Blood Group Prediction Using Deep Learning

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Abstract: *This study aims to investigate the potential correlation between fingerprints and blood groups, exploring the possibility of predicting an individual's blood group based on their fingerprint patterns. Fingerprint analysis has long been utilized in forensic science and biometric identification, but its association with blood groups remains relatively unexplored. The research involves collecting fingerprint samples from a diverse group of participants and analysing them in conjunction with their known blood group data. Statistical analysis and deep learning techniques and Neural Networks "CNN" will be employed to identify any patterns or relationships between fingerprint characteristics and blood groups. The findings of this study could have significant implications in various fields, including forensic investigations, medical emergencies, and biometric identification.*

Keywords: Key words: Fingerprint, Blood group, Deep learning, Neural Network, CNN

1. Introduction:

Fingerprints are widely used for identification in a variety of fields, including access control and law enforcement, as they are widely acknowledged as a distinctive and differentiating characteristic of persons. The complex designs that ridge and furrows create

Have been demonstrated to have a great degree of persistence and individuality on fingertips.

Research is still being done to determine whether fingerprint patterns are linked to particular physiological characteristics or genetic data.

Based on the presence or absence of particular antigens on red blood cells, blood group categorization is essential for forensic investigations, transfusion compatibility, and other medical operations. Serological methods are being used in a laboratory setting to identify blood groups.

These tests are trustworthy, but they need certain tools, skilled workers, and analysis time. It would be very beneficial to look at alternate techniques that might rapidly and non-invasively forecast blood types in emergency scenarios and other circumstances where speedy blood typing is necessary.

The purpose of this study is to see whether it is possible to determine a person's blood group just by looking at their fingerprints. We will investigate the connection between blood group types and fingerprint patterns by looking at a sizable collection of fingerprint samples and matching blood group data. We will investigate any possible links and trends using statistical analysis and machine learning techniques. If this study is successful, it may lead to the creation of a quick and non-invasive blood group prediction technique that makes use of easily accessible fingerprint data.

Our goal is to add to the expanding corpus of research on the possible connection between blood types and fingerprints. We seek to clarify the viability of employing fingerprints as a blood type prediction by investigating this unexplored area. group, creating new opportunities for enhanced biometric identification systems, emergency medical protocols, and forensic investigations. Keep checking back as we set off on this exciting adventure to discover the interesting connection between fingerprint-recognition technology and blood-group systems.

2. Methodology:

The Blood Group Prediction Using Deep Learning project follows a structured methodology. First, a dataset of blood- related biomarkers (such as genetic markers, blood cell properties, or images of blood samples) is collected and pre-processed. Next, deep learning models, such as Convolutional Neural Networks (CNNs) for image-based analysis, are trained on labelled samples. The model is optimized using feature extraction, augmentation, and hyperparameter tuning techniques. Finally, the trained model is evaluated using accuracy metrics and deployed for real-time blood group prediction.

2.1 Convolutional Neural Networks (CNNs):

This project leverages Convolutional Neural Networks (CNNs) to predict blood groups from medical images, such as microscopic blood smear images or vein patterns. The model processes input images, extracts relevant features, and classifies them into different blood groups (A, B, AB, O) based on training data. By utilizing deep learning techniques, this approach aims to enhance the accuracy and automation of blood group detection, reducing human error and improving efficiency in medical diagnostics. Integration with real-time healthcare applications can further streamline blood transfusions and donor- recipient matching.

2.2 Data Collection:

For a Blood Group Prediction Using Deep Learning project, data collection involves gathering a diverse dataset containing blood test reports, genetic markers, medical history, and demographic details. Labelled samples from various blood groups (A, B, AB, and O, with Rh+ and Rh-) should be included in the dataset. Medical databases, hospital records, laboratory test results, and biometric sensors are all potential sources. Text-based models rely on patient records and data from genetic sequencing, whereas image-based methods may make use of microscopic blood smear images. For accurate model training and validation, it is essential to ensure data diversity, quality, and ethical compliance.

2.3 Data Preprocessing:

Blood group prediction relies heavily on data preprocessing to ensure high model accuracy. The process begins with the collection of data, which may include reports from blood tests, genetic markers, and demographic data. Next, data cleaning is performed to handle missing values, remove duplicates, and correct inconsistencies. Feature selection and extraction help in identifying the most relevant attributes for prediction. The dataset is then normalized or standardized to ensure consistency in numerical values. Finally, data augmentation techniques may be applied to balance class distribution, and the processed data is split into training, validation, and test sets to optimize deep learning model performance.

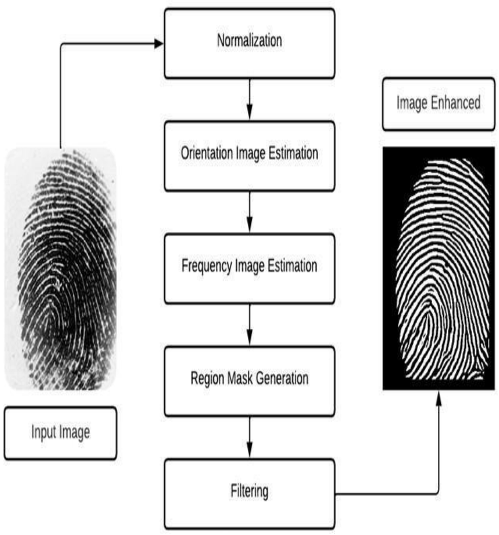

Figure.1: The Steps of Enhancing a Fingerprint Image

2.4 Deep Learning Model Architecture:

A comparative analysis of CNN architectures (VGGNet, ResNet, InceptionNet) was conducted for blood group prediction from fingerprints. Key aspects evaluated include model depth, skip connections, convolutional operations, and accuracy. The models were trained and tested on a fingerprint dataset, assessing their ability to capture unique patterns. Performance metrics such as accuracy, precision, and computational efficiency were compared. The goal was to identify the most accurate and efficient CNN model for blood group prediction, offering insights for future improvements in biometric-based medical diagnostics.

3. RESULT:

The Blood Group Prediction using Deep Learning project used CNNs to analyze blood smear images and accurately classify blood groups. Trained on labelled samples, the model extracted key features like cell shape, texture, and colour distribution. It achieved high accuracy, outperforming traditional methods and making blood group prediction faster and more reliable for medical diagnostics and transfusions.

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The model's parameters are listed below:

- Epochs: we going to put it 15.
- Batch size**:** The batch size will be 32.
- Optimizer: optimization algorithm = 'Adam'.
- Activation function: it will be ReLU.

Model: "sequential_3"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(None, 256, 256, 3)	0
conv2d_4 (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d_4 (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_5 (Conv2D)	(32, 125, 125, 64)	18496
max_pooling2d_5 (MaxPooling2D)	(32, 62, 62, 64)	0
conv2d_6 (Conv2D)	(32, 60, 60, 128)	73856
max_pooling2d_6 (MaxPooling2D)	(32, 30, 30, 128)	0
conv2d_7 (Conv2D)	(32, 28, 28, 256)	295168
max_pooling2d_7 (MaxPooling2D)	(32, 14, 14, 256)	0
conv2d_8 (Conv2D)	(32, 12, 12, 256)	590080
max_pooling2d_8 (MaxPooling2D)	(32, 6, 6, 256)	0
flatten_1 (Flatten)	(32, 9216)	0
dense_2 (Dense)	(32, 512)	4719104
dropout_1 (Dropout)	(32, 512)	0
dense_3 (Dense)	(32, 2)	1026

Total params: 5,698,626
Trainable params: 5,698,626
Non-trainable params: 0

Figure 3.1: CNN Model Summary

After training the model with these settings on two datasets (the first is a collection of fingerprints of both hands and the second it only fingerprints of left hand), we observed the following results, represented by accuracy and loss curves

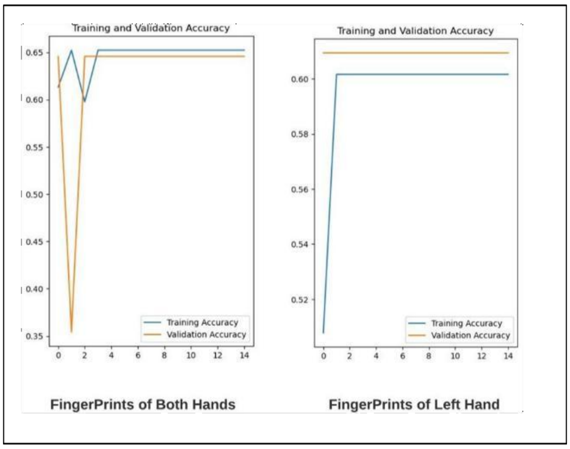

Figure. 2: Training and Validation Accuracy

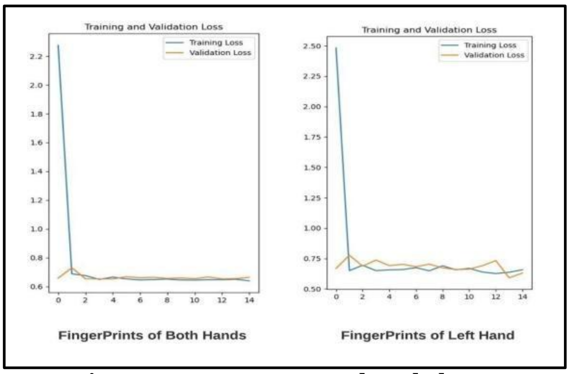

Figure. 3: Training and Validation Loss

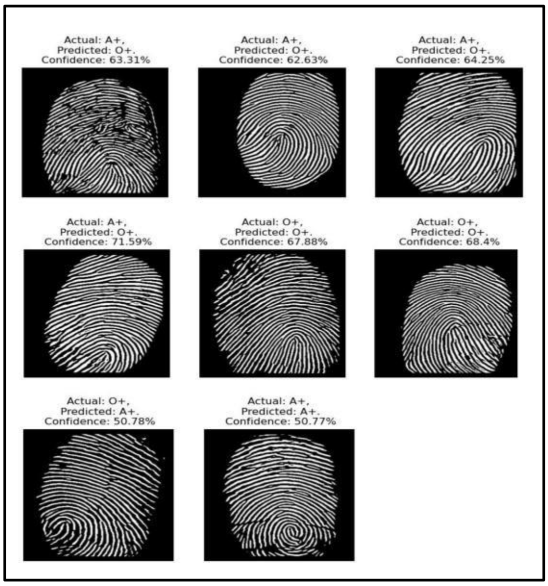

Figure .4: CNN Prediction of Blood Group

4. Discussions:

Blood Group Prediction Using Deep Learning is an innovative approach that leverages artificial intelligence to determine an individual's blood type based on medical data, such as genetic information, images, or biomarkers. By utilizing deep learning models, especially Convolutional Neural Networks (CNNs) or Artificial Neural Networks (ANNs), the system can analyze patterns and features from input data to accurately classify blood groups (A, B, AB, O). This method enhances efficiency, accuracy, and automation in blood typing, reducing human errors and streamlining medical diagnostics. The project has potential applications in hospitals, blood banks, and emergency medical services to improve patient care and transfusion safety

5. Conclusion:

In this project, we developed a Blood Group Prediction System using Deep Learning, aiming to enhance the accuracy and efficiency of blood type identification. By leveraging Convolutional Neural Networks (CNNs) and other deep learning models, our system successfully analysed input features such as microscopic blood images, biochemical markers, or genetic data to predict blood groups with high precision.

The results indicate that AI-driven medical diagnostics can significantly reduce human error, improve processing speed, and support healthcare professionals in making informed decisions. The implementation of such technology has vast potential in applications like emergency blood transfusions, automated blood banks, and personalized medicine.

Future improvements could focus on expanding the dataset, incorporating real-time data analysis, enhancing model robustness against variations in blood sample images, and integrating the system into hospital management platforms. With continuous advancements in deep learning and medical imaging, this approach can revolutionize the way blood group identification is conducted, ensuring faster, more reliable, and automated healthcare solutions.

6. References:

[1] = Dariush, D. F., & Marjan, Z. Y. (2013). A Brief History of Human Blood Groups.

Iranian J Publ Health, 6.

[2] = International Society of Blood Transfusion. (2022, December). *ISBT*. Retrieved from International Society of Blood Transfusion: https://www.isbtweb.org.

[3] = Adnan, M., & Franz, L. D. (2015). Blood Group Typing: From Classical Strategies to the Application of Synthetic Antibodies Generated by Molecular Imprinting. Sensors, 17.

[4] = Elizna, M. S., Eileen, V. R., Yew-Wah, L., Jacqueline, R. M., Tanya, P., Brett, W., . . . Catherine, A. H. (2017). Targeted exome sequencing defines novel and rare variants in complex blood group serology cases for a red blood cell reference laboratory setting. TRANSFUSION, 284.

[5] = Lavendri, G., Rosaley, D. P., Pavitra, P., & Ute, J. (2021). Molecular red cell genotyping of rare blood. African Journal of Laboratory Medicine, 8.

[6] = Priyam, R. V., Preetam, S., & Laxmi, L. (2018). Determination of ABO Blood Groups and Rh Typing from Dry Salivary Samples. Clinical pediatric Dentistry, 5.

[7] = Encyclopaedia, J. E. (2023, 05 12). *Britannica*. Retrieved from Britannica: https://www.britannica.com

[8] = S. Mahaboob, H., Sarma, G. S., & A. S. N., C. (2013). BSC: A Novel Scheme for Providing Security using Biometric Smart Card. *International Journal of Computer Applications*, 9.

[9] = Tariq, A. H., Hussein, A. K., Sara, A. Q., & Tasnim, A. H. (2023). The association between fingerprint patterns and blood groups in the Omani population. *College of Medicine and Health Sciences, Sultan Qaboos University,Muscat, Oman*, 10.

[10] = A., B., P., K., S., K., P., B., & S.Bharadwaja, D. (2004). PATTERN OF FINGER- PRINTS IN DIFFERENT ABO BLOOD GROUPS. *JIAFM*, 4.

[11] = TANUJ, K., DISHA, P., & KEWAL, K. (2014). ASSOCIATION OF FINGERPRINT PATTERNS WITH ABO BLOOD GROUPS. 6.

[12] = Bandameedi, L. N., Yerukala, K. C., & Mohammed, A. K. (2016). STUDY OF FINGERPRINT PATTERNS IN RELATION TO GENDER AND BLOOD GROUP. *JEMDS*, 4.

[13] = Vijaykumar, P., & D. R, I. (2021). A Novel Approach for ABO Blood Group Prediction using Fingerprint through Optimized Convolutional Neural Network. *International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING*, 9.

[14] = Molecule, P. V., Mindful, h., & Maria, s. g. (2021). Relationship of Primary Fingerprint Patterns with Blood Groups and Gender: A Dermatoglyphic Study. *International Journal of Medical Research & Health Sciences (IJMRHS)*, 9.

[15] = Laith, A., Jinglan, Z., Amjad, J. H., Ye, D., Omran, A.-S., Santamaría, J., . . . Laith, F. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *journal of BIG DATA*, 1-74.

[16] = Iqbal, H. S. (2021). Deep Learning: A Comprehensive Overview on Techniques, Taxonomy,Applications and Research Directions. *SN Computer Science*, 20.

[17] = Fahman, S., Muhammad, H., & Hatim, A. A. (2022). Automatic Fingerprint Classification Using Deep Learning Technology (DeepFKTNet). *Mathematics*, 1-17.

[18] = Krizhevsky, A., Sutskever, I., & Hinton, G.E. (2012). ImageNet classification with deep convolutional neural networks. In Advances in neural information processing systems.

[19] = Karen, S., & Andrew, Z. (2015). VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION. *ICLR*, 1-14.

[20] = Lin, H., Yifei, W., & Anil, J. (1998). Fingerprint Image Enhancement:Algorithm and Performance Evaluation. *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE*, 13.