International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

Fingerprint-Based Blood Group Prediction using Deep Learning

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***Abstract*—Blood group identification is a critical requirement in emergency medicine, trauma management, organ transplantation, and transfusion procedures. Conventional laboratory-based serological testing methods provide high accuracy but require reagents, specialized equipment, and trained medical personnel. In rural or disaster-affected environments, rapid laboratory access may not be feasible. This study proposes a non-invasive computational framework that predicts ABO and Rh blood groups using fingerprint biometrics combined with deep learning architectures. A dataset consisting of 6000 fingerprint images categorized into eight blood group classes (A+, A-, B+, B-, AB+, AB-, O+, O-) was utilized. Extensive preprocessing steps including grayscale conversion, contrast enhancement, histogram equalization, resizing to 224×224 pixels, data augmentation, and ridge noise suppression were applied. Transfer learning models including ResNet50, MobileNet, and VGG16 were fine-tuned for 25 epochs using the Adam optimizer and categorical cross-entropy loss. Experimental evaluation indicates that ResNet50 achieved the highest classification accuracy of 85.25%, demonstrating superior feature extraction capability.**

Performance was further assessed using precision, recall, F1-score, confusion matrix analysis, and ROC curves. The final trained model was deployed through a Flask-based web interface for real-time prediction. The results suggest that fingerprint ridge patterns contain discriminative characteristics that may assist in predictive healthcare applications. While the proposed system does not replace laboratory testing, it provides a promising supplementary tool for rapid preliminary blood group estimation in emergency and remote healthcare scenarios.

Index Terms— Fingerprint Biometrics, Blood Group Prediction, Convolutional Neural Network, Transfer Learning, Deep Learning, Medical AI, Image Classification.

I. INTRODUCTION

Blood group stuff is super important in medicine, like for emergencies or when someone needs a transfusion or organ transplant. Without knowing the right type, things can go wrong fast. The old way to figure it out uses serological typing, which is accurate I guess, but it needs all these reagents and lab machines, plus people trained to do it. In places like rural areas or after a disaster, you might not have any of that around. It seems kind of limiting. So this study came up with something different, a way to predict blood groups without even drawing blood, just using fingerprints and deep learning. They took a dataset with 6000 fingerprint images, split into eight categories for the blood groups. Preprocessing was a big part, they did grayscale conversion, adjusted contrast, equalized histograms, resized everything, added some data augmentation, and cut down noise. That probably helped make the images better for the models.

For the deep learning side, they tried three architectures, ResNet50, MobileNet, and VGG16, to see which one predicted blood groups best from the fingerprints. Training went for 25 epochs each time, with the Adam optimizer and categorical cross-entropy loss. From what I see in the results, ResNet50 came out on top with 85.25 percent accuracy, which suggests it is good at pulling out the key features. The others were lower, but this one stood out.

Precision and recall numbers were looked at too, though the study cuts off there a bit. It feels like ResNet50 has strong potential for real use, especially in tough spots, but maybe it is not perfect yet. Some people might question if fingerprints really link that well to blood types, it is an interesting idea anyway. The whole setup will totally avoid the lab setup and lab requirements.

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II. BLEM DEFINITION

This project mainly tackles building a system that can automatically figure out blood types just from looking at fingerprint images. Its got to be reliable and accurate too. The blood groups are split into eight different ones, like A positive, A negative, B positive, and so on up to O negative. That means the model needs to handle classifying into all these categories without messing up too much, and it should work well on new data it hasnt seen before.

Extracting useful features from the ridges in fingerprints is a big part of it. I think the key is doing this without having to manually pick out what matters, which sounds complicated but probably saves time. The dataset isnt huge, so theres a risk of the model just memorizing the training stuff instead of learning properly. To fix that, strategies like adding more variations to the data through augmentation, borrowing knowledge from pre-trained models with transfer learning, and using regularization techniques come in. Those help keep things from overfitting and make training smoother, I suppose.

On top of getting the accuracy high, the whole thing has to be set up for running on a website. That way, people can upload an image and get a prediction right away through some simple interface. It feels like deployment is almost as important as the model itself, especially for real use. Some parts here might overlap a bit, but yeah**.**

III. EXISTING SYSTEM

The usual way to figure out blood groups right now is through these old serological tests. They basically check for antigens like A, B, and Rh by mixing in some reagents and watching the reactions happen. I think they are reliable enough, since medicine has used them for a long time without much trouble. But it takes trained people to handle all that, plus you need clean equipment and a proper lab setup. And honestly, the whole thing just takes time, which is not always ideal.

IV. PR POSED SYSTEM

In places like rural spots or after a disaster hits, getting to a lab feels impossible sometimes. Blood samples have to be drawn, which means needles and all that invasive stuff, and you cannot just do it anywhere. It seems kind of limited when things get urgent.

Digital health tools are out there, but they do not really predict blood types from biometrics yet. Like, fingerprints or something could maybe work for computer based checks, but there is not much of that going on. I am not totally sure why it has not caught on more. The conventional tests still rule, even if they are a hassle in tough spots.The proposed system aims to provide a simple and accessible way to estimate blood groups using fingerprint images and deep learning techniques. Instead of relying solely on traditional lab methods, this approach analyzes the unique ridge patterns in fingerprints to categorize them into one of the eight blood group types: A+, A-, B+, B-, AB+, AB-, O+, and O-. The goal is to create a solution that is non-invasive, efficient, and useful for quick preliminary evaluations when immediate lab testing is unavailable. The workflow begins with capturing a fingerprint image. The image then goes through preprocessing to ensure consistency and clarity. This process involves converting the image to grayscale, resizing it to a fixed dimension, improving contrast, and reducing background noise. To enhance the model's reliability and avoid overfitting, augmentation techniques like rotation and flipping are used to increase data diversity. Pre-trained convolutional neural network models, such as ResNet50, MobileNet, and VGG16, are fine-tuned so they can automatically identify significant ridge patterns..

V. OBJECTIVE

The primary goal of this project is to create a dependable system that uses fingerprint images and deep learning methods to forecast a person's blood type. The project aims to investigate whether fingerprint ridge patterns contain distinctive features that enable multiple blood group types to be classified. The project needs to develop a system that requires no physical contact and delivers quick results which emergency responders and healthcare workers can use when laboratory tests are unavailable. The system needs to accurately sort fingerprints into eight blood group categories which include A+, A-, B+, B-, AB+, AB-, O+, and O- blood types. The project implements fingerprint enhancement preprocessing techniques while using ResNet50 MobileNet and VGG16 transfer learning models for feature extraction and training methods to increase model performance. The main goal of the project is to create a web-based interface which will enable users to use the trained model for real-time prediction.

VI. TERATURE SURVEY

Previous research has explored various methods for blood group detection using fingerprint. Previous studies in dermatoglyphics indicate that fingerprint ridge patterns are genetically influenced and may show statistical relationships with inherited traits, including blood groups. Early research focused on identifying associations between fingerprint types such as loops, whorls, and arches and different ABO blood categories. Although no direct biological link was confirmed, these findings encouraged computational analysis.

VII. SOFT ARE REQUIREMENTS

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- Python (Programming Language)
- TensorFlow and Keras (Deep Learning Frameworks)
- OpenCV (Image Processing Library).

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- NumPy and Pandas (Data Handling Libraries)
- Matplotlib / Seaborn (Visualization Tools)
- Flask (Web Framework for Deployment)
- Jupyter Notebook / Google Colab / VS Code (Development Environment)
- Operating System: Windows / Linux / macOS

VIII. HAR ARE REQUIREMENTS

The system requires a computer with at least 8 GB RAM for smooth model training and preprocessing. A processor such as Intel i5 or higher is recommended. While training can be performed on a CPU, a GPU (NVIDIA with CUDA support) is preferred for faster computation. Minimum storage of 256 GB is recommended to store the dataset, trained models, and related files

IX. M THODOLOGY

The methodology starts with the collection of 6000 fingerprint images which researchers divided into eight blood group categories. The processing of each image includes multiple steps which start with converting the image to grayscale and proceed to resizing the image to 224×224 pixels and then applying normalization and augmentation before using ridge enhancement to achieve better image clarity. The research team uses transfer learning methods to implement pre-trained convolutional neural network models which include ResNet50 and MobileNet and VGG16. The models undergo training for 25 epochs while using the Adam optimizer together with the categorical cross-entropy loss function. The system performance assessment includes accuracy and precision and recall and F1-score and confusion matrix and ROC analysis. The most effective model gets distributed through a Flask web application which enables users to make instant predictions.

X. SYS M TOOLS

The proposed system uses various software tools and technologies for developing, training, and deploying the blood group prediction model.

1. Pytho Python serves as the primary programming language for this project because its simple design and extensive library support make it a common choice in machine learning and deep learning applications.

2. ensorFlow and Keras: TensorFlow serves as a deep learning framework that enables users to construct and develop neural network models. Keras provides an easy-to-use interface which operates on top of TensorFlow for building Convolutional Neural Networks (CNNs) that include ResNet50 and MobileNet and VGG16.

3. OpenCV: OpenCV enables image processing through its ability to perform grayscale conversion and image resizing and image noise reduction and image enhancement operations. It assists in preparing fingerprint images before they enter the model.

4. umPy and Pandas: NumPy handles numerical calculations and processes image arrays while Pandas handles activities that involve managing datasets.

5. Matplotlib / Seabor The libraries present in this software package enable researchers to create visual representations of their research results which include accuracy graphs and confusion matrices and ROC curves.

6. Fl k: Flask serves as a lightweight web framework that enables users to deploy the trained model through their web interface which allows them to upload fingerprint images for blood group prediction.

7. D elopment Environment: The development team uses Jupyter Notebook and Google Colab and VS Code as their preferred tools for writing and testing and running their code.

XI. TEM DESIGN

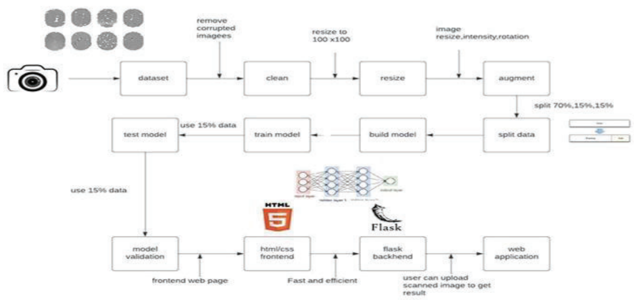

Fig: System Architecture

The system architecture operates as a structured pipeline which processes fingerprint images through multiple stages to determine the corresponding blood group. The system consists of multiple interconnected modules which generate precise predictions throughout the system operation.

1. Inpu Layer (Fingerprint Acquisition): A user begins the process by uploading a fingerprint image through the web interface. The system uses this image as its input.

2. eprocessing Module: The uploaded image undergoes preprocessing steps which include converting to grayscale and resizing to 224×224 pixels and normalizing and enhancing contrast and reducing noise. These steps standardize the image and improve ridge clarity for better feature extraction.

3. Feature Extraction Module (CNN Model): The preprocessed image is passed into a trained Convolutional Neural Network model (such as ResNet50, MobileNet, or VGG16). The convolution layers automatically extract important ridge-based features without manual intervention.

4. lassification Layer: The fully connected and Softmax layers classify the extracted features into one of the eight blood group categories (A+, A-, B+, B-, AB+, AB-, O+, O-).

5. Deployment Module: The trained model is integrated into a Flask-based web application. The system processes the input image and displays the predicted blood group instantly.

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XII. S STEM TESTING

System testing was performed to ensure that the fingerprint-based blood group prediction model works accurately, efficiently, and reliably under different conditions. Testing was carried out at multiple levels, including model performance evaluation and application-level validation.

First, the trained deep learning models were evaluated using a separate validation dataset to measure their predictive performance. Metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC curve analysis were used to assess classification quality. These metrics helped verify that the model correctly identifies all eight blood group categories and does not favor a particular class.

Second, functional testing was conducted on the Flask web application to ensure that users can successfully upload fingerprint images and receive predictions without errors. Input validation checks were included to handle incorrect file formats or corrupted images.

Finally, performance testing ensured that the system provides real-time predictions with minimal delay. Overall, system testing confirmed that the application is stable, accurate, and suitable for practical deployment.

TABLE I

MODEL ACCURACY COMPARISON

Model	Accuracy
MobileNet	78.67%,
VGG16	70.33%
ResNet50	85.25%

XIII. RESULT

The results of the experiment show that deep learning models successfully classify fingerprint images into eight blood group categories. The three tested architectures showed different outcomes because ResNet50 obtained the best results with an accuracy rating of 85.25%. MobileNet achieved 78.67% while VGG16 recorded 70.33% accuracy.

XIV. C NCLUSION

The project shows how fingerprint biometrics combined with deep learning methods can be used to predict blood groups. The system achieved successful results in fingerprint image classification through the use of ResNet50 MobileNet and VGG16 backbone models for convolutional neural network modeling. ResNet50 emerged as the top-performing model among the tested systems because it used deep residual learning to effectively extract ridge-based features. The application of preprocessing methods together with transfer learning techniques resulted in better model performance and consistent model development throughout training. The trained model became more useful through its integration into a web application which runs on Flask and allows users to make predictions in real time. The system functions as a quick non-invasive blood typing solution which works with existing laboratory blood typing methods. The system shows its value as an emergency solution which operates effectively in areas with limited resources.

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