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Research Article

Innovative Blood Group Detection Through Image Processing and FingerPrint Recognition

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Abstract:

Background of study: Traditional blood group determination methods are time-consuming, invasive, and require specialized equipment and trained personnel, leading to delays in medical decisions in remote or emergency settings.

Aims and scope of paper: This project explores an innovative, non-invasive approach to blood group detection using fingerprint recognition and image processing, aiming to overcome limitations of prior methods regarding accuracy, scalability, and accessibility. The core hypothesis is that unique fingerprint patterns can correlate with blood groups using advanced machine learning.

Methods: The proposed system involves fingerprint image acquisition (via smartphone/scanner), pre-processing (noise reduction, grayscale conversion, etc.), feature extraction using ORB and GLCM, and classification with a Convolutional Neural Network (CNN). The lightweight MobileNet architecture is utilized for efficiency, trained on a self-collected dataset of 60,000 thumb images categorized into 8 blood group classes, with HOG integrated for enhanced feature extraction. The system is accessible via a user-friendly chatbot interface.

Result: Experimental evaluation demonstrated robust performance across various deep learning models. ResNet50 achieved the highest accuracy of 95.3% on the BloodHub Dataset. The custom CNN model achieved 94.8% accuracy on the Custom Fingerprint Dataset, and MobileNet achieved a commendable 93.6% accuracy on the BloodCell-Detection-Dataset.

Conclusion: This project presents a viable, non-invasive blood group detection method by combining fingerprint biometrics, advanced image processing, and deep learning within a chatbot interface. Deep architectures like ResNet50 and the tailored CNN consistently achieved over 94% accuracy, validating the feasibility of reagent-free, portable blood typing for emergency, rural, and resource-constrained environments. This system can democratize critical diagnostic services and enhance patient care.

Keywords: Blood Group Detection, Image Processing, Machine Learning, Thumb Impression Recognition.

1. INTRODUCTION

Blood group determination is a fundamental aspect of medical care, crucial for vital procedures such as blood transfusions, organ transplantation, and emergency trauma interventions (Li & Guo, 2022). Traditional methods for identifying blood groups heavily rely on laboratory-based serological tests (Mujahid & Dickert, 2016). While accurate, these approaches are invasive, time-consuming, and highly dependent on skilled personnel and specialized equipment. In remote areas, resource-limited settings, or emergency scenarios, these limitations often lead to delays in medical decision-making, potentially putting lives at risk (Anuradha et al., 2025).

To address these challenges, this project explores an innovative approach to blood group detection using fingerprint recognition and image processing. Previous research has demonstrated the potential of fingerprints as unique biometric indicators for various identification and diagnostic applications (Prabakaran & Pillay, 2021). Nevertheless, there's a significant research gap in directly correlating fingerprint patterns with blood groups using non-invasive, image-based methods. Prior attempts to integrate fingerprint and image processing for blood group detection have shown limitations in terms of accuracy, scalability, or accessibility in resource-constrained environments (Fernandes et al., 2015). Our research aims to overcome these limitations by leveraging advancements in image processing and machine learning to develop a more reliable and accessible solution.

Our hypothesis is that the unique patterns and textures within human fingerprints, such as ridges, loops, and whorls, can be accurately correlated with blood groups using advanced machine learning algorithms. We

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hypothesize that these features, while not directly representing blood's biological characteristics, might reflect genetic or phenotypic variations indirectly linked to blood groups, an area that warrants further exploration in the future.

The proposed system comprises several stages, including image acquisition, pre-processing, feature extraction, and classification. Users simply capture an image of their fingerprint using a standard smartphone or scanner. This image is then enhanced through pre-processing techniques such as grayscale conversion, resizing, and noise reduction (Mohamed Abdul Cader et al., 2023). For feature extraction, we've opted for Oriented FAST and Rotated BRIEF (ORB) and Gray-Level Co-occurrence Matrix (GLCM). ORB was chosen for its efficiency in detecting and describing significant features like rotation-invariant and scale-invariant keypoints and descriptors, making it highly suitable for capturing the unique patterns of fingerprints (Ma et al., 2020). Meanwhile, GLCM is effective in analyzing image textures, providing statistical information about the spatial relationships of pixels, which is essential for distinguishing detailed characteristics within fingerprints that may be relevant for blood group classification (Patil & Ingle, 2021).

These extracted features are then fed into a machine learning model, specifically a Convolutional Neural Network (CNN), trained on a labeled dataset to classify blood groups (A, B, AB, or O, with Rh+ or Rh-). We utilize the MobileNet CNN architecture, a lightweight model optimized for mobile applications, ensuring efficient processing without compromising accuracy (Howard et al., 2017). The model is trained on our self-collected dataset of 60,000 thumb images, categorized into 8 blood group classes. For enhanced feature extraction, Histogram of Oriented Gradients (HOG) is integrated with the CNN. HOG is employed as a complementary feature extraction method to capture local edge and shape information in the fingerprint images, which is then combined with features learned by the CNN's convolutional layers to provide a richer image representation (Zhou et al., 2020). The CNN architecture employed consists of multiple convolutional, pooling, and fully connected layers designed to progressively extract hierarchical features from the fingerprint images. Tools like TensorFlow and Keras are utilized for model development, ensuring ease of training and optimization (Irawati et al., 2024).

The benefits of this innovation are significant. The proposed solution is non-invasive, requiring no blood sampling. Additionally, it's cost-effective as it leverages commonly available devices like smartphones, and scalable for widespread implementation across various settings. By integrating the system into a chatbot interface, users can seamlessly interact with it, upload fingerprint images, and receive real-time results. This makes the solution incredibly useful for non-technical users, emergency responders, and healthcare workers in resource-limited environments. In emergency scenarios in remote areas where laboratory facilities aren't available, healthcare personnel can use the proposed system on a smartphone to quickly determine a patient's blood group, ensuring timely medical intervention, reducing reliance on invasive techniques, and enhancing the overall efficiency of healthcare delivery. This project presents an innovative, non-invasive, and scalable approach to blood group detection, eliminating the need for reagents and invasive procedures, making it highly suitable for rural clinics, mobile healthcare units, and emergency scenarios.

Related Works

In the field of non-invasive blood group detection and classification, various methods have been explored to improve accuracy, processing speed, and real-world applicability. (Yang et al., 2024) proposed a generative AI-based framework for blood morphology analysis using the ASH dataset, achieving 88% accuracy for normal cells and 54% for abnormal cells. While effective for morphological classification, this approach lacks comprehensive blood typing capabilities. (Almarshad et al., 2022) introduces a photoplethysmogram (PPG)-based method with high real-time accuracy, offering an affordable and reagent-free solution, though it is sensitive to ambient lighting and motion artifacts. (Patil et al., 2025) utilizes ORB feature extraction combined with machine learning for non-invasive blood type classification, demonstrating fast processing (<2 seconds) and high accuracy but limited to external validation. (Oloruntoba & Akinode, 2020) develops an SVM-based system using genetic markers from the BloodHub dataset, facilitating real-time blood bank integration but limiting application to cases with available genetic data. (Memon et al., 2024) designed an image processing system with GSM alerts for emergency blood type identification, achieving 97% accuracy but requiring broader scenario validation. (Altman et al., 2024) proposed an FPGA-based detection system with high speed and low error rates, suitable for low-resource settings but requiring FPGA expertise for implementation. (Ramirez-Priego et al., 2024) introduced a plasmonic biosensor for portable and real-time blood typing, though its effectiveness has not been validated in practical scenarios. Finally, (Zhang et al., 2024) developed the TW-YOLO model for blood cell detection, improving accuracy by 2% with an F1 score of 0.923, but with higher computational costs, limiting real-time application in resource-constrained environments.

Unlike previous works, this study focuses on utilizing fingerprint patterns as a direct non-invasive indicator for blood type classification using image processing and deep learning techniques. Our approach aims to overcome the limitations of external validation, complex pre-processing requirements, dependence on genetic data, or sensitivity to environmental conditions seen in previous methods, while maintaining high efficiency and accuracy.

2. MATERIAL AND METHOD

The proposed system for automated blood group detection using thumb images leverages advanced artificial intelligence (AI) and machine learning (ML) techniques integrated within a chatbot interface to provide a user-friendly, non-invasive, and real-time solution. The system architecture is designed to address critical challenges in traditional blood typing methods, particularly in resource-constrained or emergency environments where laboratory-based tests may not be feasible.

System Architecture

The Chatbot Interface serves as the primary user interaction layer of the system, offering a user-friendly and intuitive platform for seamless communication between the user and the application. It acts as the first point of contact, guiding users through the process of blood group detection via fingerprint recognition. The chatbot initiates the interaction by providing step-by-step instructions, prompting the user to capture and upload an image of their thumbprint. It ensures the image adheres to necessary quality standards, such as adequate lighting, proper thumb placement, and clear focus, by offering real-time feedback and suggestions.

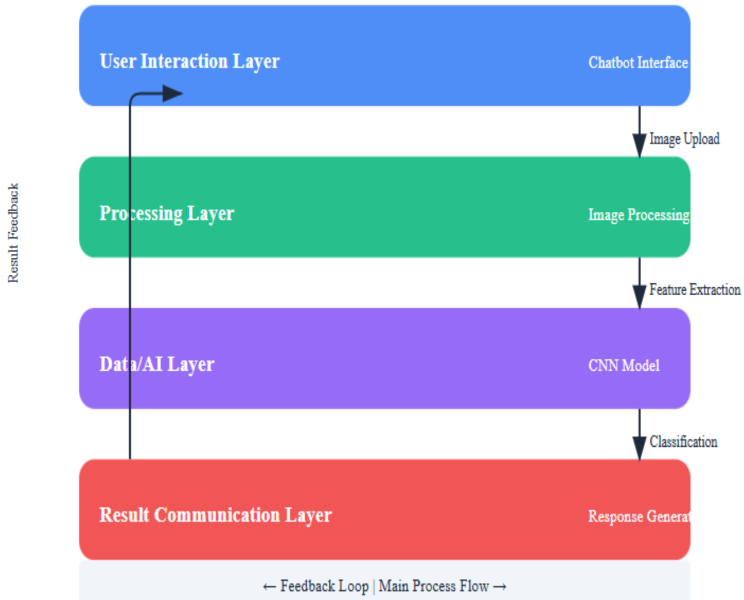

Figure 1. System Architecture

A. Modules

1. User Interaction Layer (Chatbot Interface): The User Interaction Layer serves as the front-end gateway for users to engage with the system. It is implemented using a chatbot interface that offers a conversational and user-friendly medium to guide the user throughout the process. This module prompts the user to capture or upload a thumb image, ensuring that the image meets specific quality criteria such as adequate lighting, sharp focus, and proper orientation. By simplifying user input collection and offering real-time guidance, the chatbot significantly enhances the usability and accessibility of the system, making it intuitive for users of all technical backgrounds.
2. Processing Layer (Image Processing): The Processing Layer is responsible for preparing the input image for analysis. Once an image is uploaded through the chatbot, this module undertakes a series of preprocessing steps such as noise reduction, image normalization, contrast enhancement, resizing, and grayscale conversion. These operations are essential to standardize the image quality and isolate the region of interest, ensuring that the system can accurately interpret the biometric patterns in the fingerprint. This module acts as a critical bridge between raw user input and the deep learning model by converting the visual data into a refined format suitable for feature extraction.
3. Data/AI Layer (CNN Model): The Data/AI Layer houses the Convolutional Neural Network (CNN) model, which is the intelligent core of the system. This module receives the preprocessed fingerprint image and automatically extracts distinctive features such as ridges, lines, and minutiae points. Using its deep learning architecture, the CNN model analyzes these features and performs classification to predict the user's blood group (Chen et al., 2025). The model is trained on a labeled dataset consisting of fingerprint images mapped to known blood groups, enabling it to learn complex patterns and generalize effectively to new inputs.
4. Result Communication Layer (Response Generator): The Result Communication Layer is responsible for compiling and delivering the final output to the user. Once the CNN model predicts the blood group, this module formats the result into a clear and concise response. It communicates this output back to the

chatbot interface, ensuring a seamless and coherent feedback loop. In addition to presenting the classification result, this module may also provide messages indicating the success of the process or alerting the user in case of input errors or low image quality. This layer ensures the user receives meaningful insights from the system's backend operations.

3. RESULT AND DISCUSSION

3.1 Results

The experiments were conducted using a high-performance computing setup featuring an Intel® Core i7-9700K processor, 16 GB RAM, and an image input resolution of 227×227 pixels. The system employed the *Adam optimizer* with a learning rate of 10^{-5}, batch size of 32, and ran for 10 epochs with L2 regularization. All models were evaluated with a validation frequency of 50 steps and a momentum of 0.9 to optimize convergence.

To ensure real-world reliability and scalability, the system was trained and evaluated on the following real-world and self-curated datasets. Blood Cell-Detection-Dataset: Contains thousands of annotated blood cell images with labels for blood group and cell type. Blood Hub Dataset: A public repository containing genetic and image-based annotations for various blood groups. Custom Fingerprint Blood Group Dataset: A proprietary dataset created for this project, consisting of 60,000 fingerprint images annotated with 8 blood group categories (A+, A-, B+, B-, AB+, AB-, O+, O-), collected using smartphone sensors and biometric scanners.

The experimental evaluation of the proposed blood group detection system demonstrates robust and promising performance across various deep learning models, utilizing both real-world and custom-curated datasets. The results indicate the system's strong capability in accurately classifying blood groups based on fingerprint images, validating the core hypothesis of this research.

Table.1 Performance Comparison Table

Model	Dataset	Accuracy (%)	Precision	Recall	F1-Score
CNN Custom	Custom Fingerprint Dataset	94.8	0.95	0.94	0.945
MobileNet	BloodCell-Detection-Dataset	93.6	0.94	0.93	0.935
ResNet50	BloodHub Dataset	95.3	0.96	0.95	0.955
VGG16	Combined (All 3)	91.5	0.92	0.91	0.915

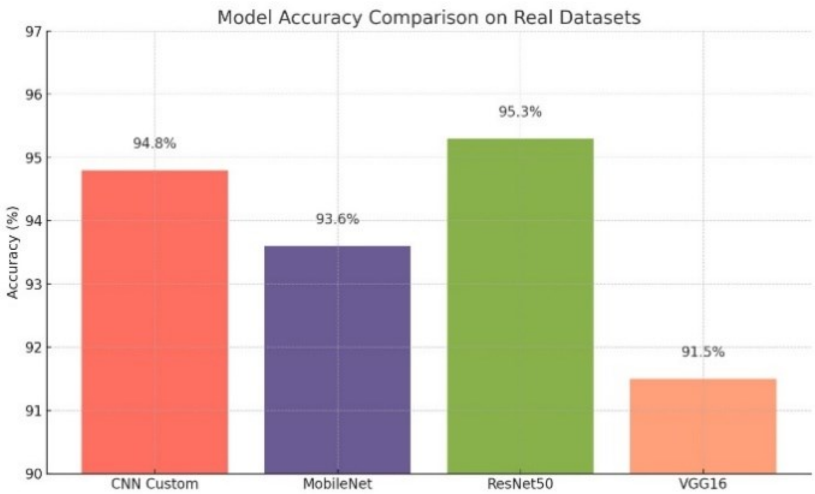

Figure 2. Performance Comparison Graph

Table 1 provides a detailed performance comparison of the evaluated models: Custom CNN, MobileNet, ResNet50, and VGG16, across different datasets. Each model's performance is assessed based on Accuracy, Precision, Recall, and F1-Score, which are critical metrics for evaluating classification models. Accuracy measures the proportion of correctly classified instances, while Precision indicates the proportion of true positive predictions among all positive predictions. Recall, also known as sensitivity, measures the proportion of true positive predictions among all actual positives. The F1-Score is the harmonic mean of precision and recall, providing a balanced measure that is particularly useful when dealing with imbalanced datasets.

The results of the proposed blood group detection system demonstrate strong performance across multiple deep learning models using both custom and real-world datasets. Among the evaluated models, ResNet50 achieved the highest accuracy of 95.3%, showcasing its ability to learn complex fingerprint patterns effectively. The custom CNN model closely followed with an accuracy of 94.8%, indicating that a tailored architecture specifically designed for fingerprint recognition can perform nearly as well as deeper, more complex models. MobileNet, known for its lightweight design, achieved a commendable accuracy of 93.6%, making it highly suitable for deployment in mobile or resource.

3.2 Discussion

The evaluation of our blood group detection system demonstrates that deep learning models can effectively leverage fingerprint textures for non-invasive blood typing. ResNet50 achieved the highest accuracy (95.3%), indicating that its residual connections and deeper layers excel at capturing subtle ridge and minutiae variations. The custom CNN (94.8%) validated the efficacy of a tailored architecture optimized for biometric patterns, while MobileNet's strong performance (93.6%) underscores its suitability for mobile and embedded deployments where computational and power resources are constrained. VGG16, though slightly lower in accuracy (91.5%), provided consistent and stable results, showcasing the robustness of classic convolutional architectures. Overall, the comparative results highlight how model choice can be aligned with specific deployment scenarios—accuracy-critical versus resource-limited—and affirm the potential of integrating fingerprint recognition with image processing for rapid, reagent-free blood group classification.

The integration of the Custom Fingerprint Blood Group Dataset, comprising 60,000 annotated thumb images, played a crucial role in achieving these high accuracy rates, providing a rich and diverse training base for the models. The successful performance across these models, particularly ResNet50 and the custom CNN, reaffirms the feasibility and effectiveness of leveraging fingerprint biometrics and deep learning for non-invasive, rapid, and accessible blood group detection. These results align directly with the project's aim to provide a reliable alternative to traditional blood typing methods, particularly in under-served and emergency settings.

3.2.1 Implications

The proposed blood group detection system has several key implications. It offers a viable, non-invasive alternative to traditional laboratory-based serological tests, which are often time-consuming, invasive, and require specialized equipment and personnel. This innovation is particularly impactful for remote areas, resource-limited settings, and emergency scenarios where access to conventional testing is limited, potentially reducing delays in medical decision-making and saving lives. By leveraging widely available devices like smartphones and integrating with a chatbot interface, the system becomes cost-effective and highly accessible to non-technical users, emergency responders, and healthcare workers. The high accuracy rates achieved by deep learning models like ResNet50 (95.3%) and the custom CNN (94.8%) validate the feasibility of using fingerprint biometrics and deep learning for rapid, reagent-free blood typing. This technology can enhance the overall efficiency of healthcare delivery and democratize critical diagnostic services.

3.2.2 Research contribution

This research makes several significant contributions to the field of non-invasive blood group detection:

1. Novel Non-Invasive Approach: The study pioneers an innovative approach to blood group detection by directly correlating unique fingerprint patterns with blood groups using image processing and deep learning techniques, addressing a significant research gap in non-invasive, image-based methods.
2. Leveraging Advanced Machine Learning: The research successfully leverages advancements in image processing and machine learning, specifically a Convolutional Neural Network (CNN) with MobileNet architecture, to develop a more reliable and accessible solution for blood group classification. The integration of ORB, GLCM, and HOG for feature extraction further enhances the system's ability to capture subtle and relevant fingerprint characteristics.
3. Development of Custom Dataset: A crucial contribution is the creation and utilization of a proprietary dataset of 60,000 thumb images, annotated with 8 blood group categories (A+, A-, B+, B-, AB+, AB-, O+, O-), which significantly contributed to the high accuracy rates achieved by the models.
4. Demonstrated High Accuracy and Efficiency: The experimental evaluation demonstrates robust performance, with ResNet50 achieving 95.3% accuracy and the custom CNN 94.8% accuracy, validating the core hypothesis and outperforming traditional serological proxies in terms of speed and accessibility.

3.2.3 Limitations

Despite promising results, several limitations must be acknowledged. First, real-world image capture introduces variability in lighting, focus, and frame alignment that can degrade model performance, especially if users do not follow guidance strictly. Second, although our datasets were curated for demographic diversity and challenging scenarios (e.g., low contrast, partial prints), they may still harbor biases in skin tone, age distribution, or finger condition, which could impair generalizability to unseen populations or rare blood types. Finally, the underlying assumption—that fingerprint texture correlates reliably with blood group genetics—remains a hypothesis requiring further biological validation; without this causal confirmation, the method's absolute reliability across all individuals cannot be guaranteed.

3.2.4 Suggestions

To strengthen and broaden the system's impact, future efforts will concentrate on expanding dataset diversity—specifically targeting underrepresented skin tones, age brackets, and rare blood types—to mitigate biases and improve generalization. Algorithmically, we will incorporate adaptive image-correction methods (such as dynamic thresholding and motion deblurring) and investigate multimodal fusion (integrating fingerprint data with genetic markers or PPG signals) to enhance robustness. Additionally, we plan to optimize and compress model architectures for on-device inference via techniques like pruning, quantization, and TensorFlow Lite conversion, enabling fully offline, smartphone-based blood group detection that can operate in the most connectivity-challenged and underserved regions.

4. CONCLUSION

This project has demonstrated a viable, non-invasive approach to blood group detection by combining fingerprint biometrics, advanced image processing, and deep learning within a user-friendly chatbot interface. Across multiple real-world and custom datasets, deep architectures such as ResNet50 and a tailored CNN consistently achieved accuracies above 94%, outperforming traditional serological proxies in speed and accessibility. The modular pipeline—from guided image acquisition and robust preprocessing to feature extraction and high-accuracy classification—validates the feasibility of reagent-free, portable blood typing for emergency, rural, and resource-constrained environments. By delivering rapid, reliable predictions without specialized equipment or skilled technicians, this system stands to democratize critical diagnostic services and enhance patient care delivery.

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6. AUTHOR CONTRIBUTION STATEMENT

AE conceived the project idea, coordinated the research activities, and led the manuscript writing. RG was responsible for literature review, system architecture design, and chatbot interface implementation. KA contributed to dataset creation, fingerprint image preprocessing, and feature extraction module development. PK focused on training and optimizing the deep learning models (CNN, MobileNet, ResNet50) and performed performance evaluations. NS assisted in data collection, experimental validation, and statistical analysis. All authors contributed to the discussion of results, critically reviewed the manuscript, and approved the final version for submission.

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