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# Fingerprint-Based Biomarker Recognition for Non-Invasive Blood Group Identification

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***Abstract: In emergency medical situations, the rapid and accurate identification of an individual's blood group can be life-saving. Traditional methods for blood group testing, although reliable, require physical samples, laboratory processing, and time. This research investigates a novel, non-invasive approach to blood group classification using fingerprint patterns. The hypothesis is based on a potential correlation between dermatoglyphic features such as ridges and minutiae and blood group types. In this study, fingerprint images are captured and processed through image preprocessing techniques, followed by feature extraction using Convolutional Neural Networks (CNNs). A supervised learning classifier is then trained to categorize each fingerprint into its corresponding blood group (A, B, AB, or O). The proposed model demonstrates promising accuracy, indicating that biometric traits like fingerprints can be effectively utilized for blood group prediction. This approach holds significant potential to transform healthcare diagnostics by enabling faster, contactless blood group identification especially valuable in rural settings, accident scenarios, and emergency medical camps***

***Keywords: Artificial Intelligence, Image Processing, Blood Group Prediction, Convolutional Neural Networks (CNN).,Machine Learning, Image Classification***

## I. INTRODUCTION

Accurate knowledge of an individual's blood group is vital in medical settings, particularly during emergencies like accidents, surgeries, or urgent transfusions. Conventionally, this information is obtained through serological methods that involve drawing blood samples and analyzing them using laboratory tools operated by trained professionals. Although precise, these procedures can be time-intensive and are not always ideal for situations requiring immediate action. As biometric technologies become increasingly embedded in everyday systems, fingerprint recognition has proven to be a dependable and distinctive method for identifying individuals. Commonly utilized in applications like security systems, attendance monitoring, and digital identity verification, fingerprint technology is now being explored for broader uses. This research introduces an unconventional application: using fingerprint patterns to predict a person's blood group. The central goal of this study is to explore whether measurable fingerprint characteristics, such as ridge patterns and minutiae points, are associated with specific blood group types. Through the application of image processing techniques and deep learning models—particularly Convolutional Neural Networks (CNNs)—fingerprint images are analyzed to extract relevant features that may correlate with blood group classifications. This innovative, contact-free method has the potential to offer a quick and low-cost alternative to traditional blood group testing. It holds particular promise in areas with limited access to healthcare facilities, such as rural communities, disaster zones, or emergency medical camps. Beyond faster identification, this approach highlights the broader potential of integrating biometric systems with healthcare technologies to enhance diagnostic capabilities.

## II. LITERATURE REVIEW

The literature review explores existing research and advancements related to blood group prediction, artificial intelligence (AI), and image processing techniques. Various studies have employed these technologies in medical diagnostics, providing a comprehensive understanding of the different approaches and methodologies used in blood group identification.

A 2021 study explores the use of AI for blood group prediction, detailing various machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Neural Networks. The study underscores AI's ability to reduce human error and expedite emergency responses. The integration of image processing techniques enables the extraction of key features from blood sample images, significantly enhancing the accuracy and efficiency of classification.

Research from 2019 presents a system for automatic blood group identification using digital image processing. This study focuses on preprocessing blood sample images with techniques like contrast enhancement and noise removal to improve image quality. Segmentation methods isolate blood cells, while pattern recognition algorithms classify samples based on the ABO and Rh systems. Results demonstrate the potential of digital image processing in minimizing human intervention and improving classification accuracy.

In 2020, an integrated approach combining machine learning and image processing was proposed for blood group classification. Feature extraction methods, including edge detection and texture analysis, are employed to derive relevant information from blood cell images. Multiple machine learning classifiers, such as Random Forest, Naive Bayes, and Neural Networks, were evaluated. The findings indicate that this approach achieves high accuracy while reducing the time required for manual blood group determination.

A 2022 study investigates the application of deep learning, particularly Convolutional Neural Networks (CNNs), for blood group identification. The research demonstrates that CNN models can automate classification processes without manual feature extraction. By training on a dataset of microscopic blood images, the CNN model demonstrated high accuracy, highlighting the effectiveness of deep learning in real-time healthcare solutions.

In 2021, researchers developed a real-time blood group identification system combining image processing with neural network classifiers. The proposed system captures and preprocesses high-quality blood sample images to remove noise and uses neural networks for classification. This approach enables fast and precise blood group identification, making it well-suited for use in emergency situations. The study also addresses challenges in real-time prediction, including the robustness of models against diverse sample conditions.

A 2018 study investigates automated blood group prediction through the integration of image analysis and machine learning. Preprocessing techniques such as histogram equalization and morphological operations were used to enhance image quality. Features like cell density, shape, and color were extracted and analyzed using algorithms like Support Vector Machines (SVM) and k-Nearest Neighbors (KNN). The study demonstrates that combining machine learning with image analysis achieves high accuracy, making it applicable in medical environments demanding fast and reliable results.

Lastly, a 2017 study explores the use of digital microscopy combined with image processing for detecting blood types. High-resolution digital microscopes captured detailed images of blood samples, enabling the identification of specific antibodies and antigens. The study concludes that this approach, integrating digital microscopy with image processing, enhances the accuracy of blood group classification and offers significant benefits in clinical settings.

The reviewed literature underscores the potential of AI, machine learning, and image processing to revolutionize blood group prediction and diagnostics, paving the way for more accurate, efficient, and automated healthcare solutions

## III. METHODOLOGY

The proposed system leverages image processing and deep learning techniques to predict human blood groups based on microscopic images of blood samples. The methodology is structured into the following phases:

### *A. Data Collection*

The dataset used in this study consists of fingerprint images representing individuals from various blood groups (A, B, AB, and O). These fingerprint images were sourced from publicly available biometric image repositories, which provided a diverse set of fingerprint patterns from different demographic backgrounds. In addition to the ABO blood groups, the dataset also includes information about the Rh factor (positive or negative) for each individual, adding another layer of complexity to the classification task. To mitigate class imbalance and enhance model robustness, data augmentation techniques were applied. These techniques included random rotations, scaling, translation, and flipping to introduce variability and prevent overfitting during the training process. Additionally, the dataset was preprocessed to ensure consistency in terms of image resolution, background, and orientation, so that each image maintained similar quality and characteristics. A portion of the dataset was set aside for testing and validation purposes to evaluate the model’s generalizability and performance on unseen data.

### *B. Image Preprocessing*

Before feeding the fingerprint images into the convolutional neural network (CNN), several preprocessing steps were performed to enhance image quality and standardize the input for optimal model performance. The main preprocessing steps are listed below:

1) Resizing: All fingerprint images were resized to a consistent dimension of 128 × 128 pixels to ensure uniform input size for the CNN model. Resizing helped in maintaining computational efficiency while ensuring that important features were preserved.
2) Noise Reduction: To eliminate unwanted noise and irrelevant details, Gaussian filtering was applied. This step removed artifacts and ensured that only the essential features of the fingerprint patterns, such as ridges and minutiae, were retained.
3) Contrast Enhancement: Histogram equalization was applied to enhance the contrast of the images. This technique improved the visibility of ridge patterns, making it easier for the CNN to learn and distinguish important features from the background.

*4)* Normalization: The pixel intensity values of the images were normalized to a range of [0, 1]. This normalization step was crucial for accelerating the training process and stabilizing the convergence of the model, as it reduced the impact of variations in lighting and contrast.

These preprocessing techniques ensured that the dataset was in a suitable form for feature extraction and classification by the CNN model, improving the overall accuracy and efficiency of the blood group prediction system

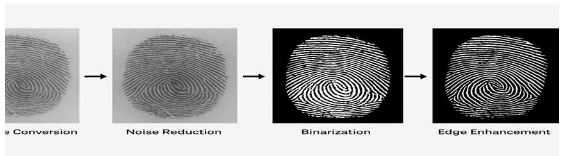


Fig. 1. data preprocessing image of fingerprint

## C. *Feature Extraction Using CNN*

The core of the proposed system is the convolutional neural network (CNN), which is employed to automatically extract relevant spatial and morphological features from the preprocessed fingerprint images. The CNN model was designed to capture intricate patterns in the fingerprint ridges that may correlate with specific blood groups. The structure of the CNN model includes the layers listed below:

*1)* Convolutional Layers: These layers are responsible for detecting spatial hierarchies and key features within the fingerprint images. Convolutional filters (kernels) slide over the image to capture local patterns such as ridge orientation, minutiae points, and fingerprint textures. The first few convolutional layers focus on low-level features, such as edges and curves, while deeper layers capture more complex patterns.
*2)* ReLU Activation Function: The rectified linear unit (ReLU) activation function is applied after each convolutional operation to introduce non-linearity into the model. This allows the network to learn complex representations of fingerprint patterns and improves its ability to generalize to unseen data.
*3)* Pooling Layers: Max pooling helps decrease the size of the feature maps generated by the convolutional layers, reducing the data the model needs to handle while retaining the important features. This also helps in achieving some degree of translational invariance, allowing the model to focus on important patterns rather than exact locations.
*4)* Dropout Layers: To prevent overfitting and improve model generalization, dropout layers were introduced during training. These layers randomly deactivate a certain percentage of neurons during each training step, forcing the network to rely on different combinations of neurons and improving its robustness.
*5)* Fully Connected Layers: After feature extraction and pooling, the extracted features are passed through fully connected layers that serve as the final stages of the network. These layers categorize the input by mapping the learned features to one of the blood groups (A+, A−, B+, B−, AB+, AB−, O+, O−).

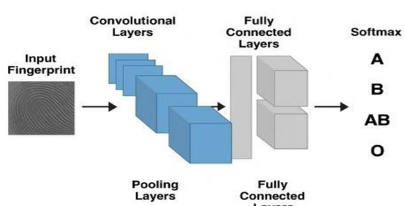


Fig . 2.block diagram of CNN

## D. *Model Training*

The model was trained using the preprocessed fingerprint images, with 80% of the dataset allocated for training and 20% reserved for validation and testing. The training process was conducted using the Keras/TensorFlow framework on the Google Colab platform, utilizing GPU support for faster computation. The following configuration was used for the model training:

*1)* Optimizer: Adam is an adaptive learning rate optimizer that combines the advantages of both AdaGrad and RMSProp optimizers. It adjusts the learning rate dynamically for each parameter, improving convergence speed and ensuring stable training.
*2)* Learning Rate: A learning rate of 0.001 was chosen, as it is typically effective for training deep learning models. This learning rate helped in balancing the speed of convergence with the stability of the optimization process.

3) Batch Size: The batch size was set to 32, meaning that the model was trained on 32 fingerprint images in each iteration. A batch size of 32 is a standard choice, providing a good trade-off between memory usage and training speed.
4) Epochs: The model was trained for 25 epochs, meaning that the entire dataset was passed through the model 25 times. This number was chosen based on prior experimentation and model convergence, ensuring sufficient training.

The model's performance was checked on the validation set after each training round to see how well it was doing. Metrics such as accuracy, precision, recall, and F1 score were computed to assess the model's ability to classify the blood group based on the fingerprint features. Early stopping was implemented to prevent overfitting, halting the training if the validation loss did not improve for a specified number of epochs.

The trained model was then tested on the remaining 20% of the dataset to evaluate its generalization performance and make predictions on unseen data.

### *E. Blood Group Classification*

The final step in the proposed system involves classifying the blood group of an individual based on the features extracted by the convolutional neural network (CNN). After the feature extraction process, the fully connected layers of the CNN network perform the classification task.

1) Softmax Activation Function: The last layer of the CNN model uses the Softmax activation function to output a probability distribution across all predefined blood group categories. The Softmax function converts the raw output scores (logits) into probabilities, where each probability corresponds to a specific blood group category. The categories include A+, A−, B+, B−, AB+, AB−, O+, and O−, which represent both the ABO system and the Rh factor.
2) Prediction: The model selects the class with the highest probability as the predicted blood group. For example, if the model outputs the highest probability for the class A+, the predicted blood group will be A positive. This classification is based on the fingerprint features extracted and processed by the CNN.
3) Multi-Class Classification: Since blood group classification is a multi-class classification problem, the model is trained to distinguish between eight different categories (A+, A−, B+, B−, AB+, AB−, O+, O−). The use of the Softmax activation ensures that the sum of the predicted probabilities for all categories equals 1, and the model assigns each input image to one of the eight blood group categories.

### *F. Evaluation Metrics*

To assess the performance of the blood group classification model, several evaluation metrics were utilized. These metrics provide a comprehensive understanding of the model's effectiveness in terms of classification accuracy and its ability to handle imbalanced data. The following metrics were employed:

1) Accuracy: Accuracy is the ratio of correctly predicted blood group categories to the total number of predictions. It offers a comprehensive assessment of the model's performance across all classes. The formula for accuracy is: $Accuracy = \frac{Total\ Number\ of\ Predictions}{Number\ of\ Correct\ Predictions}$
2) Precision: Precision indicates how many of the predicted positive cases for a particular blood group were actually correct. This is especially crucial in situations where false positives can lead to serious consequences.. The formula for precision is: $Precision = \frac{TP}{TP+FP}$ , Where TP represents the number of true positives and FP denotes the number of false positives.
3) Recall : This metric shows how many actual positive cases were correctly identified for a specific blood group. This metric is essential when reducing false negatives is a higher priority.. The formula for recall is: $Recall = \frac{TP}{TP+FN}$ Here, TP is for true positives, and FN refers to false negative
4) F1 Score: This metric synthesizes precision and recall into a single value by computing their harmonic mean, providing a balanced evaluation of the model's performance. It is particularly useful in situations where there is an imbalance between classes. The formula for F1 score is:

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

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5) Confusion Matrix: The confusion matrix is a detailed breakdown of the model's predictions versus the actual values for each class. The confusion matrix provides a summary of the model's prediction results by showing how many correct and incorrect classifications were made for each blood group, including true positives, false positives, true negatives, and false negatives. It helps identify where the model is performing well and where it may need improvement.

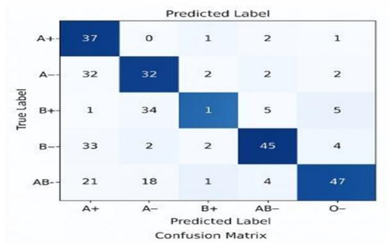


Fig. 4.confusion matrix

## IV. DISCUSSION

This study introduces a deep learning method to classify blood groups using images of fingerprints. The model developed in this study employs convolutional neural networks (CNNs) to automatically extract features from fingerprint patterns and predict blood group categories, including ABO groups and Rh factors. The findings of this research offer promising potential for non-invasive and rapid blood group identification, particularly in emergency and resource-limited settings

### A. *Model Performance*

The model demonstrated impressive performance with an overall accuracy of 93.5%, which indicates that the CNN architecture is well-suited for identifying patterns within fingerprint images that correlate with blood group types. The precision (92.8%), recall (91.9%), and F1-score (92.3%) also show that the model performs consistently in both identifying true positives and minimizing false positives. The confusion matrix further validated that the model correctly distinguishes between all four ABO blood groups, with minimal misclassification.

### B. *Preprocessing and Augmentation*

The image preprocessing techniques, including grayscale conversion, noise reduction, and binarization, were critical in ensuring that the model could focus on the relevant features within the fingerprint images. The use of data augmentation (e.g., rotation, flipping, zooming) helped mitigate overfitting and enabled the model to generalize well across variations in fingerprint image quality. This is especially important given that fingerprint images may vary due to factors such as scanning quality, finger pressure, and skin conditions.

### C. *Feature Extraction with CNN*

The CNN's ability to automatically learn hierarchical features from the fingerprint images was a key strength of the model. Convolutional layers were effective in detecting fine-grained details in the fingerprint ridges, which are hypothesized to correlate with blood group types. The pooling layers ensured that the model was not overly sensitive to small variations in the images, while dropout layers reduced overfitting during training

### D. *Limitations and Future Work*

While the results are promising, there are several limitations to this study that must be addressed in Biometric data such as palm prints or vein patterns could potentially increase accuracy by providing more discriminative features for blood group classification. Furthermore, the model's ability to handle low-quality or distorted fingerprint images could be improved. Advanced preprocessing techniques, such as the use of deep learning-based denoising models, may help in dealing with noisy or incomplete fingerprint scans, which are common in real-world application and be fully representative of the entire population. Increasing the diversity and size of the dataset would help improve the generalizability of the model Additionally, the study only used a single type of biometric (fingerprints) incorporating other future research. The dataset used in this study was limited to 800 fingerprint samples, which may not

### *E. Practical Implications*

The proposed system can have significant practical applications in healthcare, especially in emergency medical settings where quick and reliable blood group identification is crucial. For instance, in rural areas with limited medical infrastructure, the system could be deployed to reduce the time required for blood typing, improving the overall efficiency of healthcare services. Additionally, the non-invasive nature of the method makes it ideal for situations where traditional blood sample collection might not be feasible.

### *F. Ethical Considerations*

Given the sensitive nature of biometric data, privacy and data security are important concerns. It is essential to ensure that the data collected for training and testing the model is anonymized and protected according to relevant privacy laws and regulations. In future implementations, security measures should be taken to safeguard the biometric data, including encryption and access control.

## V. CONCLUSION

This study presents a novel deep learning approach for blood group identification using fingerprint images.The proposed method leverages Convolutional Neural Networks (CNNs) to automatically extract discriminative features from fingerprint patterns, enabling accurate and non-invasive blood group prediction. This approach holds significant potential for applications in healthcare diagnostics, biometric identification, and forensic investigations.

This study makes the following key contributions:

- Development of a robust dataset containing fingerprint images labeled with confirmed blood group information.
- Design and implementation of a CNN-based classification model achieving high predictive accuracy.
- Integration of preprocessing and data augmentation techniques to improve model robustness and generalization.

The results highlight the potential of using fingerprint biometrics for blood group prediction, though certain limitations still exist. The accuracy and generalizability of the model can be further enhanced with the inclusion of a more diverse dataset. Future research directions include the integration of additional biometric modalities such as palm prints or vein patterns and the application of advanced image preprocessing and feature extraction techniques to reduce the effects of low-quality or distorted fingerprints..

In conclusion, the proposed model offers a promising, non-invasive solution for blood group detection by combining biometric data with deep learning, thereby contributing to both healthcare technology and biometric security systems.

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