

Optimized Image Processing Algorithms for Precise Blood Group Detection

Dr. Dnyanda Hire ¹, Dr. Anupama Patil ², Dr. Priya Charles ³, Utkarsha Gole ⁴,
Snehal Dundagekar⁵, Prachi Gore ⁶

^{1,3} D. Y. Patil International University, Akurdi, Department of Semiconductor Engineering, Pune, Maharashtra, India

² D. Y. Patil International University, Akurdi, Pune, Maharashtra, India

^{4,5,6} Dr. D. Y. Patil Institute of Engineering, Management and Research, Akurdi, Department of Electronics and
Telecommunication Engineering, Pune, Maharashtra, India

Email Id: ¹ dnyanada.hire@dypiu.ac, ² Anupama.patil@dypiu.ac.in, ³ priya.charles@dypiu.ac.in,
⁴ utugole09@gmail.com, ⁵ snehaldundagekar1746@gmail.com, ⁶ prachigore53112gmail.com

Abstract

The need for a reliable and non-invasive method for blood group detection is increasingly recognized, particularly in regions with limited access to conventional medical testing. This paper presents a deep learning approach that utilizes fingerprint images to determine blood groups. A convolutional neural network architecture was implemented to analyze distinct patterns in fingerprint data, enabling the classification of eight blood groups. An initial model was developed to establish a baseline for classification, and its performance was evaluated through loss and accuracy metrics. Results indicate the potential for this fingerprint based method to serve as an accessible point of care solution for blood group determination, paving the way for further enhancements in model complexity and accuracy.

Keywords: Blood group detection, fingerprint pattern, Convolutional neural networks.

1. Introduction

In modern healthcare, the rapid and accurate determination of a patient's blood group is crucial for timely and effective treatment, especially in critical situations like blood transfusions, organ transplants, and emergency care. Traditionally, blood group determination relies on serological testing, which involves reacting blood samples with specific antibodies to observe agglutination. Although reliable, this process can be labor-intensive, time-consuming, and dependent on skilled personnel and laboratory resources. These constraints are especially problematic in low-resource settings where access to advanced medical facilities is limited, potentially resulting in life-threatening delays. In urgent cases, such as trauma, surgeries, or natural disasters, these limitations are further exacerbated, as timely diagnosis is critical to patient survival.

To address these challenges, our proposed model, "Optimized Image Processing Algorithms for Precise Blood Group Detection" introduces a novel approach leveraging deep learning and image processing techniques to automate blood group identification. By automating this process, we aim to create a solution

that is faster, more accurate, and less reliant on manual intervention, which can significantly reduce human error and expedite diagnosis in time-sensitive situations. The automated system can be especially advantageous in settings lacking laboratory facilities, providing immediate results that are both dependable and efficient.

Advancements in technology, particularly in image processing and artificial intelligence, have opened new possibilities for healthcare diagnostics. These innovations are transforming the field, with applications spanning disease diagnosis through imaging to patient data analysis for predictive healthcare. Deep learning, a subset of AI, has shown remarkable promise in medical diagnostics, as it can automatically identify patterns in large datasets and produce high-accuracy predictions.

In our proposed model, we apply image processing and deep learning techniques to blood group detection using fingerprint images. This non-invasive method eliminates the need for blood samples and reagents, offering a simpler and more accessible solution for blood group identification. Fingerprints, which are unique to each individual, have long been used for

identification purposes, and recent studies suggest a correlation between fingerprint patterns and biological traits like blood group. By analyzing these patterns, we can harness image processing algorithms to determine blood groups with precision.

Image processing, in essence, involves the manipulation and analysis of images to extract meaningful information. For this proposed model, we use fingerprint images as input data for blood group classification. By applying advanced image processing techniques, we can enhance image quality and extract critical features that indicate blood group type. These features are then processed by a deep learning model for classification, allowing for rapid and automated blood group detection. Automation not only reduces human involvement but also minimizes the risk of errors. Moreover, image processing can be conducted swiftly, making it ideal for emergency situations where rapid diagnosis is crucial. By automating this process, healthcare providers can access blood group results in real time, improving both the speed and accuracy of medical responses.

At the core of this proposed model is a deep learning model, specifically a Convolutional Neural Network, which enables the automation of blood group detection. CNNs are a type of neural network optimized for image data analysis, adept at recognizing patterns and features in images through a series of convolutional layers. These layers automatically learn to identify edges, textures, and other image characteristics, making CNNs particularly effective for tasks like image classification and object recognition. In our project, we use CNNs to analyze fingerprint images and classify them by blood group. The CNN is trained on a labeled dataset of fingerprint images associated with their respective blood groups, allowing the model to learn patterns that correlate with specific blood types. Once trained, the model can accurately predict the blood group of new fingerprint images.

The successful implementation of this model has the potential to transform the way blood group detection is conducted, offering improvements in speed, accuracy, and accessibility. By removing the need for traditional manual testing and specialized laboratory infrastructure, our system can be deployed in diverse settings, including rural clinics, mobile healthcare units, and field hospitals. This is particularly advantageous in areas with limited medical resources, where conventional blood group testing may be impractical or

unavailable. Additionally, automating blood group identification through fingerprint analysis can help reduce the workload on healthcare providers, enabling them to dedicate more time to other essential tasks.

In emergency situations, such as mass casualty incidents or natural disasters, our system could deliver quick and reliable blood group results, facilitating timely medical interventions and potentially saving lives. Beyond immediate applications, it opens doors to further research into leveraging deep learning and image processing for other healthcare diagnostics. The same techniques could be adapted to detect various biological markers or health conditions, such as assessing specific health issues based on skin patterns, retinal scans, or other biometric indicators. The integration of artificial intelligence and image processing in healthcare is an exciting and rapidly advancing field, and our project represents a meaningful step forward in applying these technologies for real-world, impactful solutions.

2. Related Work

In the domain of blood group determination through biometric data, T Nihar [1] have introduced an innovative approach by examining the potential of fingerprint patterns combined with deep learning, particularly Convolutional Neural Networks (CNNs). Their research utilizes established CNN architectures such as LeNet-5 and AlexNet to extract fingerprint features, achieving notable accuracy in blood group classification. The study highlights the reliability of fingerprint patterns and emphasizes the novel application of deep learning to improve blood group detection accuracy.

Another significant study by Dr. M. Prasad and Amrutha [2] investigates the use of CNNs and image processing techniques for non-invasive blood group detection. By employing methods like Scale-Invariant Feature Transform (SIFT) and Oriented FAST and Rotated BRIEF (ORB) for image matching, along with photoplethysmography (PPG) signal processing, their research proposes an accessible solution for blood group identification. This study shows promising accuracy in classification, providing a valuable tool for healthcare, especially in resource-limited environments.

In the research conducted by Rastogi et al. [3], a connection between blood groups, gender, and fingerprint patterns is explored. Among the study

participants, blood group O was most common, followed by B, A, and AB. They observed a high frequency of loop patterns in individuals with blood types A, B, AB, and O, while whorls were moderately common, and arches were relatively rare. This study provides insights into the associations between fingerprint patterns and blood groups.

Senthilkumar [4] have made notable contributions to the field of biometric-based health prediction by investigating fingerprint minutiae for blood group prediction. Their work utilizes advanced image processing techniques, including ridge frequency estimation and Gabor filtering, and incorporates the HFDU06 fingerprint scanner to enhance data collection efficiency. This study highlights the importance of including demographic and lifestyle factors to improve predictive accuracy.

The study by Azhagiri, Anitha M, Hemapriya J. [5] involved 150 participants, equally divided between males and females. Their findings revealed that loop patterns were the most frequent in the left thumb fingerprints, followed by whorls and mixed patterns, with arches being the least common. The research indicates that blood groups O and B are more likely to have loop patterns, while groups A and AB exhibit a lower frequency of loops. This work sheds light on the distribution of fingerprint patterns across different blood groups.

In her research, Nikitha V [6] presents an in-depth analysis of the connection between fingerprint patterns and blood types using advanced deep learning methods. Utilizing the VGG16 architecture with transfer learning, her study analyzes fingerprint images to detect potential blood group patterns. Although models such as VGG16, ResNet, and AlexNet were rigorously tested, the maximum prediction accuracy achieved was 76%, suggesting the complexity and limitations of detecting a clear relationship between fingerprint patterns and blood types.

Dr. D. Siva Sundhara Raja and J. Abinaya [7] make a significant contribution by combining advanced feature extraction techniques, including Gray Level Co-occurrence Matrix (GLCM), wavelet transform, texture feature laws, and minutiae extraction, alongside a Back Propagation Neural Network (BPNN) classifier to enhance blood group identification accuracy. Their approach highlights the effectiveness of these

techniques in analyzing biometric data for health-related predictions.

The study by Chebouat Djafar Aboubaker and Leila Amrane [8] explores the challenges of correlating fingerprint patterns with blood types through deep learning. Their research employed CNNs to analyze fingerprint samples from a diverse group of participants and their known blood groups. Despite training four models—VGG, ResNet, AlexNet, and a custom CNN—accuracy rates did not exceed 76%, underscoring the need for further research to better understand the complex relationships between fingerprint patterns and blood groups.

Patil and Ingle [9] present an optimized CNN model designed as an extension of AlexNet in the area of fingerprint-based blood group detection. This model leverages unique fingerprint characteristics to predict ABO and Rh blood types, achieving an accuracy of 95.27%. Their approach underscores the potential of CNNs for achieving high accuracy in biometric-based blood group identification and represents a significant advancement in this field.

3. Research Methodology

Dataset Overview

The dataset[10] used for this project was obtained from Kaggle, a well-known platform for open-access datasets. Specifically, the dataset titled “finger-print-based-blood-group-dataset” was selected, which contains a comprehensive collection of fingerprint images, categorized by blood group type. The dataset is divided into eight directories, each representing a distinct blood group:

Table 1: Dataset Distribution of Training and Validation

Label of Dataset Used	Training Images Count	Validation Images Count	Total Images
A+	452	113	565
A-	807	202	1009
B+	522	130	652
B-	592	149	741
O+	683	169	852
O-	572	140	712

Label of Dataset Used	Training Images Count	Validation Images Count	Total Images
AB+	567	141	708
AB-	608	153	761
TOTAL=	4803	1197	6000

With a total of 6,000 images distributed across eight blood group categories, the dataset is designed to ensure that the model can learn effectively while maintaining the ability to generalize to new data. This comprehensive dataset forms the backbone of the proposed model, providing the necessary foundation for developing an accurate blood group detection system using image processing algorithms.

System Specifications

The system used for model training and development had the following specifications:

Operating System: Windows 11

Processor: 11thGen Intel(R)Intel Core(TM) i5-1135G7@ 2.40GHz 2.42 GHz

RAM: 8.00 GB

System Type: 64-bit operating system, x64-based processor

These specifications ensured the smooth execution of deep learning tasks, as the computational demands of training neural networks, especially on image data, can be substantial. The GPU accelerated the process, enabling faster training times compared to CPU-only systems.

Data Preprocessing

Before feeding the dataset into the neural network, it was crucial to preprocess the images to ensure uniformity and optimize the model's learning ability. Data preprocessing included the following key steps:

Rescaling: In their raw form, the pixel values in the images range from 0 to 255, representing the intensity of each pixel. To normalize these values, they were scaled down by dividing by 255, resulting in values between 0 and 1. This rescaling improves the model's ability to converge, as neural networks tend to learn faster and more effectively with normalized inputs.

Resizing: The dataset comprised fingerprint images of varying dimensions. To standardize the input size for

the convolutional neural network (CNN), each image was resized to 128x128 pixels. This specific resolution was chosen to balance computational efficiency with the need to retain important features of the fingerprint.

Data Augmentation: To enhance the model's generalization capability and increase the diversity of training data, data augmentation techniques were employed. By randomly applying transformations such as rotations, flipping, zooming, and shifting, we artificially expanded the training dataset. This approach helped minimize the risk of overfitting, encouraging the model to recognize broader patterns and features rather than memorizing specific details from the training images.

Train-Validation Split: The dataset was divided into training and validation sets, with 80% allocated for training and 20% for validation. This split was essential for accurately evaluating the model's performance during training, as the validation set—unseen by the model during training—provided an unbiased assessment of its generalization ability.

Model Development

Input Layer: The input layer is where the network begins by taking in images sized at 128x128 pixels with RGB channels.

Convolutional Layer: The convolutional layer applies 3x3 filters across the input to create feature maps that capture critical image details like edges. By using ReLU activation, it filters out negative values, allowing the network to focus on the most relevant patterns.

Max Pooling Layer: After each convolution, the max pooling layer reduces the feature map size by selecting the highest value from each 2x2 block, which cuts down parameters, lessens computation, and minimizes overfitting. This down-sampling also improves robustness against image variations, boosting classification accuracy.

Flatten Layer: This layer transforms the multi-dimensional feature maps into a one-dimensional vector, preparing the data for the dense layers. It serves as a bridge between feature extraction and the final classification stage by condensing learned features into a format that supports accurate blood group prediction.

Dense Layer: The dense (fully connected) layer, with 64 neurons, interprets complex relationships among features to make classification decisions. Using ReLU

activation, it passes only positive activations forward, allowing for informed predictions of the blood group classes based on prior feature learning.

Output Layer: The output layer has eight neurons corresponding to each blood group. It uses the softmax function to convert raw scores into probabilities, with the highest probability indicating the predicted blood group. This probability-based approach aids in reliable blood group identification for healthcare use.

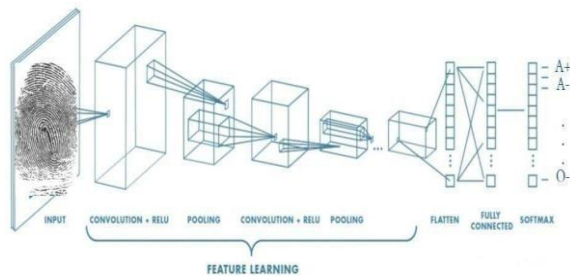


Figure 1: Architecture of the basic CNN Model for Blood Group Detection

4. Outcomes

1) Training Accuracy Calculation: During training, the model's accuracy is measured by its ability to classify images from the training set. Using the fit method in Keras, the model processes image batches, updating its parameters after each batch based on feedback from the loss function. As training progresses, the model's accuracy improves as it learns to identify blood group features in the images.

2) Validation Accuracy Calculation: Validation accuracy is calculated on a separate dataset the model hasn't seen during training. This is tracked using the validation data parameter in the fit method, allowing the model to evaluate its performance after each epoch. The validation accuracy is crucial for checking if the model is overfitting. Initially, it was lower but gradually improved as the model started generalizing better.

3) Assessing Model Performance: After training, we used the evaluate method to assess the model's final performance on the validation dataset. The model's final accuracy was around 86.97% after 20 epochs, indicating it had learned to classify blood groups well while maintaining good generalization to new data.

Table 2: Classification Report

	Precision	Recall	F1-Score	Support
A+	0.92	0.90	0.91	113

	Precision	Recall	F1-Score	Support
A-	0.83	0.90	0.87	201
AB+	0.92	0.84	0.88	141
AB-	0.92	0.88	0.90	152
B+	0.92	0.88	0.90	130
B-	0.90	0.93	0.93	148
O+	0.85	0.88	0.86	170
O-	0.85	0.85	0.85	142
Accuracy			0.88	1197
Macro avg	0.89	0.88	0.89	1197
Weighted avg	0.89	0.88	0.88	1197

4) Graphical Representation of Accuracy: To visualize the training and validation accuracy, we implemented a function to plot accuracy values over the training epochs. This graph illustrates how both accuracies change during training, allowing us to quickly assess model performance. In our implementation, we noted that the plot displayed both training and validation accuracy, highlighting their trends. This visual representation is crucial for understanding whether the model is overfitting or underfitting based on the relationship between the two accuracies.

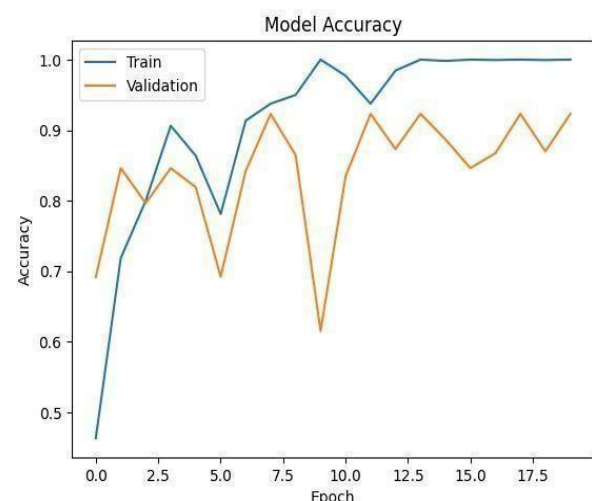


Figure 2: Training and Validation Accuracy Graph

5) Comparative Analysis with Existing Models: A bar graph is included to compare the performance of our proposed model with the accuracy rates of models referenced in the literature review, including LeNet-5, AlexNet, VGG16, and ResNet. Each of these models has been reviewed for their application in fingerprint-based blood group detection.

The graph clearly shows the incremental improvement in accuracy achieved by our model.

Table 3: Comparison with Existing Model

Sr. No	Paper Reference	Technique used	Accuracy
1	[1]	Used LeNet & AlexNet, CNN architecture	61%
2	[2]	CNNs, SIFT, ORB, PPG signals	91%
3	[4]	Ridge frequency estimation, Gabor filtering	62%
4	[6]	VGG16, ResNet, AlexNet, Transfer Learning	76%
5	[7]	GLCM, Wavelet Transform, BPNN	80%
6	[8]	CNNs (VGG, ResNet, AlexNet, Custom CNN)	76%
7	Proposed Model	CNN	86.97%

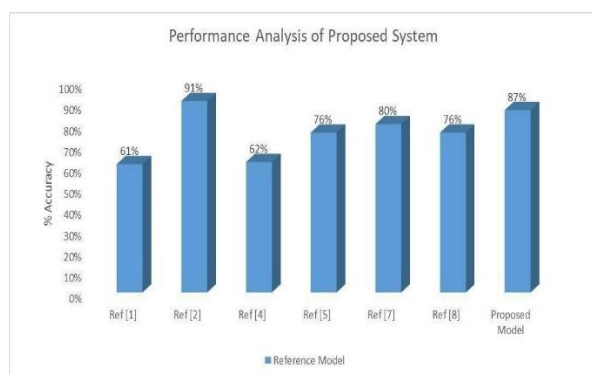


Figure 3: Performance analysis of proposed system

5. Conclusion

Proposed model achieved a solid validation accuracy of around 86.97%. Through this process, we learned a lot about how CNNs work to extract important features from images. By using several convolutional and pooling layers, we improved the model's ability to recognize specific patterns for each blood group. We also paid close attention to both the training and validation accuracy, which helped us understand how well the model learning and how it would perform on new, unseen data. Choosing the right loss function, categorical cross-entropy, and using the Adam optimizer were key to making the training process more efficient and boosting the model's performance. This phase not only gave us a better grasp of deep learning and image processing but also set a strong foundation for future improvements in blood group detection technology.

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