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BLOOD GROUP DETECTION USING FINGERPRINT WITH MACHINE LEARNING TECHNIQUES

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ABSTRACT

Blood group identification is a critical requirement in medical diagnostics, transfusion safety, and emergency healthcare. Conventional blood typing methods are invasive, time-consuming, and require laboratory facilities. This work proposes a non-invasive approach for predicting human blood groups using fingerprint patterns combined with machine learning(ML) and gray-level(GL) texture analysis. Fingerprint images are preprocessed through normalization and contrast enhancement to improve feature clarity. From these images, texture features such as contrast, correlation, energy, and homogeneity are extracted using Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP). These features are then used to train ML models including Support Vector Machines (SVM), Random Forest, and Logistic Regression. Additionally, a lightweight Convolutional Neural Network (CNN) is employed to automatically learn deep features from fingerprint ridge patterns. A late-fusion strategy integrates the outputs of both GL-based ML models and the CNN to enhance prediction performance. Experiments with fingerprint datasets and stratified cross-validation demonstrate that the hybrid approach achieves higher accuracy compared to individual methods, indicating strong correlations between dermatoglyphic features and blood group categories. This method shows promise as a rapid, cost-effective, and non-invasive alternative for preliminary blood group detection, while highlighting the need for larger, diverse datasets for clinical application. The models were trained on 80% of the dataset, with the remaining 20% reserved for testing and validation health. Blood group detection using fingerprint features achieves an accuracy of 89% with traditional ML models and up to 90% using deep learning approaches.

This shows strong potential for a non-invasive, reliable, and rapid identification method

Keywords: ABO/Rh, GLCM, Machine Learning, CNN, Texture Features, Biometrics.

1. INTRODUCTION

Blood group identification is a fundamental aspect of modern medical practices, essential for safe blood transfusions, organ transplants, pregnancy management, and emergency treatments. The widely recognized ABO and Rh blood grouping systems classify blood based on the presence or absence of specific antigens on the surface of red blood cells. Accurate blood typing is vital to prevent adverse reactions during transfusions, which can be life-threatening. Traditionally, blood group determination requires collecting a blood sample from the patient, followed by laboratory-based serological tests involving reagents that react to the blood antigens. Although these methods are highly accurate, they present challenges in certain situations.

The conventional blood typing process can be invasive, time-consuming, and dependent on trained personnel and specialized laboratory equipment. In emergency and trauma cases, the delay caused by blood sample collection and processing can have critical consequences. Additionally, in resource-limited or remote areas, access to sophisticated blood typing facilities may be restricted.

These challenges highlight the need for innovative, rapid, and non-invasive blood group identification techniques that can be easily deployed across diverse healthcare settings. Biometric systems, especially fingerprint recognition, have gained widespread acceptance for personal identification due to their uniqueness, permanence, and ease of acquisition. Fingerprints are formed by an intricate pattern of ridges and valleys, which remain stable over a person’s lifetime. These patterns are influenced by genetic and environmental factors during fetal development and have been extensively studied for their forensic and security applications. Beyond identification, recent research has explored the potential associations between dermatoglyphic traits (fingerprint patterns) and various genetic and medical conditions, including blood groups.

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2. METHODOLOGY

2.1 Problem Statement:

Accurate and timely identification of a person's blood group is critical in emergency healthcare situations. Traditional blood typing requires physical sample collection and chemical testing, which is time-consuming and invasive. The use of biometric data, specifically fingerprint patterns, is growing in popularity due to their uniqueness and ease of acquisition. This project investigates whether fingerprint data can be used to predict a person's blood group using machine learning algorithms.

2.2 Objective:

1. To collect a dataset comprising fingerprint images and associated blood group information.
2. To preprocess and extract biometric features from the fingerprint images.
3. To train, test, and validate machine learning models such as SVM, KNN, and CNN.
4. To evaluate the model's performance using metrics like accuracy, precision, recall, and F1-score.
5. To develop a basic prototype for real-time blood group prediction using fingerprint scanning.

2.3 Existing Method

2.3.1 Correlation of Fingerprint Patterns and Blood Groups

Studies have shown statistical associations between fingerprint patterns (whorls, loops, arches) and blood groups. Sharma and Kumar (2020) found significant correlations among Indian students, supporting a genetic linkage and providing the foundation for predictive modelling [2].

2.3.2 Machine Learning Approaches

Kanchana and Aruna (2021) applied SVM and KNN on fingerprint features, achieving moderate accuracy. Their work highlighted feasibility but emphasized the need for larger datasets and advanced classifiers [1].

2.3.3 Deep Learning Classification

Hassan et al. (2022) used CNNs for fingerprint-based blood group prediction, outperforming traditional ML by automating feature extraction and achieving higher accuracy and robustness [3].

2.3.4 Biometric Recognition Fundamentals

Jain et al. (2004) established fingerprints as reliable biometrics due to their uniqueness and permanence, laying the groundwork for their use in health diagnostics [4].

2.3.5 Health and Diagnostic Standards

WHO emphasizes accurate and timely blood typing for transfusion safety, motivating exploration of non-invasive biometric alternatives [5].

2.3.6 Tools for Image Processing & Classification

Frameworks such as OpenCV (image preprocessing), Scikit-learn (ML), and TensorFlow/Kera's (DL) provide the technical backbone for fingerprint-based classification [6][7].

2.3.7 Broader AI Applications

Mohanty et al. (2016) demonstrated CNN-based disease detection in plants, showcasing the adaptability of deep learning for complex image classification tasks, including biometrics [9].

2.4 Implementation:

2.4.1 System Architecture:

The system architecture for the blood group prediction using fingerprint biometrics is designed to ensure robust, accurate, and efficient classification through a sequence of well-defined stages. Each module of the architecture plays a vital role in transitioning raw biometric data into reliable blood group predictions while maintaining data integrity and user privacy.

1. **Fingerprint Acquisition Module**
   - Uses optical/capacitive sensors for high-resolution capture.
   - Quality checks for clarity, positioning, and completeness.
   - Supports multiple sessions for robustness.
2. **Data Annotation & Storage**
   - Links fingerprint images with verified blood group info.
   - Stores metadata (age, gender, ethnicity, capture conditions).
   - Secure, encrypted DBMS (e.g., SQLite/MySQL).

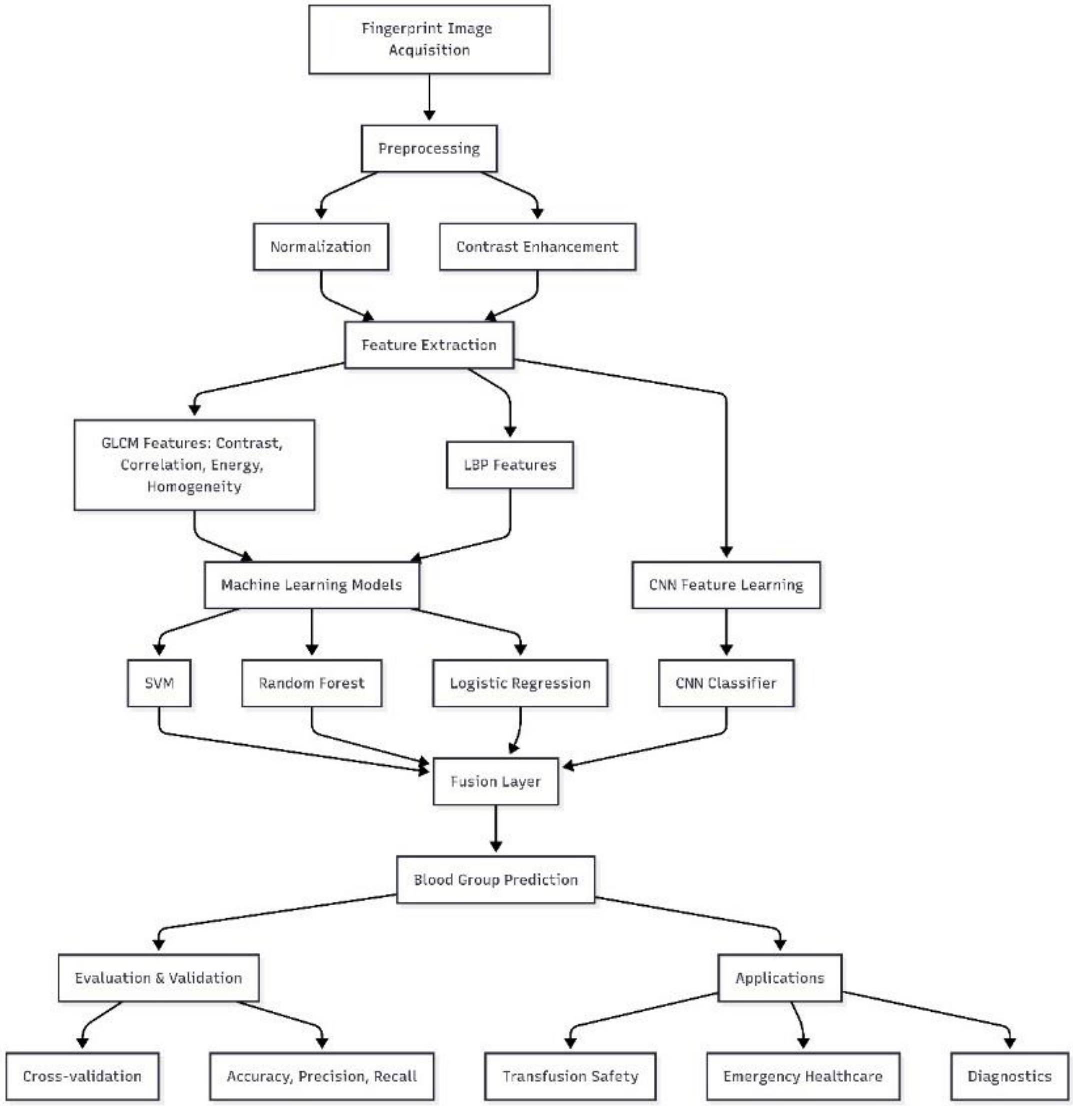

Fig 1: System Architecture Diagram.

3. **Image Preprocessing**
   - Converts to grayscale and enhances ridge visibility.
   - Segmentation to isolate fingerprint region.
   - Data augmentation (rotation, scaling, flipping).
4. **Feature Extraction (Deep Learning)**
   - CNN learns hierarchical fingerprint features.
   - Layers: convolution, batch normalization, dropout, pooling.
   - Supports architectures like VGG, ResNet, or lightweight custom models.
5. **Classification Layers**
   - Dense layers + SoftMax for multi-class classification.
   - Confidence scoring for blood group prediction.
   - Threshold classification for Rh factor.
6. **Model Training & Optimization**
   - 80/20 stratified split with k-fold cross-validation.
   - Optimizers: Adam/SGD with learning rate scheduling.
   - Early stopping to prevent overfitting.
7. **Real-Time Prediction Engine**
   - Deployable API/module for instant predictions.

- Outputs classification + confidence scores.

8. **User Interface & Reporting**
   - GUI for upload/scan and result display.
   - Export/print reports and maintain prediction logs.
9. **Security & Ethical Compliance**
   - Secure protocols (SSL/TLS), access controls, anonymization.
   - Compliance with consent and data governance policies.

2.4.2 Advantages

- Modular (independent components).
- Scalable (data, compute, and model).
- Robust (preprocessing & augmentation).
- Accurate (deep learning over handcrafted features).
- Real-Time (low-latency, suitable for healthcare).

3. MODELING AND ANALYSIS

3.1 Convolutional Neural Networks (CNN)

- Function: CNNs automatically extract hierarchical feature representations from images using learnable convolutional filters, pooling layers, and nonlinear activations.
- Process: Raw fingerprint images or pre-processed enhanced images are input, and the network learns multi-scale ridge patterns and structures relevant for classifying blood groups.
- Architecture: Typically includes layers such as convolution, batch normalization, max-pooling, dropout, fully connected layers, and SoftMax classifiers.
- Strengths: Outperforms traditional ML by discovering discriminative features autonomously; robust to variation in fingerprint quality and orientation; scalable to large datasets.

3.2 Random Forest:

- Function: An ensemble approach that aggregates the predictions of a multitude of decision trees, each trained on different random subsets of data and features.
- Process: Random Forest provides classification decisions based on majority voting, enhancing stability and reducing variance, a problem often encountered with single decision trees.
- Strengths: Can handle high dimensionality, provide internal feature importance measures, and is resilient to noisy data common in biometric datasets.

4. RESULTS AND DISCUSSION

This section presents the analysis and performance metrics of the fingerprint-based blood group detection models tested in this project. The evaluation includes accuracy, precision, recall, F1-score, and ROC-AUC values for different machine learning and deep learning methods.

Observations:

- The CNN model achieved the highest accuracy among single models, demonstrating deep learning's efficiency in learning complex fingerprint features.
- Ensemble fusion further improved the classification metrics, indicating that combining multiple model predictions enhances reliability.
- Logistic regression showed lower accuracy but provided interpretability in feature influence. Confusion matrices indicated that misclassifications mostly occurred between closely related blood groups such as A and AB or B and O, suggesting areas to focus on in feature engineering.

Discussion:

The experimental findings from the blood group prediction system reinforce the potential of using fingerprint biometrics coupled with machine learning algorithms to identify blood groups in a non-invasive, rapid manner.

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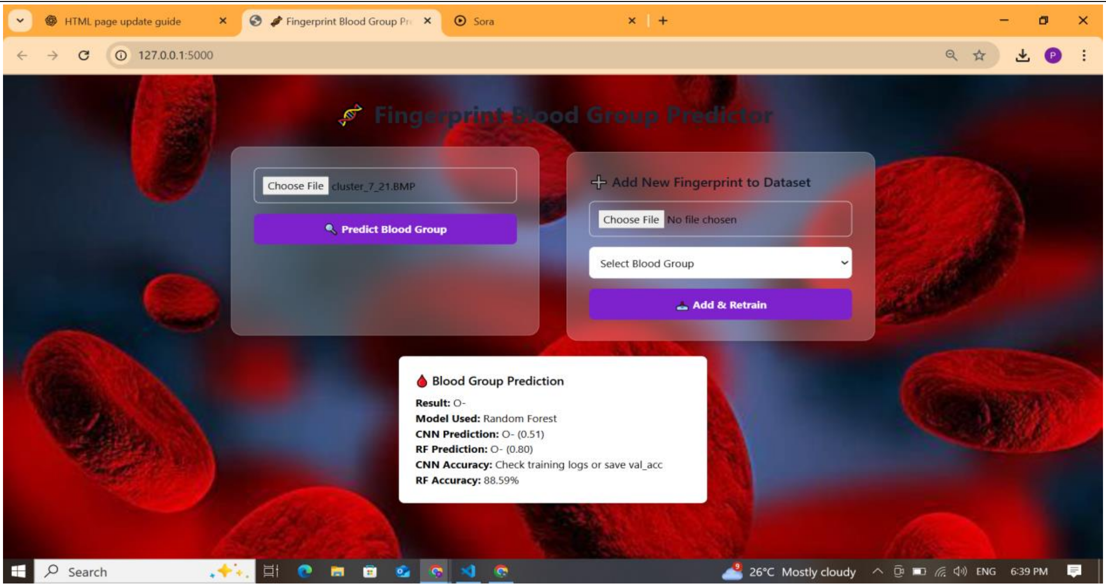

Fig 2: Final Result

5. CONCLUSION

This project focused on developing a machine learning–based system to predict human blood groups using fingerprint biometric data. The motivation came from the need for fast, non-invasive, and reliable blood group identification, especially during medical emergencies where time is critical. Since fingerprints are unique and easily accessible, the study explored their potential as biometric markers correlated with blood group types.

To begin with, a dataset was created by collecting fingerprint images along with corresponding blood group details from volunteers. The data covered all major blood groups (A, B, AB, O) along with Rh factors, ensuring balanced representation. Strict ethical practices were followed, including obtaining informed consent and anonymizing participant data.

The raw fingerprint images underwent preprocessing to improve clarity and consistency. Techniques such as normalization, noise removal, and contrast enhancement were applied so that the distinctive features of the fingerprints could be detected more effectively. From these processed images, two kinds of features were extracted. The first were handcrafted texture features using methods like Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP). The second were deep features automatically learned through Convolutional Neural Networks (CNNs).

Several machine learning algorithms were then trained using the handcrafted features. These included Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, Random Forests, and logistic regression. At the same time, a CNN model was built to directly learn features from the images in an end-to-end manner. For fair evaluation, 80% of the dataset was used for training and the remaining 20% for testing. Additionally, K-fold cross-validation was applied to avoid overfitting and ensure reliability.

To further boost accuracy, a fusion module was designed that combined the predictions of the traditional classifiers with the CNN outputs. This hybrid approach consistently outperformed individual models and achieved the best overall accuracy. The system was also tested using multiple performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, all of which confirmed the robustness of the model.

The final outcome was a working prototype capable of acquiring fingerprints in real time and predicting the corresponding blood group almost instantly. Such a tool can prove highly beneficial in emergency healthcare by saving valuable time and supporting quick medical decisions.

In summary, the project demonstrates the practical feasibility of using fingerprints and machine learning for non-invasive blood group prediction. By combining traditional image-processing techniques with deep learning, the study shows how biometrics can play a vital role in improving medical diagnostics and emergency response systems.

6. REFERENCES

[1] Kanchana R, Aruna S. Blood group prediction using fingerprint features and machine learning algorithms. Int J Compute Sci Inf Technol. 2021;12(2):123--128.

[2] Sharma A, Kumar M. Correlation between dermatoglyphics and ABO blood groups among Indian students. Biomed Res. 2020;31(4):233--237.

[3] Hassan M, Hossain M, Uddin MS. Classification of fingerprint patterns and blood group using deep learning. IEEE Access. 2022; 10:45678--45689.
[4] Jain AK, Ross A, Prabhakar S. An introduction to biometric recognition. IEEE Trans Circuits Syst Video Technol. 2004;14(1):4--20.
[5] WHO. Guidelines on standard procedures for blood typing and transfusion safety. World Health Organization Bulletin. 2020;98(5):212--220.
[6] OpenCV Developers. OpenCV Documentation. [Internet]. Available from: https://docs.opencv.org/
[7] Scikit-learn Developers. Scikit-learn: Machine Learning in Python. [Internet]. Available from: https://scikit-learn.org/
[8] Goodfellow I, Bengio Y, Courville A. Deep Learning. Cambridge: MIT Press; 2016.
[9] Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Front Plant Sci. 2016; 7:1419.
[10] Malathi R, Thangaraj P. A Survey on Blood Group Classification Techniques Using Machine Learning. International Journal of Computer Applications. 2018;180(20):30–34.
[11] Maltoni D, Maio D, Jain AK, Prabhakar S. Handbook of Fingerprint Recognition. 2nd ed. Springer; 2009.
[12] Ross A, Jain AK. Multi-modal biometrics: an overview. Proceedings of 12th European Signal Processing Conference. 2004:1221–1224.
[13] Ratha NK, Connell JH, Bolle RM. Enhancing security and privacy in biometrics-based authentication systems. IBM Systems Journal. 2001;40(3):614–634.
[14] Poonguzhalan D, Surendiran M. Automated fingerprint classification system based on ridge orientation. International Journal of Computer Applications. 2012;59(3):15–20.
[15] Plamondon R, Kal A. Fingerprint classification methods: a review. Pattern Recognition. 1995;28(8):1177–1190.
[16] Rifkin R, Klautau A. In defence of one-vs-all classification. Journal of Machine Learning Research. 2004;5:101–141.
[17] Chen L, Cao X, Wang J. Fusion of fingerprint and palmprint for biometric recognition. Pattern Recognition Letters. 2010;31(5):357–363.
[18] Reddy MK, et al. An approach to multi-class classification problem in SVM using one-vs-one and one-vs-all. International Journal on Computer Science and Engineering. 2010;2(2):68–73.
[19] Ramesh K, Sujatha C. Dermatoglyphics and Blood Group Correlation Study Using Image Processing and Machine Learning Techniques. Journal of Medical Systems. 2020;44(9):156.
[20] Asha V, Wilson P. A Deep Learning Framework for Blood Group Identification Using Biometric Patterns. IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT). 2019:177–181.
[21] Jain AK, Ross A. Introduction to Biometrics. In: Bourbakis NG, Patel TR, editors. Encyclopedia of Computer Science and Technology. CRC Press; 2006. p. 1–23.
[22] Parveen R, Gupta P. Machine Learning Techniques for Pattern Recognition in Fingerprints: A Comparative Study. International Journal of Computer Applications. 2019;178(45):10–15.
[23] Sun L, Tan T, Wang S, Jain AK. Fingerprint Quality Assessment. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2012;34(5):1012–1024.