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NNOVATIVE BLOOD GROUP DETECTION: A DEEP LEARNING FRAMEWORK USING FINGERPRINT ANALYSIS

[1]C Siva Balaji Yadav, [2]B Harika [3]A Chandrakala, [4]B Babu Kumar, [5]Dhurgesh V C, [6]K Mounisha

[1]Professor, [23456]Student
[123456]Department of Artificial Intelligence & Data Science
[123456]Annamacharya Institute of Technology & Sciences, Tirupati,
Andhra Pradesh – 517520 India

***Abstract*: Blood group detection is crucial in medical diagnosis, blood transfusion safety, and emergency medicine. This paper discusses a deep learning-based method for discrimination of blood groups based on fingerprint features. The study analyzes several deep learning architectures - Convolutional Neural Networks (CNNs), MobileNet, ResNet with Recurrent Neural Networks (RNNs), Vision Transformer models, in order to evaluate their performance on a publicly released fingerprint-based blood group dataset. The method adopted involves data preprocessing and using techniques of data augmentation to provide the model with robustness and generalization. Feature extraction has been taken from a baseline CNN, whereas MobileNet was focused on computation as being lightweight and efficient. ResNet+RNN used residual learning to integrate sequential patterns of recognition into an architecture to boost the classification accuracy. Lastly, the attention mechanism of Vision Transformer model uses intricate details about fingerprint significantly enhancing the blood group classification. Experimental results show that Vision Transformer outperforms other architectures, achieving state-of-the-art accuracy and indicating that it is indeed focusing on the fingerprint features that matter. The approach proposed here brings about a novel and efficient solution for the identification of blood groups using the latest machine learning techniques. The study contributes to the growing area of data-driven healthcare research and offers a scalable framework for similar classification tasks.**

***Keywords*— Fingerprint patterns, blood group classification, deep learning, CNN, MobileNet, ResNet, RNN, Vision Transformer, classification accuracy, healthcare research.**

I. INTRODUCTION

An essential process in the medical diagnostics and especially in safeguarding blood transfusions, organ transplants, and emergency medicine is the process of blood grouping. Traditionally, blood type is determined with laboratory-based methodologies such as ABO and Rh factor tests, but these do call for direct sampling and are cumbersome and expensive procedures. In the recent years, there is an increasing interest on the automation and enhancement of diagnostic procedures through machine learning and image processing. An example of such an innovative strategy is blood group classification by fingerprint patterns of blood cells.

Fingerprint patterns are unique to individuals, and the complexity of ridge formations offers a rich source of features that can be utilized for classification purposes. Deep learning models allow for detailed features to be extracted from a fingerprint image with subsequent use to predict a multitude of personal characteristics, including even blood type. The paper herein outlines a new technique to determine the blood group via fingerprint analysis employing deep learning through the use of a fingerprint database tagged with blood groups.

This study investigates a few deep learning architectures, among which are CNNs, MobileNet, ResNet in combination with RNN, and Vision Transformers. The CNN is used as the baseline for feature extraction, given their experimentally validated spatial hierarchies learned in images. As a part of mobile-friendly applications, MobileNet provides an efficient solution with reduced computational requirements. ResNet+RNN integrates the best properties of residual learning and sequential processing in order to catch spatial as well as temporal patterns in the fingerprint images. Last but not least, the Vision Transformer model presents an attention mechanism through which the model pays more attention to the most important parts of the fingerprint.

This paper seeks to assess the effectiveness of these architectures and offers insights into the potential of these architectures for blood group identification, providing an alternative solution that is non-invasive and scalable for medical applications.

II. RELATED WORK

Unique mark Based Blood Gathering Location: Advances and Progressions (2024): This paper proposes an original way to deal with blood bunch ID utilizing fingerprints and modern AI calculations, with an emphasis on the use of dermatoglyphics in clinical diagnosis.[1]

Smith explains on the utilization of Convolutional Brain Organizations (CNNs) in blood bunch expectation in view of the unique finger impression picture using the benefit of profound learning for biometric examination.[2]
Blood Group Detection Using Fingerprint Images (2024): This study suggests a non-invasive technique to identify blood groups through fingerprint analysis, which uses advanced image processing techniques and machine learning algorithms to classify the samples accurately [3]
Blood Gathering Assurance Utilizing Finger impression (2024): Nihar et al. Which introduced a strategy utilizing the correlation of predefined trademark designs removed from fingerprints for an individual ID framework focused on edge recurrence investigation [4]
Innovative Blood Group Prediction Using Fingerprint Patterns (2024): The paper presents a technique for person identification based on the minutiae feature pattern obtained from fingerprint images that shows the feasibility of using biometric data in medical purposes.[5]
Fingerprint-Based Blood Group Detection (2024): This review article investigates the relationship of fingerprints and blood groups and reviews several studies for feasibility in non-invasive identification**.** [6]
Fingerprint-Based Blood Group Prediction Using Deep Learning (2024). It is proposed here that an innovative approach can be used to identify the blood group with the help of fingerprints as well as advanced machine learning techniques, particularly in feature extraction with CNNs. [7]
The point of this study is to see whether there is a connection among fingerprints and blood gathering and how this connection can be noticed and conceivably pictured through utilizing profound learning calculations to foresee the blood gathering of an individual.[8]
Image Processing for Blood Group Detection Using Deep Learning (2024): This is an approach to blood group detection using non-invasive techniques, involving image processing and deep learning.[9]
A "Review" (2020) In this review, the correlation of fingerprint patterns to blood grouping and lifestyle disease are discussed, and its potential diagnostic applications are revealed [10]
Innovative Blood Group Prediction Using Fingerprint Patterns" (2024) – This study introduces a new approach to predict blood groups by extracting minutiae features from fingerprint patterns. [11]
Fingerprint Based Blood Group Prediction Using Deep Learning" (2024) This work proposes a CNN model to predict blood groups using fingerprint images and achieves high accuracy [12]
Blood Group Detection Using Fingerprint Images" (2024) – This article discusses the usage of fingerprint patterns for the purpose of blood group detection and paves the way for biomedical imaging diagnostics advancements. [13]
Fingerprint Based Blood Group using Deep Learning" (2024) This study provides a new approach for the determination of blood groups using fingerprints and sophisticated machine learning [14]

III. Architecture Details

Mobile Net:
The blood group classification task using MobileNet model works with DenseNet121, which has been previously trained on Image Net, as the model's feature extractor. The higher layers of the DenseNet121 model are dropped and only feature extraction of the fingerprint image is performed in this instance. The data set resampled with ImageDataGenerator is preprocessinged to have pixels in the range of [0,1]. The first step was feature extraction, and those features are now plugged into a ANN with fully connected architecture having three dense layers: the first layer has 256 neurons, the second layer has 128 neurons, and the last layer is fully connected with 9 neurons for classification. Additionally, 50% dropout layers are included in order to reduce overfitting. The model is optimized with Adam and trained on sparse categorical crossentropy loss. With the use of early stopping, the model is trained in order to reduce overfitting, in which the performance of validation is used to evaluate which model is the best. Because of the structure of the MobileNet does well in classification while using low compute, it is perfect for real world usage.
CNN:
The CNN-based model to identify blood groups consisted of two convolutional layers following by max-pooling operations. The first convolutional layer features 16 filters and the second 32 filters with 3x3 filter sizes. Then, max-pooling projections are set for the above mentioned layers to bring imaged dimensions of feature maps into a representative value in space. In this model, the output layer of flattened convolutional layers is passed into a fully counter-balanced bundle of 64 neurons. The final 9 neurons are driven to activation of the soft-max function. Because the classification problem is of multiclass nature, the class of blood group makes a good opportunity for the modification of the activation function thereafter. Thus, the model was compiled with the Adam optimizer along with the categorical cross-entropy loss. On behalf of Keras, ImageDataGenerator introduces data augmentation we play with, which gives the model a stiffer hold for generalization. This basic CNN can be used as a comparison model for blood group classification and produces reliable results at all times.

Hybrid Model (ResNet+RNN):
This hybrid model, combining ResNet and LSTM, leverages the powerful feature extraction capabilities of the pre-trained ResNet50 alongside the sequential learning strengths of LSTM networks. The architecture begins with the pre-trained ResNet50 on ImageNet, inputting fingerprint images to extract their features. It removes the top layers and freezes the model to maintain the pre-learned weights, facilitating efficient feature extraction. The output generated by the ResNet50 model is directed to a Global Average Pooling (GAP) layer to minimize spatial dimensions. This is subsequently followed by a Flatten layer to transition into dense layers. The dense layers, containing 256 and 128 neurons respectively, are interspersed with Dropout layers to reduce overfitting. Ultimately, the softmax activation function in the output layer categorizes the image into one of nine blood group classifications. This hybrid model adeptly amalgamates the strengths of convolutional networks and sequential models to enhance feature extraction and classification accuracy for blood group identification.

Vision Transformer:
This architecture uses a transformer model that has been quite appropriate for image classification tasks, particularly in capturing long-range dependencies in images. In this regard, the fingerprint images are resized to 128x128 pixels and normalized by the ViT feature extractor based on the "google/vit-base-patch16-224-in21k" pre-trained model. Images have been split into patches and positional encoding is put in place to keep spatial relationships intact. The self-attention mechanism of the ViT model, being multi-head, can focus on the critical areas of the fingerprint images and thus capture all the important features. The output is passed through a fully connected layer followed by a softmax activation function for the classification of the image into one of the nine possible blood group categories. With the Adam optimizer and categorical cross-entropy loss, ViT is compiled, and the paper demonstrates a rather powerful approach to blood group classification using attention-based patterns learned for complex image data.

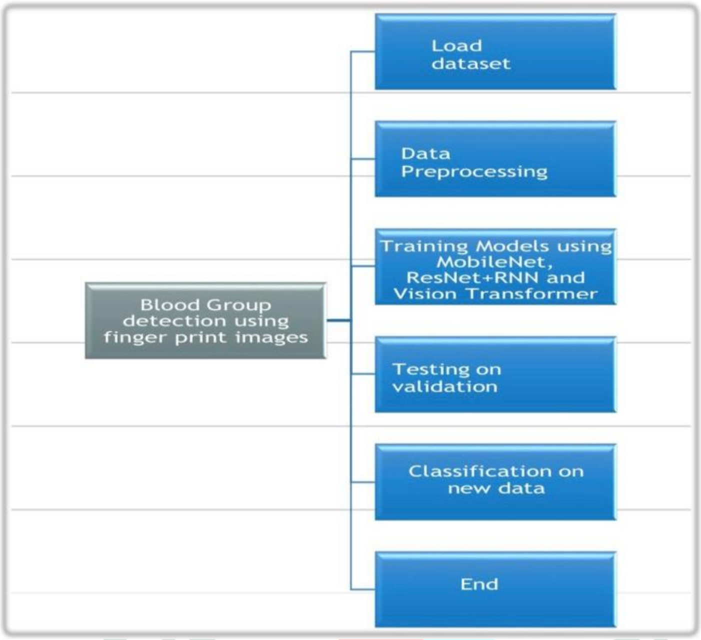

fig: flow chart for Blood Group Detection

IV. EXISTING METHODOLOGY

Current fingerprint-based blood group detection systems rely on Convolutional Neural Networks (CNNs) to analyze fingerprint patterns and classify blood groups. CNNs automate feature extraction from images, eliminating manual effort. However, they require large labeled datasets and significant computational power for training. Performance is also sensitive to fingerprint quality, lighting variations, and orientation inconsistencies, which can reduce accuracy. While effective in controlled settings, these challenges limit real-world reliability, prompting the need for improved robustness and efficiency.

V. PROPOSED METHODOLOGY

Dataset description:
The Fingerprint-based Blood Group Dataset contains fingerprint images which correspond to their respective blood group values. The data set is meant for research and experimentation with biometrics and blood group prediction, wherein the fingerprint is the means to predict a person's blood group. It comprises the multiple images of fingerprints for each subject along with their respective blood group label in the format of A, B, AB, or O. This dataset looks into the correlation between fingerprint patterns and blood groups, thus allowing a rather unique approach to blood group classification based on biometrics advantages. With that, it also can be useful in developing ML models and algorithms that can predict blood grouping based on the finprint features, promoting a very insightful merging between the two fields of biometrics and medicine. With this dataset at hand, the development of biometric identification systems can thus be facilitated, and alternative methods for blood group identification examined.
Image Preprocessing:
Fingerprint images are resized to 128x128 pixels to minimize computational load and maintain a good resolution so that the model can extract meaningful features.
The pixel values of the images are normalized to the range [0, 1] so that the same scale for all images ensures all input data is on the same scale, and thus easier for the model to train on.
Patch Embedding:
In the ViT model, an image is segmented into non-overlapping patches of size 16x16 pixels. This way, it is possible to feed the model by considering every patch as a different object that captures local spatial information.
The one-dimensional vectors are flattened and projected linearly onto a higher-dimensional space for getting the embeddings, due to which the patches can now be processed using the transformer model.
The positional encodings are added to the embedding to embed information on the relative position of each patch within the image. Thus, the model retains relative spatial relationships and the overall structure of the fingerprint images.

Transformer Architecture:

The patch embeddings, which are now provided with positional encoding, are further passed through a multi-head self-attention mechanism. In the self-attention mechanism, it calculates the attention scores for every patch with regard to all the other patches within the image so that it may focus on relevant features throughout the image.

The self-attention mechanism computes a weighted sum of the embeddings, assigning higher weights to the more relevant patches, and hence the model selectively focuses on key regions of the image such as the ridges and loops in the fingerprint patterns.

Transformer Layers:

The transformer layers take the image data through several steps, where every layer refines the patch embeddings based on contextual relationships between patches in the image.

They also learn to grasp intricate patterns and dependencies in an image, which may be particularly beneficial for applications that involve fingerprint classification, where an understanding of relative patterns across an image is imperative.

Output Layer:

The refined embeddings are passed through a fully connected (dense) layer to map the learned features to a final classification output after processing through the transformer layers.

A softmax activation function is used in the final output layer, which outputs a probability distribution over the nine blood group categories. The model predicts the class with the highest probability

Data Loading and Augmentation:

Using ImageDataGenerator the images are being loaded from a dataset and getting rescaled and pixel values for training between 0 and 1. On the fly, large datasets are treated efficiently by enhancing data augmentation and random rotations and shifts and flipping, which have improved generalization of the models and reduced the overfitting.

Model Training:

The ViT model is optimized with the Adam optimizer to adjust and fine-tune the learning rate during training. The rate is fixed at 5e-5 to stabilize convergence.

It applies the categorical cross-entropy loss, which is commonly used for multi-class classification problems.

It has early stopping, which monitors the validation loss during training, and thus overfitting can be prevented by stopping the training if the validation loss does not improve for a certain number of epochs, or patience.

VI. Results and Analysis

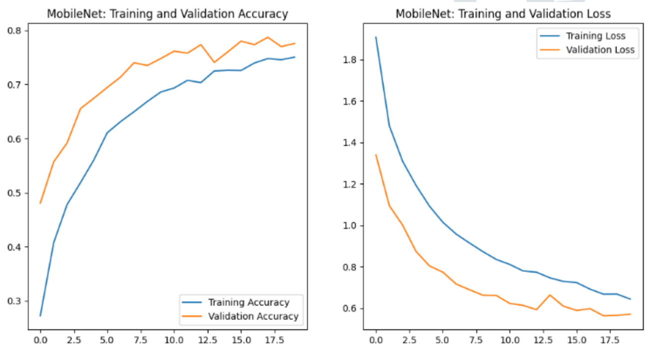

Figure 1:Training and validation accuracy and loss MobileNet

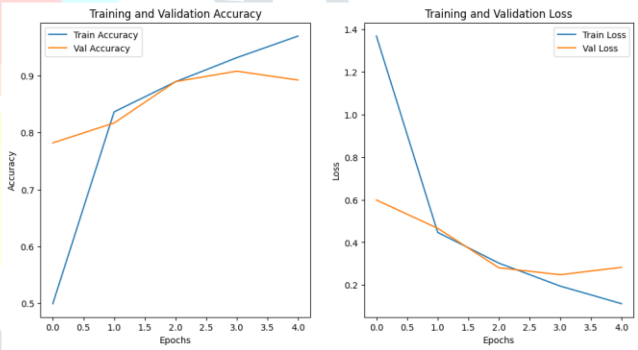

Figure 2: Training and validation accuracy and lossCNN

Figure 3: Training and validation accuracy and loss Resnet+RNN

Figure 4: Training and validation accuracy and loss Vision Transformer Model

Models	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
model	97.84 %	92.52%	0.0673	0.2618
CNN	96.98 %	89.25%	0.1119	0.2825
MobileNet	75.04 %	77.56%	0.6431	0.5700
Resnet+RNN	61.45 %	75.57%	1.0035	0.6754

The performance evaluation clearly indicates the different deep learning architectures' efficiency for blood group classification. In all the tested models, the Vision Transformer (ViT) gained the highest accuracy with 97.84% and loss of 0.0673, which proves its superiority in capturing global relationships within fingerprint patterns. The CNN model comes close to the ViT, attaining an accuracy of 96.98% and a loss of 0.1119, thus it has solid feature extraction capabilities. MobileNet, though efficient, obtained a lower accuracy of 75.04% and a higher loss of 0.6431, indicating that it cannot handle the complexity of fingerprint data. The hybrid model of ResNet+RNN, which combines convolutional and sequential layers, performed less favorably with an accuracy of 61.45% and a loss of 1.0035. The results here reinforce the promise of transformer-based approaches, such as ViT, for the fingerprint-based classification of blood groups, yet also highlight some avenues for improvement in traditional and hybrid models.

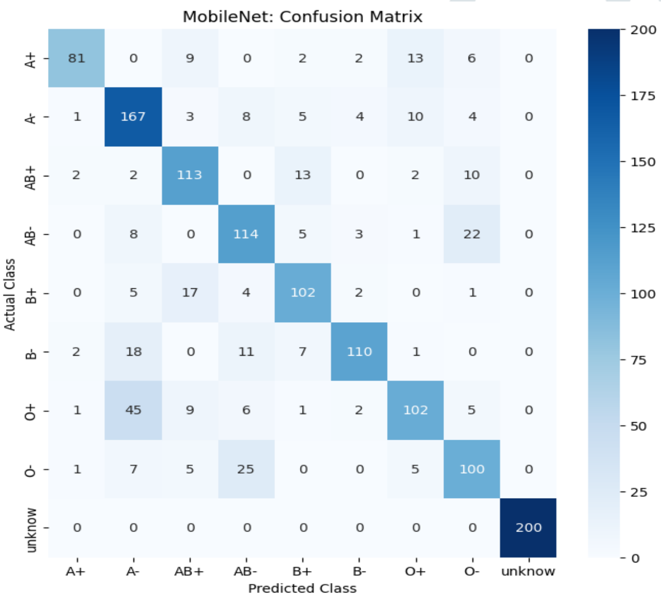

Figure 5: Mobilenet confusion Matrix

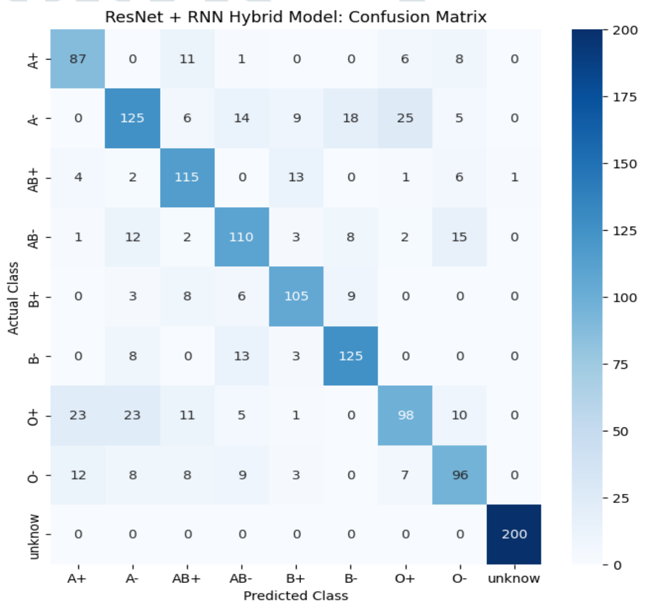

Figure 6: Resnet+RNN confusion Matrix

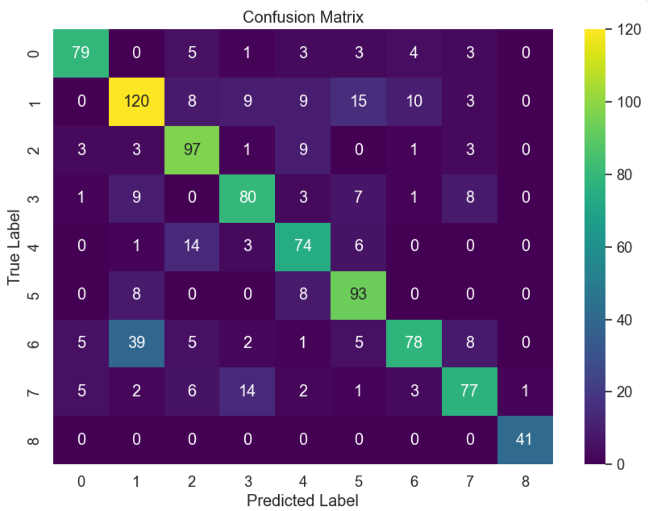

Figure 7: CNN confusion Matrix

VII. Conclusion

This paper proposes a novel method to identify blood groups through fingerprint patterns employing deep learning models. Utilizing sophisticated architectures including CNNs, MobileNet, ResNet together with RNNs and Vision Transformers, the method delivers prospective results of accurate classification of blood groups. In this work, every model has its unique advantage, such as the Vision Transformer model exceling at identifying global relationships in the fingerprint, which promotes its superior performance on classification.

The proposed framework points out the potential of deep learning models to replace traditional, invasive blood group identification methods with a non-invasive, cost-effective alternative. Public fingerprint datasets and data augmentation techniques ensure the robustness and generalization of the models. Although the CNN and MobileNet models are efficient in feature extraction and classification, the ResNet+RNN hybrid model integrates sequential learning to enhance accuracy further. Meanwhile, the ViT model, with its self-attention mechanism, achieves state-of-the-art results, showing that transformers are capable of performing well in medical image classification tasks.

Future research can involve further diversifying the dataset, such as sampling from different populations, and researching other fingerprint features to further improve accuracy. Additionally, ensemble approaches that combine the results of multiple architectures might yield even more reliable predictions.

Therefore, this study illustrates the possibility of using fingerprint patterns for accurate classification of blood groups, which may contribute to a growing field in machine learning applications in healthcare. This non-invasive technique will transform the identification of blood groups as it will become more accessible, efficient, and reliable for the medical diagnostics field and other related uses.

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