
- Performance may vary across populations, age groups, geographic regions, fingerprint sensors, and image-quality conditions.
- Rare blood groups, especially AB and Rh-negative combinations, may be underrepresented in a student-collected dataset.
- Public fingerprint datasets generally do not provide matching laboratory-confirmed ABO labels, limiting direct reuse.
- Clinical or transfusion decisions must not rely on the proposed system without validated laboratory blood typing.

XIX. CONCLUSION

This paper proposes an AI-assisted framework for estimating ABO blood group from fingerprint images using multi-finger deep feature learning, fingerprint-quality control, subject-level data separation, explainability, and uncertainty-aware prediction. The project is deliberately designed as a research investigation rather than as a clinical replacement for blood typing.

The strongest contribution for a final-year engineering study will come from a carefully collected, ethically approved dataset and a transparent experimental comparison of classical features, CNN features, and multi-finger fusion. The final publication should report only experimentally measured results and should validate the system on subjects and acquisition conditions that were not used during training.

XX. FUTURE SCOPE

- External validation across multiple institutions and fingerprint-sensor types.
- Self-supervised or contrastive pretraining on large unlabeled fingerprint collections.
- Domain-adaptation methods to reduce sensor and acquisition-session bias.
- Federated learning for privacy-preserving multi-institutional training.
- More rigorous uncertainty estimation and selective prediction.
- Prospective validation against independently performed laboratory ABO typing.

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