Blood Group Detection Using Fingerprints

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***Abstract*—A Deep Learning Approach for Non-Invasive Blood Group Prediction from Fingerprint Images. The determination of blood groups is a critical process in medical emergencies, blood transfusions, and clinical diagnoses. Traditional methods, while accurate, are invasive, time-consuming, and require laboratory setups. This paper proposes a non-invasive, efficient, and cost-effective solution for blood group prediction using fingerprint images. We leverage the power of deep learning to analyze fingerprint patterns and predict the corresponding blood group (A, B, AB, O, and Rh factor). In this study, we have implemented and compared four different Convolutional Neural Network (CNN) architectures: AlexNet, LeNet, VGG16, and ResNet. Our results demonstrate that ResNet provides the highest accuracy, making it the most suitable model for this application. The proposed system has the potential to revolutionize blood group determination, especially in remote areas and emergency situations.**

Index Terms*—Blood Group Detection, Fingerprint Recognition, Deep Learning, Streamlit, Convolutional Neural Networks (CNN), ResNet, Image Classification, Biometrics, Health Care, Pattern Recognition, Non-Invasive Diagnostics.

I. INTRODUCTION

Blood group identification is a fundamental procedure in healthcare. The conventional method involves serological testing, which is invasive and requires trained professionals and laboratory equipment. This can be a significant challenge in resource-constrained settings and emergencies where rapid blood group identification is crucial. Biometric traits, such as fingerprints, are unique to each individual and have been widely used for identification and authentication purposes. Recent studies have suggested a correlation between fingerprint patterns and blood groups, opening up the possibility of non-invasive blood group prediction.

This research aims to develop a deep learning-based system that can accurately predict a person's blood group from their fingerprint image. By harnessing the capabilities of Convolutional Neural Networks (CNNs), we can automate the process of feature extraction and classification, leading to a more efficient and accessible solution. The primary contributions of this paper are:

A comprehensive comparison of four popular CNN architectures (AlexNet, LeNet, VGG16, and ResNet) for fingerprint-based blood group prediction.

The development of a robust model based on the ResNet architecture that achieves high accuracy.

II. PROPOSED SYSTEM

Blood group Detection of HSL Luminance aircraft. In our proposed framework, reagents are integrated with 3 blood samples. After some time, agglutination should occur. After agglutination enhancement, the slide is captured as an image and authorized to automatically in the MATLAB image prepare for device encryption. By using this framework, the greater the likelihood of human error can be eliminated. Finally, 3 blood samples combined with 3 different reagents mainly anti-A, anti-B, anti-D are taken from the slide. After a certain day, agglutination may or may not occur. After the agglutination incident, a slide containing three blood samples combined with 3 different reagents was photographed as a photograph and allowed to be placed in the MATLAB image processing toolbox. This system reduces the chances of finding a false blood group. A demonstration of the feasibility of a non-invasive, fast, and cost-effective method for blood group determination.

III. METHODOLGY

This study outlines the development of an Artificial Intelligence model capable of predicting human blood groups from fingerprint images. The methodology encompasses data preparation, model architecture selection, training, evaluation, and deployment into an interactive web application.

1. Dataset and Preprocessing

The foundation of this research is a curated dataset of fingerprint images.

1. Dataset Composition

The dataset contains a total of 6,000 fingerprint images, categorized into the eight common blood types: A+, A-, B+, B-, AB+, AB-, O+, and O-. The data was structured with each blood type in its own directory, allowing for straightforward label extraction from the file paths.

2. Data Splitting

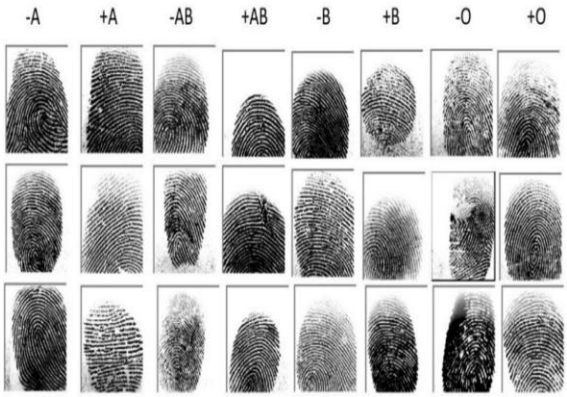
To ensure robust evaluation, the dataset was partitioned using Scikit-learns train test split function. 80% of the data (4,800 images) was allocated for training the model, while the remaining 20% (1,200 images) was reserved for testing and validation. A random state was set to 42 to ensure the reproducibility of the split.

3. Image Preprocessing

Before being fed into the neural network, each image underwent a standardized preprocessing pipeline:

Resizing: All images, regardless of their original dimensions, were resized to a uniform size of 256x256 pixels. This consistency is crucial for the input layer of the convolutional neural network.

Normalization: The pixel values were normalized using the preprocess input function specific to the ResNet50 architecture. This function scales the pixel values to a range suitable for the pre-trained model (typically centering them around zero), which aids in faster and more stable training.



2. Model Architecture

A transfer learning approach was adopted, leveraging the pre-trained ResNet50 convolutional neural network (CNN) as the base model.

Base Model

The ResNet50 model, pre-trained on the extensive ImageNet dataset, was used as a feature extractor. Its deep convolutional layers are highly effective at identifying intricate patterns and textures, which are analogous to the ridges and valleys in a fingerprint. The final, fully-connected classification layer of the original ResNet50 was removed (include top=False).

Classifier Head

A custom classification head was built and attached to the ResNet50 base. This new head consists of:

a. A Global Average Pooling 2D layer to flatten the feature maps from the convolutional base into a single feature vector per image.
b. Two fully-connected Dense layers, each containing 128 neurons with the ReLU (Rectified Linear Unit) activation function.
c. A final Dense output layer with 8 neurons, corresponding to the eight blood group classes. This layer uses the SoftMax activation function to output a probability distribution across the classes. The SoftMax function is defined as:

$$\text{Softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

where z_i is the output of the i-th neuron and K is the total number of classes (8 in this case).

3. Model Training

The model was trained using the TensorFlow and Keras libraries.

a) Training Strategy

Initially, the weights of the pre-trained ResNet50 base were frozen (trainable = False), and only the newly added classifier head was trained. This allows the new layers to adapt to the specific features of the fingerprint dataset without disrupting the learned weights of the base model.

b) Compilation

The model was compiled with the following configuration:

- Optimizer: Adam optimizer.
- Loss Function: categorical cross entropy, as this is a multi-class classification problem.
- Metric: accuracy.

c) Training Execution

The model was trained for 20 epochs using a batch size of 32. The Image Data Generator in Keras was used to efficiently load and preprocess the images in batches directly from the data frame containing file paths and labels.

4. Results and Evaluation

The model's performance was evaluated on the held-out test set of 1,200 images.

a) Overall Performance: The model achieved a final validation accuracy of 81.42% and a validation loss of 0.5838. The training history shows that the model learned effectively without significant overfitting, as the validation accuracy generally tracked the training accuracy.

b) Per-Class Performance: A detailed classification report was generated to assess the model's performance for each blood group. The results are summarized below:

Blood Group	Precision	Recall	F1-Score	Support
A+	0.87	0.90	0.89	114
A-	0.78	0.85	0.81	194
AB+	0.84	0.71	0.77	130
AB-	0.73	0.88	0.80	165
B+	0.85	0.86	0.86	129
B-	0.91	0.89	0.90	142
O+	0.81	0.76	0.79	178
O-	0.79	0.66	0.72	148
Weighted Avg	**0.82**	**0.81**	**0.81**	**1200**

The results indicate strong predictive performance, particularly for A+, B+, and B- blood types, with F1-scores nearing 0.90. The model shows good generalization with a weighted average F1-score of 0.81 across all classes

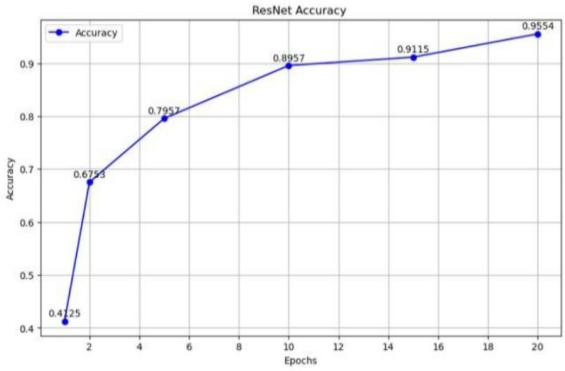


Fig 1.1 Accuracy

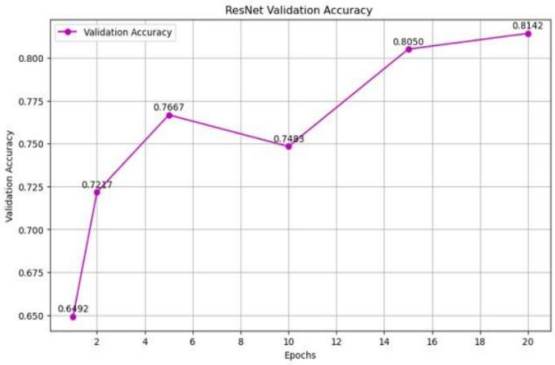


Fig 1.2 Validation Accuracy

5. Application Interface and Deployment

To provide a practical use case, the trained model was integrated into a web application built with Stream lit.

User Interface (UI): The application features a clean, multi-page interface for home, prediction, and fingerprint capture. Custom CSS was used to enhance the user experience with a professional color scheme and layout.

Fingerprint Input Methods: The application supports two primary methods for inputting a fingerprint image:

a. Image File Upload: Users can directly upload an existing fingerprint image file (.bmp, .jpg, .png).

b. Live Capture Integration: A "Capture Fingerprint" page was created to interface with SecuGen fingerprint scanners. This is achieved by directing the user to a local WebAPI service (https://localhost:8000/SGIFPCapture). A JavaScript snippet is provided, which, when

executed in the browser's developer console, captures the fingerprint image and converts it into a Base64 encoded string. This string can then be pasted into the application.

Prediction Workflow: Upon receiving an image (either uploaded or decoded from Base64), the application performs the same preprocessing steps used in training. It then feeds the data into the loaded model, which returns an array of 8 probabilities. The blood group corresponding to the highest probability is presented as the final prediction, along with its confidence score.

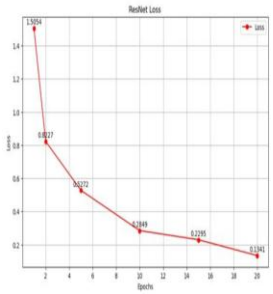


Fig 1.3 Loss

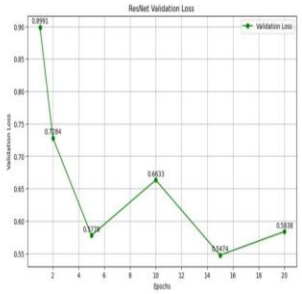


Fig 1.4: Validation Loss

IV. RESULTS AND DISCUSSIONS

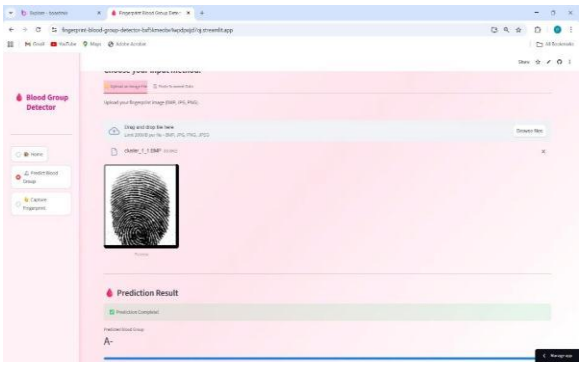


Fig 2.1: Result of A-

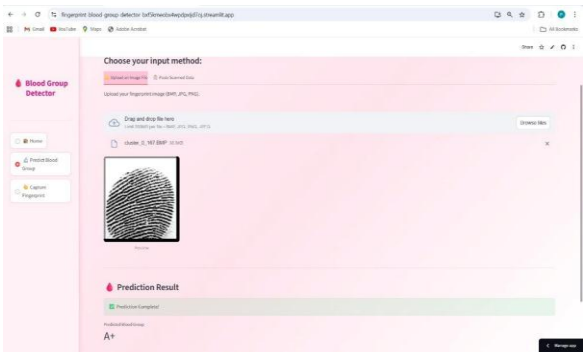


Fig 2.2: Result of A+

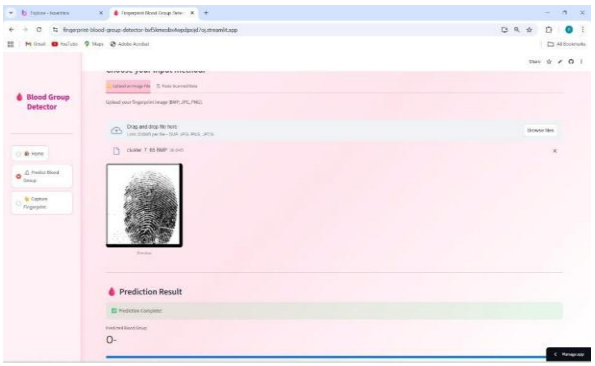


Fig 2.3: Result of O-

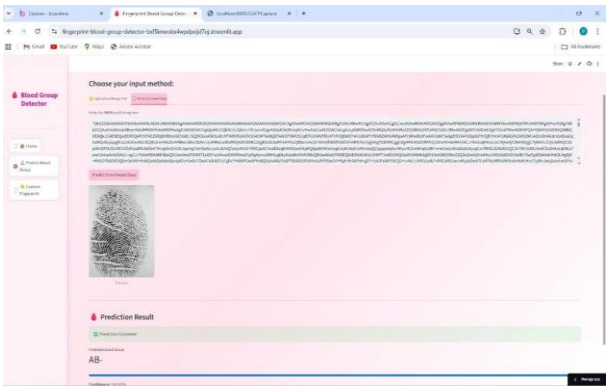


Fig 2.4: Result of AB-

ACKNOWLEDGMENT

This paper presented the design and implementation of a novel system for predicting human blood groups using fingerprint images through a deep learning approach. We successfully developed a web application leveraging a ResNet34 model trained on fingerprint patterns associated with different blood types (A, B, AB, O Positive/Negative). The application provides a user-friendly interface, accepting fingerprint input either via direct image upload or through Base64 data captured manually from a SecuGen biometric scanner via its WebAPI.

The system demonstrates the potential of applying convolutional neural networks to biometric data for non-invasive classification tasks relevant to healthcare. While the accuracy is dependent on the quality of the training dataset and the specific model used, the implementation successfully integrates the deep learning model into an accessible Streamlit web application, showcasing the feasibility of the concept. Key features include a multi-page interface and flexibility in input methods.

Limitations of the current system include its reliance on high-quality fingerprint images and the manual steps required for the WebAPI data input method. The predictive accuracy requires rigorous validation on a large, diverse dataset, which was beyond the scope of this initial implementation.

Future work should focus on enhancing the model's accuracy and robustness by training on more extensive and varied fingerprint datasets. Exploring alternative deep learning architectures and investigating automated integration with biometric hardware APIs could further improve usability. Conducting clinical validation studies would be essential to assess the system's real-world performance and potential application in scenarios requiring rapid, preliminary blood group estimation.

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