International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN: 2147-6799 www.ijisae.org Original Research Paper

Intelligent Blood Group Detection from Fingerprints Using Machine Learning Models

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Submitted:03/08/2023 **Revised**: 18/09/2023 **Accepted:** 29/09/2023

Abstract: The detection of blood groups traditionally requires invasive methods, such as blood sample collection and laboratory analysis. This paper presents a novel, non- invasive approach for predicting blood groups by analyzing fingerprint images. Fingerprint patterns are known to be influenced by genetic factors, which also govern blood group types. In this study, a dataset of fingerprint images from individuals with known blood groups (A, B, AB, and O) was analyzed using DL algorithms. Key features were extracted from the fingerprint patterns, including ridge count, ridge density, and minutiae distribution. These features were used to train a classification model for predicting the blood group. The proposed method achieved a promising accuracy of blood group detection, demonstrating the potential for integrating biometric and genetic information in non-invasive diagnostic tools. By providing a rapid, affordable, and non-invasive method of identifying blood group types, this strategy has the potential to completely transform medical diagnostic processes.

Keywords: *Fingerprint, Classification, Deep learning, Feature extraction, Blood Group.*

Introduction

Blood group detection is a fundamental aspect of medical diagnostics, often required in emergency medical procedures, transfusions, and for general health information. Traditionally, blood group determination is carried out using serological methods, which require blood samples and reagents. While effective, these methods can be time-consuming, require trained personnel, and involve the handling of biological fluids, which carries certain risks. With advancements in deep learnings (DL) and image processing techniques, there has been growing interest in non-invasive methods of determining blood groups. One such approach is using fingerprint images combined with Convolutional Neural Networks (CNNs). This method leverages the unique patterns found in fingerprints, which are thought to have a correlation with certain biological traits, including blood groups [1].

I. Related Work

New Method for Using DNN-Based Models to Measure Human Blood Component Levels Non-Invasively from Fingertip Videos Md. Asaf-Uddowla Golap, M. M. A. Hashem, S. M. Taslim Uddin Raju, and Md. Rezwanul Haque, among others. Keeping an eye on blood components such as hemoglobin, glucose, and creatinine is essential for tracking general health. However, current methods for measuring these components often rely on invasive techniques, which patients may find uncomfortable and painful. We created a novel, non-invasive method to make the procedure more practical and appropriate for usage at home. that detects hemoglobin, glucose, and creatinine levels using Deep Neural Networks (DNN) and PPG signals. We analyze fingertip films captured by 93 individuals using a smartphone. Every video produces a PPG signal, from which 46 unique features are then extracted using Fourier analysis, the PPG signal, and its first and second derivatives. Furthermore, age and gender are also included in the feature because of the substantial effects on hemoglobin, glucose, and creatinine. To avoid overfitting and redundancy, correlation-based feature selection (CFS) uses genetic algorithms (GA) to select the optimal features [1,2,3].

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Blood group classification is a critical aspect of safe and effective blood transfusion, but conventional manual methods are time-consuming and often susceptible to errors. To overcome these limitations, artificial intelligence (AI) and image processing techniques have been introduced as innovative solutions. Blood samples can be examined to extract particular traits and correctly identify them using the ABO and Rh systems by utilizing segmentation procedures and simulations in programs like MATLAB. The methodology involves capturing and processing blood sample images, extracting key characteristics, and automating the classification process. This approach significantly reduces manual intervention, enhances accuracy, and ensures rapid results. By addressing the inefficiencies and drawbacks of traditional methods, AI- powered image processing provides a more efficient, reliable, and error-free system for blood group prediction, paving the way for advancements in medical diagnostics and patient care [1]. In recent years, biometric systems have gained popularity due to their secure, reliable, and user-friendly nature, utilizing physical or behavioral traits to distinguish legitimate users from impostors. A novel approach in this field involves recognizing individuals based on the electromagnetic (EM) scattering from their hand or wrist when exposed to microwaves (MW) in the X-band (8.2 to 12.4 GHz).The process requires a person to place their hand between two antennas, with the scattering data analyzed to identify unique characteristics. To enhance recognition accuracy, researchers developed a specialized wristband with a meta surface (MTS) design, amplifying individual-specific EM traits. This method was tested using data collected from 43 individuals across two separate sessions, yielding promising results. It demonstrates potential as a standalone biometric system or in combination with existing methods,such as fingerprints or palm prints, to further enhance recognition capabilities [4,5].

Blood phenotyping is one of the most widely used and important medical tests in the world, particularly prior to surgery or blood transfusions. Despite its simplicity, even minor errors in determining blood type can have serious consequences, potentially leading to fatal outcomes. Traditional methods for blood grouping, while widely used, rely on manual procedures that can be prone to human error. This highlights the need for more advanced approaches to improve accuracy and reliability. One such method involves using image processing techniques to analyze blood samples. These techniques focus on identifying agglutination patterns that occur when blood reacts with specific reagents, a process central to determining blood type. By capturing and analyzing images of blood samples mixed with reagents, this approach can accurately detect the presence or absence of agglutination, thereby identifying the blood group. A plate test, combined with these image processing strategies, offers a more precise and automated way to handle blood grouping, reducing the risk of errors associated with manual methods and ensuring safer outcomes in clinical practices [2,3,4].

Determining blood type quickly and accurately is crucial, especially in emergency situations where transfusions are needed. Traditional methods involve manual observation, which can lead to errors and delays. To address this, an automated system using image processing techniques has been developed. The method involves capturing images of blood samples mixed with reagents and analyzing them using MATLAB. Techniques such as thresholding, morphological operations, and luminance analysis help detect agglutination, which determines blood type. This approach reduces human error and speeds up the process.Future advancements aim to make the system portable and integrate mobile notifications for real-time updates, enhancing its practicality in medical emergencies[4,5,6,7].

Diabetes management necessitates ongoing blood glucose testing, but conventional techniques entail painful finger pricks. This work uses near-infrared photoacoustic spectroscopy to provide a non-invasive glucose monitoring device. Using laser pulses, the device creates acoustic waves in tissues that change according to the amount of glucose present. These signals are processed using a field-programmable gate array (FPGA), which improves accuracy and lowers noise. Reliable glucose estimation is achieved by calibrating the data using a machine-learning algorithm. The solution allows for real-time monitoring and data sharing with medical specialists by connecting to a cloud-based platform using mobile devices. High accuracy and little departure from typical glucose readings are demonstrated by the results. In order to improve diabetes management, future improvements will incorporate more functions and optimize the system for portability[5,6,7].

Improvements in biomedical signal processing and wearable sensors have made it possible to measure blood glucose levels painlessly. Frequent blood draws are necessary for traditional invasive procedures, which can be uncomfortable and expensive. This study investigates noninvasive methods and divides them into two categories: sample-based (using fluids such as tears or saliva) and nonsample-based (using optical or nonoptical sensors). Though there are still issues with accuracy and recalibration, these techniques seek to increase comfort, affordability, and efficiency. To improve accuracy, artificial intelligence is being incorporated. In order to bridge the gap between medical technology and everyday use, future advancements will concentrate on mobility, cost, and real-time monitoring .

II. Problem Statement

To the development of an effective method for detecting blood groups using fingerprint images through Convolutional Neural Networks (CNNs). While fingerprint recognition technology is well-established, leveraging this technology to determine blood groups represents a novel challenge[3].

To the development of an effective method for detecting blood groups using fingerprint images through learning models such as CNN are used to classify the fingerprint into a specific blood group according to the features and patterns that were discovered in the training data [4].

Table 1. Comparative Analysis of Blood Group Prediction Approaches

Reference Paper (Year)	**Methodology Used**	**Dataset**	**Model Performanc e**	**Challenges**	**Application Area**	**Future Scope**
Haque, M. R., Raju,S.M.T.U., Golap, M. A.-U.,& Hashem, M. M. A. (2021)	Image Processing	DNN-based models	Accuracy: ~85%	Small dataset, No ML/DL used	measurement of human blood component levels	Improve accuracy with ML/DL, Automation
S. A. Siddiqui, Y. Zhang, J. Lloret, H. Song, and Z. Obradovic (2022)	HemoCue-based Hemoglobin Detection	Wearable Monitoring	Accuracy: ~88%	Limited to hemoglobin, Requires lab setup	Clinical Hematology	AI-based automation, Real-time integration
S. Pimenta, G. Minas, and F. O. Soares (2022)	Spectrophotometri c Blood Typing	Clinical blood samples	Accuracy: ~90%	Lab-based, Needs special equipment	Blood Banks, Labs	AI-driven automation, Mobile integration
S. Patel, A. Mehta, R. Shah (2021)	Image Processing	Blood Group data set	Accuracy: ~96%	Requires lab setup	Hospital Blood Typing	Improve portability, Cost reduction
J. Fernandes et al. (2022)	Absorption Spectrophotometry	Clinical blood samples	Accuracy: ~91%	Requires lab setup, High cost	Automated Blood Typing	AI integration, Portable device development

III. Objectives

To design and implement CNN architectures that can accurately identify and extract features from fingerprint images that are indicative of an individual's blood group[11].

To train and optimize CNN models to achieve high accuracy and reliability in predicting blood groups from fingerprint images, ensuring performance consistency across diverse populations and varying fingerprint qualities[08].

Processing Steps - Core System: This yellow circle encompasses the main processing pipeline where the magic happens.

Upload Dataset: This initial step involves ingesting the collected image dataset into the system. Processing on that dataset (RGB): "RGB" refers to the Red, Green, Blue color model, meaning the images are processed in their natural color format. Pre-processing activities like scaling photos to a consistent dimension, standardizing pixel values, or enhancing the dataset (e.g., rotating, flipping) may be included in this phase. pictures) to broaden its variety and improve the model's ability to generalize.

Feature Extraction (Size/Shape):

Before applying complex models, traditional feature extraction might occur. This involves identifying distinct characteristics of the pests in the images, such as their size, shape, color patterns, or texture.

While CNNs automatically learn features, this block might

also represent early-stage feature engineering or a conceptual understanding of what the CNN will ultimately understand.

Apply Machine Learning techniques to train the dataset: This is the core learning phase. The pre-processed and potentially feature-extracted data is fed into a machine learning algorithm.

Learning the complex correlations and patterns in the photos that differentiate one pest from another, or pests from non-pests, is the aim here. Working CNN: This box provides specific information about the deep learning model's architecture. Convolutional 2D Layers, or Con 2D, are the fundamental components of a CNN. To identify particular features like edges, textures, and more intricate patterns, they apply filters (kernels) to the incoming images. "2D" denotes that they work with two-dimensional pictures.

2. Max-pool (Max Pooling Layers): These layers minimize the feature maps produced by convolutional layers in terms of both width and height. This lessens computing complexity, avoids overfitting, and strengthens the learnt features' resistance to minute positional changes.

3. Fully-connected Layers: Following the extraction of high-level information by the convolutional and pooling layers, these layers arrive at the end of the CNN design. characteristics. They carry out the final categorization using the learnt features by connecting each neuron in one layer to every other layer's neuron. Activation Functions for Softmax/Relu: Rectified linear units, or ReLUs, are activation functions that are commonly employed in convolutional and fully connected layers to add non-linearity and enable the model to learn more intricate correlations.

$(x)=\max(0,x)$. Softmax: An activation function that is typically used in a classification model's output layer. It ensures that all probabilities add up to one by converting the raw output scores (logits) into probabilities for every class. Usually, the projected class is the one with the highest likelihood. Output (Detection of Pest): This is the final result of the system. Based on the trained model, the system can now take a new, unseen image and output whether a pest is detected in it, and often, which specific type of pest it is.

IV. System Architecture

ridge details are identified. These extracted features are then passed through a CNN-based classification algorithm, which analyses them to predict the blood group. Finally, the system outputs the predicted blood group based on the fingerprint analysis. This structured approach ensures accurate and efficient blood group classification using machine learning techniques.

V. Equation

Convolutional Neural Network (CNN) Components Layers of Convolution: CNNs rely on convolutional layers, which automatically extract hierarchical information from input images by using convolution processes.

The convolution operation is mathematically represented as:

Where:

$$Feature\_map_{k}^{uv} = \sum_{i=1}^{k}\sum_{j=1}^{k}(Kernel_{ij}, Input_{(u+i-1)(v+j-1)})$$

Feature_map_{up} output value at position (u,v) in the feature map.

Kernel$_{ij}$ is the weight at position (i, j) in the filter (kernel). Input$(u+i-1)(v+j-1)$ is the corresponding input pixel value.

k is the size of the square kernel (e.g., 3×3).

Activation Functions: Activation functions introduce non-linearity into the network, allowing it to learn complex patterns.

Rectified Linear Unit (ReLU): This is a widely used activation function that outputs the input directly if it's positive, otherwise, it outputs zero. It helps in mitigating the vanishing gradient problem

$$(x) = \max(0, x)$$

Pooling Layers: Pooling layers reduce the spatial dimensions (width and height) of the input volume for the next convolutional layer. This helps in reducing the computational power required to process the data, extracts dominant features, and makes the detection of features invariant to scale and orientation changes.

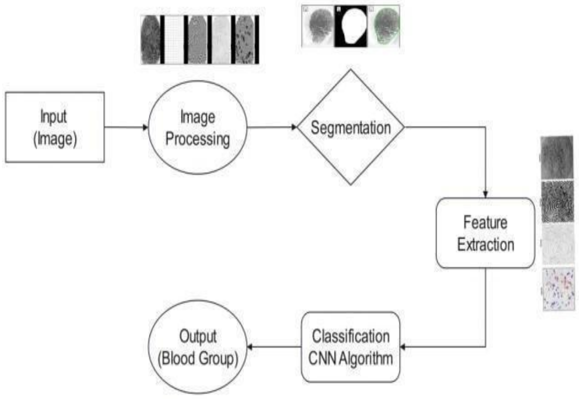

Fig 1. System Architecture

Max Pooling: This operation selects the maximum value from the portion of the feature map covered by the kernel.

$$output = \max(input_{ij}\, within\ the\ pooling\ window)$$

Softmax Function: The Softmax function is typically used in the output layer of a classification CNN. It converts a vector of raw prediction scores into a vector of probabilities, where the probabilities of each class sum up to 1.

The given image represents a flowchart for a blood group prediction system using fingerprints and a Convolutional Neural Network (CNN). The process begins with an input fingerprint image, which undergoes image processing techniques such as noise removal and enhancement to improve quality. Next, segmentation is performed to extract the region of interest, removing unnecessary parts of the image. After segmentation, feature extraction takes place, where significant fingerprint patterns, textures, or

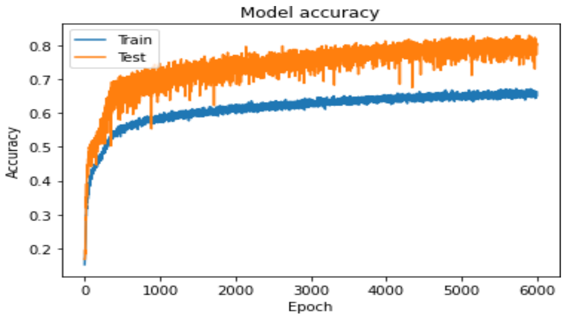

Fig 2. Accuracy Graph

Prediction Done!

Predicted: O- | Confidence: 86.84%
Time: 0.60 sec

Fig 3. Output Result

VI. Methodology

- Preprocessing: The fingerprint images are enhanced through noise removal, binarization, and normalization techniques to improve cand uniformity. Segmentation isolates the region of interest, ensuring.

- Feature Extraction: Key features such as minutiae points, ridge orientation, frequency, and points are extracted from the fingerprint. These features are crucial in identifying the unique pattern that can be associated with a specific blood group.

- Classification: After feature extraction deep learning model such as CNN are used to classify the fingerprint into specific according to the feature and pattern that were discovered from the training data .

- Model Training: Every fingerprint image in the labeled dataset used to train the algorithm is linked to a specific blood group. To guarantee accuracy and resilience in blood group prediction, training dentails modifying model parameters and assessing performance through methods like cross-validation[12].

VII. Discussion

This method offers a rapid and non-invasive method of identifying blood types by using biometric data from fingerprint images.It eliminates the need for traditional blood tests, making it particularly useful in scenarios where rapid results are essential. The methodology combines image processing, deep learning, and classification techniques to analyze fingerprint features and correlate them with blood group patterns[13,14]. However, challenges exist, including the variability in fingerprint quality due to skin conditions, scanner resolution, or environmental factors. The assumption that fingerprint patterns have a direct correlation with blood groups remains a topic for further validation through extensive datasets[10].

VIII. Conclusion

Convolutional Neural Networks (CNN) are a novel and potentially revolutionary method of blood group determination that uses fingerprint images to detect blood groups. Even though the concept could offer a non-invasive, practical, and affordable alternative to convulational blood testing methods, a number of practical and technical issues need to be resolved to guarantee its successful adoption. It is technically possible to create a CNN model that can precisely match blood group information with fingerprint traits, but it will take careful planning and training. The availability and quality of datasets are crucial since good, annotated data are necessary for efficient model operation. To get accurate findings, it is essential to make sure the models can generalize across many populations and fingerprint settings .

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