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Machine Learning Based Blood Group Prediction on Fingerprint Images

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Abstract – This paper provides a methodology for predicting blood-type classification which uses fingerprint images as input with the help of deep learning to propose an effective technique that is non-invasive, easy and more validated than conventional techniques. The main goal of this work is to determine blood group via fingerprint patterns by utilizing CNN and VGG16 architectures. The dataset of labelled fingerprint images was preprocessed before then being utilized to train and also for validate the models and we evaluated it through precision-recall curves, confusion matrices and class-wise accuracy analysis. The results indicate that VGG16 achieves higher accuracy is most of the blood group categories, while the CNN model shows a marginally better performance in classifying the A+ group. Both architectures deliver reliable outcomes with AUC scores exceeding 0.93 for all classes. These findings confirm that predicting blood groups from fingerprint patterns is not only practical but also effective with promising applications in healthcare, forensic science and biometric security.

Key Words: BloodGroup, Fingerprint, VGG16 Framework, CNN, biometric Authentication.

1.INTRODUCTION

Identifying an individual's blood group plays a vital role in medical diagnostics, especially during critical situations such as organ transplants or blood transfusions. Conventional methods rely on drawing and testing blood samples in laboratory settings, a process that often demands specific tools, chemical reagents and additional time. This study proposes fingerprint based blood type determination using machine learning to test the feasibility of detecting blood types using biometric analysis. Fingerprints are unique to each individual with a specific ridge pattern that may connect with hereditary variables like blood type. The system records and analyses fingerprint patterns using machine learning models which includes ridge density, minutiae points and pattern types (loop, whorls and arches). A trained ML algorithms like CNN and VGG16 categorizes the fingerprint images in accordance with the blood type. This technology has the potential to improve blood donation centres, emergency medical care and personal health monitoring by providing a rapid, cost-effective and non-invasive method of detecting blood groups. This paper proposes a non-invasive blood type detection method using fingerprint image processing and machine learning. This method employs fingerprint patterns to classify blood groups, unlike other approaches that requires blood samples. This technique offers a quick and affordable option for medical emergencies and blood donation centers. This method's success relies on accurate fingerprint and blood group corelations and substantial dataset training.

Table1: Relationship between blood group and fingerprint patterns

Blood Group	Primary Pattern	Secondary Pattern	Explanation
A+	Loop	Whorl	Loops are most frequent in A group individual
A-	Loop	Arch	Loops dominant but arches also appear
B+	Whorl	Loop	B group tends to show more whorls than other groups
B-	Whorl	Arch	Similar to B+ with slightly more arches observed
AB+	Mixed (Loop + Whorl)	None	Combination of A and B traits hence mixed patterns
AB-	Mixed (Whorl + Arch)	Loop	Less common and patterns may vary widely
O+	Arch	Loop	O group shows higher arch frequency especially in O+ males
O-	Loop	Arch	Loops more common but arches appear significantly too

2. RELATED WORKS

Recently, Convolutional Neural Networks (CNNs) have emerged as a prominent actor in the area of image processing and classification. Its deep and uniform architecture makes it perfect for feature extraction in medical and biometric image processing. This literature review reviews existing research on the application of machine learning in biometric systems, with a focus on approaches that use fingerprint images for classification tasks such as blood group prediction. Recent breakthroughs in deep learning have enabled revolutionary non-invasive ways for blood group identification based on biometric data. C Siva Balaji Yadav et al. [1] present a framework that compares CNN, MobileNet, ResNet+RNN and Vision Transformer (ViT) architectures, with ViT reaching maximum accuracy via self-attention methods. Their preprocessing workflow and enhanced dataset demonstrate reliable feature extraction from fingerprint ridges, providing a scalable alternative to standard blood testing. Dr. Mahmood Ali Mirza et al. [2] made a significant contribution in this area by developing a CNN based model to categorize blood types using fingerprint images. Their method involved extensive preprocessing, minutiae and texture based feature extraction and they obtained approximately 90% accuracy. It also employs CNNs, their work centered on distributing the model via a flask-based web application and boosting latent fingerprint accuracy. K Lahari et al. [3] introduced a fingerprint-based system that used the KNN algorithm and was trained on 3784 fingerprint samples, attaining high accuracy in blood group categorization. The system combines minutiae based feature extraction with AES-256 encryption to provide secure data retrieval in 3-5 seconds. Mr. P V Rama Gopal Rao et al. [4] created a CNN model using Gabor Filterss that reached 97.5% accuracy, indicating the feasibility of non-invasive testing. Their study contributes significantly to my research on portable diagnostics. Ms. Amritha Mishra et al. [5] obtained 95% classification accuracy by using a non-invasive method that uses CNN (ResNet50) to evaluate fingerprint patterns via picture preparation such as grayscale conversion, noise reduction, minutiae extraction. N Anitha et al. [6] created a system that used MobileNet, ResNet-RNN hybrid and Vision Transformers, reaching a validation accuracy of up to 90.6% using the Vision Transformer model. Prof. Chetan Padole et al. [7] provide a detailed study of fingerprint-based blood group identification systems, with a focus on CNN architectures that asses ridge patterns and minute details. Their research discusses preprocessing techniques such as Gabor Filtering. Qarat Ul Ain et al. [8] propose a CNN based framework for blood class detection based on fingerprint analysis, which used convolutional layers for ridge pattern extraction and softmax activation of dense layers for classification. Rashmi V et al. [9] illustrated the transition by replacing serological blood tests with a 98% accurate CNN system that analyzes fingerprint ridge patterns. Their pipeline coupled OpenCV preprocessing with bespoke CNN model for feature extraction and softmax classification. Siddhi Rakshe et al. [10] investigated non-invasive medical diagnostics and provide a CNN based solution to blood group prediction based on fingerprint analysis. The researchers preprocessed 6000 fingerprint photos and trained a CNN architecture, which achieved 93.4% classification accuracy for ABO/Rh groups. Their technology is depends on feature extraction of ridges and outperforms existing serological methods. Swathi Chandra M T et al. [11] introduce HemoDect, a novel technique for blood type prediction from fingerprint analysis. The researchers used a LeNet-based CNN model with preprocessing approaches on fingerprint images and achieve 73.08% accuracy across 8 blood groups. Vedika Patil et al. [12] offers a CNN based method for blood type identification and attaining 92% accuracy. On a dataset of 1000 clinically confirmed fingerprint samples. They used a 12-layer CNN architecture and enhanced image preprocessing. The model performs well for common blood types but has problems with rare ones and a flask web interface allows for real-time deployment.

3. METHODOLOGY

The methodology is described in the subsections such as system workflow, dataset description, algorithm and model training.

A. System Workflow

The flowchart demonstrates the method for predicting blood types with VGG16 and CNN models based on fingerprint image prediction.

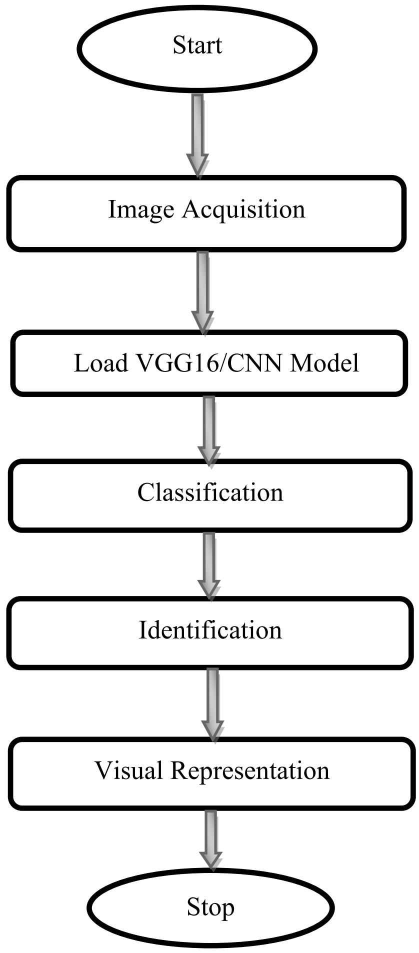

Fig 1: System Workflow

The above figure demonstrates the workflow of the proposed system. The proposed system for blood group prediction using fingerprint images begins when the user provides an image of their fingerprint either from the standard dataset or real time data. When the image is received, both the VGG16 and CNN models are loaded into the system and these models extracts the features. These models evaluate images by finding unique patterns such as loops, whorls and ridges. Based on this information the models generate predictions containing the identified blood group as well as a text to speech output and displays confidence score. The prediction findings are then processed and shown to the user in a clear visual format.

B. Dataset Description

The dataset employed in this work comprises of fingerprint photos categorized into eight different human blood groups. The images are placed in a structured directory format where the folder name represents the blood group class. Each fingerprint pattern is linked to a specific class label so it is a supervised learning. The overall attributes of the dataset are mentioned in the Table 2 and a sample preview of the dataset's architecture derived from the df.head() function is illustrated in the Table 3.

Table 2: Dataset Statistics

Dataset Name	**Fingerprint Dataset**
Total Images	6000
No. of classes	8
Images per Class	Approximately 750
Image Format	.bmp
Image Size	150x150 pixels

As showed in Table 2, the data is well structured across eight blood type classes with approximately 750 fingerprint images per class ensuring sufficient data for training. The defined image size is 150 x 150 pixels ensures uniform input to DL models and the .bmp format maintain image quality.

Table 3: Dataset Preview

Image ID	**File Path**	**Blood Group**
1	bloodgroup/dataset/A+/cluser_1_0.bmp	A+
2	bloodgroup/dataset/B-/cluser_3_7.bmp	B-
3	bloodgroup/dataset/AB+/cluser_4_4.bmp	AB+
4	bloodgroup/dataset/AB-/cluser_5_8.bmp	AB-
5	bloodgroup/dataset/O+/cluser_6_53.bmp	O+

The table 3 shows an example of the dataset structure using the df.head() function including image identifiers, file paths and a corresponding blood type labels. This method not only reduce model equality and preprocessing but also it assures that the dataset is properly formatted for reproducibility and future research. This organization facilitates the efficient handling of the dataset, allowing for easier loading of the images, efficient preprocessing, easy integration with ML pipelines and association of each fingerprint image with its true blood group label at training and model evaluation time.

C. Algorithm

➢ **Convolutional Neural Network (CNN)**

1. Input fingerprint image of size 150X150 pixels.
2. Apply preprocessing: resizing, normalization, augmentation.
3. Extract features using convolutional layers.
4. Apply ReLU activation for non-linearity.
5. Performs max-pooling to decrease dimensionality.
6. Repeat convolution + pooling to extract deeper features.
7. Flatten feature maps into a single vector.
8. Pass through fully connected dense layers.
9. Apply dropout regularization to reduce the overfitting.
10. Utilize the softmax activation in output layer to classify into the 8 blood groups.

The CNN architecture takes an input fingerprint image of dimension 150 x 150 pixels which is further subjected to preprocessing like resizing, normalization and augmentation. Deep hierarchical fingerprint features were extracted through convolutional and pooling layers with non-linearity added through ReLU activation. Max-pooling subsequently reduced the dimensionality. The feature maps are flattened and then moved through fully connected dense layers while using dropout regularization to reduce overfitting. The softmax activation function at the output layer classifies the fingerprint into one of the eight blood groups with accuracy.

➢ **VGG16**

1. Input fingerprint image of size 150 × 150 pixels.
2. Apply preprocessing: resizing and normalization.
3. Load pre-trained VGG16 model with ImageNet weights.
4. Remove the default top classification layers.
5. Add custom dense layers for 8-class classification.
6. Keep the first convolutional layers frozen to capture generic features.
7. Train added dense layers on the fingerprint dataset.
8. Refine the inner convolutional layers for adaptation.
9. Apply softmax activation at the output layer.
10. Predict the fingerprint blood group.

The VGG16 model takes fingerprint images having pixels of size 150x150. The VGG16 preprocessing steps involves resizing and normalization. This work uses a pre-trained VGG16 model with ImageNet weights. This work needs changing of default top layers of VGG16 with custom dense layers and train these layers. The initial convolutional layers are remain fixed for feature extraction whereas the incorporated dense layers are trained on the fingerprint dataset. The inner layers have been adjusted to cater to the particular characteristics of the domain while the softmax activation function at the output layer identifies the right blood group for the fingerprint.

D. Model Training

The training process include fit() method and several parameters are properly tuned. The processing of the data includes 32 sample batches to balance memory efficiency and gradient estimates quality. The model was trained for 30 epochs for VGG16 and 50 epochs for CNN which were adequate to achieve convergence without overfitting. The ImageDataGenerator generates augmented training batches in real time, while a separate validation generator assesses performance objectively. For each epoch it will make full-batch validation which involves computing metrics over the complete validation set rather than utilizing batched approximations.

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Epoch 1/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 369ms/step - accuracy: 0.1331 - loss: 2.1237
27/27 ━━━━━━━━━━━━━━━━━━━━ 14s 483ms/step - accuracy: 0.1331 - loss: 2.122
Epoch 2/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 336ms/step - accuracy: 0.1964 - loss: 2.0390
27/27 ━━━━━━━━━━━━━━━━━━━━ 12s 427ms/step - accuracy: 0.1967 - loss: 2.038
Epoch 3/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 330ms/step - accuracy: 0.2232 - loss: 1.9412
27/27 ━━━━━━━━━━━━━━━━━━━━ 12s 433ms/step - accuracy: 0.2244 - loss: 1.940
Epoch 4/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 352ms/step - accuracy: 0.3307 - loss: 1.7218
27/27 ━━━━━━━━━━━━━━━━━━━━ 12s 444ms/step - accuracy: 0.3305 - loss: 1.722
Epoch 5/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 337ms/step - accuracy: 0.4005 - loss: 1.5813
27/27 ━━━━━━━━━━━━━━━━━━━━ 12s 431ms/step - accuracy: 0.4000 - loss: 1.581
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Fig 2: Model Training

4. RESULTS AND DISCUSSIONS

The result of experiments using CNN and VGG16 models on blood group classification by fingerprint patterns are reported in this section.

A. Precision-Recall Curve

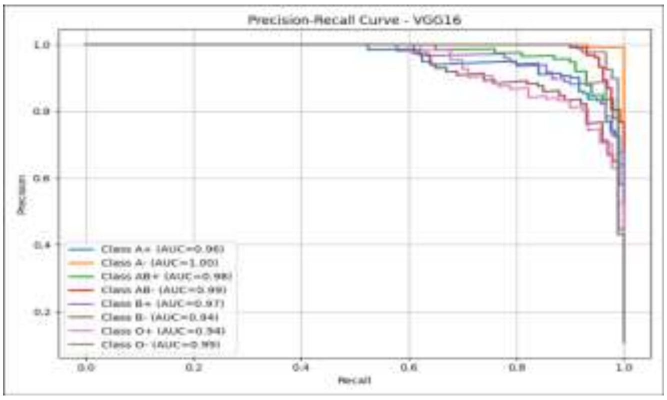

Fig 3: Precision-Recall Curve of VGG16

The Precision-Recall (PR) curve for the VGG16 model shows the link between the precision and recall for every one of the eight blood group classes. The curves are drawn using the true labels and model predictions with the AUC values given for each class. These values acts as a general measure of how well the model performs. The findings indicate the model has achieved high predictive accuracy with an AUC values between 0.94 and 1.00. The model achieves perfect classification for the class A- (AUC = 1.00) and almost perfect scores for AB+ (0.99) and O+ (0.99). The steep curves and high precision of the most recall values show that the VGG16 model can keep high accuracy even while retrieving many relevant samples. This highlights its strength and dependability for multi-class blood group determination based on fingerprint images.

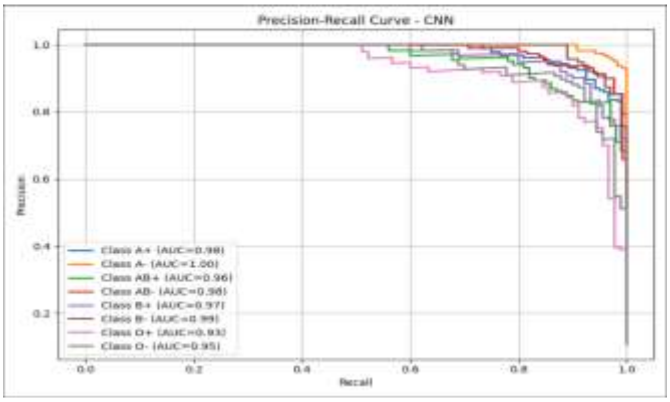

Fig 4: Precision-Recall Curve of CNN

The Precision-Recall (PR) curve for the CNN architecture shows the balance between precision and recall for every one of the eight blood group classes. Each curve's AUC score indicates the overall effectiveness of classification, with values from 0.93 to 1.00. The CNN model achieves perfect classification for class A- (AUC = 1.00) and performs well for A+ (0.98), B- (0.99), and AB+ (0.98). Although the scores for classes O+ (0.93) and O- (0.95) are slightly lower, the curves still remain steep. This suggests high precision even with higher recall values. These findings demonstrate that the CNN model is very effective for predicting multi-class blood groups. It maintains strong predictive reliability across most categories while managing the precision-recall trade-off effectively.

B. Accuracy Comparison

The accuracy comparison highlights the performance differences between the CNN and VGG16 models. Results shows that VGG16 achieves more accuracy than the CNN.

Table 4: Models Accuracy Comparison

Blood Group	CNN Accuracy(%)	VGG16 Accuracy(%)
A+	98.33	83.33
A-	97.50	99
AB+	86	87
AB-	95.38	98.46
B+	78.89	93.33
B-	90	94
O+	82.22	94.44
O-	90	96.66

The comparative accuracy table compares the effectiveness of CNN and VGG16 models for blood group classification. VGG16 surpasses CNN in most classes, particularly A+ (83.33% vs. 98.33% for CNN, where CNN is higher), B+ (93.33% vs. 78.89%), O+ (94.44% vs. 82.22%), and O- (96.66% vs. 90%), suggesting its stronger capacity to distinguish between certain blood types. CNN is more accurate for A+ (98.33% vs. 83.33% in VGG16) and comparable for AB+ (86% vs. 87%) and AB- (95.38% vs.

98.46%). While both models produce strong overall results, the accuracy differences indicate that VGG16 is more effective for groups with nuanced fingerprint patterns, whereas CNN excels in easily recognizable classes such as A+.

C. Prediction Accuracy Graphs

The prediction confidence graph depicts the model's output for a specific fingerprint sample, along with the identified blood group B- at a confidence level of 75.97%.

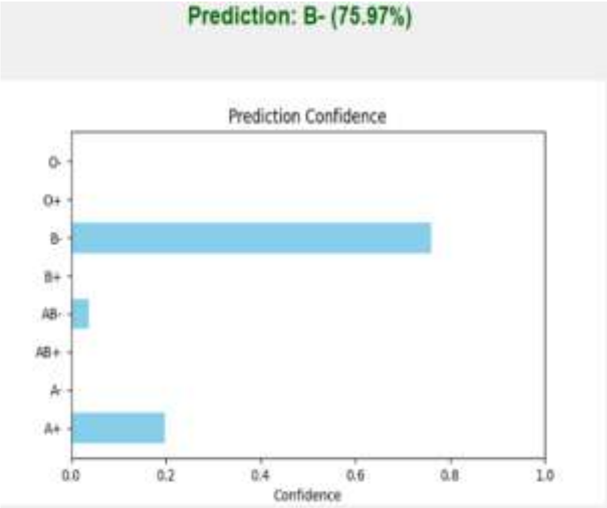

Fig 5: Prediction Accuracy of B-

The horizontal bar chart displays the confidence scores for all eight blood group classes, with B- having the highest probability, followed by A+ and minimum confidence in the other classes. This distribution indicates that the model is reasonably confident in its classification, but it also implies the presence of some uncertainty, as the confidence does not reach 100%, as is frequent in real-world biometric predictions where inter-class similarities may occur.

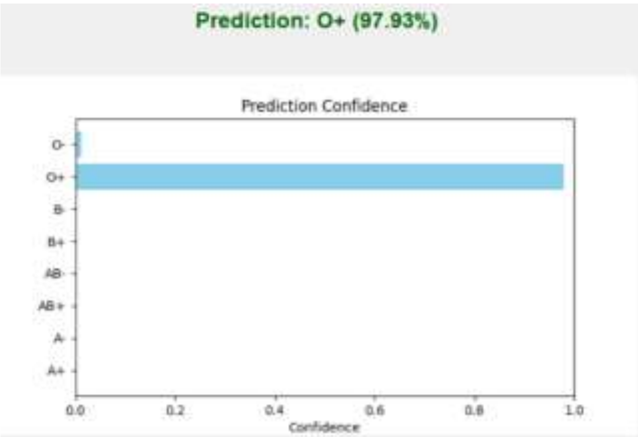

Fig 6: Prediction Accuracy of O+

The prediction confidence graph reveals that the model identified the fingerprint sample as O+ with a high confidence level of 97.93%. The horizontal bar chart shows that O+ has a significantly higher probability than all other blood group classes, which have nearly nil confidence levels. This high confidence score indicates a strong match between the input features and the learnt characteristics of the O+ class, demonstrating the model's high reliability in this specific prediction.

5. CONCLUSION

In conclusion, the proposed fingerprint-based blood group classification system exhibits good accuracy and resilience when utilizing both VGG16 and CNN models and as evidenced by performance evaluations such as precision-recall curves, confusion matrices and class-wise accuracy metrics. VGG16 outperforms CNN in the differentiating blood groups with minor fingerprint changes, although CNN performs well for some more distinct classes. The high AUC values across all classes imply significant precision-recall trade-offs and the model predictions shows high confidence levels for correctly categorized data. These findings support the use of deep learning models for non-invasive, quick, and reliable blood type identification with major potential applications in medical diagnostics, forensic science and also in biometric authentication.

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