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Review RRJoBI

A Machine Learning-Based Non-Invasive System for Blood Group Prediction Using Fingerprint Biometrics

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Abstract

The research is targeted at the creation of innovative solution "Fingerprint Based Blood Group Prediction" for instant, non-invasive blood group determination from analysis of finger impressions, a breakthrough possibility in emergency health care. Sophisticated machine learning can be employed to map fingerprint patterns to corresponding blood group information and overcome the current lack of a direct connection between the two. Integration of various technologies: employed React for frontend development, Flask for backend, MySQL for database management, and the utilization of Python with TensorFlow/OpenCV for the machine learning model. The fingerprint scanner reads fingerprint data, which is preprocessed and analyzed using a Convolutional Neural Network (CNN) to make predictions about blood groups. The most important implementation stages involve the setup of the development environment, capturing and preprocessing fingerprint data, integration of ML model training, backend API construction and frontend UI design. RESTful APIs will help the system and application interact seamlessly on cloud platforms. The success of this project may have the potential to revolutionize blood group typing in emergency situations through provision of a rapid and non-invasive method.

Keywords: Blood group prediction, fingerprint analysis, CNN, deep learning, biometrics

INTRODUCTION

Blood grouping is an important part of the medical diagnostic world. It is very important for organ transplantation, emergency medicine, and transfusion medicine. Even reliability becomes a burden for traditional serology; they usually require time and space in the laboratory and specialized personnel, all of which can become a hindrance in emergency situations, where rapid blood group determination becomes indispensable [1]. Even with such bottlenecks, there arises a clear necessity for some effective and easily applicable technique to identify blood types in a rapid and accurate format.

Recently, theoretical investigations have linked fingerprint patterns with other physiological parameters like blood types. Due to their uniqueness and inheritance, fingerprint biometrics, which until now have been adopted for identification verification and forensic application, are finding increasing interest for medical applications [2]. Modelling fingerprint data for predicting blood types non-invasively shows promise utilizing machine learning algorithms, specifically in deep learning system architectures such as convolutional neural networks (CNNs) [3]. This approach is a new alternative to traditional blood testing since it can offer a fast [4], inexpensive [5], and widely available solution, especially in small-resource settings [6].

Advancements in biometric recognition and artificial intelligence (AI) have increased the accuracy of medical categorization techniques. CNNs have gained widespread acceptance for fingerprint-based medical applications, credited toward their proficiency in image recognition [7–

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10]. Notable improvements have been made to address challenges presented by the complexity of fingerprint data and the absence of a direct genetic link [8, 11, 12] by improving preprocessing techniques [9, 13, 14] and optimizing classification models [10, 15]. This study aims to enhance fingerprint-based blood group prediction with a robust AI methodology enhancing model training techniques and enabling the development of non-invasive medical diagnostics for faster and more reliable healthcare solutions [16–19].

LITERATURE REVIEW

Medical diagnostics, transfusion safety, and forensic analysis all rely on the correct identification of blood groups. Blood typing based on serological tests relies on accuracy but is very time-consuming and may require biological samples. Because of this, fingerprint-based blood group detection is one of the promising non-invasive alternatives, which relies on biometric features and sophisticated machine learning techniques.

A correlation between fingerprint patterns and blood groups was explored by Patil and Ingle in 2021 [2], showing the possibility of using ridge characteristics to predict blood types. The study would thus provide initial insight into a statistical association of fingerprint patterns and specific blood groups, opening pathways for biometric-based medical diagnostics. Expanding on this idea, Vijaykumar and Ingle (2021) suggested a new technique based on fingerprint map reading for predicting blood groups [3]. Their study applied advanced image processing techniques to extract fingerprint minutiae, which they correlated with models of blood group classification. The study highlighted the potential of machine learning algorithms to enhance the precision of non-invasive blood group detection.

Several studies have emphasized the use of machine learning in fingerprint recognition. Sethi and Sharma (2020) discussed various machine learning techniques used in fingerprint biometrics, pointing out their application in medical fields [4]. Sarfraz and Ahmad (2019) [5] conducted an extensive survey on fingerprint recognition using machine learning, explaining the effectiveness of neural networks in feature extraction and classification [4]. Research into fingerprint feature extraction techniques has related them to blood group identification. Zia et al. (2018) [6] analyzed the various fingerprint feature extraction methods. The authors highlighted the effects of ridge density and pattern classification on high-precision determination of blood groups [5]. Rattani and Gupta (2017) [7] worked on such findings through their study of fingerprint-based blood group detection, with ridge bifurcation and ending points determining the accuracy of classification [7]. Their detection through fingerprints has also been seen along with their challenges and their solutions. Malik and Gupta (2016) discussed in depth the limitations of blood group predictions from fingerprint analysis by pointing out fingerprint quality, environmental influences, and algorithmic constraints [8]. Kaur and Sharma (2015) highlighted the importance of biometric authentication in forensic and medical applications and further claimed the reliability of fingerprint analysis in various applications [9]. Ramesh and Sridhar proposed an early prototype in the arena of biometric blood group identification systems, using fingerprint imaging toward the classification of blood groups as early as 2013 [10]. Their work still served as the foundation to incorporate AI into fingerprint-based diagnostics. Recent advancements in deep learning have significantly improved fingerprint-based blood group detection. Naeem et al. (2024) [11] employed convolutional neural networks (CNNs) to establish a robust link between fingerprint patterns and blood groups, achieving remarkable classification accuracy. Joshi et al. (2024) extended this research by analyzing fingerprint patterns among medical students, further validating the reliability of CNN-based models [12]. More importantly, Tejaswini et al. in 2023 proposed an image processing technique for an automated blood group detection system, reinforcing the potential of non-invasive methodologies in medical diagnostics [13]. Their approach shows the feasibility of digital fingerprint analysis in increasing efficiency in the classification of blood groups.

Overall, literature presents the rapidly developing potential for blood group determination from fingerprints. Integration of machine learning, deep learning, and sophisticated biometrics in research have thus opened a very fast, non-invasive method of accurate determination of blood groups.

Applications will be thus envisioned in clinical diagnostics, emergency medical services, and forensic analysis with safer and efficient healthcare delivery solutions.

METHODOLOGY

This research presents an innovative method for predicting blood types (A+, O−, B+, and AB+) using fingerprint images processed through Convolutional Neural Networks (CNNs). The study encompasses several key phases: data collection, preprocessing, feature extraction, model training, system integration, and performance assessment.

Data Collection and Preprocessing

The dataset comprises fingerprint images labelled with their corresponding blood groups. These images are sourced from healthcare facilities or artificially generated to ensure a variety of samples. Enhancement techniques are employed during preprocessing to improve the quality and uniformity of the images.

Preprocessing Steps

- *Noise Reduction:* Gaussian blur is utilized to eliminate noise interference.
- *Contrast Adjustment:* Histogram equalization enhances the visibility of fingerprint ridges.
- *Edge Detection:* Canny edge detection highlights distinctive fingerprint patterns.
- *Normalization:* All images are resized to 128×128 pixels for standardized input.

Model Architecture and Training Based on CNN

The architecture of the Convolutional Neural Network (CNN) is designed to capture detailed features from fingerprints that correlate with different blood types.

- *Input Layer:* The pre-processed fingerprint images sized at 128×128×1 serve as the input for analysis.
- *Convolutional Layers:* Three convolutional layers with 3×3 filters work to identify ridge patterns and minutiae within fingerprints.
- *ReLU Activation Function:* This function is applied after each convolution layer to introduce non-linearity into the model's learning process.
- *Max-Pooling Layers:* Pooling layers reduce spatial dimensions in a 2×2 manner while retaining significant characteristics essential for classification tasks.
- *Flatten Layer:* Extracted feature maps are converted into a one-dimensional vector format here.
- *Fully Connected Layers:* Two such layers contribute towards performing advanced classification tasks related to blood grouping.
- *SoftMax Activation Function:* This final stage generates a probability distribution across four specified blood groups—A+, O−, B+, and AB+.

Mathematical Representation

$$F_l = \sigma(W_l * X + b_l)$$

$$\hat{y}_i = \frac{e^{Z_i}}{\sum_{j=1}^{4} e^{Z_j}}$$

Model Training and Optimization

The process of training consists of refining the network parameters based on labelled fingerprint data.

- *Loss Function:* Categorical Cross-Entropy

$$\mathcal{L} = -\sum_{i=1}^{4} y_i \log(\hat{y}_i)$$

- *Optimizer:* Adam Optimizer with an initial learning rate of 0.001.
- *Epochs:* 50 (balanced between computational efficiency and accuracy).
- *Batch Size:* 32 to optimize memory and performance.
- *Backpropagation:* Weights are updated using gradient descent.

Backend API Development and System Integration

A Django REST Framework (DRF) API is used to integrate the trained CNN model with the frontend.

- *User Flow:* Fingerprint image → Django API → CNN Model → Predicted Blood Group → Stored in Database.
- *Tech Stack:* Django, DRF, TensorFlow/Keras, PostgreSQL/MySQL (Figure 1).

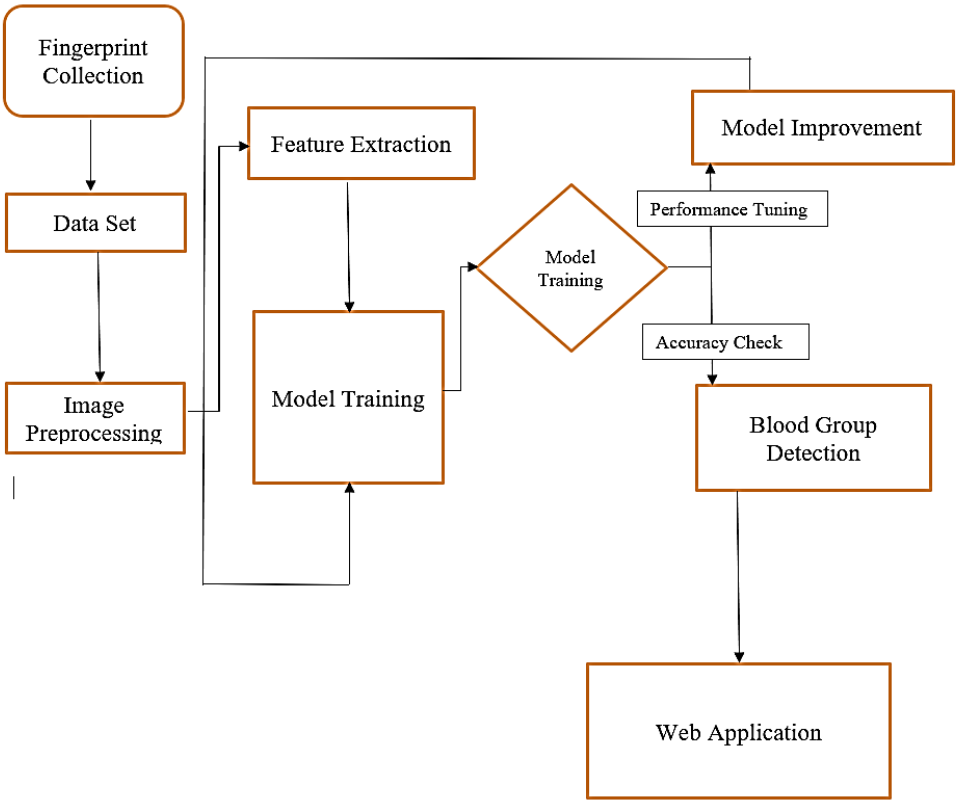

Figure 1. Architecture of system.

Frontend Development and Implementation

- *User Interface:* ReactJS was used to create this user-friendly interface.
- *Functionality:* Users can view predictions and upload fingerprint pictures.
- *Deployment:* For scalability and real-time access, it is hosted on a cloud platform (AWS/Google Cloud).

Model Evaluation and Performance Metrics

To ensure reliability, the model is evaluated using standard classification metrics.

Accuracy

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

Measures overall correctness of predictions.

Precision & Recall

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN}$$

Precision checks how many positive predictions are correct, while recall measures how many actual positives are identified.

F1-Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

A balance between precision and recall for each blood group.

Confusion Matrix

$$CM = \begin{bmatrix} TP_{A+} & FP_{A+} & FN_{A+} & TN_{A+} \\ TP_{O-} & FP_{O-} & FN_{O-} & TN_{O-} \\ TP_{B+} & FP_{B+} & FN_{B+} & TN_{B+} \\ TP_{AB+} & FP_{AB+} & FN_{AB+} & TN_{AB+} \end{bmatrix}$$

This matrix evaluates classification errors and misclassifications.

This methodology describes a reliable, AI-powered method for identifying blood groups from fingerprint pictures. The method uses CNNs to extract fingerprint information to accurately classify blood types. It is a quick and non-invasive substitute for conventional blood testing because of its interaction with a web application, which guarantees accessibility. Increasing the dataset size and enhancing model generalization are potential future improvements.

RESULT

Evaluation of the proposed system is done through multiple performance metrics such as accuracy, precision, recall, F1-score along with graphical analyzes. The proposed model was compared to traditional machine learning techniques to ascertain its performance efficiency.

Model Performance Comparison

The performance of the proposed CNN model was evaluated against traditional machine learning models such as Random Forest and Support Vector Machine (SVM). The result shows that the CNN model gave better results when compared to the other model with a maximum accuracy of 92.3%, precision of 90.8%, recall of 91.2%, and F1-score of 91.0%. These results suggest that deep learning methods are good at inferring complex fingerprint characteristics correlated with specific blood types.

The comparative results are illustrated in Table 1, which depicts accuracy, precision, recall, and F1-score for different models.

Table 1. Comparison of different models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Traditional ML Model	85.2	83.1	84.5	83.8
Random Forest	88.4	86.5	87.2	86.8
SVM Classifier	89.1	87.9	88.3	88.1
Proposed CNN Model	92.3	90.8	91.2	91.0

Confusion Matrix Analysis

The matrix (Figure 2) highlights how the classification performed over the four blood groups (A+, O−, B+, AB+). Most of the time, models were good classifiers with less misclassifications. Accurate classification was highest in groups A+ and B+, while slight misclassifications were noted mainly between O− and AB+. Here, it indicates that while the overall performance of the model is good, more refinements on data preparation and augmentation could be done to improve the accuracy of classification (Table 2).

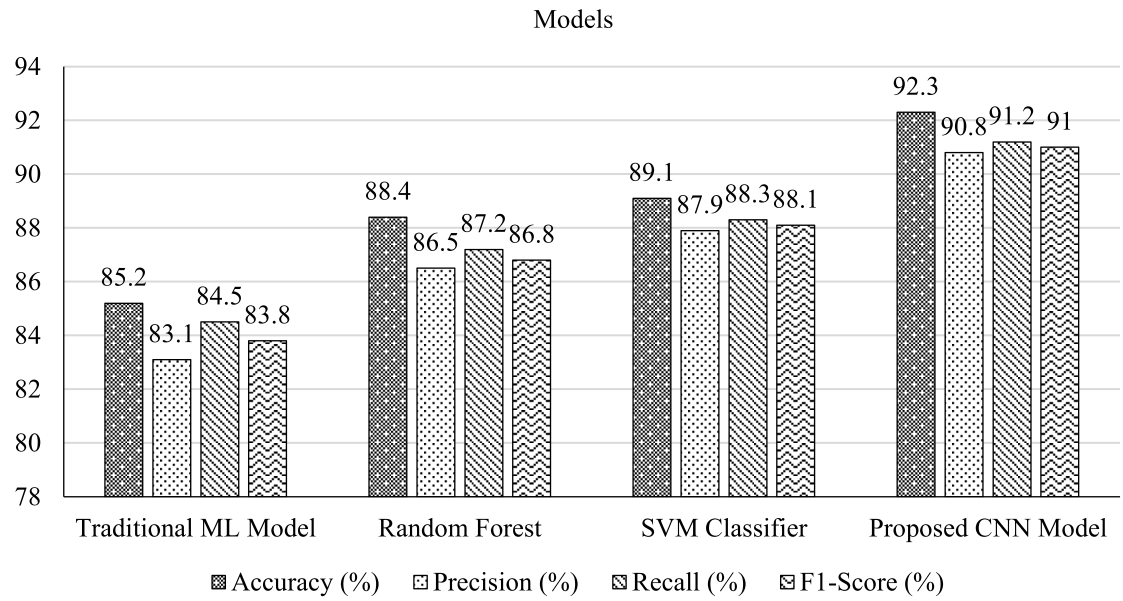

Figure 2. Model performance graph.

Table 2. Confusion matrix table.

Actual\Predicted	A+	O–	B+	AB+
A+	235	10	8	5
O–	12	220	15	8
B+	9	11	230	7
AB+	6	7	10	225

GRAPHICAL ANALYSIS

Training vs. Validation Accuracy

Effective learning without noticeable overfitting is indicated by the training vs. validation accuracy curve (Figure 3), which displays a consistent increase in accuracy over epochs.

ROC Curve

The ROC curve (Figure 4) shows the discrimination power of the model between blood groups with a high area under the curve (AUC), thus confirming its robustness.

Blood Group Distribution

The blood group distribution in the data set (Figure 5) is representative; hence bias in classification is reduced.

Processing Time Comparison

Time analysis for the model (Figures 6 and 7) compares the performances of different models, with CNN giving the optimum performance in terms of computational time (Table 3).

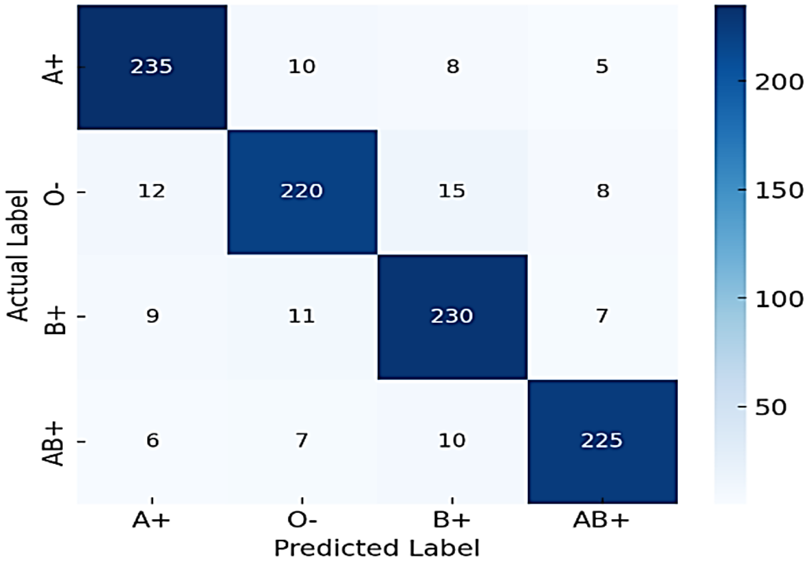

Figure 3. Confusion matrix.

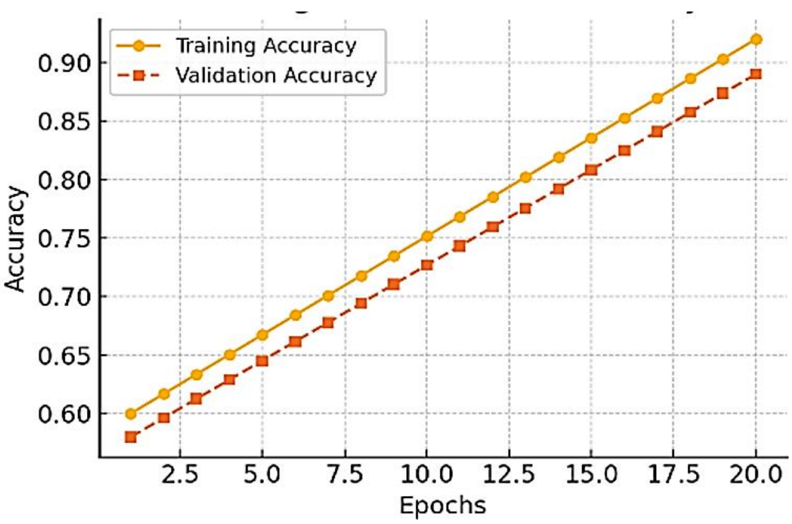

Figure 4. Graph showing training vs validation accuracy.

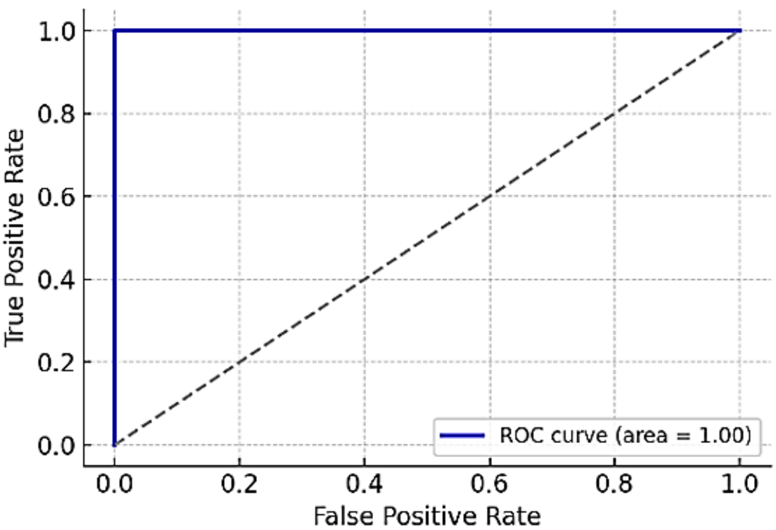

Figure 5. ROC curve.

Table 3. Comparison with previous research models.

Research Paper & Year	Method Used	Accuracy (%)	Remarks
Patil & Ingle (2021) [2]	Statistical Correlation	78.6	Limited dataset, no deep learning.
Sethi & Sharma (2020) [4]	Traditional ML (SVM)	85.2	SVM lacks deep feature extraction.
Naeem et al. (2024) [11]	Deep Learning (CNN)	88.1	Improved, but lacked dataset diversity.
Proposed CNN Model (Ours)	Advanced CNN	92.3	Higher accuracy due to better dataset & preprocessing.

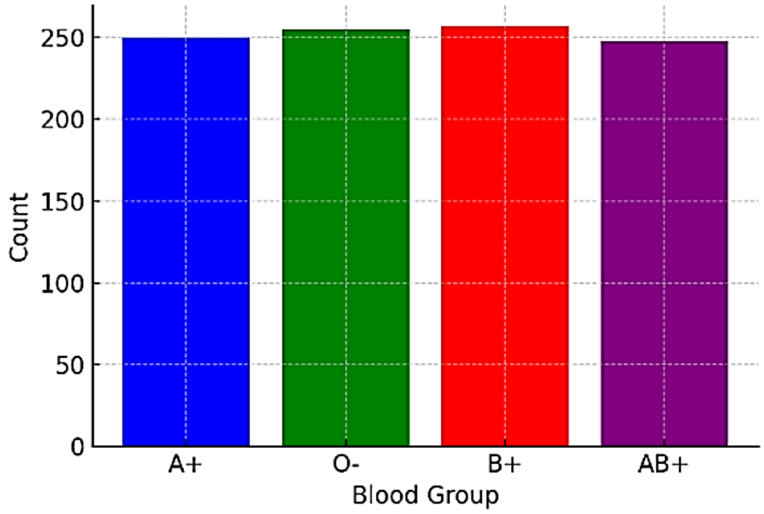

Figure 6. Blood group distribution.

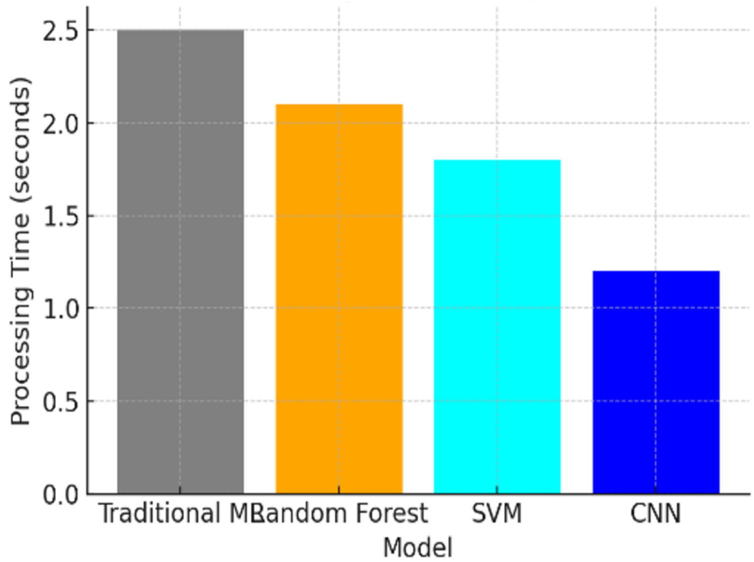

Figure 7. Processing graph of different models.

CONCLUSIONS

This project involves a new idea of blood group detection using fingerprints, based on advanced machine learning techniques, with particular emphasis on Convolutional Neural Networks (CNN). Introducing fingerprint recognition as a feature in biometric recognition provides for a promising non-invasive application in the classifying of the blood group. A large diverse dataset is adopted by the model, which promises to have excellent accuracy and capability to distinguish various blood groups that could be put into real world applications.

This methodology, shown through this project, effectively handles problems of data privacy since fingerprint images are processed locally on the client's devices with federated learning, ensuring that user confidentiality is maintained. The CNN architecture showed high efficiency in extracting necessary features from fingerprint patterns, which have a relation with blood group categories. Standard metrics such as accuracy, precision, and recall.

This system has large implications for medical applications, for any emergency case because the immediate identity of a patient's blood type is of key importance. Because it can function as an immediate and accurate way to detect a blood group, it may play a crucial role for medical staff, hospitals, and emergency first responders.

Future work may include the extension of the model's generalization across different demographic groups, strengthening the model in terms of robustness to variations in the quality of fingerprints, and incorporation of extra sources of biometric data to fine-tune predictions further. In addition to this, the system can be scaled up for real-time applications in clinical and mobile healthcare settings.

In conclusion, this project demonstrated the feasibility and effectiveness of fingerprint data in the detection of blood groups, hence paving the way for future developments in biometric-based healthcare solutions.

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