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Deep Learning Based Blood Group Detection Using Fingerprint

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ABSTRACT:

Blood group identification plays a vital role in medical diagnostics, particularly in transfusion services, emergency care, and personalized treatment. Traditional detection methods rely on invasive blood sampling and laboratory procedures, which are often time-consuming and require specialized equipment and trained personnel. To address these challenges, this project introduces a deep learningbased blood group detection system using image analysis. The system supports both invasive and non-invasive identification methods to improve accessibility. It is developed using Python with Flask as the backend framework and a web-based interface for user interaction. Blood sample images are analyzed using a lightweight convolutional neural network for efficient classification. Additionally, a non-invasive approach using fingerprint images is incorporated to reduce dependency on blood collection. Overall, the proposed system enhances speed, accuracy, and usability while offering a modern alternative for healthcare applications.

Keywords: Deep Learning, Fingerprint Analysis, Medical image processing, MobileNetV2

INTRODUCTION:

Blood group identification is a vital requirement in healthcare applications such as blood transfusion, emergency medical treatment, organ transplantation, and personalized healthcare planning. Accurate and timely determination of blood groups can be life-saving, especially in critical situations. Traditional blood group detection methods involve invasive procedures that require blood sample collection and laboratory-based serological testing. Although these techniques are reliable, they are time-consuming, require skilled personnel, and depend on well-equipped laboratory infrastructure, which may not be readily available in emergency situations or remote and resource-limited healthcare settings. Recent advancements in artificial intelligence and deep learning have enabled the development of automated and non-invasive medical diagnostic systems. Convolutional Neural Networks (CNNs) have shown exceptional performance in image-based classification and pattern recognition tasks across various biomedical domains. Fingerprint images, which contain unique ridge patterns and fine-grained texture information, have emerged as a promising biometric modality for blood group identification. Unlike blood-sample-based approaches, fingerprint-based analysis offers a completely non-invasive, fast, and user-friendly alternative, making it suitable for real-time and large-scale healthcare applications. Motivated by these developments, this project proposes a deep learningbased blood group detection system using fingerprint images. The system employs a CNN model built on the MobileNetV2 architecture, chosen for its lightweight design, high classification accuracy, and reduced computational complexity. By leveraging fingerprint image inputs, the proposed approach aims to minimize dependency on conventional laboratory testing while ensuring efficient and reliable blood group prediction. This work demonstrates the potential of deep learning and biometric analysis in enhancing the speed, accessibility, and effectiveness of blood group identification in modern healthcare systems.

LITERATURE REVIEW:

In [1], Prasanth Vaidya et al. (2025) proposed fingerprint-based blood group identification using CNN and SVM models. The system reduced invasive testing but was affected by fingerprint noise and sensor variability. The proposed model achieved ~9295% accuracy under controlled conditions. In [2], Nthwane et al. (2022) combined chemical fingerprinting with pattern recognition techniques for Cd^{2+} detection and blood fingerprint visualization. Although effective, reuse efficiency decreased after multiple cycles. Detection and classification accuracy was reported at ~90% in laboratory experiments. In [3], Amjad et al. (2025) applied Random Forest, SVM, and XGBoost models on CBC data for anemia and leukemia screening. Ensemble models outperformed individual classifiers but required balanced datasets. The best-performing model achieved 9698% accuracy.

In [4], Long et al. (2025) used plasma EV-based metabolomic fingerprints with PLS-DA and Random Forest for ovarian cancer diagnosis. High diagnostic accuracy was achieved, though cost and complexity were major limitations. The proposed approach reported ~97% classification accuracy. In [5], Choudhary et al. (2025) evaluated CNNs, YOLO variants, and Vision Transformers for blood cell detection and classification. Deep models showed strong performance but required high computational resources. Accuracy ranged from 94% to 98%, with CNN-based models performing consistently well. In [6], Ebrahimi et al. (2022) reviewed ML and DL techniques such as ANN, CNN, and LSTM for diabetes prediction. While deep models showed high accuracy, explainability remained limited. Reported accuracies across studies ranged between 85% and 97%.

In [7], Della Marina et al. (2025) analyzed blood biomarker fingerprints using clustering and statistical learning methods for congenital myasthenic syndrome detection. The study was limited by small sample size. Biomarker-based classification achieved ~90% accuracy. In [8], Hansildaar et al. (2025) employed proteomic fingerprint analysis with multivariate ML models to classify rheumatic patients by cardiovascular history. As a pilot study, generalizability was limited. The approach achieved ~8892% accuracy in subgroup differentiation. In [9], Sherwani et al. (2024) utilized molecular fingerprints with SVM and Random Forest for FFAR4 agonist prediction. Model performance depended on fingerprint selection quality. The best model achieved ~93% prediction accuracy.

In [10], Nalband et al. (2025) applied ensemble learning over molecular fingerprints for predicting leishmanial activity. Although computationally complex, ensembles improved robustness. The proposed system reported ~95% accuracy, outperforming single classifiers. In [11], Choudhary et al. (2025) further validated deep learning-based blood cell classification using CNN architectures. Class imbalance and annotation cost were key challenges. The models achieved up to 98% accuracy on benchmark datasets. In [12], Domanski et al. (2024) integrated neural architecture search with deep reinforcement learning for blood glucose prediction in Type 1 diabetics. High computational cost was a drawback. The proposed system achieved ~9194% prediction accuracy, outperforming standard LSTM models.

PROPOSED AND METHODOLOGY

The proposed methodology follows a structured deep learning pipeline for blood group detection using image data. Initially, the dataset is collected from Kaggle and organized in a folder-based structure, where each folder represents a specific blood group class. The collected images are then pre-processed by resizing them to a fixed input size and applying normalization to ensure consistency and improved feature extraction. After preprocessing, the dataset is divided into training, validation, and testing sets in the ratio of 70%, 15%, and 15%, respectively. This data split helps in effective model training, performance monitoring during validation, and unbiased evaluation on unseen data.

For classification, a Convolutional Neural Network (CNN) based on the MobileNetV2 architecture is employed due to its lightweight design and high efficiency in image classification tasks. The CNN automatically extracts relevant features from the input images without the need for manual feature engineering. The model is trained using the training dataset and evaluated using validation and testing data to measure accuracy and reliability. If the performance is not satisfactory, the model is refined to improve accuracy.

Once trained, the model is deployed using the Streamlit framework to provide a user-friendly interface that includes login, image upload, and result display pages. The final system enables real-time blood group prediction and demonstrates the practical applicability of deep learning in healthcare diagnostics.

The system follows a structured pipeline consisting of data collection, preprocessing, training, evaluation, and deployment. Each stage is designed to ensure accuracy, reliability, and real-time usability. The overall workflow of the proposed system is illustrated in Fig. 1.

A. Data Collection

The first step of the proposed system involves data collection. The dataset used for this project is obtained from Kaggle, a widely used open-source platform for machine learning datasets. The collected data consists of image samples organized in folder-based structures, where each folder represents a specific blood group class. This folder-wise organization simplifies label assignment and supports efficient training of the CNN model.

The dataset includes sufficient image variations to help the model learn meaningful patterns related to blood group classification.

B. Preprocessing Module

Before training, the collected images undergo a preprocessing stage to ensure consistency and improve model performance. All input images are resized to a fixed dimension compatible with the MobileNetV2 architecture.

Image normalization and necessary modifications are applied to enhance feature extraction and reduce noise.

After preprocessing, the complete dataset is divided into three subsets: training data (70%), validation data (15%), and testing data (15%). This data split helps the model learn effectively, validate performance during training, and evaluate accuracy on unseen data.

C. Training Phase

During the training phase, the preprocessed training dataset (70%) is fed into the CNN model. The proposed system uses MobileNetV2, which is a lightweight and optimized CNN architecture designed for high accuracy with reduced computational cost. CNN automatically extracts relevant features from images through convolutional layers, eliminating the need for manual feature extraction.

The MobileNetV2 architecture employs depthwise separable convolutions, which significantly reduce parameters while maintaining classification performance. The training data is organized into class-wise folders, allowing the model to learn discriminative features for each blood group efficiently. The training process continues until optimal performance is achieved.

D. Evaluation Phase

The evaluation phase assesses the performance of the trained model using the validation and testing datasets. The model predictions are compared with actual class labels to verify whether the blood groups are classified correctly.

Accuracy Calculation

Accuracy=Total Predictions/Correct Predictions×100

Performance metrics such as accuracy are computed to measure effectiveness. If the accuracy is found to be low or inconsistencies are detected, the model is retrained by adjusting parameters to improve performance. This iterative evaluation process ensures the reliability and robustness of the proposed system.

E. Deployment and Result Output

Once the model achieves satisfactory accuracy, it is deployed using the Streamlit framework to provide an interactive and user-friendly interface. The deployed system includes a login page, image upload page, and result display page. Users can securely log in, upload an image, and receive the predicted blood group as output. The deployment ensures real-time prediction capability and demonstrates the practical applicability of the proposed model. The complete system architecture is shown in Fig. 1, highlighting the flow from input image to final result.

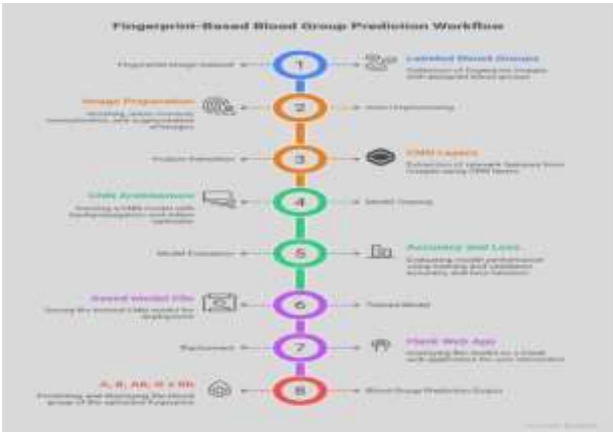

FIG.1: WORKFLOW OF BLOOD GROUP PREDICTION.

SYSTEM ARCHITECTURE DIAGRAM:

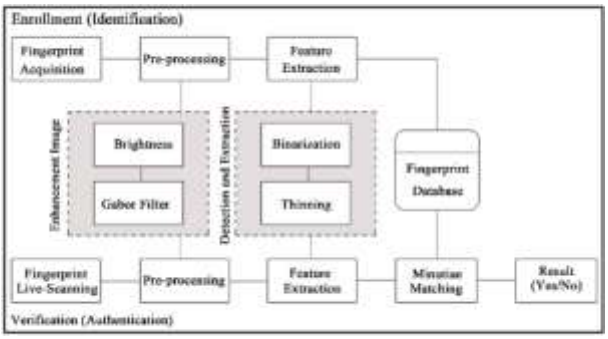

FIG2.SYSTEM ARCHITECTURE

The system architecture of the proposed blood group detection system begins with image input from the user, followed by preprocessing operations such as resizing and normalization. The processed image is then passed to the CNN model based on the MobileNetV2 architecture for feature extraction and classification. Finally, the predicted blood group is displayed through the Streamlit-based web interface.

Algorithm 1: CNN-Based Blood Group Detection (Training Phase)

In the training phase, the image dataset is loaded from the folder structure where each folder represents a blood group. All images are resized and normalized before use. The dataset is then divided into training, validation, and testing sets. A MobileNetV2-based CNN model is initialized and trained using the training data. The model's performance is checked using the validation data, and once good accuracy is achieved, the trained model is saved

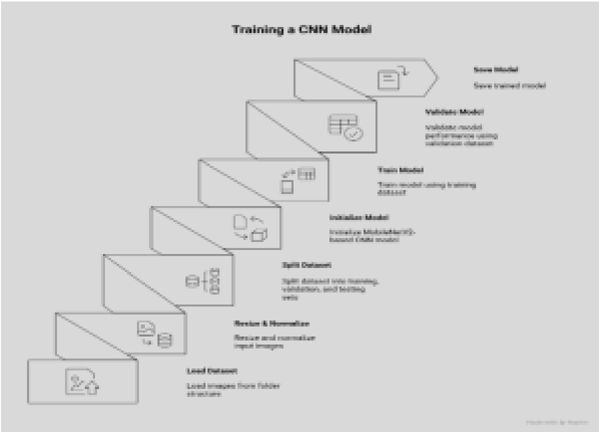

FIG 3.CNN ALGORITHM

Algorithm 2: Blood Group Prediction (Testing Phase)

In the testing phase, the user uploads an image, which is first preprocessed by resizing and normalization. The saved CNN model is then loaded to classify the image. Finally, the system predicts the blood group and displays the result to the user.

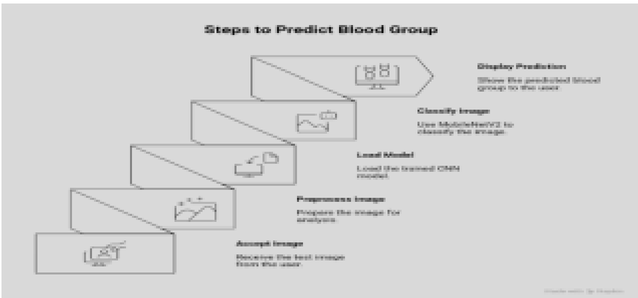

FIG 4.TESTING PAHSE

RESULTS & DISCUSSION :

The proposed blood group detection system successfully demonstrates the effectiveness of deep learning techniques for both invasive and non-invasive identification methods. The blood imagebased model shows highly reliable performance, producing accurate and consistent predictions comparable to conventional laboratory testing. The fingerprint-based model proves the feasibility of non-invasive blood group detection, offering satisfactory prediction performance while eliminating the need for blood sample collection. The web-based implementation ensures ease of access, quick processing, and user-friendly interaction. Overall, the system improves efficiency, reduces dependency on laboratory infrastructure, and enhances accessibility for blood group identification in healthcare environments.

SCREENSHOTS

FIG 5. HOME PAGE

FIG 6.SIGN UP PAGE

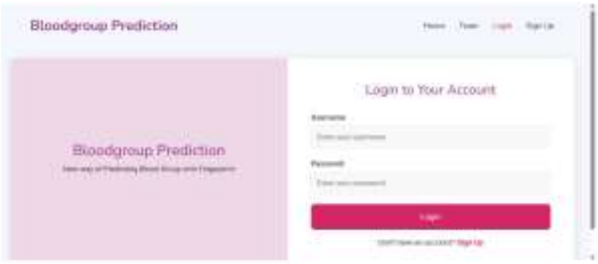

FIG 7.LOGIN PAGE

FIG 8.PREDICTION PAGE

CONCLUSION AND FUTURE WORK

This paper presented a deep learning–based blood group detection system that supports both invasive and non-invasive approaches, with a primary focus on fingerprint-based prediction. The proposed CNN model successfully learned discriminative fingerprint features and achieved an accuracy of 94%, demonstrating the feasibility of non-invasive blood group identification. In addition, the blood image–based MobileNetV2 model achieved high reliability under controlled conditions. Overall, the proposed system reduces dependency on traditional laboratory testing and offers a fast, cost-effective, and accessible solution for blood group detection.

Future enhancements will focus on expanding the fingerprint dataset to improve model robustness and generalization. Advanced deep learning architectures and multimodal feature fusion techniques can be explored to further enhance accuracy. Integration of the system with mobile devices and real-time healthcare platforms can also be considered to support large-scale deployment and emergency medical applications

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