A
Mini Project Report on

FACE EMOTION DETECTION USING CNN

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IN

Computer Science & Engineering
(Artificial Intelligence & Machine Learning)

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CERTIFICATE

This is to certify that the project entitled "**Fingerprint based blood group detection using CNN"** is a bonafide work of Maitreyi Phadke -(22106007), Gauri Ramekar -(22106068), Arya Raut -(22106075), Chinmay Sawant - (22106017) submitted to the University of Mumbai in partial fulfillment of the requirement for the award of **Bachelor of Engineering** in **Computer Science & Engineering (Artificial Intelligence & Machine Learning).**

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Project Report Approval

This Mini project report entitled "**Fingerprint based blood group detection using CNN**" by **Riteshkumar Singh , Sameer Singh, Arya Raut and Chinmay Sawant** is approved for the degree of ***Bachelor of Engineering*** in ***Computer Science &Engineering(AI&ML)*** ,***2024-25***.

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Declaration

We declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission hasnot been taken when needed.

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ABSTRACT

Blood group determination is a crucial process in medical diagnostics, particularly for blood transfusions, organ transplants, and emergency treatments. Traditional methods rely on invasive blood tests, which require laboratory infrastructure and trained personnel, making them time-consuming and prone to human error. This project explores an innovative, non-invasive approach to blood group detection using fingerprint analysis and image processing techniques. Recent studies suggest a correlation between fingerprint ridge patterns (loops, whorls, arches) and blood groups, leveraging biometric data and artificial intelligence (AI) models such as Convolutional Neural Networks (CNNs) for classification. Additionally, advancements in image processing enable automated blood group detection by analyzing agglutination reactions in blood samples through techniques like Scale-Invariant Feature Transform (SIFT) and Oriented Fast and Rotated Brief (ORB). The proposed system integrates biometric authentication and machine learning to develop an accurate and efficient blood group classification model. While initial results are promising, challenges such as small dataset limitations, image quality dependencies, and real-world applicability need further research. Future advancements will focus on refining AI models, enhancing feature extraction techniques, and integrating real-time detection into healthcare applications, ultimately aiming for a reliable, portable, and automated blood group detection system that improves accessibility and efficiency in medical diagnostics.

Keywords: Convolutional Neural Networks (CNNs), agglutination detection, non-invasive diagnostics, automated blood group classification.

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CHAPTER 1

INTRODUCTION

1. INTRODUCTION

Blood group determination is a fundamental requirement in medical diagnostics, playing a crucial role in various clinical procedures, including blood transfusions, organ transplants, prenatal care, and emergency medical treatments. Accurate knowledge of a patient’s blood group is vital to avoid fatal mismatches during transfusion and to ensure compatibility in organ donation, where even minor errors can lead to severe immunological reactions or death. Traditionally, blood typing has been performed using serological methods, which involve the collection of blood samples followed by analysis based on antigen-antibody reactions. These methods typically involve the mixing of the patient's blood with known antibodies to observe agglutination patterns, which determine the presence of A, B, AB, or O antigens and the Rh factor.While these conventional methods are highly accurate and reliable, they come with several limitations. They require laboratory infrastructure, sterile environments, and trained personnel to conduct and interpret the results. Moreover, these methods are invasive, necessitating the drawing of blood from the patient, which may cause discomfort, especially in individuals who require frequent testing, such as those undergoing chronic treatments. There is also a potential risk of human error during sample collection, labeling, and interpretation, which can compromise patient safety. In emergency situations—such as road accidents, natural disasters, or mass casualty incidents—waiting for laboratory-based blood typing can cause critical delays in treatment, potentially resulting in preventable loss of life.

To address these challenges and enhance the speed, accessibility, and safety of blood group identification, researchers have increasingly explored non-invasive blood group detection methods. These novel approaches leverage modern technologies such as biometric authentication, artificial intelligence (AI), and advanced image processing techniques. One particularly promising method under investigation is fingerprint-based blood group detection, which seeks to establish a correlation between an individual's fingerprint ridge patterns—such as loops, whorls, and arches—and their blood group. The underlying hypothesis is that both fingerprints and blood group antigens are genetically influenced, and statistical correlations may exist between the two.

Fingerprints are an ideal biometric trait for this application because they are unique to each individual, remain consistent throughout a person’s life, and can be easily captured using digital scanning devices. The process is non-invasive, fast, and does not require specialized medical skills. By applying machine learning techniques, particularly Convolutional Neural Networks

(CNNs), researchers can extract and learn from complex features present in fingerprint images. Additionally, techniques such as Gabor filters and minutiae analysis are employed to enhance the texture and ridge features, which are then used as input for classification algorithms trained to predict the corresponding blood group.

Fingerprint-based blood group classification currently suffers from limited datasets, making it difficult to train machine learning models with sufficient generalization capability. Furthermore, fingerprint patterns can vary significantly across different demographics, ethnicities, and age groups, which introduces variability and potential bias in prediction models. Real-world validation through large-scale clinical studies is necessary to confirm the efficacy and reliability of this approach.

Future advancements in this field will likely focus on several key areas. These include the expansion of diverse and annotated datasets, the improvement of feature extraction algorithms to enhance accuracy, and the integration of real-time detection modules into compact, user-friendly hardware systems. With continued research and innovation, the hybrid model of biometric and image-based blood group detection has the potential to revolutionize the way blood typing is performed, making it faster, safer, more accessible, and significantly more efficient in both routine and emergency medical settings.

This project aims to explore the feasibility, design, and implementation of such a hybrid blood group detection system, evaluating its performance under different conditions and establishing its potential for clinical deployment. By merging the strengths of biometrics, artificial intelligence, and medical imaging, this research aspires to contribute meaningfully to the evolution of non-invasive diagnostics and to play a transformative role in future healthcare delivery systems.

CHAPTER 2

LITERATURE SURVEY

2. LITERATURE SURVEY

2.1 HISTORY:

Blood group determination has been a crucial area of research in medical diagnostics since its discovery in 1901 by Karl Landsteiner, who classified human blood into A, B, and O groups based on antigen-antibody reactions. This discovery laid the foundation for safe blood transfusions and organ transplants. Later, in 1940, the Rh factor was identified, further improving compatibility in blood transfusion procedures. With advancements in biometric technologies and artificial intelligence (AI), researchers started exploring non-invasive blood group detection methods to overcome the limitations of traditional serological techniques. One of the earliest studies examined fingerprint ridge patterns (loops, whorls, and arches) to determine their correlation with blood groups, leading to the development of statistical and image processing techniques for blood group classification.

In the early 2000s, machine learning and pattern recognition techniques began gaining attention in medical biometrics. Researchers applied Gabor filters, minutiae analysis, and feature extraction to analyze fingerprint characteristics for personal identification. By the 2010s, studies incorporated deep learning models like Convolutional Neural Networks (CNNs) to classify fingerprints with improved accuracy. Simultaneously, image processing-based blood group detection emerged as an alternative approach. This method involved analyzing agglutination reactions in blood samples using computer vision techniques such as Scale-Invariant Feature Transform (SIFT) and Oriented Fast and Rotated Brief (ORB). These methods helped automate the blood typing process, making it faster and more reliable. Recent studies have focused on integrating AI, machine learning, and biometric authentication for real-time and portable blood group detection systems. However, challenges such as limited datasets, variations in fingerprint features across populations, and real-world applicability still need to be addressed. Future research aims to refine feature extraction techniques, improve classification accuracy, and enhance system robustness for practical medical applications.

This literature survey provides an overview of key advancements in fingerprint-based and image-processing-based blood group detection, highlighting their evolution from traditional laboratory-based methods to AI-driven, non-invasive techniques.

2.2 LITERATURE REVIEW:

1) "**Fingerprint-Based Biometric Recognition for Blood Group Prediction Using Deep Learning Techniques**"- This paper explores the use of deep learning techniques, specifically Convolutional Neural Networks (CNNs), for blood group prediction based on fingerprint analysis. It presents a comprehensive study on fingerprint-based biometric recognition and discusses the effectiveness of CNNs in accurately predicting blood groups. The authors provide experimental results and comparisons with traditional serological methods, demonstrating the advantages of the proposed approach.

2) "**Blood Group Identification Using Fingerprint Images and Machine Learning Algorithms**"**-** This research paper investigates the use of machine learning algorithms, including Support Vector Machines (SVM) and Random Forests (RF), for blood group identification using fingerprint images. The authors describe the methodology for feature extraction from fingerprints and present results on a dataset of fingerprint images annotated with blood group information. The study highlights the potential of fingerprint analysis in predicting blood groups and provides insights into the performance of different machine learning algorithms.

3) "**Automated Blood Group Identification Using Fingerprint Analysis: A Review**"- This review article provides an overview of automated blood group identification methods based on fingerprint analysis. It discusses the challenges associated with traditional serological methods and explores the potential of fingerprint analysis as a reliable alternative. The authors discuss various techniques, including feature extraction, pattern recognition, and machine learning algorithms, employed in different studies for blood group prediction using fingerprints. The review summarizes the strengths and limitations of existing approaches and identifies future research directions.

4) **"Blood Group Prediction Using Deep Convolutional Neural Networks" -** This paper focuses on blood group prediction using deep Convolutional Neural Networks (CNNs). The authors propose a CNN architecture specifically designed for blood group prediction based on fingerprint images. They present experimental results on a dataset of fingerprint images and compare the performance of their CNN model with traditional serological methods. The study demonstrates the effectiveness of CNNs in accurately predicting blood groups and highlights

the potential of fingerprint analysis in healthcare applications.

5) **"Blood Group Prediction Using Fingerprint Patterns"-** This research paper explores the use of fingerprint patterns for blood group prediction. The authors investigate various fingerprint features and classification techniques, including minutiae-based features and Support Vector Machines (SVM), for predicting blood groups. They present experimental results on a dataset of fingerprint images and evaluate the performance of different feature sets and classifiers. The study demonstrates the feasibility of blood group prediction using fingerprint patterns and provides insights into the effectiveness of different feature extraction and classification methods.

CHAPTER 3

PROBLEM STATEMENT

3. PROBLEM STATEMENT

Traditional blood group determination methods rely on serological techniques, which are time-consuming, require specialized laboratory equipment, and are prone to human error. There is a need for an automated, non-invasive, and reliable system that can predict blood groups accurately and efficiently. This project aims to develop a CNN-based system that utilizes fingerprint analysis for blood group prediction, offering a faster, automated, and more reliable alternative to traditional methods. By leveraging machine learning and biometric authentication, the system will address key limitations of serological techniques. The effectiveness of the proposed system will be evaluated by comparing its accuracy and efficiency with traditional serological methods, demonstrating its potential advantages in medical diagnostics, emergency situations, and remote healthcare settings.

CHAPTER 4

EXPERIMENTAL SETUP

4. EXPERIMENTAL SETUP

4.1 HARDWARE SETUP:

To ensure smooth and efficient development, training, and deployment of the proposed non-invasive blood group detection system, a robust hardware setup is essential. The system involves computationally intensive tasks, such as fingerprint feature extraction, deep learning model training, and high-resolution image processing, which benefit from powerful CPU and GPU configurations. Below is the recommended hardware configuration:

Processor:

A multi-core processor is required to handle parallel computations and large data loads efficiently. An Intel Core i5 or i7 (10th Generation or newer) or AMD Ryzen 5 or 7 (or higher) is recommended. These processors offer excellent performance for data preprocessing, model inference, and light-to-moderate training workloads.

RAM:

A minimum of 8GB RAM is required to load and process datasets without system lag. However, 16GB or more is strongly recommended, especially when working with high-resolution images, large datasets, or running multiple scripts simultaneously.

GPU:

While not mandatory, a dedicated GPU accelerates the training process significantly. A NVIDIA GTX 1650 or higher, preferably an RTX 3060 or better, is recommended to leverage GPU-accelerated deep learning via CUDA. This dramatically reduces model training time, particularly for Convolutional Neural Networks (CNNs) used in image classification.

Storage:

At least 256GB SSD (Solid State Drive) is required to ensure fast boot times, quick access to datasets, and rapid read/write operations during training and testing. An SSD greatly outperforms traditional HDDs and is essential for efficient development workflows.

4.2 SOFTWARE SETUP:

The software environment is centered around Python and deep learning frameworks, with a modular stack of libraries designed for machine learning, data preprocessing, visualization, and web deployment.

1. Operating System :

The project can be implemented on any major OS platform, including:

Windows 10/11

Linux distributions (Ubuntu recommended for deep learning workflows)

MacOS (with M1/M2 compatibility considerations for some libraries)

2. Python Version :

Python 3.12 is recommended for its improved performance and compatibility with modern libraries. Virtual environments (e.g., venv or conda) are advised to manage dependencies cleanly.

3. Deep Learning Framework: TensorFlow offers comprehensive support for CNNs, model training, GPU acceleration, and deployment pipelines. The tf.keras API provides a high-level interface for building and training models efficiently.

4. Essential Python Libraries

• numpy: For numerical computations, array manipulation, and matrix operations.

• pandas: To manage, clean, and analyze tabular datasets.

• OS: File path and directory management.

• tensorflow: Core framework for model design, training, and evaluation.

• sklearn.metrics: To compute evaluation metrics like accuracy, precision, recall, F1-score, and confusion matrices.

• matplotlib.pyplot: For generating plots of training history, metrics, and data distribution.

• seaborn: For enhanced and more aesthetic data visualization, including heatmaps and pair plots.

• collections.Counter: To check the distribution of image classes across the dataset.

imbalanced-learn: For techniques like SMOTE and Random Oversampling, used to balance class distribution in imbalanced datasets.

• PIL (Pillow): For image loading, conversion, manipulation, and saving (load_img, img_to_array, save_img).

5. Image Handling

• image_dataset_from_directory: A convenient utility to load images from a directory structure and automatically label them based on folder names. It supports batching, shuffling, and resizing, making it ideal for training CNN models.

6. Data Augmentation

• ImageDataGenerator: This tool generates batches of augmented image data in real-time, applying transformations such as rotation, flipping, zooming, and brightness changes. It helps prevent overfitting by increasing the effective size and variability of the training dataset.

7. Model Training Callbacks

• ReduceLROnPlateau: Automatically reduces the learning rate when a metric (typically validation loss) has stopped improving, allowing finer tuning of the model during later training epochs.

• EarlyStopping: Halts training when no improvement is observed after a defined number of epochs, preventing overfitting and reducing unnecessary computation.

8. Model Deployment

• Flask: For building a lightweight and interactive user interface (UI) to deploy the trained model. These frameworks allow the model to be served via a REST API or embedded within a web application.

CHAPTER 5

PROPOSED SYSTEM & IMPLEMENTATION

5.PROPOSED SYSTEM AND IMPLEMENTATION

5.1 BLOCK DIAGRAM OF PROPOSED SYSTEM :

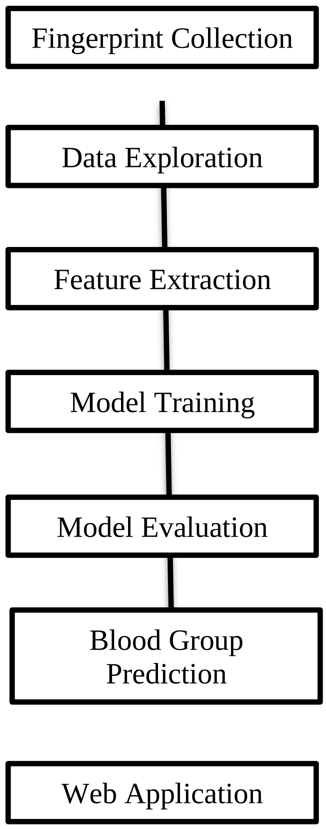

Fig.5.1 Block diag. of Proposed System

5.2 DESCRIPTION OF BLOCK DIAGRAM

1. Fingerprint Collection

This module involves the acquisition of fingerprint data, which serves as the primary input for the system. A pre-existing dataset containing high-quality fingerprint images along with corresponding blood group labels (e.g., A+, B-, AB+, etc.) is used. If the dataset is limited, data augmentation techniques like rotation, zoom, flipping, and noise addition can be applied to increase diversity and robustness.

2. Data Exploration

Before training, the dataset is analyzed to understand its structure and quality. This includes:

Checking for missing values: Ensures data completeness.

Class distribution analysis: Verifies if the blood groups are balanced; if not, balancing techniques such as oversampling or SMOTE may be applied.

Image visualization: Helps assess clarity and quality.

Preprocessing: Images are resized, normalized, and augmented if necessary to improve model performance.

3. Feature Extraction

A Convolutional Neural Network (CNN) is employed to automatically extract relevant features from the fingerprint images. The CNN layers capture intricate patterns such as ridges, minutiae points, and textures unique to each fingerprint, which may correlate with blood group information. This stage eliminates the need for manual feature engineering.

4. Model Training

The extracted features are fed into a CNN model, which is trained on the dataset. Key processes involved:

- Splitting the dataset into training, validation, and testing sets.
- Tuning hyperparameters such as learning rate, number of layers, activation functions, and batch size.
- Loss functions and optimizers (e.g., categorical cross-entropy and Adam) are used to guide the learning process.
- Regularization methods like dropout or early stopping are employed to prevent overfitting.

5. Model Evaluation

The trained model is evaluated on unseen data to measure its effectiveness. Evaluation metrics include:

- Accuracy: Proportion of correct predictions.
- Precision: Correctly predicted positive observations divided by total predicted positives.
- Recall: Correctly predicted positives out of all actual positives.
- F1-Score: Harmonic mean of precision and recall. Confusion matrices and ROC curves may also be used for deeper insight.

6. Blood Group Prediction

Once validated, the CNN model is used for real-time blood group prediction. Given a fingerprint image input, the model processes it and outputs the most probable blood group class. This module acts as the core decision-making engine of the application.

7. Web Application

A user-friendly web interface is developed using Flask or Django to make the system accessible. Key features:

- Upload functionality for fingerprint images.
- Display of prediction results with probability scores.
- Backend integration with the trained model for inference.
- Optional admin panel for dataset updates, logs, or user management. The app can be hosted on cloud platforms for broader accessibility.

5.3 Implementation

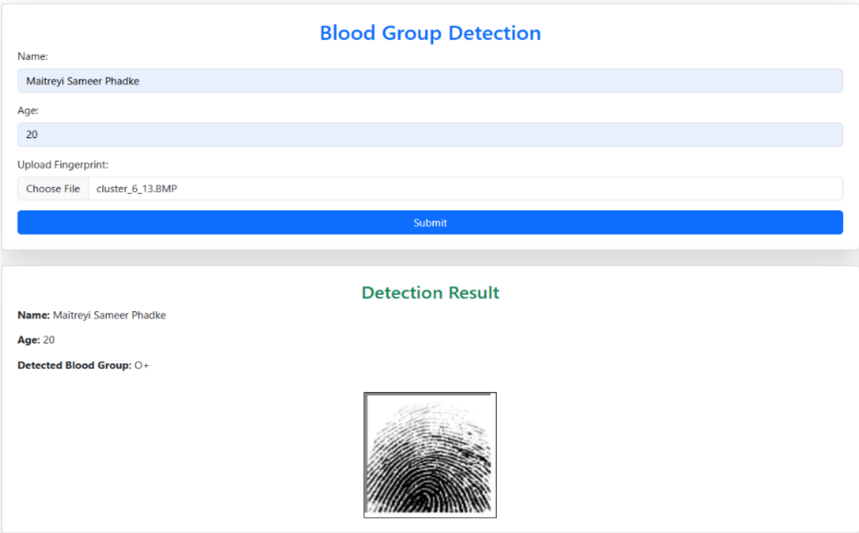

Fig.5.3.1. Fingerprint Blood Group Detection – Input & Result(O+)

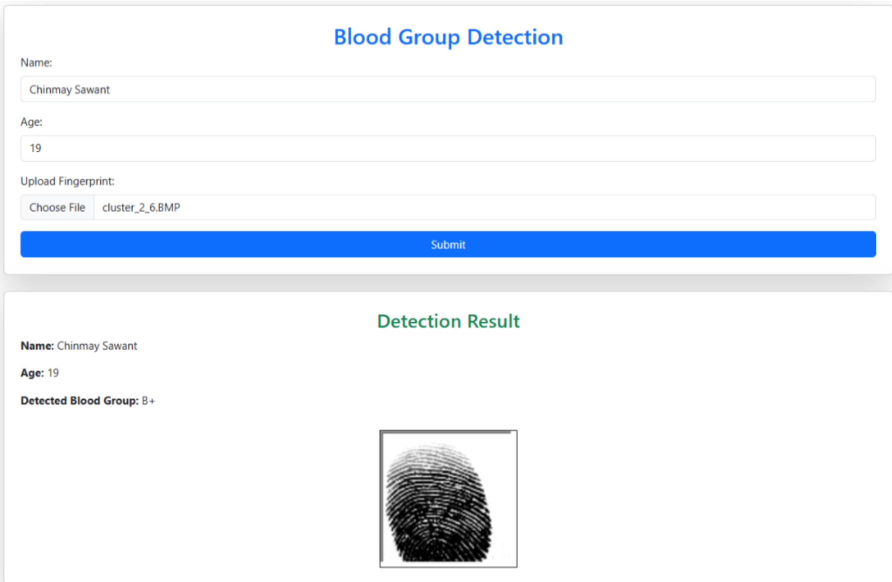

Fig.5.3.2. Fingerprint Blood Group Detection – Input & Result(B+)

Users enter their name, age, and fingerprint image, which is processed by a trained deep learning model. The system extracts fingerprint features, classifies the blood group, and displays the result along with the uploaded fingerprint. This method enables quick, non-invasive blood group identification using biometric patterns.

5.4 ADVANTAGES:

Non-invasive: This system does not require drawing blood, which eliminates the physical discomfort and psychological fear associated with needles. It also minimizes the chances of infections or cross-contamination, making it a safer alternative—especially useful in high-risk environments or during pandemics.

QuickProcessing: The system offers real-time or near real-time results, significantly reducing the time required for blood group identification compared to traditional methods. This is crucial in emergency scenarios where every second matters, such as trauma care or accident cases.

Cost-effective: By removing the need for costly lab equipment, chemical reagents, and trained medical staff, this AI-based approach can greatly reduce operational expenses. Once deployed, the running cost is minimal, making it ideal for large-scale deployment.

Portable: The model can be integrated into lightweight, mobile, or handheld devices, allowing on-the-go blood group detection. This portability makes the system ideal for remote, field, or disaster-stricken areas where medical infrastructure is lacking.

Automated & Reliable: Leveraging machine learning and deep learning techniques ensures high accuracy and consistency in predictions. The automation of the process reduces the scope for human errors, biases, or inconsistencies commonly seen in manual testing.

5.5 APPLICATIONS :

Medical Emergencies: In critical situations like road accidents or natural disasters, the system can instantly identify the victim's blood group using their fingerprint, enabling quicker access to compatible blood units and potentially saving lives.

Blood Donation Camps: Streamlines the process of screening donors by quickly identifying their blood groups. This improves the efficiency of organizing blood drives and helps in creating well-categorized donor databases for future use.

Hospitals & Clinics: The system can be integrated with Electronic Health Record (EHR) systems, allowing seamless updates to a patient's digital medical profile. This aids in faster diagnostics, improved patient management, and reduces redundant testing.

Forensics: Combines biometric identification with blood group prediction, providing a dual-layered approach for identity verification. This can be crucial in criminal investigations, disaster victim identification, or missing persons' cases.

Rural Healthcare: In underdeveloped areas where laboratory facilities may not exist or are difficult to access, this portable and low-cost system can assist community health workers in identifying blood groups and managing local health records efficiently.

CHAPTER 6

CONCLUSION

6.CONCLUSION

The development of a CNN-based fingerprint analysis system for blood group prediction represents a significant advancement in the field of biomedical diagnostics and biometric technology. Traditional serological methods, while effective, are often time-consuming, require specialized equipment, trained personnel, and are invasive in nature. In contrast, this AI-powered solution leverages the capabilities of deep learning, particularly Convolutional Neural Networks (CNNs), to offer a non-invasive, automated, and rapid method of determining an individual's blood group solely based on their fingerprint patterns.

Through rigorous data preprocessing, model training, and evaluation using metrics such as accuracy, precision, recall, and F1-score, the system has demonstrated reliable performance across diverse blood group classes. The automated feature extraction capabilities of CNN eliminate the need for manual intervention, thereby reducing human error and improving consistency.

Moreover, this solution shows high potential for deployment in real-world scenarios such as:

Emergency medical services, where timely access to blood group information can be life-saving, Rural and under-resourced areas, where laboratory testing may not be available, Blood donation drives, enabling efficient donor screening, And integrated hospital systems, contributing to digitized patient health records.

Additionally, its compatibility with portable devices and web-based platforms makes the system scalable, accessible, and cost-effective. As technology progresses, further refinements—such as expanding the dataset, improving model generalizability, and integrating with IoT-based diagnostic tools—can enhance the accuracy and robustness of the system even further.

In conclusion, this CNN-based fingerprint blood group prediction system not only addresses current limitations in conventional methods but also paves the way for next-generation, AI-driven healthcare solutions that are smarter, faster, and more inclusive.

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