An Improved Blood Group Detection Using Deep Learning Model

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Abstract- Blood type determination is crucial, particularly in life-threatening situations such as organ transplants, transfusion compatibility, medical crises, diagnostic procedures, and prenatal care. The serological methods used in conventional blood group testing are accurate, but they are intrusive and necessitate laboratory infrastructure. Furthermore, human error may occur during technician-performed manual testing. The goal of this research is to employ pre-captured palm photos to create an accurate and effective blood type system in order to overcome these obstacles.

The suggested approach analyzes fingerprint photos and finds distinctive patterns linked to blood group phenotypes by combining cutting-edge image processing methods with machine learning, specifically Convolutional Neural Networks (CNNs). Rapid blood group detection has been increasingly important in the forensic and medical domains in recent years. Conventional techniques are frequently labor-intensive, call for skilled workers, and aren't always feasible in an emergency. This study presents an alternate method for precise and effective blood type identification that combines machine learning techniques—specifically CNNs—with fingerprint image analysis. This approach is based on fingerprint ridge patterns, which have demonstrated possible associations with blood types. A CNN model shows remarkable accuracy in blood group prediction after being trained on a large dataset of labeled fingerprint photos.

Keywords: Non-Invasive Medical Diagnostics, Fingerprint images, Deep Learning, Feature Learning, Pattern Recognition, Convolutional Neural Networks (CNNs) Model.

1. INTRODUCTION

1.1 Introduction

By merging cutting-edge deep learning algorithms with medical data, fingerprint analysis offers a novel and painless way to determine blood group. By analyzing the distinct patterns of ridges and valleys in a person's fingerprint, this method determines blood type—information that is essential for medical practitioners. This fingerprint-based approach provides a less intrusive and more comfortable experience than traditional blood tests, which can be uncomfortable because of the use of needles [1].

Fingerprint patterns are among the most reliable and unique means of identification, because they don't change over the course of a person's lifetime [11]. Fingerprints are frequently considered essential evidence, even in legal contexts. It is extremely rare for two people, especially identical twins, to have the same minute characteristics in their fingerprints—roughly one in 64 million. In addition, the ridge pattern is distinct and constant from birth. Another inherited trait that doesn't change is blood group. The danger of infection is considerably decreased when fingerprints are used for analysis. However, disease diagnosis and blood collection necessitate traditional blood tests, which require drawing blood with needles and then undergoing costly antibody processes [12]. The lack of diverse fingerprint samples is one of the primary challenges in developing a blood group prediction model. The study of fingerprints as a biometric for blood group prediction and age-related disease detection is still in its infancy [13-15].

The direction and arrangement of the ridges determine whether a fingerprint pattern is looped, whorled, or arched. The most common kind, loops, are distinguished by ridges that resemble loops. Circular or spiral ridge patterns, with many variations, are what define whorls. Simpler arches have ridges that run across them without deltas. Accurate classification in

forensic and biometric applications depends on the examination of these patterns, which include ridge orientation and delta count [6].

1.2 Contributions

Among the contributions of this study are:

• The creation of a machine learning-based, non-invasive method for identifying blood groups from palm/fingerprint photographs.

• Convolutional Neural Networks (CNNs) are integrated for precise blood group categorization and pattern identification.

• Using Python Flask, the trained model is deployed to produce a scalable and easily navigable web application.

• A thorough assessment of the system's performance based on important metrics like F1-score, recall, accuracy, and precision

The paper's remaining sections include: Section 2: System Architecture: This section explains the blood type system's general architecture, which includes the CNN model design, image acquisition modules, preprocessing units, and deployment infrastructure. The proposed fingerprint-based blood typing system's purpose and operation are described in Section 3: Proposed System, which also emphasizes the relationship between blood group phenotypes and ridge patterns. The training procedure, CNN architecture, feature extraction strategies, and image preparation approaches are all covered in Section 4: Methodology and Implementation. The Python and Flask implementation framework is also included in this part. The dataset, training and testing split, evaluation criteria, and model results are presented in Section 5: Experimental Results and Performance Analysis. This offers comprehensive findings that display performance indicators including F1-score, recall, accuracy, and precision. In Section 6: Conclusion and Future Work, the results are summarized, the system's efficacy and potential are highlighted, and future improvements including multi-modal biometric analysis, real-time mobile integration, and larger datasets are outlined.

2. LITERATURE REVIEW

According to Vijay Kumar et al. [2], fingerprint-based biometric identification is a very reliable method that may be used for a variety of purposes. This work presents a practical method for using fingerprint analysis to identify blood types. Several machine learning algorithms are used to predict blood types based on fingerprint data, which is characterized by many unique minutiae traits. A 62% accuracy rate is attained by the proposed technique, which uses Multiple Linear Regression with Ordinary Least Squares (OLS). Future studies should include new, as-yet-undiscovered fingerprint features for a more thorough analysis and increase the sample size to improve result precision.

Verma et al. [7] talk about the many machine learning techniques, like pattern recognition and feature extraction, that have been utilized in several research to determine blood type based on fingerprints. The paper highlights the advantages and disadvantages of the existing methodologies and offers suggestions for future avenues of inquiry. An overview of automated techniques for blood type determination based on fingerprint analysis is provided in this review study. It discusses the drawbacks of serological techniques and investigates the potential of finger analysis as a reliable substitute.

Table 1: Literature Review work

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.[2]	Multiple Linear Regression (OLS)	Achieved 62% accuracy; suggests increasing sample size for better precision.
2	Automated Blood Identification Using Fingerprint Analysis	Verma, et al., .[7]	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	Tariq et al., .[4]	SVM, minutiae-based features, classification methods	Explores the impact of different features on classification effectiveness.

4	Deep CNN for Blood Prediction	Nanda kumar, R et al.,[8]	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	Smith, J et al., [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	Fernandes et al., [10]	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.

Using fingerprint patterns, Jeevesh Gupta et al. [6] looked into blood group detection. The authors investigate a range of fingerprint traits and classification techniques, including minutiae-based features and support vector machines (SVM) for blood group detection. They evaluate the impact of different set features as well as classifiers and present experimental findings using fingerprint image data. The study shows the feasibility of using fingerprint patterns to predict blood types and offers data on the efficacy of several feature extraction and classification techniques. CNN architecture was proposed by Nanda Kumar, R. et al. [8] as a framework for blood group prediction based on fingerprint scans. They report the experimental results on a set of fingerprint images and contrast the CNN model's performance with traditional serological methods. The study highlights the potential applications of fingerprint analysis in medical contexts and demonstrates how well CNNs can detect blood types.

Dr. D. Shiva Sundhara Raja et al. [3] came to the conclusion that basic testing techniques based on the plate test method and measuring optical density (OD) can be used to group blood in an efficient and effective manner. This method makes it easier to create a gadget that is automated, affordable, small, and portable. In order to improve the precision and effectiveness of the blood type procedure, we intend to develop and deploy a customized light source system in the future that makes use of Light Emitting Diodes (LEDs). An accurate method for detecting agglutination and determining the patient's blood type was developed by Tariq, A. et al. [4]. Using image processing techniques

makes it possible to automatically detect agglutination and quickly ascertain the patient's blood type, which is useful in emergency situations. The system will be improved in the future by becoming smaller to make it portable and incorporating GSM technology to send a message to the laboratory technician's mobile device, preventing needless travel.

An efficient technique for fingerprint identification and recognition based on detail features was presented by Smith et al. [5]. Beginning with the initial step of pre-processing to eliminate extra material and enhance fingerprint clarity, the entire procedure proceeds methodically. The content extractor algorithm is then used to carry out the extraction procedure in the second step, paying particular attention to endings and forks [9].

3. SYSTEM ARCHITECTURE

3.1 Types of Fingerprint Patterns

1.Loop: Among fingerprint patterns, loop patterns are the most common. The ridges of this type enter the finger from one side, curve to create a loop, and then leave the finger through the same side. Loops are further divided into groups according to the direction of ridge flow:

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

2. Whorl: Ridges grouped in spiral or circular patterns make up whorl designs. There are several subtypes of this pattern, including:

• Plain Whorls
• Central Pocket Loops
• Double Loops

- Accidental Whorls

3. Arch: Ridges that move from one side of the finger to the other in a wave-like pattern define arch patterns. Arch patterns lack noticeable deltas (triangular ridge structures), in contrast to loops and whorls. They are examined and categorized according to the direction and arrangement of ridges, as well as particular traits like the number of ridges and the existence of deltas.
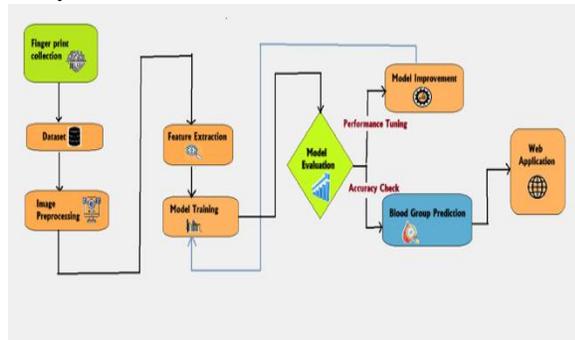

Fig-1 Fingerprint Patterns

3.2 System Architecture:

Fig-2 Project Basic Architecture

• Fingerprint Collection: Gathering fingerprint samples is the first step in the procedure. To guarantee clarity and accuracy, these are probably recorded with professional equipment.
• Dataset Creation: To create a dataset that forms the basis for additional analysis, the gathered fingerprints are organized and saved.
• Image Preprocessing: To increase their quality and retrieve valuable information, fingerprint images go through preprocessing stages like noise reduction, enhancement, and segmentation.
• Feature Extraction: To produce a representation appropriate for machine learning, significant

fingerprint features such as ridge patterns, minute details, or distinctive identifiers are retrieved [16-18].
• Model Training: A machine learning model is trained using the extracted data to find patterns and correlations, such as the ability to predict blood group based on fingerprint characteristics [19].
• Model Evaluation: To guarantee dependability, the trained model's performance is assessed using measures like accuracy and precision [20].
• Model Improvement: To improve accuracy and efficiency, a model that performs poorly may be optimized, retrained, or performance tuned [21].
• Blood Group Prediction: Using input fingerprints, the model predicts blood groups after it has been improved. To verify the system, the precision of these forecasts is examined [24].
• Web Application Integration: Users can easily access the blood group prediction capability once the final, optimized model has been incorporated into a web application [22-23].

4. PROPOSED SYSTEM

CNNs [25] are a promising technology for fingerprint-based blood group detection because of their impressive abilities in image processing and pattern recognition. CNNs can learn to recognize intricate patterns and correlations related to blood types by being trained on large datasets of annotated fingerprint pictures. Nevertheless, there are obstacles to the creation and application of such systems, such as the requirement for substantial processing capacity, intricate network architectures, and big, precisely labeled datasets.

The use of CNNs for fingerprint-based blood type detection is still largely unexplored, despite its potential. There is a dearth of practical applications and research in this field. The accuracy and dependability required for broad use in medical diagnostics are not present in current systems. Research on creating extensive, annotated fingerprint datasets and on optimizing CNN architectures especially for this use is conspicuously lacking. By outperforming previously published methods in terms of accuracy, my research fills this gap.
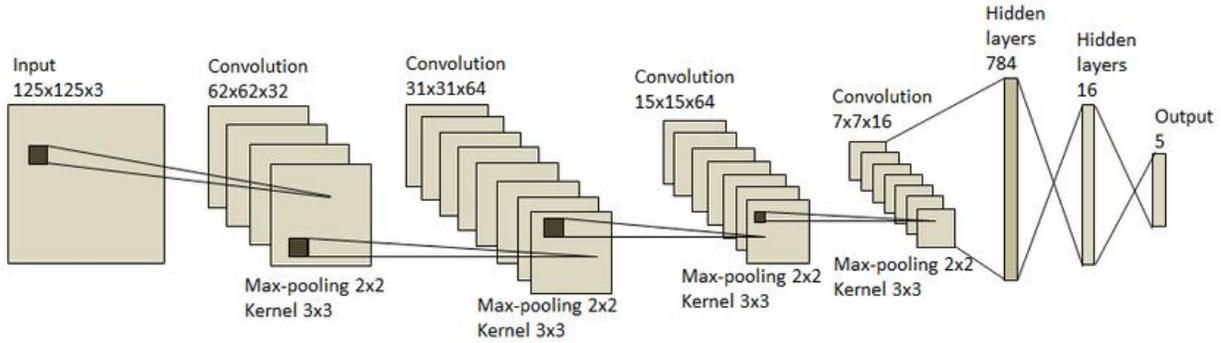
Fig-3 CNN Model Basic Architecture

5. IMPLEMENTATION

Python [27] is used to create the suggested non-invasive blood group detection system, making use of its powerful image processing and deep learning tools. Jupyter Notebook [26], an intuitive interactive coding environment ideal for machine learning applications, was used for the whole development and testing process.

The following hardware and software configurations are used in the development and testing of the system:

- 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:
  o Python 3.x
  o Jupyter Notebook
  o TensorFlow / Keras for implementing Convolutional Neural Networks (CNNs)
  o OpenCV and NumPy for image processing and numerical operations
  o Flask framework for deploying the trained model as a web application

The following are the main steps in the implementation workflow:

1. Data collection: Obtaining excellent fingerprint pictures that are identified by the blood group types they match to.

2. Preprocessing: For the best feature extraction, images should be normalized, resized, noise-reduced, and ridge patterns enhanced.

3. Model Development: Creating and refining a CNN model specifically for fingerprint image pattern detection.

4. Model Evaluation: Metrics including as accuracy, precision, recall, and F1-score are used to evaluate the model's performance.

5. Web Deployment: Including the learned model for real-time predictions and convenient access in a Python Flask web application.

This implementation architecture is appropriate for real-time and scalable deployment in medical or forensic applications since it guarantees fast computing, effective model training, and seamless performance.

The project's main goal is to assess the concept's viability and develop a reliable fingerprint-based blood group test by utilizing the association between blood type and details. A bespoke model can be built for improved performance when the model is first assessed using CNN architectures that are already in use.

6. METHODOLOGY

6.1 Feature Extraction [28]:Latent fingerprint matching heavily relies on feature extraction. The thought transform algorithm requires minute details. In order to match, minutiae points are retrieved. These are particular locations in a fingerprint image that are identified by the ridge lines' termination or bifurcation.
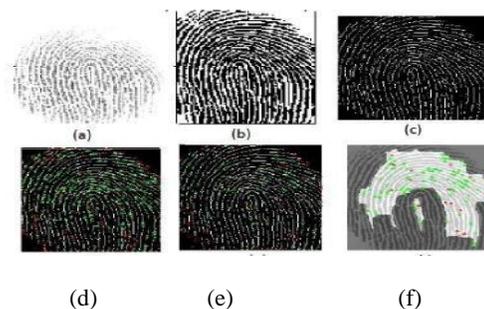

(d)   (e)   (f)

Fig-4 Feature Extraction steps

(a)Input image
(b)Smoothing
(c)Thinning
(d) Minutiae identification
(e) Removal of false minutiae
(f)Region of Interest

A feature vector, which is a condensed representation of the input data that includes details about the most significant features of the data, is obtained using feature extraction techniques. A convolutional neural network is used to classify this feature vector. The process of lowering a binary image's line or edge thickness to a single pixel width while maintaining the shapes' structural information and connectedness is known as "thinning images." In order to simplify the representation of shapes and make them better suited for tasks involving pattern recognition or additional analysis, thinning is frequently used. We can currently obtain a basic representation of fingerprints that preserves their structure and essential details.

Minutiae Detection: Minutiae points are certain places in a fingerprint where ridge patterns display distinctive traits. Bifurcations and ridge ends are the two most prevalent kinds of minutiae. Ridge endings happen where a ridge ends, whereas bifurcations happen when a ridge splits in two. Finding and detecting these minute details in a fingerprint image is known as minutiae detection. In fingerprint identification systems, this procedure usually occurs during the feature extraction stage.

Real tiny: The actual tiny points on a person's fingertip are referred to as real minutiae. These are the biometrically significant characteristics that make a fingerprint distinctive. The points that fingerprint matching algorithms utilize to differentiate one fingerprint from another are known as real minutiae.

Data augmentation is a technique used in deep learning and machine learning to increase the amount of data by adding new or modified information to already-existing data. This is done to improve the effectiveness, generalization, and resilience of machine learning models, especially when data is scarce. We must enlarge the current data in order to develop a more accurate model because there aren't many documents with fingerprints and associated blood.

6.2 Improving the accuracy of Latent Matching Approach using texture features
Following the reconstruction of latent fingerprints, we suggest automating the fingerprint matching procedure. Following the improvement of the input photos, we performed the Hough transform matching. We must align the minutiae points for matching after feature extraction. The Hough transform is used to determine how similar the minutiae points are based on that alignment approach. To increase the accuracy, we use texture-based features such as energy, homogeneity, contrast, correlation, and entropy.
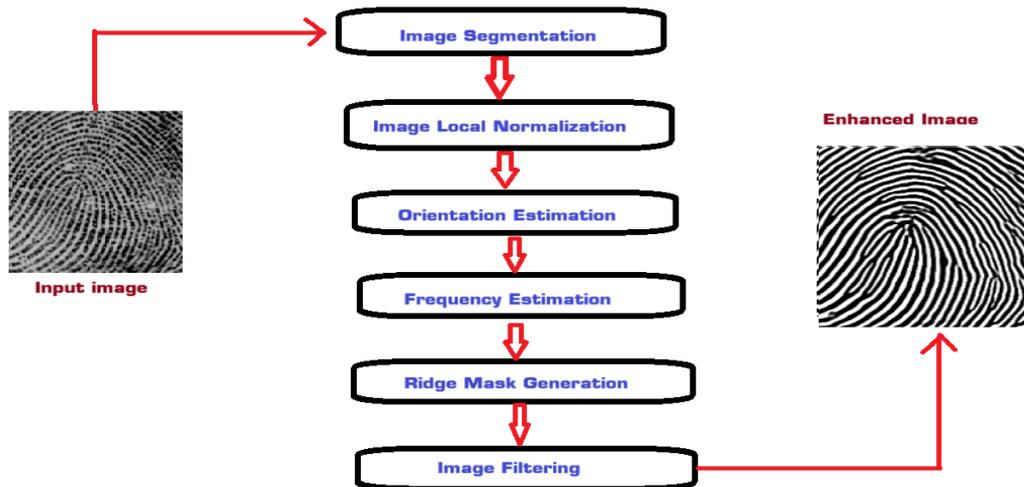

Fig-6 Enhancement steps

The processes carried out during latent fingerprint enhancement include segmentation, normalization, local orientation estimation, ridge frequency estimation, region mask estimation, and filtering. Each pixel's variance is calculated as a result of segmentation. The technique that modifies the range of pixel intensity values is called normalization. Each pixel's local orientation in a fingerprint image is then calculated. The ridge map is extracted to determine the ridge frequency. Masking is the process of classifying pixels as either retrievable or unretrievable. Filtering aids in noise reduction.

7. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

7.1 Interface

Fig: 7 Register page

Fig:8 Login Page

7.2 CNN Model Performance
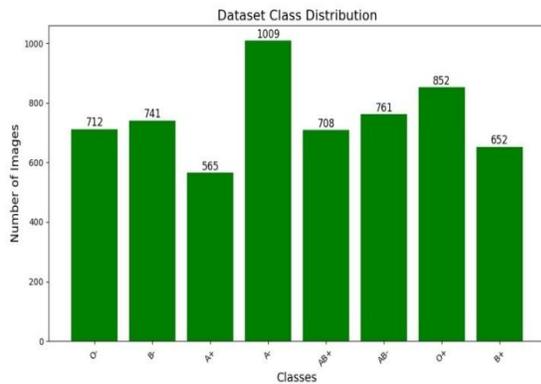
Fig: 09 Data set Classification
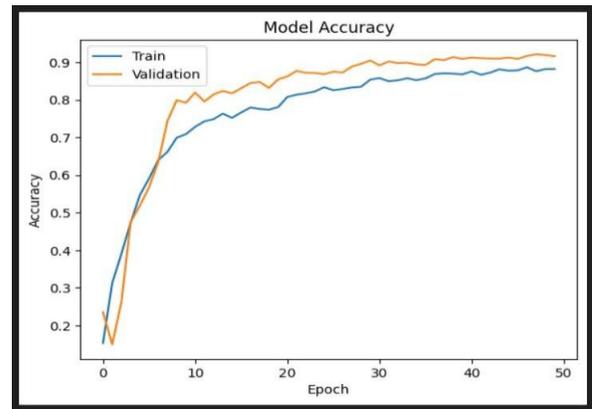
Fig-10. Model accuracy of trained dataset

Fig-11 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
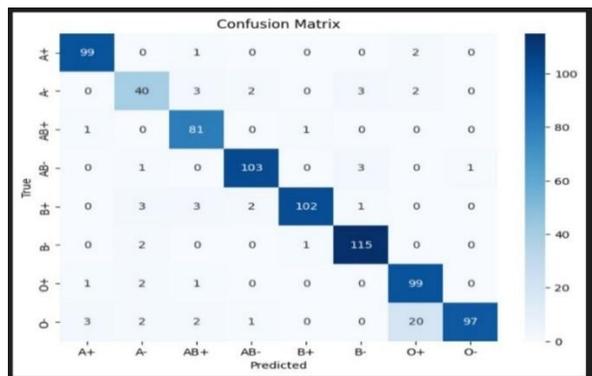
Fig: 12 Confusion matrix

7.3 Results

Fig-13 User Form to Enter and predict Blood group

Fig-14 Result of A+

Fig-17 Result of A-

Fig-18 Result of O+

Fig-19 Result of O-

Fig-20 Result of B-

Fig-21 Result of AB+

Fig-22 Result of AB-

Fig-23 Result of B+

8. CONCLUSION

Our study shows the potential of using cutting-edge techniques like Convolutional Neural Networks (CNNs) to overcome the limitations of accurately predicting blood groups solely from fingerprint patterns, which have been highlighted by previous research due to shared patterns and the complex interplay of various factors. With an astounding 90% accuracy rate, our CNN model indicates that deep learning algorithms can successfully identify minute patterns and characteristics in fingerprint photos that could be linked to blood types. This discovery emphasizes how crucial it is to use advanced computational techniques in order to decipher the complex connection between blood types and fingerprints.

To completely comprehend the underlying mechanisms and confirm the generalizability of our findings, more investigation is required. Nonetheless, our findings offer a strong basis for further research and open the door to the creation of novel, non-invasive blood type techniques with improved precision and dependability. This has the potential to completely transform blood type procedures, especially in situations with limited resources and emergency medical care.

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