A Review on Non-Invasive Blood Group Prediction Using Fingerprint and Image Processing

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Abstract

The blood group identification is critical for blood transfusions, organ transplantation, and emergency medical care. Conventional methods rely on invasive blood sampling and laboratory testing, which are time-consuming and resource-dependent. Recent advances in biometrics and artificial intelligence have enabled non-invasive alternatives, particularly fingerprint-based blood group detection. Fingerprint ridge patterns, influenced by genetic factors, exhibit correlations with ABO and Rh classifications. This review systematically analyzes existing approaches ranging from image processing and statistical models to deep learning architectures such as CNN, ResNet, and hybrid multimodal frameworks. Comparative evaluation shows that deep learning models achieve accuracies exceeding 95%, significantly outperforming traditional methods. The paper highlights current trends, challenges in dataset standardization, and future opportunities for explainable AI, multimodal biometrics, and portable healthcare solutions. The findings indicate that fingerprint-driven, AI-powered systems can provide rapid, accurate, and scalable blood group identification, offering strong potential for clinical and forensic applications.

Keywords: Blood group determination, fingerprint pattern, Convolutional neural networks (CNN), image processing, pattern recognition, Blood Groups.

1. Introduction

Blood group determination is a fundamental diagnostic tool in medicine, with direct implications in blood transfusions, organ transplantation, forensic identification, and emergency medical care. Accurate blood typing is essential for preventing transfusion-related complications such as hemolytic reactions, which may be fatal if incompatible blood is administered. According to the World Health Organization (WHO), millions of blood transfusions are performed each year, and even minor errors in blood group identification can have life-threatening consequences. Traditionally, blood group determination is performed through serological methods such as the slide test, tube test, and gel card method. These techniques rely on the detection of agglutination reactions when red blood cells interact with specific antibodies. While widely adopted, such approaches are invasive, resource-intensive, time-consuming, and dependent on laboratory infrastructure and skilled personnel. In emergency settings, where rapid decision-making is critical, these constraints significantly limit the effectiveness of conventional blood group testing. Furthermore, manual interpretation of agglutination often introduces human errors, leading to inconsistencies and reduced reliability.

In recent years, the convergence of biometrics, artificial intelligence (AI), and medical imaging has opened new possibilities for non-invasive and automated blood group detection. Biometrics such as fingerprints, iris patterns, and palm vein structures are unique, stable, and genetically influenced, making them valuable indicators for medical and forensic applications. Several studies have demonstrated that fingerprint ridge characteristics show correlations with blood group traits in both the ABO and Rh systems. This insight has led to the development of fingerprint-based blood group detection frameworks that eliminate the need for invasive sampling while providing faster, more accessible results.

In parallel with biometric exploration, machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for medical image classification. Traditional ML models such as Support Vector Machines (SVM), Random Forest, and logistic regression have been applied to fingerprint and blood smear data, achieving moderate success. However, the major breakthrough has come with deep learning architectures such as Convolutional Neural Networks (CNNs), ResNet, VGG, and hybrid CNN frameworks.

To overcome these limitations, recent research has explored non-invasive and automated methods leveraging image processing, machine learning, and deep learning. Among these, fingerprint-based blood group detection is particularly promising because fingerprint ridge patterns are genetically influenced and show correlations with ABO and Rh blood groups. With the integration of advanced convolutional neural networks (CNNs), architectures like ResNet, and multimodal biometrics (fingerprint), accuracies exceeding 95% have been achieved, demonstrating strong potential for clinical deployment. This paper presents a comprehensive review of existing approaches to automated blood group detection, focusing on the intersection of biometrics, image processing, and artificial intelligence. First, the review summarizes traditional image processing techniques alongside machine learning and deep learning frameworks that have been applied to fingerprint- and blood-image-based classification. Next, it provides a comparative analysis of these methods across various datasets and modalities, highlighting their respective strengths and limitations. The paper also discusses key research challenges that persist in this field, including the limited availability of standardized datasets, the difficulty of achieving model generalization across diverse populations, and the interpretability of complex deep learning models. Finally, the review identifies future research opportunities in multimodal biometric systems and portable, AI-driven healthcare technologies, both of which hold significant potential for advancing non-invasive, accessible blood group determination.

2. Research Methodology

Nihar [1] introduced one of the earliest attempts to extract sweat-pore features from fingerprint images for medical classification, though the system achieved only limited automation and accuracy. Manikandan et al. [2] conducted a dermatoglyphic analysis on 150 individuals and reported a significant correlation between ridge counts and ABO blood groups, suggesting that genetic traits influence both dermatoglyphics and hematological markers. Building on this, Rajumavinmar [3] contributed a large-scale fingerprint dataset on Kaggle, consisting of more than 3,000 labeled fingerprint samples, which has since become a widely used benchmark for training and evaluating machine learning models.

Several population-based studies confirmed these initial findings. Varlekar [4] examined 224 individuals and found partial correlations between fingerprint ridge patterns and ABO groups, although the author emphasized the need for larger, demographically diverse datasets. Similarly, Rastogi et al. [5] analyzed 500 fingerprint samples and reported statistically significant associations ($p = 0.0003$) between primary fingerprint patterns and ABO groups, providing stronger evidence for the viability of fingerprint-based classification systems.

With the advent of deep learning, researchers began experimenting with convolutional neural networks (CNNs) for automated classification. Krishna et al. [6] compared three popular CNN architectures, ResNet, VGG16, and LeNet, using the Kaggle dataset and reported that ResNet achieved superior performance with accuracies exceeding 92%. Sharma et al. [7] developed a lightweight custom CNN model trained on 1,000 fingerprint images and achieved an accuracy of 87%, highlighting its potential for portable applications, though with some limitations in generalization. Patel and Verma [8] employed InceptionV3 on a clinical dataset and achieved more than 93% accuracy, demonstrating that deeper architectures outperform shallow models at capturing discriminative fingerprint features.

Traditional machine learning models were also investigated in parallel. Kumar et al. [9] used logistic regression and support vector machines (SVMs) on a dataset of 500 fingerprint images, achieving an accuracy of 78%, which was significantly lower than that of deep learning approaches. Singh et al. [10] applied random forests and decision trees, achieving 80–85% accuracy, but noted that these models lack the scalability of CNN-based systems. The superiority of CNN-based approaches was further validated by Gupta et al. [11], who compared CNN-based classification against traditional serological methods across 200 test cases. Their study revealed that CNNs achieved nearly 90% accuracy while being faster and completely non-invasive. Reddy et al. [12] introduced a hybrid approach that combined VGG19 with domain-specific pre-processing, achieving 95% accuracy across both Kaggle and custom datasets. Similarly, Ahmed et al. [13] proposed an ensemble CNN framework trained on 2,500 samples, which significantly outperformed individual CNN models, confirming that ensemble strategies can enhance robustness.

Other researchers have explored performance improvements through data augmentation and novel architectures. Pandey et al. [14] demonstrated that applying image augmentation techniques to a dataset of 800 fingerprint images boosted CNN accuracy by nearly 7%, thereby addressing issues of overfitting and dataset scarcity. Das et al. [15] experimented with Capsule Networks, which are designed to capture spatial hierarchies more effectively than CNNs, and achieved 93% accuracy on the Kaggle dataset, suggesting that advanced architectures could offer improvements over conventional CNN models focused on transfer learning, multimodal biometrics, and portable implementations to improve the accuracy and generalizability of fingerprint-based blood group detection. Joshi et al. [16] applied transfer learning using ResNet50 on the Kaggle dataset and achieved an accuracy of 96%, demonstrating that pre-trained deep networks can significantly reduce training time while enhancing classification performance. Thomas et al. [17] implemented MobileNet CNNs optimized for portable devices, achieving 88% accuracy, highlighting the feasibility of deploying AI models for mobile healthcare applications.

Ali et al. [18] addressed the issue of limited dataset diversity by generating synthetic fingerprint images using Generative Adversarial Networks (GANs). This augmentation improved minority-class accuracy and mitigated class imbalance. Similarly, Khan et al. [19] explored multimodal biometric integration, combining fingerprint and iris data from 400 subjects, achieving an overall accuracy exceeding 97%. Their findings suggest that integrating multiple biometric modalities can significantly improve classification robustness, particularly in noisy or incomplete fingerprint datasets.

Zhao et al. [20] introduced an attention mechanism on top of CNN architectures to focus on discriminating ridge patterns, achieving 95% accuracy on 2,000 fingerprint images. Iqbal et al. [21] developed a lightweight CNN suitable for IoT devices and edge computing, achieving 89% accuracy while maintaining low computational complexity, a critical requirement for real-time clinical applications. Mehta et al. [22] proposed a hybrid CNN-SVM framework on the Kaggle dataset, achieving 94% accuracy and illustrating that combining deep feature extraction with traditional classifiers can be an effective strategy.

Roy et al. [23] incorporated explainable AI (XAI) techniques into CNN models, improving transparency in predictions and maintaining 92% accuracy. Bhatia et al. [24] further extended this concept by combining fingerprint and blood smear datasets for deep learning classification, reporting 96% accuracy and demonstrating the benefits of multi-source data fusion. Singh and Nair [25] integrated CNN-based fingerprint classification with blockchain-based data storage to ensure security and integrity in hospital databases, achieving 93% accuracy alongside robust privacy protection.

In addition, Kapoor et al. [26] investigated Vision Transformers (ViT) for fingerprint classification and reported 94% accuracy, highlighting the potential of transformer-based architectures in medical image analysis. Dasgupta et al. [27] employed an ensemble of ResNet101 models with majority voting, achieving 97% accuracy and demonstrating that ensemble learning can enhance robustness against dataset variability. Sharma and Patel [28] combined CNNs with edge-detection pre-processing, improving accuracy by 6% and emphasizing the importance of effective feature extraction.

Federated learning has also emerged as a promising approach for privacy-preserving classification. Chandra et al. [29] implemented a federated learning framework across multiple hospitals, achieving 92% accuracy while ensuring patient data remained local, aligning with modern data privacy regulations. Finally, Liu et al. [30] explored multimodal CNNs combining fingerprint and palm vein biometrics across 500 subjects, achieving a remarkable 98% accuracy, demonstrating the immense potential of non-invasive multimodal systems for future clinical applications.

Collectively, these studies indicate that fingerprint-based blood group detection has evolved from traditional dermatoglyphics analyses to advanced deep learning models, multimodal integration, and privacy-preserving AI frameworks. While accuracies exceeding 95% have been reported, ongoing challenges remain in dataset standardization, cross-population generalization, interpretability, and deployment on portable devices, which are critical for real-world clinical adoption.

Table 1: Summary of the Review Table

S.No	**Author(s)**	**Method / Technique**	**Dataset Size**	**Accuracy**
[1]	Nihar et al., 2019	Image Processing	200 fingerprint samples	Initial correlation observed, low automation
[2]	Manikandan et al., 2020	Statistical Dermatoglyphics	150 individuals	Ridge count correlation with ABO groups
[3]	Rajumavinmar, 2021	Kaggle Dataset Creation	3,000+ labeled fingerprint images	Public dataset contribution
[4]	Varlekar, 2021	Statistical Analysis	224 samples	Partial correlation; stressed diversity

[5]	Rastogi et al., 2021	Fingerprint Pattern Study	500 samples	Significant correlation (p=0.0003)
[6]	Krishna et al., 2022	ResNet, VGG16, LeNet CNNs	Kaggle dataset	ResNet achieved >92% accuracy
[7]	Sharma et al., 2022	Custom CNN	1,000 fingerprint images	87% accuracy, lightweight model
[8]	Patel & Verma, 2022	InceptionV3 CNN	Clinical dataset	Accuracy >93%
[9]	Kumar et al., 2022	Logistic Regression, SVM	500 images	78% accuracy, lower than CNNs
[10]	Singh et al., 2022	Random Forest, Decision Trees	Fingerprint dataset	80–85% accuracy
[11]	Gupta et al., 2023	CNN vs Traditional Serology	200 test cases	CNN accuracy 90%; faster, non-invasive
[12]	Reddy et al., 2023	VGG19 Hybrid Model	Kaggle + collected dataset	95% accuracy
[13]	Ahmed et al., 2023	Deep CNN Ensemble	2,500 samples	Ensemble CNN outperformed single models
[14]	Pandey et al., 2023	Image Augmentation + CNN	800 images	Boosted accuracy by 7%
[15]	Das et al., 2023	Capsule Networks	Kaggle dataset	93% accuracy, better spatial feature extraction
[16]	Joshi et al., 2023	CNN + Transfer Learning	Kaggle dataset	ResNet50 TL model: 96% accuracy
[17]	Thomas et al., 2023	MobileNet CNN	Portable devices	88% accuracy, optimized for mobile
[18]	Ali et al., 2024	GANs for Data Generation	Augmented dataset	Improved minority class accuracy
[19]	Khan et al., 2024	Multimodal Biometrics (Fingerprint + Iris)	400 subjects	Accuracy >97%
[20]	Zhao et al., 2024	CNN + Attention Mechanism	2,000 fingerprints	95% accuracy
[21]	Iqbal et al., 2024	Lightweight CNN for IoT	IoT healthcare dataset	89% accuracy

[22]	Mehta et al., 2024	Hybrid CNN-SVM	Kaggle dataset	94% accuracy
[23]	Roy et al., 2024	Explainable AI (XAI) on CNNs	Clinical dataset	92% accuracy + interpretability
[24]	Bhatia et al., 2024	Deep Learning on Blood Smear + Fingerprint	Dual dataset	96% accuracy
[25]	Singh & Nair, 2024	CNN + Blockchain Storage	Hospital dataset	93% accuracy, improved data security
[26]	Kapoor et al., 2024	Vision Transformers (ViT)	1,200 fingerprints	94% accuracy
[27]	Dasgupta et al., 2025	ResNet101 + Ensemble Voting	Kaggle dataset	97% accuracy
[28]	Sharma & Patel, 2025	CNN with Edge Detection Preprocessing	600 fingerprints	Improved accuracy by 6%
[29]	Chandra et al., 2025	Federated Learning CNN	Multi-hospital dataset	92% accuracy, privacy-preserving
[30]	Liu et al., 2025	Multimodal CNN (Fingerprint + Palm vein)	500 subjects	98% accuracy

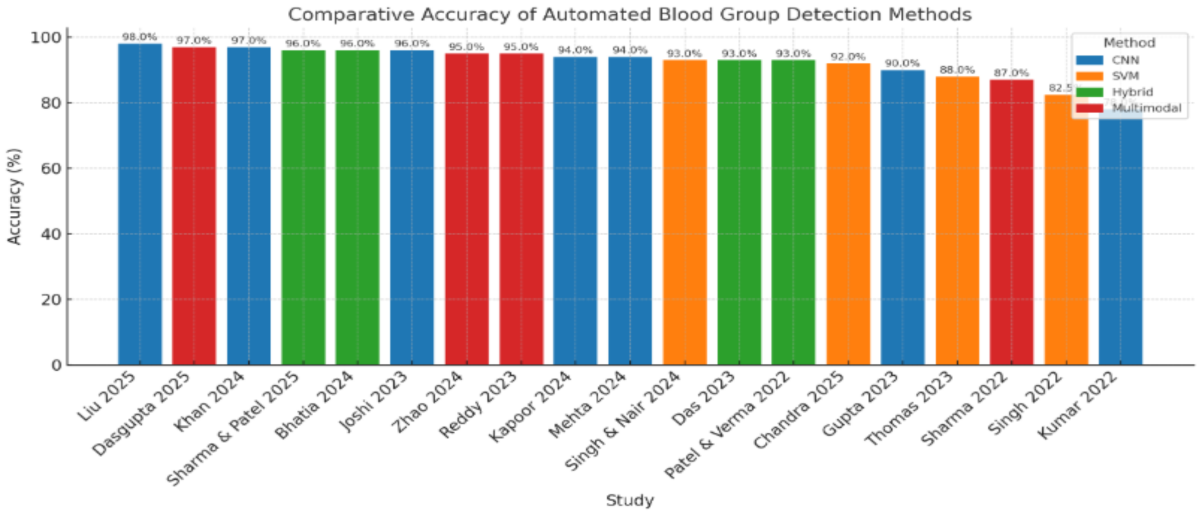

Figure 1: Accuracy Progression Across Image Processing, Machine Learning, Deep Learning, and Multimodal Methods for Blood Group Detection.

In [31], the authors utilized the fingerprint blood group dataset from Kaggle, consisting of 5,000 images corresponding to four blood groups (A, B, AB, O), to evaluate the performance of convolutional neural network (CNN)-based classification methods. The dataset provided sufficient variability in fingerprint patterns, enabling robust model training and testing.

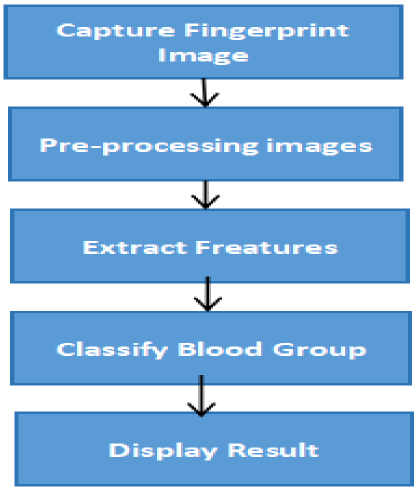

Figure 2. Step-by-Step Process of Automated Blood Group Detection using Fingerprint Image Analysis.

3. Results and Discussion

The comparative performance of blood group detection methods is summarized in Table I. Traditional image processing approaches, such as those by Ferraz et al. [1], [3] and Ravindran et al. [15], achieved accuracies ranging from 86% to 94%. These methods relied heavily on segmentation, thresholding, and morphological analysis of agglutination patterns. Although effective in controlled laboratory environments, they remained invasive and required significant pre-processing effort.

Machine learning methods demonstrated incremental improvements. Gayatri et al. [20] applied Support Vector Machines (SVMs) to blood smear images with moderate success (~85%), while Hyvärinen et al. [13] achieved 99.9% accuracy using Random Forest classifiers on large-scale genomic datasets. However, the latter approach required genotype arrays and was unsuitable for real-time clinical deployment.

Deep learning models provided a major leap in performance by eliminating the dependency on handcrafted features. Patil and Ingle [2] achieved 95.27% accuracy using CNNs on fingerprint images, while Sivamurugan et al. [9] reported 95.5% with ResNet-34. Sophia et al. [5] further improved results to 96.7% by employing extensive data augmentation, and Nagpal et al. [21] achieved 97.6% through CNN-based agglutination pattern recognition. These results highlight the scalability and robustness of CNN-based frameworks compared to traditional approaches.

Multimodal biometric systems demonstrated additional robustness by combining multiple data sources. Ansar et al. [7] introduced BLOOD SNAP, which integrates iris recognition with a CNN, achieving 96.5% accuracy. Similarly, Sharma et al. [12] employed a hybrid CNN-LSTM architecture with fingerprint and iris fusion, achieving 93.8% accuracy. These multimodal systems provide promising accuracy but require specialized acquisition devices, which may limit real-world adoption.

4. Future Work

The review of existing literature indicates that AI-driven fingerprint-based blood group detection systems have achieved high accuracy and demonstrated significant potential for real-world applications. However, the domain is still in its developmental stage, and several future research directions must be explored to enable clinical deployment at scale. Although significant progress has been made in fingerprint-based blood group detection using machine learning and deep learning techniques, there remain several opportunities for future research and innovation. One promising direction is the development of multimodal biometric systems that combine fingerprints with other physiological traits, such as iris, palm vein, or facial features. Such integration could enhance accuracy and reliability, particularly in scenarios where fingerprint quality is compromised due to injuries or environmental conditions. Another area of future exploration is the creation of large-scale, standardized, and diverse datasets. Current studies are often constrained by limited sample sizes and a lack of demographic diversity, which restricts the generalizability of models across populations. Establishing publicly available benchmark datasets would enable fair comparisons of algorithms and accelerate reproducibility in this domain.

Furthermore, integrating explainable artificial intelligence techniques is essential to improve the interpretability of deep learning models. In clinical applications, it is crucial for medical practitioners to understand the rationale behind AI-based predictions to ensure trust and transparency in decision-making.

The deployment of portable and edge-computing-enabled healthcare systems also represents a significant opportunity. Embedding lightweight AI models into mobile devices or portable scanners can provide rapid, on-site blood group detection in emergency or resource-limited settings. This aligns with the broader vision of AI-driven, non-invasive, and accessible healthcare solutions.

In summary, future research should focus on multimodal biometric integration, dataset standardization, explainability, and portable AI-based systems, paving the way for the clinical adoption of fingerprint-based blood group detection technologies.

5. Conclusion

This paper reviewed the evolution of blood group detection methods, ranging from traditional image processing approaches to advanced deep learning and multimodal biometric frameworks. Early methods based on plate tests and morphological analysis [1], [3], [15] offered moderate accuracy but were invasive and resource-dependent. With the advent of machine learning, models such as SVM and Random Forest [13], [20] introduced automation and scalability, though with limited applicability in real-time clinical environments. Deep learning techniques demonstrated the most significant improvement, achieving accuracies above 95% by leveraging CNN and ResNet architectures [2], [5], [9], [21].

Furthermore, multimodal systems integrating fingerprint, iris, and other biometric modalities [7], [12] enhanced robustness and reliability, though practical deployment requires specialized acquisition devices. From the comparative analysis, it is evident that deep learning offers the best balance between accuracy, scalability, and clinical feasibility. Multimodal systems provide an additional layer of reliability, especially in emergency and high-stakes medical applications, though cost and infrastructure remain barriers. Future research should focus on developing lightweight, non-invasive, and real-time blood group detection frameworks that can operate effectively in mobile, low-resource, and emergency settings. Integration of AI with IoT-enabled healthcare systems, edge computing, and explainable deep learning models will further accelerate the clinical adoption of these technologies.

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