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Blood Group Detection Using Vision Transformer

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Abstract: The "Blood Group Detection using Vision Transformer" project focuses on creating a novel system based on thumb impressions to detect blood groups. The system increases accuracy and efficiency in detecting blood groups by utilizing deep learning methods, i.e., Convolutional Neural network (CNN) variants like ResNet integrated with Recurrent Neural Network (RNN) and MobileNet and Vision Transformer. The user Interface has made this project more interactive by using Flask in the backend. In the evaluation of model performance across different architectures, the results reveal distinct levels of accuracy. The MobileNet achieved an accuracy of 75.04% on the training set and 77.56% on the validation set, demonstrating a solid performance with a loss of 0.6431 and 0.5700, respectively. The ResNet combined with an RNN exhibited lower accuracy, achieving 61.45% on the training data and 75.57% on validation, with corresponding losses of 1.0035 and 0.6754, The Vision Transformer outperformed all models, reaching an impressive accuracy of 97.84% on the training set and 92.52% on validation, accompanied by a loss of 0.0673 and 0.2618.

Keywords: Fingerprint detection, Blood group identification, deep learning, ResNet, RNN, MobileNet, Vision transformer

I. INTRODUCTION

Identification of blood groups is an essential element of medical diagnostics, and its importance cannot be overstated for transfusions, emergency medical intervention, and targeted treatment protocols. Traditional blood typing involves invasive measures that necessitate laboratory testing, which is labour-intensive, takes time, and is less convenient in emergency situations.[1]This paper introduces a novel, non-invasive blood group detection technique based on fingerprint analysis [2]. Utilizing based on fingerprint analysis. Utilizing deep learning technologies, including Convolutional Neural Network (CNN) variants such as ResNet, MobileNet, Recurrent Neural Network (RNN) and Vision Transformer (ViT), the proposed system is expected to increase accuracy and efficiency in classification. Contrasting with conventional techniques, this biometric technique minimizes blood sample collection, providing a speedy, affordable, and scalable solution for real-time use in healthcare environments [3].With extensive experimentation, this study assesses the practicability of using fingerprint to detect blood group and its potential inclusion in biometric health systems. The results confirm that deep learning algorithms can successfully recognize blood group patterns from blood group patterns from fingerprints, opening up prospects for developing medical diagnosis and emergency response systems.

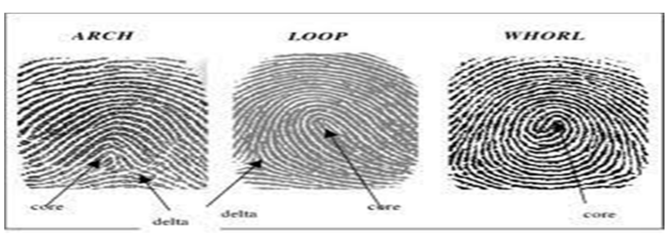


Fig1: Types of fingerprint patterns

1) Loops: The most frequent fingerprint pattern, where ridges enter through one side, make a loop, and emerge from the same side through which they entered. Loop patterns further divide into ulnar loops (ridge direction towards the little finger) or radial loops (ridge direction towards the thumb) [4].
2) Whorl: In whorl, the Ridges come in a circle or spiral formation from whorl patterns. They may have several types of subtypes, including accidental whorls, double loops, central pocket loops, and plain whorls[5].
3) Arch: In arch Ridges that run from one edge of the fingerprint to another, forming a wave-like pattern, are what characterize arch patterns. They do not have distinct deltas, or triangle-shaped ridge patterns, unlike loops and whorls. Depending on the direction and the way the ridges are lined up, together with the presence of specific traits such as deltas and ridge numbers, fingerprint patterns are analysed and classified[5].

These patterns are utilized by computerized fingerprint recognition system to create unique templates for each individual, enabling accurate identification and verification in various environments, including access control, border control, and law enforcement.

Blood group identification is required for many medical procedures, such as organ transplants, blood transfusions, and forensic analysis. Blood typing has previously been performed through serological methods, which can be time and labor-consuming and require specialized lab equipment. But as increasingly more advanced technology becomes accessible, there's an increasing demand to develop automated, accurate blood group predicting systems.

II. LITERATURE SURVEY

consistently in accuracy and flexibility[13].Das et.al., has developed CNN to finger-vein biometric verification Patil, Ingle et.al., has developed A Novel Approach for ABO Blood Group Prediction using Fingerprint. They used CNN algorithm because it effectively extracts features. Their approach demonstrated high performance, achieving an accuracy of 95.27%, showing the strength of deep learning in feature extraction and classification tasks[6].Nihar et.al., has developed CNN based fingerprint analysis and Management, they used a deep learning-based approach. They used CNN and LSTM algorithm because CNN is excellent extracting spatial features and LSTM captures sequential dependencies and confirmed a predictive accuracy of 89.12%, their findings corroborated the hypothesis that dermal ridge patterns are associated with blood group traits, providing further validation of the biometric-health connection[7].Mahmod et.al., has developed image processing and machine learning techniques outside fingerprints, employing histogram-based thresholding for blood group classification they chosen this approach to extract general visual features from non-fingerprint images. General visual features were targeted, and the accuracy was a moderate 84%, so it is less ideal for real-time use than CNN-based fingerprint models [8].Pradhan et.al., has developed hybrid CNN-LSTM model for biomedical image classification, which they optimized with hierarchical clustering algorithm(HCA) they combined CNN for powerful feature extraction and LSTM for capturing sequential dependencies and contextual patterns within image data. The inclusion of HCA helped in fine-tuning the model by optimizing feature grouping. Such an architecture enhanced memory retention and context awareness and brought accuracy levels over 94% in the case of medical imaging tasks and implied its application suitability for fingerprint-based classification too[9].Wang & Cao et.al., has developed data augmentation methods with CNNs for blood cell classification, they chose CNN due to its strong capability in extracting spatial features form medical images which while not specifically applied to blood group identification from fingerprints. Their Approach was highly robust under data scarcity, with an accuracy of 93.5%[10].Vijaykumar & Ingle et.al., has developed fingerprint map-reading method for blood group prediction .their model, although not employing CNNs,they chose this approach to reduce computational complexity, making it lightweight and faster for execution. utilized image preprocessing and feature matching to attain accuracy of up to 88.3%. the benefit was lower computational complexity, albeit at the expense of accuracy[11]. Ahmad & Karmakar et.al., has developed statistical correction analysis of fingerprint patterns with blood groups. They selected this approach to identify pattern-based associations manually without using automation or deep learning All these results found loops most frequent in O+ and A+ groups, while and arches correspond to B and AB groups, finding a moderate correlation(~70-75%). But they did not involve automation or integration with deep learning[12].Kirola et.al., has developed an extensive of machine learning in healthcare, with emphasis on model performance and data issues. Their comparative findings indicate CNN and deep hybrid models outperform classical ML models, a nearby biometric domain. The approach emphazed the necessity of extracting deep features, which attained 91.2% in verification of identities, suggesting transferable methods for fingerprint-based blood group identification. The authors favored these algorithms due to their robustness in large datasets and their ability to automatically learn hierarchical patterns.[14].Amrane & Chebouat investigated deep learning architectures for the prediction of blood groups and confirmed the viability of end-to-end systems.they had their model trained on a specific datset and achieved 92.8% accuracy, promoting deep models over traditional machine learning algorithms[15]

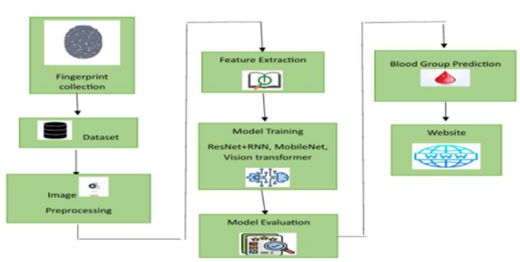


Fig2: System Architecture

III. METHODOLOGY

The System proposed combines two state-of-the-art methods: ResNet and Recurrent Neural Networks (RNN) and MobileNet for blood group identification from fingerprint images. The hybrid method leverages the strengths of both models to improve accuracy and efficiency in detection.

1) Dataset Description: The Fingerprint-Based Group Dataset is an unusual opportunity to research the link between human biometric fingerprint patterns and blood groups. The dataset includes grayscale, high-resolution fingerprint images that have one of the eight largest blood groups, which include A+, A-, B+, B-, AB+, AB-, O+, O-, unknown.
2) Data Collection: Obtain fingerprint images and their corresponding blood group labels from different sources with high quality and consistency. This involves retrieving structured data from medical records and unstructured data from additional sources such as healthcare databases and patient surveys.
3) Data Preprocessing: select and extract dominant features of the fingerprint images that reflect blood group features. Image processing and deep learning-based feature extraction techniques will be utilized to improve model performance.
4) Model Integration: Use a combination of ResNet with RNN, and mobilenet and Vision Transformer as standalone models to develop a strong predictive model for blood group classification. Each model will bring its its strengths to enhance overall accuracy and reliability.
5) ResNet + RNN Method: ResNet, due to its residual learning architecture, allows training very deep networks without the degradation issue of regular CNNs. The addition of RNN enables the model to process sequential data well, learning temporal relationships in fingerprint patterns. The combination of both strengthens the model’s capacity for detecting slight differences and complex details in thumb impressions, with notable improvement in detection accuracy.
6) MobileNet Strategy: MobileNet is optimized to be both lightweight and efficient, making it perfect for real-time applications, especially within environments that lack in resources. This model employs depth wise separable convolutions, which imply lower computational load while preserving the high performance. By using MobileNet for the detection of blood groups, the system presented gains quicker inference times, which make it fit for use in real-life clinical practice where timely results are of extreme importance.
7) Vision Transformer: Vision Transformer is a state-of-the-art architecture that has become popular due to its capacity to process image data by employing transformer mechanismsthat have been conventionally employed in natural language processing. Rather than employing convolutional layers, ViT splits an image into patches, linearly embeds them, and processes the patches with self-attention mechanisms. This enables the model to learn global context, which is critical for tasks such as blood group classification fingerprint images, covering a range of demographic factors like age, ethnicity, and geographic location in for adjustments and ensure that the system has real-world applicability

IV. RESULT ANALYSIS

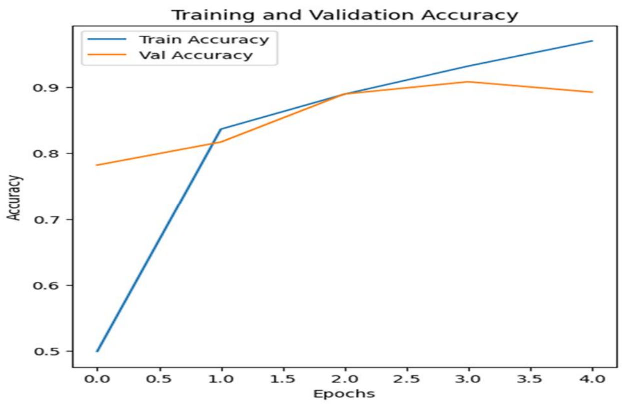
The findings from other deep learning models illustrate the prospects of fingerprint-based blood group classification. All the models had their strengths in how accurately they achieved, their losses, and in generalization.

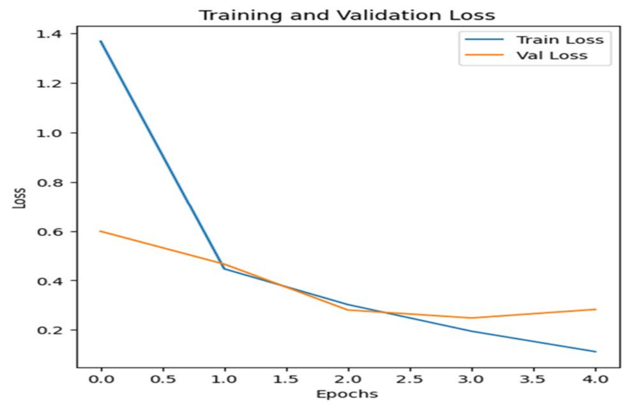
Although CNN and Vision Transformer (ViT) recorded the best training and validation accuracies that signify great learning with little overfitting, MobileNet showed a reliable yet lightweight alternative whose performance was okay. The ResNet+RNN hybrid model demonstrated acceptable generalization with lower training accuracy while stressing its resilience. These varied performances demonstrate the efficacy and usability of state-of-the-art deep learning architectures for biometric blood group prediction.

This 70/30 division guarantees the models learn well while being probed for generalization and robustness on novel fingerprint images.

A. CNN Algorithm

The model shows clear learning capability, with high training and validation accuracy after some epochs. The slight increase in validation loss and decrease in validation accuracy during the final epoch as early stopping has been employed for better generalization. The Training Accuracy for this Algorithm is around 96.98% and Validation Accuracy around 89.25% and Training loss around 0.1119 and Validation loss around 0.2825.





B. MobileNet

The Mobilenet model demonstrates a good and stable training performance. Both accuracy and loss measures indicate that model is not overfitting, and it has good validation performance, which make it a good choice for blood group classification based on fingerprints.

The Training Accuracy for this Algorithm is 75.04% and Validate Accuracy around 77.56% and Training Loss around 0.6431 and Validate loss around 0.5700.

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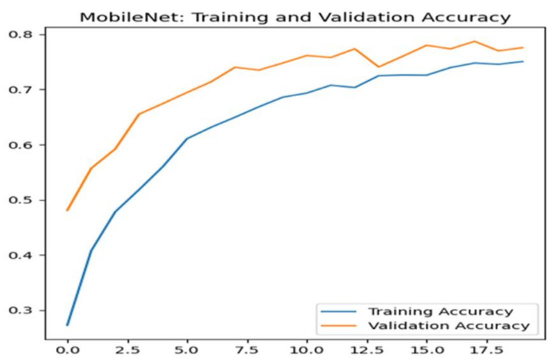
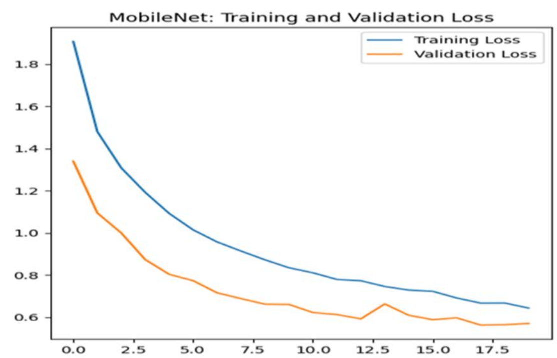
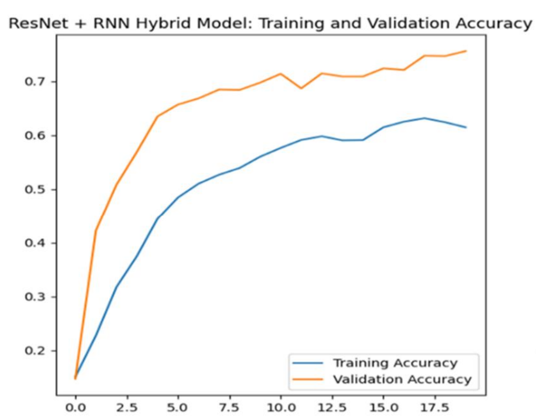
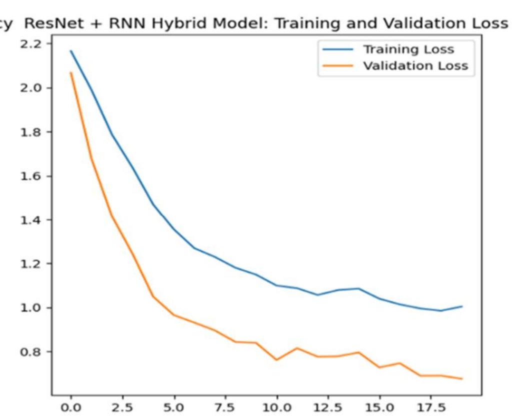




C. ResNet+RNN

ResNet + RNN hybrid model exhibits consistent accuracy improvement during training and validation. Validation accuracy is higher than training accuracy, indicating robust generalization and no overfitting. Training and validation losses reduce steadily, which means learning is stable. The model performs satisfactorily on unseen data. This makes it a trustworthy option for blood group classification from fingerprint images. Training Accuracy is around 61.54% and Validate Accuracy is Around 75.57%.





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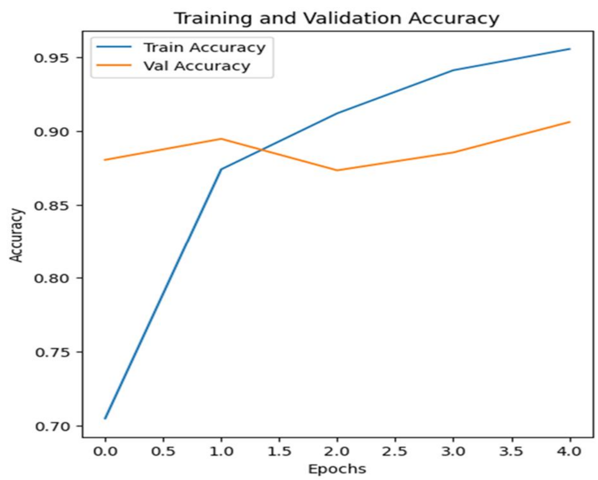
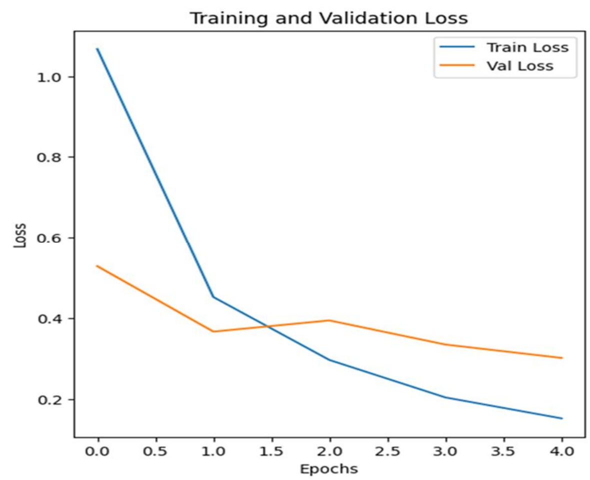
D. Vision Transformer

The model shows strong training accuracy also shows consistent strong generalization. Training and validation loss both steadily decline, representing good learning. While there's a small discrepancy between training and validation accuracy, overfitting is negligible. This model shows good validation accuracy, overfitting is negligible. This model shows good performance and can be applied to blood group classification. The training accuracy is around 97.84% and validation accuracy is around 92.52% and training loss is around 0.0673 and validation loss is around 0.2618.





Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
Vision Transformer	97.84 %	92.52 %	0.0673	0.2618
CNN	96.98 %	89.25%	0.1119	0.2825
Mobile Net	75.04%	77.56%	0.6431	0.5700
ResNet+RNN	61.45%	75.57%	1.0035	0.6754

Fig3. Comparison Table

In the evaluation of model performance across different architectures, the results reveal distinct levels of accuracy. The MobileNet achieved an accuracy of 75.04% on the training set and 77.56% on the validation set, demonstrating a solid performance with a loss of 0.6431 and 0.5700, respectively. The ResNet combined with an RNN exhibited lower accuracy, achieving 61.45% on the training data and 75.57% on validation, with corresponding losses of 1.0035 and 0.6754, The Vision Transformer outperformed all models, reaching an impressive accuracy of 97.84% on the training set and 92.52% on validation, accompanied by a loss of 0.0673 and 0.26

V. CONCLUSION

This research presents a non-surgical method blood group categorization based on fingerprint patterns that does not require surgical interventions or invasive tools. Utilizing sophisticated deep learning algorithms such as MobileNet, ResNet with RNN, and vision transformer, the approach guarantees high-quality analysis. It solves the shortcomings of conventional blood typing by minimizing invasiveness and inaccuracies due to human error, thus improving reliability. Moreover, the method allows for quick blood group identification, which makes it extremely relevant for emergency health conditions. Apart from immediate uses, this innovation creates new frontiers for study, promoting the incorporation of biometric systems into healthcare and eventually enhancing patient care.

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