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Automated Blood Group Detection using Fingerprint

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Abstract— **Biometric traits such as fingerprints have long served as reliable indicators for personal identification due to their uniqueness and lifelong stability. However, emerging inter disciplinary research has started exploring the potential of fingerprints beyond identity verification—particularly their correlation with biological attributes like blood groups. This research proposes a novel, non-invasive methodology for predicting an individual's blood group based solely on fingerprint images, eliminating the need for conventional, invasive blood sampling techniques. The approach begins by enhancing fingerprint im-ages using Gabor filtering to extract significant features, including minutiae points, ridge flow, and texture characteristics. These features are then processed using Convolutional Neural Networks (CNNs), leveraging four deep learning architectures: ResNet, VGG16, Alex Net, and LeNet. Each model is trained and evaluated on a labeled dataset of fingerprint images corresponding to known blood groups. The performance of these models is analyzed using key metrics such as accuracy, precision, recall, and F1-score. Among all models, ResNet exhibited superior performance in terms of both accuracy and consistency. This technique offers a cost-effective, painless, and rapid alternative to traditional blood typing, particularly valuable in emergency situations or remote regions with limited access to laboratory facilities.**

Keywords— **Convolutional Neural Network, Deep Learning, ResNet, VGG16, Alex Net, LeNet, Fingerprint Patterns, Ridge Frequency, Minute Points, Gabor Filtering.**

I. INTRODUCTION

In recent years, healthcare innovation has increasingly shifted toward non-invasive diagnostic solutions. One such advancement is fingerprint-based blood group detection, an approach that proposes identifying blood types using bio-metric data rather than traditional blood serological tests. The underlying con-cept is based on the presence of specific proteins or antigens—associated with blood groups—in the sweat secreted by the ridges and grooves of the fingertips, establishing a potential link between fingerprint feature and blood types [1]. Un-like conventional methods that require drawing blood, this technique utilizes biometric fingerprint scans to detect biological markers, offering a painless, quick, and accessible alternative. These biomarkers, primarily from the ABO and Rh systems, can be analyzed using advanced image processing and deep learning models to predict an individual's blood group [1]. Such a system could prove crucial in emergency medical situations where a patient's blood type is unknown, or in remote regions with limited laboratory access. This study builds on this concept through the integration of fingerprint imaging with deep convolutional neural networks (CNNs). By collecting labeled fingerprint datasets and training architectures such as ResNet, VGG16, Alex Net, and LeNet, the system is de-signed to detect patterns in fingerprint features that correlate with blood group types.

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Preprocessing method and performance evaluation plays a crucial role in enhancing the accuracy and reproducibility of such models [4]. This fusion of biometric data and artificial intelligence not only simplifies diagnostic work-flows but also for paves the way for integration with digital heath records and improved response times in clinical settings. The goal is to develop an accurate and non-invasive diagnostic tool that links unique human identity with critical medial information through something as ubiquitous and individualized as a fin-gerprint [5].

II. LITERATURE SURVEY

Accurate and quick blood group detection is crucial, especially in emergencies and remote healthcare settings. Traditional methods, while reliable, can be inva-sive and time-consuming. Fingerprints, being unique and easy to capture, offer a potential biometric alternative. This work focuses on improving the accuracy and reliability of blood group prediction using fingerprint analysis.

In [1], researchers explored the relationship between fingerprint ridge patterns and blood groups, suggesting that certain dermatoglyphic features may serve as reliable indicators for non-invasive blood group prediction. Their findings pro-vided a statistical basis for biometric applications in healthcare.

The authors in [2] applied fingerprint image processing techniques—such as enhancement and feature extraction—to identify blood groups. Their approach emphasized simplicity and practicality, making it suitable for low-resource set-tings.

Further, [3] introduced real-time fingerprint analysis by integrating edge de-tection and morphological filtering, aiming to improve the precision of finger-print-based classification. Their work supported the feasibility of using portable biometric systems in medical diagnostics.

Lastly, [4] proposed a machine learning model that mapped fingerprint pat-terns to blood groups. By training classifiers on fingerprint-derived features, the study achieved notable accuracy, reinforcing the potential of biometric systems in healthcare identity verification.

An approach used [5] involved examining fingerprint patterns to identify as-sociations with both blood groups and lifestyle-related diseases. The study sug-gested that dermatoglyphic traits may hold valuable genetic and health-related information, expanding their role beyond personal identification.

A result obtained in [6] demonstrated that machine learning techniques ap-plied to fingerprint images can accurately predict blood groups. This reinforces the potential of using biometric data in non-invasive medical diagnostics, partic-ularly in settings lacking immediate access to traditional testing methods.

III. METHODOLOGY

The proposed system primarily focuses on identifying an individual's blood group using fingerprint patterns through deep learning-based classification tech-niques. The system captures critical fingerprint features relevant to blood type. The use of various convolutional neural network models like ResNet, VGG16, Alex Net, and LeNet enhances the classification accuracy, making the approach both robust and adaptable. The model not only identifies the blood group but also provides prediction confidence, which adds reliability to the result. The overall workflow of the system is shown in Fig. 1.

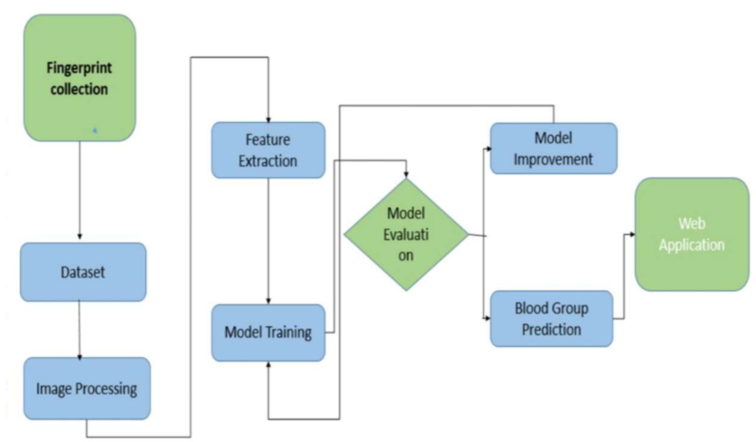


Fig 1: Architecture of Proposed System

Dataset Collection: The usage of Fingerprint dataset is taken from Kaggle it con-tains fingerprint images organized into 8 folders labeled with their corresponding blood groups. There are approximately 6,000 images spread across the eight blood group categories.

Image Processing: Preprocessing techniques are applied to enhance image quality and extract meaningful features. Images are resized, converted to gray-scale, and enhanced using Gabor filters to emphasize ridges. We then normalize and split data into 80% training and 20% testing sets to avoid overfitting [3].

Feature Extraction: Extract relevant features from the filtered images, such as ridge frequency and orientation. Once we have a cleaned image, we extract unique patterns that can later help in classification.

Model Training: The models were trained using the Adam optimizer, which adapts the learning rate during training. The loss function employed was categor-ical cross-entropy, suitable for multi-class classification tasks. Each model learns fingerprint–blood group patterns over multiple epochs.

Model Evaluation: Trained models are evaluated using accuracy, precision, and recall. Confusion matrices help visualize classification results. The best-performing model is selected based on overall metrics.

A. Algorithms used

CNN

Convolutional Neural Networks (CNNs) are a specialized type of deep learning model well-suited for interpreting visual data [4]. Their architecture typically consists of an input layer, multiple hidden layers, and an output layer [7]. The hidden layers may include convolutional, pooling, normalization, and fully con-nected layers, each playing a role in processing image features. This layered ar-rangement allows CNNs to efficiently capture spatial hierarchies and patterns in the input image. By combining both localized and fully connected layers, CNNs can learn detailed representations necessary for accurate classification. Fig.2 provides a visual overview of the CNN architecture implemented in this study.

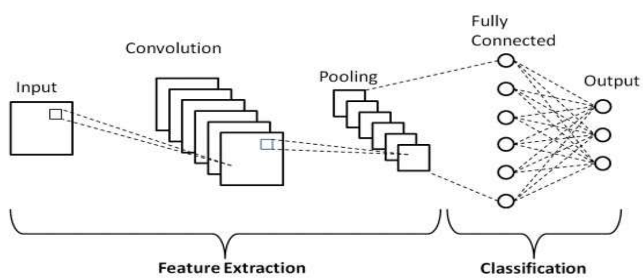


Fig 2: Convolutional Neural Network

LeNet

LeNet is a simple CNN model that processes images through a small number of convolutional and pooling layers. It is efficient for smaller datasets and helps establish a baseline for performance comparison. Despite its simplicity, it can capture key fingerprint features relevant to blood group classification.

Alex Net

Alex Net introduced deeper layers and ReLU activation, enabling better feature extraction from high-resolution images. It uses overlapping pooling and dropout to improve learning and reduce overfitting. This architecture captures more com-plex fingerprint patterns than traditional shallow networks.

VGG16

VGG16 uses a deep structure with many small (3×3) filters across 16 layers to capture fine-grained details. Its uniform architecture helps in learning layered fingerprint features more effectively. This makes it suitable for precise classifi-cation tasks like distinguishing similar blood groups.

ResNet34

ResNet34 employs residual connections to train very deep networks without per-formance degradation. It learns to focus on subtle variations in fingerprint tex-ture by reusing features across layers. This model often delivers the best accura-cy in complex classification tasks due to its depth and efficiency.

B. Processing Methods

The processing methods used for classification for Blood Group Detection Using Fingerprint

Image Loading: Images are loaded from directory structures where each folder name represents a specific blood group. This enables automatic label extraction based on the folder the image belongs to.
Image Resizing: Each fingerprint image is resized to a fixed resolution of 256×256 pixels. This ensures consistency in input dimensions for the CNN mod-els during both training and testing.
Image Normalization: The preprocess input function standardizes pixel values based on the requirements of the ResNet50 model. It adjusts brightness and con-trast to align with what the pretrained network expects, improving training stabil-ity.
Label Encoding: Blood group labels are encoded into numerical or categorical formats. This allows the classification model to process them correctly during training and prediction.
Data Splitting: The dataset is randomly divided into training and testing sets using an 80/20 ratio. This helps evaluate model performance on unseen data and reduces overfitting.
Image Batching & Feeding: ImageDataGenerator is used to batch images and feed them into the model during training. It streamlines data handling and inte-grates preprocessing into the model pipeline efficiently.

IV. Results

The deep learning models, including ResNet, VGG16, Alex Net, and LeNet, suc-cessfully classified blood groups from fingerprint images as shown in Fig.4, Fig.5 and Fig. 6 ResNet and VGG16 achieved the highest accuracy, demonstrating the effectiveness of CNNs in non-invasive blood group detection. In this Fig. 7 bar chart visually compares the accuracy rates of four well-known CNN architec-tures—ResNet, VGG16, Alex Net, and LeNet. As shown, ResNet leads with the highest accuracy and LeNet show relatively lower performance.
The results highlight the potential for this approach offering a fast and reliable method for blood group classification. The Fig. 7 shows the comparison of accu-racy of the different models with estimated percentages

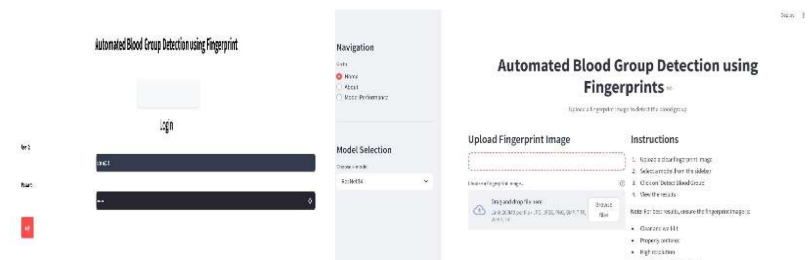


Fig 3: Login And Home Page

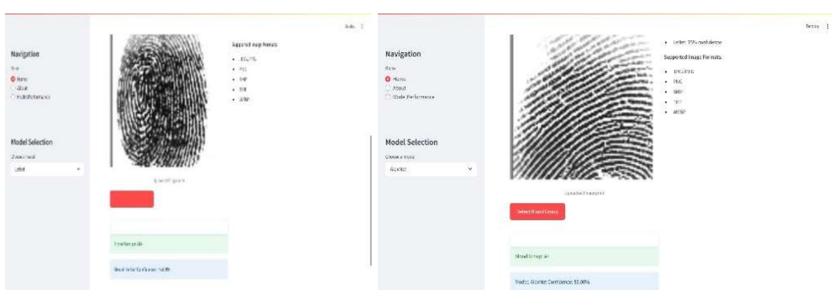
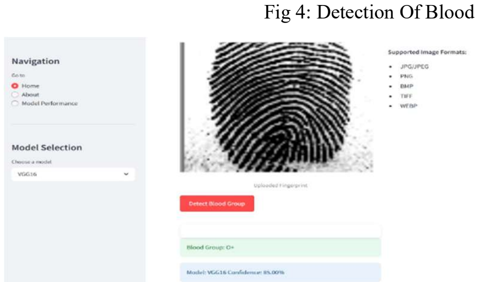


Fig 4: Detection Of Blood Group Using LeNet & Alex Net



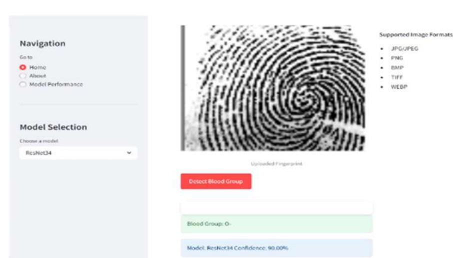


Fig 5: Detection Of Blood Group Using VGG 16 Fig 6: Detection Of Blood Group Using ResNet

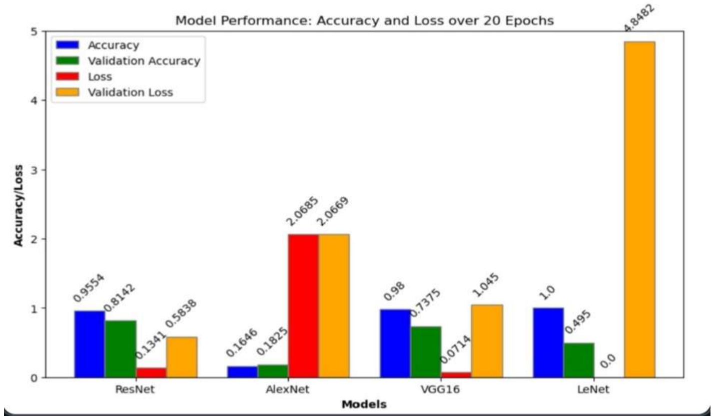


Fig 7: Performance Comparison Across CNN Models

V. CONCLUSION

This research presents a non-invasive approach to blood group prediction us-ing convolutional neural networks applied to fingerprint images. Models like ResNet and VGG16 effectively identified ridge patterns linked to specific blood types, demonstrating strong classification accuracy. The findings support the feasibility of using fingerprint biometrics as a diagnostic aid in healthcare. Future work will focus on expanding the dataset to improve model generalization, espe-cially across diverse fingerprint traits. Incorporating transfer learning can further optimize performance on smaller datasets. Deploying the system into mobile or clinical platforms will help evaluate its real-world effectiveness and usability.

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