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Enhanced Blood Group Prediction with Fingerprint Images using Deep Learning

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Abstract- **Blood group prediction is a crucial process in medical diagnostics and emergency care, traditionally carried out through serological tests that require blood samples and specialized laboratory equipment. These conventional methods, while accurate, are invasive, time-consuming, and may be impractical in situations where resources are limited or unavailable in urgent situations. This research explores a novel approach of using fingerprint images for blood group detection, applying deep learning, specifically Convolutional Neural Networks (CNN) with good architectures. By analyzing the unique patterns in fingerprints, these models may offer a non-invasive, faster, and more efficient alternative to traditional methods. This study examines the feasibility of this approach, providing insights into how deep learning could potentially be utilized for blood group prediction.**

Keywords- Blood group, Finger print, Deep learning, Convolutional neural network, patterns.

I. INTRODUCTION

Fingerprints are a fundamental biometric feature, uniquely identifying individuals through the intricate patterns formed by the ridges and valleys on their fingertips. These patterns develop in the fetal stage and remain unchanged throughout a person's life, making them a reliable means of identification. The primary fingerprint patterns are categorized into three main types: loops, whorls, and arches. Loops the most common fingerprint pattern, loops form a curved ridge that doubles back on itself, creating a loop shape. Loops can further be classified into radial loops (opening towards the thumb) and ulnar loops (opening towards the little finger). Approximately 60-70% of all fingerprints exhibit loop patterns. Whorls are characterized by circular or spiral patterns, with at least one ridge making a complete circuit. They are further classified into plain whorls, central pocket whorls, double loop whorls, and accidental whorls. Whorls are found in about 25-35% of fingerprints. Arches the least common pattern, arches, form wave-like structures where ridges flow from one side of the finger to the other without doubling back. Arches can be further divided into plain arches and tented arches. Only about 5% of fingerprints display this pattern. Beyond these basic patterns, fingerprints also exhibit minutiae points, such as bifurcations, ridge endings, islands, and enclosures, which add further uniqueness to each fingerprint. These minute details make fingerprints an invaluable tool for personal identification and security applications. However, the potential of these patterns extends beyond identity verification, as recent research suggests that the ridges and minutiae of fingerprints may also carry subtle biological information. Blood groups, another vital biological marker, are determined by the presence or absence of specific antigens on the surface of red blood cells. The major blood group systems include A, B, AB, and O, with each group further classified by the Rh factor into positive and negative types.

Fig1: Different types of fingerprint patterns

Accurate determination of blood groups is essential in medical contexts, particularly for blood transfusions, organ transplants, and managing haemolytic diseases. Traditionally, blood groups are identified through serological methods, which involve mixing blood samples with antibodies and observing the reaction. While these methods are accurate, they are invasive, requiring blood samples, and

depend on laboratory facilities, which may not always be available, especially in emergency or resource-limited settings the idea of determining blood groups through fingerprint images presents an innovative, non-invasive alternative. By leveraging the power of deep learning, particularly Convolutional Neural Networks (CNNs), Unlike models such as RNNs and ANNs etc., CNNs excel in handling spatial data like images by leveraging convolutional layers, which effectively capture local patterns and reduce computational complexity. This makes CNNs particularly suited for fingerprint image analysis, ensuring high accuracy and efficiency. The CNN identifies intricate fingerprint patterns by learning features from ridge endings, bifurcations, and minutiae points in the image. These are critical to distinguishing different classes. LeNet5, AlexNet, VGG16, and ResNet-34 are effective in image classification tasks, leveraging convolutional layers to automatically extract features while mitigating issues like vanishing gradients. Their architectural innovations such as pooling layers in LeNet5, the deep structure of AlexNet and VGG16, and the residual connections in ResNet-34 provide a robust framework for accurately capturing the patterns in fingerprint images for blood group prediction, making them more suitable than other models. This research aims to explore the feasibility of using deep learning models such as LeNet5, AlexNet, ResNet-34, and VGG16 to detect blood groups from fingerprint images. By comparing these models, able to understand their effectiveness and accuracy in this novel application, opening up new possibilities for rapid and non-invasive blood group detection.

II. Literature Review

[1] T Nihar and his team published a paper titled "Blood group determination using fingerprint." They propose using Convolutional Neural Networks (CNNs) like LeNet or AlexNet for fingerprint image classification to correlate patterns with blood groups. The method involves ridge frequency assessment and Gabor filters for feature extraction. While accuracy isn't specified, the study suggests this non-invasive approach could revolutionize blood typing in healthcare and forensics. Future work aims to expand the sample size and explore more fingerprint features to enhance precision.[2] Vijaykumar, Patil N. and D. R. Ingle published a paper titled "A Novel Approach to Predict Blood Group using Fingerprint Map Reading" in 2021. They utilized ridge frequency estimation and Gabor filters to extract spatial features from fingerprints. Their proposed system used Multiple Linear Regression with Ordinary Least Squares (OLS) to predict blood groups, achieving an accuracy of 62%. [3] Swathi P and her team published a paper titled "Fingerprint Based Blood Group Prediction Using Deep Learning." They utilized Convolutional Neural Networks (CNNs) with intricate fingerprint image features for their research. The model was trained on fingerprint patterns, focusing on predicting blood groups, and it achieved an accuracy rate of 62%.[4] Amit Patil et al. published a paper titled "Fingerprint patterns in relation to gender and blood groups - A study in Navi Mumbai". They analyzed fingerprint patterns and blood groups of 170 subjects (100 females, 70 males) aged 18-65 years. Fingerprints were classified into loops, whorls, and arches using Henry's system. Chi-square tests were used for statistical analysis. The study found loops to be the most common pattern (62.35%), followed by whorls (32.94%) and arches (4.7%). A significant association was found between fingerprint patterns and ABO blood groups ($p<0.05$), but not with gender or Rh factor. The research suggests potential for predicting ABO blood groups from fingerprint patterns in forensic investigations.[5] Harem Othman Smail et al. investigated the relationship between fingerprint patterns and blood groups in 450 university students. They categorized fingerprints into loops (49.62%), whorls (42.48%), and arches (7.88%), and analyzed their distribution across ABO and Rh blood types. Using chi-square tests, they found significant associations between fingerprint patterns and blood groups A, B, and AB ($p < 0.05$), but not for group O. The study suggests potential for predicting certain blood groups based on fingerprint patterns. [6] Dr. D. Siva Sundhara Raja and J. Abinaya published a paper titled "A Cost-Effective Method for Blood Group Detection Using Fingerprints" in 2019, They propose using unique fingerprint patterns as a non-invasive, cost-effective alternative to traditional blood group testing. Their research identifies correlations between fingerprints and blood groups, offering a simpler, more accessible solution, particularly for resource-limited settings.

III. Methodology

Existing Methodology:

In the current healthcare landscape, blood group detection is primarily conducted through well-established serological methods. These methods rely on the interaction between antigens on the surface of red blood cells and specific antibodies to identify the blood group of an individual. The key existing systems and techniques are as follows:

1. Serological Testing: ABO and Rh Typing: The most common method involves mixing a blood sample with anti-A, anti-B, and anti-Rh antibodies. The presence or absence of agglutination (clumping) in the blood indicates the blood type (A, B, AB, or O) and Rh factor (positive or negative).

Cross-Matching: Before blood transfusions, cross-matching tests are performed to ensure compatibility between the donor’s and recipient’s blood. This involves mixing the recipient's plasma with the donor's red blood cells to check for any adverse reactions.

2. Automated Blood Typing Systems: Automated Analyzers: These machines streamline the blood typing process by automating the mixing of blood samples with reagents, reading the results using optical sensors, and providing rapid and accurate blood group identification. These systems are commonly used in large hospitals and blood banks.

3. Genotyping: DNA-Based Methods: Molecular techniques can be used to determine blood groups by analyzing specific genes responsible for the expression of blood group antigens. While this approach is highly accurate, it is not commonly used for routine blood typing due to its cost and complexity.

Proposed Methodology:

The proposed methodology for detecting blood groups using fingerprint images involves a comprehensive approach

leveraging advanced deep learning techniques. A large, diverse dataset of fingerprint images, categorized by the corresponding blood group of each individual. The dataset consists of a total of **6,000** fingerprint images, representing the four primary blood groups A, B, AB, and O. Each blood group category is equally represented within the dataset to ensure balanced training and unbiased model performance.

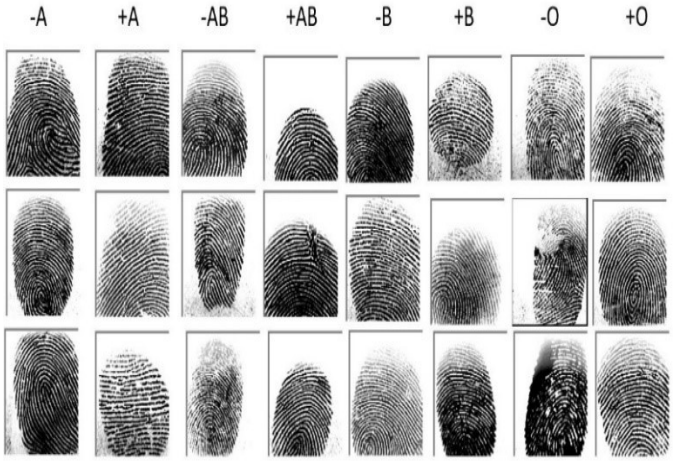

Fig 2: Dataset of fingerprints of different blood groups

The dataset undergoes pre-processing to enhance image quality and ensure consistency, using techniques such as normalization and augmentation. Then apply several Convolutional Neural Networks (CNNs), deep learning models such as LeNet5, Alex Net, ResNet-34, and VGG16 to the pre-processed dataset. The models will be trained to identify distinctive patterns within the fingerprints that correlate with specific blood groups. During training, the model will go under rigorous validation methods to fine-tune model parameters and prevent overfitting, while evaluating performance based on metrics such as accuracy, precision, and recall. The model exhibiting the highest performance is selected for deployment. After training the model, when fingerprint image is uploaded and can receive the predicted blood group. The final aim to provide a quick, non-invasive alternative to traditional blood typing methods and could significantly impact diagnostic practices, especially in resource-limited settings.

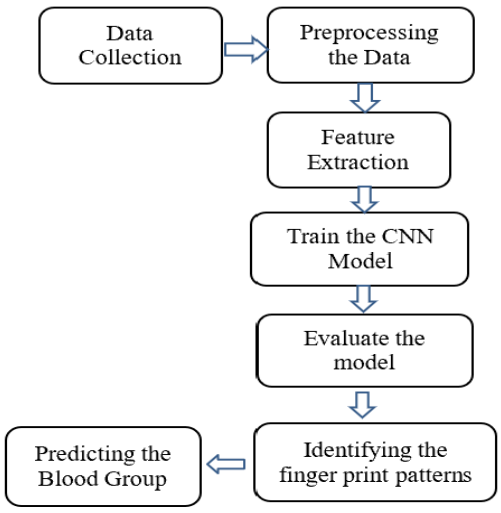

Fig 3: Blood group prediction with finger print images framework

One of the most significant contributions of this research is the collection and utilization of a novel dataset of fingerprint images labeled with corresponding blood groups. Unlike existing datasets, which often focus on fingerprint identification or verification, this dataset is specifically designed for the task of predicting blood groups. The dataset is composed of high-quality fingerprint images from a diverse group of volunteers, covering all major blood types, along with positive and negative labels. This is the first dataset to combine biometric fingerprint patterns with blood group information, enabling deeper exploration into the feasibility of non-invasive blood group detection using machine learning techniques. By making this dataset available, we hope to pave the way for further research into biometric-based health diagnostics and inspire similar efforts in related fields.

A. Data Collection:

A dataset of 6,000 fingerprint images was collected from friends, students, peers in the college, and other sources like kaggle, with each image labeled by blood group. The dataset was evenly distributed across the four primary blood groups A, B, AB, and O categorized into positive and negative types, as illustrated in Figure 2. To ensure diversity in fingerprint patterns, the images were sourced from a varied population, with each fingerprint accurately labeled with its corresponding blood group.

B. Preprocessing the data:

Preprocessing enhances fingerprint image quality for model training. First convert images to grayscale, reducing complexity, and normalize pixel values between 0 and 1 for consistency. Noise is removed using Gaussian filtering, and contrast is adjusted to highlight fingerprint patterns. Lastly, images are resized to meet the CNN model's input requirements.

C. Feature Extraction:

After preprocessing, the CNN uses filters to identify key features like edges, textures, and ridges in the fingerprint images. Initial layers capture simple patterns, while deeper layers recognize complex structures, with pooling layers down-sampling feature maps to retain essential information. The flattened features are then passed to fully connected layers for accurate blood group predictions.

D. Train the CNN Model:

To train the CNN model , the dataset is divided into training, validation, and test sets. The model is compiled with a loss function and optimizer, and trained to minimize loss through backpropagation while monitored on the validation set. Its performance is then evaluated on the test set to determine accuracy and generalization.

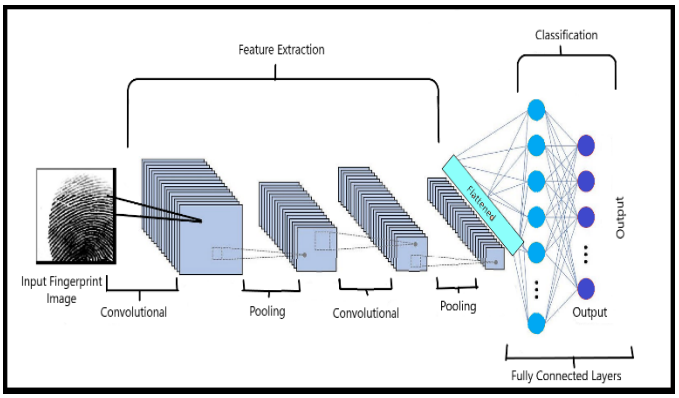

Fig 4: Convolutional neural network process

E. Evaluate the Model:

The trained CNN's model performance is evaluated using the validation and testing sets. Metrics like accuracy, loss, validation accuracy, and validation loss are computed to assess the model's ability to predict the blood group from the fingerprint images. This thorough evaluation ensures the model's effectiveness and reliability.

F. Identifying Fingerprint Patterns:

The best-performing model was chosen for predicting blood groups by analyzing fingerprint patterns. This model was used to identify the key patterns and features within the fingerprints that contribute to accurate blood group prediction.

G. Predicting the Blood Group:

The final step is the best-performing model was chosen for predicting blood groups by analyzing fingerprint patterns. This model was used to identify the key patterns and features within the fingerprints that contribute to accurate blood group prediction.

Proposed Learning Algorithm:

1. Input: Fingerprint image of size (m x n)
2. Define ResNet Block:
   a. Input: X (input tensor), filters, stride
   b. Convolution Layer 1: Apply a convolutional layer with specified filters, stride, and padding.
   c. Batch Normalization: Normalize the output of the convolution.
   d. Activation: Apply ReLU activation function.
   e. Convolution Layer 2: Apply a second convolutional layer with filters and stride 1.
   f. Batch Normalization: Normalize the output of the convolution.
   g. Skip Connection:
      i. If dimensions of input and output do not match, apply a convolutional layer to input X.
      ii. Add the transformed input X to the output of Convolution Layer 2.
   h. Activation: Apply ReLU to the output of the skip connection.
   i. Output: Residual block output.
3. Model Architecture:
   a. Input Layer: Input image of size (m x n)
   b. Initial Convolution: Apply a convolutional layer with large kernel size and stride.
   c. Max Pooling: Apply max pooling to reduce spatial dimensions.
   d. Residual Blocks: Stack multiple residual blocks with increasing filters at each stage.
   e. Global Average Pooling: Replace fully connected layers with global average pooling.
   f. Output Layer: Apply a dense layer with softmax activation for blood group classification.
4. Compile Model:
   a. Loss Function: Categorical cross-entropy for multi-class classification.
   b. Optimizer: Adam or SGD.
5. Train the model on the fingerprint dataset.
6. Output: Blood group prediction (A, B, AB, or O) based on fingerprint image.

IV. RESULT AND DISCUSSION

After training all the models LeNet5, AlexNet, ResNet34, and VGG16 over 20 epochs, obtained comprehensive results for accuracy, loss, validation accuracy, and validation loss.

Table 1: Metrics of Each Model

Epoch	Metric	ResNet	AlexNet	VGG16	LeNet
Epoch 1	Accuracy	0.4125	0.1600	0.4765	0.1510
	Loss	1.5054	15.2819	1.4881	99.0777
	Val_Accuracy	0.6492	0.1825	0.6300	0.1533
	Val_Loss	0.8991	2.0675	0.9685	2.0684
Epoch 2	Accuracy	0.6753	0.1606	0.6798	0.1904
	Loss	0.8227	2.0846	0.8375	2.0519
	Val_Accuracy	0.7217	0.1825	0.6483	0.1642
	Val_Loss	0.7284	2.0658	0.9460	2.0422
Epoch 5	Accuracy	0.7957	0.1642	0.8050	0.8648
	Loss	0.5272	2.0689	0.5160	0.4535
	Val_Accuracy	0.7667	0.1825	0.7442	0.4042
	Val_Loss	0.5778	2.0673	0.6732	2.0682
Epoch 10	Accuracy	0.8957	0.1654	0.8948	1.0000
	Loss	0.2849	2.0670	0.2894	**0.0009**
	Val_Accuracy	0.7483	0.1825	0.7283	0.4758
	Val_Loss	0.6633	2.0679	0.7657	3.5716
Epoch 15	Accuracy	0.9115	0.1646	0.9427	1.0000
	Loss	0.2295	2.0669	0.1588	**0.000032**
	Val_Accuracy	0.8050	0.1825	0.7417	0.4992
	Val_Loss	0.5474	2.0671	0.9221	4.3545
Epoch 20	Accuracy	0.9554	0.1646	0.9800	1.0000
	Loss	0.1341	2.0685	0.0714	**0.0515**
	Val_Accuracy	0.8142	0.1825	0.7375	0.4950
	Val_Loss	0.5838	2.0669	1.0450	4.8482

To determine which model performed the best and carefully examined these key metrics, Accuracy: A higher accuracy reflects a model's ability to correctly predict outcomes on the training data. Loss: A lower loss value indicates that the model's predictions are closer to the actual values, showing how well the model is learning. Validation Accuracy: This

metric is crucial as it measures how well the model generalizes to new, unseen data a higher value here means better generalization. Validation Loss: A lower validation loss suggests that the model maintains its accuracy on unseen data, without overfitting. By analysing these metrics, all can identify the model that not only learns effectively during training but also performs robustly on new data, making it the most reliable choice for real-world applications. Here's a comparative analysis of the models, focusing on their performance across epochs. This is clearly lays out the criteria on for evaluating the models The analysis will highlight differences in accuracy, loss, validation accuracy, and validation loss for each model.

1. LeNet 5:

LeNet-5 achieved perfect training accuracy (100%) and extremely low training loss. High validation loss (4.8482) and lower validation accuracy (49.50%) indicate overfitting. It memorized the training data but failed to generalize well to new data.

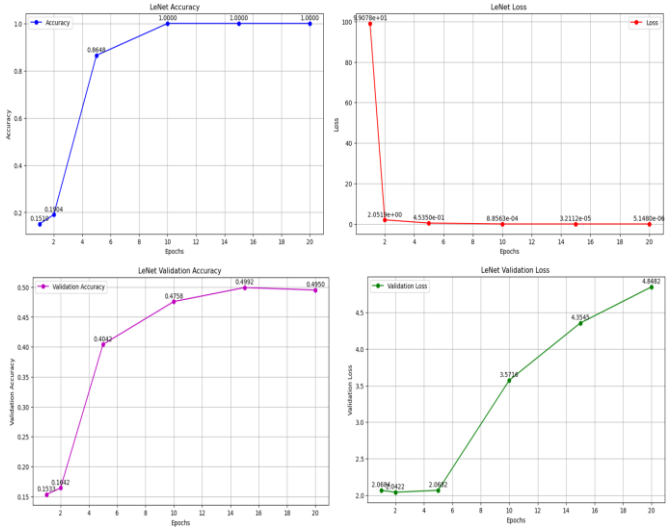

Fig 6: Performance graph of LeNet-5

2. VGG 16:

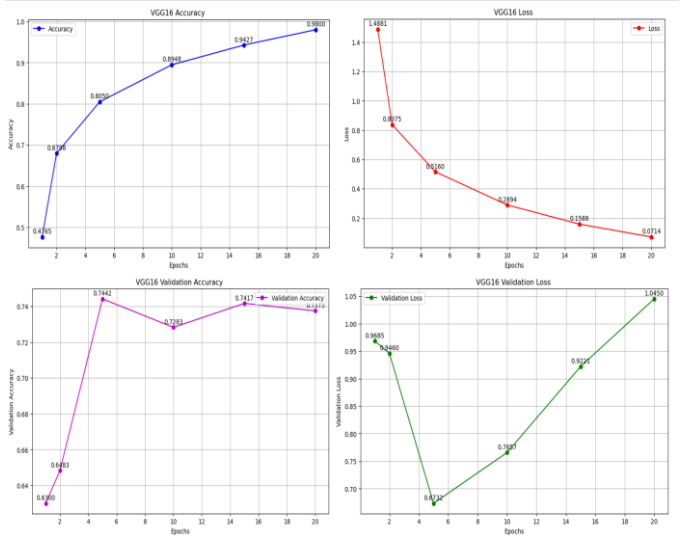

Fig 7: Performance graph of VGG 16

VGG-16 achieved very high training accuracy (98.00%) and moderate validation accuracy (73.75%). Lower validation loss compared to LeNet. Although it has high training accuracy, the validation loss (1.0450) is still relatively high compared to the training loss, suggesting some level of overfitting, but less severe than LeNet.

3. ResNet-34:

ResNet-34 has given strong performance with a good balance between training accuracy (95.54%) and validation accuracy (81.42%). The validation loss (0.5838) is relatively low, indicating good generalization to unseen data. Although not as high in training accuracy as VGG16 or LeNet, ResNet's validation performance is better, showing it generalizes well.

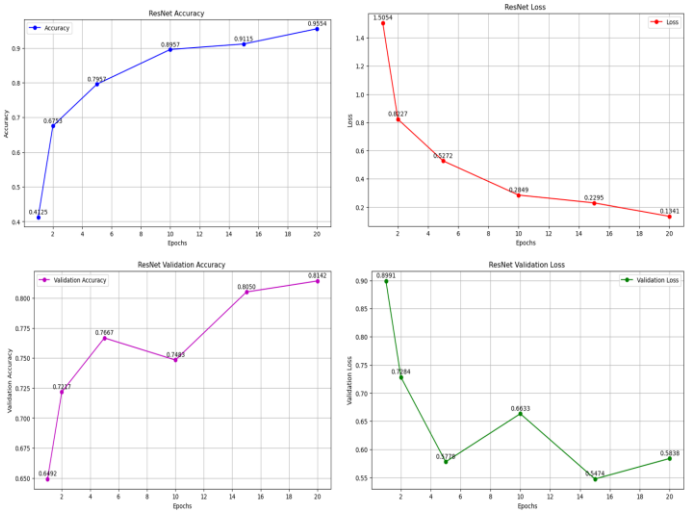

Fig 8: Performance graph of ResNet-34

4. AlexNet:

AlexNet showing consistently poor performance with low training accuracy (16.46%) and low validation accuracy (18.25%). High loss values indicate that the model struggled to learn effectively from the data. Although LeNet achieves perfect training accuracy (1.00), it likely suffers from overfitting, as shown by its much lower validation accuracy (0.495).

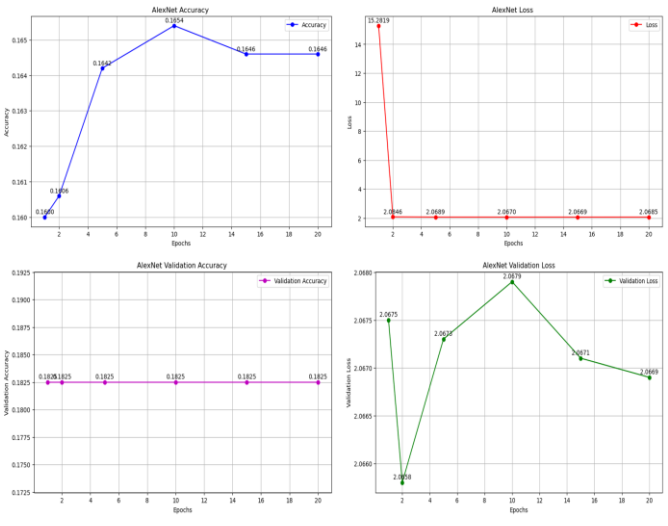

Fig 9: Performance graph of AlexNet

This indicates that while it performs well on the training data, it struggles to generalize to new, unseen data. LeNet's simpler architecture is designed for basic tasks, making it less effective for complex problems like fingerprint-based blood group detection. On the other hand, ResNet, with a training accuracy of (0.9554) and a higher validation accuracy of (0.8142), has a deeper architecture capable of capturing intricate patterns, offering more balanced performance and making it a more reliable choice for such tasks.

By comparing all the models ResNet34 emerged as the best-performing model, balancing high accuracy with low loss and strong validation performance, indicating good generalization. **VGG16** also performed well but showed some signs of overfitting in later epochs. **LeNet5,** while achieving perfect accuracy, struggled with overfitting, as indicated by its high validation loss. **AlexNet** consistently underperformed across all epochs, with low accuracy and high loss, both on training and validation data.

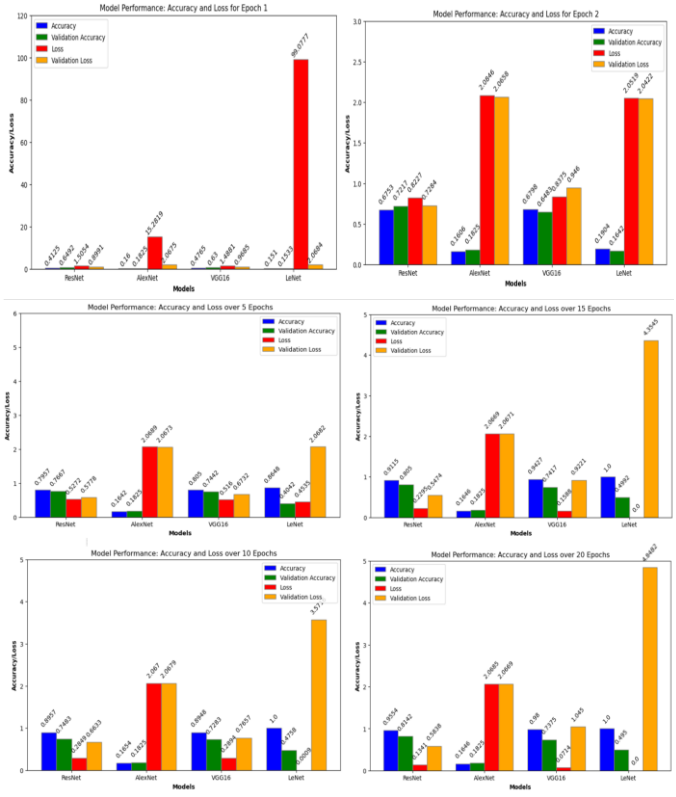

Fig 10: Overall Performance of Models

Fig 11: Test result of predicting blood of finger print image

In figure 11 the image showcases the predicted blood group derived from analyzing the fingerprint image using the ResNet34 model. The fingerprint's unique patterns were analyzed, and the result is shown clearly alongside the image, indicating the blood group identified through this process.

V. CONCLUSION & FUTURE SCOPE

This research study evaluates four CNN architectures LeNet, AlexNet, VGGNet, and ResNet for predicting blood groups from fingerprint images. ResNet34 emerged as the most effective model, achieving an accuracy of 95.54% and a validation accuracy of 81.42%. Its depth, residual connections, and robust feature extraction capabilities enabled it to detect subtle fingerprint patterns associated with different blood groups. To advance this approach, future research could integrate additional biometric or genetic data, explore more sophisticated deep learning models, refine feature extraction techniques, and validate the model with larger and more diverse datasets, making fingerprint-based blood group detection more practical and reliable and it can be integrated with the real time data to get the output in our future research.

REFERENCES

[1] Nihar, T. & Yeswanth, K. & Prabhakar, K.. (2024). Blood group determination using fingerprint. MATEC Web of Conferences. 392. 10.1051/matecconf/202439201069.

[2] P. N. Vijaykumar and D. R. Ingle, "A Novel Approach to Predict Blood Group using Fingerprint Map Reading," *2021 6th International Conference for Convergence in Technology (I2CT)*, Maharashtra, India, 2021, pp. 1-7, doi: 10.1109/I2CT51068.2021.9418114.

[3] P, Swathi & K, Sushmita & Horadi, Prof. (2024). Fingerprint Based Blood Group using Deep Learning. International Journal of Advanced Research in Science, Communication and Technology. 699-708. 10.48175/IJARSCT-15393.

[4] Patil, Amit, Amrit Malik, and Treza Shirole. "Fingerprint patterns in relation to gender and blood groups-A study in Navi Mumbai." *Indian Journal of Forensic and Community Medicine* 4, no. 3 (2017): 204-208.

[5] Smail, Harem Othman, Dlnya Ahmed Wahab, and Zhino Yahia Abdullah. "Relationship between pattern of fingerprints and blood groups." *J Adv Lab Res Biol* 10, no. 3 (2019): 84-90.

[6] Raja, D. Siva Sundhara, and J. Abinaya. "A cost-effective method for blood group detection using fingerprints." *International Journal of Advance Study and Research Work* 2 (2019).

[7] Bashir, Abdallah. "RELATIONSHIP BETWEEN FINGERPRINT PATTERNS AND BLOOD GROUPS IN LIBYAN STUDENTS: A COMPARATIVE STUDY." *Global Journal of Medical and Pharmaceutical Sciences* 3, no. 07 (2024): 1-6.

[8] Al Habsi, Tariq, Hussein Al Khabori, Sara Al Qasmi, Tasnim Al Habsi, Mohamed Al Mushaiqri, Srijit Das, and Srinivasa Rao Sirasanagandla. "The association between fingerprint patterns and blood groups in the Omani population." *Arab Gulf Journal of Scientific Research* 41, no. 3 (2023): 283-292.

[9] Aamir, Yasmin & Masood, Riffat & Irshad, Nasim & Malik, Dr & Farid, Noreen & Shahab, Muhammad. (2022). Relationship between Pattern of Fingerprints and Blood Groups. Pakistan Journal of Medical and Health Sciences. 16. 698-700. 10.53350/pjmhs22169698.

[10] Fayrouz, I. Noor Eldin, Noor Farida, and A. H. Irshad. "Relation between fingerprints and different blood groups." *Journal of forensic and legal medicine* 19, no. 1 (2012): 18-21.

[11] Patil, Vijaykumar, and D. R. Ingle. "An association between fingerprint patterns with blood group and lifestyle based diseases: a review." *Artificial intelligence review* 54, no. 3 (2021): 1803-1839.

[12] Mondal, M., U. K. Suma, M. Katun, R. Biswas, and Md Rafiqul Islam. "Blood group identification based on fingerprint by using 2D discrete

wavelet and binary transform." *Journal homepage: http://iieta. org/journals/mmc_a* 80, no. 2-4 (2019): 57-70.

[13] Ravindran, G., T. Joby, M. Pravin, and P. Pandiyan. "Determination and classification of blood types using image processing techniques." *International Journal of Computer Applications* 157, no. 1 (2017): 12-16.

[14] Banu, A. Narkis, and V. Kalpana. "An automatic system to detect human blood group of many individuals in a parellel manner using image processing." *International Journal of Pure and Applied Mathematics* 118, no. 20 (2018): 3119-3127.

[15] Joshi, S., D. Garg, P. Bajaj, and V. Jindal. "Efficacy of fingerprint to determine gender and blood group." *J Dent Oral Care Med* 2, no. 1 (2016): 103.

[16] Kc, Sudikshya, Niroj Maharjan, Nischita Adhikari, and Pragya Shrestha. "Qualitative analysis of primary fingerprint pattern in different blood group and gender in Nepalese." *Anatomy research international* 2018, no. 1 (2018): 2848974.