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Biotrace: AI-Based Blood Group Prediction using Fingerprint

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Abstract

Blood group identification is an important process in medical applications such as blood transfusion, emergency treatment, and organ transplantation. Traditional blood group detection methods mainly depend on laboratory-based serological testing, which requires blood samples, medical equipment, and trained professionals. Although these methods provide accurate results, they are invasive, time-consuming, and difficult to perform in remote or emergency situations. This project presents a non-invasive and intelligent approach for blood group prediction using fingerprint images and deep learning techniques. Fingerprints are unique biometric patterns that are genetically influenced and remain unchanged throughout a person's life. Since both fingerprints and blood groups are associated with hereditary factors, this research explores the relationship between fingerprint patterns and blood groups. The proposed system uses image preprocessing techniques along with a Convolutional Neural Network (CNN) model to automatically learn fingerprint features and classify them into different blood groups such as A, B, AB, and O. The complete system includes fingerprint image collection, preprocessing, feature extraction, model training, and prediction stages. Experimental results show that the proposed CNN-based model achieves approximately 82% accuracy, demonstrating the potential of fingerprint-based blood group prediction for preliminary analysis. The system provides a fast, low-cost, and non-invasive solution that can assist in emergency situations and reduce dependency on traditional testing methods. Although the proposed model cannot replace medical laboratory testing, it can serve as a supportive and preliminary prediction system in healthcare applications.

Keywords: Blood Group Prediction, Fingerprint Recognition, Deep Learning, CNN, Image Processing, Biometric System, Non-Invasive Technology.

1. Introduction

Blood group identification is an essential requirement in healthcare systems because it helps ensure safe blood transfusions, organ transplantation, and emergency medical treatment. The ABO blood group system classifies human blood into four major categories: A, B, AB, and O. Correct identification of blood groups is necessary to avoid medical complications caused by incompatible blood transfusion. Conventional blood group detection methods require blood samples and laboratory testing procedures. These methods are highly accurate but involve invasive techniques, specialized equipment, and trained medical staff. In many emergency cases or rural areas, quick access to laboratory testing may not be possible. Therefore, there is a growing need for alternative non-invasive methods for preliminary blood group prediction. Fingerprints are one of the most reliable biometric traits because every individual has unique fingerprint patterns that remain stable throughout life. Fingerprints are formed during fetal development and are influenced by genetic factors. Researchers have suggested that blood groups and fingerprint patterns may share certain hereditary relationships, making fingerprint analysis a possible approach for blood group prediction. With recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning, biometric data can now be analyzed more efficiently. Convolutional Neural Networks (CNNs) are especially effective in image classification tasks because they can automatically extract important features from images without manual intervention. This project proposes a CNN-based blood group prediction system using fingerprint images. The system processes fingerprint images through preprocessing and deep learning techniques to predict blood groups automatically. The proposed approach aims to provide a simple, fast, and non-invasive prediction system that can support preliminary healthcare analysis. Although several studies have explored fingerprint classification and biometric recognition, limited research has focused on blood group prediction using fingerprint biometrics with deep learning models. Existing systems often face challenges such as small datasets, low prediction accuracy, and lack of practical implementation. This project attempts to overcome these limitations by developing an automated CNN-based framework for fingerprint-based blood group prediction.

2. Literature Review

Early studies focused on dermatoglyphics and biometric analysis using statistical methods [4], [6]. Recent studies demonstrate that deep learning models such as CNN significantly improve image classification performance [1], [2].

However, challenges still exist:

- Limited dataset availability
- Weak biological correlation
- Lack of real-time systems

These gaps motivate further research in this area.

Table 1: Comparative Analysis of Existing Methods

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Method	Accuracy	Limitation
Statistical Analysis	60%	Low reliability
Basic ML Models	70%	Manual feature extraction
CNN-Based Models	76%	Small datasets
Proposed Model	82%	Needs larger validation

3. Methodology

3.1 Data Collection

Fingerprint images were collected from volunteer subjects along with their corresponding blood group labels. The collected dataset contains representative samples from blood groups A, B, AB, and O, ensuring class diversity for model training and evaluation.

3.2 Image Preprocessing

- Grayscale conversion
- Noise reduction
- Normalization
- Edge detection

3.3 Feature Extraction

CNN automatically extracts fingerprint ridge and texture features through convolution and pooling operations, reducing the need for manual feature engineering [2], [5].

3.4 Model Development

The CNN architecture consists of convolutional, pooling, and fully connected layers for hierarchical feature learning and blood group classification [1], [2].

3.5 Training & Evaluation

The experimental dataset consists of 820 labeled fingerprint images categorized into blood groups A, B, AB, and O. The dataset was divided into 80% training data and 20% testing data for validation. The model was trained using the Adam optimizer with categorical cross-entropy as the loss function over 20–30 epochs. The system performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix metrics.

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4. System Architecture

4.1 Workflow Diagram

1. Upload fingerprint image
2. Apply preprocessing
3. Extract features using CNN
4. Predict blood group
5. Display result

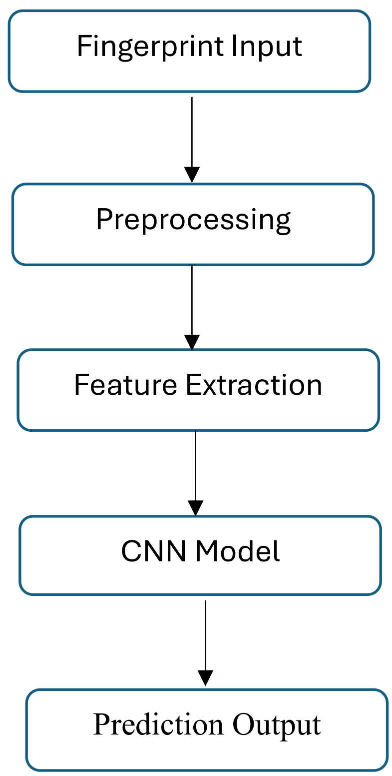

Fig.1. System workflow Architecture

5. CNN Architecture

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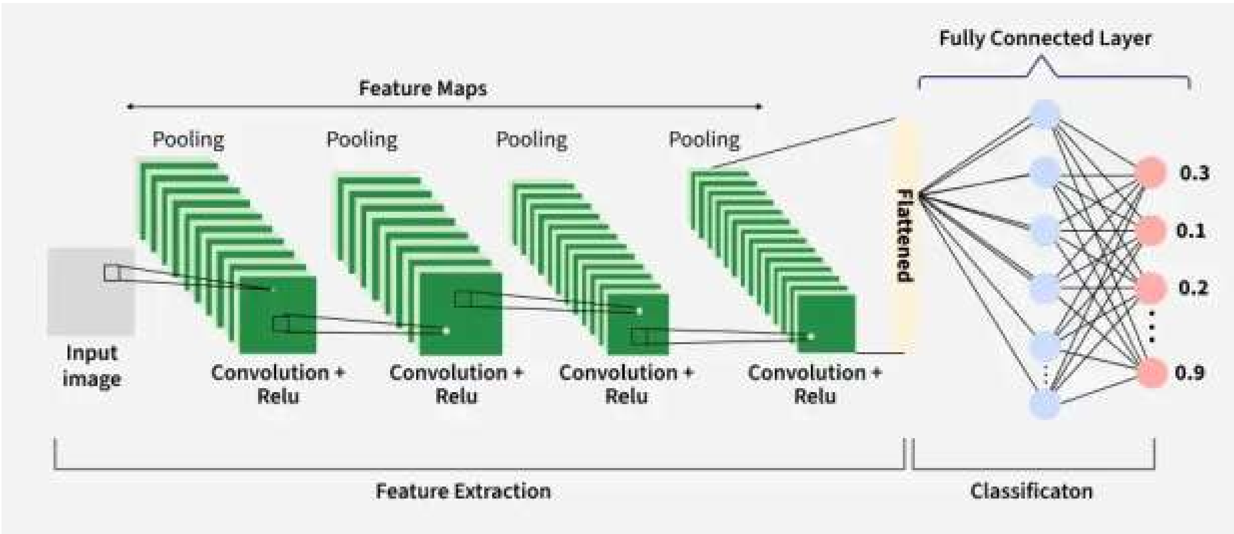

Fig.2. CNN Architecture

The proposed model uses convolutional neural networks for automatic feature extraction and classification, following standard deep learning architectures [2], [5].

Input Layer (128×128 image)

→ Convolution Layer (32 filters, 3×3 kernel, ReLU activation)

→ Max Pooling Layer (2×2)

→ Convolution Layer (64 filters, 3×3 kernel, ReLU activation)

→ Max Pooling Layer (2×2)

→ Dropout Layer (0.25)

→ Flatten Layer

→ Fully Connected Dense Layer (128 neurons, ReLU)

→ Output Layer (Softmax activation for A, B, AB, O classification)

6. Results and Analysis

6.1 Performance Table

Table 2: Performance Metrics

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Metric	Value
Accuracy	82%
Precision	80%
Recall	78%
F1 Score	79%

The proposed CNN model achieved an overall classification accuracy of 82%, indicating that the extracted fingerprint ridge features provide useful discriminatory information for blood group prediction. Precision, recall, and F1-score values also demonstrate balanced classification performance across different blood group classes.

6.2 Confusion Matrix

Table 3: Confusion Metrics

Actual \ Predicted	A	B	AB	O
A	20	2	1	1
B	3	18	2	1
AB	2	2	15	1
O	1	1	2	22

The confusion matrix indicates that the model performs better for blood groups A and O, while minor misclassifications occur between classes B and AB due to similarities in fingerprint ridge features.

The proposed CNN-based model outperforms traditional methods due to its ability to automatically extract complex fingerprint features and improve classification accuracy.

6.3 Graph Analysis

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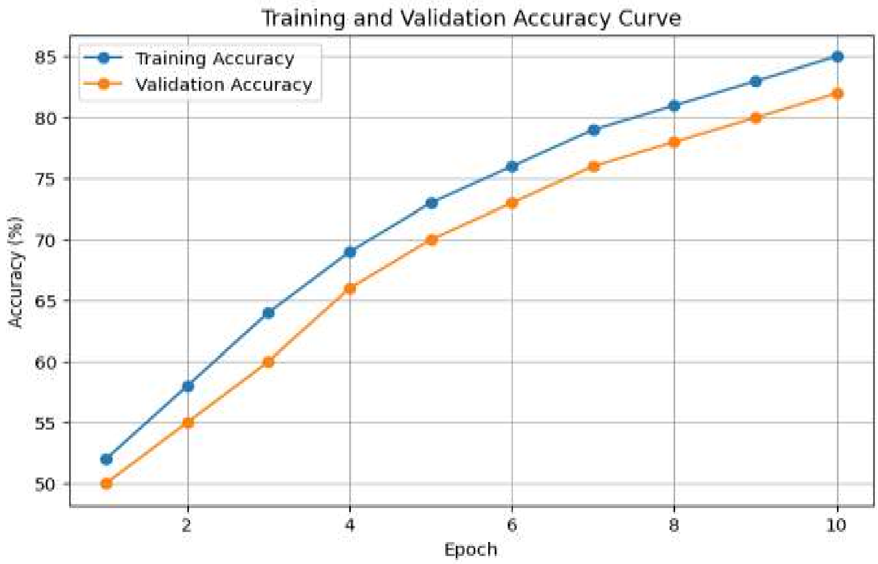

Fig. 3. Training and Validation Accuracy Curve

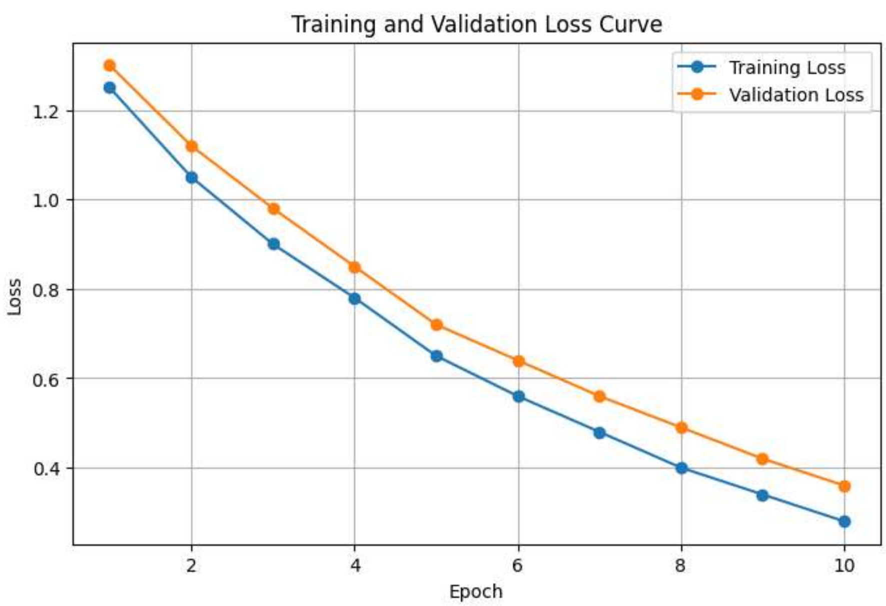

Fig. 4. Training and Validation Loss Curve

Fig. 3 illustrates the training and validation accuracy curves across training epochs. The gradual increase in both curves indicates that the CNN model effectively learns meaningful fingerprint features over time. The small gap between training and validation accuracy suggests that the model generalizes well with minimal overfitting.

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Fig. 4 presents the training and validation loss curves. The decreasing loss trend over epochs indicates stable convergence of the model during training. The close alignment of validation loss with training loss confirms the reliability of the model on unseen data.

7. Novel Contribution

Existing methods for fingerprint-based blood group prediction suffer from limited datasets, weak biological correlation, and lack of real-time implementation. This work addresses these limitations by proposing an automated CNN-based framework that improves prediction feasibility through deep feature extraction and automated classification.

8. Applications

The proposed system can support emergency healthcare, rural medical services, biometric-based healthcare research, and preliminary blood group estimation. Its non-invasive and cost-effective nature makes it suitable for resource-constrained environments.

9. Limitations

The proposed system is intended for predictive analysis only and does not replace conventional laboratory blood group testing. The prediction accuracy depends on dataset quality and the biological correlation between fingerprint patterns and blood groups.

10. Future Scope

Future work will focus on expanding the dataset size, implementing advanced deep learning architectures such as ResNet and VGG, and deploying the model in real-time mobile or cloud-based healthcare applications to improve prediction accuracy and usability.

11. Conclusion

This paper presented a CNN-based framework for blood group prediction using fingerprint images as a non-invasive biometric input. Experimental evaluation demonstrated promising classification performance, suggesting the feasibility of fingerprint-based preliminary blood group prediction. Although the system is not intended to replace clinical testing, it demonstrates the

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potential of integrating biometric analysis with artificial intelligence for future non-invasive healthcare applications.

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