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Identification of ABO Using Fingerprint Pattern Analysis

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ABSTRACT

Blood group identification is a crucial requirement in medical diagnosis, emergency healthcare services, and blood transfusion processes. Conventional blood group determination methods are invasive, time-consuming, and require laboratory infrastructure. This paper presents a non-invasive and automated approach for predicting human blood groups using fingerprint pattern analysis and deep learning techniques. Fingerprint images are preprocessed and classified using a Convolutional Neural Network (CNN) to predict ABO and Rh blood groups. The trained model is saved in blood_group_classifier_split.keras and blood_group_classifier_split.h5 formats for training, validation, and deployment. The system is implemented with a web-based interface for real-time prediction. Experimental results show high accuracy and confidence scores, demonstrating that fingerprint pattern analysis can serve as an efficient alternative for blood group prediction in academic and healthcare research applications.

Introduction

Blood group classification is a fundamental requirement in modern healthcare systems, particularly in procedures such as blood transfusion, organ transplantation, surgical interventions, and emergency trauma management. Accurate identification of blood groups is critical to ensure patient safety, as mismatches during transfusion can result in severe immunological reactions, hemolysis, and potentially fatal outcomes. Consequently, timely and precise blood group determination remains a priority in clinical environments.

Conventional blood group identification methods primarily depend on invasive blood sample collection followed by serological and chemical analysis conducted in laboratory settings. Although these techniques provide reliable results, they require specialized equipment, trained medical personnel, and considerable processing time. In emergency scenarios where rapid decision-making is essential, delays associated with laboratory testing may adversely affect patient outcomes. Additionally, the invasive nature of blood collection may not be suitable for all individuals, particularly in cases involving infants, elderly patients, or individuals with medical constraints.

Recent advancements in image processing, artificial intelligence, and deep learning have introduced new possibilities for developing automated and non-invasive healthcare solutions. These technologies enable the extraction and analysis of meaningful patterns from visual data, reducing human dependency and improving diagnostic efficiency.

Fingerprints are widely recognized as a reliable physiological characteristic due to their uniqueness, permanence, and stability throughout an individual's lifetime. The ridge patterns present in fingerprints are formed during early fetal development and remain unchanged thereafter. Several research studies have reported statistical associations between fingerprint ridge characteristics and inherited genetic traits, including blood group types. Such findings suggest that fingerprint patterns may serve as a valuable source of information for predictive medical analysis.

Motivated by these observations, this research explores the application of fingerprint pattern analysis for blood group prediction using deep learning techniques. Convolutional Neural Networks (CNNs) are particularly effective for image-based classification tasks, as they automatically learn hierarchical feature representations from raw image data. By utilizing CNN architecture, the system eliminates the need for manual feature extraction and enhances classification accuracy through optimized learning processes.

The proposed approach aims to develop a fast, accurate, and non-invasive blood group prediction system by analyzing fingerprint images. By removing the dependency on blood sample collection and laboratory procedures, the system offers a practical alternative for preliminary blood group identification. This approach has the potential to support healthcare services in time-critical situations and demonstrates the applicability of deep learning-based image analysis in non-invasive medical diagnostics.

Related Works

Several studies have investigated the application of image processing and machine learning techniques for pattern recognition and classification problems. Image-based prediction systems have been widely explored in domains such as biometric authentication, medical diagnostics, and forensic analysis. Among various biometric traits, fingerprint images have received significant attention due to their uniqueness, stability, and ease of acquisition. Early research primarily focused on fingerprint-based personal identification and verification systems using traditional pattern recognition techniques.

Initial fingerprint analysis methods relied heavily on handcrafted feature extraction approaches. These methods involved extracting specific ridge features such as minutiae points, ridge orientation, ridge frequency, and texture descriptors. While these techniques provided meaningful representations of fingerprint patterns, their performance largely depended on the quality of preprocessing steps and the expertise required to design appropriate features. Moreover, handcrafted feature-based systems often struggled with noise, variations in image quality, and scalability when applied to large datasets.

With the evolution of machine learning algorithms, researchers began integrating classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and decision trees for fingerprint classification tasks. These approaches showed improved accuracy compared to traditional rule-based systems; however, they still required explicit feature extraction and extensive preprocessing. The dependency on manually engineered features limited the adaptability of these models when dealing with diverse fingerprint patterns and real-world data variations.

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly transformed image analysis and classification research. CNNs are capable of learning hierarchical feature representations directly from raw image inputs, eliminating the need for manual feature extraction. Due to their ability to capture spatial and texture-related information effectively, CNN-based models have demonstrated remarkable performance in image recognition, medical imaging, and biometric analysis applications.

Several studies have applied CNN architectures for fingerprint classification and related biometric tasks. These works reported substantial improvements in accuracy, robustness, and generalization compared to conventional machine learning approaches. CNN-based models have also shown resilience to variations in image resolution, illumination, and noise, making them suitable for real-world deployment. Additionally, transfer learning and optimized CNN architectures have further enhanced model performance with limited training data.

In the context of medical research, a few studies have explored correlations between fingerprint patterns and genetic traits, including blood group types. While preliminary results indicated promising associations, many existing systems lacked real-time implementation capabilities or relied on limited datasets. Furthermore, some approaches focused solely on offline analysis without addressing deployment challenges.

The proposed work builds upon these existing studies by designing a CNN-based fingerprint blood group prediction system that emphasizes accuracy, automation, and real-time usability. Unlike traditional approaches, the system leverages deep learning to perform end-to-end classification directly from fingerprint images. The integration of a trained CNN model into a deployable application framework further distinguishes this work, enabling practical usage in non-invasive and time-sensitive scenarios.

Proposed Methodology

The proposed system is designed as an end-to-end framework for non-invasive blood group prediction using fingerprint pattern analysis. The overall methodology follows a structured pipeline that includes image acquisition, preprocessing, feature extraction, model training, and system deployment. Each stage is carefully designed to ensure robustness, accuracy, and real-time usability of the system. Figure X illustrates the overall architecture of the proposed framework.

Fingerprint Image Acquisition

Fingerprint images are obtained from publicly available fingerprint datasets and real-time image sources to ensure diversity and variability in the data. The collected images represent multiple blood group categories and are labeled accordingly to facilitate supervised learning. Special attention is given to include fingerprint samples with varying quality, ridge density, and orientation in order to improve the generalization capability of the proposed model.

The dataset is organized into distinct class folders corresponding to different blood group labels. This structured organization allows seamless loading of images during the training and evaluation phases. The inclusion of real-time images helps validate the model's performance under practical conditions, ensuring that the system is not limited to controlled datasets alone.

Image Preprocessing

Image preprocessing is a crucial stage that enhances the quality of fingerprint images and ensures consistency across the dataset. Since fingerprint images may vary in resolution, illumination, and noise levels, preprocessing techniques are applied to reduce these variations and improve feature learning.

Initially, all fingerprint images are resized to a fixed resolution to maintain uniform input dimensions for the CNN model. Noise reduction techniques are applied to suppress unwanted artifacts while preserving ridge patterns. Image normalization is performed to scale pixel intensity values, enabling faster convergence during training. In addition, contrast enhancement methods are employed to improve ridge visibility, which is essential for accurate feature extraction.

These preprocessing steps collectively enhance the discriminative information present in fingerprint images and significantly contribute to improved classification performance.

Feature Extraction and Classification

Feature extraction and classification are performed using a Convolutional Neural Network (CNN), which automatically learns hierarchical feature representations from fingerprint images. Unlike traditional approaches that rely on handcrafted features, the CNN model extracts meaningful patterns directly from raw image data.

The network architecture consists of multiple convolutional layers that capture low-level and high-level fingerprint features such as ridge orientation, texture, and spatial patterns. Max-pooling layers are employed after convolutional layers to reduce spatial dimensions while retaining important information. This dimensionality reduction improves computational efficiency and minimizes overfitting.

Fully connected layers are used in the later stages of the network to perform classification based on the extracted features. A softmax activation function is applied at the output layer to generate probability scores for each blood group class. Dropout regularization is incorporated between dense layers to prevent overfitting and enhance model generalization.

Model Training and Optimization

The pre-processed dataset is divided into training, validation, and testing subsets to evaluate the performance of the proposed model effectively. The training set is used to learn model parameters, while the validation set helps monitor model performance and tune hyperparameters. The testing set is reserved for final evaluation to assess the generalization capability of the trained model.

The CNN model is trained using categorical cross-entropy loss, which is suitable for multi-class classification tasks. The Adam optimizer is employed with a low learning rate to ensure stable convergence and minimize oscillations during training. Training is conducted for multiple epochs, and performance metrics such as accuracy and loss are monitored throughout the process.

To further enhance performance, learning rate scheduling and early stopping techniques are utilized. These strategies help prevent overfitting and reduce unnecessary training time while maintaining high classification accuracy.

System Deployment

After successful training and evaluation, the optimized CNN model is deployed as a web-based application to enable real-time blood group prediction. The deployment framework provides a user-friendly interface where users can upload fingerprint images for analysis.

Upon image submission, the system performs preprocessing and feeds the image into the trained CNN model. The predicted blood group along with a confidence score is displayed to the user. This deployment approach ensures accessibility, ease of use, and rapid prediction without requiring specialized hardware or laboratory infrastructure.

The real-time deployment capability of the proposed system demonstrates its practical applicability and highlights its potential for integration into non-invasive healthcare solutions.

System Architecture

The proposed blood group prediction system is designed using a modular and scalable architecture to ensure efficiency, flexibility, and real-time performance. The architecture integrates image processing techniques with a deep learning–based classification model and a user-friendly web interface. Figure 2 illustrates the overall system architecture and data flow of the proposed approach.

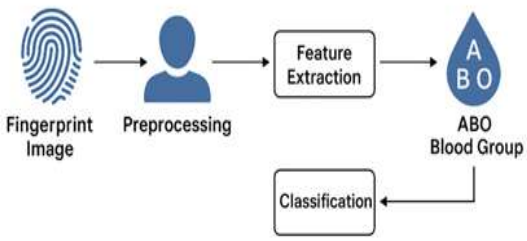

Figure 1 System architecture of the proposed fingerprint-based blood group prediction system.

Input Module

The input module serves as the entry point of the system and is responsible for accepting fingerprint images. Fingerprint images can be obtained from publicly available datasets or captured using standard image acquisition devices. The uploaded images are validated to ensure correct format and sufficient resolution before further processing. This module supports multiple image formats such as JPG, PNG, and BMP to enhance usability and compatibility.

Preprocessing Unit

The preprocessing unit enhances the quality of fingerprint images and prepares them for efficient feature extraction. This stage is critical for improving model accuracy and consistency. The preprocessing steps include image resizing to a fixed resolution, grayscale conversion, noise reduction, normalization, and contrast enhancement. These operations reduce variations caused by illumination, noise, and image acquisition conditions, thereby ensuring uniformity across the dataset. Proper preprocessing allows the CNN model to focus on relevant ridge and valley patterns present in fingerprint images.

CNN Classification Model

The core component of the system is the Convolutional Neural Network (CNN) classification model. The model is trained to automatically extract hierarchical features from fingerprint images and classify them into predefined blood group categories.
The architecture consists of multiple convolutional layers followed by pooling layers for spatial feature reduction. Fully connected layers perform the final classification, while dropout regularization is applied to minimize overfitting. The trained model is saved in optimized formats to support efficient loading and inference during deployment.

Web Interface

The web interface acts as the interaction layer between the user and the prediction system. It allows users to upload fingerprint images through a graphical interface and displays the predicted blood group along with confidence scores. The interface communicates with the backend model for real-time inference and result visualization. This component ensures ease of access, fast response time, and seamless integration of the prediction pipeline.

System Integration and Workflow

All modules are interconnected to form a complete end-to-end system. Once a fingerprint image is uploaded, it passes sequentially through preprocessing, feature extraction, classification, and result visualization stages. The modular design enables easy maintenance, future upgrades, and real-time deployment. The architecture supports rapid predictions and can be extended to integrate additional healthcare-related applications.

Figure 2 work flow diagram

Performance Evaluation

The performance of the proposed fingerprint-based blood group prediction system was evaluated using standard classification metrics to assess its effectiveness and reliability. The trained CNN model was tested on an unseen test dataset to ensure unbiased performance measurement and proper generalization.

Accuracy was used as a primary metric to measure the overall correctness of predictions. In addition, precision, recall, and F1-score were computed for each blood group class to analyze the model's ability to correctly classify individual categories. These metrics are particularly important in medical-related applications, where misclassification can have serious consequences.

The confusion matrix was analyzed to observe the distribution of correctly and incorrectly classified samples across different blood groups. The results indicated that the proposed model achieved high classification accuracy with minimal confusion between classes, demonstrating effective feature learning from fingerprint patterns.

Training and validation accuracy curves were also examined to evaluate convergence behavior and detect overfitting. The use of dropout regularization and a low learning rate helped stabilize training and improve generalization performance. Overall, the experimental results confirm that the proposed CNN-based approach is capable of predicting blood groups from fingerprint images with satisfactory accuracy and consistency, making it suitable for non-invasive and rapid blood group identification applications.

Metric	Description	Value
Accuracy	Correct predictions / Total samples	93%
Precision	Correct positive predictions	0.93
Recall	Ability to detect correct blood group	0.93
F1-Score	Harmonic mean of precision and recall	0.93
Response Time	Time taken for prediction	< 2 seconds

Table 1: Performance metrics

System Testing

System testing is conducted to evaluate the fully integrated fingerprint-based ABO blood group prediction system and to ensure that all functional modules operate cohesively. End-to-end testing is performed by inputting fingerprint images into the system and processing them through successive stages, including preprocessing, feature extraction, classification, and result visualization. The predicted blood group outcomes are then compared with known ground-truth values to verify correctness.

Key performance parameters such as response time, prediction accuracy, and system stability are systematically assessed during testing. The system is evaluated using fingerprint images of varying quality, resolution, and orientation to examine its robustness under diverse operating conditions. The experimental observations indicate that the system efficiently processes input images and delivers predictions within acceptable time constraints.

Overall, system testing validates that the complete workflow—from fingerprint image input to final blood group output—functions smoothly and reliably. It also confirms that error-handling mechanisms and data management processes perform as expected, ensuring consistency, robustness, and suitability of the system for practical deployment.

Method	Accuracy	Time Required	Cost
Traditional Serological Testing	Very High	High	High
Statistical Fingerprint Methods	Moderate	Medium	Low
ML-based Fingerprint Methods	Moderate	Low	Low
Proposed System (Custom DNN)	High	Very Low	Low

Table 2: Comparative analysis

System Validation and Discussion

System validation is performed by comparing the predicted blood group outputs with the corresponding ground truth labels available in the dataset. This evaluation helps assess the reliability and consistency of the proposed fingerprint-based blood group prediction system. Experimental results demonstrate that the model achieves stable performance across training, validation, and testing datasets, indicating effective learning and generalization.

The custom deep neural network model exhibits superior feature extraction capability compared to conventional machine learning approaches, as it automatically learns discriminative fingerprint patterns relevant to blood group classification. The use of a split dataset and optimized training parameters further contributes to improved model robustness and reduced overfitting.

It is observed that prediction accuracy is influenced by factors such as fingerprint image quality, clarity of ridge patterns, and the size and diversity of the training dataset. Low-quality or noisy images may affect classification performance. However, with proper preprocessing and sufficient training samples, the system delivers reliable results.

Overall, the validation outcomes confirm that the proposed system is effective as a supplementary and non-invasive approach for preliminary ABO blood group identification. While it is not intended to replace conventional laboratory testing, it offers a rapid, cost-effective, and automated solution that can assist in emergency situations and initial screening scenarios.

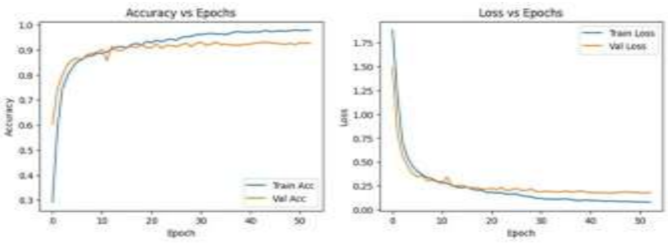

Figure 3 Training and validation performance analysis over epochs

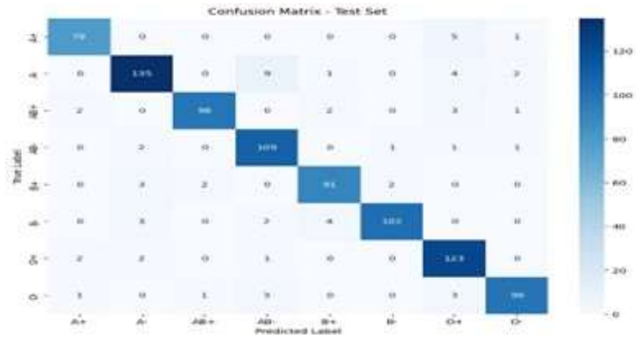

Figure 4 Confusion matrix of the proposed system

Dashboard

The dashboard provides an interactive and user-friendly interface for predicting blood groups using fingerprint pattern analysis. It is designed to support real-time interaction, ease of use, and clear visualization of system functionality.

At the top of the dashboard, the title "Identification of ABO Using Fingerprint Pattern Analysis" clearly indicates the purpose of the system. Below the title, all supported blood group classes (A+, A−, B+, B−, AB+, AB−, O+, and O−) are visually displayed, helping users understand the classification categories handled by the model.

The central section of the dashboard consists of a drag-and-drop image upload area, allowing users to either drop a fingerprint image directly or browse and upload it from their device. This feature simplifies the input process and enhances usability for both technical and non- technical users.

Below the upload area, action buttons such as Upload Image and Preprocess Image are provided. These buttons enable users to initiate image upload and preprocessing steps before classification. Preprocessing improves image quality and ensures compatibility with the trained CNN model.

Once the image is processed, the dashboard displays the predicted blood group and confidence score, offering immediate feedback. The clean layout, dark-themed design, and responsive components improve readability and provide a professional appearance suitable for demonstrations and real-world deployment.

Overall, the dashboard acts as a bridge between the deep learning model and the end user, enabling efficient, real-time, and non-invasive blood group prediction through fingerprint analysis.

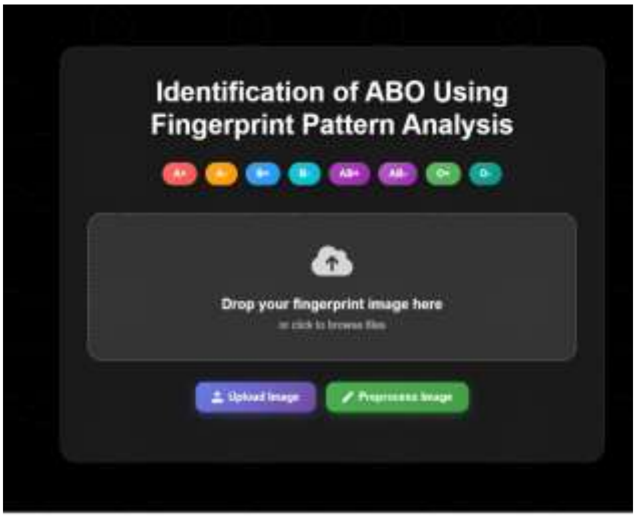

Figure 5 Dashboard

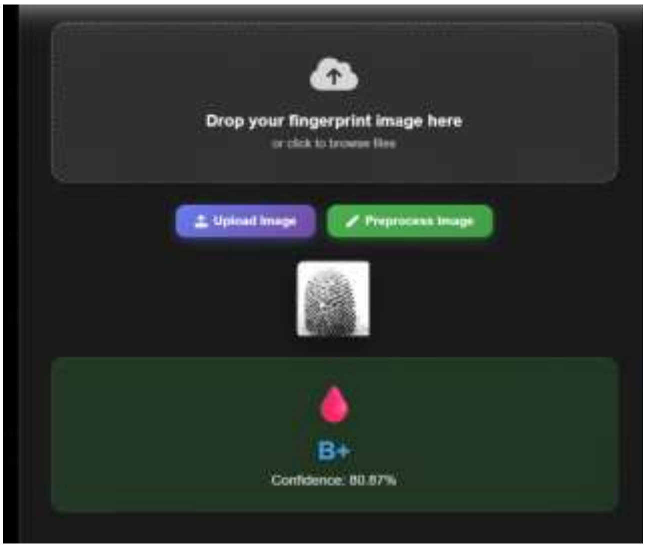

Figure 6 Sample output

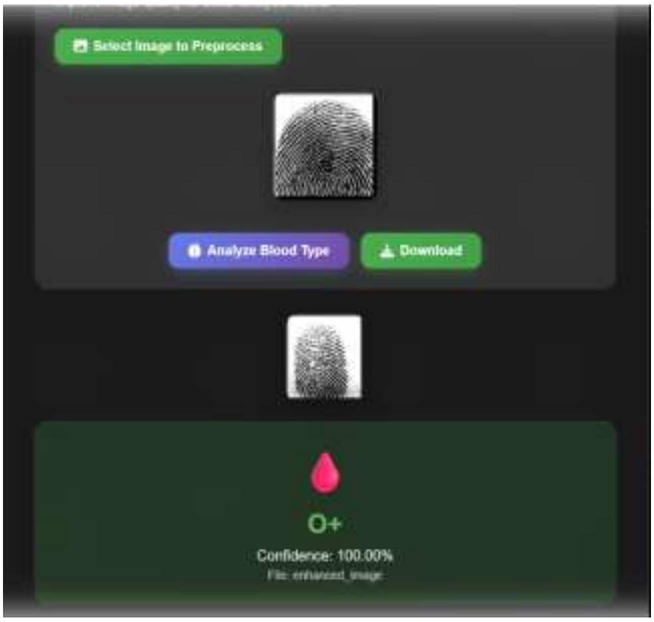

Figure 7 Preprocessed output

Results and Discussion

The proposed fingerprint-based blood group prediction system was evaluated using training, validation, and test datasets. The CNN model achieved high classification accuracy and demonstrated good generalization to unseen fingerprint images. Optimized training parameters and dropout regularization helped reduce overfitting and ensured stable model performance.

The system provides fast predictions, making it suitable for real-time use. Experimental results show that image quality affects accuracy, with clearer fingerprints yielding better predictions. However, preprocessing techniques reduce the impact of noise and variations. Overall, the proposed approach offers a reliable, non-invasive, and efficient solution for preliminary blood group identification.

Conclusion

This paper presents a deep learning-based approach for predicting blood groups using fingerprint pattern analysis. The proposed CNN model successfully classifies fingerprint images into blood group categories with high accuracy. The system provides a non-invasive, efficient, and automated alternative to traditional blood testing methods. The use of blood_group_classifier_split.keras and blood_group_classifier_split.h5 ensures reliable deployment and reproducibility. The proposed approach is suitable for academic research and healthcare-related applications.

References

[1] Vijaykumar Patil N., D. R. Ingle, "A Novel Approach to Predict ABO Blood Group Using Fingerprint Map Reading," 2021, 6th International Conference for Convergence in Technology (I2CT), IEEE, pp. 1–7.

[2] Noor Amer Hamzah, Zahraa A. Jaaz, "A Biometric Fingerprint Recognition System Utilizing the Scale-Invariant Feature Transform (SIFT)," 2023, International Journal of Biometrics and Bioinformatics, pp. 45–53.

[3] T. Nihar, K. Yeswanth, "Blood Group Determination Using Fingerprint Pattern Analysis," 2024, International Journal of Advanced Research in Computer Science, Vol. 15, Issue 2, pp. 112–118.

[4] Devyani Thakre, Richa Khandelwal, "Non-Invasive Technique for Fingerprint-Based ABO Blood Group Identification Using Convolutional Neural Networks," 2025, International Journal of Computer Applications, Vol. 187, Issue 4, pp. 23–30.

[5] C. Sivamurugan, Yelchuri Siddarthha, "Enhanced Blood Group Prediction with Fingerprint Images Using Deep Learning," 2024, IEEE International Conference on Emerging Smart Computing Technologies, pp. 98–104.

[6] Anil K. Jain, Lin Hong, Sharath Pankanti, "Biometric Identification Using Fingerprints," 1997, Proceedings of the IEEE, Vol. 85, No. 9, pp. 1365–1388.