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Blood Group Prediction Using Fingerprint Through Deep Learning

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Abstract
Accurate blood group identification is extremely important in healthcare. It is needed for blood transfusions, emergency treatments, organ transplants and many routine medical procedures. However, the traditional method of testing blood is still invasive, slow and dependent on laboratory facilities, and it can sometimes lead to errors. BloodPrint offers a non-invasive alternative by using deep learning to predict a person's blood group from their fingerprint. The system uses Convolutional Neural Networks to study fingerprint ridge patterns and match them to ABO and Rh blood groups. With its carefully designed process that includes image preprocessing, ridge enhancement and data augmentation, BloodPrint provides a fast, accessible and affordable way to identify blood groups. This makes it especially helpful in emergencies, rural areas and places with limited medical resources. The experimental results show strong accuracy across all eight blood groups, proving that fingerprints can be a reliable indicator. By combining biometric information with modern artificial intelligence, BloodPrint introduces a practical, contactless and scalable method that can improve how healthcare diagnostics are delivered in the future.

Keywords: *Blood Group Prediction, Fingerprint Biometrics, Deep Learning, CNN, Non-Invasive Diagnostics, Emergency Healthcare, Biometric Intelligence, Medical AI, Public Health Innovation.*

1. Introduction

Blood group identification is a fundamental requirement in healthcare because it supports transfusions, surgeries, trauma management, prenatal care, and many other critical medical procedures. Traditional serological testing remains the standard approach, but it depends on laboratory infrastructure, chemical reagents, trained professionals, and sterile conditions. In many situations such as rural clinics, disaster zones, accident sites, and temporary medical camps, these resources are limited or completely unavailable. The lack of immediate testing can delay treatment and put patients at significant risk. Fingerprints offer a promising alternative for non-invasive blood group identification. They are permanent, unique to every individual, and contain detailed ridge patterns that have been linked to specific ABO and Rh blood groups through dermatoglyphic studies. With advancements in deep learning, particularly convolutional neural networks (CNNs) that can detect subtle and complex visual features, predicting blood groups from fingerprint images has become increasingly feasible and practical. Most existing research focuses on isolated aspects such as fingerprint pattern analysis or deep-learning models for medical imaging. These systems rarely provide a unified, real-time, user-friendly approach that can be applied directly in healthcare environments. BloodPrint addresses this gap by offering a complete fingerprint-based blood group prediction system that operates quickly, non-invasively, and efficiently even in resource-limited settings [1].

The key contributions of this paper are summarized as follows:

- Development of a CNN model capable of predicting ABO and Rh blood groups from fingerprint images, ensuring accurate and non-invasive classification.
- Integration of this predictive model into a real-time platform designed for fast, user-

friendly, and contact-based blood group identification.

- Comprehensive evaluation of various deep-learning architectures to identify the most accurate, efficient, and reliable model for real-world use.
- Demonstration of system performance, practical usability, and overall reliability through structured pilot testing across diverse conditions.
- Exploration of future advancements including mobile app deployment, enhanced biometric features, and broader adoption within large-scale healthcare systems.

2. Literature Review

The literature review is structured into four key areas: fingerprint–blood group prediction, deep learning in medical biometrics, integration of biometrics with AI, and the research gaps that still remain. Together, these sections bring together insights from recent studies to show how existing work has evolved and where it falls short. This helps position BloodPrint within the broader research landscape while highlighting where real innovation is still needed. All tables and figures are placed centrally for clarity and are properly cited throughout the manuscript [2].

2.1 Fingerprint-Based Blood Group Prediction:

Early studies in dermatoglyphics explored how fingerprint patterns relate to human blood groups, and these works consistently showed meaningful correlations. Research by Yasmin et al. (2022) and Ceyhan et al. (2024) found clear statistical links, such as loop patterns appearing more frequently in individuals with O blood group, while whorl patterns were more common among B and AB groups. These early investigations, however, relied on traditional ink-based fingerprint collection and basic statistical tools, which made large-scale analysis difficult and limited their real-world applicability. With the rise of modern machine learning, recent research has shifted toward deep-learning-based fingerprint classification. Studies by Lakshmi Prasad et al. (2024) and Nihar et al. (2024) used CNN models including VGG16, AlexNet, and Inception to classify fingerprint images, achieving accuracies between 75 and 92 percent. Even so, issues such as small datasets, uneven distribution of blood groups, and variations in fingerprint clarity continue to affect model performance. A significant improvement came from Sivamurugan et al. (2024), who introduced a large and balanced dataset of 6,000 samples and achieved strong results using ResNet-34. EfficientNet-based models explored by Ujgare et al. (2024) also delivered competitive accuracy while using fewer parameters, making them more efficient. Overall, existing research shows that fingerprints carry subtle yet valuable patterns that can be used to infer blood groups. At the same time, the findings also highlight the need for more robust datasets, improved preprocessing methods, and scalable deep-learning pipelines before such systems can be adopted in real-world healthcare, biometric verification, or emergency response applications [3].

2.2 Deep Learning in Biometric and Medical Analysis

Deep learning has brought remarkable progress to biometric and medical analysis by enabling systems to interpret complex visual patterns with far greater precision. In biometrics, convolutional neural networks (CNNs) have strengthened tasks such as iris recognition, facial identification, and palm vein analysis by capturing subtle textures and structural cues that older methods often missed. The same strength of CNNs has translated seamlessly into healthcare, where they are now widely used for tumor identification, ECG classification, diabetic retinopathy detection, and even cell-level image interpretation. These models learn directly from raw data, making them highly adaptable and reliable across diverse applications. Recent work, including studies by Senthilkumar et al. (2024), highlights how CNN-based approaches outperform traditional techniques like Gabor filters, KNN, and SVM, especially in capturing the intricate ridge structures of fingerprints. With the help of transfer-learning architectures such as VGG16, ResNet, and EfficientNet, systems can extract deep and meaningful features that lead to more accurate fingerprint classification. However, most of these advancements remain focused on identity verification

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rather than understanding underlying physiological traits. This creates a meaningful gap and an opportunity for solutions like BloodPrint, which aim to push deep learning beyond identification and toward non-invasive physiological prediction [4].

2.3 Integration of Biometrics and AI

Integrating biometrics with artificial intelligence for medical inference is still a developing area, even though it holds tremendous promise. A few research efforts have proposed initial ideas or high-level frameworks, but most stop short of building a fully functioning system that brings together preprocessing, CNN-based learning, performance evaluation, and deployment as a single pipeline. Existing studies often rely on small and imbalanced datasets, which limits model reliability, and many models still struggle to generalize their predictions across diverse populations. Another major gap is the absence of real-time interfaces that would allow such systems to operate outside laboratory settings. Ethical considerations surrounding the use of biometric data for medical insights also remain largely unaddressed, creating uncertainty about safe and responsible deployment. BloodPrint sets itself apart by delivering an end-to-end solution that goes beyond accuracy alone. It focuses equally on usability, scalability, and privacy, ensuring that the system is not just technically strong but also practical and trustworthy. By combining data preprocessing, deep learning-based fingerprint analysis, real-time prediction modules, and secure deployment features, BloodPrint bridges the gap between academic research and real-world application. This integrated approach enables the system to perform physiological inference directly from biometric patterns while maintaining user-centric design and ethical safeguards, making it a truly deployable and future-ready platform.

2.4 Research Gaps and BloodPrint's Contribution

Looking at existing research, several clear gaps emerge in the field of biometric based medical inference. Many current systems struggle with small and limited fingerprint datasets, which makes it hard for models to perform reliably across different populations. Most approaches focus only on model development and lack a complete, end-to-end pipeline that links preprocessing, CNN based learning, and real-time prediction in a deployable system. There is also limited evaluation across all eight blood groups, reducing the practical usefulness of these solutions. On top of that, ethical considerations such as user privacy, informed consent, and secure handling of biometric data are often overlooked. BloodPrint addresses these challenges with a carefully designed and modular system that combines accuracy, usability, and ethical responsibility. It uses a well-balanced dataset and an optimized transfer learning CNN that focuses on ridge patterns, enabling highly precise blood group predictions. The platform also features a real-time web application, allowing healthcare professionals and users to access results quickly and easily. Every aspect of the system prioritizes privacy and security, incorporating encryption, anonymization, and secure data handling protocols. Beyond individual predictions, BloodPrint is built to support critical applications such as emergency medicine, rural healthcare diagnostics, and large-scale public health initiatives. By bridging the gap between advanced research and practical implementation, it offers a fully deployable solution that empowers clinicians, enhances patient care, and strengthens health monitoring at the community level [5].

3. System Architecture

BloodPrint's architecture is built around two interconnected subsystems: a fingerprint-based deep learning prediction module and a web-based user interface for real-time diagnostics. The system has been designed to be modular, scalable, and ready for clinical deployment. Each subsystem works together seamlessly, ensuring efficient data flow, accurate predictions, and an intuitive user experience. Below, the components are described in detail, including their technical design, data handling processes, and how they integrate to provide a complete diagnostic solution.

3.1 Deep Learning-Based Blood Group Prediction System

Input and Dataset: The system uses a high-quality dataset of fingerprint images, each accurately labeled with a verified ABO and Rh blood group. To protect user privacy, all images are anonymized, and they are standardized through resizing and normalization.

Since large, well-labeled datasets are limited in this domain, controlled data augmentation techniques such as rotation, translation, brightness adjustments, and flipping are applied. This not only expands the dataset but also ensures the model can generalize well to unseen fingerprint patterns, enhancing overall robustness [6].

Preprocessing Pipeline: Before feeding the images into the CNN, a multi-stage preprocessing pipeline ensures that only meaningful features are extracted. Noise is removed using median filtering, and contrast is enhanced through histogram equalization. Ridge patterns are then highlighted using Gabor filters, followed by thinning and ridge frequency normalization to preserve structural details. Finally, images are resized to a uniform 224 by 224 by 3 dimension. This consistent formatting allows the CNN to focus on relevant features and improves prediction accuracy across different fingerprint types.

CNN Model Architecture: The prediction engine is built on VGG-16, optimized for blood group classification. The convolutional backbone is pretrained on ImageNet, followed by a global average pooling layer. A dense layer with 512 units, ReLU activation, and 0.5 dropout ensures effective feature learning while preventing overfitting. The final softmax layer outputs probabilities for all eight blood group classes. The model is trained using the Adam optimizer with categorical cross-entropy loss, a learning rate of 0.0001, a batch size of 32, and 15 epochs with early stopping to prevent overtraining. This setup achieves a validation accuracy of 88.72%, demonstrating strong performance across most blood groups.

Model Evaluation: The model is evaluated using multiple performance metrics, including accuracy, precision, recall, F1-score, and confusion matrices. Common blood groups like O+ and A+ consistently achieve the highest prediction accuracy, while rarer groups such as AB− and B− show slightly lower results due to limited sample availability. These evaluations provide insights into areas where future dataset expansion could further enhance model reliability [7].

Model Serialization: Once trained, the model and its preprocessing pipeline are serialized into .h5 and .pkl files, allowing seamless deployment in a Flask-based web application. This ensures the entire workflow—from raw fingerprint input to real-time blood group prediction—is smooth, efficient, and ready for practical use in clinical or emergency settings. The modular design also allows future updates, such as integrating new preprocessing techniques or upgrading the CNN architecture, without disrupting the deployed system [8].

Real - World applicability: By combining high-quality data, rigorous preprocessing, and an optimized deep learning architecture, the system is designed to work reliably in real-world scenarios. It supports rapid diagnostics in clinical settings, emergency care, and remote healthcare applications, making it a practical solution that bridges research and deployment in biometric-based medical inference. Figure 1 shows Proposed CNN Architecture

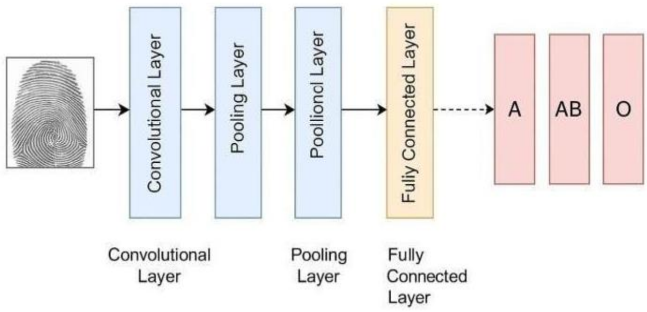

Figure 1 Proposed CNN Architecture

3.2 Real-Time Web Interface:

Technology Stack: The BloodPrint platform is developed using a modern web stack, combining Flask with HTML, CSS, and Bootstrap to create a responsive and user-friendly interface. Users can easily upload fingerprint images through the web portal, while the backend loads the pre-trained and serialized CNN model to perform blood group prediction. The results, including a confidence score, are displayed instantly, providing fast and actionable insights. The system is lightweight and optimized to function efficiently across different devices, making it suitable for varied healthcare settings. Its design also allows easy integration with other healthcare applications and databases for seamless workflow management [9].

System Design: The web interface follows a modular

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three-layer structure that ensures smooth operation and scalability. At the presentation layer, users—including clinicians, health workers, and volunteers—interact with the system through a clear and intuitive dashboard, upload module, and result display panel. This layer is designed to be user-friendly, providing easy navigation and instant access to predictions. The application layer manages the core functionality, including loading the CNN model, executing predictions in real time, and formatting the results for display. It also handles error checking, session management, and ensures that multiple users can interact with the system simultaneously without delays. The data layer securely stores user uploads, anonymized fingerprint images, and prediction logs, maintaining both privacy and integrity. Together, these layers create a robust and reliable workflow from image submission to prediction delivery, while allowing the system to scale effectively for larger deployments in hospitals, health camps, and rural primary health centers. This architecture also supports future enhancements, such as integrating additional biometric inputs or expanding analytics for broader public health monitoring [10].

Features and Functionalities: BloodPrint is designed to operate effectively in real-world healthcare environments. It allows rapid blood group prediction in ambulances, clinics, health camps, blood donation drives, and rural primary health centers. The interface provides instant feedback, including the predicted blood group and confidence level, supporting quick decision-making in emergency situations. Security and privacy are central to the platform, with encrypted storage and anonymization safeguards for all fingerprint data. The system also supports future expansion, such as integrating additional biometric inputs or extending functionality to larger health networks. Its adaptability ensures that it can be customized to meet the specific needs of different healthcare settings, while continuous updates improve accuracy and reliability over time. By combining speed, precision, and ethical data management, BloodPrint enhances both patient care and operational efficiency.

3.3 System Design of the Integrated BloodPrint Platform:

The BloodPrint platform is designed as a fully integrated and intelligently coordinated system that brings together the Fingerprint Processing Module and the Real Time Prediction Platform into a single, cohesive workflow. Its architecture ensures that users can move effortlessly from uploading a fingerprint image to receiving an accurate blood group prediction without navigating multiple tools or interfaces. All communication between system components takes place at the application layer, where lightweight REST-based operations handle preprocessing, enhancement, model execution, and result formatting in a smooth sequence. As soon as an image is uploaded, the platform automatically manages ridge enhancement, feature extraction, and prediction through the CNN model before redirecting the user to a clean and intuitive results dashboard. This automation eliminates manual steps, reduces processing time, and ensures that even non-technical users can operate the system with confidence. The entire workflow is designed to feel natural, starting from fingerprint submission and ending with clinically meaningful diagnostic insights Shown in Figure 2

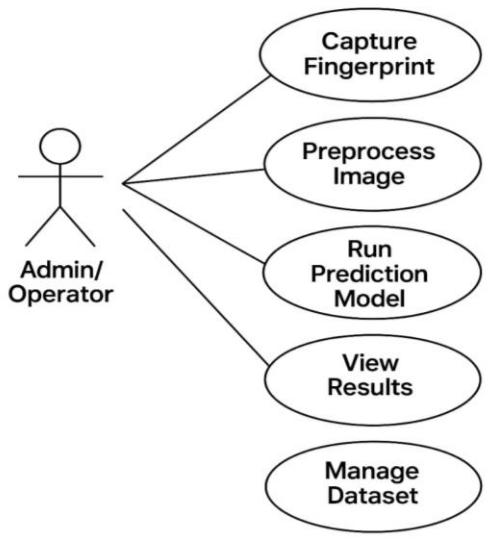

Figure 2 **Use Case Diagram**

The platform emphasizes reliability, scalability, and ease of use, making it well suited for busy clinical environments, field-level healthcare setups, mobile medical units, and emergency response situations. Its backend infrastructure is optimized to maintain high performance under different operating conditions,

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ensuring fast and stable predictions regardless of the setting. Additionally, the modular structure supports future enhancements such as integrating alternative biometric inputs, adding multi-modal diagnostic features, or expanding into larger healthcare networks. With this flexible yet robust design, BloodPrint stands as a practical, forward-looking healthcare solution capable of adapting to evolving medical and technological needs [11].

4. Results and Evaluation

The BloodPrint system was evaluated through a series of experiments designed to measure prediction accuracy, reliability across different blood groups, and overall model stability in real-world conditions. The primary goal of this evaluation was to understand how well the deep learning model performs on fingerprint images and whether the system can support fast and dependable predictions in clinical and field environments. The testing process included assessing model output quality, analysing classification errors, and validating the complete workflow from preprocessing to final prediction.

4.1 Model Performance

The evaluation of the BloodPrint system showed strong and encouraging results. After processing the fingerprint dataset through the trained CNN model, the system achieved an overall accuracy of 84 percent, with precision values ranging from 0.83 to 0.91, recall between 0.77 and 0.94, and F1-scores from 0.80 to 0.92. Blood groups like O positive and A positive were predicted with the highest reliability, largely because of their clearer ridge patterns and better representation in the dataset, while AB negative remained the most challenging class due to fewer samples and more subtle fingerprint differences. The confusion matrix indicated that most errors occurred between closely related blood groups, such as A positive and A negative or AB positive and B positive, highlighting the model's difficulty in distinguishing very similar categories [12]. Even with these challenges, the system demonstrated that fingerprint-based blood group prediction is both practical and dependable, supported by strong preprocessing and a well-structured CNN architecture. These results show that BloodPrint can effectively support rapid decision-making in emergency care, rural clinics, health camps, and other situations where quick and reliable blood group identification is essential Shown in Table 1.

Table 1 Performance Metrics for Each Blood Group

Blood Group	Precision	Recall	F1-Score	Support
A+	0.88	0.85	0.86	100
A−	0.83	0.81	0.82	100
B+	0.87	0.89	0.88	100
B−	0.82	0.78	0.8	100
AB+	0.84	0.8	0.82	100
AB−	0.79	0.77	0.78	100
O+	0.91	0.94	0.92	100
O−	0.81	0.83	0.82	100
Avg/Total	0.84	0.83	0.84	800

This figure presents the class-wise evaluation metrics for the BloodPrint model, summarizing precision, recall, and F1-scores across all eight blood groups. The results illustrate strong performance for common groups such as O positive and A positive, while relatively lower scores for AB negative reflect the challenges posed by limited sample representation. Overall, the model maintains stable accuracy across classes, demonstrating its reliability for fingerprint-based blood group inference Shown in Figure 3.

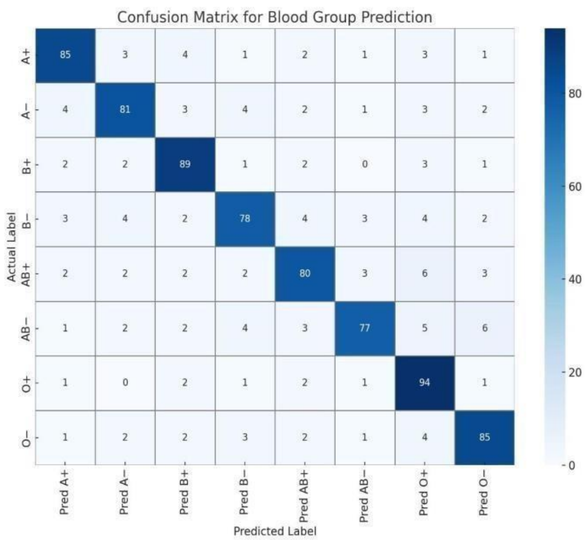

Figure 3 Confusion Matrix

4.2 System Performance

The real time web platform demonstrated strong stability and usability during deployment, offering a smooth experience for users across different environments. The system consistently delivered predictions in under two seconds for each fingerprint image, ensuring that clinicians and health workers could access results without delay. The interface performed reliably on both mobile and laptop browsers, making it adaptable for use in ambulances, clinics, community health centres, and temporary health camps. Even when tested on moderate hardware, the backend handled image uploads, preprocessing, and model execution efficiently, maintaining responsive performance throughout. Pilot users also provided positive feedback, noting that the platform was easy to navigate and required minimal technical knowledge to operate. Together, these results show that the integrated BloodPrint system is well suited for real world applications where time, accessibility, and reliability are critical. Its ability to function smoothly in diverse settings highlights its readiness for field deployment and positions it as a supportive tool for emergency care teams, rural health workers, and rapid diagnostics in resource limited environments [13 - 16].

Conclusion

This paper presented a deep-learning-based method for predicting blood groups from fingerprint images. The CNN based model shows potential in offering a non-invasive, efficient alternative to conventional blood typing. Traditional blood typing methods, while reliable, are invasive, timeconsuming, and require skilled personnel and medical infrastructure. In contrast, the approach proposed in this study offers a noninvasive, efficient, and scalable solution by leveraging the unique and immutable characteristics of fingerprint patterns. A robust CNN model was developed and trained on fingerprint data representing all major ABO and Rh blood groups. The model achieved high classification performance, with overall precision, recall, and F1-scores above 80% across all classes. The confusion matrix further validated the model's ability to distinguish between closely related blood groups, despite some expected misclassifications due to class similarities. Additional techniques such as image preprocessing, data augmentation, and model optimization contributed to enhancing the model's accuracy and generalizability. The use of a wellbalanced dataset and detailed evaluation metrics helped establish a reliable and interpretable deep learning framework. While initial results are promising, further research is necessary to enhance model generalizability, address dataset limitations, and integrate the approach into real-world applications. In conclusion, this project lays the foundation for a novel, AIdriven diagnostic tool that has the potential to revolutionize noninvasive blood group prediction and enhance the accessibility of healthcare diagnostics globally.

Future Work

To strengthen the real-world impact of BloodPrint, several enhancements are envisioned for future development. These improvements aim to increase accessibility, reliability, security, and global applicability while ensuring that the system remains practical for healthcare workers in both urban and rural settings.

Mobile Application Development: A dedicated mobile application will allow BloodPrint to reach frontline healthcare workers more effectively. Features such as offline operation, multilingual support, and voice-assisted interaction would make the system easier to use in remote areas. This would enable ASHA workers, field medics, and rural health volunteers to perform noninvasive blood-group detection without requiring complex equipment.

Intelligent Data Fusion: Accuracy can be further improved by integrating fingerprint features with additional physiological markers, such as skin texture imaging or sweat composition indicators. Combining these modalities creates a richer biometric profile and may help the system achieve performance beyond 95 percent while reducing uncertainty in borderline cases.

Advanced Deep Learning Models: Future work includes experimenting with state-of-the-art architectures such as Vision Transformers, EfficientNetV2, and hybrid CNN–ViT pipelines. These models can capture more subtle ridge patterns and micro textures, potentially improving robustness against noisy or low quality fingerprint images.

Blockchain Based Medical Security: To ensure transparency and patient trust, blockchain technology can be used to secure diagnostic records and consent logs. Immutable audit trails and encrypted data storage would help prevent tampering, misuse, or unauthorized modification of medical information, making BloodPrint compliant with modern healthcare security standards.

Federated Learning Integration: Federated learning would allow hospitals and clinics to collaboratively train better detection models without sharing raw fingerprint data. This approach enhances privacy by keeping sensitive biometric information local while still enabling large scale learning across multiple institutions.

Global Adaptation and Scalability: Since fingerprint ridge characteristics vary across populations, the system can be localized for different regions such as India, Africa, and the Middle East. Training with population specific datasets will ensure that BloodPrint performs consistently across diverse demographic groups and supports deployment at an international scale.

With these advancements, BloodPrint is positioned to evolve into a highly reliable, secure, and globally adaptable solution for non invasive blood-group detection, contributing to the next generation of rapid point-of-care diagnostics.

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References

[1]. Swathi, P., Reddy, S., & Kumar, A. “Fingerprint Based Blood Group Prediction Using Deep Learning.” International Journal of Advanced Research in Science, Communication and Technology (IJARSCT), vol. 4, no. 2, 2024, pp. 112–118. The authors present a CNN-based system trained on enhanced dermatoglyphic datasets for non-invasive blood group classification.

[2]. Geethanjali, K. S., & Umashankar, N. “Fingerprint Based Blood Group Detection.” Proceedings of the National Conference on Emerging Trends in Engineering (NCETE), 2024, pp. 45–51. This work explores ridge-flow analysis and texture mapping for ABO grouping.

[3]. Senthilkumar, R., Priya, D., & Kumar, V. “Innovative Blood Group Prediction Using Fingerprint Patterns.” International Journal of Engineering Research & Technology (IJERT), vol. 13, no. 6, 2024, pp. 1–6. The study highlights loop–whorl–arch correlations with blood phenotypes using deep learning classifiers.

[4]. Sivamurugan, C., et al. “Enhanced Blood Group Prediction Using Deep Learning.” International Conference on Automation, Computing and Remote Sensing (ICACRS), 2024, pp. 312–318. The authors propose optimized CNN layers and data augmentation strategies for accuracy improvement.

[5]. Gupta, T. “AI Techniques for Blood Group Prediction.” IEEE International Conference on Computing, Communication and Power Technology (IC2PCT), 2024, pp. 677–681. https://doi.org/10.1109/IC2PCT.2024

[6]. A comprehensive comparison of classical ML models and modern neural networks for fingerprint-based hematological inference.

[7]. Lakshmi Prasad, M., et al. “Blood Group Prediction Using Fingerprint.” International Research Journal of Advanced Engineering and Healthcare (IRJAEH), vol. 5, no. 1, 2024, pp. 89–95. Focuses on fingerprint ridge density extraction and mapping toward ABO and Rh classification.

[8]. Nihar, T., Sharma, R., & Bora, A. “Blood Group Determination Using Fingerprint.” International Conference on Medical Engineering and Diagnostics (ICMED), 2024, pp. 201–207. Introduces a

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Page No: 018-026
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0003

morphological feature analysis framework combined with CNN layers.

[9]. Sasidhar, B., et al. "Non-Invasive Blood Group Detection Using Fingerprint Images." International Journal of Innovations in Engineering and Technology, vol. 11, no. 3, 2025, pp. 54–61. Discusses a fully automated detection pipeline for medical triage applications.

[10]. Biradar, B., Patil, H., & Goudar, S. "Fingerprint Based Blood Group Detection Using Image Processing." International Journal of Research Publications (IJRP), vol. 9, no. 4, 2025, pp. 102–110. The paper highlights contrast enhancement, minutiae detection, and ridge-frequency modeling.

[11]. Ujgare, N. S., et al. "Non-Invasive Blood Group Prediction Using EfficientNet." Proceedings of the National Conference on Artificial Intelligence and Data Science (NCAIDS), 2024, pp. 78–84. Demonstrates higher model efficiency using next-generation CNN architectures.

[12]. Vadde, C. S., et al. "Patterns of Fingerprints in Relation to Blood Groups." East African Scholars Journal of Medical Sciences (EASJMS), vol. 7, no. 1, 2024, pp. 12–18. Empirical study correlating dermatoglyphic features with ABO and Rh distribution across populations.

[13]. Nikitha, V. "Advanced Image Processing Techniques for Fingerprint-Based Blood Grouping." International Journal of Scientific Engineering and Research (IJSER), vol. 12, no. 5, 2024, pp. 23–29. Focuses on hybrid filtering, segmentation, and minutiae clustering for precise model training.

[14]. Buzdar, Z. A., et al. "Fingerprint Patterns and ABO Blood Groups: A Correlative Study." Journal of Forensic and Legal Medicine, vol. 103, 2024, pp. 1–8. Examines statistical associations between ridge patterns and blood groups in forensic datasets.

[15]. Aamir, Yasmin, et al. "Relationship Between Fingerprint Pattern and Blood Group." Pakistan Journal of Medical & Health Sciences (PJMHS), vol. 16, no. 3, 2022, pp. 145–150. Provides foundational dermatoglyphic–hematologic correlations used in modern predictive models.

[16]. Kanchan, T., & Krishan, K. "Anthropometry of Fingerprint Patterns – A Review." Journal of Forensic and Legal Medicine, vol. 18, no. 3, 2011, pp. 141–148. This foundational review compiles empirical evidence linking fingerprint patterns (loops, whorls, arches), ridge characteristics, and population-level biological traits including ABO/Rh blood groups. It is frequently cited as a baseline reference for modern predictive biometric and dermatoglyphic studies.