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BLOOD GROUP DETECTION USING FINGERPRINT-BASED DEEP LEARNING

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Abstract: Knowing a patient's blood group quickly matters in diagnosis, transfusion, and emergency care, yet standard typing still depends on drawing blood and running it through a lab. This paper looks at whether a fingerprint alone can get us there instead. A convolutional neural network (CNN) is trained on labeled fingerprint images, learning how ridge features such as loops, whorls, and arches relate to ABO and Rh blood group classes; the resulting model is deployed behind a Flask web interface, which takes an uploaded fingerprint and returns a predicted blood group with a confidence score. The system architecture, dataset requirements, and implementation pipeline are laid out, and four architectures—CNN, VGG, ResNet, and AlexNet—are compared on the same task. The best of these reached 0.76 classification accuracy, which shows that fingerprint–blood group correlations are real at a statistical level but not yet reliable enough to stand alone. The paper closes by discussing where the approach falls short and what would need to change for it to become clinically useful.

Index Terms: Blood group detection, fingerprint recognition, deep learning, convolutional neural network, biometrics, non-invasive diagnostics.

I. INTRODUCTION

Determining a patient's blood group underpins diagnostics, transfusion, and emergency healthcare, so delays here carry real consequences. The trouble is that conventional typing still means drawing blood and sending it to a lab, which takes time few emergency rooms can spare. Recent progress in biometrics and machine learning suggests a way around this: instead of a blood sample, could a fingerprint tell us enough on its own? This paper looks at fingerprint-based blood group detection through that lens, using deep learning to make the connection.

There is no known biological mechanism that directly ties blood group to fingerprint pattern, yet a handful of studies keep turning up a statistical correlation between the two. Both traits do have a genetic basis: ABO and Rh types come from specific inherited genes, and ridge patterns—loops, whorls, arches—take shape between roughly the 13th and 19th week of fetal development, shaped by a mix of genetic and environmental factors in the womb. Since some of the same genes that set blood type could plausibly influence ridge formation as well, researchers have asked whether fingerprints might work as an indirect, non-deterministic signal for blood group.

Fig. 1. Fingerprint pattern types.

Fingerprints fall into three broad categories—loops (60–65% of cases), whorls (30–35%), and arches (5–10%)—and early statistical work hints at an uneven distribution across blood groups: loops skew toward group O, whorls toward group B, arches toward group A, with mixed patterns showing up more often in group AB. None of this amounts to a rule; it is a tendency at best. That is exactly the kind of noisy, statistical pattern a data-driven deep learning model is suited to pick apart, which is the motivation for the approach taken here.

A. Scope

The scope here is a non-invasive way to read blood group off a fingerprint, sidestepping the blood draw entirely. Hospitals, blood banks, and emergency services stand to benefit most, anywhere a fast, contactless check matters, and the same idea carries over to biometric and forensic identity work. Because the pipeline is lightweight, it also fits reasonably well on mobile and wearable hardware, opening the door to real-time, on-the-go use.

B. Objectives

- Build a faster, cheaper alternative to blood typing, aimed especially at emergency rooms and remote clinics with limited lab access.
- Use deep learning to map fingerprint ridge patterns onto blood group characteristics.
- Test how far the fingerprint–blood type link can be pushed for forensic and biometric use cases.
- Cut down reliance on invasive blood tests, and with it the risk of infection and lab error.

II. LITERATURE SURVEY

Several threads of prior work feed into this paper—biological, biometric, and computational. Fayrouz et al. [1] were among the first to show statistical evidence linking fingerprint patterns to ABO/Rh blood groups, and that finding underlies much of the biometric blood-group literature since. On the lab-technology side, Pimenta et al. [2] and Fernandes [3] built automated spectrophotometric devices that made conventional typing faster and more reliable, though still invasive. Ali [4] worked on minutiae-based fingerprint recognition for identity verification, and Sandhu [5] looked at how lip prints, fingerprints, and ABO blood groups correlate for forensic purposes.

Alshehri [6] combined descriptors to match fingerprints across different sensors, while Ezeobiejesi [7] used a patch-based deep learning method to match latent fingerprints even under poor image quality. The two studies nearest to this one are Vijaykumar [9], who built predictive models linking blood groups to fingerprint map features, and Patil [8], who surveyed the wider literature connecting fingerprint patterns to blood groups and lifestyle-related disease. Saponara [10] took a different angle, using a CNN autoencoder to reconstruct fingerprint images from incomplete data. Table 1 lays these studies out side by side.

III. PROBLEM STATEMENT

Standard blood typing means collecting a sample and sending it to a lab—slow, costly, and often impractical when time is short. A growing body of research points to a possible correlation between fingerprint patterns and ABO blood types, which raises the possibility of biometric data standing in for a blood test. But the research base here is thin, and nobody has yet built a computational model that explores the relationship in a systematic way.

This paper builds a CNN-based model to read blood group from fingerprint ridge patterns, trained on a dataset of fingerprint images paired with known blood types. A few obstacles stand in the way: pinning down a statistical correlation solid enough to be useful, gathering a dataset that is both large and diverse, hitting a workable accuracy, handling the privacy questions that come with inferring health information from a biometric, and dealing with the fact that common ridge types like loops and whorls overlap across blood groups, which drags classification accuracy down.

IV. SYSTEM DESIGN

The system design lays out the architecture, modules, interfaces, and data flow needed to meet the stated requirements. At a high level, the pipeline runs from fingerprint acquisition through preprocessing, feature extraction, model training and evaluation, and finally prediction delivery through a web application, shown in Fig. 2.

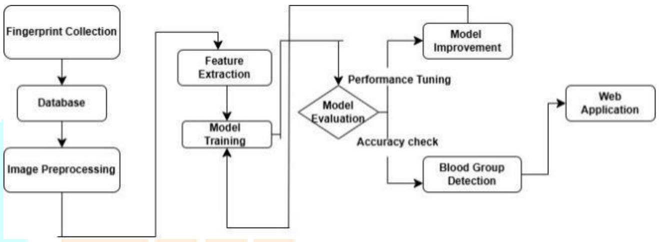

Fig. 2. System architecture / process pipeline.

As Fig. 2 shows, a fingerprint scanner captures the raw image first, and preprocessing cleans and enhances it from there. A CNN-based feature extractor then picks out ridge patterns, and the network trains on these to learn how they relate to blood group labels. Once trained, the model is evaluated, tuned further where needed, and finally used to predict blood group for new fingerprint inputs, with the result sent back through the web application.

Activity, sequence, and class diagrams for the system exist alongside this but are left out here for space; they spell out in more detail how the fingerprint scanner, preprocessing module, feature extractor, CNN classifier, and the web interface's result-display component all interact.

V. IMPLEMENTATION

The implementation runs on Python 3.10.9 inside a virtual environment, built in Visual Studio Code. Flask forms the backend, serving the trained CNN model and handling fingerprint uploads, preprocessing, and prediction requests through a set of RESTful routes. User accounts are managed through a SQLite database via Flask-SQLAlchemy, with Flask-Bcrypt handling password hashing and Flask-Login handling sessions.

A. Libraries and Tools

- TensorFlow/Keras — designs, trains, and evaluates the CNN architecture for fingerprint classification.
- NumPy — handles numerical computation and array manipulation during feature extraction and preprocessing.
- Matplotlib — plots dataset distributions and tracks model performance.
- Pillow/OpenCV — handles image preprocessing: resizing, grayscale conversion, contrast enhancement.

The trained model, saved as blood_group_model.h5, sorts an input fingerprint into one of eight ABO/Rh categories: A+, A−, AB+, AB−, B+, B−, O+, or O−. Each uploaded image is resized to 128×128 pixels, normalized, and fed through the network, and the dashboard displays the predicted class alongside its confidence score.

VI. RESULTS AND DISCUSSION

A. Model Training

Four architectures—CNN, VGG, ResNet, and AlexNet—were trained and tested on the fingerprint dataset, scored on accuracy, precision, recall, and F1-score. The CNN was trained for 200 epochs at a batch size of 32, using the Adam optimizer, ReLU activations, and a categorical cross-entropy loss appropriate for multi-class blood-group classification. To help the model generalize across right-hand, left-hand, and combined fingerprint samples, the training data was augmented with rotation, scaling, and flipping.

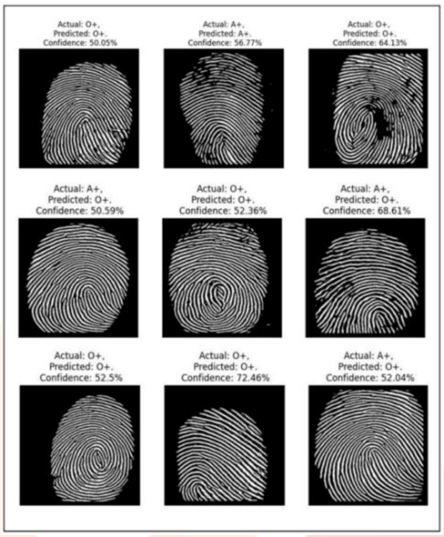

Fig. 3. Sample CNN-based blood group prediction output.

B. Discussion

None of the four models topped 0.76 accuracy, which indicates the fingerprint signal for blood group classification is not distinctive enough to fully separate the classes. The ridge-type statistics explain part of why: within blood group O, for instance, 54% of fingerprints showed loop patterns, 31% whorl, and 15% arch—numbers not that different from the other blood groups. Ridge patterns thought to line up with a particular blood group turned up just as often in samples from other groups, a good sign that fingerprint features on their own cannot reliably predict blood type.

The dataset itself added to the problem. Some participants were reluctant to take part, which limited how diverse the data could get, and rarer blood types ended up underrepresented, leaving a class imbalance the model had to work around. Taken together, these results point to fingerprint-based biometric signals being, at most, a weak statistical hint toward blood group, not something to rely on for prediction.

C. Limitations

- No confirmed direct biological link between fingerprints and blood groups.
- Accuracy rests on statistical trends, not deterministic rules, so results carry inherent uncertainty.
- Poor image quality hurts feature extraction and, in turn, the results.
- The model may not generalize well to populations outside the training set.
- Limited, imbalanced training data leaves the model prone to overfitting.

VII. CONCLUSION AND FUTURE SCOPE

This paper built and tested a fingerprint-based blood group detection system, combining image processing with deep learning to offer a non-invasive, contactless alternative to standard blood typing. Training CNN, VGG, ResNet, and AlexNet models on extracted fingerprint features showed that estimating blood group this way is feasible, at a peak accuracy of 0.76—feasible, though not yet reliable. A statistical association between fingerprint patterns and blood groups does seem to exist, but current models fall short of the accuracy clinical use would demand.

Going forward, a larger and more balanced dataset across all blood groups would help most, alongside testing additional biometric features together with fingerprints and bringing in genetic or clinical validation to give the biological basis more weight. As deep learning architectures and image processing keep improving, they may narrow the gap between biometric pattern recognition and medical diagnostics, pushing fingerprint-based blood typing closer to something both practical and scientifically sound.

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