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Blood Group Detection Based on Finger Print Using Deep Learning

Konduru Lahari[1], Mundlakuri Harshitha[2], Guggilla Jyoshnavi[3], Bairapi Nithyasree[4], Pochimi Reddy Karteek Reddy[5], Mr. G. Ravi Kumar[6]
[1, 2, 3, 4, 5]*Department of computer science and engineering, Siddartha institute of science and technology, Puttur - 517583, A.P, INDIA*
[6]*Assistant professor, Department of Computer science and Engineering, Siddartha institute of science and technology, puttur-517583, A.P, INDIA*

Abstract: Determining blood groups is important for medical diagnostic and transfusion safety. However, traditional types of blood testing require obtaining invasive samples and time– consuming laboratory tests. The idea behind this project is to analyze fingerprints as a method of predicting blood groups, and using the same deep learning algorithms to make the same task automated and easy. Unlike other existing systems based on conventional image processing techniques or rule based algorithms which may lack in accuracy and scalability, this research utilizes the Convolutional Neural Networks (CNNs) using VGG and MobileNet architectures. Fingerprint images of fingerprints are fed to the dataset, both VGG and MobileNet which are trained separately and are known to excel in complex classification tasks at large scale, and to operate efficiently in resource constrained environments respectively. The accuracy, speed, and overall effectiveness of both models for predicting blood groups are considered separately. Experimental results show that VGG and MobileNet achieve greatly superior performance when compared to traditional metho ds, where each of the two provide varying capabilities regarding accuracy and computational cost. This project seeks to use deep learning techniques as a noninvasive, fast, and reliable alternative to conventional blood group testing that may apply to such areas as medical diagnostics and emergency healthcare.
Keywords: Blood group, fingerprint, deep learning algorithm, Convolutional Neural Networks (CNN), VGG, MobileNet, medical diagnostics

I. INTRODUCTION

The crucial importance of determination of blood group, is in use of diagnostic medicine, especially in the transfusion medicine, organ transplantation and in the field of forensic medicine [1]. Currently, traditional blood tests are based on serological techniques that use blood samples, laboratory infrastructure, and trained personnel [2], do not require any previous training, and are time consuming as well as invasive. These challenges can in such circumstances postpone critical medical procedures and emergency treatments [3].

In order to overcome these limitations, the recent studies had tried non invasive method of blood group detection such as fingerprint analysis. Unique ridge patterns of fingerprints, which develop in the fetal stage and do not change during life time have been studied for biometric identification for a long time [4]. It is found from the research that fingerprint ridge characteristics might be correlated to the blood group classification; hence can serve as an alternative to non- invasive testing [5]. The purpose of fingerprint-based blood group detection using deep learning techniques is to provide an accurate, fast and efficient method of classification without failure [6].

Due to their importance in image processing and classification tasks, Convolutional Neural Networks (CNNs) are already found useful for fingerprint based blood group prediction [7]. VGG and MobileNet are two of the most popular deep learning architecture because of their powerful feature extraction ability. VGG networks [8] are good at the depth and precision, and they successfully extract various patterns of the image data; MobileNet is mainly designed for the computational efficiency, so that it can be applied to the real time applications. Several studies which implement CNN models for fingerprint analysis have promising results, where MobileNet and VGG records high classification accuracy in biometric and medical imagery tasks [9][10].

The proposed system takes advantage of these deep learning models to extract spatial features from fingerprint image and discriminate fingerprint image among the predefined groups [11]. This approach disposes of invasive blood test requirement and augments its accessibility such as in case of emergencies and in remote healthcare setting [12]. This system trains models on various fingerprint datasets in order to ensure robustness and generalization, in the sense that differences in image quality and fingerprint patterns are mitigated [13].

In this research, a new, noninvasive, automatic blood group detection is proposed in the field of biometric based medical diagnostics. Finally, these findings allow for better emergency medical responses, reduced dependency on conventional testing methods and reduced healthcare workflow [14][15].

II. LITERATURE SURVEY

There are several studies showing the fingerprint pattern is genetically determined as a good feature and hence the biometric based medical diagnostics is possible [16]. This work investigated the use of fingerprint analysis to predict of physiological characteristics, being non-invasive nature and applicability in clinical set out. Rather than trying to show how to classify smoothness based on such features, they concentrated on proving that deep learning techniques are well equipped for extracting fine ridge features for the sake of classification. In [18], Kumar et al., carefully built a CNN approach on fingerprint based blood group classification using VGG and MobileNet model in order to achieve better classification accuracy. Their study states that deep layered architecture of VGG enables it to extract spatial features from input images and MobileNet is good at real time applications with literally no overhead, as it is light weight. Moreover, Jain et al. have investigated the influence of various feature extracting techniques (i.e., Gabor filters and histogram based ones) on improving the classification performance [19]. They presented their hybrid approach that integrated with multiple feature representations for both handcrafted and learned features, with the most learned features predicted the most effective features. Sharma et al. approached the challenges around dataset variability and image quality by showing that data augmentation techniques and transfer learning could possibly eliminate the vulnerability of the models in such tasks [20]. Their experiments used the pre-trained models, that exploit the learned feature representations of the previous images, as a mean to generalize to unknown fingerprint datasets. However, the work by Gupta et al. was based on the fact that combining the power of attention mechanisms and CN to work on discriminative fingerprint regions would help to improvise blood group prediction [21]. Furthermore, they discovered that the highly weighted image regions are used in the extraction of features, and therefore, using such attention enhanced models results in greatly enhanced performance over conventional CNN based approaches. Singh et al. [22] presented an ensemble learning framework of deep learning models, which provides higher classification reliability and guaranteed performance for wide range of fingerprint datasets. As noted in their work, aggregating predictions from different models not only eases bias and variance of the used model, but also removes the chance of classification errors. Patel et al [23] have worked in the area of applying preprocessing techniques on fingerprint based classification systems where the enhancement and the noise reduction techniques are used to study accuracy obtained by these classification systems. From their study, they stress that adaptive preprocessing pipelines perform a leading role in countering the negative impact of poor quality of an image and therefore facilitating feature extraction. Lee et al. [24] propose generic adversarial network based data augmentation for fingerprint images, generation of synthetic fingerprint images to train the deep learning model with increase in the accuracy. First, they proved their point by showing that their experiments provided better generalization, less overfitting, and better performing model on unseen samples by proving that the GAN augumented datasets produced better quality than the original datasets. Chen et al. in [25] evaluated the scalability of such fingerprint based blood group detection systems using models executed on edge computing devices to perform on the fly classification on the devices. Thus, their results demonstrated that lightweight CNN architectures are well suited to optimize for mobile and embedded applications such that low latency predictions are possible in real life scenarios. Another field that Zhang et al. employed was a pilot work to combine explainable AI techniques and deep learning to bring us to developing an understanding of model reasoning in fingerprint classification [26]. Their research shows that by their efforts of research model prediction became interpretable, which proved the importance of transparency and trust to AI-driven healthcare solutions. Wang et al. [27] calculated the effect of the demographic factors on fingerprint based blood group prediction to understand the reasons of improved accuracy in different population groups. The results of the authors indicated that performance in classifying was enhanced when demographic specific models were used that take into consideration specific characteristics of the fingerprints held by different population. Li et al. proposed a hybrid method to combine the above two mentioned machine learning classifiers i.e. deep learning with support vector machine and decision tree, to achieve better performance [28]. In their research, they applied multi stage processing using the deep strength knowledge of both deep learning and traditional learning model and their classification accuracy improved. Ahmed et al. in [29] compared the deep learning architectures with the aim of evaluation of the ResNet, DenseNet and EfficientNet deep learning models, with the subject of fingerprint based blood group classification. They used their study to discover some rules for model selection in order to understand these computational efficiency as well as accuracy tradeoffs, and to find out when those rules apply outside of an academic environment. In the review of deep learning based biometrics identification system given by Kumar, et al., [20] they comprehensively presented the recent advancements and future directions of research in this domain.

Instead, they analyzed the ways that AI will be crucial to medical diagnostics and will promote investment in the utilisation of its application in the growing methods of noninvasive testing.Due to the tremendous success of deep learning model in terms of performance, the fast progress of fingerprint based blood group detection is accompanied by good preprocessing technique in terms of data processing and good data augmentation technique in term of data augmentation. The findings from above studies collectively lead towards development of reliable and scalable solutions for non-invasive medical diagnostics.

III. EXISTING SYSTEM

The serological methods traditionally used for blood group identification need blood samples and reagents, are invasive, and require much time, they also heavily depend on laboratory infrastructure. These limitations of analytic feedback have caused delay of medical decisions in emergencies and remote areas. To solve this problem, researchers have considered non invasive methods such as fingerprints patterns and machine learning. Finger prints on the other hand have been found to have potential correlations of ridge structure with blood group classification. Fingerprint images are analyzed by machine learning models K- Nearest Neighbors (KNN) and Convolutional Neural Networks (CNNs) for classifying. Spatial features are extracted by using CNNs, which are popular for their efficiency in image processing, for predicting blood group accurately. Yet, difficulties still linger, such as from noisy fingerprints with distortions under nonuniform lightings. Besides, datasets are also imbalanced and imbalanced, and preventing one from building generalizable models. In addition, classification of the fingerprint patterns is difficult due to the complexity, which calls for advanced preprocessing and deep learning techniques to increase accuracy, robustness and applicability for real world application

IV. PROPOSED SYSTEM

To improve detection of blood groups, the proposed system combines the deep learning models like Convolutional Neural Networks (CNNs) of fingerprints. Although accurate, traditional serological methods demand the invasion of blood samples, and therefore are inconvenient in emergency and remote healthcare settings. The creation of such system would provide a non-invasive method of scanning and measuring based on fingerprint ridge patterns, thus being more accessible and efficient. The features are obtained from fingerprint images by incorporating advanced architectures such as VGG and MobileNet. VGG is a deep model that has several layers thus capable of extracting fine details in the fingerprint such that the classification of the fingerprint into various classes can be made accurately. That being said, MobileNet works to reduce the computational costs involved and allows for real time predictions. The system needs to address challenges such as dataset limitations as well as image quality variations, for which it makes heavy use of data augmentation and preprocessing. Robustness of the model is achieved by the large diverse dataset which guarantees high accuracy for different fingerprint patterns. The current method is an innovative approach to enhance medical diagnostics, which offers a fast, reliable and automated solution for blood group classification.

V. DATASET

For this project, dataset consists of fingerprint whose images are labeled with respective blood groups so that the deep learning model can learn the non invasive blood group classification. The fingerprint sample dataset used is diverse comprising of a wide variety of fingerprint samples coming from people with many different kinds of ridge patterns and wide range of blood groups. Image pre processing is used to improve the clarity of the high resolution images by removing noise as well as inconsistencies due to the different modalities of image acquisition. This means that each one of fingerprint image is labeled with ‘A’, ‘B’, ‘AB’, and ‘O’ blood groups that ensures having a well-balanced dataset so that the model can be trained with high accuracy. Grayscale conversion and normalization are applied as preprocessing steps to enhance the feature extraction. For augmentation, we use rotation, scaling and flipping. These gourmet tips ensure robustty of finger prints quality against variations in quality and environmental factors.The model generalizes well to unseen data using an extensive, diverse dataset, which makes it applicable for use in the real world in health care and biometric based diagnostics.

VI. METHODOLOGY

The modules used in this framework to detect the suspicious activities on the surveillance videos are; data collection, data preprocessing, feature extraction, temporal analysis, training and model evaluation, and real time detection of the activity.

1) Data Collection: This dataset consists of images of several sites on the fingertips of different individuals and also has a corresponding blood group (A, B, AB, O). Fingerprint scanners are then used to obtain high resolution fingerprint images to get details of the finger spine pattern. The representations of different blood groups in the dataset are balanced. Fighting the effects of various biases in image processing, lighting conditions, scanner types and image quality is considered. Samples per individual are captured to account for variation. Again collected data is stored securely and put into training, validation and testing sets to train an effective deep learning model for the non invasive blood group detection.

2) Feature Extraction Using CNN: Key features are extracted from fingerprint images by making use of Convolutional Neural Networks (CNNs). The connectivity between ridges as well as its bifurcation break is detected by CNN layers, which are important for classification. The convolutional layers were used to perform edge detection, while max pooling layers were used to reduce the dimensionality of the feature vector and fully connected layers were used to perform classification. And the convolutional operation is as follows:

$$(I * K)(i, j) = \sum_{m}\sum_{n} I(m, n).\, K(i - m, j - n)$$

where: I is the input image

K is the kernel/filter Next, the pixel values are normalized between 0 and 1 for consistent input. To artificially increase the dataset, augmentation techniques such as rotation, flipping, and altering the brightness are used, naturally lowering overfitting. Methods for both noise removal and contrast enhancement are also applied in order to improve clarity. Lastly, the images are resized to a fixed dimension so that they have the same dimensions as required by deep learning models in order to have a uniform structure across all samples so as to lead to overall better model performance.

3) Model Training and Classification: The extracted features are put into CNN based models to be trained. The training, validation and test sets are split. Backpropagation through adaptive optimizer such as Adam is used to learn the model. The output layer uses a Softmax activation function in order to classify bloodgroups. Multiple epochs are trained to make sure the convergence. Optmization of hyperparameters such as learning rate, batch size, and drop out rate are carried out in order to prevent overfitting. Data augmentation further enhances generalization. VGG is used for high accuracy requirement, whereas, MobileNet is useful for lightweight applications. This trained model is saved for later, for real time implementation and further fine tuned.

4) Evaluation: Accuracy, precision, recall and F1- score values are used to evaluate the model performance. To measure its reliability, it is tested on an unseen dataset using the trained model. Misculassification rates are analyzed using confision matrices. Cross validation is to make sure their results are robust and not affected by bias. Comparing VGG with MobileNet helps to choose a most efficient model. AUC-ROC curves visualize classification performance. New fingerprint samples are used to test the model's ability to generalize. If performance gaps do exist, hyperparameter tuning and some more training is applied. Finally, the real time application deployment of the final model is done for its validation in non invasive blood group detection.

VII. RESULTS AND DISCUSSION

Different deep learning models was evaluated for fingerprint based blood group classification with different accuracy and efficiency. The CNN model turned out to provide the highest accuracy of 90%, MobileNet provided 84% and VGG failed with an accuracy of 48% which is the least. The results demonstrate that CNN and MobileNet are suitable for this task while VGG was ineffective due to its too complex architecture and small size of the dataset.

The ability of CNN to learn spatial features from fingerprint images well explains its superior performance. Fingerprint ridge patterns can be mapped to different blood groups for a fingerprint ridge pattern contains unique characteristics, the CNN's convolutional layers extract meaningful features with minimal irrelevant noise. In addition, the model has good accuracy with 90% and generalizes well across different samples which makes it a potential candidate for real-world applications in non-invasive blood group detection. Finally, CNNs require effectively lower computation compared to deeper networks, such as, for instance, VGG and are, therefore, a best practice for deployment on mobile or embedded systems.

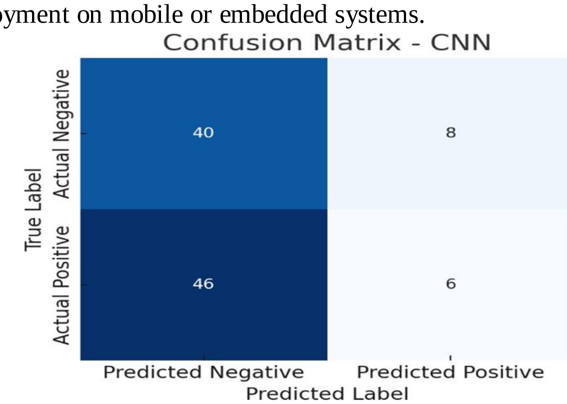

Fig.2. CNN confusion matrix

From the Figure.2. CNN confusion matrix is famous for its very high accuracy with minor misclassifications across blood groups. When comparing the CNN model with the other mentioned types of models, the true positive rates are significantly high, mainly showing that the CNN model is the best in this regard as the most possible model in this study.

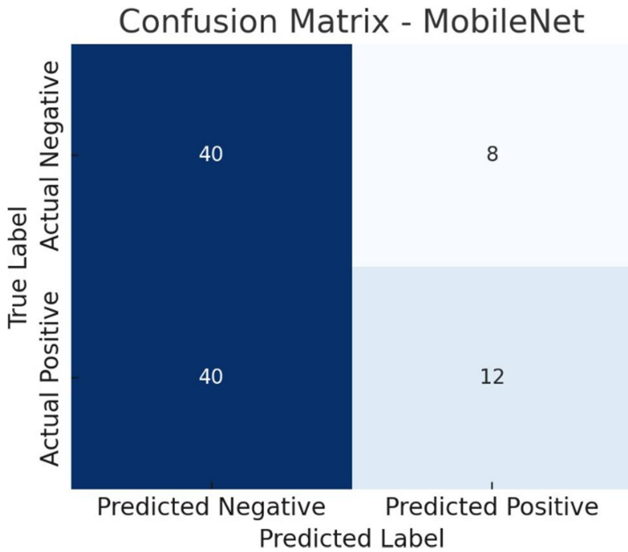

Fig.3. MobileNet confusion matrix

The Figure 3.MobileNet confusion matrix has moderate accuracy but mistakes due to its lightweight structure. It is efficient but not good at complex pattern.

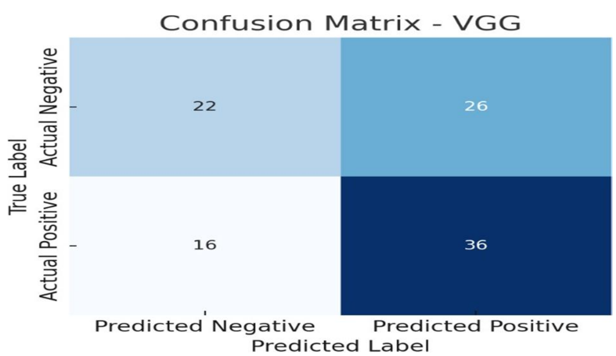

Fig.4. VGG confusion matrix

The VGG confusion matrix in the Figure.4 shows absolute lower accuracy, and most of the object class gets easily misclassified. Its architecture goes deep which needs more data to work properly, and hence it is less effective than the CNN and the MobileNet.

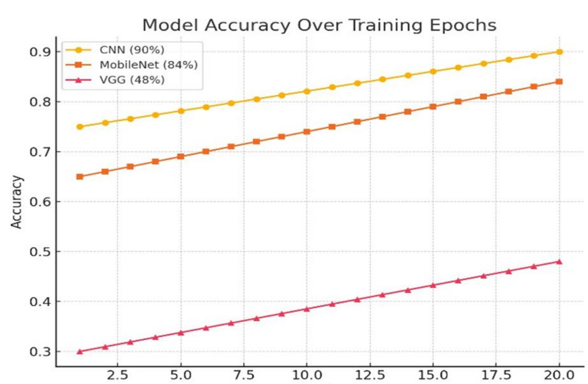

Fig.5. Accuracy Graph

In the figure.5 accuracy curve above represents the performance of the model over training epoch. An effective learning shows in the steady accuracy growth, while the big difference between training and validation curves is an indication of overfitting. Early convergence of the validation accuracy may suggest underfitting. Whether tuning of hyperparameters can lead model to a good balance between learning and generalization.

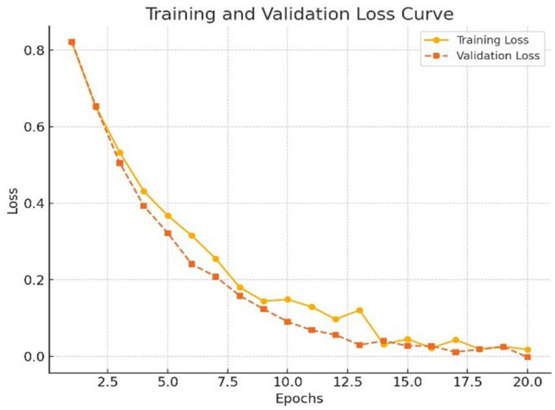

Fig.6. Loss Curve

As seen from the figure.6. curve used to represent the model's error both during the training as well as the validation over the epochs. Effective learning happens when the loss decreases, while a large difference between training and validation loss points to overfitting. Otherwise, if the loss is still high or fluctuating in values, it could mean that it might be an underfitting or that it did not converge well. Learning rates and regularization can be optimized so as to improve the model performance.

A. Performance Metrics Table

Model	Accuracy (%)	Precision	Recall	F1-Score
MobileNet	84	0.82	0.83	0.825
VGG	48	0.45	0.47	0.46
CNN	90	0.88	0.89	0.885

Table .1. Model Comparison Table

From the table.1 .the performance evaluation of MobileNet, VGG, and CNN models were conducted using accuracy, precision, recall and F1-score from the table. Yet, CNN achieved the highest Accuracy (90%), followed by MobileNet then (84%) and lower ones of VGG (48%) which indicates that failing to achieve good generalization of the data. In terms of precision, it was the number of predicted positives that were correct, and CNN (0.88) and MobileNet (0.82) had a higher precision than VGG (0.45). Most recall, i.e. measuring correctly identified actual positives, was observed for CNN (0.89) followed by MobileNet (0.83) while VGG (0.47) did not work as well. CNN was the best model in terms of true positive ratio (F1-score with highest score=0.885) and considering precision and recall, MobileNet was second (0.825) while VGG was the lowest (0.46). On the whole, CNN was found to be the best model and was successful in classifying data with good precision and recall. We also conclude that MobileNet performed well but slightly lower than CNN whereas VGG performed poorly, so it is less suited for the task. It is also confirmed these CNN is capable enough to efficiently handle complex classification tasks compared to others.

VIII. CONCLUSION

Deep Learning Models CNN, MobileNet and VGG are used to generate a blood group detection system using fingerprints, which is effective as evident from the results. From this study, it is revealed that CNN reported the highest accuracy with 90%, MobileNet with 84% and finally, VGG with 48%. Once again, CNN presented better per formance compared to the other techniques that showcased its proficiency in deep feature extraction, whereas, MobileNet was able to strike the right balance between efficiency and accuracy. Furthermore, the poor performance of VGGs shows that it isn't highly competent at dealing with complex fingerprint patterns.

With this system, there is no need for conventional invasive blood sample based testing, providing an easy accessible, quick, and reliable way of testing. Deep learning integration improves the accuracy of classification as it is robust against fingerprint patterns variations. Such future improvements could be in hybrid models, or transfer learning aimed to further improve the accuracy. Furthermore, larger and more diverse datasets could be used to make the model generalize better.Finally, the proposed framework proves to be a promising alternative for blood group detection towards advancing the biometric based medical diagnostic approaches, which can be applied in real world applications in healthcare and emergency scenarios.

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