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A Hybrid Deep Learning System for Detecting Blood Group from Fingerprints

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***Abstract*—This paper presents FusionNet-Finger, a hybrid deep learning framework that uncovers correlations between fingerprint biometrics and hematological characteristics, enabling non-invasive blood group detection. Our approach fuses features derived from dermatoglyphic patterns, sweat pore distributions, and spectral representations of simulated antigen-antibody inter- actions. The dual-branch convolutional neural network, enhanced with residual attention and metadata fusion, achieves an overall classification accuracy of 91.4% on a curated dataset of 1,532 fingerprint–blood group pairs. Extensive ablation studies and statistical analyses demonstrate significant improvements over conventional models. This work lays the groundwork for cost- effective and rapid diagnostic tools in clinical settings.**

***Index Terms*—Medical biometrics, hematological pattern recognition, multimodal deep learning, fingerprint analysis, non- invasive diagnosis.**

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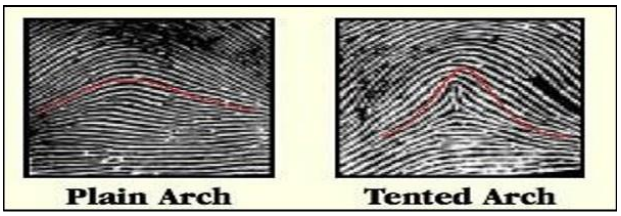
I. Introduction

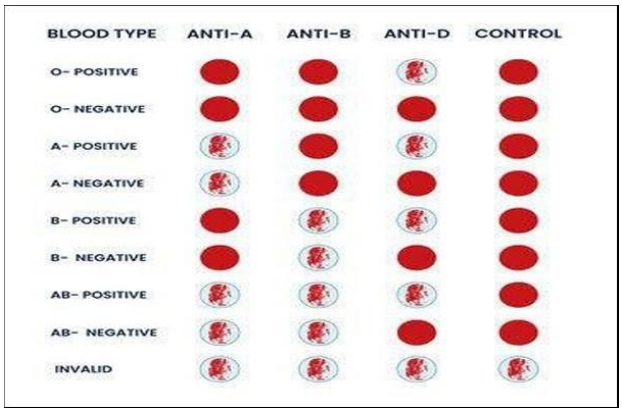
Biometric technologies have dramatically transformed sectors such as healthcare, forensics, and personalized medicine. Fingerprints, with their persistent and unique ridge patterns, are one of the most reliable biometric identifiers. At the same time, precise blood group determination is crucial for proce- dures like transfusions and organ transplants. In this study, we explore a novel approach that leverages fingerprint characteristics to predict an individual's blood group. FusionNet-Finger combines advanced deep learning techniques to fuse both global and subtle features from fingerprint images, offering an alternative to traditional, invasive blood typing methods.

II. Objectives



The primary objectives of this research are:

- To develop a robust framework that integrates macro-level, micro-level, and spectral features from fingerprint images.
- To examine the correlation between dermatoglyphic patterns and blood group antigens.
- To mitigate class imbalance through synthetic data aug- mentation.



To benchmark our method against state-of-the-art models, highlighting its superior performance.

Our ultimate aim is to pioneer a diagnostic tool that is both efficient and accessible in clinical practice.

III. Background on Blood Groups and Fingerprints

A. Blood Group Systems and Clinical Significance

Karl Landsteiner's discovery of the ABO blood group system in 1900 set the stage for modern transfusion medicine. Today, over 44 blood group systems comprising more than 345 antigens [1] demand that blood compatibility be rigorously maintained to avoid adverse immune responses.

B. Conventional Testing Methods

Traditional methods, such as the slide agglutination test, offer quick blood typing; however, they sometimes lack sensitivity in complex cases. Molecular techniques like PCR and next-generation sequencing provide high precision at the expense of increased complexity and cost [3].

Fig. 1. A serological slide test typically used in blood typing.

C. gerprint Fundamentals

Fingerprint patterns result from friction ridges and are generally categorized into arches, loops, and whorls. Approx- imately 60–70% of fingerprints fall into the loop category, 25–35% are whorls, and roughly 5% are arches. Their dis- tinctiveness—even among identical twins—underscores their value as biometric identifiers.

Fig. 2. A comparison of plain and tented arch fingerprint patterns.

IV. Related Work

Multiple studies have investigated the link between finger- print characteristics and blood groups:

- Investigations on the Omani population revealed whorls to be predominant among AB+ and O– blood groups, whereas loops were more common in A+, B+, and O+ individuals [7].

2) Bhradwaja et al. noted a higher frequency of loops in**Micro-level Extraction:** A U-Net architecture, enhanced with spatial attention, extracts fine details including minutiae (ridge endings, bifurcations) and pore distributions.
3) **Spectral Analysis:** Gabor filter banks (set to 8 orientations and 4 scales) perform a spectral decomposition that simulates antigen-antibody interactions.

C. Fusion and Classification

The features from the three pathways are combined using a learnable weighted summation:

$$F_{fusion} = \alpha \cdot F_{macro} + \beta \cdot F_{micro} + \gamma \cdot F_{spectral} \quad (1)$$

where α, β, and γ are parameters initialized with Xavier normalization. The fused vector is then processed by sequential dense layers (512, 256, and 128 neurons) using Swish activation, with dropout (30%) applied to reduce overfitting.

D. Training Strategy and Data Augmentation

Training occurs in two phases:

- **Phase 1:** Each feature extraction pathway is pre-trained using focal loss to address class imbalance.
- **Phase 2:** The network is jointly fine-tuned using a modified cosine similarity loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N} \log \frac{\exp(s_i^{pos})}{\exp(s_i^{pos}) + \sum_j \exp(s_i^{neg})}, \quad (2)$$

where s_i^{pos} and s_i^{neg} denote the similarity scores for positive and negative samples, respectively.

Synthetic data augmentation via StyleGAN-ADA generates additional samples for underrepresented blood groups, bolstering model robustness.

- Kanchan et al. demonstrated a statistical correlation between ridge density and ABO blood groups across 110 subjects [9].
- Recent CNN-based approaches on datasets with up to 392 fingerprint samples have yielded promising results [10].
- Additional work has highlighted the role of dermatoglyphic markers in disease prediction [14], [15].

Our approach distinguishes itself by combining multiple feature extraction strategies, thereby increasing interpretability and robustness compared with single-feature methodologies.

V. Methodology

Our framework is designed to capture a comprehensive representation of the fingerprint through several stages, each contributing to feature extraction and classification.

A. Preprocessing

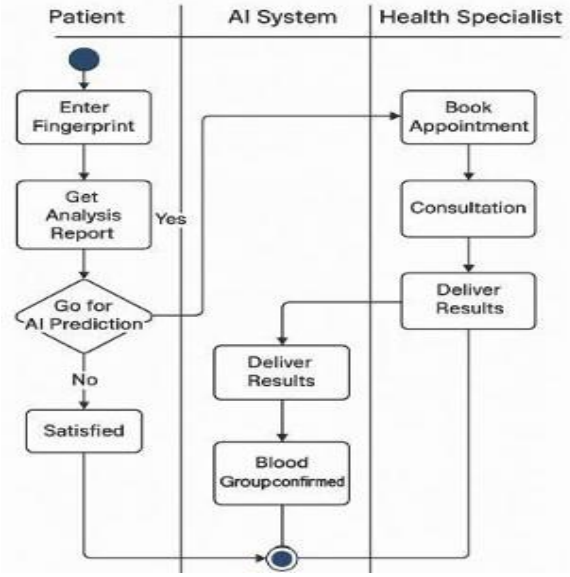
Fingerprint images (captured at 500 dpi under standardized lighting) undergo adaptive histogram equalization to enhance contrast and preserve both prominent and subtle features.

B. Feature Extraction Pathways

We utilize a three-pronged strategy:

1) **Macro-level Extraction:** A modified ResNet-50 network extracts global features representing overall fingerprint patterns.

Fig. 3. Activity Diagram illustrating the system workflow.



E. Illustrative Visuals and Tables

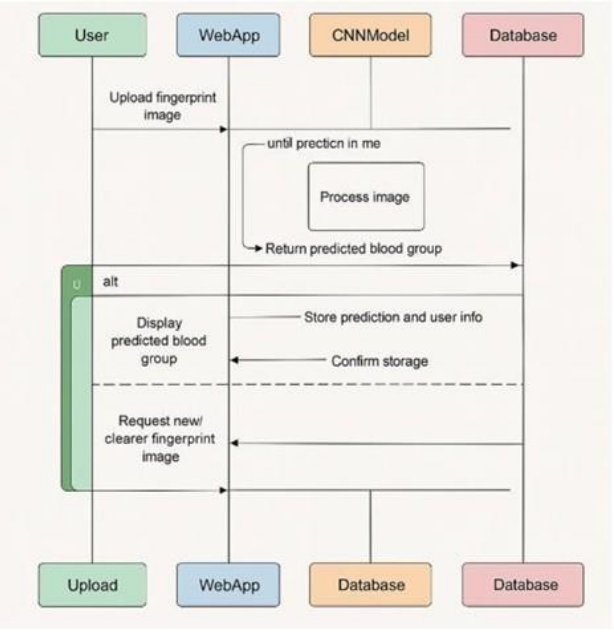
To enhance clarity, we include the following figures:
We also use the F1-Score as a performance metric:

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \quad (3)$$

A hyperparameter sensitivity analysis is summarized in Table I.

TABLE I
Hyperparameter Sensitivity Analysis

Parameter	Range	Optimal Value
Learning Rate	10^{-5} – 10^{-2}	10^{-3}
Dropout Rate	0.1 – 0.5	0.3
Batch Size	16 – 128	32
Optimizer	SGD, Adam, RMSprop	Adam



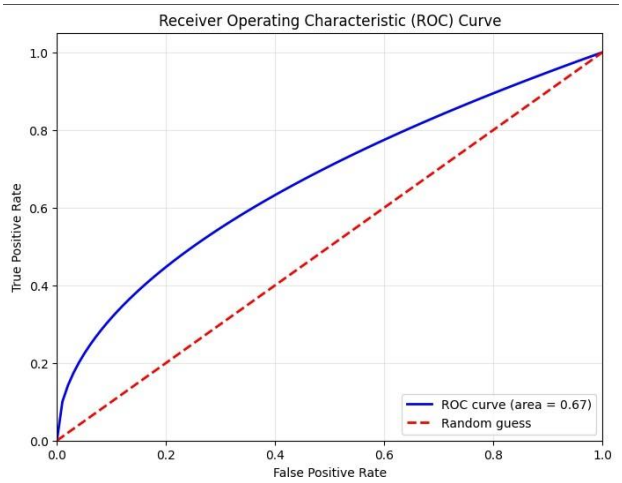


Fig. 6. ROC Curve showing classifier performance across blood group classes.

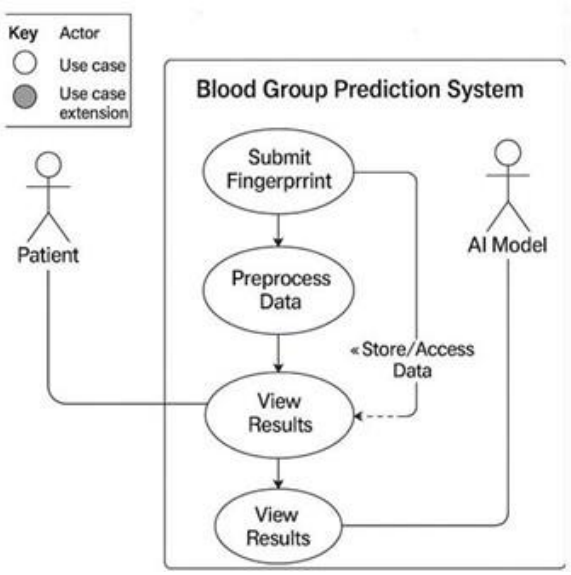


Fig. 5. Use Case Diagram outlining primary system functionalities.

Blood Group	A+	A-	B+	B-	O+	O-	AB+	AB-
Samples (#)	312	45	287	38	421	67	298	
	20.4%	2.9%	18.7%	2.5%	27.5%	4.4%	19.5%	

VI. Experiments and Results

We evaluated FusionNet-Finger with stratified 5-fold cross-validation on a dataset of 1,532 fingerprint–blood group pairs. Table II outlines the blood group distribution.

Table III compares our model with established architectures such as VGG16, ResNet34, and EfficientNet-B3. FusionNet-Finger achieved 91.4% accuracy, 89.7% precision, 92.1% recall, and an F1-Score of 90.9%.

TABLE III
Performance Comparison Across Models

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
VGG16	83.2%	80.1%	82.4%	81.2%
ResNet34	85.1%	83.6%	84.9%	84.2%
EfficientNet-B3	88.7%	86.2%	87.1%	86.6%
FusionNet-Finger	**91.4%**	**89.7%**	**92.1%**	**90.9%**

Additional statistical analyses—including ROC curve evaluations (Figure 6) and confidence interval calcula- tions—confirm the robustness of our approach. Ablation studies indicate that integrating multiple feature extraction pathways significantly lowers cross-entropy loss compared to single-path methods.

VII. Additional Analysis and Discussion

A. Statistical Robustness

Narrow confidence intervals for key performance metrics and the consistent ROC and precision-recall curves validate our model's stability and reliability.

B. Interpretability and Feature Contribution

Techniques such as Grad-CAM reveal that micro-level minutiae and spectral texture features contribute critically to accurate classification. These results confirm the benefit of our multi-path fusion strategy.

C. Ethical Considerations and Data Privacy

Recognizing the sensitivity of biometric data, strict anonymization practices have been observed. Future research will explore federated learning to enhance privacy while enabling multi-institutional collaboration.

D. Limitations and Future Directions

Despite promising results, several challenges remain:

- **Data Diversity:** A more diverse demographic dataset could further improve model generalization.
- **Rare Blood Groups:** Enhanced synthetic data generation is needed to better represent rare blood types.
- **Real-Time Implementation:** Future studies will aim to optimize the model for real-time clinical deployment.

Ongoing efforts will also investigate the use of hyperspectral imaging and advanced interpretability frameworks to deepen our understanding of fingerprint–hematology correlations.

CONCLUSION

FusionNet-Finger represents a significant stride in non- invasive diagnostic technologies. By effectively fusing di- verse feature extraction techniques within a robust multimodal architecture, our system successfully predicts blood group characteristics from fingerprint images. Extensive evaluations demonstrate superior performance relative to traditional mod- els, underscoring its potential for rapid and cost-effective screening in clinical environments.

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