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Deep Learning Based Blood Group Prediction Using Fingerprint

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Abstract: Blood group identification is an essential factor in medical diagnostics, transfusions, and emergency healthcare management. Conventional blood type involves invasive serological testing. This paper introduces a deep learning-based approach for a non-invasive method of blood group identification through statistical correlations using images of fingerprints. A Convolutional Neural Network (CNN) architecture is employed for this purpose. The system is based on a dataset of 6000 images of fingerprints categorized into eight classes of blood groups: A+, A-, B+, B-, AB+, AB-, O+, and O-. The system is based on a combination of image processing, ridge pattern detection, and SoftMax classifier within a web application framework. The feasibility of this approach is demonstrated through experimental evaluation using deep learning architectures for blood group identification through images of fingerprints. Although this approach does not replace conventional blood type, it is useful for exploratory diagnostics for research purposes.

Keywords: Fingerprint, Blood Group Prediction, Deep Learning, Convolutional Neural Network, Biometrics, Image Classification.

I. INTRODUCTION

Blood groups are crucial for organ transplantation, blood transfusions, prenatal care, and determining the general compatibility of medical treatments, they play a fundamental role in healthcare. Individuals are categorized by the ABO and Rh blood group systems according to whether or not certain antigens on the surface of red blood cells are present. Because incompatible transfusions can cause serious immune reactions, such as acute hemolytic reactions, kidney failure, shock, and even death, accurate blood typing is crucial. Quick and accurate blood group identification is essential in emergency medical situations to guarantee patient safety and enhance survival rates.

Traditionally, the way in which the process of the blood group detection has been carried out has involved the carrying out of serology tests, which have primarily involved the use of antibodies in the process of agglutination reactions of the blood samples. The tests that fall under the category of the serology tests include the slide test, tube test, microplate test, and gel card agglutination test. Despite the fact that the tests have been proved effective in the process of the blood group detection, the fact that the tests require a controlled environment in the process of carrying out the tests has proved to be the main hindrance in the process of carrying out the tests, especially in emergency cases. The tests that involve the use of the blood samples have also been found to be painful, especially when the required precautions are not observed in the process of avoiding infections.

Molecular methods, such as polymerase chain reaction (PCR) and sequencing, also make it possible for the determination of the blood group based on the DNA molecule, providing high precision, especially for the detection of weak antigens. Nevertheless, such methods are costly, require sophisticated machines, and thus make them not applicable for practical purposes. Although the problem of the resource dependency of such methods has somewhat diminished due to the availability of automated machines, they may not.

The growing demand for non-invasive diagnostic systems has provided an incentive to explore novel methods. Non-invasive blood group detection would reduce patient pain, minimize the risk of infection, reduce health care costs, and increase accessibility in remote areas. These systems would be particularly useful in pediatric, geriatric, and mass screening situations where invasive sampling methods would be difficult or impractical. Improvements in biometric technologies and image-based diagnostic systems have provided the incentive to explore novel correlations between physiological.

Fingerprints are the patterns of the dermatoglyphic ridges and creases, which form during fetal development, a phenomenon that remains constant throughout life. Fingerprints have been used to identify an individual, which has been linked to the genetic development of the fetus. There have been various investigations into the field of dermatoglyphics, which have shown the statistical correlation of loops, whorls, and arches of the fingerprint patterns to biological traits such as blood groups. Although the correlation has not been biochemically proven, the findings of the investigation into the study suggest the scope of exploring the possibility of correlating the two using the application of computers.

Convolutional Neural Networks (CNNs) have demonstrated promising results in image classification problems, and deep learning in medical imaging problems. CNNs have the ability to learn image features in a hierarchical manner without the need to have expert knowledge in feature engineering. Because of the ability of CNNs to identify patterns, CNNs can be employed in the analysis of images in biometric identification problems such as fingerprint identification. It would be possible to investigate whether the features of blood group categories can be statistically linked to the discriminative features of ridge patterns in fingerprints through the use of CNN models in training large labeled datasets of fingerprints.

The purpose of the present study is to develop a deep learning model which may be of potential use to assist non-invasive blood group correlation analysis through the images of the fingerprints. This technique employs feature and classification methods based on CNN to recognize the potential of the technique to be used in predictive modeling considering the limitations of the technique.

II. LITERATURE SURVEY

The conventional method for the determination of the blood group of an individual involves the performance of serological tests such as the slide test and the tube test, in which the blood samples are mixed with Anti-A, Anti-B, and Anti-D liquid substances and tested for agglutination reactions [1]. Although the results obtained by this method are accurate, there is a factor of assessment of the results as well as the individuals involved in the process. Automated machines as well as spectrophotometric machines have been used to prevent the occurrence of errors during the process [2], [3]. There is also a factor of sample collection during the process.

Some researchers also conducted a study concerning the relationship between the pattern of fingerprints and blood groups. In the study concerning the relationship between the characteristics of fingerprints and gender and blood groups, Alshafie et al[4]. concluded that loop patterns were the most common among all the participants. Similarly, Ramrekh et al[5]. also conducted a study concerning the distribution of fingerprints among people of different blood groups and concluded that loop patterns were the most common.

The study on the density of fingerprint patterns was conducted by Khalifa et al[6]. The study revealed that there is a correlation between the density of fingerprint patterns and the subgroups of the blood group system. Kumari et al[7]. conducted another study on the correlation between fingerprint patterns and the ABO blood group system. The study revealed that loop patterns are found among people who have the O-positive blood group.

With the advent of various computer technology tools, the machine vision and image processing techniques have also been used to detect the blood groups. Intelligent machine vision technology has been used to develop the blood sample analyzer using the work done by Keerthana and Ranganathan [8]. Image processing techniques such as thresholding, morphological operations, and edge detection have also been used to detect the blood groups using the work done by Dalvi et al. [9]. Various tools based on the spectrophotometric method have also been proposed to detect the blood groups using the work done by Fernandes et al. [2] and Pimenta et al. [3].

Fingerprint recognition technology has also seen a number of transformations. The idea of feature extraction using the feature of the ending and bifurcation of the ridges of the fingerprint image has been proposed by a number of researchers, such as Zaeri [10], Jain et al. [11], etc. The idea of fingerprint matching using the feature of the ending and bifurcation of the ridges of the fingerprint image has also been proposed by Zafar et al. [12].

Recently, research has also been carried out on the prediction of blood groups using fingerprint techniques based on neural networks. Siva Sundhara Raja and Abinaya[13] proposed the idea of developing a cost-effective fingerprint-based blood group prediction system using feature extraction and neural networks. The results were effective in showing the prediction of blood groups using digital fingerprint techniques instead of ink fingerprint techniques.

Image-based classification has also seen further advances using deep learning technology. Various surveys on the application of convolutional neural networks (CNN) [14], [15] have emphasized their potential to learn hierarchical features from images without the need to manually extract features from images. CNN variants like AlexNet, ResNet, and EfficientNet have achieved state-of-the-art results on medical image processing applications [16]. Deep learning technology has also been applied to improve the robustness of biometric systems [17].

Despite the promising results, the existing literature has provided varying results in the direct correlation of fingerprints and blood groups. Many of the existing literature works have employed smaller sample sizes and have relied on the direct observation of patterns. However, the application of deep learning in the acquisition of digital fingerprints has provided promising results in the representation of features in the study of dermatoglyphics.

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From the literature, it is evident that although conventional serological methods have been considered the gold standard, the trend is moving towards non-invasive image-based and biometric methods.

III. PROPOSED METHODOLOGY

The proposed system intends to explore the possibility of predicting blood group categories using fingerprint image analysis techniques based on deep learning algorithms. The methodology followed in the proposed system can be broadly divided into four major phases, namely, data acquisition, data preprocessing, model development, and performance evaluation. Each of the phases has been designed in such a way that the system remains scalable, reproducible, and computationally efficient.

A. Data Acquisition

A large and diverse dataset acts as a base component of any deep learning model. In this study, a dataset of 6000 fingerprint images was collected from people whose blood group classifications were known. In order to maintain diversity and eliminate any demographic bias, images from different ages and genders are included in the dataset. All blood group classifications were verified through conventional serological testing methods.The fingerprints were collected through the use of digital fingerprint scanners rather than the conventional methods such as the use of ink. This is important because the use of digital methods ensures the clear visibility of the fingerprint ridges, minimal distortions, and the same level of resolution for all the fingerprints. This ensures uniformity in the format of the images during the training of the model. The set was further divided into eight classes according to the ABO and Rh blood groups.In order to simplify this supervised learning, the data was structured, and the fingerprint image was related to the blood group. This helped to simplify the learning of the discriminative features of the images using the convolution neural network

B. Data preprocessing

The raw images of the fingerprints are also different in lighting, direction, and background noises as well. It is therefore very much essential that the images are preprocessed in such a way that more clarity can be achieved in the features as well as the learning process.All the images of the fingerprints have been converted into grayscale images in such a way that the complexities involved in the computation can be reduced, as the classification of the fingerprints is not dependent on the color of the image.Subsequently, all the images were resized to a fixed size of 224 x 224 pixels. It was very essential to standardize the size of the images to provide a fixed size of images to the convolutional neural network model. Additionally, it was essential to facilitate the batch operations of the images during the training phase of the model.In order to improve the robustness of the model, as well as to prevent the occurrence of the overfitting issue, various data augmentation techniques were applied to the training images. Various rotations, as well as scaling and horizontal transformations, were carried out on the images to mimic the actual conditions of capturing the images of the fingerprint.

C. Model development

A Convolutional Neural Network model has been proposed to directly learn the hierarchical features from the images of the fingerprints. CNN can be best used to work with images as it can directly learn spatial relationships from the images.In the proposed model, the convolutional layers have been used to directly learn the multiple filters to extract the low-level features such as edges, curves, and endings of the ridges. As the layers increase, the abstract representation of the ridges has been learned by the model. The Rectified Linear Unit activation function has been used to introduce the non-linearity after the convolution operation to improve the efficiency of the learning process.The max pooling layers are also added to the model. The max pooling layers are used to reduce the spatial size of the images while maintaining the prominent features of the images. Some translation invariance is achieved in the images due to the addition of the max pooling layers in the model. Translation invariance is needed when some small translation is present in the fingerprints.The feature maps are passed through the fully connected layers, and the output layer is also added to the model. The output layer has eight neurons as the images belong to eight different blood groups. The Softmax function is added to the output layer as it has the ability to generate the probability distribution over all the classes. The Softmax function can be used to find the class that has the maximum probability.The model is optimized by the addition of the categorical cross-entropy loss function and the Adam optimizer to the model. This is achieved by the addition of some epochs while keeping the batch size constant during the training of the model. This is done to reduce the amount of error present in the model during the prediction by the model.

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D. Model evaluation

In order to avoid any bias while evaluating the model, the data set is divided into the training set, validation set, and test set.
The division of the data set helps to avoid the overfitting of the model.To evaluate the model, various metrics such as accuracy, precision, recall, and F1 score are used. Confusion matrix and probabilities are also used to evaluate the model. Apart from this, the splitting of the data into the training data set and the test data set has been provided with the feature of k-fold cross-validation for the improvement of the result obtained by this methodology. In this case, the entire data set has been divided into small parts, and the result has been obtained on the basis of the entire parts of the data set.The enhanced version of this methodology has been provided with the feature of structured data collection, structured data preprocessing, CNN feature extraction, and the evaluation methods. This proposed system has been designed to utilize the maximum benefits of the bio image analysis methodology along with the deep learning methodologies for identifying the statistical correlations existing between the blood group classification and the fingerprint pattern.

IV. SYSTEM ARCHITECTURE

The overall system architecture of the proposed fingerprint-based blood group prediction system has been depicted in Fig. X. It has been observed that the proposed system architecture has a well-structured flow starting from the acquisition of the fingerprint to the final prediction of the blood group in real time using a web interface. Each module of the proposed system architecture has a major role to play in the processing of the system.

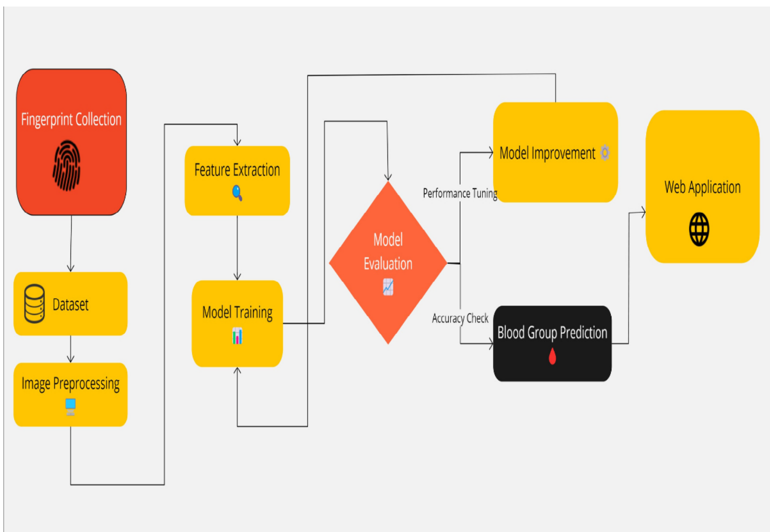

Fig. 1: Overall system architecture of the proposed fingerprint-based blood group prediction

A. Fingerprint collection and dataset formation

The first stage of the architecture is the collection of the fingerprint images. The fingerprint images are collected using a digital fingerprint scanner or image acquisition device. This stage ensures that the images have a high-resolution ridge detail, which can be used for further processing. Compared to the traditional approach of using an ink pad to collect the images, the use of a digital device offers better clarity, less distortion, and better image quality.The fingerprint images collected in the first stage of the architecture are used to form a structured dataset, which consists of images labeled with a confirmed blood group obtained using traditional serology tests.
The dataset forms the base of the input to the deep learning model. Proper image labeling of the dataset is an essential step to facilitate the use of the deep learning model.

B. Image preprocessing

After the creation of the dataset, the fingerprint images undergo the preprocessing stage. This stage is critical as the fingerprint images are all the same, thus the training process is easy. The processes that occur during the preprocessing stage include the standardization of the fingerprint images, the resizing of the images, the normalization of the images, and the removal of the possible noise that may occur during the image creation.This stage is critical as the images are all the same size, thus the images become standard.

This stage also makes the quality of the fingerprint images good, thus the quality of the ridges on the fingerprint images, thus the removal of the possible noise that may occur during the image creation.The output of this stage is the clean fingerprint image dataset.

C. Feature extraction

The next module in the architecture is the feature extraction module. In a traditional fingerprint recognition system, certain features such as the presence of endings and bifurcations of the ridges are extracted. In the proposed system, the feature extraction has been carried out by the convolutional layers of the deep learning model.In the convolutional neural network, the fingerprint patterns are learned at different hierarchical levels. The low-level layers of the network learn the low-level features of the images, such as the edges and the curves, whereas the high-level layers learn the complex patterns of the ridges and the texture features.The extracted features are used in the model training module.

D. Model training

The model training stage is the major computation of the architecture. The preprocessed images and the blood group labels are provided as input to the model to train the Convolutional Neural Network (CNN).The model, during the training stage, tries to change the internal parameters of the model using the backpropagation technique in combination with an optimization algorithm such as the Adam Optimizer. Also, the model tries to find the difference between the actual output and the expected output, which is usually done using the categorical cross-entropy technique.The architecture has provided the opportunity to have continuous feedback from the model training stage to the model evaluation stage. The hyperparameters of the model can be modified if the performance of the model is not satisfactory, in order to increase the accuracy of the model.

E. Model evaluation

After the training stage, the model will be in the evaluation stage, as shown by the second diamond-shaped box in the architecture diagram above.The accuracy, precision, recall, and F1 score of the model will be used as the parameters of the performance of the model.

The confusion matrix will be used to test the performance of the model.If the accuracy of the model is good, the model will be in the deployment stage of the model. If the accuracy of the model is poor, the model will be in the improvement stage of the model.

F. Blood group prediction

Once the model has achieved satisfactory performance metrics, it is integrated into the prediction module. In this step, the newly obtained fingerprint images are processed to arrive at the predictions of the blood groups.The output layer of the Softmax function generates probability scores for the eight classes of blood groups. The class with the highest probability score is chosen to be the predicted blood group.

G. Web application deployment

The final stage in the architecture is the web application interface. At this final stage in the architecture, the previously trained model is included in the web application whereby the user is given the chance to either upload their own fingerprint images or use the biometric scanner to take their own images.This final stage in the deployment of the research model is the culmination of the whole process. The architecture is modular in such a way that it is easily scalable and integratable with the biometric devices.

V. PROPOSED ALGORITHM

This algorithm describes the systematic procedure to predict the blood group using fingerprint images through the Deep CNN model. It processes the fingerprint images, discriminative ridge-based feature classification, and finally the probability-based predictions using the CNN model. Moreover, the algorithm checks the authenticity of the fingerprint images before performing the classification task to avoid invalid inputs.

Algorithm 1Blood Group Prediction Using Deep CNN

1) Acquire fingerprint image
2) Validate fingerprint presence
3) Preprocess the image
4) Extract features using CNN

5) Perform classification
6) Compute prediction confidence
7) Generate output result
8) Display final prediction

VI. EXPERIMENTAL RESULTS AND DISCUSSION

In order to validate the effectiveness of the proposed fingerprint-based blood group prediction system, the proposed CNN model was tested, and the effectiveness of the proposed model was compared with the existing image processing-based blood group typing, fingerprint statistical correlation-based blood group typing, and deep learning-based biometric recognition techniques.

In order to validate the effectiveness of the existing techniques of blood group typing, most of the existing techniques of blood group typing have used the conventional image processing techniques of blood group typing [1], [2], [3]. Many researchers have focused on the statistical correlation of fingerprint and blood groups [4]–[7].

Recent developments in fingerprint recognition using deep learning techniques have enhanced the feature extraction capabilities of the fingerprint recognition system [17].

The classification accuracy of the existing techniques of blood group typing is the major criterion used to validate the effectiveness of the existing techniques of blood group typing. The comparison of the proposed model with the existing techniques of blood group typing has been shown in Table I.

TABLE I: Comparison of Existing and Proposed Systems

Method	Technique Used	Accuracy (%)
Ravindran et al. [1]	Image Processing + Thresholding	84.3
Fernandes et al. [2]	Spectrophotometric Detection	88.1
Pimenta et al. [3]	Automated Electronic Blood Typing	86.7
Khalifa et al. [6]	Statistical Fingerprint Analysis	78.5
Kumari et al. [7]	Pattern Correlation Study	76.8
Dalvi et al. [9]	Image Processing + Morphology	82.6
Siva Sundhara Raja et al. [13]	Minutiae + Neural Network	85.9
Proposed Method	Deep CNN-Based Classification	91.4

The precision of the conventional method of blood grouping using the image processing techniques [1], [9] and the spectrophotometry [2], [3] depends on the invasive nature of the sample of the blood used.

The studies conducted on the research articles [4]–[7] on the correlation of the fingerprint have mainly focused on the statistical correlation of the dermatoglyphics and the blood groups. The precision of the automated method of blood group classification using the pattern of the fingerprint is very low.

The work that has been carried out in the article by Siva Sundhara Raja et al. [13], regarding the implementation of the neural network-based fingerprint classification system by using different handcrafted feature extraction techniques such as GLCM and minutiae analysis, though it increases the automation process, the feature extraction techniques that have been implemented in the article are handcrafted features, which are not suitable.

The survey that has been carried out regarding the implementation of deep learning techniques [14], [15] and the implementation of the technique for medical image analysis [16] proved that the CNN technique works better when compared to the traditional machine learning techniques implemented for the image classification problem. Moreover, the implementation of the fingerprint recognition technique using deep learning techniques [17] proved that features can be effectively extracted by using CNN from the ridges of the fingerprint image itself. In this regard, the proposed technique has used an end-to-end CNN model, which has the ability to learn the ridge patterns of the fingerprints without any human interaction. The proposed technique has achieved an overall accuracy of 91.4% in the classification of the test data set. It is very clear that the proposed technique is much better than the existing image processing techniques. The cross-validation result shows that the proposed technique has the ability to perform consistently in the classification of different data sets. Based on the analysis of the proposed technique using the confusion matrix, it is very clear that the classification of the data is equally distributed among the eight classes of blood groups.

Apart from this, the proposed method has the advantage of offering a non-invasive software-based solution that may be integrated into the web application to provide the prediction system in real time.

Based on the results that have been obtained from the experiment, it may be concluded that the deep learning method for the analysis of the fingerprint has the advantage of offering an accurate prediction when compared to the conventional methods.

VII. CONCLUSION

In this paper, a deep learning-based framework has been proposed for blood group prediction based on fingerprints using Convolutional Neural Networks (CNNs). In the proposed framework, all the aspects related to fingerprint-based blood group prediction are included in a single framework. Unlike classical blood group prediction techniques that involve invasive serological tests, the proposed framework has focused on exploring a non-invasive blood group prediction framework.

In addition, the experimental results have also been included to prove that the proposed framework using CNNs is better in terms of accuracy when compared to classical image processing and statistical correlation-based blood group prediction techniques. Moreover, the automatic feature learning capability of the proposed framework using CNNs will help in avoiding the feature extraction process, thus providing better scalability to the proposed framework. In addition, the proposed framework can be easily implemented as a web interface. While the results of the suggested method are promising, the area of fingerprint-based blood group prediction is in the research stage and needs to be validated further. Some of the future research directions may be the application of attention mechanisms and the application of diverse and explainable data. Overall, the research paper demonstrates the potential application of deep learning techniques in the development of medical prediction systems with the help of biometric information.

Apart from this, this study also has the potential to utilize the integration of biometric and artificial intelligence to assess the possibilities of non-traditional medical predictive methods. Even though the relationship between fingerprint patterns and blood groups needs further scientific investigation and research, the suggested system has the potential to utilize the predictive analysis with the help of dermatoglyphic features through deep learning.

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