International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 10 | Oct - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

Fingerprint-Based Blood Group Prediction Using Deep Learning: A Study of Dermatoglyphic Patterns

Ms. Nischitha C B, Assistant Professor
Department of Computer Science, St. Joseph's First Grade College, Mysuru, Karnataka, India

Abstract—This paper presents a software system that explores the prediction of ABO and Rh blood-group classes from fingerprint images using deep-learning-based image classification. The proposed workflow accepts a fingerprint image, preprocesses it, and applies a convolutional neural network (CNN) model implemented through a web application. MobileNetV2 is identified as the primary lightweight architecture, while the report also discusses DenseNet as an alternative architecture. The application supports user registration and login, fingerprint-image upload, prediction display, and storage of prediction history. A Flask backend, TensorFlow/Keras model loading, image-processing utilities, and an SQLite database are described in the implementation. The report includes functional test cases for prediction, upload handling, and error conditions. However, it does not provide sufficient numerical evaluation results to establish clinical accuracy or reliability. Fingerprint-based blood-group prediction should therefore be treated as an experimental research concept and must not replace validated serological blood typing.

Index Terms—Fingerprint analysis, dermatoglyphics, blood-group prediction, convolutional neural network, MobileNetV2, deep learning, image processing.

I. INTRODUCTION

Fingerprints are stable biometric patterns widely used for personal identification. Their ridge structures, including loops, whorls, and arches, are formed during prenatal development and have been studied in relation to inherited traits. Recent image-analysis techniques make it possible to process fingerprint images automatically and investigate potential statistical associations between their features and other biological characteristics.

Conventional blood grouping is performed using validated serological procedures that detect blood-cell antigens. These methods remain essential for clinical decisions and transfusion safety. The project examined here explores whether image-based deep learning can identify patterns associated with blood-group labels, with the longer-term aim of creating an inexpensive, non-invasive screening interface. This study does not establish that fingerprints can determine blood group reliably.

II. RELATED WORK

The project report surveys studies investigating dermatoglyphic patterns and blood groups. A 2021 study involving 178 medical students reported loops as the most common fingerprint pattern and described a possible association with group O. A 2022 cross-sectional study of 200 students, however, reported no strong or consistent relationship between thumbprint patterns and blood groups. Other studies described in the report apply image enhancement, thresholding, thinning, and feature extraction to fingerprint images.

Taken together, the surveyed work suggests that the relationship is uncertain and that image quality, dataset composition, and weak biological association may limit prediction. The report's bibliography lists general works on deep learning, medical-image analysis, and CNN architectures. Full bibliographic metadata should be checked against the original publications before formal submission.

III. SYSTEM OBJECTIVES AND DESIGN

The system is intended to: (1) accept fingerprint images through a web interface; (2) standardize and preprocess images; (3) classify images into eight labels—A+, A−, B+, B−, AB+, AB−, O+, and O−; (4) present the predicted label; and (5) retain prediction history for a logged-in user.

A. Architecture

The reported architecture consists of image acquisition, preprocessing, deep-learning inference, result presentation, and history storage. Users upload a fingerprint image through a Flask-based interface. The backend loads a trained model, resizes the image to 224 × 224 pixels, converts it to an array, normalizes pixel values, and submits it for prediction. The predicted class is selected from a predefined label list and displayed to the user.

B. Data and storage

The implementation uses SQLite tables for user information and prediction history. The history record includes a username, predicted label, image path, phone number, and timestamp. The report also describes optional SMS reporting. Because fingerprint images are sensitive biometric data, access controls, secure storage, retention limits, and protection of credentials are important deployment requirements.

IV. METHODOLOGY

A. Image preprocessing

The methodology describes image resizing, normalization, noise reduction, and fingerprint enhancement. These steps aim to standardize input images and reduce variations caused by capture conditions. The implementation shown in the report loads images at 224 × 224 × 3 and scales pixel values by dividing by 255. An optional preprocessing module is described, with fallback to standard prediction if preprocessing is unavailable.

B. Deep-learning classification

A CNN learns spatial features from image pixels rather than relying exclusively on manually engineered features. MobileNetV2 is proposed because depth-wise separable convolutions reduce computational cost, making it suitable for resource-constrained devices. DenseNet is also discussed as an architecture that promotes feature reuse through dense connections. The report's code loads pretrained model files and uses the highest-scoring output class as the predicted label.

C. Inference pipeline

The system workflow is: (1) capture or upload a fingerprint image; (2) validate and preprocess the image; (3) pass the image to the trained network; (4) map the output index to one of the eight blood-group labels; (5) display the prediction; and (6) store the result in the user's history. A confidence score and model-version record would be useful for traceability, but the report does not document a complete quantitative evaluation of these outputs.

V. IMPLEMENTATION

The reported software stack includes Python 3, Flask, TensorFlow/Keras, NumPy, OpenCV-related preprocessing, and SQLite, with Visual Studio Code as the development environment. The interface includes registration, login, image upload, prediction, and history pages. The backend protects selected routes by checking the login session. The report also describes optional integration with an SMS gateway.

The implementation description contains references to more than one model file and to both MobileNetV2 and DenseNet. For reproducibility, a final paper should identify the exact architecture used for each experiment, model-training configuration, dataset source and size, class distribution, train/validation/test split, and preprocessing parameters. These details are not consistently specified in the available report.

VI. TESTING AND DISCUSSION

The report lists functional test cases for prediction, metric generation, successful image upload, invalid file upload, and submission without an image. The listed test outcomes indicate that the application interface and basic error-handling paths were exercised. The report also describes five-fold cross-validation and confusion-matrix analysis as validation approaches.

No complete set of numerical results—such as test-set accuracy, per-class precision and recall, F1-score, confusion-matrix counts, or confidence intervals—is provided in the material reviewed for this paper. Consequently, no performance percentage is reported here, and the system's predictive accuracy cannot be independently assessed. Passing software-functionality tests demonstrates application behavior, not medical validity.

A rigorous evaluation should use a sufficiently large, diverse, independently labelled dataset; prevent the same participant's fingerprints from appearing across training and test partitions; compare predictions with laboratory-confirmed blood groups; and report per-class metrics and uncertainty. External validation and ethics/privacy review would also be necessary before any health-related use.

VII. LIMITATIONS

The principal limitation is scientific: a dependable biological relationship between fingerprint patterns and ABO/Rh blood groups has not been established by the project report. A model may learn dataset-specific artifacts or class imbalance rather than a causal biological signal. Image capture variation and demographic bias may further affect performance. The system is therefore not suitable for transfusion decisions, emergency treatment, or replacing laboratory testing.

VIII. CONCLUSION AND FUTURE WORK

This paper reformulates a project report describing a web-based fingerprint image classification system for exploratory blood-group prediction. Its workflow combines image preprocessing, CNN inference, a Flask interface, and prediction-history storage. The implementation provides a software foundation for experimentation, but the available report does not establish clinical validity or quantified predictive performance.

Future work should prioritize a scientifically justified study design, larger and more diverse datasets, participant-independent evaluation, comparison of model architectures, explainability methods, secure biometric-data handling, and external validation. Any result should be clearly labelled experimental until independently validated against established serological testing.

REFERENCES

[1] Y. Aamir, R. Masood, N. Irshad, R. Malik, N. Farid, and M. A. Shahab, "Relationship Between Pattern of Fingerprints and Blood Groups," 2021. Full publication details should be verified.

[2] G. Perween, A. K. Prasad, S. Hussain, and A. Abhishek, "Analysis of Thumb Print Patterns in Relation with Blood Group Among Medical Students: A Cross-Sectional Study," 2022. Full publication details should be verified.

[3] M. Prasad and Amrutha, "Blood Group Detection Through Fingerprint Images Using Image Processing," 2023. Full publication details should be verified.

[4] R. Senthilkumar, M. Harish, R. M., and A. Navinkumar, "Innovative Blood Group Prediction Using Fingerprint Patterns," 2024. Full publication details should be verified.

[5] G. Litjens et al., "A Survey on Deep Learning in Medical Image Analysis," Medical Image Analysis, 2017.

[6] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," in Proc. MICCAI, 2015.

[7] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. MIT Press, 2016.

[8] C. Szegedy et al., "Going Deeper with Convolutions," in Proc. IEEE Conference on Computer Vision and Pattern Recognition, 2015.

[9] TensorFlow, "TensorFlow Documentation." Available: https://www.tensorflow.org/ (accessed Oct. 2026).