International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

HemoDetect: Blood Group Detection from Fingerprint Using Machine Learning and Deep Learning Methodologies

Swathi Chandra M T[1], Adhithya K V[2], Adith A[3], Avani Sajeevan[4], K Muhammed Adil[5]
Department of Computer Science and Engineering
(Artificial Intelligence and Data Science)
Vimal Jyothi Engineering College, Chemperi, Kannur, Kerala, India

***Abstract*—Fingerprints are a unique identification mechanism that is useful for determining human identity. Hardly one in more than 64,000 million people share a similar fingerprint pattern. The minute pattern of the fingerprint of each individual is unmatched with minimal possibility of similarity. The science behind detecting the blood group from the fingerprint is derived from the presence of proteins and antigens present in sweat on the ridges and grooves of the fingerprint. This paper uses advanced image processing and machine learning algorithms to compare fingerprint patterns and various blood groups. This research aims to contribute to biometric applications and thus improve healthcare through innovative approaches using the latest technology, such as artificial intelligence. Deep learning methodologies such as the Convolutional Neural Network (CNN) extract hidden patterns inside the image and make the necessary predictions. Traditional blood group detection methods are time-consuming and can cause human errors. To make blood group determination error-free and less time-consuming, various machine learning and image processing techniques can be implemented. The detection of blood groups is important for cases such as medical diagnosis, blood transfusions, etc. This study shows the correlation between fingerprint patterns and the different blood groups.**

***Keywords*—Blood Group, Fingerprint, Machine Learning, Deep Learning, Image Processing**

I. Introduction

Fingerprint patterns have been used for authentication purposes. The most common fingerprint patterns comprise of Tented Arch, Radial Loop, Arch, and Ulnar. The identification of fingerprints is divided into four phases. The first phase is the capturing of the fingerprint image, the second is the pre-processing phase for enhancement, and later binarization and thinning. Blood is a combination of solids and liquids. It comprises of water and plasma. Blood is used to transport proteins and nutrients across the body. The determination of the blood group of an individual is necessary in order to do blood transfusions. Transfusion performed in the absence of determination of the blood group can cause serious problems and can even cause death for the patient. The blood group varies for different individuals. There are various categories of blood types. The ABO blood organization is the most complicated blood transfusion. There are eight different blood groups based on the ABO and Rhesus blood schemes(A+, A-, AB+, AB-, B+, B-, O+, O-). Traditional blood group detection systems require human involvement and specialized equipment. Recent advancements in deep learning, particularly in Convolutional Neural Network (CNN), has the capability to improve the process of blood group determination without human involvement thus reducing any possible errors by using image processing methodology. This research aims to develop a LeNet-based CNN model for classification of blood group and to evaluate the model's performance on a diverse dataset of blood group images. This paper aims to accurately predict the blood group of an individual by accepting fingerprint images as input and providing the respective blood group as output.

II. Literature Survey

The study proposes an approach for automating blood group identification using image processing with the help of machine learning and deep learning techniques. The limitations of conventional manual methods such as consumption of time, error-prone, etc. are pointed out. Traditional techniques typically involve the manual mixing of blood samples with antigens and observing clumping reactions on slides. The proposed system utilizes image processing techniques such as segmentation, feature extraction, and pattern recognition to automate the ABO and Rh systems based on blood group classification. The system makes use of MATLAB simulations in conjunction with deep learning techniques, including logistic regression [6]. The preprocessing stages include cleaning glass slides, capturing images, and data dimensionality reduction. This automated method not only improves efficiency but also provides greater precision in blood typing while reducing manual intervention.

The study conveys a system for the determination and classification of different blood groups with the help of image processing and machine learning techniques. The system was developed to reduce or eliminate errors that occur because of humans that may occur in laboratories. The proposed system includes three stages, namely blood sampling, image gathering using a camera, and analysis using MATLAB-based image processing and ML models, which are handled using the Orange software [8]. The approach based on MATLAB provides an accuracy of 100 percent with processing time varying between 1.5-1.6 seconds, on the other hand, the neural network model implemented in Orange gave an accuracy of 99.7 percent with training and testing time varying between 13.7 and 1.2 seconds, respectively. The findings of this paper suggest that machine learning and image processing techniques are effective alternatives to traditional methods for blood group detection that offer more accuracy and shorter processing time. These findings can be further developed for the detection of blood groups using even more efficient mechanisms.

The study elevates the uniqueness of fingerprint patterns and their unchanging nature throughout the individual's life. These patterns are evaluated to find out their correlation with blood types and related disease detection. The research focuses on executing deep learning and machine learning methodologies including Convolutional Neural Network (CNN) to predict blood groups along with the classification of blood-related lifestyles like diabetes, arthritis, and hypertension based on fingerprint features [12]. Fingerprint image processing including preprocessing activities such as segmentation, normalization, ridge estimation along feature extraction is carried out using Gabor filters and orientation maps. The review interconnects ideologies from dermatoglyphics and medical studies linking fingerprint patterns to health conditions. The application of this research spans different disciplines such as forensic science, health diagnostics, and anthropological research.

The study aims to establish a correlation between fingerprint features and blood group types, offering an alternative to traditional invasive blood testing methods. A dataset of fingerprint images and corresponding blood groups was collected from 82 students (48 males and 34 females) from Bharati Vidyapeeth College of Engineering, Navi Mumbai. Fingerprints from all ten fingers were captured using the HFDU06 optical scanner, alongside demographic details such as age, height, skin tone, and dietary habits [13]. Fingerprint images were enhanced through segmentation, normalization, binarization, and Gabor filtering to remove noise and highlight key features. Features such as ridge thickness, ridge frequency, minutiae angles, and patterns (loops, whorls, arches) were extracted and organized into a feature matrix. Multiple Linear Regression was applied to predict blood group types based on the extracted fingerprint features [13]. Statistical analyses, including Chi-square tests, were performed to evaluate correlations between gender and blood group distribution. Loops emerged as the most common fingerprint type, predominantly associated with blood groups B and O. Arches were the least frequent pattern across all blood groups. The Chi-square test led to the conclusion that there was no significant relationship between gender and blood group types (p-value = 0.885). The machine learning model achieved a moderate accuracy of 62 percent in predicting blood groups, indicating the potential of this approach. The methodology provides a non-invasive, fast, and accessible alternative to blood typing, with applications in remote or emergency settings where traditional blood testing methods may not be feasible [13]. The study demonstrates the feasibility of using fingerprint patterns as a predictive tool for blood typing. However, the current accuracy can be improved by increasing the sample size and exploring additional fingerprint features. Future work should also incorporate advanced machine learning algorithms to enhance predictive performance and applicability across diverse populations.

The study opens new possibilities for determining blood groups using fingerprint analysis, leveraging the unique ridge patterns being present in human fingerprints. Traditional methods involve drawing blood samples, which can be uncomfortable. However, this research proposes a non-invasive approach where fingerprint sweat, containing different antigens related to the Rh and Rh blood group systems, can be examined to infer blood type. Techniques like Gabor filters and Convolutional Neural Networks (CNNs) are used for extracting ridge frequency and spatial features, making blood group determination more accessible and efficient [10]. This method has potential applications in forensic science, emergency medical care, and biometric identification. Most studies have explored the connection between fingerprint patterns and blood groups. Previous research indicates a strong correlation between ridge patterns and blood types, with loops being a common pattern associated with blood group O. The use of machine learning models such as multiple linear regression and CNNs has been explored to enhance the accuracy of fingerprint-based blood group detection. Certain studies also link fingerprint patterns to lifestyle diseases like hypertension and diabetes, suggesting that fingerprint analysis could have wide medical applications. Despite the promise of this method, challenges remain, including the need for larger datasets and improvements in image processing to increase accuracy. Further research is needed to standardize this approach and integrate it into mainstream medical and forensic applications.

The study shows the relation between fingerprint patterns and blood groups among medical students. Fingerprints are unique and permanent features that are formed during fatal development and have been mainly used for identification. The research was conducted on 178 medical students aged 17 to 23 and differentiated the fingerprint patterns into loops, whorls, arches, and composites. Blood group distribution among participants shows that type O was the most prevalent (42.1%), A (29.8%), B (17.4%), and AB (10.7%). The results indicated that loop patterns were common among individuals with blood group O. Also, Rh-positive blood groups were more frequent (90.4%) than Rh-negative [1]. The study aligns with previous research that has found an association between dermatoglyphics patterns and blood groups. Studies suggest that fingerprints and blood groups, both genetically determined, may exhibit a relation due to shared developmental paths. Prior research supports the findings that loops are common fingerprint patterns and that group O individuals exhibit this pattern mostly. Studies have noted higher incidences of whorls in individuals with Rh-negative blood groups. The findings highlight potential forensic and medical applications of fingerprint analysis in predicting genetic features and assisting in personal identification.

The study investigates the relationship between fingerprint determination and ABO blood groups in 450 randomly selected university students at Koya University: 224 males and 226 females. Fingerprints were classified by the researchers as loops, whorls, or arches. Most of these patterns were loops, followed by whorls and at the least, arches [17]. This deduction reveals the unpredictability of deducing one's blood type merely based on fingerprint pattern classifications. The study boosts the research on biometrics, forensic medicine, and medical genetics, endorsing the hereditary nature of fingerprint formation along with environmental control during the process of embryonic development. It also points out the completion of fingerprint formation between the 12 and the 16-week gestational period and remains unaffected through life. The outcomes of this research are consistent with previous studies in dermatoglyphics that support the uniqueness of fingerprints even in identical twins. Statistically, loops were found to prevail in thumbs and little fingers, while whorls were associated more with ring fingers. Slight gender variations could also be observed in the results, implying differences in fingerprint distribution patterns at a minor level.

Various deep learning architectures are used in image preprocessing, segmentation, classification, and feature extraction while also evaluating their performance on several datasets in medical images or satellite and real-time applications. While those neural networks operate image restoration performance metrics such as mean square error (MSE), Peak Signal-To Noise Ratio (PSNR), and Structural Similarity Index (SSIM), segmentation models are evaluated by Intersection over Union (IOU) and Dice similarity coefficients [3]. With the development of deep neural network architectures to improve the above-mentioned road map, challenges in model generalization, computational costs, and training complexity are still prevalent. As the field moves on, however, there will be a greater demand to balance efficiency, interpretability, and computational resource usage to map more of deep learning's potential to image processing. The present one is to finish a comprehensive study of the diverse and complex territory of Image Processing (IP) techniques, concerning image enhancement, segmentation, feature extraction, classification, and restoration. Each area stands as a pillar in the domain of visual data manipulation, one that contributes to cleaning, basically deciphering, and applying images to a wide range of applications [3]. Extraction, which is absent of any overt engineering.

The healthcare sector is undergoing a transformational paradigm change due to efficiency domains, accuracy of diagnosis, and AI in patient management domains. Machine learning algorithms are important in handling vast amounts of medical data, such as electronic health records, medical imaging, and genetic data. AI-based applications help doctors to diagnose a disease, predict health risks, and personalize treatment based on patient data. In terms of medical imaging analysis, AI detects discrepancies in X-rays and MRIs and will allow more accuracy than any traditional means [16]. Drug designs and clinical trials simultaneously depend a lot on the AI algorithm that develops biological data for potential new remedies and reduces the time and cost to get drugs in the market. AI systems improve accuracy and reduce human error in robot-assisted surgery, The distance helps manage chronic conditions by continuously measuring the important signals of the patient for the patient's monitoring. AI also adopts hospital resource capabilities, an actively adopting streamlined strategy, it makes it possible to interfere quickly and provide preventive care, which results in both reduction and savings in health care expenses of life [16]. AI-run virtual assistants revolutionize patient participation and help. Chatbots and virtual nurses offer patients Continuous help addressing inquiries, arrangements for appointments, and faraway supervision symptoms.

Recent research shows the detection of fingerprints for analysing blood groups using machine learning, image processing, and K Nearest Neighbour (KNN) models. Traditional serological methods even though it is accurate need specialized equipment for performing various activities. Studies show that ridge patterns of fingerprints are unique and stable and make them applicable for various applications. Machine learning algorithms such as SVM, KNN, and random forests are mainly used for the classification processes. There are different types of fingerprint patterns like whorl where ridges are arranged in a circle or spiral makeup, loop which is the most common one, arch where ridges flow from one side to another. Ridge patterns and minutiae points are been taken up by image processing for easy analysing. Also, we have Von Neumann Architecture [9] that permits the sequential use of single memory and hardware architecture which help in the storage of data and instructions. Challenges such as variability in datasets and standardization exist and matter. When the world gets advanced it will lead to better detection of blood groups by using more precise tools and techniques.

The accuracy and automation of blood group detection are being improved by using certain deep learning and image processing techniques. Traditional methods may sometimes lead to error so better advanced techniques of machine learning and so on are being used for better results. Studies explore methods like Convolutional Neural Network (CNN) along with Scale Invariant Feature Transform (SIFT), Oriented FAST, and Rotated BRIEF(ORB) which are used for classifying blood groups from images [5]. Merging these classifications can result in high accuracy and better feature extraction. Even under variable image conditions, some deep learning can provide exact predictions of blood groups. Emergency response and transfusion management are being improved during this process. Future works will be implemented by better datasets and perfectly extracting the features needed for the implementation.

Fingerprints are widely used everywhere because of their uniqueness, permanence, and ease of capture. The process includes phases such as image acquisition, pre-processing, feature extraction, and matching. Pre-processing techniques such as enhancement, binarization, and thinning increase the image clarity used for the classification processes. Minutiae based traits involve ridge patterns. For identification, it is 1:N matching and for verification, it is 1:1 matching. Experiments are being created using databases such as FVC2000 and FVC2002 which results in high accuracy [2]. Certain challenges are still there for improving false minutiae removal and increased feature extraction.

Another widely accepted mechanism in image and data processing including sound recognition is the Siamese Neural Network. It is mainly used as an extensive Convolutional Neural Network (CNN). A Siamese Neural Network is a coupling setup established between two artificial neural networks. It consists of two CNNs that share the weight. The images can be preprocessed by standardizing the images by normalization and grayscale conversion [7]. Gabor filter can be used to enhance the images by using its ridge and valley sharpening technique. Binarization of the uniform data representation can also be done as part of data preprocessing. Features from fingerprint are extracted using an improved VGG16 network architecture [7]. The model is trained with 66 unique fingerprints with augmented data to enhance the robustness of the model. This method achieved 92% accuracy, 0.87 f1score when the threshold reaches 91%, 1.11% False Rejection Rate (FRR), and 1.41% False Acceptance Rate (FAR), Correctly Recognized Rate (CR) of 97.48%. Exclusion of the minutiae extraction step helps to decrease the complexity of the computation of the model. [7] The method is compatible with other fingerprint systems as it directly uses direct preprocessed fingerprint images. This model has good robustness and real-time action capacity. Still expanding the datasets for improving the generalization of the model, optimization of real-time processing algorithm, etc, serve as drawbacks.

Gabor filters are a sophisticated mechanism used in the context of fingerprint identification, along with Gabor filters deep learning methodologies for the identification of fingerprints. The primary objective of this approach is to enhance the efficiency and accuracy of the classification of fingerprints by combining the advantages of the traditional feature extraction mechanisms with the modern Convolutional Neural Network (CNN). Dimensionality reduction techniques like Principal Component Analysis (PCA) are adopted to improve performance and reduce overfitting [11]. Methodologies such as Gabor filters are used to extract features by enhancing ridge and valley structures along with capturing orientationspecific details. CNN feature extraction methods are used to obtain complex features from fingerprint images. The features extracted from the previous two methodologies (Gabor filters and CNN) are combined to form a robust feature vector. PCA is applied to this feature vector to reduce feature dimensions while retaining necessary information. CNN is implemented against various classifiers such as Support Vector Machine (SVM), Random forests, and K Nearest Neighbour (KNN) to classify fingerprints into five classes which are Arch, Left Loop, Right Loop, Tented Arch, and Whorl. CNN achieved an accuracy of 99.87% overtaking random forest (96.75%) and SVM (94.97%) [11]. The robustness of the model is confirmed by K-fold cross-validation (98.89%) and generalization (97.75%). A richer feature set is obtained by combining features of Gabor Filters and CNN. Operations like dilation and erosion consume more processing time and possess more computational complexity [11].

The Back Propagation Neural Network (BPNN) classifier can also be employed with several feature extraction methods. Biometric fingerprint sensor R305 is employed to capture based on Frustrated Total Internal Reflection (FTIR). Histogram equalization, Image resizing, and thinning are the major data preprocessing activities done to also enhance image quality thereby improving the clarity of ridge valley structures. Gray Level Co-occurrence Matrix (GLCM) which is used to capture textural features such as contrast, connection, homogeneity, and energy, and Wavelet Transforms which decomposes images into different frequency components are among some of the techniques used in feature extraction [14]. Back Propagation Neural Network (BPNN) does template matching and classification by comparing extracted features with a preexisting database to predict the blood group [14]. It has a cost-effective design that consists of a combination of multiple feature extraction techniques.

The study shows an automated blood group detection system with the help of image processing techniques to reduce the probability of human error and provide results faster and more precisely. These errors can cause serious issues when it comes to blood transfusions. This study presents a transformation from traditional methods to efficient image processing techniques. The techniques include clustering, feature extraction, and HSV luminance [4]. HSV luminance is implemented to facilitate reliable and fast blood group prediction. This method increases accuracy and decreases delays and errors caused by traditional methods. This system is implemented using image processing techniques and OpenCV methods [4].

The study presents an approach for identifying blood groups with the help of image processing. The author utilizes techniques like thresholding and morphological operations on images that are obtained from test slides. This enables the detection of agglutination used to classify blood groups accordingly. The reagents are mixed with three types of blood samples. When the agglutination is formed, the image of the slide is captured and processed in MATLAB. The HSL illumination stands for Hue, Saturation, and Lightness [15].

Traditional methods are available for blood typing and replacing them with image processing techniques provides a new sophisticated mechanism. The new techniques are to improve accuracy and speed as compared to traditional plate and card methods. They are often time-consuming and delayed. This approach uses MATLAB-based image analysis to identify agglutination by calculating the standard deviation of pixel intensity values [18]. This allows the automatic classification of blood groups with a high amount of precision. This method reduces human interference and reduces delay [18].

III. METHODOLOGY

A. DATASET

To build an effective model, we collected a vast dataset containing fingerprint images with their corresponding blood groups. The dataset ensures the presence of images from all the major blood groups(A+, A-, B+, B-, AB+, AB-, O+, O-). The images are stored in BMP format. A visualization of the images in the dataset along with their labels is given in Fig 1.

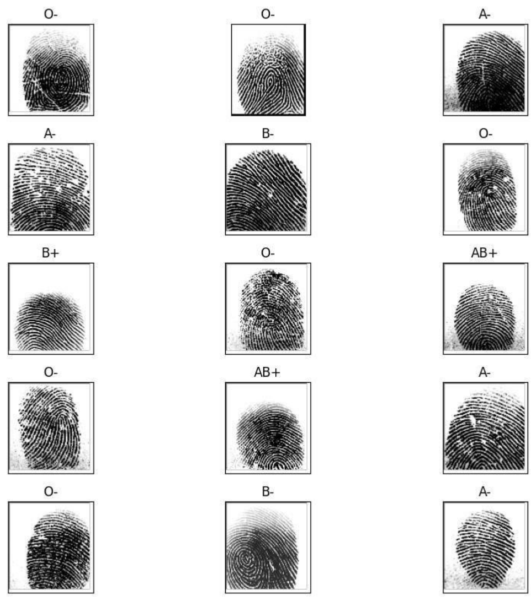

Fig. 1. Representation of images in the dataset along with their corresponding blood group labels

B. PREPROCESSING AND AUGMENTATION

To make the prediction accurate, the dataset needs to be free from noise variations, distortions, and lighting issues. This can be done with the help of several processing steps.

1) Resizing: To ensure uniform input dimensions for the deep learning model, all images were resized to 224x224 pixels.

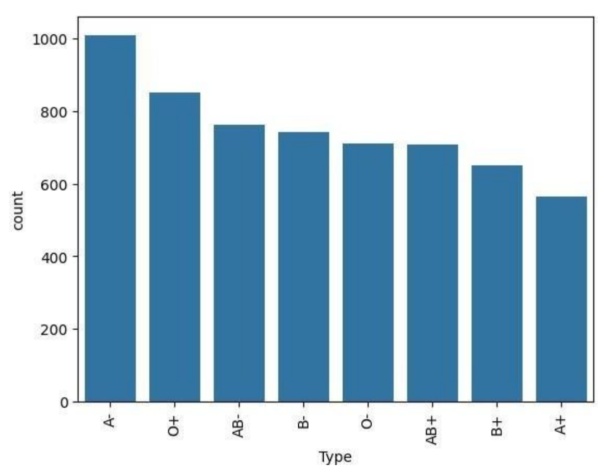

Fig. 2. distribution of blood group in the dataset

2) Normalization: When working with images for deep learning, we need to make sure the model can process them effectively. Raw images come with pixel values that range from 0 to 255 (for 8-bit images). If we feed these raw values into a deep learning model, some pixels with higher intensities might dominate, making it harder for the model to learn meaningful patterns. Normalization is a simple but powerful technique that helps solve this issue by adjusting pixel values to a consistent range—typically between 0 and 1 or -1 and 1. This makes it easier for the model to compare features across different images.

3) Data Augmentation: Techniques such as rotation, flipping, and noise addition were applied to increase variability in the dataset making the model more robust to real-world inconsistencies. In fingerprint images, noise can lead to real-life distortions such as smudges, lighting changes, or partial prints, helping the model generalize better and reducing overfitting.

C. MODEL ARCHITECTURE

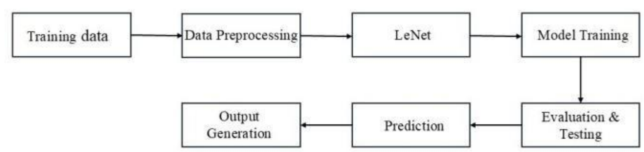

Fig. 3. Architecture diagram

For the classification task, the LeNet Convolutional Neural Network (CNN), a well-established deep learning model known for its efficiency in image recognition tasks was implemented. This model was chosen because of its ability to automatically extract important patterns from fingerprint images while maintaining computational efficiency. The LeNet architecture follows a structured approach with multiple layers, each playing a specific role in feature extraction and classification:

1) Convolutional Layers:

- These layers serve as feature detectors, scanning the fingerprint images with 5×5 filters to capture important patterns such as ridges and unique textures.
- They help identify distinct characteristics in the fingerprint that may correlate with blood group classification. *2) Pooling Layers:*
- Pooling layers reduce the dimensionality of the feature maps while retaining essential patterns.
- We used max pooling, which selects the most prominent pixel values from small regions of the image, ensuring that the most important fingerprint features are preserved. *3) Fully Connected Layers:*
- Once the relevant features are extracted, they are flattened and passed through dense layers.
- These layers process the extracted patterns, learn complex relationships, and refine the classification process.

4) Output Layer:

- The final layer uses a Softmax activation function, which converts the model's predictions into probability values.
- Each fingerprint is classified into one of the eight blood groups (A+, A-, B+, B-, AB+, AB-, O+, O-), based on the highest probability score.

D. TRAINING AND EVALUATION

To ensure effective learning and generalization, the model is trained following a structured methodology. The process involve data splitting, optimization, performance assessment, and model evaluation.

1) Data Splitting: The data is divided into two sets :

- Training Set(80%) : Used to train the model, enabling it to learn patterns and extract relevant features from fingerprint images.
- Testing Set(20%) : Reserved for evaluating the model's performance on unseen data, ensuring its ability to generalize effectively.

2) Training Process: The proposed model is trained using the Adam optimizer, which dynamically adjusts the learning rate for faster and more stable learning. To enhance classification accuracy, the categorical cross-entropy loss function is used, refining predictions by minimizing the difference between predicted and actual class labels.

3) Performance Matrix:

- Accuracy: Measures how many fingerprint images were classified correctly out of the total test set.
- Precision: Evaluates how many of the predicted blood groups were actually correct, reducing false positives.
- Recall: Measures how well the model correctly identifies all instances of a particular blood group, reducing false negatives.
- F1-Score: A balanced metric that considers both precision and recall, providing a single performance score for each blood group classification.

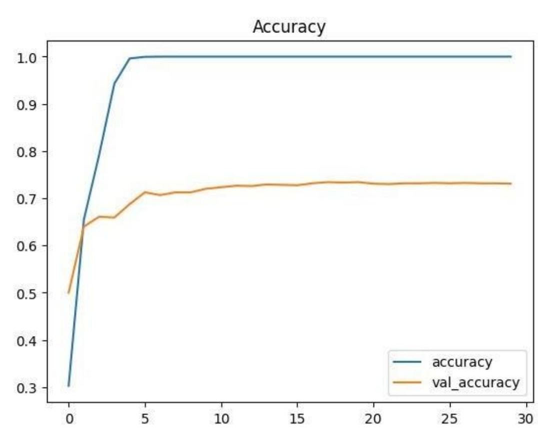

Fig. 4. Accuracy trend of a deep learning model over multiple training epochs

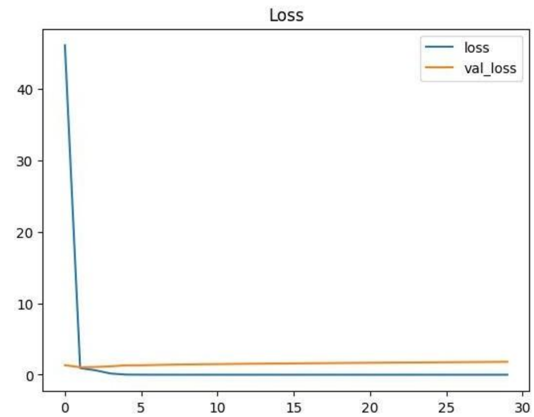

Fig. 5. Loss trend of a deep learning model over multiple training epochs

4) Evaluation: A confusion matrix was used to visually represent how many times the model predicted the correct blood group versus how many times it made errors.This helped us identify which blood groups were frequently confused. By following this structured training and evaluation approach, It was ensured that the model achieved high accuracy while minimizing classification errors, making it a reliable tool for non-invasive blood group detection.

IV. RESULTS AND DISCUSSIONS

After training for 30 epochs, the model attained an accuracy of 73.08% and tends to improve accuracy as the number of epochs increases. The model performed well on the test dataset and accurately predicted the blood group of the fingerprint image that was provided as the input.The confusion matrix analysis revealed that errors were primarily observed between similar blood groups, highlighting areas for further refinement. Additional dataset expansion and advanced feature extraction techniques could further enhance accuracy. The proposed system provides a non-invasive approach for blood group detection when compared to traditional blood group detection methods. Deep Learning has paved the way to this automated alternative which can make a significant impact in the healthcare sector.

V. IMPLEMENTATION AND DEPLOYMENT

To make the model accessible to users, we developed a userfriendly web application using Gradio. This application allows users to upload fingerprint images and receive an instant blood group prediction based on our trained model. The key features of the deployment include:

- Simple Interface: Users can easily upload fingerprint images without requiring technical expertise.
- Instant Predictions: The model processes images in realtime and provides accurate blood group classifications.
- Cloud Hosting: The application is hosted online, ensuring accessibility across different devices.

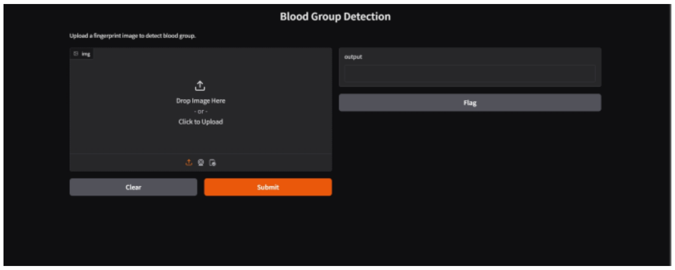

Fig. 6. Interface of hemodetect

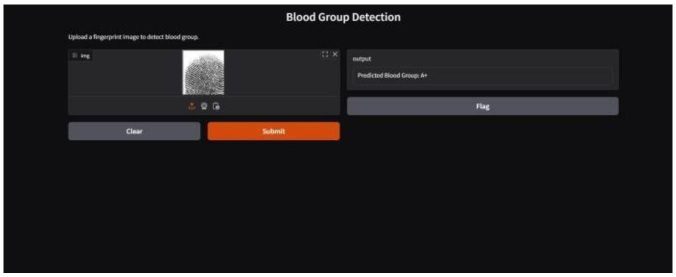

Fig. 7. Interface after predicting the corresponding fingerprint

VI. CONCLUSION AND FUTURE ENHANCEMENTS

This research highlights the chances of making use of fingerprint analysis for blood group determination from advanced machine learning and deep learning methodology, especially Convolutional Neural Network (CNN). The research shows the strong relation between fingerprint patterns and blood groups, demonstrating that image processing, deep learning and machine learning techniques. The adoption of CNN architectures like LeNet-5 resulted in very effective extraction and analysis of fingerprint features, which eventually led to accurate mapping of fingerprints to blood groups. This approach offers a non-invasive, convenient, and scalable solution compared to traditional blood testing methods, making it highly applicable in healthcare diagnostics, forensic science, and emergency scenarios. Future enhancements may involve developing custom CNN architectures, improving data collection methods, and employing more robust datasets to increase classification accuracy and reliability.

REFERENCES

[1] Aamir, Y., Masood, R., Irshad, N., Malik, R., Farid, N., Shahab, M.A.: Relationship between pattern of fingerprints and blood groups. P J M H S 16(09), 698–700 (2022). https://doi.org/10.53350/pjmhs22169698

[2] Ali, M.M., Mahale, V.H., Yannawar, P., Gaikwad, A.: Fingerprint recognition for person identification and verification based on minutiae matching. In: 2016 IEEE 6th International Conference on Advanced Computing (IACC). pp. 324– 329. IEEE (2016). https://doi.org/10.1109/IACC.2016.69, https://www.researchgate.net/publication/306304227

[3] Archana, R., Jeevaraj, P.S.E.: Deep learning models for digital image processing: A review. Artificial Intelligence Review 57, 11 (2024). https://doi.org/10.1007/s10462-023-10631-z

[4] Dhande, A., Bhoir, P., Gade, V.: Identifying the blood group using image processing. International Research Journal of Engineering and Technology (IRJET) 5(3) (March 2018), https://www.irjet.net

[5] Ganta, J.S.S., Y, M.R., Rishitha, M., Pulivarthi, J.S.: Blood group detection using image processing and deep learning. International Research Journal of Engineering and Technology (IRJET) 11(04), 97–103 (2024), https://www.irjet.net

[6] Gupta, T.: Artificial intelligence and image processing techniques for blood group prediction. In: 2024 International Conference on Computing, Power, and Communication Technologies (IC2PCT). pp. 1022–1028. IEEE, Punjab, India (2024). https://doi.org/10.1109/IC2PCT60090.2024.10486628

[7] Li, Z., Wang, Y., Yang, Z., Tian, X., Zhai, L., Wu, X., Yu, J., Gu, S., Huang, L., Zhang, Y.: A novel fingerprint recognition method based on a siamese neural network. Journal of Intelligent Systems 31, 690–705 (2022). https://doi.org/10.1515/jisys-2022-0055, https://doi.org/10.1515/jisys-2022-0055

[8] Mahmood, M.F.: Recognition and categorization of blood groups by machine learning and image processing method. Innovative Biosystems and Bioengineering 8(2), 53–68 (2024). https://doi.org/10.20535/ibb.2024.8.2.298201

[9] Mounika, G., Anusha, M., Gopika, D., Kumari, B.S.: Blood group detection through fingerprint images using image processing (knn). International Research Journal of Engineering and Technology (IRJET) 11(03), 1225–1228 (2024), https://www.irjet.net

[10] Nihar, T., Yeswanth, K., Prabhakar, K.: Blood group determination using fingerprint. MATEC Web of Conferences 392 (2024). https://doi.org/https://doi.org/10.1051/matecconf/202439201069

[11] Nur-A-Alam, Ahsan, M., Based, M., Haider, J., Kowalski, M.: An intelligent system for automatic fingerprint identification using feature fusion by gabor filter and deep learning. Computers and Electrical Engineering 95, 107387 (2021). https://doi.org/10.1016/j.compeleceng.2021.107387, https://doi.org/10.1016/j.compeleceng.2021.107387

[12] Patil, V., Ingle, D.R.: An association between fingerprint patterns with blood group and lifestyle-based diseases: A review. Artificial Intelligence Review 54, 1803–1839 (2021). https://doi.org/10.1007/s10462020-09891-w

[13] Patil, V., Ingle, D.R.: A novel approach to predict blood group using fingerprint map reading. In: 2021 7th International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE (April 2021). https://doi.org/10.1109/I2CT51068.2021.9418114, https://www.researchgate.net/publication/351487579

[14] Raja, D.D.S.S., Abinaya, J.: A cost-effective method for blood group detection using fingerprints. International Journal of Advance Study and Research Work 2(3) (March 2019). https://doi.org/10.5281/zenodo.2591955, http://www.ijasrw.com

[15] Ravindran, G., Titus, T.J., Pravin, M., Pandiyan, P.: Determination and classification of blood types using image processing techniques. International Journal of Computer Applications 157(1) (January 2017). https://doi.org/10.5120/ijca2017912592, https://www.researchgate.net/publication/312494841 [16] Saxena, A.K., Ness, S., Khinvasara, T.: The influence of ai: The revolutionary effects of artificial intelligence in healthcare sector. Journal of Engineering Research and Reports 26(3), 49–62 (2024). https://doi.org/10.9734/JERR/2024/v26i31092, https://www.sdiarticle5.com/review-history/113277

[17] Smail, H.O., Wahab, D.A., Abdullah, Z.Y.: Relationship between pattern of fingerprints and blood groups. Journal of Advanced Laboratory Research in Biology 10(3), 84–90 (2019). https://doi.org/10.1122/1.4903346

[18] Talukder, M.H., Reza, M.M., Begum, M., Islam, M.R., Hasan, M.M.: Improvement of accuracy of human blood groups determination using image processing techniques. International Journal of Advanced Research in Computer and Communication Engineering 4(10) (October 2015). https://doi.org/10.17148/IJARCCE.2015.41090, https://www.researchgate.net/publication/309439109