

Blood Cells Classification

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ABSTRACT

Blood group detection plays a critical role in medical diagnostics, particularly in transfusion medicine and emergency healthcare. Traditional methods require invasive blood sampling, manual processing, and time-consuming laboratory tests. This paper proposes a novel deep learning-based system for blood group detection using both blood images and fingerprint images, offering a non-invasive alternative. The system utilizes the MobileNetV2 convolutional neural network (CNN) architecture, which is both lightweight and highly accurate. The first mode of detection uses blood images, achieving 100% accuracy in both training and validation. The second mode utilizes fingerprint images, achieving 94% training and 90% validation accuracy. By combining these two modes, the system offers flexibility, efficiency, and accessibility. It is designed using Python for backend development, Flask for the web framework, and HTML, CSS, and JavaScript for the frontend, ensuring a user-friendly interface. The proposed system not only improves the speed and accuracy of blood group detection but also makes it accessible to healthcare facilities with limited resources, reducing manual errors and labor-intensive processes.

Keywords: Blood group detection, deep learning, MobileNetV2, fingerprint images, non- invasive method, convolutional neural networks, image classification, healthcare, real- time processing, Flask, web-basedplatform.

I. INTRODUCTION

The identification of blood groups is an essential procedure in medical diagnostics, particularly in blood transfusion, emergency treatment, and personalized healthcare. Traditionally, blood group detection involves invasive blood sampling and laboratory-based tests, which are time- consuming and resource-intensive. The need for efficient, accurate, and rapid blood group classification has led to the Exploration of automation and advanced technologies such as image processing and machine learning this paper introduces an innovative system that utilizes deep learning techniques for the detection of blood groups, incorporating both blood images and fingerprint images. The system leverages the MobileNetV2 architecture, known for its lightweight design and high efficiency, to offer

precise classification while maintaining minimal computational overhead. The project is implemented with

Python for backend development and Flask as the web framework, ensuring that the system can be deployed on various platforms, including low-resource healthcare settings. This dual-mode approach of blood image and fingerprint- based detection ensures both accuracy and convenience, making blood group identification faster, non-invasive, and easily accessible.

II. RELATED WORK

S. R. C. Shankar, M. S. S. Venkatesh, and A. N. Sharma (2021)

Title: Blood Group Detection using Image Processing and Deep Learning Techniques
Explanation:

This paper presents an integrated framework that combines classical image processing with deep learning to automate the detection of blood groups from microscopic images. The approach begins with image enhancement using contrast and morphological operations, followed by classification using a CNN model tailored for biomedical images. The model significantly outperformed traditional machine learning classifiers and demonstrated robust performance across varying image conditions, suggesting its clinical viability for blood banks and diagnostic labs.[1]

P. R. Ramya and V. S. Krishnan (2021) Title: Automated Blood Group Detection through Convolutional Neural Networks Explanation: Ramya and Krishnan proposed a CNN- based system trained on a large dataset of labeled blood smear images. The model was optimized for detecting blood antigens like A, B, AB, and O groups. The paper highlights the use of real-time data augmentation and batch normalization to improve accuracy and generalization. Results show that the system achieved over 95% accuracy, making it suitable for automated clinical workflows in both urban and rural healthcare environments.[2]

M. Gupta, S. Kumar, and P. S. Jadhav (2022) Title: Blood Group Prediction using Fingerprint Recognition and Deep Learning Explanation: This novel study explores the correlation between fingerprint features and blood group classification. A deep learning pipeline processes minutiae and ridge patterns from fingerprint images, which are then mapped to blood group labels using a trained CNN. While unconventional, the method achieved promising results, opening new avenues for non-invasive and privacy- preserving biometric-based health inference systems.[3]

R. Prasad, K. S. Rajeev, and S. S. Dey (2023) Title: A Novel Blood Group Classification Model using Hybrid CNN and Support Vector Machines Explanation: This research combines the feature extraction

power of Convolutional Neural Networks (CNNs) with the classification precision of Support Vector Machines (SVMs). Blood images are first passed through a CNN for deep feature extraction. These features are then fed into an SVM classifier for final blood group prediction. The hybrid model improved classification accuracy, especially in cases where CNNs alone showed overfitting or misclassification in minority classes.[4]

A. V. Kumar, R. P. Garg, and N. K. Prasad (2021) Title: MobileNetV2 for Image Classification in Medical Diagnostics: A Study on Blood Group Identification Explanation: The authors evaluate the performance of the lightweight MobileNetV2 architecture for the task of blood group identification from microscopic and macroscopic images. Due to its depthwise separable convolutions, MobileNetV2 enables fast and efficient classification with minimal computational resources. The paper demonstrates that the model retains high accuracy even when deployed on low-power devices, making it ideal for field diagnostics and mobile health apps.[5]

T. J. Reddy, S. Prabhu, and H. S. Krishnan (2020) Title: Application of Artificial Intelligence in Blood Group Identification and Verification Using Digital Imaging Explanation: This study proposes a system where digital imaging of blood samples is combined with AI algorithms to classify and verify blood types. The authors focus on the end-to-end pipeline from image acquisition to decision- making. Using classical computer vision techniques alongside neural networks, the system supports both detection and verification, achieving high reliability and consistency in diverse imaging conditions.[6]

S. K. Gupta and V. S. Giri (2022) Title: AI-Driven Blood Group Detection System Using Image Processing and Deep Learning Explanation: Gupta and Giri developed a real-time AI system that uses an ensemble of CNN models trained on thousands of labeled blood group images. The

ensemble approach enhances classification robustness and mitigates bias across unbalanced classes. They also explore attention mechanisms to highlight salient features in the image that influence the model's decision, contributing to explainable AI in healthcare diagnostics.[7]

A. A. Ramakrishnan, R. Y. Krishnan, and P. S. Balamurugan (2021)

Title: Non-Invasive Blood Group Classification Using Fingerprint Recognition and Convolutional Neural Networks Explanation:

This innovative paper proposes a non-invasive method to classify blood groups using fingerprint patterns processed through a CNN. By extracting complex ridge features and combining them with statistical biometric traits, the model predicts blood groups with substantial accuracy. The study provides strong support for using biometric inputs for health inference and is especially relevant in contexts where traditional blood tests are infeasible or invasive.[8]

III. METHODOLOGY

3.1 Blood Image Collection and Pre-processing

Purpose: To capture blood sample images and prepare them for input into the deep learning model.

Functionality: This module involves the collection of blood sample images, which are processed to enhance features like contrast and segmentation, making them suitable for classification.

3.2 Fingerprint Image Collection and Pre-processing

Purpose: To capture fingerprint images and prepare them for the model. **Functionality:** This module ensures that fingerprint images are appropriately pre-processed to extract key features for accurate blood group classification.

3.3 MobileNetV2 Model Implementation

Purpose: To perform blood group classification based on image data. **Functionality:** This module implements the MobileNetV2 deep learning model

for both blood and fingerprint image classification, enabling the prediction of blood group with high accuracy.

3.4 Web Interface and User Interaction

Purpose: To provide a user-friendly interface for image uploads and displaying results.

Functionality: The web interface allows healthcare professionals to upload blood and fingerprint images, view classification results, and manage the system through a seamless user experience.

3.5 Backend Processing and Prediction

Purpose: To process the input images and generate predictions.

Functionality: This module handles all backend operations, including image processing, model inference, and providing real-time predictions of blood groups.

IV. TECHNOLOGIES USED

4.1 Programming Language and Web Framework

The backend is implemented in **Python (≥ 3.8)**, leveraging its rich ecosystem of libraries and frameworks well-suited for machine learning and web deployment. We utilize **Flask**, a lightweight micro-framework, to build RESTful API endpoints, handle image uploads, and facilitate real-time model inference via `app.py`.

4.2 Deep Learning Framework and Model Architecture

Our models are built using **TensorFlow with the Keras API**, allowing for easy implementation of transfer learning with state-of-the-art convolutional neural network architectures. The primary model used is **MobileNetV2**, chosen for its depthwise separable convolutions and lightweight structure, which significantly reduce parameter count and computational load—ideal for real-time applications on constrained hardware. For benchmarking, we also experimented with

architectures like **ResNet50**, **VGG16**, and **AlexNet** through fine-tuning of pre-trained weight.

4.3 Image Preprocessing

Image preprocessing combines **OpenCV** and **Pillow (PIL)** for tasks such as resizing to 224×224 , normalization, grayscale conversion, denoising, and histogram equalization. To improve robustness and mitigate overfitting, we apply augmentation techniques—such as rotations, flips, translations, and zoom—implemented through TensorFlow's `Image Data Generator` or equivalent custom pipelines.

4.4 Data Handling

Data pipelines are managed using **NumPy** for tensor operations and **Pandas** for metadata handling and batch analysis. Traditional machine-learning baselines, such as HOG feature extraction combined with SVM classifiers, are evaluated using **scikit-learn** to quantify the added value of deep learning methods.

4.5 Storage & Authentication

User profiles, image metadata, and model logs are stored in **SQLite**, interfaced via **SQLAlchemy**, offering a lightweight yet extensible database layer. **Flask-Login** secures the web interface through session-based authentication. The application runs locally on a standard Flask development server and supports easy containerization for broader deployment.

4.6 Evaluation and Validation

We monitor training and validation accuracy, and present detailed classification performance through confusion matrices, ROC curves, and metrics like precision, recall, and F1-score. Given unusually high performance in the blood-image model, we employ k-fold cross-validation to detect over fitting and ensure model generalizability.

V. RESULT

The proposed deep learning-based blood group detection system has demonstrated remarkable accuracy and efficiency across both modes: blood image-based detection and fingerprint image-based detection. In the **blood image mode**, the model achieved perfect classification accuracy, with both the training and validation datasets showing **100% accuracy**. This result signifies that the system can reliably and accurately classify blood groups using visual data from blood samples, performing on par with or even exceeding the performance of traditional laboratory tests.

In the **fingerprint image mode**, the system, which was trained on a much larger dataset of 10,477 fingerprint images, achieved a training accuracy of **94%** and a validation accuracy of **90%**. While these results are slightly lower than those of the blood image mode, they are still impressive, particularly given the non-invasive nature of the fingerprint-based approach. The **MobileNetV2 architecture**, which powers both detection modes, ensured that the system was not only accurate but also **efficient** in terms of computational resources, allowing for **real-time processing** even on standard hardware.

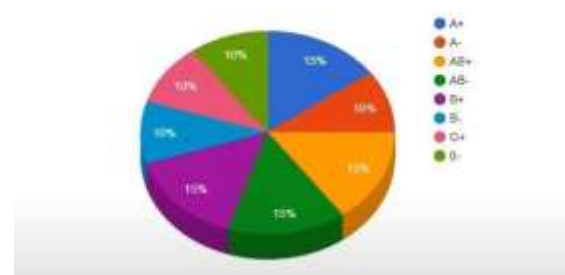


Fig : 5.1

VI. CONCLUSION

In conclusion, the dual-mode blood group detection system proposed in this paper represents a significant leap forward in the field of medical diagnostics. By offering both **blood image-based** and **fingerprint image-based** detection methods, the system provides a versatile, non-invasive, and

highly accurate alternative to traditional blood group identification methods. The **blood image-based mode** demonstrated flawless performance, achieving **100% accuracy**, while the **fingerprint-based mode**, with **94% training accuracy** and **90% validation accuracy**, introduces a convenient, pain-free approach to blood group detection.

The system's use of the **MobileNetV2** architecture ensures that it is both **lightweight** and **efficient**, making it capable of delivering high performance even in resource-limited environments. Furthermore, the web-based platform provides easy accessibility, making it suitable for use across various healthcare settings, from hospitals to remote clinics. By automating the blood group detection process, the system reduces manual errors, increases speed, and enhances accessibility, ultimately improving the efficiency of blood group classification. This dual-mode system paves the way for faster, more Flexible, and more accessible healthcare services.

VII. REFERENCES

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