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BioRidge: Unlocking Blood Group via Fingerprint Ridge Analysis

Neha P[1], Chaitra M[2] and Nidhi Chandru[3]
[1-3]Department of Computer Science and Engineering, BNM Institute of Technology, Bangalore, India
Email: p.neha244@gmail.com, chaitram@bnmit.in, nidhichandru15@gmail.com

***Abstract*— The method of identifying people using biometric information has grown in popularity for both security and medical applications. Fingerprint recognition is unique among biometric modalities. Medical diagnostics depend on blood group determinations. Traditional techniques require time-consuming, invasive procedures. This study proposes an invasive-free blood group identification system that utilizes Convolutional Neural Networks (CNNs) to analyze fingerprint images and achieve accurate predictions. This technology enables the integration of biometric and physiological data collection, especially useful in emergency and resource-constrained settings. The ResNet34 design proves to be the most effective choice for blood group detection.**

***Index Terms*— Blood group, fingerprint, deep learning, ResNet34, convolutional neural network.**

I. INTRODUCTION

Since biometric techniques have so many uses in fields like forensics, security, and healthcare, there has been an increase in interest in using them to identify people [1]. By relying on characteristics that are specific to each person, whether they be behavioral or physical, these systems provide a trustworthy means of verifying someone's identity. As a result, biometrics are now widely used in sectors where security, speed, and accuracy are crucial [2]. Fingerprint recognition is one of the most reliable biometric techniques available. Fingerprints are extremely reliable for identification because they carry unique patterns and remain consistent throughout an individual's life. Fingerprint data is widely used, from everyday tools like unlocking mobile phones to law enforcement, due to its ease of collection.

Accurate blood typing is essential for transfusions, emergency medicine treatments, and organ transplant methods. The standard method used for identifying blood groups is serological testing. It examines red blood cell antigens by causing agglutination reactions. Due to the precise nature of these clinical procedures, skilled personnel in laboratories with adequate equipment are required. These precise tests are not advantageous for immediate field-based testing or emergency healthcare needs because of their long durations and lengthy procedures [3]. These traditional techniques are difficult to apply in settings with limited resources because they require intricate processes and specialised tools.

Deep learning models based on CNNs are used in the development of fingerprint-to- blood group prediction systems, which examine fingerprint images to identify the corresponding blood group [4]. Because CNNs effectively extract all the intricate visual patterns while creating hierarchical features, they have demonstrated encouraging results in a variety of image-based classification tasks.

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Models can uncover hidden details in individual fingerprint images thanks to this design. CNNs can quickly perform blood group analysis through pattern recognition when deep learning models are applied to large fingerprint databases and blood type records.
Research continues to determine whether CNNs can effectively identify blood groups through fingerprint analysis. The preliminary findings suggest deep learning technology has the potential for reliable blood type identification. Exploring CNNs in blood group classification requires additional studies to optimize their predictive capabilities in actual practice. Integrated biometric-physiological data fusion systems allow individuals to access essential health information and secure identification through a single streamlined process.

II. Literature Survey

Verma, A., & Bhatt, V., in "Automated Blood Identification Using Fingerprint Analysis [5], analyzed numerous machine learning technologies for predicting blood groups from fingerprint patterns, including feature extraction, pattern recognition, and classification models. Their study highlighted the limitations of conventional serological testing and proposed fingerprint biometrics as a non-invasive alternative. They also assessed different approaches by contrasting their implementation barriers, precision rates, and scalability results. The study identified system weaknesses while providing research suggestions to enhance fingerprint-based blood group identification technology performance and reliability. Overall, the review offers a current perspective on the field and guides future developments in biometric–physiological integration.
Gupta, A., Agarwal, S., & Jain, R., in "Blood Group Identification Using Finger Images and Algorithms of ML" [6], studied how ML techniques can be used to predict blood group patterns from the fingerprint analysis. They combined Random Forest (RF) and Support Vector Machine (SVM) to develop a non-invasive method for blood type verification. The research evaluated SVM and RF on the grounds of robustness, accuracy, and computational efficiency from many perspectives. The training dataset provided fingerprint images, and these images had blood group labels attached to them. The classification of fingerprint pattern features was undertaken on the model. The results showed that SVM and RF could classify fingerprint features effectively, confirming the potential of fingerprint biometrics for blood group prediction.
Hyvärinen, K. et al., in "A Machine-Learning Method for Biobank-Scale Genetic Prediction of Blood Group Antigens" [7] aimed to improve blood transfusion safety through a machine learning system that analyses genotyping information to identify blood groups. The study highlighted limitations of traditional ABO and RhD matching, which may not prevent alloimmunization, particularly in patients receiving multiple transfusions. The authors used Finnish biobank data to create a Random Forest classification model for red blood cell antigen prediction, which achieved validation through a Danish cohort. Array genotyping techniques provide scalable and economical solutions that increase the capacity of donor screening processes, according to the research. Additionally, the research introduced the RANGER package to carry out high-dimensional data analysis at local computing levels for efficiency. The designed model demonstrates strong capability to automate the detection of blood groups and antigen-negative donors, which enhances both compatibility testing and transfusion success rates.
Sharma, S., Gupta, S., & Yadav, P.K., in "Sex and Blood Group Determination from Hair Using ATR-FTIR Spectroscopy and Chemometrics", examined blood type identification from human hair through ATR-FTIR spectroscopy, together with chemometric methods. The authors establish through vibrational pattern and chemical group assessment of hair proteins that this non-invasive procedure shows promise for blood group identification. The study uses chemometric algorithms, PCA, and PLS-DA for spectral data processing to establish a new forensic technique that suits criminal investigations where DNA profiling is not possible [8].

III. Proposed System

The developed system offers a rapid, non-invasive approach for identifying blood groups by analyzing fingerprint images, providing an alternative to conventional serological testing methods. The system employs the CNN-based deep learning frameworks to recognize fingerprint image patterns that indicate specific blood groups [9].
Fig. 1 illustrates the workflow of the developed system for classifying blood groups. The system pipeline begins with the fingerprint image acquisition, followed by a labeling process using the recognizable blood types such as A+, A−, B+, B−, AB+, AB−, O+, and O− [10]. The preprocessing operations are applied to enhance image quality while uniformly standardizing the images throughout the dataset. The preprocessing workflow includes

three essential steps: transforming images into grayscale, resizing them according to input size requirements, and performing pixel normalization [11].

The preprocessed images are subsequently fed into multiple deep learning models for training. This work studies the feature learning potential of four famous CNN architectures, which include LeNet, AlexNet, VGG16, and ResNet34, for blood group classification [12]. The chosen models demonstrate different levels of depth and show notable success in image categorization. The system is designed to achieve accurate blood group classification of new fingerprint images.

The successful implementation of this system would establish essential real-time healthcare support systems that help medical institutions in emergency conditions and rural and remote areas when conventional blood tests are difficult to obtain.

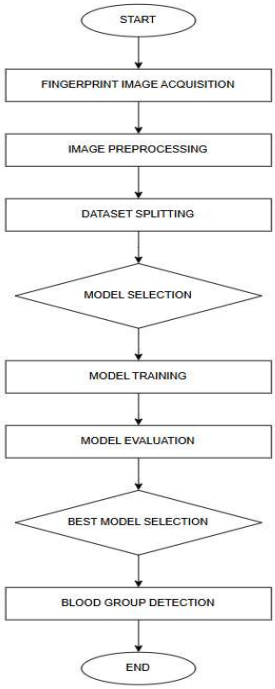

Fig. 1. Flowchart of the proposed blood group classification system.

IV. METHODOLOGY

A. Data Collection and Preparation

The fingerprint dataset consists of 6,000 images distributed across eight human blood groups: A+ (565), A− (1,009), B+ (652), B− (741), AB+ (708), AB− (761), O+ (852), and O− (712). Each image is labeled by hand with its matching blood group to ensure accuracy for model development and validation. Fig. 2 illustrates a balanced distribution and representation of the fingerprint images across the different blood groups. The structured classification folders ease label retrieval during model development and proceed with stratified partitioning for training and validation datasets. 80% of the data is allocated to training subsets, while 20% is allocated to testing subsets. This method maintains a proportional distribution of classes throughout all subsets.

B. Image Preprocessing

The preprocessing stage is essential for enhancing the accuracy and uniformity of the input data. A sequence of preprocessing operations is applied to the fingerprint images to make them compatible with the deep learning models. The steps are illustrated with sample preprocessed images in Fig. 3 and described below:

- Grayscale Conversion: Fingerprint Recognition does not need the color information. Thus, RGB images are converted to grayscale or binary to eliminate complexity, while the internal structures of images are preserved.

- Image Resizing: As each CNN model accepts the input image of a fixed dimension, all the images are resized, e.g., 32×32 pixels for LeNet and 224×224 pixels for AlexNet, VGG16, and ResNet34.
- Noise Removal: A Gaussian filter is used optionally as part of the process to eliminate background noise while enhancing the ridge patterns in fingerprint images.
- Normalization: Pixel values are scaled between 0 and 1, promoting stable and efficient training while preventing issues such as exploding or vanishing gradients during backpropagation.
- Data Augmentation: It improves the training dataset diversity by implementing horizontal/vertical flipping together with rotation (±10°) and zooming and brightness variation methods.

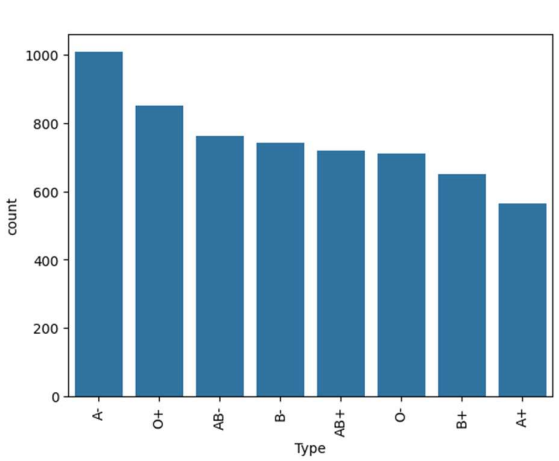

Fig. 2. Distribution of fingerprint images across different blood groups.

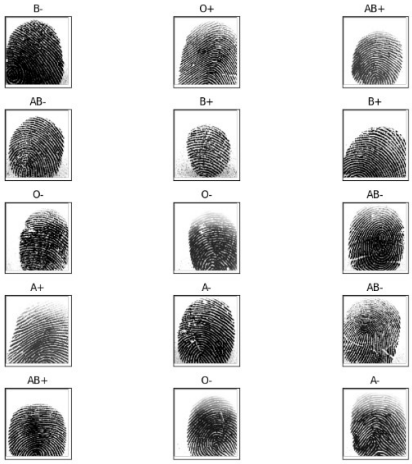

Fig. 3. Preprocessed Sample Images from the Dataset

C. Model Architectures

The system implements four deep learning models of increasing depth, which define its main operational structure.

- LeNet: LeNet operates as the fundamental model, which works on monochromatic fingerprint images to identify basic structural elements like ridges and edges.
- AlexNet: The architecture of AlexNet goes further into the image than LeNet, which enables the detection of intricate fingerprint textures and patterns.
- VGG16: The features needed for image analysis are obtained through VGG16 processing. Its complex structure helps the system identify detailed ridge patterns in addition to processing difficult fingerprint details, thus boosting categorization results.
- Resnet34: ResNet34 includes residual connections that increase the network depth for successful training of additional layers while maintaining stability. This project efficiently extracts complex fingerprint patterns, which enhances the model's capability for making generalized blood group predictions across different fingerprint samples.

D. Model Training and Optimization

All models underwent 20 training cycles with batches of 32 samples each, yielding 151 batches per epoch. To maintain consistency across trials, Adam optimization paired with categorical cross-entropy loss was applied throughout. Core accuracy was maintained during training and validation to prevent overfitting.

The LeNet model was built from scratch with randomly initialized weights. Due to its simple architecture, transfer learning or freezing was not applicable, and the entire model was trained end-to-end. The training accuracy of the model reached nearly 100% (close to 1.0) within just a few epochs and successfully managed to minimize the training loss to almost zero, as shown in Fig. 4.

The AlexNet model was implemented with the dropout layers in between fully connected layers. This acted as a method to prevent overfitting. As illustrated in Fig. 5, the model exhibited highly unstable training behavior, with training and validation accuracy fluctuating between 0.16 and 0.18 throughout the process and showing no significant convergence. The loss curves also showed similar chaotic behavior with dramatic fluctuations, indicating that the architecture was unable to establish consistent parameter optimization for the fingerprint-based blood group classification task.

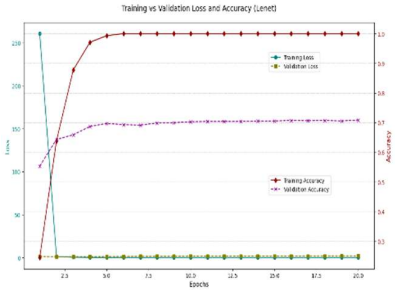

Fig. 4. LeNet training, validation accuracy and loss

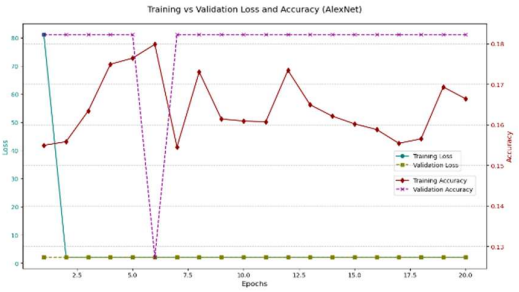

Fig. 5. AlexNet training, validation accuracy and loss

The VGG16 model was implemented using transfer learning. Only the top (fully connected) layers of VGG16 received training for the blood group classification purpose, as the convolutional base remained frozen. Over the course of 20 epochs, the training accuracy of the VGG16 model increased steadily and consistently, from about 0.4 to almost 1.0, while maintaining stable convergence free from unpredictable fluctuations as shown in Fig. 6. Through its multiple convolutional and pooling layers, the deeper convolutional architecture successfully extracted hierarchical feature representations from the fingerprint images and established robust mappings between biometric patterns and blood group classifications.

The same transfer learning procedure was applied to the ResNet34 model by freezing its initial layers while training only the classifier layers of the model. Training accuracy rose steadily from 0.2 to almost 0.9, and training loss remained continuously low throughout, with large values becoming increasingly smaller and closer to zero, highlighting the progressive learning characteristics of the ResNet model as shown in Fig. 7.

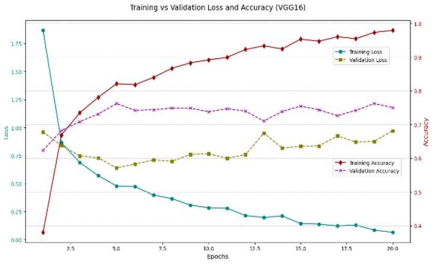

Fig. 6. VGG16 training, validation accuracy and loss

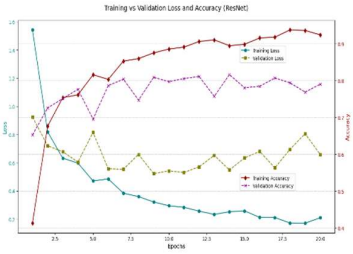

Fig. 7. ResNet34 training, validation accuracy and loss

V. RESULTS

A. Inference: Analysis of Model Performance

Analyzing the models' performance provides key insights into their individual advantages and drawbacks in classifying blood types. The evaluation metrics, test accuracy, test loss, and macro F1-score, yield the following results:

- The ResNet34 model delivered the best performance according to testing results, with 79.03% test accuracy combined with the best test loss at 0.65754. The model exhibits reliable performance through its 0.79 macro F1-score that represents uniformly balanced precision and recall throughout all classes. The ResNet34 model emerges as the most trustworthy solution due to its excellent performance on unidentified data sets.
- VGG16 secured remarkable success in model performance by reaching 75.04% test accuracy and a robust macro F1-score of 0.76. This model performs quite well through its test loss value of 0.97069, which demonstrates proper predictive capabilities and generalization across blood type categories.
- The evaluation results of LeNet showed a moderate performance through its test accuracy of 70.88%. Despite consistent precision and recall across most classes, the model exhibits lower classification efficiency based on its higher test loss (1.86163) combined with the lower macro F1-score (0.71). This model shows insufficient capability to differentiate between the two blood types AB+ and AB-.
- The test results for AlexNet revealed a bad performance with 18.22% accuracy and extreme test loss (2.06555). The model presents its insufficient ability to learn important blood type features, as shown by its 0.04 macro F1-score with negligible precision and recall values across all classes. AlexNet shows limited suitability for this task, likely due to the poor adjustments or overfitting.

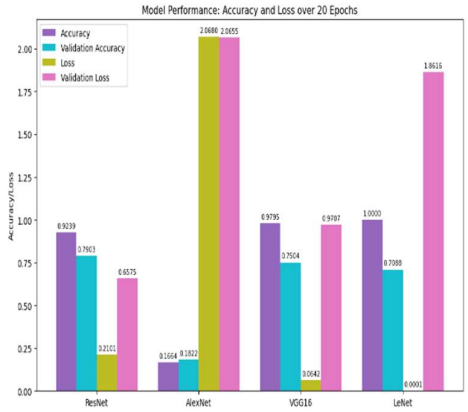

Fig. 8. Accuracy and loss comparison of ResNet, AlexNet, VGG16 and LeNet over 20 epochs.

The comparison of training, validation accuracy and loss across ResNet34, AlexNet, VGG16, and LeNet models over 20 epochs is shown in Fig. 8.

B. Evaluation Metrics

Table 1 presents the visual representation of the evaluation metrics for each model, aiding in a clearer comparison of their performance. Similar performance evaluation approaches have been used in prior fingerprint-based biometric classification studies.

TABLE I: SUMMARY OF EVALUATION METRICS

Model	Test Loss	Test Accuracy	Weighted Average Precision	Weighted Average Recall	Weighted Average F1-Score
ResNet34	0.6575	79.03%	0.81	0.79	0.79
VGG16	0.9706	75.04%	0.75	0.75	0.75
LeNet	1.8616	70.88%	0.71	0.71	0.71
Alexnet	2.0655	18.22%	0.03	0.18	0.06

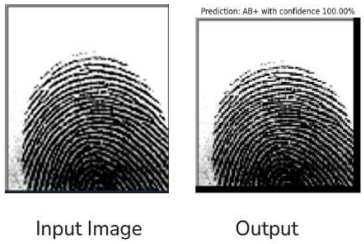

Fig. 9. Fingerprint based blood group detection showing input sample with the predicted outcome

The user uploads an image of the fingerprint. After the image is uploaded, the model analyzes the image, extracts the features and predicts the corresponding blood group of the user. The fingerprint sample is shown along with its predicted blood group, illustrating the effectiveness of the ResNet34-based detection method as shown in Fig. 9.

VI. CONCLUSION AND FUTURE SCOPE

The research introduces an innovative non-contact blood group identification method that leverages deep learning analysis of fingerprint images. The comparative study of four convolutional neural network (CNN) models demonstrates that deeper architectures with residual connections, such as ResNet34, capture ridge and texture patterns more effectively. In contrast, AlexNet struggled with poor accuracy, mainly due to overfitting and lack of batch normalization, highlighting the need for improved training strategies or modernized architectures.

While the results are promising, challenges remain. The relatively small dataset limits population-wide generalizability, and future work should expand to larger, more diverse samples across multiple sensors and

environments. Environmental factors such as lighting, finger moisture, and scanner quality must also be addressed to ensure consistent performance. Importantly, ethical and clinical considerations—including privacy safeguards, fairness across demographics, and regulatory approval—are essential for responsible deployment.
Looking ahead, future efforts should focus on validating the system under real-world healthcare conditions, integrating multimodal biometric approaches, and exploring advanced architectures such as transformers and transfer learning techniques. With these enhancements, fingerprint ridge analysis could evolve into a robust, non-invasive solution for rapid blood group identification in clinical and emergency settings.

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