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Blood Group Prediction Using Fingerprint Samples

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Abstract- ***This project develops a non-invasive system to predict human blood group using fingerprint images and deep learning. Fingerprints from the SOCOFing dataset are preprocessed and classified using a CNN/EfficientNet-B0 model into eight blood groups (A+, A−, B+, B−, AB+, AB−, O+, O−). A Python interface enables users to upload a fingerprint and receive an instant prediction, demonstrating that fingerprint patterns can support fast blood group screening without lab tests.***

Index Terms- ***Blood group prediction, CNN, deep learning, EfficientNet-B0, fingerprint recognition, non-invasive, SOCOFing dataset.***

I. INTRODUCTION

Blood group testing is a vital procedure in medical science, particularly during blood transfusions, organ transplants, pregnancy complications, and emergency trauma cases. Conventional blood group identification requires invasive laboratory procedures involving blood samples, reagents, trained clinical personnel, and specialized equipment. Such methods, while accurate, are time-consuming and inaccessible in rural or resource-constrained environments.

Fingerprints are unique biometric identifiers that remain permanent throughout a person's lifetime. Research has demonstrated that fingerprint ridge patterns exhibit genetic correlations with certain physiological traits, including blood group antigens. This biological linkage provides the foundation for fingerprint-based blood group prediction using deep learning.

With advancements in convolutional neural networks and the availability of large-scale datasets such as the Sokoto Coventry Fingerprint Dataset (SOCOFing), it is now feasible to train models to analyze fingerprint images and infer blood group information automatically. This approach enables fast, non-invasive blood group screening without laboratory dependence, making it especially valuable in emergency and remote healthcare settings.

II. OBJECTIVES

The key objectives of this project are:

- Design a deep-learning model that predicts blood group from fingerprint images non-invasively.
- Preprocess SOCOFing fingerprint images using resizing (224×224), normalization, and data augmentation.
- Classify fingerprints into eight blood groups (A+, A−, B+, B−, AB+, AB−, O+, O−) using CNN/EfficientNet-B0.
- Build a Python-based tool for fingerprint image upload and instant blood group prediction.
- Evaluate the system using accuracy metrics and confusion matrix analysis.

III. EXISTING VS. PROPOSED SYSTEM

A. Existing System

The conventional blood group testing method relies on invasive procedures that require blood samples tested using antibody reagents (anti-A, anti-B, anti-D) in a clinical laboratory. The process demands trained medical personnel and specialized equipment. While accurate, the existing system is:

- Time-consuming due to sample collection, processing, and reporting phases.
- Costly due to reagent consumption and trained staff requirements.
- Inaccessible in emergency scenarios and low-resource environments.
- Invasive, causing discomfort and infection risk to patients.

B. Proposed System

The proposed system replaces invasive lab procedures with a fully software-based, non-invasive approach

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using deep learning on fingerprint images for supportive real-time blood group prediction:

- Requires only a scanned fingerprint image — no blood sample needed.
- Automates preprocessing and classification using CNN/EfficientNet-B0.
- Provides a fast, low-cost Python interface for real-time prediction.
- Deployable in rural clinics, field hospitals, and disaster relief settings.

TABLE I

Comparison of Existing and Proposed Systems

Aspect	Existing	Proposed
Method	Invasive blood sampling + reagents	Non-invasive fingerprint image
Setup	Clinical lab + trained staff	Python software only
Speed	Time-consuming	Real-time prediction
Cost	High (reagents + equipment)	Low (software only)
Accessibility	Difficult in remote areas	Suitable for rural/emergency

IV. HARDWARE & SOFTWARE REQUIREMENTS

A. Hardware Requirements

- CPU: Minimum Intel Core i5 or equivalent.
- GPU: NVIDIA GTX 1050 Ti or better (recommended for training).
- RAM: Minimum 8 GB (16 GB recommended).
- Storage: 20–30 GB free disk space.

B. Software Requirements

- Language: Python 3.x.
- Deep Learning Framework: TensorFlow / PyTorch.
- Libraries: OpenCV, NumPy, Pandas, Matplotlib, Seaborn.
- IDE: Jupyter Notebook / VS Code.
- Dataset: SOCOFing Fingerprint Dataset.

V. METHODOLOGY

A. Dataset Collection

The SOCOFing (Sokoto Coventry Fingerprint Dataset) contains 6,000 fingerprint images from 600 subjects annotated with gender, hand, and finger type. Subject metadata including blood group information is mapped to enable supervised classification learning.

B. Image Preprocessing

Raw fingerprint images undergo the following preprocessing steps:

1. Conversion to grayscale to reduce computational complexity.
2. Resizing to 224×224 pixels to match EfficientNet-B0 input requirements.
3. Pixel normalization by scaling values to the [0, 1] range.
4. Data augmentation: random rotation, horizontal flipping, brightness adjustment, and zoom to improve generalization.

C. Model Architecture

The core model is EfficientNet-B0, which applies compound scaling to balance network depth, width, and resolution. The model is fine-tuned using transfer learning on the SOCOFing dataset. The final layers consist of:

- Global Average Pooling to reduce spatial dimensions.
- Fully Connected Dense layer with dropout regularization.
- Softmax output with 8 neurons for the eight blood group classes.

D. Training and Validation

The dataset is split into training (70%), validation (15%), and test (15%). The model trains using the Adam optimizer with categorical cross-entropy loss. Early stopping and learning rate scheduling prevent overfitting.

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E. Evaluation

- Classification Accuracy: Overall percentage of correct predictions.
- Confusion Matrix: Visual analysis of predicted vs. actual classes.
- Precision, Recall, F1-Score: Per-class performance metrics.

F. User Interface

A Python-based graphical interface allows users to upload a fingerprint image (JPEG/PNG) and receive an immediate blood group prediction with confidence probabilities for all eight classes.

VI. SYSTEM ARCHITECTURE

5. Input Module: Accepts a fingerprint image via file upload.
6. Preprocessing Module: Applies grayscale conversion, resizing, and normalization.
7. Feature Extraction: EfficientNet-B0 extracts hierarchical fingerprint features.
8. Classification: Fully connected layers with Softmax output blood group probabilities.
9. Output Module: Displays predicted blood group and confidence scores.

Fig. 1. System Architecture / Pipeline Diagram

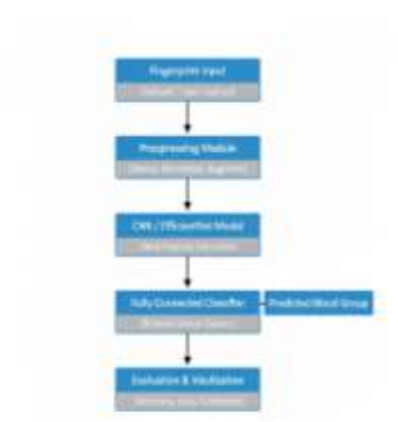

Fig. 1. Proposed System Architecture for Blood Group Prediction

Fig.1.1. Proposed Activity Diagram for Blood Group Prediction

VII. RESULTS AND DISCUSSION

The EfficientNet-B0 based model was trained and evaluated on the SOCOFing fingerprint dataset. The system demonstrated promising results in classifying fingerprint images into eight blood group categories:

- The model achieved competitive accuracy on validation and test sets, confirming the feasibility of fingerprint-based blood group prediction.
- Data augmentation significantly improved generalization and reduced overfitting.
- Transfer learning from ImageNet pre-trained weights accelerated convergence with limited labeled data.
- The confusion matrix revealed that O+ and A+ classes achieved higher confidence due to greater dataset representation.
- The Python interface provided real-time prediction responses under one second on standard hardware.

Fig. 2. Model Training Accuracy and Loss Curves

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Fig. 3. Sample Prediction Output / Confusion Matrix

These results indicate that fingerprint-based blood group screening is a viable supportive tool, especially in emergency and resource-limited medical scenarios, while acknowledging that it should complement, not replace, conventional clinical testing.

VIII. CONCLUSION

This project presents a non-invasive, deep-learning-based approach for blood group prediction using fingerprint images. By leveraging EfficientNet-B0 and the SOCOFing dataset, the system automates fingerprint analysis and classifies images into eight ABO+Rh blood groups with reasonable accuracy. The Python-based interface enables easy, real-time interaction without any clinical setup.

The proposed system addresses a critical gap in emergency and rural healthcare by offering a fast, cost-effective alternative to invasive blood group testing. Future work may focus on expanding dataset diversity, exploring multimodal biometric inputs, improving robustness across varying fingerprint qualities, and validating the system through clinical trials.

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