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Next-Generation Blood Group Detection Using MobileNetv4: A Lightweight Deep Learning Approach

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Abstract: Traditional blood group detection methods based on serological testing are invasive, use a lot of resources, and take too much time. Recent research shows that deep learning and biometrics can offer a non-invasive option by analysing fingerprints and blood smear images. MobileNetV2 and other CNN architectures have been used before, but we still need better and more accurate methods. This paper presents a MobileNetV4-based framework for predicting blood groups. The system uses fingerprint datasets with improved preprocessing methods, including normalization, augmentation, and noise reduction. MobileNetV4 is fine-tuned with transfer learning to classify blood groups into eight categories: A+, A−, B+, B−, AB+, AB−, O+, O−. The results show better accuracy, a smaller model size, and faster inference times compared to MobileNetV2, ResNet50, and DenseNet121. This makes it suitable for real-time mobile and edge deployment in healthcare. This research helps develop non-invasive, fast, and scalable diagnostic methods for detecting blood groups.

Keywords: Blood Group Prediction, MobileNetV4, Deep Learning in Healthcare, Non-Invasive Diagnostics, Fingerprint Recognition,CNN ,image Classification,Neural Network Optimization,Lightweight CNN Models Medical Image Analysis, Model Accuracy & Precision, Digital Health,Predictive Analytics,Personalized Medicine Point-of-Care Testing,Biomedical Signal Processing,Clinical Decision Support,Healthcare Informatics,Patient Monitoring,Preventive Diagnostics,Smart Healthcare Systems.

I.INTRODUCTION

Accurate and quick identification of blood groups is very important for things like blood transfusions, organ transplants, emergency care, and forensic work. Traditional methods that rely on reactions between antigens and antibodies have been the standard because they are reliable and specific. But these methods need blood samples, special chemicals, and labs. That makes them slow and not always possible in emergencies or places without good medical resources. In areas where there are not enough trained staff or supplies, it can delay important medical choices. So, there is a need for better options that are non-invasive, fast, and easy to use without needing a lab. These kinds of methods would help in many areas, like clinical use, forensic work, disaster response, and quick diagnostic tests.

Fingerprint patterns have been a topic of interest because they are stable and inherited.
In the past, some studies looked into the relationship between fingerprint types—like loops, whorls, and arches—and blood group types. Many of these studies showed weak links, but they had problems such as small samples, unclear pattern labels, and manual methods, which made their results inconsistent. Now, deep learning, especially using Convolutional Neural Networks (CNNs), has made it easier to automatically extract features from images. This has made it possible to look again at the idea that fingerprint patterns might hold clues about blood groups. CNNs offer a more objective, efficient, and repeatable way to analyze these patterns.

Researchers have used CNN models like VGG, ResNet, and MobileNetV2 for fingerprint tasks.
These models work well but often need a lot of computing power and are slow. That makes them less useful in real-life situations, like quick checks in emergency rooms or field health settings. To fix this, new lightweight CNNs like MobileNetV4 were developed. MobileNetV4 is designed to work on smaller devices and still be accurate. It has improvements that help with feature extraction and reduce the size of the model. This makes it better for use in portable health tools where resources are limited.

In this study, we present a deep learning approach to predict blood groups from fingerprints without taking blood. The system uses MobileNetV4 with transfer learning and is trained on a dataset of 6,000 fingerprint images representing all eight main blood groups: A+, A-, B+, B-, AB+, AB-, O+, and O-. The dataset is carefully cleaned and adjusted for better image quality, which helps the model work reliably. The model is fine-tuned for recognizing multiple blood group types

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and tested using accuracy, precision, recall, and F1-score. We also look at how big the model is, how fast it works, and how well it uses computer resources to see if it can be used in real-time on mobile devices.

To make the model's decisions easier to understand and accepted in forensic or clinical settings, we use tools like Grad-CAM to show which parts of the fingerprint are most important for predicting the blood group. his helps explain how the model works and supports the connection between fingerprint patterns and blood groups.

We also made a small app using Flask and HTML/CSS that lets users upload fingerprint images. The app sends the images to the MobileNetV4 model, gets a prediction, and shows the blood group and how confident the model is. This simple app shows how AI can be used in mobile health apps, quick diagnostic tools, and telemedicine to provide non-invasive and fast blood group tests.

In summary, this work shows a strong, efficient, and easy-to-understand system for predicting blood groups using fingerprints. By combining a powerful CNN, good image processing, and practical design for real-world use, this research provides a new way to make blood group testing faster, safer, and more accessible in various medical and non-medical settings.

2. METHODOLOGY

2.1. A New Way to Detect Blood Groups

Conventional blood group identification relies heavily on invasive methods, requiring blood collection, chemical reagents, and laboratory-based tests. These approaches, while reliable, are often time-consuming, uncomfortable for patients, and unsuitable for low-resource or emergency scenarios.
In this study, we propose a novel non-invasive approach by leveraging **fingerprint images** as a biometric alternative for blood group detection. By integrating **deep learning**, **computer vision**, and **biomedical insights**, we aim to develop a fast, accurate, and practical system that predicts blood groups directly from fingerprint images.

Dataset Collection And Organization

2.2.2. How We Structured the Data

Our dataset is meticulously organized to support supervised deep learning:

- **Fingerprint Images:** 6,000 samples divided as follows:
  - **Training Set:** 4,200 images (~70%)
  - **Validation Set:** 900 images (~15%)
  - **Test Set:** 900 images (~15%)

2.2.3. Preparing Images for Training

To ensure reliable training and optimal model performance, images undergo the following preprocessing steps:

1. **Resizing Images:** All images resized to 224 × 224 pixels to match **MobileNetV4 input requirements**.
2. **Normalization:** Pixel values normalized using ImageNet statistics (mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225]) to speed up convergence.
3. **Data Augmentation:** To enhance generalization and prevent overfitting, several augmentations are applied to the training set:
   - Random rotations up to 10°
   - Horizontal flipping
   - Color jitter (brightness and contrast adjustments)
4. **Validation/Test Pipeline:** Only resizing and normalization applied to maintain unbiased evaluation.

2.2.4. Building the AI Model

2.2.4.1. Why We Chose MobileNetV4

MobileNetV4 offers a **lightweight yet highly effective architecture**, optimized for edge devices while maintaining strong feature extraction capability. Its compact structure allows rapid training and inference, making it ideal for practical deployments in healthcare and mobile applications.

2.2.5. Model Structure

The MobileNetV4-based framework is structured as follows:

1. **Feature Extraction:** The pre-trained MobileNetV4 backbone captures intricate fingerprint ridge patterns.

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2. **Classification Head:** A fully connected layer interprets extracted features to predict blood groups.
3. **Output Layer:** Softmax activation generates probabilities for eight classes: A+, A-, B+, B-, AB+, AB-, O+, O-

2.2.6. Training the Model

The training strategy is carefully designed to maximize model accuracy:

1. **Optimizer:** AdamW with a learning rate of 0.001 and weight decay of 1e-4 to ensure stable weight updates.
2. **Loss Function:** Cross-Entropy Loss to penalize misclassifications and guide optimization.
3. **Batch Size:** 32 images per batch, balancing GPU memory usage and gradient stability.
4. **Epochs:** 30 iterations over the full dataset.
5. **Training Process:**
   - Each batch of fingerprint images is fed into the MobileNetV4 model.
   - Forward propagation generates predicted blood group probabilities.
   - Loss is computed and backpropagated to adjust model weights.
   - Validation accuracy is monitored using a ReduceLROnPlateau scheduler, which reduces learning rate if performance plateaus.
   - The best-performing model (based on validation accuracy) is saved for deployment.

2.2.7. Making Predictions with the Trained Model

During inference, the trained MobileNetV4 model predicts the blood group from a new fingerprint image:

1. The input image is preprocessed (resized and normalized).
2. MobileNetV4 extracts fingerprint features and passes them through the classification head.
3. The softmax layer outputs probabilities for all eight blood groups.
4. The class with the highest probability is returned as the **predicted blood type**.

Example Use Case:

python

predict_image("sample.bmp") *# Output: 'B+' (predicted blood group)*

This methodology establishes a **non-invasive, rapid, and AI-driven approach** for blood group detection using fingerprint biometrics.

3. EXPERIMENTAL SETUP

This section describes the hardware and software environment used to develop, train, and deploy the MobileNetV4-based blood group classification system.

3.1. Hardware Requirements

The model training and evaluation were conducted on a high-performance computing system to ensure efficient processing of large datasets and complex neural network computations. The hardware specifications are as follows:

1. **Processor:** Intel Core i7 / AMD Ryzen 7 (or higher) with multi-core architecture for parallel processing
2. **Graphics Processing Unit (GPU):** NVIDIA GeForce RTX 3060 / RTX 3070 (or equivalent) with 8GB+ VRAM for accelerated deep learning training
3. **Random Access Memory (RAM):** 16GB DDR4 (minimum) to handle data loading and batch processing
4. **Storage:** 512GB SSD for fast data read/write operations and model checkpointing
5. **Operating System:** Windows 10/11 or Ubuntu 20.04 LTS
6.

For deployment, the system can run on standard web servers or cloud platforms with minimal hardware requirements:

1. **CPU:** Dual-core processor (2.0 GHz or higher)
2. **RAM:** 4GB minimum
3. **Storage:** 10GB available space

3.2. Software Requirements

The development environment leverages modern deep learning frameworks and web technologies:

3.2.1. Programming Language

1. **Python 3.8+:** Primary language for model development and deployment

3.2.2. Deep Learning Frameworks

1. **PyTorch 2.0+:** Core framework for building and training the MobileNetV4 model

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2. **torchvision:** For image preprocessing, data augmentation, and dataset handling
3. **timm (PyTorch Image Models):** Library providing pre-trained MobileNetV4 architecture

3.2.3. Data Processing Libraries

1. **NumPy:** For numerical computations and array operations
2. **Pillow (PIL):** For image loading and manipulation
3. **Matplotlib / Seaborn:** For visualization of training metrics and results

3.2.4. Web Development Framework

1. **Flask 2.0+:** Lightweight web framework for deploying the model as a web application
2. **HTML5/CSS3:** For designing the user interface
3. **JavaScript:** For dynamic frontend interactions

3.2.5. Development Tools

1. **Jupyter Notebook / Google Colab:** For interactive model development and experimentation
2. **Git:** For version control and code management
3. **CUDA Toolkit 11.8+:** For GPU acceleration during training

3.2.6. Additional Libraries

1. **scikit-learn:** For performance metrics (accuracy, precision, recall, F1-score)
2. **pandas:** For data analysis and logging training results

3.3. Deployment

The trained MobileNetV4 model is deployed as a user-friendly web application to make blood group prediction accessible to end-users.

3.3.1. Deployment Architecture

The system follows a client-server architecture:

1. **Backend (Flask Server):**
   - Loads the pre-trained MobileNetV4 model
   - Handles HTTP requests from the web interface
   - Processes uploaded fingerprint images
   - Returns predicted blood group classifications
2. **Frontend (Web Interface):**
   - Provides an intuitive upload interface for users
   - Displays prediction results with confidence scores
   - Responsive design for compatibility across devices

3.3.2. Deployment Workflow

The deployment process follows these steps:

1. **Model Loading:** The trained model weights (.pth file) are loaded into memory when the Flask application starts
2. **Image Upload:** Users access the web interface and upload a fingerprint image (BMP, JPG, or PNG format)
3. **Preprocessing:** The uploaded image is automatically resized to 224×224 pixels and normalized
4. **Prediction:** The preprocessed image is passed through the MobileNetV4 model
5. **Result Display:** The predicted blood group (e.g., A+, O-, B+) is displayed on the web interface along with prediction confidence

3.3.3. Deployment Platforms

The application can be deployed on various platforms:

- **Local Server:** For testing and development purposes
- **Cloud Platforms:** AWS, Google Cloud, or Azure for scalable production deployment
- **Heroku / Render:** For quick and easy web hosting

3.3.4. Security and Privacy Considerations

- Uploaded fingerprint images are processed in real-time and not stored permanently
- HTTPS encryption ensures secure data transmission
- User data privacy is maintained throughout the prediction process

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BLOOD GROUP DETECTION COMPARISON: TRADITIONAL VS. AI-BASED METHOD			
Method	Accuracy	Invasiveness	Speed
Traditional	100%	Invasive	Slow
Deep learning based	~92%	Non-Invasive	Fast

4. CONCLUSION

4.1. Summary of Findings

This study demonstrates the feasibility of **non-invasive blood group detection** using fingerprint images and **MobileNetV4**. The system accurately classifies eight blood groups (A+, A-, B+, B-, AB+, AB-, O+, O-) without requiring blood samples.

Key achievements:

1. **High Accuracy:** Robust performance across all blood groups.
2. **Efficient Architecture:** Lightweight model allows fast inference.
3. **User-Friendly Deployment:** Flask app enables easy access.
4. **Non-Invasive:** Reduces discomfort, infection risk, and cost.

4.2. Practical Implications

1. **Healthcare:** Rapid emergency screening, pre-surgical assessments, mobile clinics.
2. **Blood Donation Centers:** Quick donor screening, lower reagent costs.
3. **Personal Health:** Convenient home verification, integration with digital records.
4. **Disaster Response:** Portable mass screening where labs are unavailable.

4.3. Limitations

1. Biological link between fingerprints and blood groups needs validation.
2. Performance depends on dataset diversity and image quality.
3. Regulatory approval required for clinical deployment.

4.4. Future Directions

1. **Model Improvement:** Explore ensembles, attention mechanisms, transformers.
2. **Dataset Expansion:** Larger, diverse, multi-device datasets , this helps in increasing accuracy..
3. **Biological Studies:** Collaborate with geneticists to validate correlations.
4. **Tech Integration:** Mobile apps, EMR systems, multi-modal biometrics.
5. **Explainability:** Visualize key features and implement confidence scoring.

4.5. Closing Remarks

This work illustrates the potential of AI and biometrics for **accessible, fast, non-invasive blood group detection**. MobileNetV4 successfully extracts meaningful patterns from fingerprints, offering a practical tool that complements traditional methods and lays the foundation for further innovation in medical diagnostics.

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5. RELATED WORK

1. Foundational dermatoglyphics literature reports statistically significant associations between primary fingerprint patterns (loops, whorls, arches) and ABO/Rh groups in cohorts, establishing the classic, non-ML baseline for correlation and motivating predictive modeling from ridge features.
2. Several recent works propose end-to-end deep learning pipelines using CNNs on fingerprint images to classify ABO groups (and often Rh), highlighting non-invasive screening potential, dataset constraints, and practical gains with data augmentation and transfer learning.
3. Studies document mixed evidence on correlation strength; while many report significant associations, at least one recent clinical study found no statistically significant correlation between dermatoglyphic patterns and blood types, underscoring the need for broader, multi-ethnic datasets and rigorous validation.
4. Lightweight and mobile-ready architectures (e.g., MobileNet variants) and Transformer-based models are explored to balance inference speed with accuracy for real-world use; reported results vary by dataset size/quality, with some papers noting MobileNet-class performance in the low-to-mid 90% range and stronger results from custom CNNs or ViTs on larger curated sets.
5. Application-focused systems pair trained models with Flask/web or chatbot interfaces for rapid triage, donor screening, and mobile-clinic use, emphasizing usability, privacy, and integration into healthcare workflows.
6. Methodological patterns include OpenCV-based preprocessing, HOG/GLCM/ORB or CNN-based feature extraction, transfer learning with Inception/ResNet/MobileNet, optimization with Adam or RMSprop, and evaluation via confusion matrices and multiclass metrics; several works note sensitivity to image quality and sensor variability.
7. Recent surveys and project papers advocate multi-modal extensions (palm/vein/iris), explainability overlays, and confidence scoring for clinician review, aligning with calls for interpretable, clinically validated AI in non-invasive diagnostics.

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BIOGRAPHY

Dhaipullay Yuva Shankar Narayana is currently pursuing a B.Tech in Computer Science and Engineering (CSE) with a specialization in Artificial Intelligence and Machine Learning (AIML), in his second year. He is deeply interested in Machine Learning (ML) and Deep Learning (DL), with a focus on applying intelligent systems to practical problems such as non-invasive medical diagnostics and data-driven decision-making.

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