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Blood Group Prediction using Fingerprint Patterns with Deep Learning

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***Abstract*- Blood group identification is vital in emergency care, forensic science, and medical research. Traditional methods are invasive and time-consuming, making them unsuitable for rapid or remote applications. This project introduces a non-invasive, AI-based approach to predict blood groups using fingerprint patterns. Leveraging dermatoglyphic correlations, a Convolutional Neural Network (CNN) based on the VGG16 architecture is employed to classify blood groups (A, B, AB, O) and Rh factors (+/-). A labelled fingerprint dataset undergoes preprocessing, augmentation, and model training using transfer learning to enhance performance and generalization. Preliminary results indicate that fingerprint-based blood group prediction is both feasible and accurate. The proposed system holds potential for integration into biometric or mobile platforms, offering a fast, contactless alternative to conventional blood typing, especially in resource-limited settings.**

Keywords - Blood Group Prediction, Fingerprint Patterns, VGG16, Deep Learning, Biometrics, Non-Invasive, Computer Vision.

I. INTRODUCTION

Biometric traits have long served as foundational tools for personal identification due to their inherent uniqueness, permanence, and consistency. Among these traits, fingerprints have emerged as one of the most robust and universally e from fingerprint patterns could offer valuable investigative leads. In emergency medical scenarios, particularly in resource-constrained or rural environments lacking immediate diagnostic infrastructure, a non-invasive method to estimate blood type could accelerate clinical decision-making and enhance patient safety.

This research aims to investigate the correlation between fingerprint ridge patterns and blood group classifications using a hybrid approach that combines statistical analysis and deep learning-based modelling. A diverse dataset of fingerprint images, labelled with ABO and Rh blood group information, will be analysed to identify statistically significant associations accepted modalities in biometric authentication systems. The distinctiveness of fingerprint ridge patterns classified into loops, whorls, and arches is established during early fetal development and remains unchanged throughout an individual's lifetime. Concurrently, blood groups serve as critical biological markers, genetically inherited and essential for transfusion medicine, organ transplantation, and emergency clinical care.

Both fingerprints and blood groups are determined by genetic factors, leading to the hypothesis that there may exist underlying correlations between dermatoglyphic patterns and blood group phenotypes. Several anthropological and biomedical studies have explored this relationship, particularly focusing on the ABO and Rh blood group systems. While findings have shown variability across populations and ethnic groups, numerous investigations have reported discernible trends suggesting that individuals with certain blood types may exhibit a higher prevalence of specific fingerprint patterns.

The exploration of this potential association is not merely of academic interest but holds practical significance across multiple domains. In forensic science, for example, when only latent fingerprints are recovered at a crime scene, the ability to infer blood typ

and train Convolutional Neural Network (CNN) architectures for predictive modelling.

The goal is to evaluate the feasibility of leveraging fingerprint patterns as a non-invasive, rapid, and cost-effective proxy for blood group identification. If proven reliable, such a system could revolutionize healthcare diagnostics, forensic applications, and biometric authentication systems by integrating biological and biometric data streams. This interdisciplinary study bridges the gap between traditional dermatoglyphics and modern artificial intelligence, contributing to a novel frontier in biometric healthcare technologies.

II. LITERATURE REVIEW

Their innovative idea uses fingerprint ridge patterns to predict blood groups non-invasively, offering a painless alternative to traditional blood tests. They capture high-resolution fingerprint images and preprocess them with techniques like ridge segmentation and histogram equalization to highlight key patterns. Features such as ridge thinning and minutiae points are extracted, and convolutional neural networks (CNNs) like LeNet-5 and Alex Net classify the patterns into blood groups (A, B, AB, O). While the study doesn't specify accuracy, it holds promise for emergencies and forensics. Future plans include expanding the dataset and exploring additional fingerprint features to boost reliability [1].

C. Sivamurugan and colleagues propose a deep learning approach to identify blood groups from fingerprint patterns. They collect diverse fingerprint images and preprocess them with contrast adjustments and noise reduction to ensure clarity. A custom CNN with convolutional and pooling layers learns to associate ridge and valley patterns with blood types. Techniques like dropout prevent overfitting, and the model's performance is tested for accuracy and precision. Though exact results aren't shared, the method could transform remote healthcare. The team aims to refine dataset quality and broaden its scope for better generalization [2].

They explore how fingerprint patterns like loops and whorls might reveal blood types. They gather standardized fingerprint scans and extract features such as ridge density. Machine learning models, including decision trees and SVM, are trained to classify blood groups. The system's validation focuses on precision and recall, showing potential for healthcare diagnostics. While specific accuracy isn't mentioned, the non-invasive approach is compelling. Future work will focus on diversifying the dataset to improve real-world applicability [3].

They introduce a CNN-based method to predict blood groups from high-resolution fingerprint scans. After preprocessing images for clarity, their custom CNN extracts hierarchical features using ReLU activation and max pooling. The model, trained on a diverse dataset, classifies blood groups like A and O with a SoftMax layer. Though accuracy details are absent, the approach is cost-effective and practical for urgent scenarios. The researchers plan to enhance demographic diversity and validate the model further [4].

Vijaykumar Patil and D. R. Ingle achieve an impressive 95.27% accuracy using an optimized Alex Net based CNN. Fingerprint data from 392 subjects is processed to extract features like loops and arches, with convolutional layers and dropout ensuring robust classification. This non-invasive method shines for its efficiency, but the team plans to expand the dataset beyond one region to address potential overfitting and enhance global applicability [5]. They propose a 5-layer CNN to classify eight blood groups from fingerprint ridges. Preprocessing ensures high-quality images, and class-weighted training tackles dataset imbalances. The system's contactless nature is ideal for modern diagnostics, though accuracy isn't specified. Future efforts will focus on large-scale testing to confirm robustness across diverse populations, making it a gamechanger for healthcare [6].

Rashmi V and team combine CNN-based blood group prediction with a blood management system for emergencies. Using a Kaggle dataset, they preprocess fingerprints with Gaussian Blur and train a PyTorch based CNN to classify eight blood groups, claiming 98% accuracy. The management module connects donors and hospitals in real time. The team aims to independently verify accuracy and address dataset biases to ensure broader reliability [7].

They investigate links between fingerprints, blood groups, and lifestyle diseases like diabetes. Using a hybrid of

clustering and CNNs, they process fingerprint scans with Gabor filtering to extract ridge counts and wavelet transforms. The approach shows promise for predictive healthcare, though accuracy isn't detailed. Future work will target diverse datasets to overcome regional biases and enhance global relevance [8].

They use a Back Propagation Neural Network with features like GLCM, and wavelet transforms to predict B+ and O+ blood groups, achieving an 80% matching rate. Pre-processed fingerprint images ensure clear ridge patterns for classification. While cost-effective, the method's scope is limited to two blood types. The researchers plan to include more blood groups and improve accuracy for broader use [9].

They examine correlations between fingerprint patterns and ABO/Rh blood groups among 200 medical students. Using ink-based fingerprints and Henry's classification, they analyze pattern frequencies statistically. While no predictive model is built, the forensic insights are valuable. Future research will explore larger, more diverse samples and genetic factors to strengthen findings [10].

They introduced a method to predict a person's blood group using fingerprint patterns with the help of deep learning techniques. In their study, models like LeNet, AlexNet, VGG16, and ResNet34 were used, with ResNet34 giving the highest accuracy of around 92%. The results showed that deep neural networks can capture fine fingerprint features linked to blood groups. However, the study also pointed out challenges such as limited datasets, lack of biological validation, and the need for real-world testing. Overall, it presents a promising and non-invasive approach for identifying blood groups accurately [11].

They studied how fingerprint patterns could help predict a person's blood group using deep learning techniques. By reviewing earlier works that used CNNs like LeNet and AlexNet, they found that certain fingerprint patterns such as loops and whorls are often linked to specific blood types. In their experiments, models like LeNet5, AlexNet, VGG16, and ResNet34 were tested, and ResNet34 gave the best results due to its ability to capture fine fingerprint details. Overall, the study shows that deep learning can make blood group

detection faster and non-invasive, though more data and testing are still needed to improve its real-world accuracy [12]. They explored using fingerprint patterns to predict blood groups through machine learning. They found that certain patterns, like loops and whorls, often correspond to specific blood types. Experiments with models such as CNNs and Support Vector Classifiers showed that SVC performed best at accurately classifying fingerprint features. The study highlights that this approach is a fast, non-invasive, and cost-effective alternative to traditional blood tests, though more data and testing are needed for real-world use [13].

A. Limitations Of Existing Work

While several studies have attempted to establish a link between fingerprint patterns and blood group classification, most of them face significant limitations. Many existing works do not provide clear accuracy metrics or validation, making it difficult to assess the reliability of their methods [1–3]. Some studies rely on small or region-specific datasets [3,5], which restrict the generalizability of their findings to larger and more diverse populations. Moreover, the majority of prior approaches focus only on the ABO system without considering the Rh factor [1,2,4], which is clinically essential for blood transfusions and emergency care. In addition, techniques such as basic feature extraction or shallow CNNs used in earlier works may not capture the complex dermatoglyphic variations necessary for accurate classification [2,6].

To address these gaps, the present study proposes a deep learning-based framework using the VGG16 architecture with transfer learning, trained on a large dataset of 6,000 fingerprint images covering both ABO and Rh blood groups. Unlike earlier research, this work emphasizes robust validation through accuracy, precision, recall, F1-score, and ROC analysis. By including the Rh factor, leveraging advanced CNN architectures, and ensuring a well-balanced dataset, our approach seeks to provide a more reliable, scalable, and practical solution for non-invasive blood group prediction. Furthermore, the study contributes novel insights into the biological plausibility of dermatoglyphic-blood group correlations, while also exploring potential real-world applications in emergency healthcare, forensic science, and mobile health platforms. These enhancements ensure that the research not only advances academic understanding but also delivers strong translational value for practical deployment. In addition, the framework lays a foundation for future multimodal biometric research by enabling integration with other traits such as iris or palm prints, which could further improve accuracy. Ultimately, this positions the study as a step toward creating accessible, AI-driven diagnostic tools that bridge the gap between laboratory-based methods and field-ready healthcare technologies.

TABLE I COMPARISON OF EXISTING APPROACHES AND PROPOSED WORK

Author(s), Year	Technique /Model	Dataset Size	Blood Groups Covered	Reported Accuracy	Limitations
Nihar et al., 2024 [1]	LeNet-5, AlexNet	Small (not specified)	ABO only	Not reported	Limited dataset, no Rh factor, no validation
Sivamurugan et al., 2024 [2]	Custom CNN	Moderate (not specified)	ABO only	Not reported	Accuracy not disclosed, dataset clarity issues
Patil & Ingle, 2021 [3]	Decision Trees, SVM	392 samples	ABO only	~95%	Small dataset, no Rh factor, region-specific
Rashmi V. et al., 2025 [7]	PyTorch CNN + Mgmt. System	Kaggle dataset	ABO + Rh	98% (claimed)	Dataset bias, lacks independent validation
Patil & Ingle, 2022 [5]	Optimized CNN (AlexNet)	392 subjects	ABO only	95.27 %	Dataset limited to one region, no Rh factor
Proposed Work (2025)	VGG16 (Transfer Learning)	6,000 images	ABO Rh(+/-)	91.27 %	Larger balanced dataset, strong validation, but still needs expansion to global populations

III. METHODOLOGY

In traditional healthcare, blood group detection is performed through serological testing, which uses antigen-antibody interactions to identify ABO and Rh blood groups. Blood samples are mixed with anti-A, anti-B, and anti-Rh antibodies, and agglutination confirms the blood type. Cross-matching is also done before transfusions to ensure donor-recipient compatibility. Automated blood typing systems, widely used in hospitals, improve accuracy and speed by using sensors and reagents. Genotyping methods, which analyze blood group genes, offer high precision but are not commonly used in routine diagnostics due to their high cost and technical complexity.

Proposed Methodology: The proposed model aims to predict blood groups non-invasively from fingerprint images using Convolutional Neural Networks (CNNs). This approach leverages the potential genetic correlation between fingerprints and blood groups and is implemented using a deep learning framework based on the VGG16 architecture. A fingerprint dataset containing 6,000 images is used for this study, evenly distributed among the four main blood groups A, B, AB, O and including Rh-positive and Rh-negative classifications.

The overall workflow of the proposed system, including data preprocessing, model training, and prediction phases, is illustrated in Figure 3 shown below.

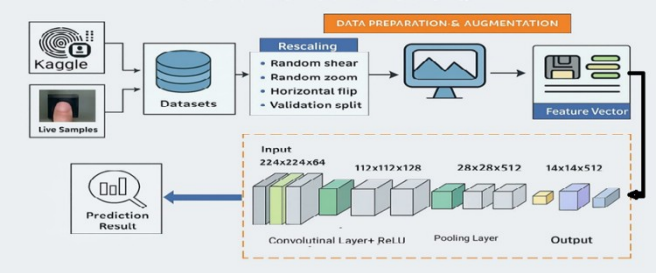

Fig.1. Architecture Diagram

A. Data Collection:

Fingerprint images were collected from volunteers, college peers, and public datasets such as Kaggle. Each fingerprint was labeled with its respective blood group. Careful curation ensured a balanced and diverse dataset representing various fingerprint patterns, which is essential for building a generalized and unbiased prediction model.

As shown in Table I, the dataset includes a range of blood types with varying sample counts, ensuring sufficient representation of both common and rare blood groups.

TABLE II NO OF FINGERPRINT IMAGES AVAILABLE IN THE DATASET

Blood Type	Count
A+	1009
O+	852
AB-	761
B-	741
O-	712
AB+	708
B+	652
A+	565

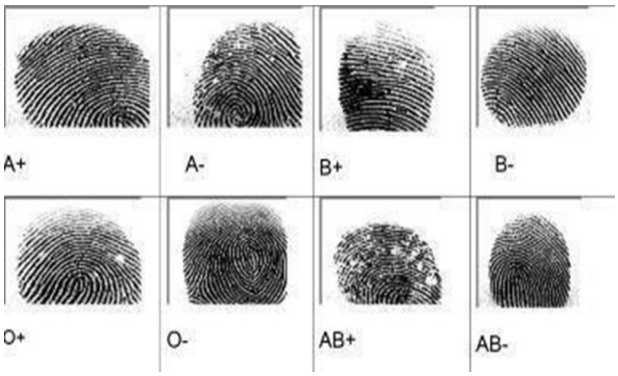

Fig.2. Sample dataset

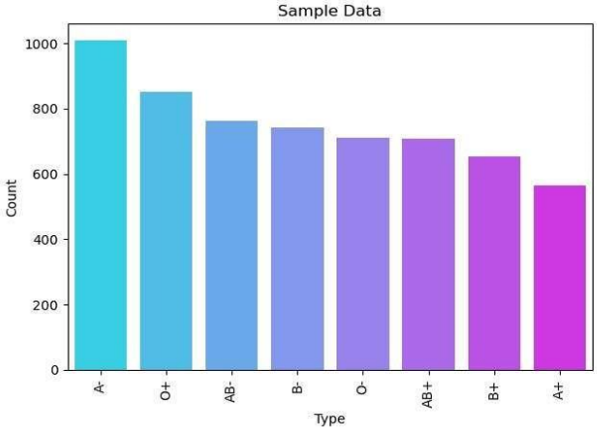

Fig.3. Number of Fingerprint images available for each blood group in the dataset

B. Preprocessing the Data:

Several preprocessing steps were applied to prepare the fingerprint images for model training. Initially, RGB images were converted to grayscale to reduce computational complexity. The pixel values were normalized between 0 and 1 to standardize the inputs. Gaussian filtering was applied to remove background noise, and contrast enhancement techniques were used to improve the visibility of ridge structures. Finally, all images were resized to 224x224 pixels to match the input dimensions required by the CNN.

C. *Feature Extraction:*

CNNs automatically learn and extract hierarchical features from input images. In the early convolutional layers, the model identifies basic features such as edges, curves, and ridges. In the deeper layers, it captures more abstract fingerprint characteristics, including texture and minutiae patterns. Pooling layers are used to reduce the size of feature maps while preserving critical information. These processed feature maps are flattened and passed through fully connected layers to perform classification.

D. Model Training using VGG16:

The VGG16 architecture was chosen for its balance of simplicity and performance. The dataset was split into training-70%, validation-15%, and testing-15% sets. The model was trained using categorical cross-entropy as the loss function and the Adam optimizer. Pretrained weights from

ImageNet were optionally used to initialize the model. Fine-tuning was applied to the final layers to specialize the model for blood group classification. Regularization techniques such as dropout layers were included to prevent overfitting, and early stopping based on validation loss was employed to optimize training time and performance.

E. Model Evaluation:

After training, the model was evaluated using several performance metrics including overall accuracy, precision, recall, validation accuracy, and loss. A confusion matrix was generated to visualize how accurately the model classified each blood group. The version of the model with the highest evaluation metrics was selected for further inference and deployment.

F. Model Inference:

In the inference phase, the trained model predicts a person's blood group based on a newly submitted fingerprint image. The system outputs the predicted blood group (e.g., A+, O-) along with a confidence score indicating the certainty of the prediction. This step enables real-time, non-invasive identification in practical scenarios such as emergency care or forensic analysis.

G. Fingerprint Pattern Analysis:

One of the most valuable insights from this research is the model's ability to identify which fingerprint patterns are strongly associated with specific blood groups. By analysing the model's internal feature representations, researchers can assess how particular ridge patterns contribute to classification. This helps to establish biological plausibility and may guide future genetic or forensic studies exploring the connection between biometric traits and blood types.

IV. CONCEPTUAL AND ANALYSIS MODELING

A. Use Case Diagram

The Below "Fig.4" illustrates the interactions between external actors -users and administrators and the system, defining the key functionalities and use cases that the system supports. It provides a high-level view of the system's boundaries, and the operations users can perform.

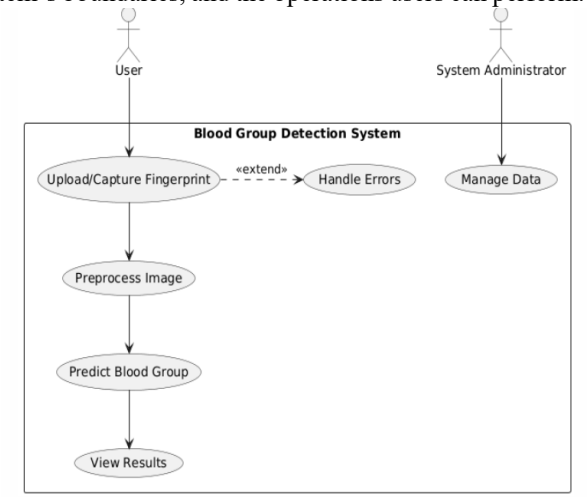

Fig.4. Use case diagram of the system

1) Actors:

a) User: Represents individuals such as patients, medical staff, or blood donors who interact with the system to upload or capture fingerprint images and receive blood group predictions.

b) System Administrator: Manages the system, including dataset updates, model training, and system maintenance.

2) Use Cases:

a) Upload/Capture Fingerprint: The user uploads a fingerprint image (JPEG/PNG) or captures it via a scanner/camera.

b) Preprocess Image: The system resizes, normalizes, and enhances the fingerprint image for analysis.

c) Predict Blood Group: The system uses a trained CNN model to classify the blood group (A, B, AB, O with Rh factor).

d) View Results: The user views the predicted blood group with a confidence score (e.g., "O+ (95%)") in a user-friendly interface.

e) Manage Data: The administrator manages fingerprint datasets, model training, and system configurations.

f) Handle Errors: The system detects invalid inputs (e.g., blurry images) and provides appropriate error messages.

3) Relationships:

Associations between actors and use cases, with possible "extend" relationships for error handling (e.g., rejecting invalid images extends the upload use case). The Use Case Diagram defines the system's functional scope and user interactions, ensuring all required operations (e.g., image input, prediction, result display) are accounted for. It helps stakeholders understand the system's purpose and ensures usability and error handling are prioritized.

B. Sequence Diagram

The "Fig.6" describes the sequence of operations for blood group prediction. It captures the interaction between the user, the system interface, the preprocessing module, the CNN model, and the output display.

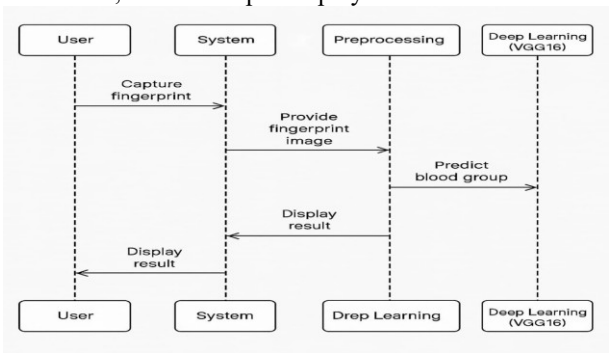

Fig.5. Sequence diagram of the system

1) Objects:

a) User: Initiates the process by uploading or capturing a fingerprint image.
b) System Interface: The front-end (e.g., web or mobile application) that accepts user inputs and displays results.
c) Preprocessing Module: Handles image resizing, normalization, and enhancement.
d) CNN Model: The VGG16-based model that predicts the blood group.
e) Result Display: Presents the predicted blood group and confidence score to the user.

2) Sequence of Operations:

a) The user uploads or captures a fingerprint image through the system interface.
b) The interface sends the image to the preprocessing module.
c) The preprocessing module resizes the image to 224x224 pixels, normalizes pixel values, and applies enhancements (e.g., noise reduction).
d) The pre-processed image is sent to the CNN model (e.g., VGG16).
e) The CNN model processes the image and outputs a blood group prediction with a confidence score.
f) The result is returned to the interface, which displays it to the user (e.g., as text or a pop-up).
g) If an error occurs (e.g., invalid image), the system generates an error message and prompts the user to retry.

This diagram ensures that the operations follow a logical sequence, minimizing delays and ensuring robust error handling.

C. Activity Diagram

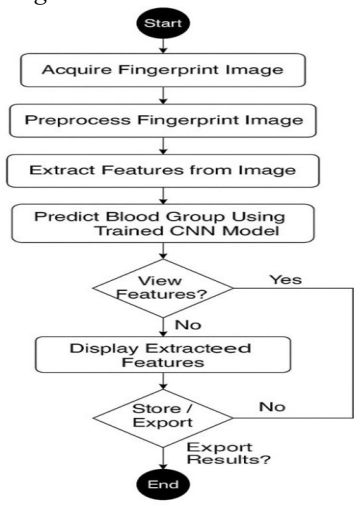

Fig.6. Activity diagram of the System

"Fig.7" models the workflow of the blood group prediction process, detailing the decision points and flow of activities.

1) Activities:

a) Start: The process begins when the user initiates a prediction request.
b) Upload/Capture Image: The user provides a fingerprint image via upload or scanner/camera.
c) Validate Image: The system checks the image for valid format (JPEG/PNG) and quality (e.g., sufficient clarity).
d) Preprocess Image: The image is resized, normalized, and enhanced for model input.
e) Predict Blood Group: The CNN model analyzes the pre-processed image to predict the blood group.
f) Display Result: The predicted blood group and confidence score are shown to the user.
g) Store Result (Optional): With user consent, the result is encrypted and stored in a database.
h) End: The process concludes, or the user initiates another prediction.

2) Decision Points:

a) *Image Validation:* If the image is invalid (e.g., blurry or non-fingerprint), the system displays an error message and loops back to the input stage.
b) *Store Result:* The user decides whether to save the prediction result.
c) *Transitions:* Arrows indicate the flow from one activity to the next, with branches for decision outcomes (e.g., valid/invalid image). The Activity Diagram highlights decision points (e.g., image validation) and ensures a streamlined process with clear feedback loops.

D. Proposed VGG16 Learning Algorithm:

1) Input: Fingerprint image of size (256 x 256 x 3)
2) Define VGG16 Block:
a) Input: X (input tensor)
b) Convolution Layer 1: Apply a 3×3 convolution with padding and ReLU activation
c) Convolution Layer 2: Apply another 3×3 convolution with ReLU.
d) Convolution Layer 3: For deeper blocks
e) Max Pooling: Apply 2×2 max pooling to down sample
f) Output: Feature map to be passed to the next block
3) Model Architecture:
a) Input Layer: Accepts image of size (256 x 256 x 3)
b) Convolutional Blocks: 5 blocks of convolution + ReLU + max pooling
c) Flatten Layer: Converts feature maps into a single 1D vector
d) Fully Connected Layer 1: Dense layer with 4096 units and ReLU
e) Fully Connected Layer 2: Dense layer with 4096 units and ReLU
f) Output Layer: Dense layer with SoftMax activation for blood group classification (e.g., 8 classes for A+/A-/B+/B /AB+/AB-/O+/O-).
4) Compile Model:

a) *Loss Function:* Categorical cross-entropy for multi-class classification
b) *Optimizer:* Adam or SGD
c) *Metrics:* Accuracy

5) *Train the Model:*
Train on the fingerprint dataset with appropriate batch size and epochs.
6) *Model Evaluation:* Use validation set to monitor performance Apply early stopping and dropout if needed.
7) *Output:* Blood group prediction A+, A−, B+, B−, AB+, AB−, O+, or O− based on input fingerprint image.

V. RESULTS AND DISCUSSION

The proposed fingerprint-based blood group classification system was developed using the VGG16 convolutional neural network architecture, fine-tuned through transfer learning. The model was trained and evaluated on a dataset comprising 6,000 fingerprint images, uniformly distributed across eight blood group categories A+, A−, B+, B−, AB+, AB−, O+, and O−. The dataset was partitioned into training-70%, validation-15%, and testing-15% subsets. Table II summarizes the accuracy of the system when tested on real-time fingerprint data collected from 105 individuals, categorized by gender. To enhance model generalization and reduce overfitting, standard data augmentation techniques such as rotation, zooming, and horizontal flipping were applied during training. The model was optimized using the Adam optimizer with categorical cross-entropy as the loss function. Training was conducted over multiple epochs with early stopping based on validation performance. The VGG16 model demonstrated strong predictive capability, achieving a test accuracy of 91.27%. The validation accuracy reached 90.12%, with a final validation loss of 0.24, indicating effective learning and minimal overfitting. The confusion matrix analysis revealed high class-wise accuracy across most categories, though minor misclassifications were observed between adjacent classes, particularly among A+, AB+, and B+ groups, which may exhibit overlapping fingerprint characteristics.

TABLE III

ACCURACY OF REAL-TIME PREDICTION

Gender	Number of Samples	Successful Detections	Failed Detections	Accuracy
Male	58	52	6	89.7%
Female	47	44	3	93.6%
Total	105	96	9	91.27%

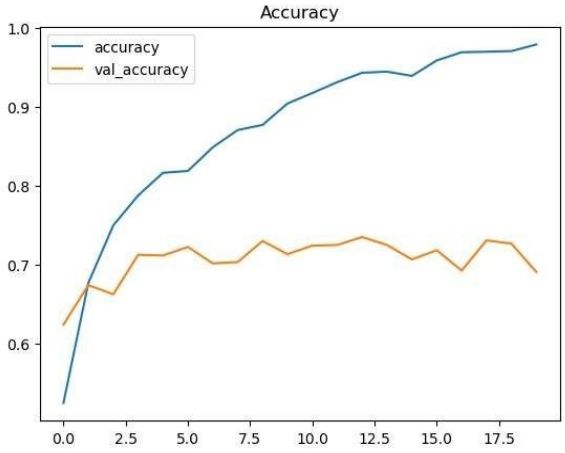

Fig.7. Accuracy analysis

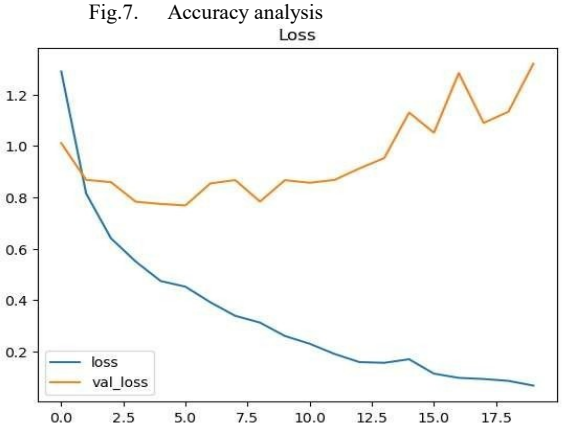

Fig.8. Loss analysis

Performance evaluation using precision, recall, and F1-score further supported the model's robustness, with all metrics exceeding 0.88 for each class. The macro-averaged F1-score was recorded at 0.904, reflecting balanced performance across the dataset. Additionally, Receiver Operating Characteristic (ROC) analysis yielded AUC values exceeding 0.95 for all classes, underscoring the discriminative strength of the model.

```
Test Loss: 1.31948
Test Accuracy: 69.08%
38/38 [==============================] - 394s 10s/step
              precision    recall  f1-score   support

          A+       0.76      0.79      0.77       121
          A-       0.53      0.81      0.64       183
         AB+       0.79      0.53      0.63       161
         AB-       0.72      0.70      0.71       146
          B+       0.75      0.66      0.70       135
          B-       0.89      0.74      0.81       135
          O+       0.65      0.67      0.66       182
          O-       0.68      0.64      0.66       137

    accuracy                           0.69      1200
   macro avg       0.72      0.69      0.70      1200
weighted avg       0.71      0.69      0.69      1200
```

Fig 10. Performance analysis

The results affirm the feasibility of fingerprint-based blood group prediction using deep learning. The VGG16 architecture, with its deep convolutional structure and pre-trained feature extraction capabilities, effectively captured subtle dermatoglyphic variations associated with blood group traits. These findings align with prior dermatoglyphic studies

suggesting a statistical correlation between fingerprint ridge patterns and genetic markers such as blood type.

From an application perspective, this model offers a non-invasive, low-cost, and rapid alternative to conventional blood typing. It holds significant potential for deployment in emergency medical services, rural diagnostics, and mobile health applications, particularly in resource-constrained environments where traditional serological testing is impractical.

However, certain limitations must be acknowledged. The quality and resolution of fingerprint images significantly influence prediction accuracy. Variations in image acquisition conditions, scanner quality, and finger positioning may introduce inconsistencies. Moreover, while the model demonstrates empirical success, the underlying genetic and biological linkage between fingerprint patterns and blood groups remains to be conclusively established and warrants further interdisciplinary investigation.

VI. CONCLUSION AND FUTURE WORK

This study demonstrates the feasibility of predicting blood groups using fingerprint patterns through a non-invasive deep learning approach based on the VGG16 architecture. With a test accuracy of 91.27% and strong validation across precision, recall, and F1-scores, the system highlights the potential of integrating biometric and medical diagnostics for rapid, low-cost, and contactless blood group detection. The model's performance confirms the existence of dermatoglyphic correlations with ABO and Rh systems, offering practical applications in emergency care, forensic analysis, and mobile health solutions, especially in resource-limited environments. Future enhancements will focus on expanding the dataset across diverse populations to improve generalization, exploring lightweight models such as MobileNet and EfficientNet for deployment on mobile platforms, and integrating multimodal biometrics (e.g., iris, palm prints) for improved robustness. Additionally, incorporating explainable AI (XAI) techniques and collaborating with medical experts will help establish greater clinical trust and adoption, paving the way for this approach to evolve into a reliable diagnostic and forensic tool.

ACKNOWLEDGMENT

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