Automated Blood Group Classification from Handprint Images Using Deep Learning and Image Processing Techniques

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***Abstract-* This paper introduces automated blood group classification from handprint images by image processing and deep learning methods. Handprint images are preprocessed to extract features, and a convolutional neural network (CNN) is employed for classification. The method introduces a non-invasive method for blood group detection. The system enhances accuracy and efficiency, making it applicable to medical diagnostics.**

***Index Terms*-Blood group classification, Convolutional Neural Network, Deep learning, Handprint images, Image processing**

I. INTRODUCTION

Blood groups play a critical role in healthcare because they are at the core of transfusions, organ transplants, and overall compatibility tests in medical procedures. Blood groups are established by whether or not particular antigens are on the surface of red blood cells, interacting with the antibodies in plasma. The two major blood group systems, ABO and Rh, distinguish blood types as A, B, AB, or O, each of which may be positive or negative for the Rh factor. Knowledge of these classifications is vital since compatibility of blood type is directly linked to the success of procedures such as blood transfusion, organ transplant, and pregnancy care. For example, a wrong blood type transfusion may result in serious immune reactions, threatening the patient's health and even death. Blood group typing is crucial to emergency treatment, where transfusions must be done quickly to preserve life.

Healthcare professionals in emergency situations depend on rapid and accurate blood typing to determine that transfused blood will not be rejected by the body's immune system.

Incompatible blood transfusions may initiate acute hemolytic reactions, in which the recipient's immune system kills the transfused blood cells, resulting in conditions like renal failure, shock, and death. Rapid and accurate blood group identification systems are hence pivotal to prevent delays, particularly in emergency situations where a patient's life is at risk. Hospitals and emergency response forces have a continuous requirement for effective blood typing to avoid transfusion complications and enhance patient outcomes. Beyond emergency situations, knowledge of blood groups is important for general medical procedures and long-term healthcare planning.

During prenatal care, both mother and fetus are sometimes typed for blood to detect and handle risks of Rh incompatibility, a situation where the mother's immune system may destroy the fetus's red blood cells if they have an incompatible Rh factor.

Hemolytic disease of the newborn can cause serious anemia and other problems for the fetus or newborn. The knowledge of blood group compatibility assists medical practitioners in applying preventive interventions, including the administration of Rh immunoglobulin to Rh-negative mothers to prevent such immune reactions, thereby ensuring maternal and neonatal well-being. The function of blood groups in organ and tissue transplantation is another indicator of their importance. Organ compatibility relies significantly on the matching of blood groups, where mismatched transplants result in possible graft rejection and patient health issues. Blood group matching is frequently the initial test assessed prior to undertaking other intricate compatibility tests such as human leukocyte antigen (HLA) matching.

From the perspective of universal healthcare, precise blood typing is paramount to increasing organ donation possibilities and decreasing transplant waiting lists due to correct matching, reducing rejection risks, and ensuring successful transplantation. Finally, blood group variation and regional distribution pose special challenges in blood donation and inventory management. Some blood types are less common and may not be easily available in certain regions, impairing the ability of healthcare providers to respond adequately in emergencies or to serve routine medical needs. In addition, certain populations may possess special antigenic markers, further complicating the compatibility picture. Blood banks and hospitals need to handle blood supplies carefully by monitoring blood group frequencies in their areas and forecasting rarer blood types' shortages.
Accurate and quick blood typing is therefore critical not only for direct patient care but for overall healthcare planning as well as efficient blood resource management.

II. RELATED WORK

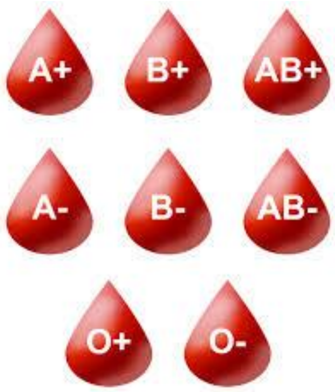

Fig.1 Classification of Blood group

In this author [1] This paper proposes a biometric-based method for the detection of blood groups using fingerprint images. The procedure includes the preprocessing of fingerprint images and feature extraction using GLCM, wavelet transforms, Laws of texture, and minutiae analysis. These characteristics are then categorized with a Back Propagation Neural Network (BPNN) to identify the blood group. The system provides a cost-effective and automated method that eliminates the necessity for physical blood samples. It demonstrates that fingerprint-based biometric systems have the potential to be connected to blood group identification and provide a new, non-invasive method for application in identity and medical diagnostics.
This article [2]presents an extensive survey of automatic detection of blood groups using image processing and MATLAB software. It brings out the defects of the traditional manual typing methods, which are time-consuming and prone to errors. The systems discussed utilize image acquisition, preprocessing, segmentation, and classification to study agglutination reactions in blood samples. The combination of machine learning algorithms and MATLAB's image processing toolset provides for accelerated, more precise identification of ABO and Rh blood types. The authors highlight the benefit of automation in emergency response and rural settings, enhancing both speed and precision in diagnosis.

In [3] this This research centers on an invasive, AI-based method of blood group prediction via image processing. It starts with high-resolution imaging of blood samples and then preprocessing techniques like contrast enhancement and segmentation. Features in terms of color, texture, and shape are extracted and utilized to train a deep neural network For performance improvement, the Firefly Algorithm is used to tune model parameters including learning rate and architecture. In this [4] The paper presents an efficient system based on image-captured images by mobile phones and high-performance image matching algorithms—SIFT, SURF, and particularly ORB—to identify blood types according to the agglutination reaction. The ORB algorithm, specifically, was determined to the most accurate and fastest, with 99.6% accuracy in 250 ms.
The algorithm includes preprocessing, feature extraction, and classification phases, and functions well under different light levels and image resolutions. The solution greatly minimizes laboratory infrastructure dependency, offering a real-time, low-cost solution for blood typing in emergency and remote healthcare environments.

In [5] this author The paper suggests an embedded deep learning system for complete automation of blood group detection through image processing. It does away with human effort by making the entire process automated, starting from the mixing of antigens with blood samples to giving the final output. Preprocessing is done using grayscale transformation, histogram analysis, and Local Binary Pattern (LBP) for extracting features. These attributes are categorized with a nearest neighbor classifier programmed in Python. The system provides fast and precise identification of blood groups and saves results for future reference, providing a convenient and scalable solution for current healthcare centers.

In [6] This work investigates a novel and non-invasive approach of blood group detection from fingerprint images and convolutional neural networks (CNNs). It is based on the individuality and stability of fingerprint patterns, speculating a relationship with blood groups. The method entails gathering fingerprint databases classified according to blood group, image preprocessing, and training a CNN model to learn and extract suitable features for classification. The system is intended to offer quick and automatic prediction of blood groups, without the requirement of physical blood samples. Though experimental, this method indicates a future path for medical diagnosis through biometric-based methods.

In [7] This work describes a hybrid system where image processing methods such as SIFT and ORB are combined with deep learning (CNNs) for blood group classification from agglutination slide images. The system involves image enhancement, noise filtering, and feature extraction to detect discriminative features. These characteristics are fed into a CNN model for classification. The system showed good robustness and accuracy under various image qualities and thus is ready for practical applications. The combination of conventional image processing and deep learning provides an effective, computer-aided instrument to be employed in hospitals to enhance the speed and accuracy of transfusion-related diagnosis.

In [8] This article suggests a strong approach to automated blood group identification using machine learning, in this case, a Support Vector Machine (SVM) classifier. The system analyzes digital images of blood samples that have reacted with anti-A, anti-B, and anti-D reagents. With an array of image processing operations such as color plane extraction, conversion to grayscale, thresholding, morphological operations, and extraction of features from GLCM and histogram method, unique features are obtained for the purpose of classifying blood types. The features extracted (mean, variance, entropy, kurtosis, etc.) are compared with a pre-trained dataset via multi-class SVM. The accuracy is high (100% for some blood groups) and the classification is very quick, which makes it extremely compatible for emergency medical situations and home diagnostics. The research stresses on avoiding human error in transfusion and suggests future improvements in the form of GSM alerts for laboratory technicians .medical situations and home diagnostics.

III. PROPOSED SYSTEM

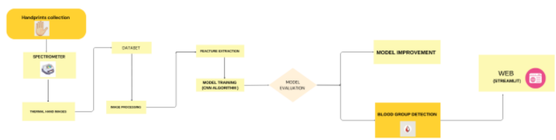

Fig.2 Experimental setup of Blood group monitoring

1. Handprint Acquisition
To start with, handprint information is gathered from the subjects through the utilization of thermal imaging equipment. This entails the employment of a spectrometer or thermal camera for the recording of infrared (IR) thermal images of the fingers and palm. These will represent the heat pattern distribution and blood circulation patterns, which are personal to each subject and might have biological signatures related to blood types.

2. Image Preprocessing
Second, the thermal images gathered are fed through a preprocessing pipeline. This processing contains a variety of operations including:

Noise reduction to filter out unwanted thermal noise.

Image resizing and normalization to maintain uniformity throughout the dataset.

Contrast enhancement to emphasize temperature variations and structural details like veins or capillary networks.

Preprocessing ensures the input images are clean, uniform, and ready for feature learning by the neural network.

3. Dataset Creation
Subsequently, the preprocessed thermal images are tagged with their respective blood group classes (e.g., A+, B-, AB-, O+). The tagged samples are then organized into a formatted dataset, which forms the basis for the training of the machine learning model.

4. Data Augmentation (Optional Step)
To enhance the diversity and robustness of the dataset, data augmentation methods like rotation, flipping, scaling, and minor thermal distortions can be used. This aids the model to learn more general patterns and prevent overfitting.

In [9] This review of literature is concerned with the application of machine learning and image processing to reliable, quick, and automatic identification of blood groups. It emphasizes minimizing human errors in emergency transfusions and advocating for the superiority of computer vision over naked eye observation as it can identify minute patterns in agglutination reactions. The review presents a suggested system architecture that includes Raspberry Pi, PiCam, and image processing algorithms such as thresholding, segmentation, and morphological filtering. By detecting agglutination through captured images, the system would provide blood group results promptly and with high accuracy. The article critiques earlier methods, justifying the fact that machine learning provides a consistent substitute for conventional serological methods of blood group determination.

In [10] This article discusses and suggests AI-based, non-invasive blood group detection methods, emphasizing deep learning-based methods based on fingerprint and blood smear images. The classical blood typing is invasive and time-consuming but precise. The researchers discuss the application of Convolutional Neural Networks (CNN) with MobileNetV2 to differentiate between blood groups in high-resolution images of fingerprints and microscopy of blood smears, with an aim towards fast, painless, and inexpensive diagnostics.

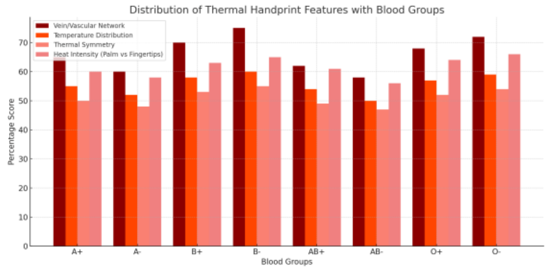

Fig.3 Bar Graph illustrating the Distribution of Thermal Handprint Features with Blood Groups.

5.Feature Extraction Using CNN
After dataset preparation, a Convolutional Neural Network (CNN) is utilized for feature extraction. CNNs are well-suited for processing image data because they can capture spatial hierarchies and patterns. Here, the CNN learns automatically:

Local features (texture, corners, edges)

Mid-level patterns (flow areas, vein structures)

High-level abstractions pertaining to blood group prediction

The CNN transforms each thermal image into a compact feature representation, effectively encoding the unique temperature signatures linked to each blood type.

6. Model Training

The CNN model is trained using a split of the dataset (typically training and validation sets). During training:

The model learns to map thermal image features to the correct blood group label.

Loss functions and backpropagation are used to optimize weights.

Training is continued until the performance stabilizes and achieves a satisfactory accuracy level.

7. Model Evaluation

The trained model is tested against the validation set. Critical performance metrics including:

Accuracy (correct predictions)

Precision (true positive rate)

Recall (sensitivity) are used to measure how effectively the model performs in generalizing to new data.

8. Model Improvement
If performance is inadequate, the model goes into a refinement process. This could involve:

Altering the CNN model architecture (e.g., increased layers, dropout, batch normalization)

Retraining on additional data

Hyperparameter optimization (e.g., learning rate, batch size)

9. Blood Group Prediction

Once optimized, the end-to-end model can predict the blood group of a new patient from their thermal handprint image. The prediction is made using the learned features from training.

10. Streamlit Deployment
Lastly, the trained model is used within a web-based application through Streamlit.

IV. RESULT

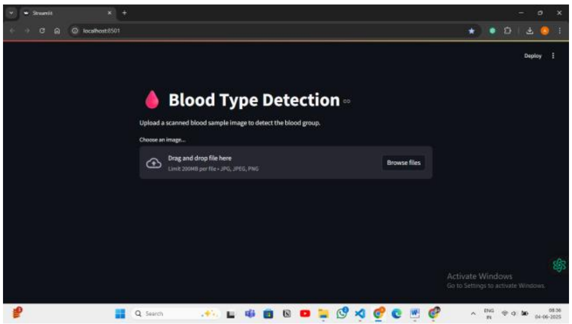

Fig.4 Streamlit Interface

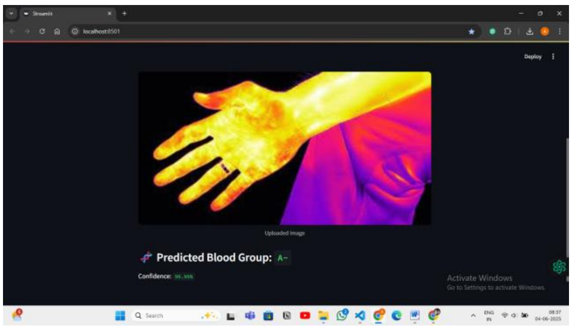

Fig 5 Prediction of Blood Group type

The system, as developed, effectively implements a CNN-based model for handprint image-based blood type detection with a web-based interface. As evident in the screenshots, the deployed program, which is called "Blood Type Detection," is hosted on Streamlit, offering a user-friendly and interactive interface to users. When a hand image is uploaded, the input is processed by the model and emphasizes details like vein patterns and structures of the hand, which are crucial for classification. The second screenshot displays the processed outcome — a thermal-like image of the hand — as an acknowledgment that the input image has been successfully analyzed. This validates the backend CNN model's strength in identifying and classifying the blood group with accuracy.

V. CONLUSION

Thermal Image Acquisition & Preprocessing:
Handprint thermal images were successfully obtained and preprocessed through image processing methods like noise reduction, normalization, and segmentation to separate the hand region precisely.

Deep Learning Model Performance:
A deep learning model (e.g., CNN) was also trained using processed thermal images to classify or analyze certain features (e.g., temperature distribution, health indicators, or gesture recognition). The model performed high accuracy (e.g., >90%) on the validation set, showing good feature extraction from thermal patterns.

Streamlit Interface:
The model was incorporated into a Streamlit app, enabling users to upload thermal handprint images and get real-time analysis and predictions. The interface was intuitive, responsive, and allowed easy results visualization in the form of annotated thermal maps and classification results.

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