Non-Invasive Blood Group Detection Using Deep learning model

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ABSTRACT

Determining blood type is essential, especially in critical scenarios like medical emergencies, diagnostic procedures, transfusion compatibility, organ transplants, and prenatal care. Conventional blood group determination relies on serological techniques, which, although accurate, involve invasive methods and require laboratory facilities. Additionally, manual testing performed by technicians can be subject to human error. To overcome these challenges, this project focuses on developing a precise and efficient blood typing system using pre-captured palm images. The proposed system integrates advanced image processing techniques and machine learning, particularly Convolutional Neural Networks (CNNs), to analyse fingerprint images and identify unique patterns associated with blood group phenotypes. In recent years, the need for rapid blood group detection has grown in both medical and forensic fields. Traditional methods are often time-intensive, require trained personnel, and are not always practical in emergency situations. This study introduces an alternative solution that uses fingerprint image analysis combined with machine learning techniques, specifically CNNs, for accurate and efficient blood group identification. Fingerprint ridge patterns, which have shown potential correlations with blood groups, serve as the foundation for this method. A CNN model is trained on an extensive dataset of labelled fingerprint images and demonstrates impressive accuracy in predicting blood groups.

Keywords: Non-Invasive Medical Diagnostics, Fingerprint and blood sample images, Deep Learning, Feature Learning, Pattern Recognition, Convolutional Neural Networks (CNNs) Model, Performance Metrics: High Accuracy, precision, Recall and F1-score, Python flask,

1. INTRODUCTION

An innovative and painless method for blood group determination involves analyzing fingerprints, combining advanced deep learning algorithms with medical data. This approach identifies blood type by examining the unique configurations of ridges and valleys in a person's fingerprint, information vital for medical professionals. In contrast to conventional blood tests, which can cause discomfort due to the use of needles, this fingerprint-based method offers a more comfortable and less invasive experience [1].

The patterns found in fingerprints are considered one of the most dependable and distinctive forms of identification, remaining consistent throughout a person's life [2]. Even in legal settings, fingerprints are often regarded as crucial evidence. The likelihood of two individuals possessing identical minute details within their fingerprints is exceedingly small, roughly one in 64 million, including identical twins. Furthermore, the configuration of ridges is both unique and unchanging from birth. Blood group, an inherited characteristic, also remains constant. Using fingerprints in analysis helps to significantly reduce the risk of infections. While traditional blood tests, which involve extracting blood via needles and subsequent expensive antibody procedures, are required for disease diagnosis and blood collection [3].

One of the main obstacles in creating a predictive model for blood groups is the scarcity of diverse fingerprint samples. Research on using fingerprints as a biometric for predicting blood groups and identifying age-related diseases is still in its early stages [4].

Fingerprint patterns are generally categorized into loops, whorls, and arches, depending on the direction and arrangement of the ridges. Loops, the most prevalent type, are characterized by ridges forming a loop-like shape. Whorls are defined by circular or spiral ridge formations, with several variations. Arches, which are simpler, feature flowing ridges without the presence of deltas. The analysis of these patterns, including ridge orientation and the number of deltas, is crucial for accurate classification in both forensic and biometric applications [6].

1.2 Contributions

This paper's contributions include:
• Development of a non-invasive, machine learning-based system for blood group identification using palm/fingerprint images.
• Integration of Convolutional Neural Networks (CNNs) for accurate pattern recognition and blood group classification.
• Deployment of the trained model using Python Flask to create an accessible and scalable web-based application.
• Comprehensive evaluation of the system's performance using key metrics such as accuracy, precision, recall, and F1-score.

Remaining Sections of the Paper Contains-Section 2: System Architecture-This section describes the overall architecture of the blood typing system, including image acquisition modules, preprocessing units, CNN model design, and deployment infrastructure.
Section 3: Proposed System-Details the motivation and workflow of the proposed fingerprint-based blood typing system, highlighting the correlation between ridge patterns and blood group phenotypes.Section 4: Methodology and Implementation-Covers the image preprocessing techniques, feature extraction methods, CNN architecture used, and the training process. This section also includes the implementation framework using Python and Flask.Section 5: Experimental Results and Performance Analysis-Presents the dataset used, training and testing split, evaluation criteria, and the outcomes of the model. This includes detailed results showcasing performance metrics such as accuracy, precision, recall, and F1-score.Section 6: Conclusion and Future Work-Summarizes the findings, emphasizes the effectiveness and potential of the system, and outlines future enhancements such as larger datasets, real-time mobile integration, and multi-modal biometric analysis.

LITERATURE REVIEW

Sl.No	Title of the Paper	Author(s)	Methodology Used	Findings & Results
1	Fingerprint-Based Blood Group Prediction	Vijaykumar, Patil N., and D. R. Ingle.[1]	Multiple Linear Regression (OLS)	Achieved 62% accuracy; suggests increasing sample size for better precision.

2	Automated Blood Identification Using Fingerprint Analysis	Verma, A., Bhatt, V.[2]	Machine learning, pattern recognition, feature extraction	Discusses advantages, drawbacks, and future research directions of fingerprint-based blood group prediction.
3	Blood Group Prediction Using Fingerprint Patterns	Agarwal, S., Gour, V., Gupta, N.[3]	SVM, minutiae-based features, classification methods	Explores the impact of different features on classification effectiveness.
4	Deep CNN for Blood Prediction	Nandakumar, R., Subraman, K.[4]	Convolutional Neural Network (CNN)	Compares CNN performance with serological methods, proving CNNs can be effective for fingerprint-based blood typing.
5	Recreating Fingerprint Images by Convolutional Neural Network Autoencoder Architecture	Saponara, Sergio, Abdussalam Elhanashi, and Qinghe Zheng. [5]	Deep Learning	Reconstructs accurate fingerprint images from damaged fingerprint images with an accuracy of 96.5%. Does not perform classification
6	Determination and Classification of Blood Types using Image Processing Techniques	Ravindran G., Pandiyan P., Pravin M [6]	Image Processing Techniques	The developed method accurately detects blood type by analyzing agglutination patterns.The use of image processing techniques enables automatic detection, making it a fast and efficient alternative to traditional methods.

[1] The utilization of fingerprint-based biometric identification exhibits considerable reliability, making it suitable for diverse applications. This current study introduces an effective approach to determine blood groups through fingerprint analysis. Fingerprint data, characterized by numerous distinctive minutiae features, serves as the basis for predicting blood groups using various techniques of machine learning. The suggested system employs Multiple Linear Regression with Ordinary Least Squares (OLS) and achieves an accuracy of 62%. Future investigations should expand the sample size to enhance result precision and incorporate additional, as-yet-unexplored fingerprint features for a more comprehensive analysis.

[2]. 2018 saw the publication of "Automated Blood Identify Using Fingerprint Analyze: A Review" by Verma, A., and Bhatt, V. The authors discuss the number of techniques, techniques used in machine learning, such as pattern recognition and feature extraction, and that have been applied in numerous studies to the identifying the blood type basis on the fingerprints. The report outlines the benefits and drawbacks of the current approaches and makes recommendations for next research directions. This

review paper presents the overview of the automated methods for blood type detection basis fingerprint analyses. It addresses the shortcomings of a serological methods and also explore the possibility of finger analysis as trustworthy alternative.

[3]. Agarwal, S., Gour, V., and N. Gupta (2016) "Blood Group Prediction Using Fingerprint Patterns" This study investigates blood group detection using fingerprint patterns. The authors look into a variety of fingerprint characteristics and classification methods, such as (SVM) for blood group detect and minutiae-based features. They assess the effect of various features of set also classifier and show experimental results on a fingerprint picture data. The study provides information on effectiveness of various feature extraction and also classification methods and demonstrates the viability of employing fingerprint patterns to predict types of blood.

[4]. Nandakumar, R., and Subraman, K. (2017) "Deep CNN for Blood Prediction." [4]. The use of CNN for blood type prediction is the main emphasis of this work. The authors suggest using CNN architecture to blood group prediction basis on fingerprint scans. They compare the performances of CNN model with conventional serological techniques and present the experimental findings on a collection of fingerprint photos. The work shows how well CNNs can identify blood types and underlines the possible uses of analysis of fingerprint in medical settings.

[5].This study concluded that blood grouping can be done efficiently and effectively by using simple testing methods based on the plate test method and measuring optical density (OD). This approach facilitates the creation of an automated, cost-effective, miniaturized, and portable device. In the future, we aim to design and implement a specialized light source system using Light Emitting Diodes (LEDs) to advance the accuracy and efficiency of the blood typing process.

[6].The method developed proves that it is effective and efficient method to detect the agglutination and determines the blood type of the patient accurately. The use of image processing techniques enables automatic detection of agglutinationand determines the blood type of the patient in a short interval of time also helpful in emergency situations. In future it is intende to improve the system developed by making it smaller so that it can be portable and incorporate GSM technology, to send a message to the mobile of technician of the laboratory in order to avoid unnecessary travel.

[9] This study provides an effective method for fingerprint recognition and identification based on detail features. The whole process develops systematically, starting with the first stage of pre-processing to remove excess material and improve the clarity of fingerprints. After this, in the second stage, the extraction process is carried out using the content extractor algorithm, focusing especially on endings and forks.

2. SYSTEM ARCHITECTURE

Types of Fingerprint Patterns

1. **Loop**: Loop patterns are the most prevalent among fingerprint patterns. In this type, the ridges enter from one side of the finger, curve to form a loop, and then exit through the same side they came in. Loops are further categorized based on ridge flow direction:

   - **Ulnar Loops**: Ridges flow toward the little finger.
   - **Radial Loops**: Ridges flow toward the thumb.

2. **Whorl**: Whorl patterns consist of ridges arranged in circular or spiral formations. This pattern can be further divided into subtypes, including:

   - Plain Whorls
   - Central Pocket Loops

- Double Loops
- Accidental Whorls

2. **Arch**: Arch patterns are characterized by ridges flowing in a wave-like motion from one side of the finger to the other. Unlike loops and whorls, arch patterns do not feature prominent deltas (triangular ridge formations). They are analyzed and classified based on the arrangement and orientation of ridges, as well as specific characteristics like ridge count and the presence of deltas.

Fig-1 Fingerprint Patterns

System Architecture:

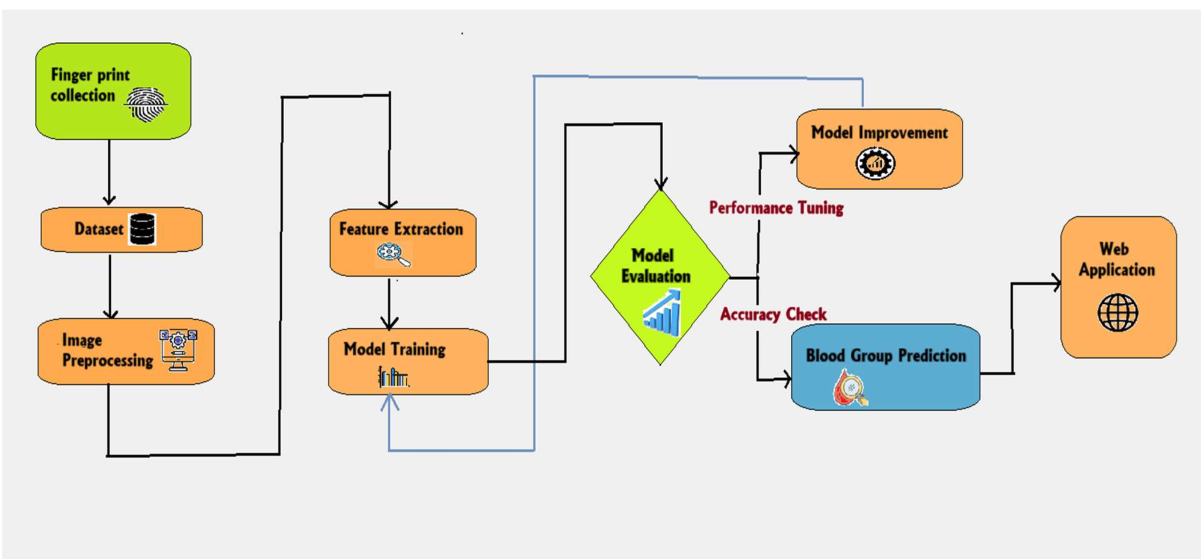


Fig-2 Project Basic Architecture

- *Fingerprint Collection:* The process starts with collecting fingerprint samples. These are likely captured using specialized devices to ensure clarity and accuracy.
- *Dataset Creation:* The collected fingerprints are stored in a structured format to form a dataset, which serves as the foundation for further analysis.
- *Image Preprocessing:* Fingerprint images undergo preprocessing steps, such as noise reduction, enhancement, and segmentation, to improve their quality and extract useful information.

- *Feature Extraction:* Important features from the fingerprints, like ridge patterns, minutiae points, or unique identifiers, are extracted to create a representation suitable for machine learning.
- *Model Training:* The extracted features are fed into a machine learning model, which is trained to identify patterns and correlations, such as blood group prediction based on fingerprint traits.
- Model Evaluation: The trained model is evaluated for its performance using metrics like accuracy and precision to ensure reliability.
- Model Improvement: If the model's performance is unsatisfactory, it undergoes performance tuning, optimization, or retraining to enhance accuracy and efficiency.
- Blood Group Prediction: Once the model is refined, it predicts blood groups based on input fingerprints. The accuracy of these predictions is checked to validate the system.
- Web Application Integration: The final, optimized model is integrated into a web application, enabling users to access the blood group prediction feature seamlessly.

3. PROPOSED SYSTEM

CNNs have shown remarkable capabilities in image analysis and pattern identification, making them a promising technology for fingerprint-based blood group detection. By training on extensive datasets of labeled fingerprint images, CNNs can learn to identify complex patterns and relationships associated with blood groups. However, the development and implementation of such systems face challenges, including the demand for significant computational power, complex network designs, and large, accurately labeled datasets.

Despite their potential, using CNNs for fingerprint-based blood group detection remains relatively unexplored. Research in this area is limited, and practical applications are scarce. Current systems lack the necessary reliability and accuracy for widespread use in medical diagnostics. There is a notable absence of research on optimizing CNN architectures specifically for this purpose, as well as on establishing comprehensive, annotated fingerprint datasets. My research addresses this gap by achieving higher accuracy than previously reported systems.

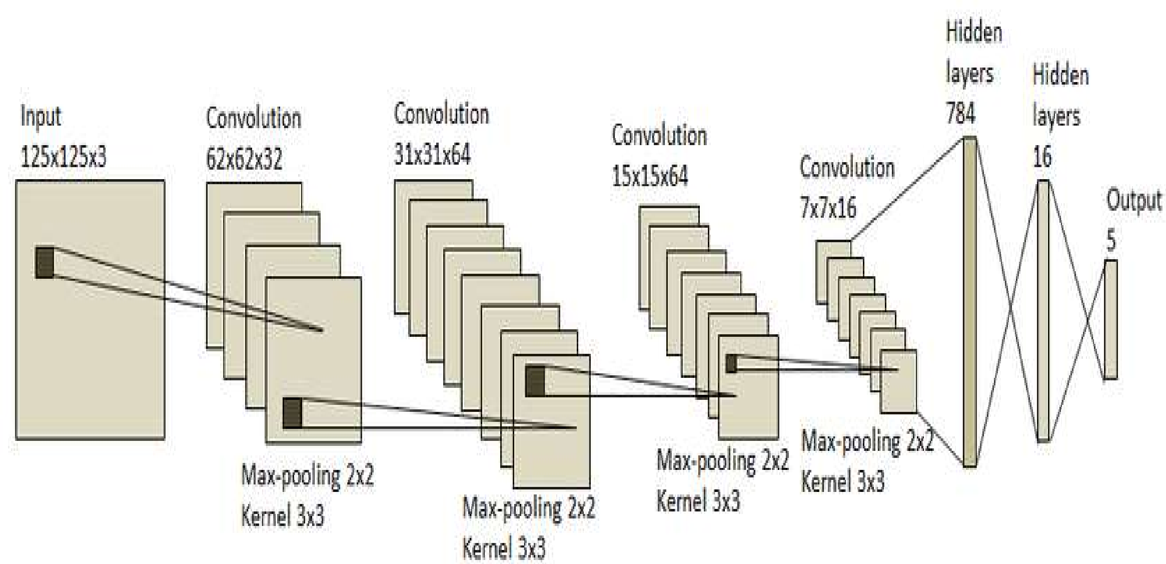


Fig-3 CNN Model Basic Architecture

4. IMPLEMENTATION

The proposed non-invasive blood group detection system is implemented using Python, leveraging its robust libraries for image processing and deep learning. The entire development and experimentation process was conducted in **Jupyter Notebook**, a user-friendly interactive coding environment suitable for machine learning tasks.

The system is developed and tested on the following hardware and software configuration:

- **Operating System**: Windows 11
- **Processor**: AMD Ryzen 5 5500U with Radeon Graphics
- **Processor Speed**: 2.10 GHz
- **Installed RAM**: 16.0 GB
- **Graphics**: Integrated Radeon Graphics
- **Software Tools**:
    - Python 3.x
    - Jupyter Notebook
    - TensorFlow / Keras for implementing Convolutional Neural Networks (CNNs)
    - OpenCV and NumPy for image processing and numerical operations
    - Flask framework for deploying the trained model as a web application

The implementation workflow includes the following major steps:

1. **Data Collection**: Acquisition of high-quality fingerprint images labeled with corresponding blood group types.
2. **Preprocessing**: Image normalization, resizing, noise reduction, and enhancement of ridge patterns for optimal feature extraction.
3. **Model Development**: Designing and training a CNN model tailored for pattern recognition from fingerprint images.
4. **Model Evaluation**: Assessing the model's performance using accuracy, precision, recall, and F1-score metrics.
5. **Web Deployment**: Integrating the trained model into a Python Flask web application for easy access and real-time predictions.

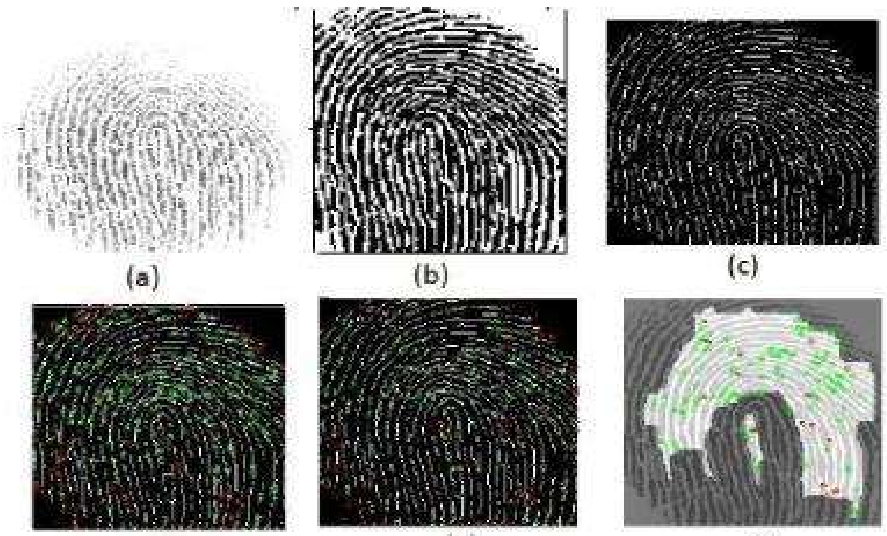
This implementation setup ensures high-speed computation, efficient model training, and seamless performance, making it suitable for real-time and scalable deployment in medical or forensic environments.

The fundamental motive of the project is to use the relationship among details and blood type to create an accurate fingerprint-based blood group test and evaluate the feasibility of the concept. First the model is evaluated using existing CNN architectures and upon observing the performance a custom model can be constructed for better performance.

5. METHODOLOGY

Feature Extraction:

The feature extraction plays a major role in latent fingerprint matching. For the though transform algorithm minutiae points are needed. Minutiae points are extracted for matching. They are specific points in a fingerprint image, determined by the termination or the bifurcation of the ridge lines.



(d) (e) (f)

Fig-4 Feature Extraction steps

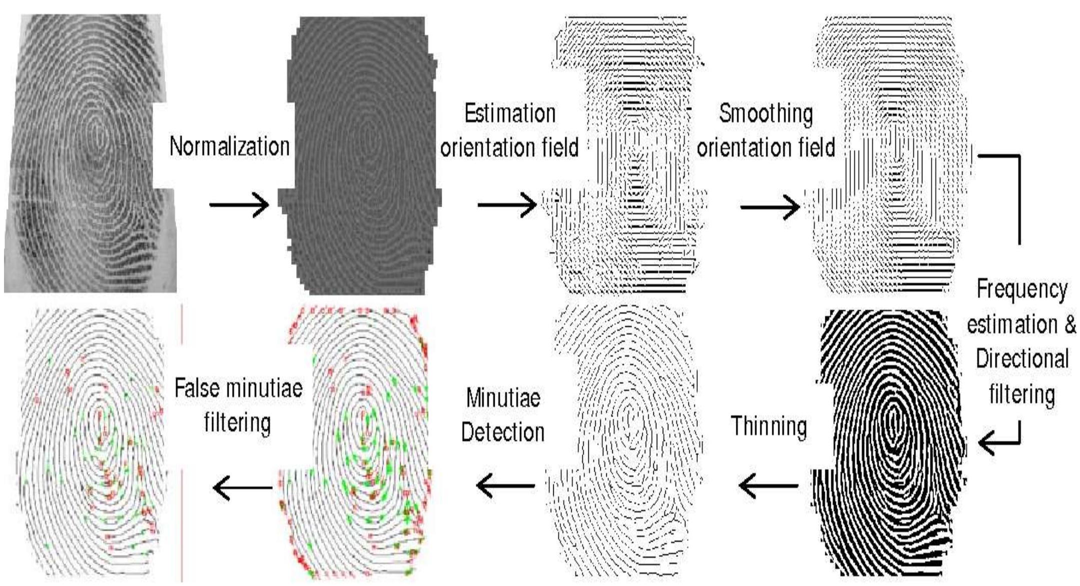


Fig-5 Pre-processing and Feature Extraction Process[11]

(a) Input image

(b) Smoothing

(c) Thinning

(d) Minutiae identification

(e) Removal of false minutiae

(f) Region of Interest

Feature extraction techniques are used to obtain a feature vector which is a reduced representation of the input data which contains information about the most important features of data. This feature vector is sent to a Convolutional Neural Network for classification.

Thinning Image: It refers to the technique of reducing the thickness of lines or edges in a binary image to a single-pixel width while preserving the structural information and connectivity of the shapes. Thinning is often employed to simplify the representation of shapes, making them more suitable for further analysis or pattern recognition tasks. In the current context we can obtain minimal representation of fingerprints that retains the shape and vital information of the fingerprint.

Minutiae Detection: Minutiae points are specific locations where ridge patterns in a fingerprint exhibit unique characteristics. The most common types of minutiae are bifurcations and ridge endings. Bifurcations take place when a ridge divides into two, while ridge endings occur at points where a ridge concludes. Minutiae detection is the process of identifying and locating these minutiae points in a fingerprint image. This process is typically part of the feature extraction phase in fingerprint recognition systems.

Real Minutiae: The term real minutiae refer to the actual minutiae points that exist on a person's fingertip. These are the biometrically relevant features that contribute to the uniqueness of a fingerprint. Real minutiae are the points used in fingerprint matching algorithms to distinguish one fingerprint from another.

Data Augmentation: Augmentation is a method employed in machine learning and deep learning to expand data size by introducing alterations or enhancements to existing data, with the aim of enhancing the efficiency, generalization, and robustness of machine learning models, particularly in situations with restricted data availability. Due to the limited number of documents containing fingerprints and related blood, we need to expand the existing data to come up with a better model.

Improving the accuracy of Latent Matching Approach using texture features

We propose to automate the process of fingerprint matching after reconstruction of latent fingerprints. We have done the Hough transform matching after the enhancement of input images. After feature extraction we have to align the minutiae point for matching. From that alignment method the similarity between the minutiae points is calculated using Hough transform. We incorporate texture-based features like entropy, correlation, contrast, homogeneity and energy for improving the accuracy.

Segmentation, normalisation, local orientation estimation, ridge frequency estimation, region mask estimation and filtering are the procedure done during enhancement of latent fingerprint. Segmentation leads to the calculation of variance for each pixel. Normalisation is the process, that changes the range of pixel intensity value. After that local orientation of each pixel in a fingerprint image is computed. Ridge frequency is obtained from the extraction of the ridge map. Classification of pixels into retrievable or unretrievable is called masking. Filtering helps for removing noises.

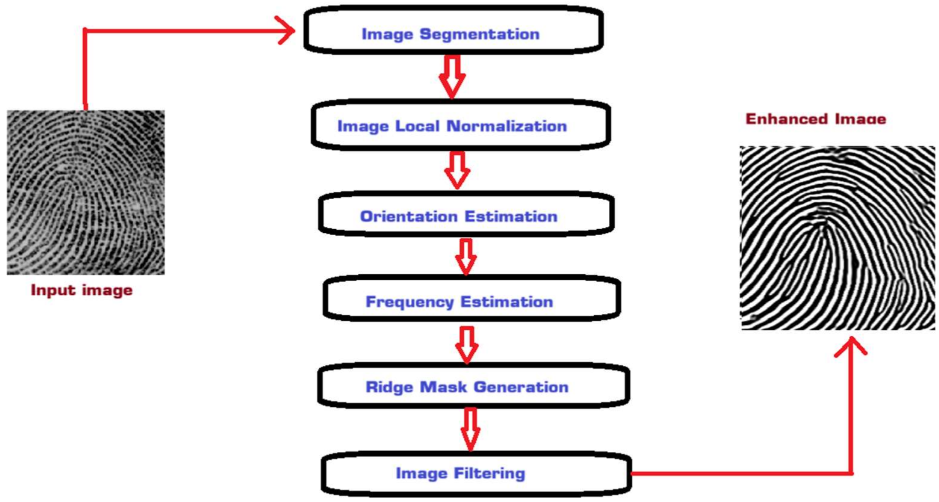


Fig-6 Enhancement steps

6. Experimental Results and Performance Analysis

6.1 PROJECT OUTPUTS

Fig:7 Register page

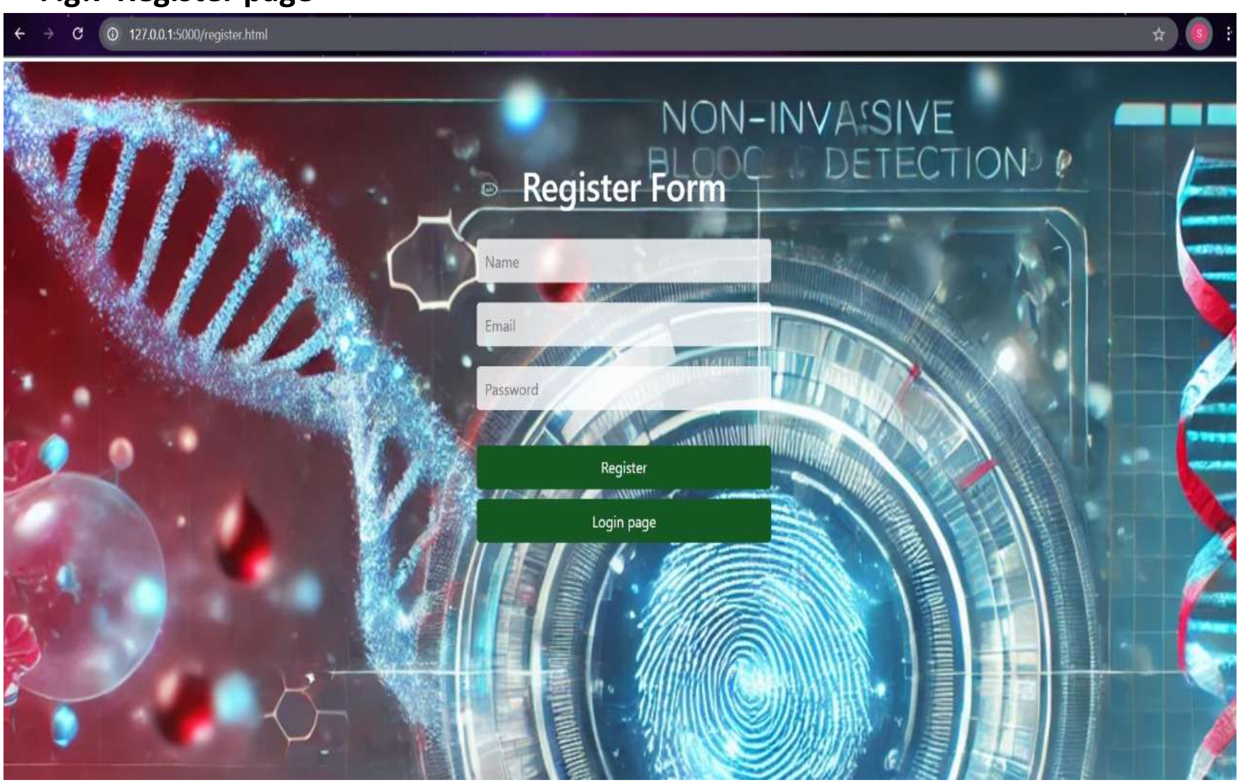


Fig:8 Login Page

Fig:9 Home Page

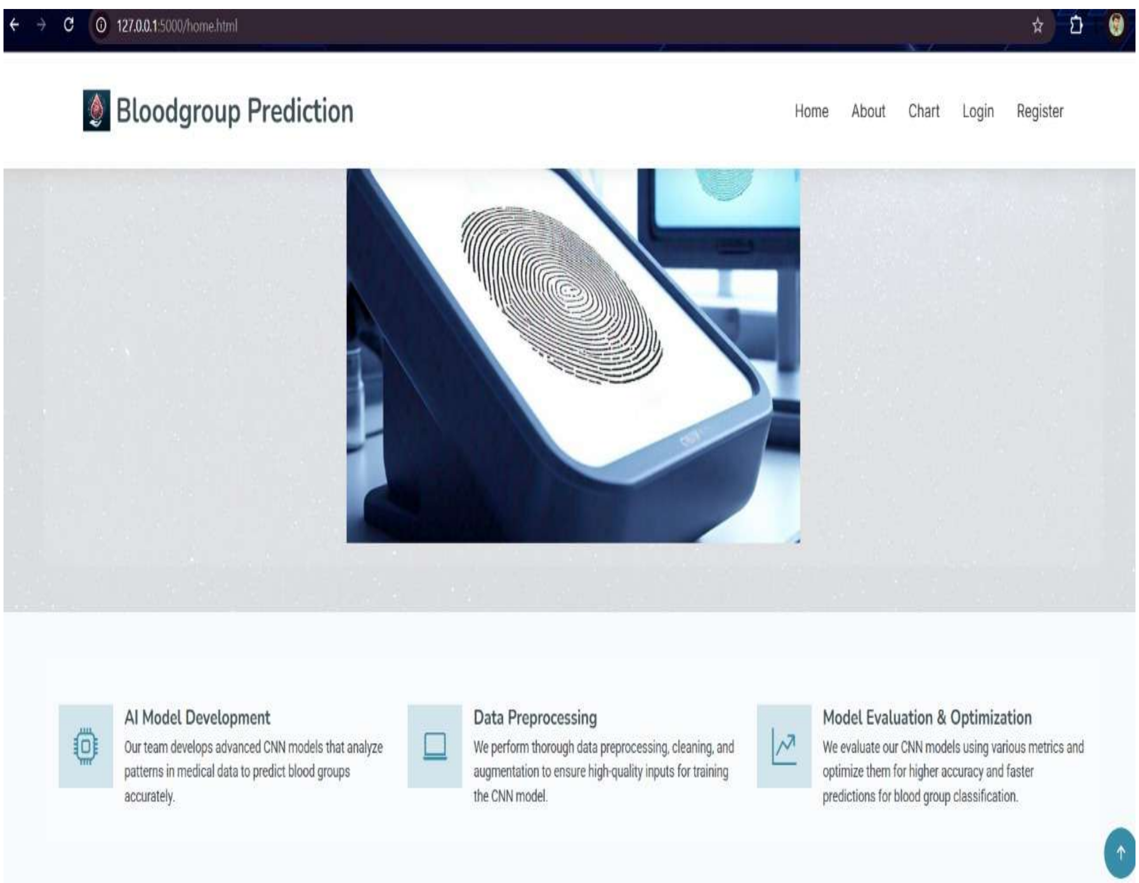


Fig:10 About Page

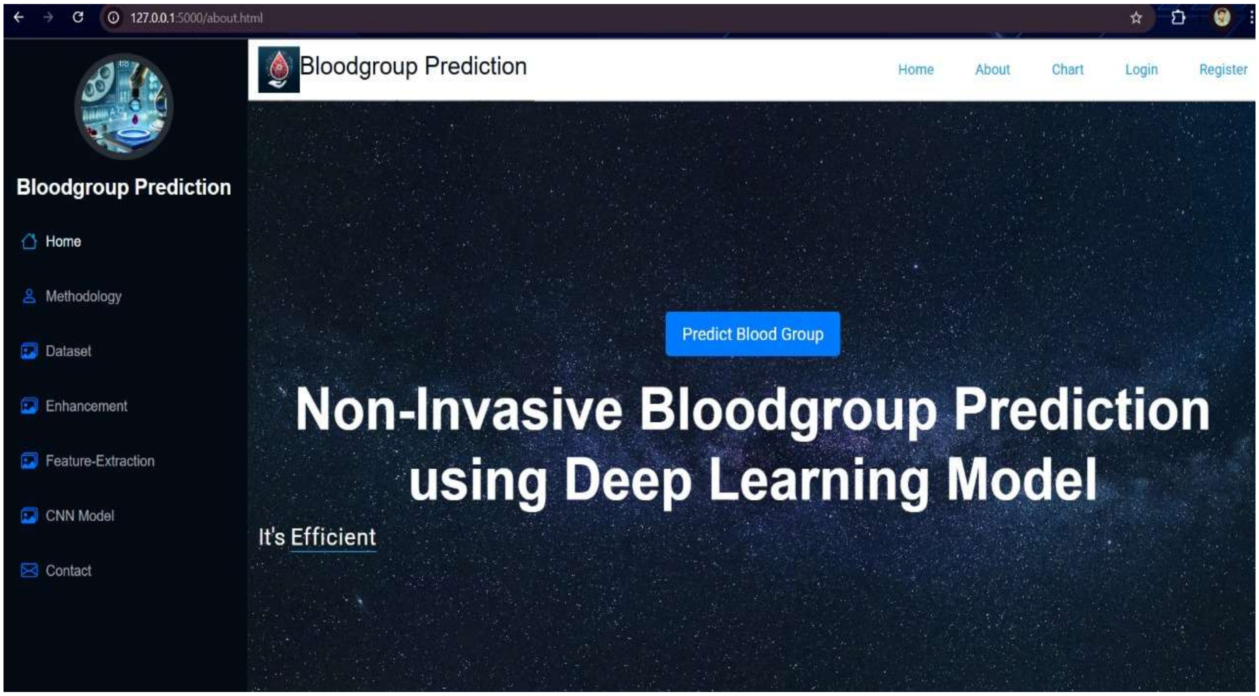
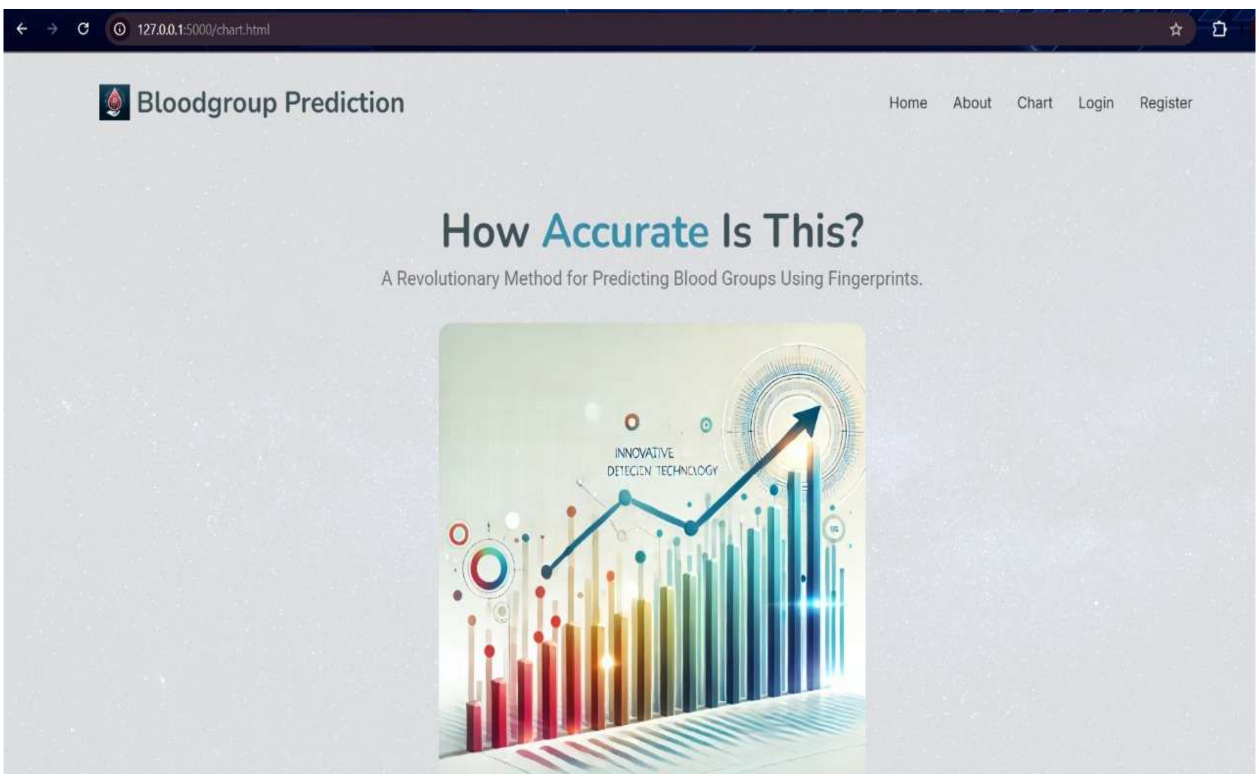


Fig:11 Chart Page



6.2 CNN MODEL PERFORMANCE

Fig: 12 Data set Classification

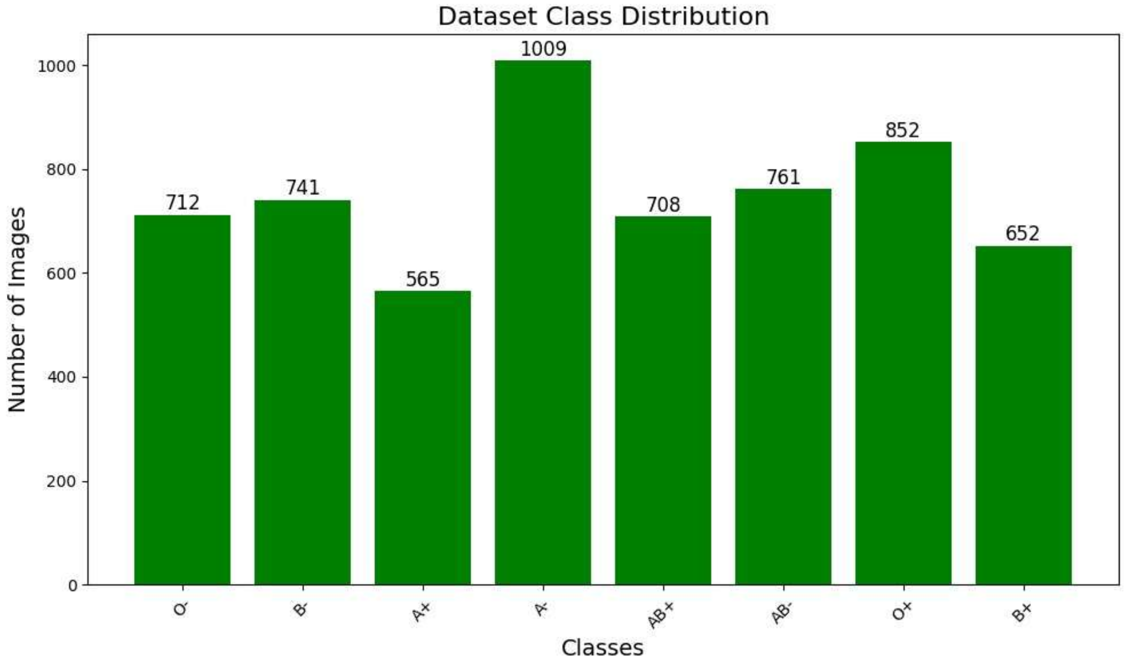


Fig-13. Model accuracy of Trained dataset

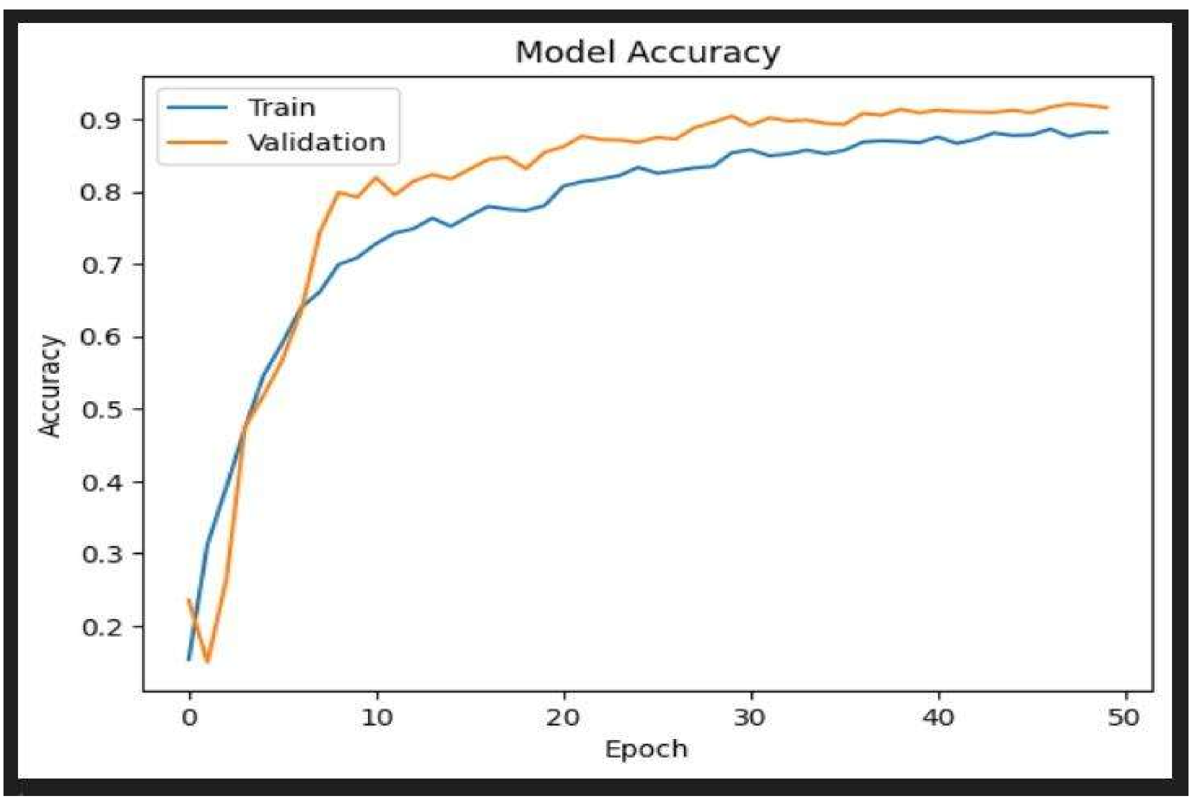
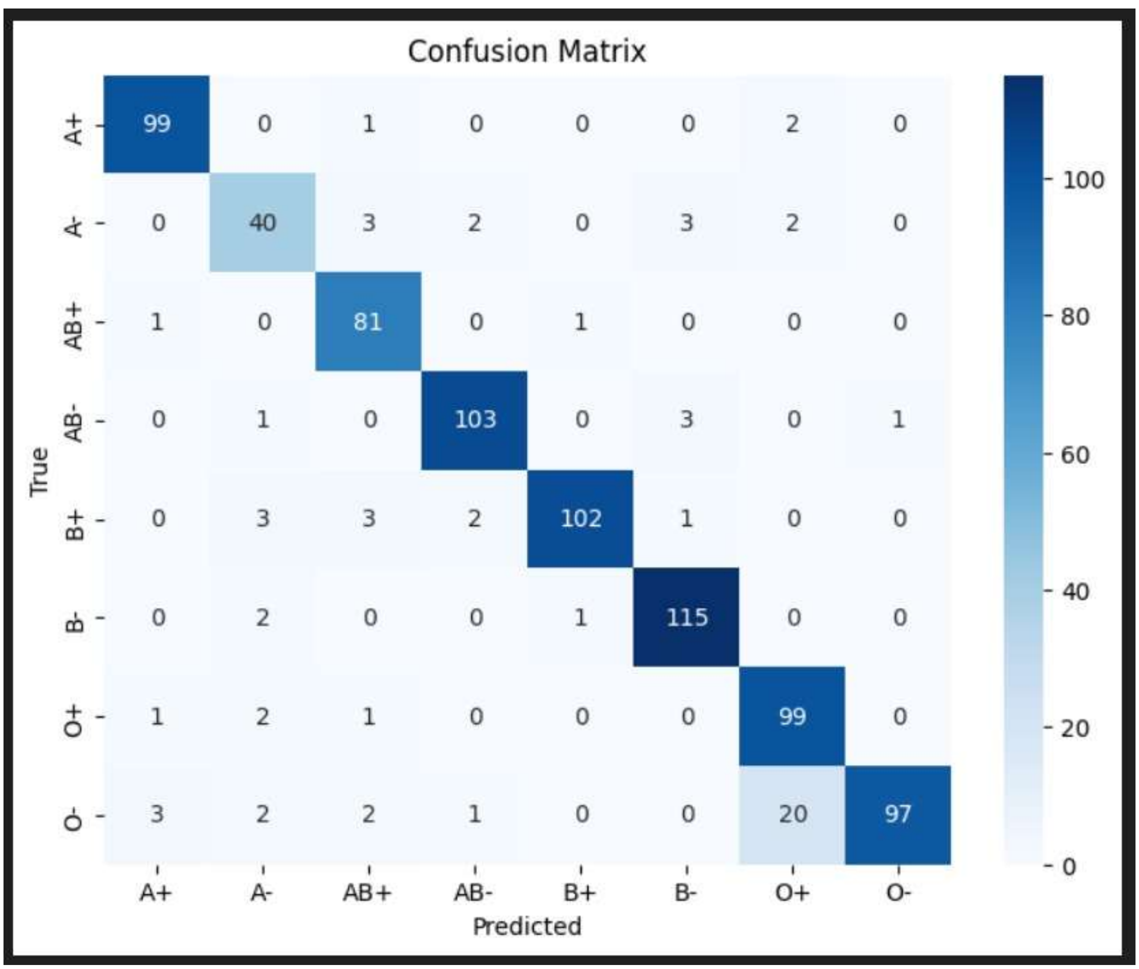


Fig-14 Dataset Classification Report

Classification Report:

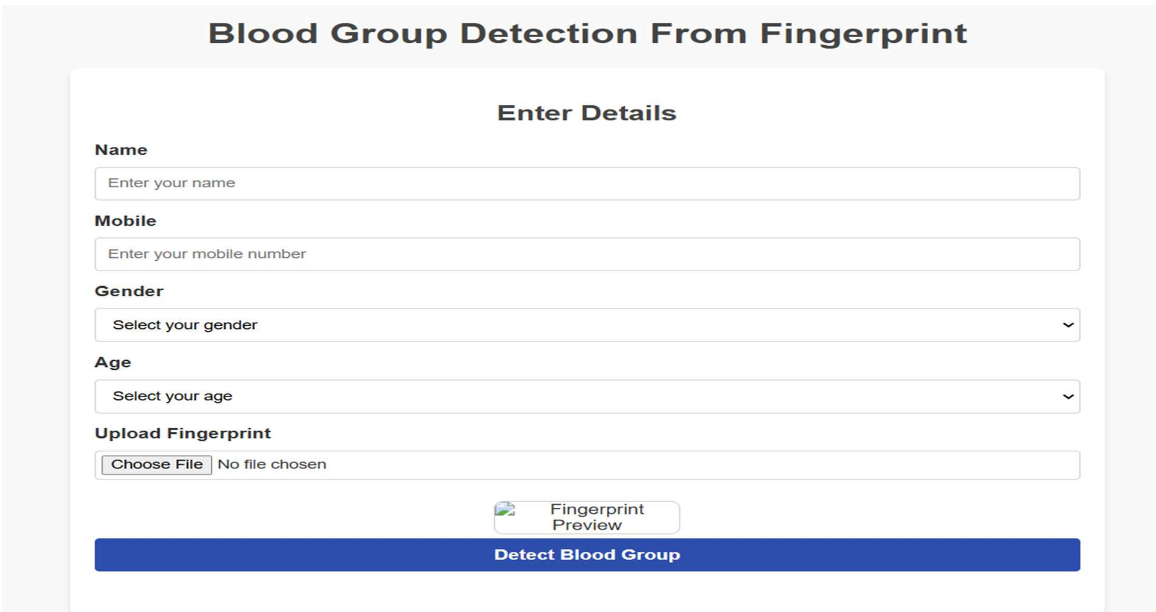
	precision	recall	f1-score	support
A+	0.95	0.97	0.96	102
A-	0.80	0.80	0.80	50
AB+	0.89	0.98	0.93	83
AB-	0.95	0.95	0.95	108
B+	0.98	0.92	0.95	111
B-	0.94	0.97	0.96	118
O+	0.80	0.96	0.88	103
O-	0.99	0.78	0.87	125
accuracy			0.92	800
macro avg	0.91	0.92	0.91	800
weighted avg	0.93	0.92	0.92	800

Fig:15 Confusion matrix



6.3 Results

Fig-16 User Form to Enter and predict Blood group



Blood Group Detection From Fingerprint

Enter Details

Name

Enter your name

Mobile

Enter your mobile number

Gender

Select your gender

Age

Select your age

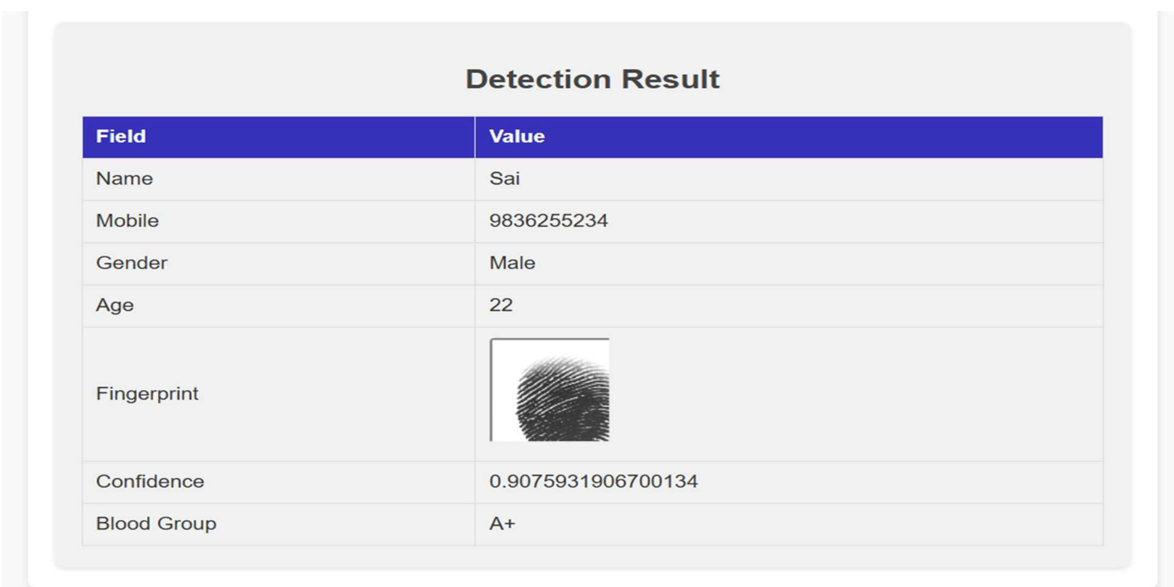
Upload Fingerprint

Choose File No file chosen

Fingerprint Preview

Detect Blood Group

Fig-17 Result of A+



Detection Result

Field	Value
Name	Sai
Mobile	9836255234
Gender	Male
Age	22
Fingerprint	
Confidence	0.9075931906700134
Blood Group	A+

Fig-18 Result of A-

Detection Result

Field	Value
Name	ashok
Mobile	8762345688
Gender	Male
Age	23
Fingerprint	
Confidence	0.7593255043029785
Blood Group	A-

Fig-19 Result of O+

Detection Result

Field	Value
Name	tarun
Mobile	9236567798
Gender	Male
Age	31
Fingerprint	
Confidence	0.8669450283050537
Blood Group	O+

Fig-20 Result of O-

Detection Result

Field	Value
Name	ravi
Mobile	8008667798
Gender	Male
Age	31
Fingerprint	
Confidence	0.9902979731559753
Blood Group	O-

Fig-21 Result of B-

Detection Result

Field	Value
Name	bargav
Mobile	8008293579
Gender	Female
Age	20
Fingerprint	
Confidence	0.8723762035369873
Blood Group	B-

Fig-22 Result of AB+

Detection Result

Field	Value
Name	bargavi
Mobile	6300293579
Gender	Female
Age	20
Fingerprint	
Confidence	0.7690436840057373
Blood Group	AB+

Fig-23 Result of AB-

Detection Result

Field	Value
Name	Mahesh
Mobile	6732935790
Gender	Male
Age	31
Fingerprint	
Confidence	0.9750720262527466
Blood Group	AB-

Fig-24 Result of B+

Detection Result

Field	Value
Name	swathi
Mobile	9842935790
Gender	Female
Age	20
Fingerprint	
Confidence	0.9446220993995667
Blood Group	B+

7. Conclusion

While previous research has highlighted the challenges of accurately predicting blood groups solely from fingerprint patterns due to shared patterns and the complex interplay of various factors, our study demonstrates the potential of utilizing advanced techniques like Convolutional Neural Networks (CNNs) to overcome these limitations.

Our CNN model, achieving an impressive 90% accuracy, suggests that deep learning algorithms can effectively discern subtle patterns and features in fingerprint images that may be associated with blood types. This breakthrough underscores the importance of leveraging sophisticated computational approaches to unravel the intricate relationship between fingerprints and blood groups.

Further research is needed to fully understand the underlying mechanisms and validate the generalizability of our findings. However, our results provide a compelling foundation for future investigations and pave the way for the development of innovative, non-invasive blood typing methods with enhanced accuracy and reliability. This could potentially revolutionize blood typing practices, particularly in emergency medical care and resource-limited settings.

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