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Automated Blood Group Detection Using Fingerprint Biometrics and Deep Learning

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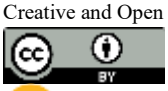

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Abstract---Blood group identification is an important requirement in transfusion medicine, emergency care, surgery, and healthcare record management. Conventional ABO and Rh typing is highly established and normally relies on a biological blood sample and serological reactions. This paper presents an artificial-intelligence-based research prototype that investigates whether fingerprint images can be used as a non-invasive input for predicting the eight common ABO/Rh classes: A+, A−, B+, B−, AB+, AB−, O+, and O−. The proposed pipeline accepts a fingerprint image, performs image quality enhancement and normalization, extracts discriminative ridge features using a convolutional neural network (CNN), and assigns the image to a blood-group class. The system is designed as a screening and decision-support prototype rather than a replacement for clinical blood typing. Recent studies have reported promising classification performance on fingerprint datasets, while other clinical and dermatoglyphic investigations have found inconsistent or statistically weak relationships between fingerprints and blood groups. Therefore, this work emphasizes reproducible image processing, supervised learning.

KEYWORDS
Fingerprint Analysis, Blood Group Prediction, Machine Learning, Image Processing, Deep Learning, Classification

I. INTRODUCTION

Blood group identification is an important component of healthcare and biomedical practice. Accurate identification of blood groups is particularly significant in blood transfusion, emergency medical procedures, blood donation, and other clinical applications. Conventional blood-group identification is generally performed using blood samples and laboratory-based procedures. Although these methods are established and reliable, they require sample collection, appropriate reagents, and laboratory facilities.

Fingerprint biometrics provides a distinctive means of identifying individuals based on the ridge patterns present on their fingers. Fingerprints are widely used in biometric identification because their patterns are highly distinctive and remain relatively stable throughout an individual's lifetime. Beyond personal identification, researchers have investigated whether fingerprint characteristics may exhibit associations with physiological and biological characteristics, including blood-group categories. Fayrouz et al. studied the distribution of fingerprint patterns in relation to ABO and Rh blood groups and reported associations between particular fingerprint patterns and blood-group categories. Similar investigations have subsequently examined the relationship between fingerprint patterns and blood groups in different populations .

The development of machine learning and deep learning has created new possibilities for analyzing complex biometric images. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in automatically learning spatial features from image data. Instead of relying entirely on manually selected fingerprint characteristics, CNN-based models can learn hierarchical representations directly from fingerprint images. Patil and Ingle proposed a CNN-based approach for predicting ABO blood groups from fingerprint images, demonstrating the potential of deep learning for this task . Their subsequent IEEE conference work also investigated blood-group prediction using fingerprint map reading and machine-learning techniques.

More recent research has continued to investigate automated fingerprint-based blood-group prediction. A 2024 IEEE conference study explored deep-learning-based blood-group prediction using fingerprint images [5]. Another IEEE study presented a non-invasive fingerprint-based approach involving image preprocessing, feature extraction, and classification for predicting ABO and Rh blood groups [6]. These developments indicate growing interest in combining biometric image analysis with artificial intelligence for blood-group prediction.

Despite these developments, the task remains challenging because fingerprint images can vary considerably in quality, acquisition conditions, ridge patterns, and representation across individuals. In addition, the reliability of a prediction model depends strongly on the size, quality, and diversity of the labeled dataset used for training and evaluation. Therefore, further investigation is required to develop robust computational approaches and evaluate their performance under controlled experimental conditions.

In this work, an automated blood group prediction system based on fingerprint biometrics and artificial intelligence is proposed. The system performs fingerprint image preprocessing and uses a CNN-based classification model to learn relevant fingerprint features and predict the corresponding blood-group category. The proposed framework is intended to provide an automated and non-invasive prediction approach for research purposes. The system is evaluated using standard performance measures, and its results are analyzed to understand the effectiveness and limitations of fingerprint-based blood-group classification.

II. LITERATURE REVIEW

A. Traditional Academic Systems

Traditional blood-group identification is performed using laboratory-based methods involving a blood sample. These methods are designed to determine blood-group characteristics through established testing procedures. They provide a reference for evaluating experimental approaches such as the system presented in this paper.

From a computational perspective, traditional testing does not require image classification or deep-learning algorithms. The proposed project differs because it attempts to infer the blood-group label from a fingerprint image using a supervised machine-learning model.

B. Rule-Based Chatbot Systems

Rule-based systems are not directly related to fingerprint classification. However, conventional image-classification systems can similarly depend on manually selected features and predefined decision rules. Traditional fingerprint-processing approaches may extract features such as ridge characteristics, texture information, minutiae, and other structural properties before applying a classifier.

The limitation of manually designed features is that their effectiveness depends strongly on the selected feature-extraction technique and image quality. Deep-learning approaches provide an alternative by allowing the model to learn useful image representations directly from labelled training data.

C. Large Language Model Systems

Large Language Models are primarily designed for processing and generating natural language and are therefore not the primary technology used in the proposed system. The input to the present project is an image rather than a textual query.

For fingerprint classification, CNN-based architectures are more directly suited to learning spatial patterns from images. The proposed system therefore uses a CNN rather than a language model.

D. Retrieval-Augmented Generation

Retrieval-Augmented Generation is not used in the supplied fingerprint blood-group detection project. Instead, the proposed system follows a supervised image-classification approach. Fingerprint images with corresponding blood-group labels are used to train a CNN model.

The main research challenge is therefore not document retrieval but the quality of the labelled fingerprint dataset, consistency of preprocessing, class imbalance, and the ability of the trained model to generalize to previously unseen fingerprint images.

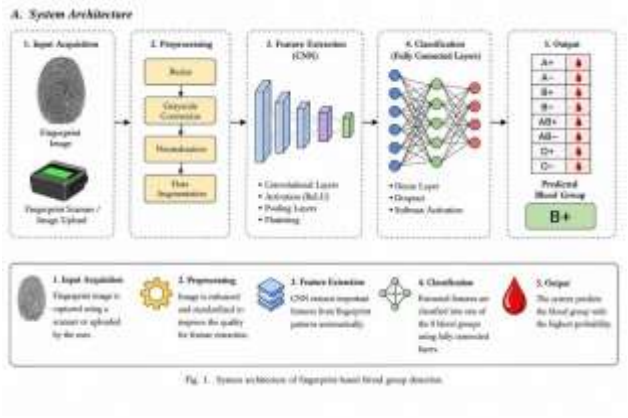
III. PROPOSED SYSTEM

A. System Architecture

The proposed system consists of a fingerprint dataset, preprocessing pipeline, CNN classification model, model-storage component, Flask backend, and web-based user interface.The overall architecture begins with a fingerprint image. During training, the images are validated and organized into the eight blood-group classes. The images are resized to 128×128 pixels and converted to RGB representation. Pixel values are normalized to the required range.

The CNN contains four major convolutional blocks. The blocks use 32, 64, 128, and 256 filters respectively. Each convolutional stage is followed by operations such as batch normalization, ReLU activation, max pooling, and dropout. These operations enable the model to learn increasingly complex visual representations while reducing the spatial dimensions of the feature maps.

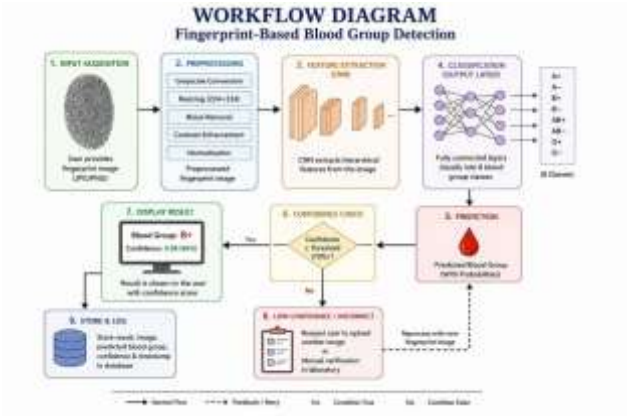
After the convolutional feature-extraction stages, Global Average Pooling is applied. The resulting representation is passed to a dense layer containing 128 neurons with ReLU activation. Dropout is applied before the final classification layer. The final layer contains eight output neurons corresponding to the eight blood-group classes.



B. System Workflow

The system workflow begins when a fingerprint image is provided to the application. The uploaded image is validated before processing. The application converts the image into RGB format and resizes it to 128×128 pixels.

The processed image is then normalized using the same preprocessing procedure used during model training. The resulting image tensor is passed to the trained CNN model.



The CNN generates a probability distribution over the eight blood-group classes. The class having the highest probability is selected as the predicted blood group. The web application displays the predicted label and confidence information to the user.

The complete workflow can be represented as:

Start → Upload Fingerprint → Validate Image → Resize → Normalize → CNN Prediction → Calculate Class Probabilities → Select Highest Probability → Display Blood Group → End

C. Mathematical Model

Let X represent a preprocessed fingerprint image and let fθ represent the trained CNN model parameterized by θ. The model generates a probability for each blood-group class.

The probability assigned to class i is represented as:

$$P(C_i \mid X) = f\theta(X)_i$$

where C_i represents one of the eight blood-group classes.

The predicted class is determined using:

$$\hat{C} = \arg\max_i P(C_i \mid X)$$

where $\hat{C}$ represents the predicted blood-group class.

The model is trained using sparse categorical cross-entropy as the classification loss. The Adam optimization algorithm is used to update the model parameters during training.

IV. METHODOLOGY AND EVALUATION

A. Data Collection

The supplied project contains fingerprint images organized into eight blood-group categories. After dataset preparation and validation, the total number of usable images is 5,985.

The eight classes and their image counts are shown in Table I.

TABLE I

DATASET DESCRIPTION

Blood Group	No. of Images	Training	Validation	Test
A+	565	395	85	85
A−	1008	706	151	151
AB+	648	454	97	97
AB−	741	519	111	111
B+	705	493	106	106
B−	760	532	114	114
O+	851	595	128	128
O−	707	495	106	106
Total	**5985**	**4189**	**898**	**898**

The dataset preparation process is an important component of the project. The supplied preparation pipeline validates image files and removes unsuitable

data. It also addresses known dataset-organization issues and removes exact duplicate images.

The final split uses approximately 70% of the data for training, 15% for validation, and 15% for testing. Stratification is used to maintain class representation across the subsets.

The dataset is not perfectly balanced. For example, A− contains substantially more images than A+, while O+ also contains a relatively large number of samples. This imbalance is considered during training through the use of class weights.

B. System Implementation

The project is implemented using Python and TensorFlow/Keras for deep learning. Image processing is performed using appropriate Python image-processing libraries, while Flask is used to expose the trained model through a web application.

The input image is resized to **128×128 pixels** and converted into RGB format. Pixel values are normalized by scaling them to the range required by the trained model.

The training pipeline applies augmentation only to training images. The augmentation operations include transformations such as rotation, translation, zoom, and contrast adjustment. Applying augmentation only to the training data prevents artificially modified validation and test samples from affecting the evaluation.

Class weights are also calculated from the training distribution. This helps reduce the influence of class imbalance during optimization.

The CNN architecture used by the supplied project contains four convolutional stages:

- First convolutional block: 32 filters
- Second convolutional block: 64 filters
- Third convolutional block: 128 filters
- Fourth convolutional block: 256 filters

These blocks are followed by Global Average Pooling, a 128-neuron dense layer, dropout, and the eight-class softmax output layer.

The training configuration also uses mechanisms such as early stopping, model checkpointing, and learning-rate reduction. The best model is selected according to validation performance.

fig. 3. Implementation block diagram based on the supplied project.

During prediction, the application loads the trained model and class metadata. This is important because the mapping between output indices and blood-group names must remain identical during both training and inference.

C. Evaluation

The model is evaluated using an independent test set that is not used for model training. This is necessary to obtain an unbiased estimate of how the classifier performs on unseen fingerprint images.

The training process uses the validation set for monitoring model performance and selecting the best checkpoint. After training, the best model is restored and evaluated on the test set.

The evaluation should include overall accuracy and class-level performance. A confusion matrix is particularly useful for this project because it shows which blood-group classes are being confused by the model.

The supplied project artifacts contain the training and evaluation pipeline but do not contain the final results of a completed corrected retraining run. Therefore, numerical performance values should be inserted only after the final model has been trained and evaluated.

This avoids reporting an estimated or fabricated accuracy.

fingerprint-based blood-group classification through a web interface

D. Evaluation Metrics

Several metrics can be used to evaluate the eight-class classification model.

1) Accuracy

Accuracy represents the proportion of correctly classified test samples:

Accuracy = Correct Predictions / Total Predictions

2) Precision

Precision measures the proportion of samples predicted as a particular class that actually belong to that class.

Precision = TP / (TP + FP)

3) Recall

Recall measures the proportion of actual samples belonging to a class that are correctly predicted.

Recall = TP / (TP + FN)

4) F1-Score

The F1-score combines precision and recall:

F1 = 2 × (Precision × Recall) / (Precision + Recall)

5) Confusion Matrix

A confusion matrix provides a class-by-class representation of the predictions. It can identify whether particular blood groups are frequently confused with other classes.

VI. CHALLENGES

A. Hallucination and Reliability

Although hallucination is primarily associated with generative AI systems, reliability is equally important in the proposed classification system. A CNN can produce a probability distribution even when the input image does not contain sufficient information for a reliable classification.

A high confidence score should therefore not automatically be interpreted as medical certainty. Model confidence and actual correctness are different concepts.

For this reason, evaluation on an independent test set is necessary. In addition, class-level metrics and a confusion matrix should be reported instead of relying only on overall accuracy.

B. Multilingual Understanding

Multilingual understanding is not directly applicable to the current project because the proposed system processes fingerprint images rather than natural-language queries.

The corresponding challenge for this system is image variability. Fingerprint images can differ in quality, scale, orientation, contrast, background, and acquisition device. These differences can influence the model's predictions.

C. Document Quality and Retrieval

Document retrieval is not used in the proposed system. Instead, the corresponding concern is dataset quality and label reliability.

The supplied dataset-preparation pipeline performs image validation and handles known organizational issues. Exact duplicate images are also removed to reduce the possibility of duplicate information being present across dataset subsets.

Correct blood-group labels are particularly important because supervised learning depends on the relationship between the input image and its assigned target class.

D. Computational Resources

Training a CNN requires more computational resources than making a single prediction. The supplied project uses batch-based training and multiple training-control mechanisms to manage the training process.

The trained model can subsequently be used for inference through the Flask application. Once the model is loaded, prediction for an individual fingerprint image is considerably less computationally demanding than training.

The computational requirement also depends on the CNN architecture, batch size, number of epochs, image resolution, and available hardware.

VII. FUTURE TRENDS

A. AI-Based Personalized Academic Assistance

This subsection is retained to follow the structure of the supplied IEEE paper, but academic assistance is not a direct component of the fingerprint blood-group project.

A project-specific future direction would instead be personalized image-quality assessment. Before classification, the system could determine whether a fingerprint image is sufficiently clear, correctly positioned, and suitable for processing.

B. Voice-Based Multilingual Interaction

Voice interaction is not part of the current system. A more relevant future extension would be a mobile application that guides users while capturing fingerprint images.

The application could provide feedback regarding image quality, positioning, lighting, and whether another fingerprint capture is required.

C. Intelligent Agentic RAG Systems

RAG-based systems are outside the scope of the current project. Future research should instead investigate more advanced CNN architectures and transfer-learning approaches.

Additional research could include:

- Transfer learning
- Ensemble learning
- Explainable AI
- Improved image preprocessing
- Advanced augmentation
- Cross-device testing
- Cross-dataset validation
- Calibration of prediction confidence

Explainability methods could also be used to investigate which visual regions contribute most strongly to a model's prediction.

D. Cloud-Based Multi-Institution Systems

The existing Flask-based application can potentially be deployed on a server or cloud platform. A future cloud implementation could support centralized model deployment and controlled access.

However, storing fingerprint information introduces important privacy and security considerations because fingerprints are biometric data. Any real deployment would require appropriate data protection, access control,

secure transmission, and responsible handling of biometric information.

VIII. CONCLUSION

This paper presented an experimental deep-learning approach for blood-group classification from fingerprint images. The proposed system combines fingerprint image preprocessing, a convolutional neural network, multi-class classification, model evaluation, and a Flask-based web application.

The supplied project contains 5,985 valid fingerprint images distributed among eight blood-group classes: A+, A−, AB+, AB−, B+, B−, O+, and O−. The dataset is divided into training, validation, and testing subsets using a stratified 70:15:15 split. The training pipeline incorporates image augmentation and class weighting to address variability and class imbalance.

The CNN architecture uses four convolutional blocks with increasing filter sizes of 32, 64, 128, and 256, followed by global average pooling, a 128-unit dense layer, dropout, and an eight-class softmax output. The model is connected to a Flask application that accepts fingerprint images and returns the predicted blood-group class.

The experimental nature of the proposed approach is an important consideration. The model's performance must be established using an independent test dataset, and the final accuracy, precision, recall, F1-score, and confusion matrix should be obtained from the final training and evaluation run. No unsupported performance values have been reported in this paper.

Future work should focus on increasing dataset diversity, performing cross-dataset and cross-device validation, investigating stronger architectures, improving explainability, and comparing predictions with independently verified blood-group measurements. Most importantly, extensive scientific and clinical validation would be required before such a system could be considered for any real-world medical application.

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