Blood group determination using fingerprint.

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Abstract. The fingerprint pattern stands out as the most authentic and unique characteristic defining human identity. This unique pattern is immutable and persists unaltered until an individual's demise. In various circumstances, particularly in legal proceedings, fingerprint evidence is highly regarded. The distinctive minutiae pattern of each person is unparalleled, with the probability of resemblance being exceedingly low, nearly one in sixty-four thousand million. This distinctiveness holds true even for identical duplet. The individualistic ridge pattern persists unchanged from birth, serving as a constant aspect of personal identity. This paper presents a method involving the comparison of specific feature patterns derived from fingerprints for personal identification systems. Fingerprint data is employed in the investigation of blood group determination as well. In the process of fingerprint matching, ridge frequency is assessed, and spatial features are extracted using a Gabor filter for this specific purpose. Consequently, blood group determination can be performed using fingerprint analysis.

Keywords. Blood group determination, fingerprint pattern, ridge frequency, Gabor filter, Convolutional neural networks

1 Introduction

Detecting blood groups using fingerprints is an innovative and non-invasive approach that combines biometric technology with medical information. This method leverages the unique patterns found in an individual's fingerprint to determine their blood type, which is an important piece of medical information for healthcare professionals. The concept is based on the idea that specific proteins or antigens associated with different blood groups can be detected in the sweat found in the ridges and grooves of a person's fingerprint. The traditional method of determining blood groups involves a blood test, which can be uncomfortable and may involve needles. However, with fingerprint-based blood group detection, the process becomes more convenient and less invasive [1]. This technology has the potential to streamline medical procedures, improve patient care, and facilitate emergency medical responses, especially in situations where access to a person's blood type is critical.

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Fingerprint-based blood group detection may also find applications in forensic science and disaster management, where quickly identifying a person's blood type can be essential for providing appropriate medical care. As this technology continues to evolve, it holds promise for enhancing the efficiency and accuracy of healthcare systems and emergency services [2].

Fingerprint recognition is extensively employed in biometric identification, particularly in access control and security systems, due to the distinctiveness and enduring stability of fingerprint patterns unique to each individual throughout their life. This uniqueness and stability make fingerprints an ideal candidate for linking personal medical data like blood type to a specific individual. Blood group detection through fingerprints is based on the presence of proteins or antigens related to an individual's blood type, which are found in the sweat secreted by sweat glands in the ridges and grooves of the fingertips[3]. These antigens correspond to the ABO and Rh blood group systems. By analysing the composition of these antigens in the sweat, it is possible to infer a person's blood type. Fingerprint-based blood group detection is non-invasive and painless, making it a more comfortable alternative to traditional blood tests that require drawing blood using needles.

This can be particularly beneficial for children, the elderly, and individuals with a fear of needles[4].Fingerprint blood group detection can be used in forensic science to help identify victims in mass casualty incidents, or in cases where traditional identification methods may not be feasible in emergency situations, such as accidents, natural disasters, or during surgery when a patient's medical history is not available, fingerprint-based blood group detection can quickly provide essential information for appropriate medical treatment. Integrating blood group information into an individual's medical record using fingerprints can improve the accuracy and accessibility of this critical medical information. It can aid healthcare professionals in emergency situations, surgery, and blood transfusions [5]. Research in this field continues to evolve, and advancements in sensor technology and data analysis techniques are likely to improve the accuracy and practicality of fingerprint- based blood group detection. This has the capability to transform the way we handle and leverage medical information. In summary, fingerprint-based blood group detection is a promising and non-invasive approach to quickly and accurately find out people’s blood type. It has applications in healthcare, emergency response, and forensics, and ongoing research aims to further refine and expand its capabilities [6].

The process begins by collecting the fingerprint of the individual. This can be done using standard fingerprint scanners or more specialized biometric devices designed for medical purposes. It possesses the potential to revolutionize the management and utilization of medical information. This sweat contains proteins or antigens that are associated with the person's blood type. The collected fingerprint is then analyzed to determine the composition of antigens present in the sweat. The system specifically targets antigens related to the ABO and Rh blood group systems, the predominant classifications in blood grouping

By examining the antigen composition, the system can make an educated inference about the individual's blood type. For example, if the analysis reveals the presence of A antigens and Rh antigens, the person is likely to have blood type A positive (A+) [7]. Once the analysis is complete, the determined blood type is presented as the result. This information can be displayed on a computer screen, printed as a report, or integrated into electronic medical records for healthcare professionals to access. Ensuring the accuracy of this method is crucial. Extensive research and validation are carried out to establish a reliable correlation between sweat antigen composition and blood type. This involves comparing the results obtained through fingerprint analysis with traditional blood tests to confirm the method's accuracy. Continuous research and technological progress are directed towards improving the precision and dependability of blood group identification through fingerprint analysis. Improvements in sensor technology, data analysis techniques, and data standardization may contribute to its broader adoption in the medical field [8].

2 Literature Review

2.2 Related works

[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] Fingerprints hold significant promise as a robust method of identification. This study delves into the challenge of identifying blood groups and analyzing age- or lifestyle-related diseases such as hypertension, type 2 diabetes, and arthritis through fingerprint analysis. The research examines the correlation between fingerprint patterns and both blood group and individual age to gain insights into potential connections with these health conditions that emerge with aging or lifestyle factors.

[3] 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. Our work concludes with the matching phase, comprising two segments: the verification process, employing (1:N) matching, and the verification process, known as (1:1) matching. Here, a detailed matching algorithm utilizing the Euclidean distance measure is applied to assess the similarity score between two fingerprint images.

[4] The unique properties of the finger are derived from various types of sensors, such as pattern bumps and dots. The scheme is based on three types of annotations: routing, BGP and GaborHoG. Directional identifiers define the instruction projection in the foreground of the finger. Meanwhile, BGP and GaborHoG descriptors provide a representation of fingerprints by encoding many local ridge patterns and local directions around points.

[5] The findings showed a positive correlation between finger patterns and ABO blood groups. With the continuous advancement of fingerprint technology and the development of accurate and fast matching fingerprint algorithm, automatic identification has become a powerful contribution to the identification process. always check.

[6] Type II lip lines and ulnar ring (UL) finger patterns are common ectodermal features in both genders. B+ type blood is more common in both men and women. More importantly, a population study of Indo-Aryan (Northwestern India) ethnicity found significant correlations between lip lines, fingers, and ABO blood in both sexes. The results of our regional study, which included various samples, clearly show that additional physical evidence such as lip prints, fingerprints and ABO blood group obtained through simple and cost-effective methods can be used as additional tools in criminal investigations. Residents of Srinagar were used for the investigation.

[7] 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.

[8] Research shows that the equipment can perform ABO, Rh phenotyping, reversal and matching of human blood quickly and accurately near the patient without the need for a specialized laboratory. Results are obtained in just 5 minutes, making it advantageous for emergency situations compared to traditional systems with a 30-minute response time. The methodology is simple, requiring no sample dilutions or incubations.

The following table lists some reference papers used for the current paper. It lists the approaches and findings of the respective papers. The limitations do not imply the direct limitations of paper per se, but in the context of the current application. The limitations imply how the approach of a given paper falls short for blood group determination using fingerprints and not the original intended purposes of those respective papers.

Table 1. Related Works Summary

S.no	**Author , Title of the Paper , Journal , Year of Publish**	**Methods Used**	**Findings**	**Limitations**
1	Vijaykumar, Patil N., and D. R. Ingle. [1].	Computer Vision, Multiple Linear Regression	Relation between Fingerprints and blood group	Machine learning approaches used, extremely limited datasets, and an accuracy of 62%.
2	Patil, Vijaykumar, and D. R. Ingle. [2]	Literature review.	Literature review that shows relation between fingerprints, lifestyle diseases, and gender.	A literature survey and analysis without any experimental method.
3	Ali, Mouad MH, et al. [3]	Computer Vision,	Provides an effective machine learning algorithm for finger print	Preprocessing and machine learning approach may not

		Machine Learning	matching leveraging minute patterns.	extend to current use case.
4	Alshehri, Helala, et al.[4]	Computer Vision	The sensor-independent fingerprint extraction method outperforms traditional methods by capturing consistent and accurate data.	Performance is worse for distorted fingerprints.
5	Fayrouz IN, Farida N, Irshad AH. [5].	Statistical Methods	Correlation between fingerprint patterns also has the potential for other forms of personal identification. Loops are the most common structure, accounting for 50.5%; This is followed by threads (35.1%) and belts (14.4%).	Requires a larger dataset to make conclusions and does not include enough data about rare non ABO blood groups.
6	Sandhu, Harpreet, et al. [6]	Survey, Image Analysis and Statistical Methods	Analyzes and correlates lip, fingerprint patterns and gender, associates them with corresponding blood groups.	A pure statistical analysis with manual sampling.
7	Saponara, Sergio, Abdussalam Elhanashi, and Qinghe Zheng. [7]	Deep Learning	Reconstructs accurate fingerprint images from damaged fingerprint images with an accuracy of 96.5%.	Does not perform classification

Our ongoing research will exploit the connection between fingerprint patterns and blood groups, employing deep learning techniques to categorize the fingerprint data. Since the input is in form of images, we propose using Convolutional Neural Networks (CNN) to process and classify the input fingerprint images with greater accuracy taking advantage of patterns in the images. Convolutional Neural Networks can be trained to identify the loops, whorls, arches and their combinations to map them to a blood group type they are highly correlated to. Image processing and feature extraction techniques will help extract the most important features of data and get rid of noise, improving the performance of the CNN.

3 Research Methodology

The fundamental motive of the research 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.

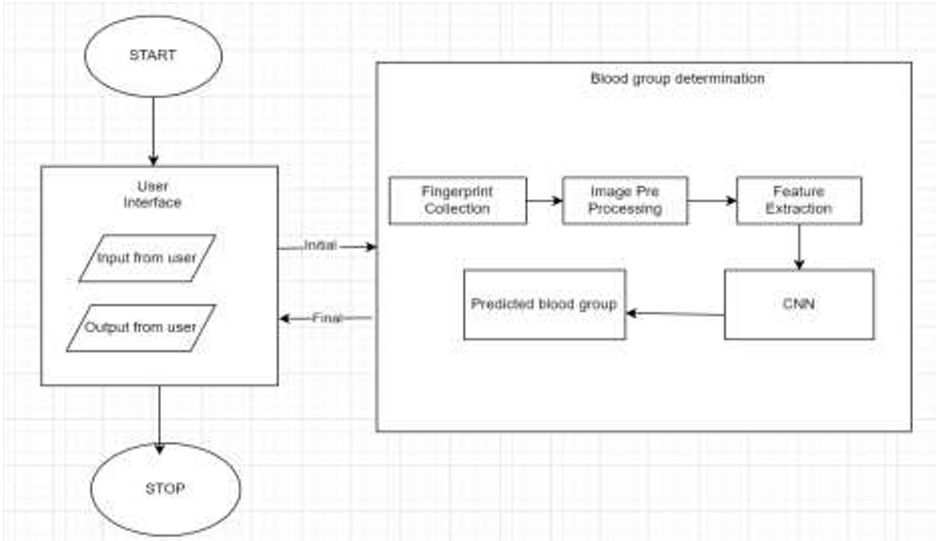

Fig. 1. Architecture of the study

3.1 Data Collection

The data for the analysis is mainly collected from medical surveys carried out, which contain details about fingerprints and associated blood groups of people belonging to various age groups, demographics, and gender. A fingerprint sensor will also enable a manual survey that can be conducted to gather data. Then image processing and feature extraction techniques are used to find the feature vector. We require fingerprints and the associated blood groups of individuals. Such a specific dataset is not available in internet platforms and requires physical survey to gather finger prints and map them to their blood groups. Either fingerprint sensor devices can be used or, we can use ink- based methods although this will lead to an inaccurate model. In the paper titled 'Blood Group Identification Based on Fingerprint by Using 2D Discrete Wavelet and Binary Transform', the authors conducted a survey and found the fingerprints and associated blood groups and tabulated.

3.2 Data Preprocessing

Essential preprocessing techniques are applied to the fingerprint data prior to its submission for classification.

Ridge Segment : It involves the separation of ridge patterns from the background and non-ridge areas in a fingerprint image. This process aims to isolate the ridges (raised lines) from the valleys and any other extraneous details present in the fingerprint image.

Histogram Equitation: Histogram Equalization, a technique in computer image processing, enhances image contrast by redistributing the most common intensity values, effectively expanding the image's intensity range. This method is generally used to increase contrast in images with similar values, allowing areas with low contrast to achieve high contrast again.

Binarization: The process of binarization involves transforming an image from grayscale or color into a binary representation. In a binary image, each pixel can have only one of two values: usually 0 (black) or 1 (white). The process involves setting a threshold that separates the pixels into these two categories based on their intensity or colour values. We obtain a black and white image of the fingerprint that highlights the features of the fingerprint.

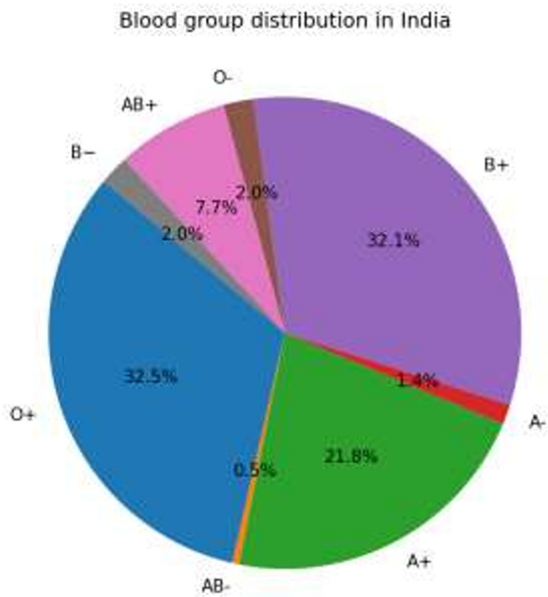

Fig. 2. Blood group distribution in India

3.3 Feature Extraction

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 refers 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.

3.4 Classification

The feature vector obtained after feature extraction is sent as input to a Convolutional Neural Network for classification. Convolutional Neural Networks are primarily used for tasks involving visual data such as images and videos. CNNs can also capture patterns present in the images using the right pooling layer.

We start with LeNet or AlexNet CNN architecture initially. These architectures provide a good starting point since we have limited data sets and they have a relatively simple architecture. Depending on the performance, more advanced architectures such as ResNet, Inception, or EfficientNet can be used.

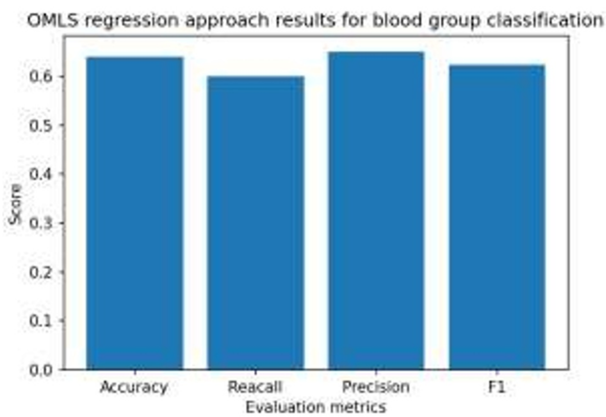

Fig. 3. Evaluation metrics for blood group classification using OMLS regression.

LeNet-5:

Introduced by Yann LeCun in 1989, LeNet is a convolutional neural network commonly referred to as LeNet-5. It utilizes the average pooling layer for subsampling and employs the 'tanh' activation function. The final classifier consists of Multi-Layered Perceptron or Fully Connected Layers. The sparse connections between layers effectively reduce computational complexity. The architectural structure of LeNet-5 consists of seven layers, incorporating three convolutional layers, two subsampling layers, and two fully connected layers.

AlexNet:

AlexNet marked the advent of GPU utilization for enhanced performance in convolutional networks. The architecture of AlexNet contains 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer. Non-linear activation functions, specifically ReLU, are applied to all convolutional layers and filters. Maximum pooling is done in the pooling layer. Due to the full linking process the text size remains constant, always set to 224x224x3, but sometimes it can be 227x227x3 when padding is taken into account. AlexNet boasts a total of 60 million parameters, featuring notable characteristics like overlapping and ReLU non-linearity. Leveraging the simplicity of AlexNet, we have chosen it as one of the fundamental CNN architectures for implementation in our application.

4 Conclusion

The correlation of blood group to blood group has been observed from the literature review of relevant works. Further the presence of recurring patterns common to certain blood groups has been studied from various sources. Fingerprint matching algorithms help extract feature necessary for building a deep learning model. Deep learning methods are used in the field of dactylography for reconstruction of fingerprints, latent fingerprint matching and fingerprint classification. Such implementations further the case of utilizing deep learning approaches to associate finger prints with blood groups. Convolutional neural networks can give flattened representations of images that can be used as input for fully connected neural networks that classify the input images. Since the concept of mapping fingerprints is novel and has no standardized approaches, preconfigured CNN architectures like AlexNet, and LeNet-5 are used to initially classify the input fingerprint data. The performance of each of these models are evaluated to understand the optimal features and based on evaluations a specific CNN is built for the application.

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