Blood Group Detection using Fingerprint: A CNN based Non-invasive Prediction Model

Maheswar Das
OmDayal Group of Institutions
Birshibpur, Howrah, West Bengal, India

Dhrubajyoti Ghosh, PhD
OmDayal Group of Institutions
Birshibpur, Howrah, West Bengal, India

ABSTRACT
Blood group detection is a crucial fundamental procedure in medical treatment. It helps to ensure safe blood transfusions, organ and tissue transplantation, genetic studies and many more. Traditional blood group detection techniques are invasive and time-consuming. It is typically done using serological techniques that require laboratory equipment, trained laboratory personnel, reagents such as Anti-A Anti-B, Anti-D antisera. A non-invasive novel approach for blood group detection is proposed in this research. Using Convolutional Neural Network (CNN), a model is designed that is capable of identifying blood groups from fingerprints. This system indicates that an individual's blood group can be predicted based on his/her fingerprint. The proposed system contains fingerprint dataset acquisition, image preprocessing, feature extraction, model training and blood group prediction. This is an easy, cost-effective and promising approach. Detecting blood groups using fingerprints should be considered a decision-support tool rather than a substitute for standard serological blood tests until validated through extensive clinical studies.

General Terms
Deep learning in Healthcare, Fingerprint analysis

Keywords
Blood Group Detection, Convolutional Neural Network (CNN), VGG16, Biometrics.

1. INTRODUCTION
Fingerprint patterns are distinct for every individual and it remains the same until a person's demise. The probability of getting the same fingerprint pattern of two different individuals is very low, nearly one in sixty-four thousand million. Also for twins minutiae patterns are different. Fingerprint images contain some lines, called ridge. The lighter areas in between ridges are called valleys. Ridges break in some points, called miniature points. Loops, Whorls, Arches are three types of fingerprint plans found in fingers. In loop ridge lines enter from one side of the finger, curve around, and exit from the same side. Ridge lines form circular, spiral, or concentric patterns in Whorls. In Arches ridge lines enter from one side, rise in the center like a wave or hill, and exit from the opposite side.

A Convolutional Neural Network (CNN) is a type of deep learning model designed primarily for processing images and other grid-like data. CNNs automatically learn important features like edges, textures, shapes, and objects from images without requiring manual feature extraction.

Here a CNN based model has developed that is capable of identifying some characteristics in the same blood groups fingerprints. It can predict blood groups of unseen images. This research showed that some similar features are present in the same blood group fingerprints although all fingerprints are unique.

This paper consists with five sections. Section one contains introduction, section two describes the literature survey, section three briefly explained the methodology, section four discussed about the results and finally section five shows the conclusion.

2. LITERATURE REVIEW
This literature review evaluates several previous studies focused on using machine learning for blood group detection. In 2024 a paper named, “Blood group detection through finger print images using image processing (KNN)”[7], by G. Mounika, M. Anusha, D. Gopika and B. Siva kumari, proposed a K- Nearest Neighbor (KNN) based machine learning model for blood group identification using fingerprints. They used Ridge frequency estimate for matching the blood groups. Dr. M. Lakshmi Prasad, K. Niharika, D. Harshitha, SK. John Saida, compared various machine learning models and shows their accuracies in a research paper named "Blood Group Prediction Using Fingerprint"[8], They used AdaBoost Classifier, Decision Tree Classifier, Logistic Regression, Random Forest Classifier for prediction. A paper named “Blood group determination using fingerprint”[9], by T Nihar, K Yeswanth and K Prabhakar , shows that using a Gabor filter features can be extract that can identify blood group from fingerprint images. N. Patil and D. R. Ingle in their research paper, "A Novel Approach to Predict Blood Group Using Fingerprint Map Reading"[5], proposed a fingerprint map reading approach for predicting blood groups using machine learning. Their work investigated the association between fingerprint ridge characteristics and blood group information and demonstrated the feasibility of non-invasive prediction techniques, motivating further research into deep learning-based solutions.

3. METHODOLOGY
The methodology is summarized in the processing model flowchart:

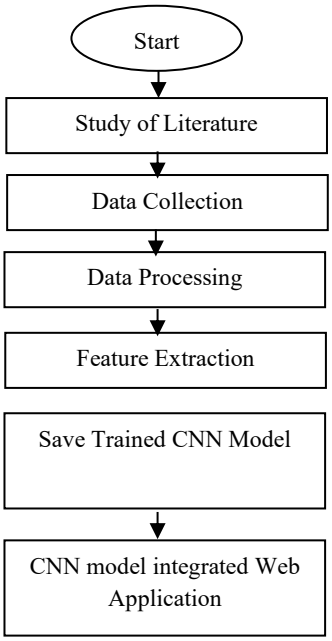

Fig 1: **Model accuracy graph**

The process includes gathering the fingerprint dataset, preprocessing, splitting the data, train a CNN model and finally develop a Web Application with integration of that model.

3.1 Data Collection

Fingerprints and the associated blood groups of individuals required for this proposed system. Manual medical surveys carried out, where various age groups, demographics, and gender people fingerprints and their blood groups were collected using fingerprint sensors. Such datasets are available on the internet.

Dataset[10] was used to train the CNN model. This dataset contains eight thousand fingerprint images divided into eight blood groups. Each group contains one thousand images.

Dataset[11] is organized into eight blood group classes. A+ contains four hundred and two images. A- contains one thousand and nine images. AB+ contains seven hundred and eight images. AB- have seven hundred and sixty one images. B+ have six hundred and fifty two images. B- contains seven hundred forty one images. O+ consist of eight hundred and fifty two images. O- have seven hundred and twelve images.

Both datasets images are in .BMP (BitMaP Image) format. The dimensions of all images are 96×103 pixels.

3.2 Data Preprocessing

To improve the reliability and accuracy of blood group prediction from fingerprint images, a comprehensive image preprocessing pipeline was implemented before training the deep learning model. The primary objective of preprocessing is to enhance the quality of the fingerprint images, reduce unwanted artifacts, and emphasize the ridge characteristics that contain discriminative information.

Initially, noise reduction techniques were applied to eliminate image distortions and random noise that could negatively affect feature extraction. Subsequently, contrast enhancement was performed to improve the visibility of fingerprint ridges and valleys, making the structural patterns more distinguishable. Pixel values were normalized to the range of 0–1 to improve training stability. Ridge pattern enhancement techniques were further employed to strengthen the fingerprint ridge structures, enabling the model to extract more meaningful and robust features.

After preprocessing, all fingerprint images were resized to a fixed dimension of 224 × 224 pixels, ensuring a uniform input size compatible with the convolutional neural network (CNN) architecture. During model training, a batch size of 32 was used to optimize computational efficiency while maintaining stable gradient updates.

The prepared dataset was divided into training and validation subsets following an 80:20 split. Specifically, 80% of the fingerprint images were used for training the CNN model, allowing it to learn representative features associated with different blood groups, while the remaining 20% of the images were reserved for validation to evaluate the model's generalization capability and monitor its performance on previously unseen data. This data partitioning strategy helps reduce overfitting and provides a reliable assessment of the model's predictive performance.

VGG16 is a popular Convolutional Neural Network (CNN) architecture developed by the Visual Geometry Group at the University of Oxford in 2014. It was introduced by Karen Simonyan and Andrew Zisserman. It became well known for its simple architecture and excellent performance in image classification tasks. It has 16 learnable layers, where 13 Convolution layers and 3 Fully connected layers.

3.3 Feature Extraction

Feature extraction was performed using the VGG16 through transfer learning. The convolutional layers of VGG16 automatically extracted hierarchical fingerprint features, including ridge orientations, texture patterns, local edge information, and fine structural characteristics. These deep features provide a more discriminative representation than handcrafted descriptors. The pre-trained convolutional layers were retained as a feature extractor, while the original classification layers were replaced with custom dense layers suitable for fingerprint-based blood group prediction. This approach reduced training time and improved feature learning by utilizing knowledge acquired from large-scale image datasets.

3.4 Classification

After feature extraction, the learned feature vectors were passed through fully connected layers followed by a Softmax output layer to classify the fingerprint into one of the eight blood group categories. The model was trained using the categorical cross-entropy loss function and optimized using the Adam optimizer. During training, the network iteratively adjusted its weights through backpropagation to minimize classification error. The trained model was finally integrated into a web application, where users can upload a fingerprint image and obtain the predicted blood group in real time.

4. RESULT

The model was trained for 20 epochs using the preprocessed dataset. After 20 training epochs, the model achieved a training accuracy of 97% and a validation accuracy of 87% (Fig -2).

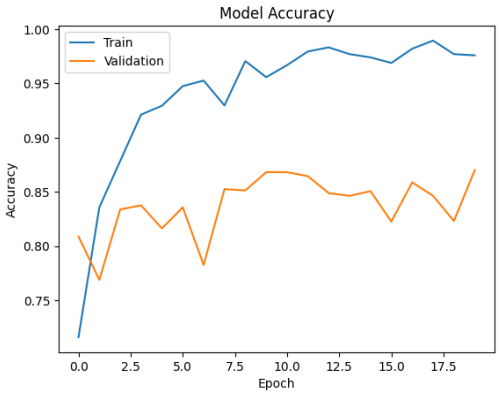

Fig 2: **Model accuracy graph**

The high training accuracy indicates that the model successfully learned discriminative fingerprint features, while the validation accuracy demonstrates its ability to generalize to previously unseen fingerprint images. The difference between training and validation accuracy suggests a moderate level of overfitting, which is common in deep learning models trained on relatively limited datasets.

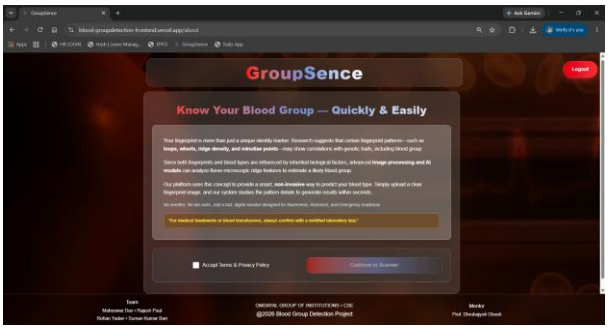

Fig 3 : About Page

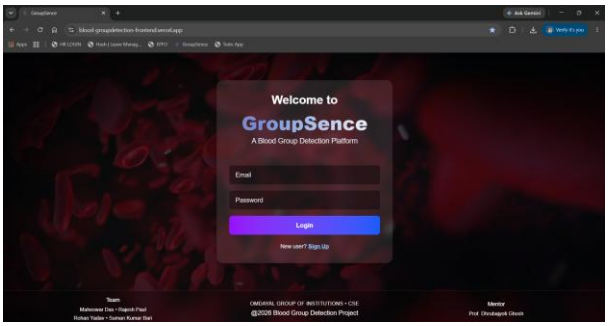

Fig 4 : Login Page

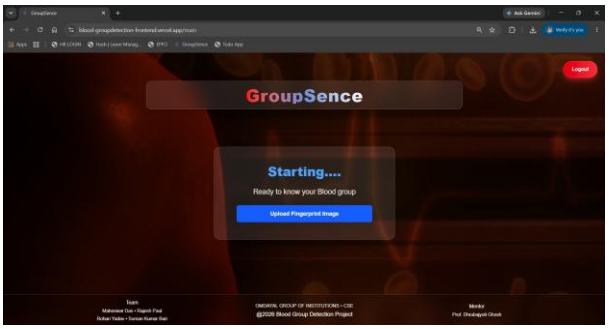

Fig 5 : Main Page (click on upload fingerprint and add the image)

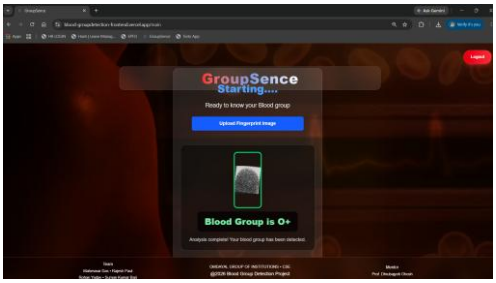

Fig 6 : Result (click on image and blood group will show)

The trained model was integrated into a web-based application (Fig – 3,4,5,6) that enables users to upload a fingerprint image and receive the predicted blood group in real time. Experimental results indicate that the combination of image preprocessing, VGG16-based feature extraction, and Softmax classification provides an effective framework for fingerprint-based blood group prediction. However, the proposed system is intended as a research-oriented prediction model and should not replace conventional serological blood group testing without extensive clinical validation on larger and more diverse datasets.

5. CONCLUSIONS

However the proposed model showed promising results still it can be enhanced in terms of accuracy, reliability, computational efficiency, and generalization capabilities through several future research directions. Major limitations of the proposed model was the availability of a limited dataset. In future research, the model should be trained and evaluated using a significantly larger dataset containing fingerprint images from individuals belonging to different age groups, genders, ethnic backgrounds, and geographical regions. A diverse dataset would help the model learn more generalized fingerprint patterns and reduce the possibility of overfitting. Investigation may be done with more advanced deep learning architectures to improve feature extraction and classification performance. Models such as EfficientNet, Vision Transformers (ViT), DenseNet, and ConvNeXt can be explored and compared with the existing architecture. Also an important future direction is the development of a multimodal biometric-based prediction system. Instead of relying exclusively on fingerprint images, the proposed approach can be extended by combining multiple biometric characteristics, such as fingerprints, retinal images, and facial features. Fingerprint images can be combined with eye-related biometric images to investigate whether complementary features improve the model's prediction performance. However, the contribution of each biometric modality must be experimentally validated.

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