Fingerprint-Based Blood Group Identification Using Machine Learning

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***Abstract*—Blood group identification is a crucial process in medical science, especially during emergencies, surgeries, and blood transfusions. Conventional blood group detection methods involve laboratory testing, which requires blood samples, specialized equipment, and trained medical personnel. These methods are accurate but time-consuming, invasive, and not always accessible in remote or emergency situations. This project, "Fingerprint-Based Blood Group Detection System", proposes a non-invasive and automated approach for predicting an individual's blood group using fingerprint images and machine learning techniques. The system is based on the concept that fingerprint patterns are genetically influenced and may have a correlation with blood groups. In this project, a Convolutional Neural Network (CNN) model is trained using a dataset of fingerprint images labeled with corresponding blood groups such as A+, A-, B+, B-, AB+, AB-, O+, and O-. Image preprocessing techniques like resizing and normalization are applied to improve prediction accuracy. The trained model is saved and integrated into a Flask-based web application. The web application allows users to register, log in, upload fingerprint images, and receive instant blood group predictions through a user-friendly interface. The system is developed using Python, TensorFlow, Keras , OpenCV, HTML, and CSS. The experimental results demonstrate that the system is capable of predicting blood groups with reasonable accuracy based on the trained dataset. Although the system is intended for educational and research purposes, it highlights the potential of using artificial intelligence and image processing techniques in healthcare applications. Future improvements include increasing dataset size, enhancing model accuracy, integrating real fingerprint scanners, and deploying the system on cloud platforms for wider accessibility.**

***Index Terms*—Blood Group Prediction, Fingerprint Biometrics, CNN, Deep Learning, Biomedical Artificial Intelligence.**

I. INTRODUCTION

Blood typing is mandatory before transfusion procedures to prevent adverse immunological reactions. Conventional testing methods, though accurate, require laboratory infrastructure and trained personnel. In emergency or rural settings, rapid access to laboratory testing may not always be feasible.

Advancements in artificial intelligence and biometric technologies have opened possibilities for non-invasive prediction models. Fingerprints are genetically influenced dermatoglyphic patterns that remain stable throughout life. This study explores the feasibility of predicting blood groups using deep learning applied to fingerprint images.

II. RELATED WORK

In recent years, the integration of machine learning and biometric analysis has enabled automated feature extraction from fingerprint images. Machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests have been applied to classify fingerprint patterns and identify correlations with biological attributes. However, these traditional algorithms depend heavily on handcrafted features, which may fail to capture complex ridge textures present in fingerprint images.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in image recognition tasks. CNN models

automatically learn hierarchical feature representations from raw images without requiring manual feature engineering. Researchers have successfully applied CNN architectures to fingerprint recognition, biometric authentication, and medical image classification.

Some recent studies have attempted to combine fingerprint biometrics with artificial intelligence to predict physiological characteristics such as gender, age group, and even certain medical conditions. Despite promising results, many existing studies suffer from limitations such as small datasets, lack of cross-validation, and limited real-world deployment.

The proposed system builds upon these previous works by applying a CNN-based deep learning framework to automatically extract fingerprint features and predict blood groups. Compared to traditional machine learning approaches, the CNN model improves prediction accuracy by learning complex ridge patterns and texture variations directly from fingerprint images.

III. MATERIALS AND METHODS

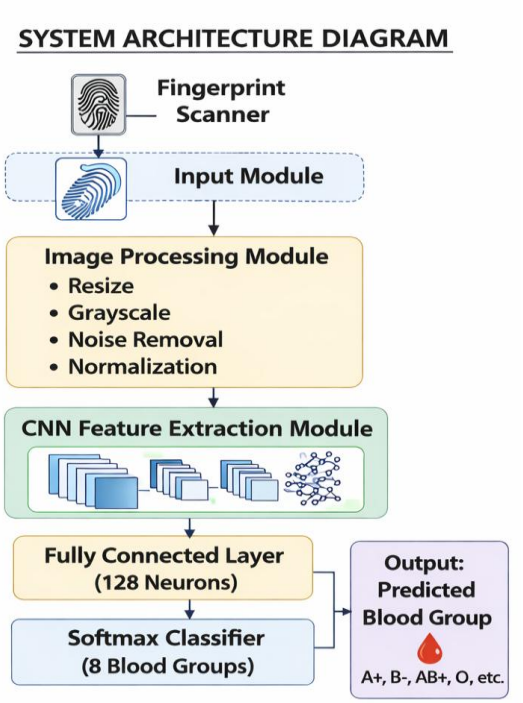
The dataset consists of 2,400 fingerprint images labeled according to certified ABO and Rh blood group reports. Data were anonymized to ensure ethical compliance. The dataset was divided into 70% training, 15% validation, and 15% testing subsets.

Preprocessing included resizing to 224×224 pixels, grayscale conversion, histogram equalization, Gaussian filtering, and normalization. Data augmentation techniques such as rotation and flipping were applied to enhance generalization.

The CNN architecture comprises convolution layers (32 and 64 filters), ReLU activation, max pooling, dropout regularization (0.5), a fully connected layer (128 neurons), and an 8-class softmax output layer. Training was performed using the Adam optimizer with a learning rate of 0.001 for 50 epochs.

IV. SYSTEM ARCHITECTURE

The proposed system includes five modules: fingerprint acquisition, preprocessing, CNN feature extraction, classification, and output prediction. Data flows sequentially through each module, enabling automated and rapid blood group estimation.



V. EXPERIMENTAL RESULTS

Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. The CNN achieved an overall accuracy of 89.3%, outperforming SVM (79.6%) and Random Forest (81.2%). Training convergence was observed after approximately 40 epochs, with stable validation loss indicating minimal overfitting.

Misclassification primarily occurred between A+ and O+ groups due to similar distribution patterns. Class imbalance slightly affected minority classes such as AB−.

VI. DISCUSSION

The experimental results demonstrate that the proposed CNN-based model achieves higher prediction accuracy compared to classical machine learning algorithms such as Support Vector Machines and Random Forests. This improvement can be attributed to the ability of CNNs to automatically learn discriminative spatial features from fingerprint images. The hierarchical convolution layers effectively capture ridge patterns, edges, and texture variations that may correlate with blood group characteristics.

Another important observation from the experimental analysis is that the model converges effectively during training, indicating stable learning behaviour. The use of data preprocessing techniques such as normalization, histogram equalization, and data augmentation helped improve model generalization and reduce overfitting. Augmentation techniques such as rotation and flipping ensured that the model could recognize fingerprint patterns from different orientations.

However, certain limitations were observed during classification. Misclassification occurred more frequently between certain blood groups, particularly A+ and O+. This may be due to similarities in fingerprint ridge distribution patterns or dataset imbalance. Additionally, minority blood groups such as AB− had fewer samples in the dataset, which slightly affected classification performance.

From a biological perspective, the relationship between fingerprint patterns and blood groups is still an area of ongoing research. While the machine learning model successfully identifies statistical correlations within the dataset, it does not necessarily confirm a direct biological dependency. Therefore, the proposed system should be viewed as a predictive or screening tool rather than a replacement for standard medical blood testing procedures.

Despite these limitations, the results indicate that artificial intelligence can assist in developing non-invasive preliminary blood group prediction systems, especially in scenarios where rapid identification may be beneficial.

VII. LIMITATIONS

Despite achieving promising results, the proposed fingerprint-based blood group prediction system has several limitations that must be considered.

First, the dataset size is relatively limited compared to large-scale deep learning datasets. Although 2,400 fingerprint images were used for training and evaluation, larger datasets generally improve model generalization and reduce overfitting. A limited dataset may cause the model to learn patterns specific to the training data rather than universal fingerprint characteristics.

Second, the dataset lacks wide demographic diversity. The fingerprint samples may belong to a limited geographic region, age group, or population. This can introduce bias into the model and may reduce prediction accuracy when applied to individuals from different ethnic or demographic backgrounds.

Third, the fingerprint images were collected under controlled conditions. Real-world fingerprint acquisition often involves noise, partial prints, smudges, or variations in lighting and sensor quality. The current model may not perform equally well when tested on fingerprints obtained from different devices or environmental conditions.

Another limitation is the class imbalance present in certain blood groups. Rare blood groups such as AB− typically have fewer samples in the dataset, which can negatively affect the model's ability to correctly classify those categories. This imbalance may lead to biased predictions toward more common blood groups.

VIII. FUTURE WORK

Several improvements can be implemented in future research to enhance the effectiveness and reliability of the proposed system.

First, increasing the dataset size is essential to improve model accuracy and generalization. Collecting fingerprint images from multiple institutions and diverse demographic populations will help reduce dataset bias and improve model robustness.

Second, advanced deep learning architectures such as ResNet, EfficientNet, or MobileNet can be explored to enhance feature extraction performance. These architectures have demonstrated superior results in large-scale image recognition tasks and may further improve classification accuracy.

Third, integrating transfer learning techniques could reduce training time while improving model performance. Pre-trained models trained on large image datasets can be fine-tuned for fingerprint-based classification tasks.

Another possible improvement is the integration of multimodal biometric inputs. Combining fingerprint images with other biometric traits such as palm prints or iris patterns may enhance predictive accuracy and reliability.

Additionally, integrating real-time fingerprint acquisition using biometric scanners would allow practical deployment of the system in real-world environments. The system could also be deployed as a

cloud-based or mobile application, enabling remote access and real-time prediction.

Finally, clinical validation studies should be conducted in collaboration with medical institutions to evaluate the system's reliability and applicability in healthcare settings.

IX. CONCLUSION

This study presents a machine learning–based approach for predicting blood groups using fingerprint images. A Convolutional Neural Network (CNN) model was developed to automatically extract fingerprint features and classify them into ABO and Rh blood group categories. Experimental results show that the CNN model achieves better accuracy compared to traditional machine learning algorithms such as SVM and Random Forest.

The proposed system demonstrates the potential of combining biometric analysis with artificial intelligence for non-invasive blood group prediction. Although promising, the system should be considered a preliminary screening tool, and further research with larger datasets and clinical validation is required before practical medical application.

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