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IoT based Blood Group Prediction using Fingerprints

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Abstract
This research paper aims to contribute to the field of non-invasive medical diagnostics. Blood group identification is a crucial aspect of medical diagnostics, emergency healthcare, and forensic investigations, as it plays a vital role in blood transfusions, organ transplants, and forensic identification. Traditional blood typing methods rely on serological testing, which involves chemical reagents, specialized laboratory equipment, and trained medical personnel. While these methods are accurate, they can be time-consuming, invasive, and impractical in remote or emergency scenarios. To overcome these challenges, this study presents a novel, non-invasive approach for blood group detection using fingerprint images and deep learning techniques. The research explores the hypothesis that there exists a correlation between fingerprint ridge patterns and blood groups, enabling automated classification without requiring a blood sample. A fingerprint dataset is utilized to train a deep learning-based model for blood group prediction. A Convolutional Neural Network (CNN) is employed to extract high-level features from fingerprint images, which are further analysed using supervised machine learning classifiers. The dataset undergoes a series of preprocessing steps, including noise reduction, contrast enhancement, edge detection, and feature scaling, to optimize the input for deep learning models. The CNN model is trained on labelled fingerprint images, and its performance is evaluated using key classification metrics such as accuracy, precision, recall, and F1-score. This research paves the way for further advancements in AI-driven medical diagnostics and bioinformatics, promoting innovation in healthcare technology.
Keyword; Artificial Intelligence (AI), Convolutional Neural Network (CNN).

1. Introduction

Blood group identification is an essential procedure in medical diagnostics, blood transfusion compatibility, organ transplantation, and forensic science. Traditional blood typing methods rely on serological techniques that involve chemical reagents and laboratory infrastructure, making them invasive, time-consuming, and inaccessible in resource-limited settings. To address these challenges, recent advancements in AI and machine learning have opened new possibilities for non-invasive blood group detection through biometric features such as fingerprint analysis.

Fingerprints have unique ridge patterns that have been widely used for identification and authentication purposes. Recent studies suggest [1] a correlation between fingerprint features and blood groups, allowing the development of AI-driven models to classify blood groups based on fingerprint images. This study proposes a deep learning-based approach using CNN and supervised machine learning techniques to

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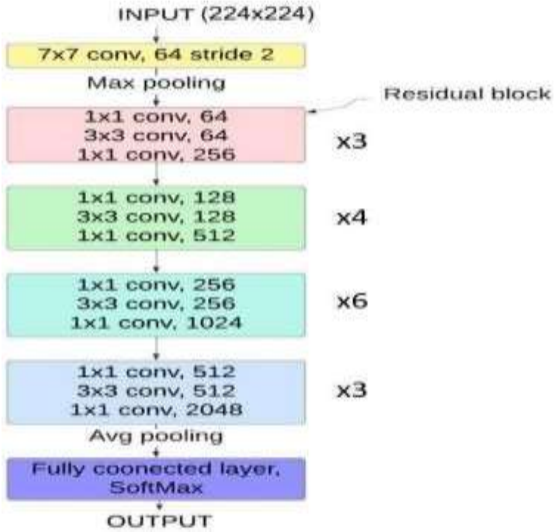
detect blood groups from fingerprint images. The proposed method leverages the [2] ResNet50 enables efficient feature extraction by utilizing skip connections that mitigate the



vanishing gradient problem in deep networks. The extracted features are then used for blood group classification using various supervised machine learning algorithms like Softmax Regression. The study involves preprocessing the fingerprint dataset to enhance image quality by applying noise reduction, contrast enhancement, and edge detection techniques. The dataset is then used to train and evaluate different models.

2. Related Work

2.1 Resnet50 architecture

The Resnet50 Layer Structure consists of following elements: -

1. Initial Convolution: A 7x7 convolution [4] with 64 filters and stride 2 is applied, followed by max pooling to reduce spatial dimensions.
2. Residual Blocks: The network consist of four stages of residual blocks. Each block contains 3 convolutional layers:

- 1x1 for dimension reduction.
- 3x3 for feature extraction.
- 1x1 dimension expansion.

A. Global Average Pooling: Reduce the feature map dimensions.

B. Fully Connected Layer + SoftMax: Outputs class probabilities for classification.

Figure1. Resnet50 Layer Structure

2.2 Skip Connection

2.2.1. Identity Block:

Identity block has the same spatial dimension at both the input and output side. The input goes through a series of convolutional layers to extract features. [5] Instead of just passing through the convolutional layers, the input bypasses them using a skip connection. The output of the convolutional layers is added elementwise to the input from skip connection helping gradient flow during backpropagation.

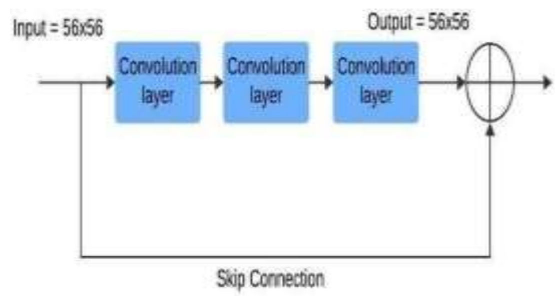


Figure 2. Identity Block

2.2.2. Convolution Block:

The input is passed through a series of convolutional layers. These layers apply filters (kernels) to detect patterns such as edges, textures, and shapes. During this process, the spatial size of the feature map is reduced to half which may happen due to Stride convolution. [5] For this an extra convolutional layer is added to reduce input dimensions. The output of the convolutional layers is added elementwise to the input from skip connection helping gradient flow during backpropagation.

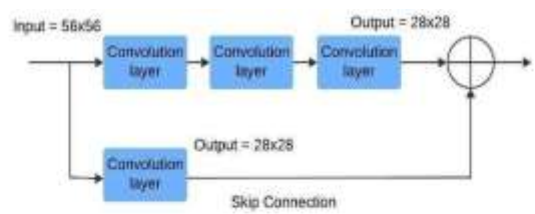


Figure 3. Convolution Block

3. Proposed Methodology

This research paper focuses on creating a CNN model that can classify fingerprint images in different blood group categories.

The steps taken are as follows: -

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3.1 Data Collection

We have collected images of different blood groups viz. A+, AB+, O+, B+, A-, AB-, O- and B- from Kaggle website.

3.2 Pre-processing

We used an Image Data Generator library that helps preprocess images.

Resizing: All images are resized to 224x224 pixels as model demanded.

Data augmentation: It helps to [1] diversify data.

Normalization: Rescaled the pixel values between 0 and 1.

3.3 Feature Extraction

The [6] images contain patterns like whorl, arches, loops and composite [7] that can help in extraction of valuable insights.

3.4 Model Building

We used a pretrained model Resnet50 to extract features and predict the Blood group. The model has a total of 50 layers to process the images and uses SoftMax activation function for classification of images.

3.5 Training

Labelled images are supplied to the model during training.

Batch size: A size of 32 is used for training.

Epoch: 100 passes carried out on training data for better accuracy.

Optimizer: RMS Prop [4] algorithm is used to automatically adjust the learning rate.

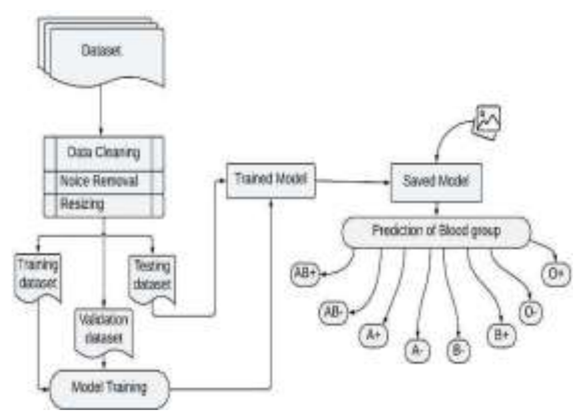

Figure 4. Block Diagram

4. Result

The fingerprint data was supplied to the trained model to calculate the performance of the model as follows:

- Accuracy: Model performs 98% accurately on fingerprint images.
- Precision: Model's precision score is about 97%.
- Recall: The calculated recall score is about 97%.
- F1-score: The balanced performance of the model is 98%

Figure 5. Uploaded Image

Figure 6. Predicted Blood Group

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5. Conclusion

The proposed method for blood group detection using the ResNet50 CNN on fingerprint images presents a viable alternative to conventional serological testing. ResNet50, known for its deep architecture and powerful feature extraction capabilities, effectively analyzes fingerprint patterns to predict blood groups with a high degree of automation. This approach offers a non-invasive, rapid, and cost-efficient solution, reducing reliance on laboratory-based techniques and specialized personnel. [3] By leveraging deep learning, ResNet50 enhances accuracy while minimizing human error, making blood group detection more accessible, particularly in resource-constrained environments.

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