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Blood_Group_Detection_using_Fingerprint_patterns__A_De...

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Blood Group Detection Using Fingerprint Patterns A Deep Learning Approach

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***Abstract*—Accurate and timely blood group identification is crucial in medical diagnostics, transfusion medicine, and forensic science. Traditional blood typing methods rely on laboratory-based serological testing, which is accurate but invasive, time-consuming, and resource-intensive. This research proposes a non-invasive approach to blood group classification using fingerprint patterns and deep learning techniques. By leveraging the unique ridge patterns in fingerprints, a Convolutional Neural Network (CNN) based model was developed to predict blood groups with a high accuracy. The dataset was preprocessed thoroughly, including class balancing, image normalization, and augmentation to enhance the model's performance. The trained CNN was evaluated using standard classification metrics, including accuracy, recall, precision, and confusion matrix, which showed promising results in predicting blood groups. The results show the potential of deep learning models in biometric-based blood typing, a cost-effective, scalable, and rapid alternative to traditional methods. Future works should focus on increasing dataset diversity (a real-time dataset, like different age groups biometrics), transfer learning, and validating the model in real-world clinical settings to improve its robustness and generalizability.**

Keywords: Blood Group Classification, Deep Learning, CNNs, Fingerprint Recognition, Image Processing, Non-Invasive Blood Typing, Machine Learning, Feature Extraction and Medical Diagnostics.

1. INTRODUCTION

Through decades of research, a fingerprint has been recognized as a strong tool within the identification of psychological, medical and genetic conditions. The most common use of fingerprints is pattern recognition for identity verification which is employed in majority of Indian enterprises[1].

There has been a growing interest in exploring alternative methods for blood group detection in order to tackle the traditional invasive methods that require a blood sample. One such approach is the use of fingerprints to determine or predict an individual's blood group[8]. This method has gained attention due to its non-invasive nature, accuracy, and speed. It uses Convolutional Neural Network for feature extraction and predictions[9][10].

Recent studies suggests that there is a possible correlation between fingerprint ridge patterns and blood groups[14]. The unique arrangements of whorls, loops, and arches in fingerprints, influenced by psychological and genetic factors, has given rise to the hypothesis that fingerprint patterns can be used as a predictive feature for blood group classification[9]. Various Deep Learning and Machine Learning techniques, including Gray-Level Co-Occurrence Matrix (GLCM), K-Nearest Neighbor, and wavelet transform have been applied for the analysis of fingerprint patterns and correlate them with blood group characteristics[2][3][10].

In this study, a Deep Learning model based on CNN has been implemented to identify blood groups from fingerprint images. To improve model performance, the dataset is preprocessed using techniques like class balancing, image normalization, and augmentation. Accuracy, precision, recall and a confusion matrix are among the classification metrics used to assess the model after it has been trained with optimized hyperparameters. This method seeks to offer a quick, affordable, and non-invasive substitute for conventional blood group identification methods.

By using Deep Learning for non-invasive blood group classification, this study advances the expanding field of biometric-based medical diagnostics. The suggested method is especially helpful in emergency situations and remote healthcare settings since it not only increases efficiency but also does away with the need for traditional blood sampling. Future developments might involve diversifying datasets, incorporating transfer learning with pretrained models and evaluating the model in practical clinical setting.

2. RELATED WORK

The correlation between blood group classification and fingerprint patterns has been the subject of numerous investigations. Using distinctive ridge features, traditional fingerprint-based identification has been widely used for forensic and security applications. Using a variety of machine learning and deep learning approaches, researchers have tried to expand this biometric application to blood group classification.

The research presented here offers a practical approach for using fingerprint analysis to identify blood groups. Several machine learning techniques are used to predict blood groups based on fingerprint data, which is comprised of many unique minutiae features. With the use of Ordinary Least Squares (OLS) and Multiple Linear Regression, the proposed system attains a 62% accuracy rate. Future research should include more, as-yet-undiscovered fingerprint features for a more thorough analysis and increase the sample size to improve result precision.[1].

This research describes an affordable approach involving the identification of blood types with fingerprints. The technique for extracting features from fingerprint images con-

sists of GLCM (Gray Level Co-occurrence Matrix), wavelet transforms, texture feature extractions, and minutiae feature extraction. These features are then classified using a Back Propagation Neural Network (BPNN). The method identifies the blood group by matching fingerprint features to a database developed from previously classified images at an accuracy of about 80%. This technology aims to provide quicker and less invasive methods than current blood group testing methods [2].

This paper addresses the design of an automated system capable of determining human blood groups by using image processing techniques, all at a low cost. A CCD camera was used to acquire pictures of blood samples mixed with specific serums. Agglutination was detected by using the photos taken with the camera and special software (IMAQ Vision), which indicated the blood group. The process allows for a simple and fast way to find a blood type which may be useful in emergency situations. The authors suggest building a portable, low-cost device based on the concept and the system described[5].

This research presents two innovative genetic technologies for blood group genotyping. It outlines the reasoning indicating that single nucleotide variant (SNV) mapping using DNA micro-arrays and massively parallel sequencing (MPS) enhance accuracy in predicting blood group antigen phenotypes. The study mentions that SNV mapping has advantages associated with testing common blood groups while mentioning disadvantages in that it cannot identify new or rare alleles. MPS also has a higher throughput than SNV mapping and can identify genetic variants that have not been determined regardless of frequency, but MPS has much greater resource demands and generates massive amounts of data that requires substantial bio-informatics analysis. The study continues discussing how each of these technologies can improve transfusion safety by providing far more complete blood group typing. While SNV micro-arrays are feasible today, MPS could be the new gold standard[13].

The study describes a system for automating blood type detection with image processing technology. In emergency scenarios where quick and accurate blood group identification is critical, this technology enables the simultaneous testing of several blood samples, decreasing human error and increasing efficiency. Blood samples are mixed with certain antigens, and photos of the reactions are captured using a camera. The photos are then analyzed to identify blood type based on agglutination. The suggested technology enhances the speed and precision of blood type identification, making it perfect for high-demand situations like blood transfusions and roadside emergencies. The use of image processing ensures little human interaction, reducing errors and requiring specialized professionals[12].

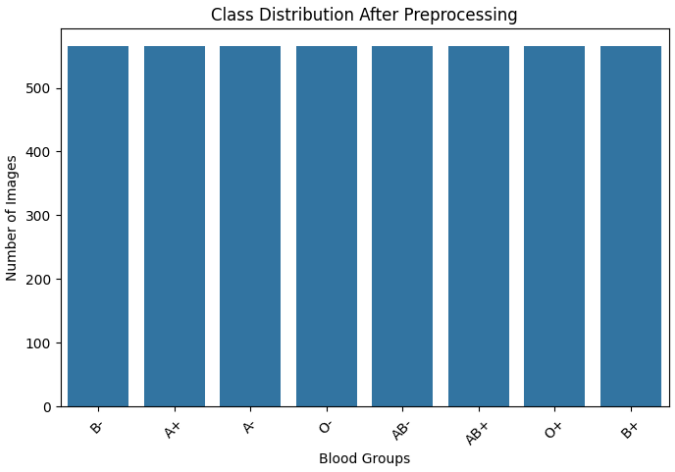
This research provides a new, non-invasive method for estimating human blood component levels (such as hemoglobin, glucose, and creatinine) from fingertip video data captured by a smartphone. The method employs photoplethysmogram (PPG) signals from fingertip videos illuminated by near-infrared (NIR) light-emitting diodes (LEDs). The study estimates blood component levels by extracting 46 standard features from the PPG signal, both its derivatives and through Fourier analysis, and using deep neural network (DNN) models. The models used genetic algorithms for feature selection and to minimize overfitting, which significantly assisted in yielding high accuracy estimates of hemoglobin, glucose and creatinine levels. The results suggest that the technology could be a noninvasive, easy alternative to obtain real-time health information in place of a blood sample[11].

Our work is based on previous literature that used a CNN-based model with a balanced dataset of fingerprint images. While previous studies either applied standard machine learning algorithms or a deeper neural network, the model presented in this study includes deep feature extraction to improve accuracy. We also incorporated preprocessing steps for abnormal dataset imbalance to facilitate better model training.

4. Methodology

A. Dataset Preparation and Preprocessing

The dataset utilized in this research is composed of fingerprint images sorted by blood group. This data was initially saved in compressed format and was unpacked to organized directories for processing. The dataset contained a different number of images in each class (blood group), resulting in the dataset not being balanced. In order to balance the dataset, images from each of the classes, except for the one that was the smallest class, were downsampled to achieve the same number of images in all the classes. This will prevent the model from being biased toward a dominant class.



The dataset was then split for 80% for training and 20% for testing to ensure proper generalization of the model. For image normalization, pixel values were rescaled between the values of 0 and 1 through the use of the ImageDataGenerator function. This step helps with convergence and the accuracy of classification. The model will utilize data augmentation techniques such as rotations, flipping, and zooming, in order to

enhance the generalization of the model and reduce overfitting. Through these augmentation techniques, the model can learn more robust features for real-world performance.

B. Model Architecture

The suggested model is a Convolutional Neural Network (CNN) that employs fingerprint images for blood group classification. The model consists of the following:

[1] Input Layer: Accepts fingerprint images of size (150x150) as input.

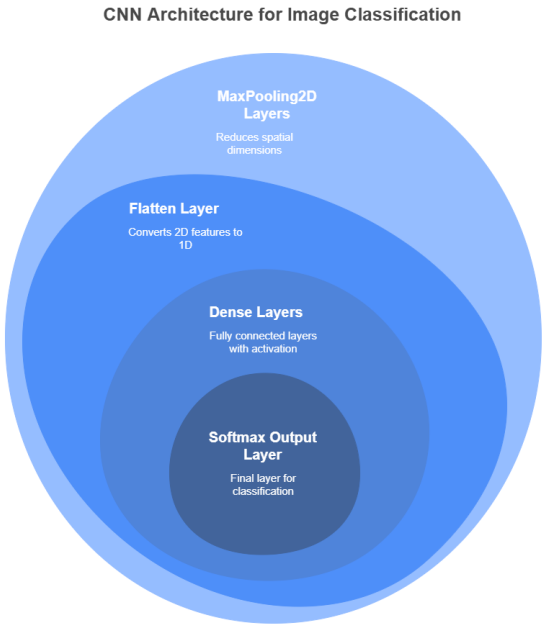
[2] Convolutional Layers: Three Conv2D layers consisting of 32, 64, and 128 filters, each utilizing a 3x3 kernel and ReLU activation. These layers extract hierarchical features from fingerprint images, portrayed in the previous face of efficient representation.

[3] MaxPooling Layers: A layer of MaxPooling2D (pool size 2x2) follows each convolution layer for reducing the spatial dimensions size and computational complexity.

[4] Flatten Layer: The features extracted in the earlier layers are converted into a one-dimensional vector for classification.

[5] Dense Layers: A dense layer with 512 neurons and ReLU activation provides high-level representation learning of the data.

[6] Output Layer: A dense layer softmax layer with the number of classes equaling the number of blood groups in the dataset. It produces probability scores for each class as output.



The following configurations were used to compile the model:

[1] Optimizer: Adam (a fine-tuning optimization algorithm that uses an adaptive learning rate).

[2] Loss Function: Categorical cross-entropy (a loss function designed for multi-class classification problems).

[3] Evaluation Metric: Accuracy (a metric for assessing classification performance).

The CNN model was trained for a total of 10 epochs with a batch size of 32, and the model performance was validated using a separate test dataset.

C. Results and Evaluation

C.1 Model Performance

The classification accuracy of the trained CNN model was assessed using the test dataset. The model showed a test accuracy of 88%, which indicates its ability to tell blood group patterns from fingerprint images.

Classification Report:

	precision	recall	f1-score	support
A+	0.91	0.94	0.92	113
A-	0.81	0.89	0.85	113
AB+	0.87	0.94	0.90	113
AB-	0.93	0.75	0.83	113
B+	0.90	0.93	0.91	113
B-	0.82	0.94	0.88	113
O+	0.93	0.79	0.85	113
O-	0.90	0.86	0.88	113
accuracy			0.88	904
macro avg	0.88	0.88	0.88	904
weighted avg	0.88	0.88	0.88	904

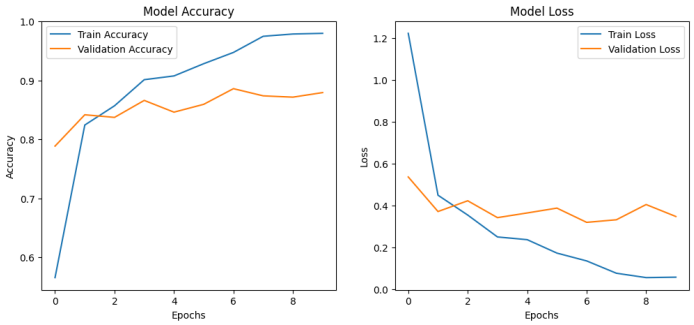
C.2 Accuracy and Loss Analysis

The model's learning performance was evaluated by plotting both accuracy and loss curves for training and validation sets. The results indicated that:

[1] Training accuracy improved steadily over the epochs, which represented the model's learned useful patterns from training data.

[2] Validation accuracy was relatively stable, which meant the model generalized well without significant overfitting.

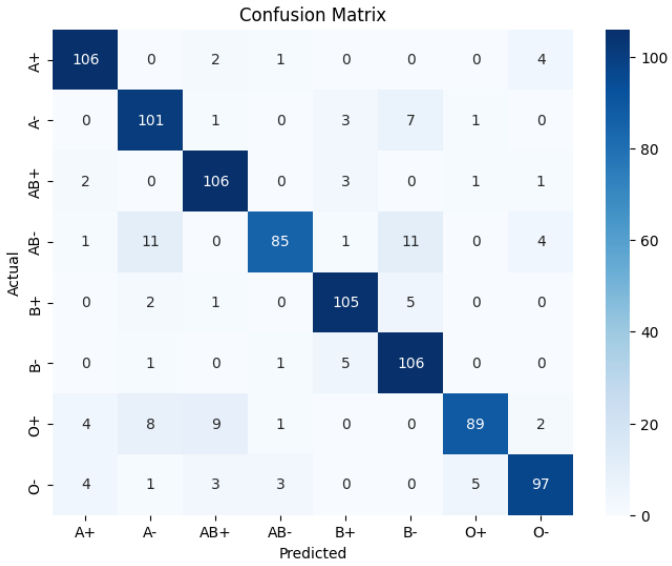
[3] Training loss decreased over the course of learning, suggesting that the model was optimizing well and a small gap training vs. validation loss means that the model is well regularized.



C.3 Confusion Matrix and Classification Report

A confusion matrix was created to assess the model's ability to accurately classify different blood groups. The

matrix offered insights into:
[1] True and false positive rates for each blood group category.
[2] Misclassification patterns revealed which blood groups were more likely to be confused with others.



The categorization report comprised precision, recall, and F1-score metrics:
[i] Precision refers to the fraction of accurately anticipated examples per class.
[ii] Recall represented the percentage of genuine positives accurately identified.
[iii] The F1-score was a harmonic mean of precision and recall, indicating overall model performance.

C.4 Comparison with Existing Studies

The achieved results were compared to prior studies on fingerprint-based blood group classification. When compared to classic machine learning algorithms like multiple linear regression and support vector machines, the CNN model outperformed them in terms of accuracy and resilience. Additionally, data augmentation and dataset balancing helped to enhance performance.

5. CONCLUSION

The present study describes a deep learning-based method for non-invasive blood type classification with fingerprint pictures. The proposed CNN model effectively harvests and learns discriminatory fingerprint characteristics, resulting in competitive classification accuracy. The model increased its generalization capabilities by resolving dataset inconsistencies using preprocessing techniques and data augmentation.

Despite these developments, several difficulties persist. The model's accuracy is affected by fingerprint image quality and dataset size. Future study should look into larger and more diverse datasets to improve robustness. Furthermore, combining transfer learning with pre-trained models like VGG16 or ResNet may improve performance. Another interesting approach is to use explainable AI approaches to evaluate model decisions and increase reliability in medical diagnoses.

Expanding the suggested approach to real-world healthcare contexts, such as automatic blood group identification in hospitals and emergency situations, could considerably improve the approach's usefulness. Further advances in sensor technology and fingerprint preprocessing approaches can help to boost the precision and uptake of biometric-based blood group classification.

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