Grenze International Journal of Engineering and Technology, June Issue

Fingerprint based Blood Group Detection

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***Abstract*— This paper provides a full-fleet of frame-based deep learning structure of blood group identification through fingerprint images. The data of the fingerprints of eight types of blood groups was in a dataset that included eight blood groups, namely, A, A-, B, B-, AB, AB-, O and O-, which was processed. The workflow contains data preparation, augmentation, transfer learning, model training, evaluation, as well as prediction. The four popular CNN architectures ResNet, VGG16, AlexNet, and LeNet were trained and evaluated in similar conditions. Accuracy, precision, recall and F1-score were used as the model performance measures.**

***Index Terms*— Fingerprint recognition, Blood group classification, Transfer learning, ResNet, VGG16, AlexNet, LeNet, Deep learning.**

I. INTRODUCTION

Artificial Intelligence (AI) has increasingly enabled data-driven inference of physiological attributes through biometric signals. Let a fingerprint image be represented as a function:

$$I : \Omega \subset \mathrm{R}^2 \rightarrow [0, 255] \qquad (1)$$

where Ω denotes the spatial domain and pixel intensities lie within grayscale range. Fingerprint ridge structures can be mathematically modeled as a set of continuous patterns:

$$R = \{r_i \mid i = 1, 2, \ldots, N\} \qquad (2)$$

where each r_i represents a ridge curve capturing local texture information. These ridge features encode discriminative patterns that can be mapped to physiological traits.
Let the blood group label space be defined as:

$$C = \{A^+, A^-, B^+, B^-, AB^+, AB^-, O^+, O^-\} \qquad (3)$$

The objective is to learn a mapping:

$$f_\theta : I \rightarrow C \qquad (4)$$

where f_θ is a deep neural network parameterized by θ.
The prediction problem is formulated as a multi-class classification task:

$$\hat{c} = \arg\max_{c \in C} P(c \mid I; \theta) \qquad (5)$$

Grenze ID: 01.GIJET.12.2.207_24

Given a dataset: Given a dataset:

$$D = \{(I_i, c_i)\}_{i=1}^{M} \tag{6}$$

the training objective minimizes categorical cross-entropy loss:

$$\mathcal{L}(\theta) = -\sum_{i=1}^{M}\sum_{c\in\mathcal{C}} y_{ic} \log\left(f_\theta(\mathbf{I}_i)_c\right), \tag{7}$$

where y_{ic} is the one-hot encoded ground truth label.

A. Objectives

- To construct mapping $f_\theta : I \to C$
- To compare CNN architectures under identical constraints
- To evaluate models using statistical performance metrics
- To identify optimal architecture for real-world deployment

II. LITERATURE REVIEW

In addition to the previously discussed studies, several recent contributions have further advanced fingerprint-driven blood group detection. Phadke et al. [1] demonstrated one of the early CNN-based formulations capable of learning discriminative ridge–pattern features directly from fingerprint impressions. Building on computational efficiency, Mavani et al. [2] proposed an optimized deeplearning pipeline suitable for real-time deployment with minimal latency. Tripathy et al. [3] introduced a hybrid framework that integrates machine-learning classifiers with handcrafted fingerprint descriptors, showing that non–deep-learning models remain competitive for controlled datasets. A non-invasive biometric acquisition workflow was examined by Thakre et al. [4], who emphasized enhanced preprocessing to stabilize prediction accuracy under heterogeneous fingerprint quality. Sivamurugan et al. [5] further strengthened deep feature extraction through an improved CNN architecture capable of capturing fine-grained ridge information. Complementing technical contributions, Padole et al. [6] presented a comprehensive review of fingerprint-based blood group identification using CNNs, outlining current advances and persisting challenges.

Sharma et al. [7] proposed an ML-centric classification approach driven by statistical pattern attributes, while Khan and Shekhar [8] extended the domain by incorporating both prediction and data-management modules into a unified system. Sarath Chandra et al. [9] explored deep hierarchical feature mapping for robust classification across varying ridge patterns, and Hegde et al. [10] developed an automated ML-driven blood group classification system tailored for biomedical screening environments. Collectively, these works broaden the methodological landscape and contribute to establishing fingerprint-based blood group identification as a viable and scalable biometric solution.

III. PROPOSED METHODOLOGY

The suggested system addresses blood group prediction as a type of image classification problem based on deep Convolutional Neural Networks (CNNs). The entire workflow is broken into several consecutive steps to provide effective learning and correct prediction.

A. Dataset Preparation

A labeled dataset of fingerprint images belonging to eight blood groups (A+, A-, B+, B-, AB+, AB-, O+, O-) is used. All images are resized to a standard size of 256 x 256 pixels to ensure uniformity among the models. The data is further broken down into training and testing in 80:20 proportion to guarantee appropriate model testing and prevent bias.

B. Preprocessing and Data Augmentation

The images are scaled to a standard range, prior to training, enhancing numerical stability during training. Image generator is used to apply data augmentation techniques which include rotation, zooming, horizontal flipping and slight shifting. This makes the datasets more varied and the model more generalized to unknown data, thus minimizing overfitting.

C. Model Architecture Design

The successful- ness of CNN architectures in this task is analyzed using four CNN architectures: LeNet, AlexNet, VGG16, and ResNet34. In the case of VGG16 and ResNet34, transfer learning is achieved by using pre-trained ImageNet weights as an initializer. Each model has the convolutional base that extracts spatial features of fingerprint images, including ridges and textures. A Global Average Pooling layer is introduced to decrease feature dimensions and still maintain valuable information. This is preceded by fully connected layers with ReLU activation to learn high-level representations. Lastly, the probability distribution of the blood group classes is produced by a softmax layer that has eight neurons.

D. Training Strategy

Adam optimizer and categorical cross-entropy loss are used to train the models. The best balance should be made between the computational efficiency and performance, so a batch size of 32 and 20 training epochs are used. In preliminary training, the convolutional layers are frozen to preserve previously learned features on large scale data. Thereafter, one can use fine-tuning to enhance task-specific performance.

E. Model Evaluation

All models are trained in the same conditions to have a fair comparison. The accuracy, precision, recall, and F1-score are used to measure performance. Besides, training and validation curves are tracked to identify overfitting or underfitting.

F. Prediction and Deployment

The most effective model (ResNet34) is chosen after the training process depending on the validation performance. The model is stored and utilised to estimate blood group labels to unknown fingerprint images. The system provides the estimated category and its level of confidence that can be used in practical real-life applications.

IV. Experimental Setup

A. Dataset Preparation

The dataset consists of fingerprint images categorized into eight classes. Each image is resized to:

$$256 \times 256 \times 3 \tag{8}$$

The dataset is split into training and testing sets:

$$D = D_{train} \cup D_{test}, \qquad |D_{train}| = 0.8M \tag{9}$$

B. Training Configuration

The models are trained using:

- Optimizer: Adam
- Loss: Categorical Cross-Entropy
- Epochs: 20
- Batch size: 32

C. Evaluation Metrics

Model performance is evaluated using:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{13}$$

D. Results Analysis

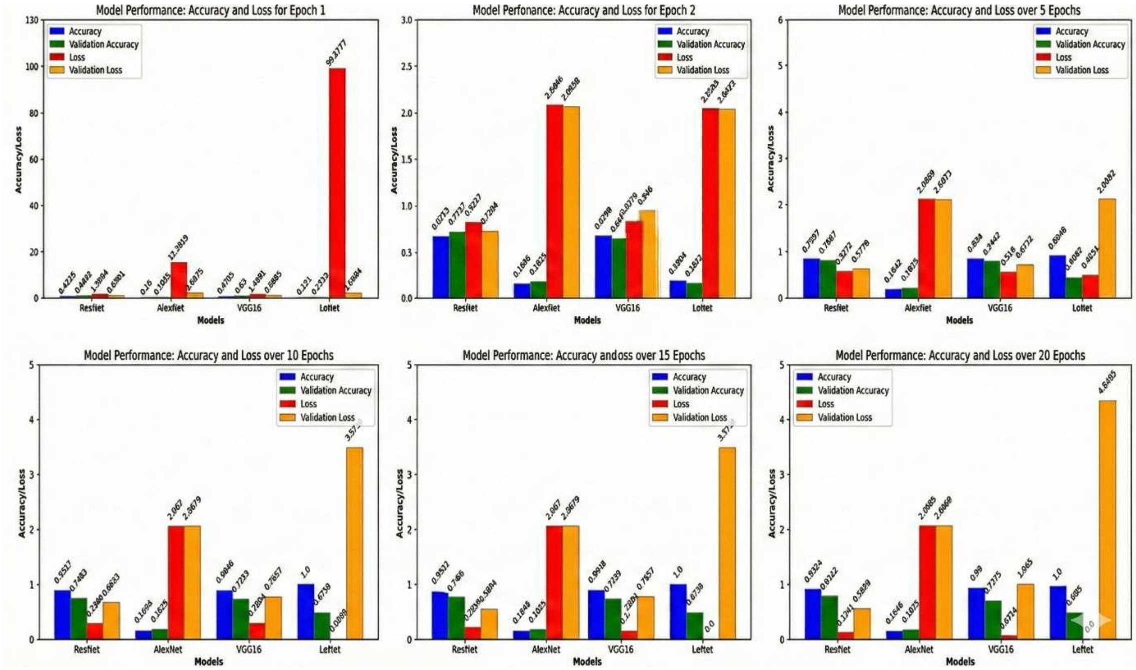

Figure 1. Epoch-wise performance comparison

ResNet34 shows the most stable convergence with increasing accuracy and decreasing loss. VGG16 performs moderately but shows slight overfitting. AlexNet fails to learn meaningful features, while LeNet overfits due to low capacity.

E. Performance Metrics

Epoch	Metric	ResNet	AlexNet	VGG16	LeNet
Epoch 1	Accuracy	0.4125	0.1600	0.4765	0.1510
	Loss	1.5054	15.2819	1.4881	99.0777
	Val_Accuracy	0.6492	0.1825	0.6300	0.1533
	Val_Loss	0.8991	2.0675	0.9685	2.0684
Epoch 2	Accuracy	0.6753	0.1606	0.6798	0.1904
	Loss	0.8227	2.0846	0.8375	2.0519
	Val_Accuracy	0.7217	0.1825	0.6483	0.1642
	Val_Loss	0.7284	2.0658	0.9460	2.0422
Epoch 5	Accuracy	0.7957	0.1642	0.8050	0.8648
	Loss	0.5272	2.0689	0.5160	0.4535
	Val_Accuracy	0.7667	0.1825	0.7442	0.4042
	Val_Loss	0.5778	2.0673	0.6732	2.0682
Epoch 10	Accuracy	0.8957	0.1654	0.8948	1.0000
	Loss	0.2849	2.0670	0.2894	**0.0009**
	Val_Accuracy	0.7483	0.1825	0.7283	0.4758
	Val_Loss	0.6633	2.0679	0.7657	3.5716
Epoch 15	Accuracy	0.9115	0.1646	0.9427	1.0000
	Loss	0.2295	2.0669	0.1588	**0.000032**
	Val_Accuracy	0.8050	0.1825	0.7417	0.4992
	Val_Loss	0.5474	2.0671	0.9221	4.3545
Epoch 20	Accuracy	0.9554	0.1646	0.9800	1.0000
	Loss	0.1341	2.0685	0.0714	**0.0515**
	Val_Accuracy	0.8142	0.1825	0.7375	0.4950
	Val_Loss	0.5838	2.0669	1.0450	4.8482

Figure 2. Performance comparison across models

ResNet34 achieves the best balance between accuracy and generalization, making it the most suitable architecture for this task.

V. Conclusion

A study has been conducted that utilizes a deep-learning-based method for identifying blood groups through finger print images without using any invasive techniques. The methodology of the study was set up as an image recognition classification problem to identify the different blood types from finger print images and evaluated using four separate convolutional neural network architectures including LeNet, AlexNet, VGG16, and ResNet34. The three different networks were analyzed under controlled experimental conditions.

In the results, it was shown that the deeper CNN architectures that used transfer learning performed much better than the shallow configurations did. The best performing CNN for accuracy and generalizability was the ResNet34 architecture because of the use of a residual learning method employed within this network architecture, allowing for more efficient training of the deeper network levels. VGG16 performed well but did show some signs of training overfitting (too much tuning to the training set). AlexNet provided poor performance in recognizing complex features of fingerprints, while LeNet showed very poor performance due to its lack of representation capability resulting in severe over fitting.

Overall, the findings demonstrate that it is possible to predict someone's blood type solely by analyzing their fingerprints and that this method can be used in a non-invasive and rapid way versus traditional methods of determining blood type. The system proposed is scalable and can be automated, thus making it an ideal candidate for use in medical screening, emergencies, or remote health care.

Future Scope

- Increasing the size and diversity of the dataset will enhance the generalizability of the model across the population and sensor types used.
- Consideration of including more advanced deep learning architectures (such as EfficientNet or Vision Transformers) could improve camera performance.
- The use of hybrid methods (i.e., combining CNNs with attention mechanisms) could enhance the feature extraction process.
- The creation of a web-based or mobile-based application will facilitate the real-time deployment of the camera.
- XAI techniques should be added to improve the interpretability and trust in medical decisions made by the model.

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