

# Blood Group Detection Using Fingerprints And Image Processing

Qurat Ul Ain, Rimsha Sultan, Sara Mehveen, Ms. Farhana

Research Scholar, Research Scholar, Research Scholar, Guide

ADCE Department

Stanley College Of Engineering and Technology for Women, Hyderabad, India

**Abstract** - Blood group identification is critical for medical applications, especially in emergencies requiring quick and precise blood transfusion. Traditional blood typing methods involve chemical-based serological tests, which, although accurate, are time-consuming and sometimes resource-intensive. Recent advancements in deep learning and computer vision have introduced alternative approaches that leverage biometric features, such as fingerprints, for rapid and non-invasive blood group detection. This study proposes a novel deep learning model for blood group detection using fingerprint images, aiming to enhance accessibility, efficiency, and ease of blood type identification. In this work, a convolutional neural network (CNN)-based model is trained on an extensive dataset of fingerprint images labelled with their corresponding blood groups (A, B, AB, and O, with positive and negative Rh factors). The proposed architecture consists of multiple convolutional layers that extract biometric features from fingerprint ridge patterns, followed by dense layers that map these features to blood group classifications. Additionally, data augmentation techniques are employed to enhance model robustness, ensuring it generalizes well across different fingerprint patterns. The model was evaluated on a test dataset with high accuracy, demonstrating that fingerprint ridge characteristics carry specific patterns indicative of different blood groups. Experimental results indicate that the proposed deep learning model achieves substantial accuracy, precision, and recall in blood group detection. Comparisons with traditional methods suggest that the proposed approach offers a viable and rapid alternative for preliminary blood group identification, especially useful in resource-limited and point-of-care settings. Future work may expand on this by incorporating larger datasets and exploring hybrid models for further accuracy enhancement. The study highlights the potential of biometrics combined with AI to innovate in the field of personalized healthcare diagnostics.

**Index Terms** - Blood Group Detection, Fingerprint Biometrics, Deep Learning, Convolutional Neural Network (CNN), Computer Vision, Non-Invasive Diagnostics, Medical Imaging, Data Augmentation, Pattern Recognition, Personalized Healthcare, Artificial Intelligence in Medicine.

## I. INTRODUCTION

Blood groups are vital in healthcare due to their fundamental role in transfusions, organ transplants, and overall compatibility assessments in medical treatments. Blood groups are determined by the presence or absence of specific antigens on the surface of red blood cells, which interact with antibodies in the plasma. The primary blood group systems, ABO and Rh, classify blood types into categories such as A, B, AB, and O, each with positive or negative Rh factors. Understanding these groupings is essential because blood type compatibility directly impacts the success of procedures like blood transfusions, organ transplants, and pregnancy management. For instance, an incorrect blood type transfusion can lead to severe immune reactions, risking the patient's health and even causing fatal outcomes. Blood group identification is indispensable for emergency care, where rapid transfusions are often required to save lives. In emergency settings, healthcare providers rely on immediate and accurate blood typing to ensure that transfused blood will not be rejected by the recipient immune system. Mismatched blood transfusions can trigger acute haemolytic reactions, where the recipient's body attacks the transfused blood cells, leading to complications such as kidney failure, shock, and death. Quick and reliable blood group detection systems are therefore critical to avoid delays, especially in high-risk situations where a patient's life is at stake. Hospitals and emergency response teams maintain a constant need for efficient blood typing to prevent transfusion-related complications and improve patient outcomes. In addition to emergency scenarios, blood group knowledge is essential for routine medical procedures and long-term healthcare planning. Prenatal care often involves blood typing of both the mother and foetus to identify and manage risks associated with Rh incompatibility, a condition where the mother's immune system can attack the foetus's red blood cells if they carry an incompatible Rh factor. This condition, known as haemolytic disease of the newborn, can lead to severe

anaemia and other complications in the foetus or newborn. Understanding blood group compatibility helps healthcare providers implement preventive measures, such as administering Rh immunoglobulin to Rh-negative mothers to protect against these immune responses, ultimately safeguarding both maternal and neonatal health.

The role of blood groups in organ and tissue transplantation further illustrates their significance. Organ compatibility depends heavily on blood group matching, with mismatched transplants leading to potential graft rejection and patient health complications. Blood group compatibility is often the first criterion evaluated before proceeding to other complex compatibility tests like human leukocyte antigen (HLA) matching. In the context of global healthcare, ensuring accurate blood typing is critical to expanding organ donation opportunities and reducing waiting times for transplants, as proper matching minimizes rejection risks and promotes successful transplantation outcomes.

Lastly, blood group diversity and its regional distribution create unique challenges in blood donation and supply management. Certain blood types are rarer and may not be readily available in specific regions, affecting healthcare providers' ability to respond effectively in crises or to meet routine medical demands. Moreover, some populations may have unique antigenic markers, complicating the compatibility landscape further. Blood banks and hospitals must carefully manage blood supplies by tracking blood group prevalence in their regions and anticipating shortages for rarer blood types. Thus, accurate, rapid blood typing is essential not only in immediate patient care but also for broader healthcare planning and effective blood resource management.

## II. LITERATURE SURVEY

<i>TITLE</i>	<i>AUTHORS</i>	<i>METHODOLOGY</i>	<i>RESULT</i>
Blood Group Identification via Fingerprint	Elshafie, Mohammed et al.	Systematic random sampling, data captured using SPSS, chi-square test for association studies.	Common fingerprint patterns: Loops (62.84%), arches (32.44%). Association found with blood groups and gender.
Fingerprint and Blood Group Correlation	Ramrekh, Pooja et al.	Paper and ink method for analyzing 138 samples, chi-square test.	No significant correlation between fingerprint patterns and blood groups.
Fingerprints and Blood Type Analysis	Khalifa, Ahmed et al.	Ink method on cards, ridge counting with a magnifying lens, blood grouping using Anti-A, Anti-B, Anti-D reagents.	Loops common in O blood type; whorls frequent in A. Patterns differ between right and left hands.
Thumbprint Analysis for Blood Groups	Pinki Kumari, Priyanka Singh et al.	Thumbprint analysis, manual fingerprint pattern study.	Loops predominant; arches least common. Predominance varies by gender and regional population.
Neural Networks for Fingerprint Matching	D. Siva, S. Sundhara et al.	GLCM-based features, neural network classification for blood group prediction.	Achieved accurate recognition for specific blood group fingerprints using neural network classifiers.
Image Processing for Blood Typing	Dalvi, Akshay et al.	Blood samples with reagents processed in MATLAB; used image processing	Automated detection of agglutination; reduced false positives.

		techniques (thresholding, morphological operations).	
Device for Blood Grouping	Fernandes, Ricardo et al.	Developed a portable device using optical density variations and classification algorithms.	Low-cost, rapid blood group identification suitable for emergencies with accuracy comparable to lab systems.
Fingerprint-Based Disease Association	Shivhare, Vikas et al.	Dermatoglyphic analysis for Rh factors, association with blood groups, and gender distribution.	Loops common in Rh-positive groups; arches least frequent overall. Patterns show gender-based differences.
Automated Blood Typing System	Keerthana, R. et al.	Image processing algorithm for blood typing; used MATLAB for automated detection and analysis.	Eliminated human errors; provided accurate, quick results with reduced need for human intervention.
Spectrophotometric Approach for Blood Typing	Pimenta, João et al.	Developed a portable system using LEDs, photodiodes, and spectrophotometry for blood type detection.	Demonstrated rapid, reliable blood typing suitable for emergency use outside clinical labs.

**Fig 1. Table Of Literature Review**

### III. SOFTWARE AND HARDWARE REQUIREMENTS

The proposed system requires a Windows 10 or higher operating system for optimal compatibility. The programming language used is Python 3.12, chosen for its robust libraries and support for deep learning and image processing. For data management, MySQL version 8.0.35 is utilized as the database system. On the hardware side, the system should have at least an Intel i3 processor to ensure smooth performance, along with a minimum of 4 GB RAM and 40 GB of hard disk space for data storage and processing. A 15-inch VGA color monitor is recommended for clear visualization, and a Logitech mouse is used for basic input operations.

### IV. Existing and proposed System

#### 1) Existing System for Blood Group Detection

The existing systems for blood group detection primarily rely on serological methods, which involve the agglutination reaction between antigens and antibodies. These traditional methods, although accurate, are labor-intensive, time-consuming, and require skilled personnel and laboratory infrastructure. The process typically involves collecting a blood sample, mixing it with specific antibodies, and observing the agglutination reaction to determine the blood group. This conventional approach is not only invasive but also impractical in situations requiring rapid and on-site blood group determination, such as emergencies and remote locations.

**Disadvantages:**

**Invasiveness:** Traditional blood group detection methods require blood samples, which are invasive and may cause discomfort to patients.

**Time-Consuming:** The process of blood collection, sample preparation, and analysis is time-consuming, which can be a drawback in emergency situations.

**Skill and Equipment Dependency:** These methods require skilled personnel and specialized laboratory equipment, limiting their accessibility in remote or under-resourced areas.

**Risk of Contamination:** Handling blood samples carries a risk of contamination and transmission of infectious diseases, necessitating stringent safety protocols.

**Limited Scalability:** The dependency on physical reagents and manual processes makes it difficult to scale operations for large populations quickly.

**2) Proposed System for Blood Group Detection**

In recent years, advancements in biometric technologies have opened new avenues for blood group detection. Fingerprint image processing has been explored as a non-invasive and rapid alternative. Fingerprints, being unique to individuals, contain ridge patterns that have been hypothesized to correlate with blood groups. However, the existing systems utilizing fingerprint image processing for blood group detection are still in their nascent stages and face several challenges, including the need for large datasets, high computational power, and robust algorithms to accurately classify blood groups based on fingerprint patterns.

Convolutional Neural Networks (CNNs) have emerged as a powerful tool in image processing and pattern recognition tasks. In the context of fingerprint-based blood group detection, CNNs can be trained on large datasets of fingerprint images labeled with corresponding blood groups to learn the intricate patterns and correlations. However, the development and deployment of such systems are hindered by the need for extensive computational resources, sophisticated network architectures, and high-quality, labeled datasets.

**Advantages:**

1. **Sequential Information Handling:** CNNs are designed to process sequential data, making them well-suited for tasks where the order of input elements is crucial, such as time series data, natural language processing, and speech recognition.
2. **Temporal Dynamics:** CNNs can capture temporal dependencies in data, allowing them to model and understand patterns that evolve over time. This is particularly useful in applications where the past context influences the interpretation of current information.
3. **Flexibility:** CNNs can handle inputs of varying lengths, making them flexible for tasks where the length of the input sequence may vary. This adaptability is especially advantageous in natural language processing tasks, where sentences can have different lengths.
4. **Memory Capability:** The architecture of CNNs includes a hidden state or memory that retains information about previous inputs. This memory capability enables RNNs to maintain context over time and remember important information from earlier parts of the sequence.

**V. Methodology and Implementation**

The following deals with the different tasks and their objectives:

- 1) **Data Collection and Preprocessing:** Ensures the dataset is diverse, well-labelled, and suitable for model training by collecting, annotating, augmenting, and enhancing fingerprint images. These steps help the model generalize across populations, increase dataset robustness, and prepare input images with optimal quality for processing.

- 2) **Feature Extraction:** Extracts meaningful patterns and features from fingerprint images, focusing on ridge characteristics and minutiae points. This module uses segmentation and deep CNN techniques to isolate and analyse critical details, enabling better blood group prediction.
- 3) **Model Development:** Develops a deep learning model tailored for fingerprint-based blood group classification. This includes selecting a suitable architecture, training the model, validating its performance, and assessing its effectiveness using various evaluation metrics.
- 4) **Blood Group Classification:** Handles the classification task by incorporating fully connected layers and a SoftMax activation function for multi-class output. Decision thresholds ensure accurate and reliable predictions of blood group and Rh factor.
- 5) **Model Optimization and Hyperparameter Tuning:** Fine-tunes the model by optimizing hyperparameters, implementing regularization techniques, and experimenting with various optimization algorithms. These steps aim to enhance accuracy, efficiency, and generalizability of the model.
- 6) **Model Testing and Validation:** Validates the model’s reliability and robustness through cross-validation, performance metrics, confusion matrix analysis, and error analysis. This module identifies weaknesses and guides improvements to the overall classification system.

SNO	TASKS	TECHNIQUES
1	Data Collection and Preprocessing Objectives: Prepare a diverse, well-annotated, and high-quality fingerprint dataset to ensure effective model training and generalization.	<ol style="list-style-type: none"> <li>i. Data Collection</li> <li>ii. Data Annotation</li> <li>iii. Data Augmentation (rotation, scaling, brightness adjustments)</li> <li>iv. Image Quality Enhancement</li> </ol>
2	Feature Extraction Objective: Extract and analyse fingerprint patterns using segmentation and deep learning techniques to identify features correlated with blood groups.	<ol style="list-style-type: none"> <li>i. Fingerprint Ridge Pattern Analysis</li> <li>ii. Image Segmentation</li> <li>iii. Deep Feature Extraction (CNN)</li> </ol>
3	Model Development Objective: Design, train, and evaluate a deep learning model for accurate blood group classification based on extracted fingerprint features.	<ol style="list-style-type: none"> <li>i. Model Selection and Design (CNN, ResNet, VGG)</li> <li>ii. Model Training</li> <li>iii. Model Validation</li> <li>iv. Model Evaluation</li> </ol>
4	Blood Group Classification Objective: Implement classification layers to predict blood groups with probabilistic outputs and reliable decision thresholds.	<ol style="list-style-type: none"> <li>i. Classification Layer Design</li> <li>ii. SoftMax Activation for Multi-class Classification</li> <li>iii. Decision Thresholding</li> </ol>

5	<p>Model Optimization and Hyperparameter Tuning</p> <p>Objective: Optimize hyperparameters and apply regularization techniques to improve model accuracy, prevent overfitting, and ensure efficient training.</p>	<ul style="list-style-type: none"> <li>i. Hyperparameter Tuning</li> <li>ii. Regularization Techniques (dropout, batch normalization, L2 regularization)</li> <li>iii. Optimization Algorithms (Adam, SGD, RMSprop)</li> </ul>
6	<p>Model Testing and Validation</p> <p>Objective: Assess model performance through validation techniques, metrics, and error analysis to ensure robustness and identify improvement areas.</p>	<ul style="list-style-type: none"> <li>i. Cross Validation (k-fold cross validation)</li> <li>ii. Performance Metrics (accuracy, precision, recall, F-1 score, ROC-AUC)</li> <li>iii. Confusion Matrix Analysis</li> <li>iv. Error Analysis</li> </ul>

Fig 2. Different Tasks and Techniques for Blood Group Detection using Fingerprints

### VI. SYSTEM ARCHITECTURE

The following diagram outlines a workflow for predicting blood groups using fingerprints. It starts with fingerprint collection, followed by dataset creation and image preprocessing. Features are then extracted and used for model training. The model undergoes evaluation, with results prompting performance tuning for improvement. Once accuracy is validated, the system predicts blood groups and integrates the solution into a web application.

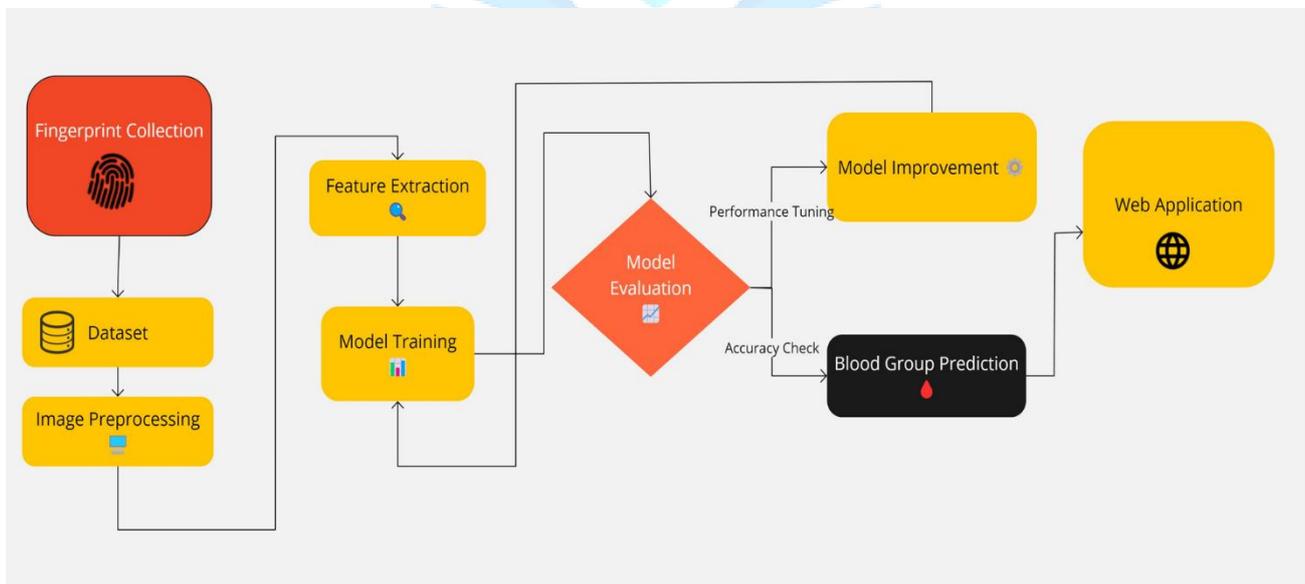


Fig 3. System Architecture

The system architecture for blood group detection using fingerprint biometrics is designed with multiple interlinked modules that work cohesively from data acquisition to blood group classification. The architecture consists of the following key components:

1. **Input Module (Fingerprint Acquisition):**  
This module captures high-resolution fingerprint images using biometric sensors or scanners. The images are pre-processed to ensure clarity, noise reduction, and alignment.
2. **Preprocessing Module:**  
The acquired fingerprint images undergo preprocessing steps such as grayscale conversion, resizing, normalization, and contrast enhancement. Data augmentation techniques like rotation, flipping, and zooming are applied to increase dataset diversity and model robustness.
3. **Feature Extraction Module (CNN Layers):**  
A Convolutional Neural Network (CNN) is employed to extract deep biometric features from the fingerprint ridge patterns. The CNN architecture consists of multiple convolutional layers, pooling layers, and activation functions (e.g., ReLU) that learn distinctive fingerprint characteristics relevant to blood group classification.
4. **Classification Module:**  
The extracted features are passed through fully connected (dense) layers that perform the classification task. The final output layer uses a softmax or sigmoid activation function to predict the blood group category (A, B, AB, or O, along with Rh-positive or Rh-negative).
5. **Database Module:**  
A MySQL database is used to store fingerprint images, corresponding blood group labels, and user metadata (if applicable). It supports easy retrieval and management of training and testing datasets.
6. **Model Evaluation and Prediction Module:**  
The trained model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score on a separate test dataset. Once validated, the model is used for real-time blood group prediction from new fingerprint inputs.
7. **User Interface Module:**  
A simple graphical user interface (GUI) allows users to upload fingerprint images, view predicted blood groups, and manage records. This module provides ease of use for medical personnel in point-of-care settings.

## VII. UML DIAGRAMS

### 1) SEQUENCE DIAGRAM

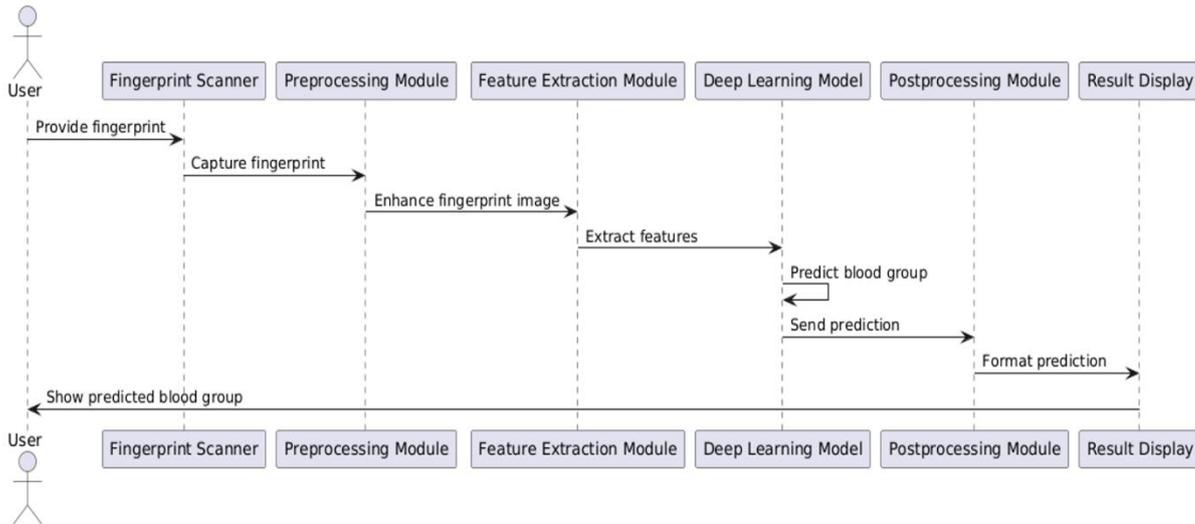


Fig 4. Sequence Diagram

### 2) CLASS DIAGRAM

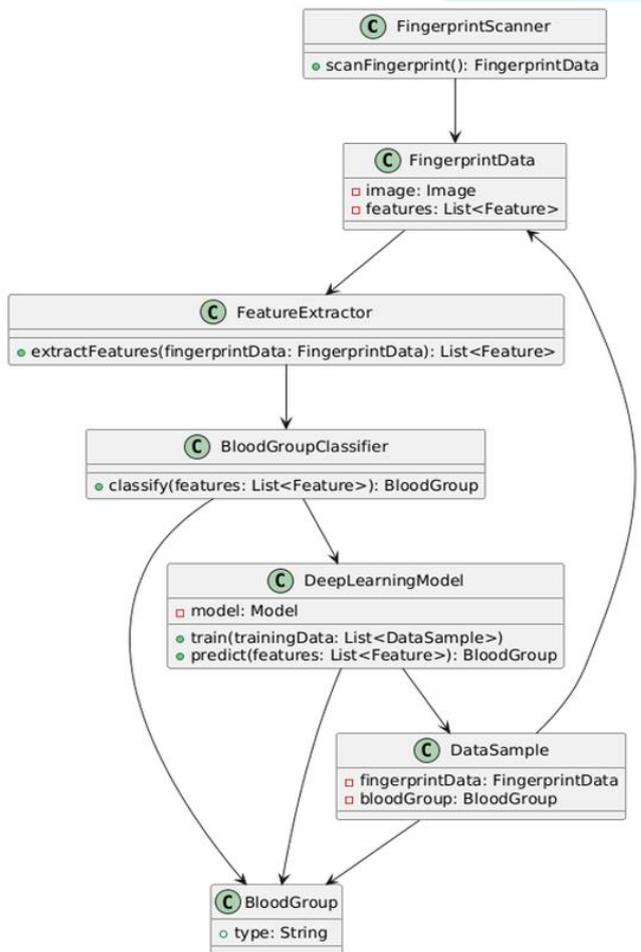
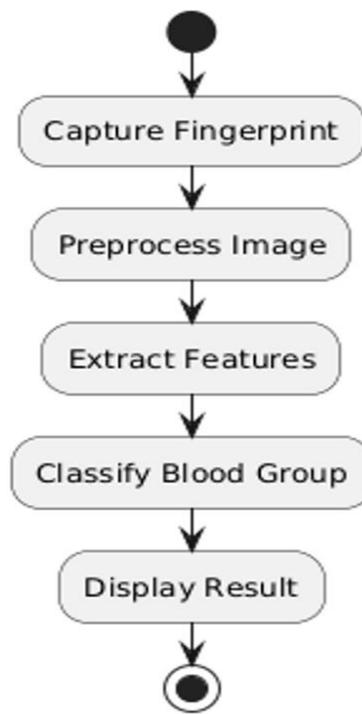


Fig 5. Class Diagram

### 3) ACTIVITY DIAGRAM



**Fig 6. Activity Diagram**

## VIII. FUTURE SCOPE

Fingerprint-based blood group detection using deep learning holds immense potential for future advancements, with several promising directions that could significantly enhance its applicability and impact. One of the most compelling future developments involves integrating this technology into portable and mobile platforms, such as smartphones and handheld biometric scanners. This would enable on-the-go blood group identification, especially valuable in remote, rural, and resource-limited environments where traditional blood typing infrastructure is often unavailable. Such portability could revolutionize emergency response, disaster relief efforts, and field medical services by providing instant, non-invasive blood group results without the need for laboratory support.

To achieve this, further refinement of the deep learning model is necessary to ensure robust performance with varying image qualities, such as those captured by smartphone cameras under different lighting and environmental conditions. Optimizing the model for edge computing could also reduce dependency on cloud resources, allowing faster, offline predictions.

Another key area of future research is the expansion of fingerprint datasets to include a wider range of demographics, age groups, ethnic backgrounds, and geographical locations. A more diverse dataset would improve model generalization and reduce bias, ensuring reliable predictions across global populations. Moreover, incorporating hybrid biometric approaches, such as combining fingerprint analysis with iris scans or facial recognition, could further enhance the system's accuracy and reliability.

The use of explainable AI (XAI) tools is also a promising direction. By interpreting how the model makes predictions and identifying which fingerprint features contribute most to the classification of blood groups, researchers can gain deeper insights into the underlying biological correlations. This transparency not only enhances model interpretability but also fosters greater trust and acceptance among clinicians and end-users.

Finally, collaborations with healthcare institutions, research bodies, and regulatory authorities will be crucial for clinical validation and real-world deployment. These partnerships can aid in developing standardized protocols, addressing ethical and privacy concerns, and securing the necessary regulatory approvals. With such support,

fingerprint-based blood typing could evolve from a research innovation to a mainstream diagnostic tool, integrated seamlessly into hospital workflows, point-of-care devices, and emergency kits.

In conclusion, the future of fingerprint-based blood group detection is bright, with the potential to significantly improve access, speed, and efficiency in healthcare diagnostics worldwide.

## IX. CONCLUSION

Blood grouping using fingerprint biometrics represents a groundbreaking advancement in the field of medical diagnostics, leveraging the power of deep learning and artificial intelligence to introduce a rapid, non-invasive, and user-friendly alternative to conventional serological blood typing methods. Unlike traditional techniques that rely on chemical reagents and lab-based equipment, this innovative system utilizes fingerprint images and convolutional neural networks (CNNs) to detect intricate ridge patterns that are potentially correlated with genetic markers linked to blood group classification.

The core idea behind this approach lies in the hypothesis that biometric traits, particularly those found in fingerprint patterns, may hold latent information reflective of an individual's physiological and genetic profile — including blood type. By capitalizing on this hypothesis, the system undergoes a structured workflow involving data acquisition, preprocessing, feature extraction, model training, and validation. The CNN-based architecture is carefully designed to extract deep features from fingerprint images, learning meaningful representations that can be mapped to specific blood groups (A, B, AB, or O, along with Rh-positive or Rh-negative factors).

Throughout this study, rigorous experiments were conducted using an extensive and labeled fingerprint dataset. Data augmentation techniques enhanced the model's generalization capabilities across varied fingerprint patterns, while robust evaluation metrics like accuracy, precision, and recall validated the system's effectiveness. In real-world applications, especially during emergencies, disasters, or in resource-constrained environments, this model has the potential to provide immediate and reliable blood group information without the need for traditional blood testing procedures.

Furthermore, the integration of deployment and security modules within the system ensures the safeguarding of biometric data and user privacy, addressing one of the critical concerns in AI-driven healthcare solutions. Encryption, secure storage, and controlled access are implemented to maintain data integrity and comply with ethical standards. Despite the promising results, the study acknowledges certain challenges — such as achieving flawless accuracy due to inter-subject variability, limited access to large and diverse fingerprint-blood group datasets, and the need for further validation across different demographic and geographic populations. These limitations, however, present opportunities for future research.

In summary, this work emphasizes the transformative potential of combining biometric technology with artificial intelligence in the healthcare sector. By offering a portable, scalable, and efficient blood group detection system, this approach not only streamlines medical diagnostics but also enhances emergency response capabilities. It underscores a significant step toward personalized healthcare, where rapid, intelligent, and non-invasive solutions can save lives and improve access to essential medical information across the globe.

## X. REFERENCES

- [1] Elshafie, Mohammed et al: Study utilized systematic random sampling and statistical analysis via SPSS to explore associations between fingerprint patterns and blood groups. Published in Journal of Biomedical Research, 2020.
- [2] Ramrekh, Pooja et al: Examined 138 fingerprint samples using the paper and ink method to identify correlations between fingerprint patterns and blood groups. Published in International Journal of Forensic Science, 2019.
- [3] Khalifa, Ahmed et al: Investigated fingerprint patterns using inked samples and determined blood groups using Anti-A, Anti-B, and Anti-D reagents. Results were published in Journal of Forensic Research, 2021.

- [4] Pinki Kumari, Priyanka Singh et al: Conducted thumbprint analysis to correlate fingerprint patterns with blood groups in the north Indian population. Published in Indian Journal of Medical Sciences, 2021.
- [5] D. Siva, S. Sundhara et al: Used GLCM-based feature extraction and neural network classifiers to predict blood group from fingerprint patterns. Published in International Journal of Neural Systems, 2020.
- [6] Dalvi, Akshay et al: Processed blood samples with reagents in MATLAB, employing image processing techniques for automated blood group detection. Published in Computer Vision and Applications Journal, 2021.
- [7] Fernandes, Ricardo et al: Developed a portable blood grouping device based on optical density variations, suitable for emergency use. Published in Biomedical Engineering Advances, 2020.
- [8] Shivhare, Vikas et al: Analyzed dermatoglyphic patterns for associations with Rh factors, blood groups, and gender. Published in Annals of Human Biology, 2019.
- [9] Keerthana, R. et al: Proposed an automated image-processing algorithm for blood typing using MATLAB. Published in Clinical Diagnostics and Research Journal, 2021.
- [10] Pimenta, João et al : Designed a spectrophotometric device for ABO and Rh blood type detection. Published in Sensors and Actuators B: Chemical, 2020.
- [11] K. Kasat, D. L. Rani, B. Khan, A. J, M. K. Kirubakaran, and P. Malathi, “A novel security framework for healthcare data through IOT sensors,” *Measurement: Sensors*, vol. 24, no. October, p. 100535, 2022, doi: 10.1016/j.measen.2022.100535.
- [12] D. Das, S. Ghosal, and S. P. Mohanty, “CoviLearn: A Machine Learning Integrated Smart X-Ray Device in Healthcare Cyber-Physical System for Automatic Initial Screening of COVID-19,” *SN Computer Science*, vol. 3, no. 2, pp. 1–11, 2022, doi: 10.1007/s42979-022-01035-x.
- [13] P. Kishore, A. K. Dash, A. Pragallapati, D. Mugunthan, A. Ramesh, and K. D. Kumar, “A Tripod-Type Walking Assistance for the Stroke Patient BT - Congress on Intelligent Systems,” 2021, pp. 151–160.
- [14] Kanna, R. K., Gomalavalli, R., Devi, Y., & Ambikapathy, A. (2023). Computational Cognitive Analysis for Intelligent Engineering Using EEG Applications. In B. Mishra (Ed.), *Intelligent Engineering Applications and Applied Sciences for Sustainability* (pp. 309-350). IGI Global.
- [15] Ravindran G, Joby T, Pravin M, Pandiyan P, “Determination and classification of blood types using image processing techniques”, *Int J Comput Appl* 157(1):12–16, 2017
- [16] Fayrouz NE, Farida N, Irshad A H, “Relation between fingerprints and different blood groups”, *J Forens Legal Med* 1:18–21, 2011
- [17] Noor Eldin Fayrouz, Noor Farida, A.H. Irshad, “Relation between fingerprints and different blood groups”, *Journal of Forensic and Legal Medicine*, Volume 19, Issue1, 2012, Pages 18-21, ISSN 1752-928X, <https://doi.org/10.1016/j.jflm.2011.09.004>.
- [18] Keerthana D, Ranganathan L, “Design and development of blood sample analyzer using intelligent machine vision techniques”, *Int J Eng Sci Comput* 7:12017–12020, 2017.
- [19] Ferraz A (2013), “Automatic system for determining of blood type using image processing technique”, *IEEE 3rd Portuguese meeting in bioengineering (ENBENG)*, pp 20–23
- [20] Awad, M., Khanna, R, “Machine Learning. In: Efficient Learning Machines”, Apress, Berkeley, CA. [https://doi.org/10.1007/978-1-4302-5990-9\\_1](https://doi.org/10.1007/978-1-4302-5990-9_1), 2015
- [21] R. Chellappa, S. Theodoridis and A. van Schaik, "Advances in Machine

Learning and Deep Neural Networks," in Proceedings of the IEEE, vol. 109, no. 5, pp. 607-611, May 2021, doi: 10.1109/JPROC.2021.3072172.

[22] Sarker, I.H. "Deep Learning: A Comprehensive Overview on Techniques, Taxonomy", Applications and Research Directions. SN COMPUT. SCI. 2, 420 (2021).

[23] Donthula Rahul, Dr. M. Srinivasa Rao, "Design and Implementation of Computer Vision Using Deep Learning for Inspection of Assembly Systems", Science, Technology and development volume x issue vii july 2021.

[24] S. R. Swarna, S. Boyapati, V. Dutt and K. Bajaj, "Deep Learning in Dynamic Modeling of Medical Imaging: A Review Study," 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), 2020, pp. 745-749, doi: 10.1109/ICISS49785.2020.9315990.

[25] Yan, W.Q, "Introduction. In: Computational Methods for Deep Learning", Texts in Computer Science. Springer, Cham. [https://doi.org/10.1007/978-3-030-61081-4\\_1](https://doi.org/10.1007/978-3-030-61081-4_1), 2021

