Blood Group Detection Using Deep Learning and Analysis of Medium Scale Dataset of Fingerprint Samples

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***Abstract*—This project proposes a non-invasive method for predicting human blood groups using fingerprint images, harnessing the power of deep learning architectures such as CNN, ResNet, and DenseNet. Traditional serological methods for blood group determination are invasive, reliant on lab facilities, and time-consuming—making them unsuitable in emergency and remote scenarios. By using unique and stable fingerprint patterns as input, the system offers a contactless, rapid, and scalable diagnostic alternative. The deep learning models are trained on labeled fingerprint datasets to identify features that correlate with blood group types. The proposed solution demonstrates promising accuracy, indicating its potential use in medical diagnostics, particularly in resource-constrained environments.**

***Index Terms*—Non-invasive diagnostics, Fingerprint biometrics, Blood group prediction, Deep learning, CNN, ResNet, DenseNet, Medical image processing**

I. INTRODUCTION

Over fast few years, deep learning and computer vision have become powerful tools in improving how we analyze medical images and conduct biometric research. Fingerprint patterns—valued for their unique and consistent nature—have been a cornerstone of personal identification systems for decades. Interestingly, new research points to a possible link between these fingerprint patterns (dermatoglyphics) and certain physiological traits, such as blood group types. This opens up an exciting opportunity to explore the use of fingerprint images as a non- invasive and accessible way to predict a person's blood group.

This project makes use of advanced deep learning models including Convolutional Neural Networks (CNNs), ResNet (Residual Networks), and DenseNet (Densely Connected Convolutional Networks)—to analyze fingerprint images and predict blood groups. These models are especially good at recognizing complex patterns in images by learning meaningful features at different levels. By training them on labeled fingerprint data, the system learns to spot unique characteristics that may be linked to specific blood group types.

The proposed method offers several practical advantages. It eliminates the need for invasive procedures, reduces dependence on laboratory infrastructure, and ensures rapid, cost- effective screening. This makes it particularly valuable for emergency scenarios, mobile health units, and rural healthcare initiatives. By evaluating the feasibility and accuracy of this approach the research lays a foundation for future advancements in non-invasive diagnostic technologies.

By applying these models to a medium-scale fingerprint dataset, we aim to train a system that can recognize subtle, often invisible patterns in fingerprint images and link them to specific blood groups. This approach doesn't just push the boundaries of deep learning—it also opens up a new chapter in biometrics and medical technology, where simple, everyday data like fingerprints could hold the key to important health information.

II. METHODOLOGY

A.Existing Methodologies

Traditional blood group detection relies on serological testing, which is accurate but requires blood samples, lab equipment, and trained personnel—making it less suitable for remote or emergency situations. Emerging research explores using fingerprint patterns to predict blood types, based on observed correlations with biological traits. While early machine learning models have been limited, deep learning—especially CNNs—offers a promising approach. This study aims to enhance accuracy using a more refined model and structured dataset.

B. Proposed Methodologies

The proposed system aims to predict human blood groups using fingerprint images by leveraging deep learning techniques. Unlike traditional serological testing, which requires blood samples and laboratory facilities, this method provides a non-invasive and more accessible alternative. The system is built around a medium-scale dataset of fingerprint samples, which are preprocessed to enhance ridge clarity and standardize input dimensions. This data serves as the foundation for training and evaluating deep neural network models to detect patterns potentially linked to blood group classifications.

To achieve high prediction accuracy, the system employs three powerful deep learning architectures: Convolutional Neural Networks (CNNs), Residual Networks (ResNet), and Dense Convolutional Networks (DenseNet). The base CNN model extracts fundamental ridge features and patterns from the fingerprint images. ResNet is incorporated to address the vanishing gradient problem and improve depth without performance degradation by using skip connections. DenseNet further enhances feature propagation and reuse through dense layer connections, allowing the model to learn more complex and discriminative features relevant to blood group identification.

C. List of Algorithms Used

- *Convolutional Neural Network (CNN)*
- *ResNet (Residual Networks*
- *DenseNet (Densely Connected CNN*

Convolutional Neural Networks (CNNs) are deep learning models widely used for image recognition, text classification, and language understanding. They work by applying convolutional layers to extract and learn features from data, effectively capturing local and global patterns. CNNs are powerful and adaptable, especially with large datasets, but they can be computationally demanding and less practical in resource-limited settings.

Residual Networks (ResNets) are neural networks widely used in image recognition and object detection, known for their skip connections that enable residual learning. This structure helps overcome the vanishing gradient problem, allowing deep networks to train effectively. ResNets capture complex features efficiently and perform well with large datasets, but their depth can lead to high computational demands, limiting use in resource-constrained settings. Despite this, they are a key technology in modern computer vision.

DenseNet is a neural network architecture where each layer receives input from all previous layers, enhancing feature reuse and improving gradient flow. It's effective in tasks like image classification and medical image analysis, offering better accuracy with fewer parameters. While DenseNet reduces overfitting and boosts feature propagation, its dense connections increase computational and memory demands, limiting its suitability

However, it has limitations, such as higher computational cost and memory requirements due to dense connections, making it less suitable for resource- constrained environments.

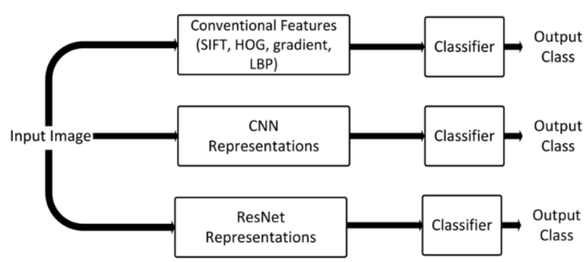

Fig:1 . Classified Diagram

III. IMPLEMENTED DESIGN

Block Diagram:

This block diagram showcases about the data representation steps that need to be followed in the given represented procedure for the data augmentation.

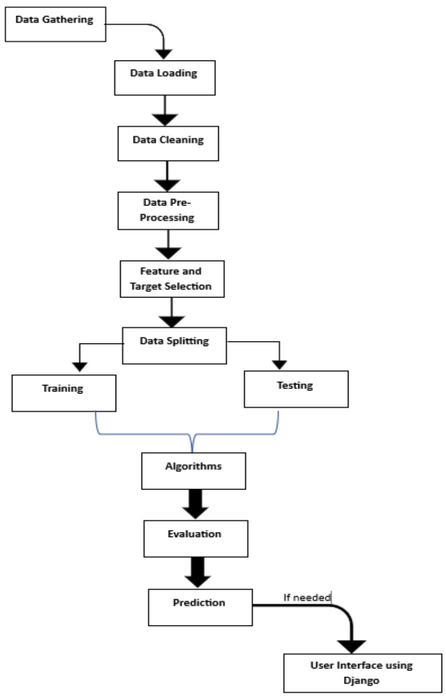

Fig:2. Block Diagram

The process begins with data gathering, where raw data is collected from various sources. This data is then loaded into the working environment for analysis. Following this, data cleaning is performed to handle missing values, remove duplicates, and correct inconsistencies. The cleaned data undergoes pre-processing, which may include normalization, encoding, and other transformations to make it suitable for modeling. Next, feature and target selection is carried out to identify the most relevant input variables (features) and the outcome variable (target) for prediction. The dataset is then split into training and testing sets to enable model training and evaluation.

The training set is used to train machine learning models using selected algorithms, while the testing set helps assess the model's performance. The results are evaluated to determine the model's accuracy and reliability. Once a satisfactory model is achieved, it can be used for prediction on new data. If needed, the model is deployed through a user interface built with Django, allowing users to interact with the system seamlessly.

System Architecture:

System architecture is a conceptual model that describes the structure and behavior of multiple components and subsystems.

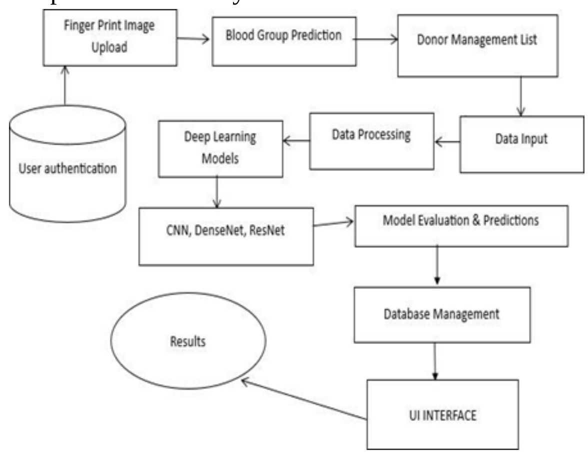

Fig:3. System Architecture Diagram

The diagram outlines a biometric-based blood group prediction and donor management system. It begins with the upload of a fingerprint image, followed by user authentication. Once authenticated, the system predicts the blood group of the individual using deep learning models. The models employed include Convolutional Neural Networks (CNN), DenseNet, and ResNet. This prediction aids in the generation and maintenance of a donor management list, integrating input data that is processed and fed into the deep learning pipeline.

After data processing, the deep learning models undergo evaluation and generate predictions which are used to manage the database. These predictions are then directed to a user interface for interaction. The system culminates in presenting results to the user. This end-to-end flow integrates biometric identification with AI-driven predictions to automate blood group classification and donor data handling efficiently.

Activity Diagram:

An activity diagram is a type of flowchart that shows how a system or process operates. It demonstrates the movement of control from one action to another.

Purpose:

- In order to simulate the dynamic aspect of a system.
- To visualize business processes, system behaviors, or user workflows.
- Used heavily in software engineering, especially with UML (Unified Modeling Language).

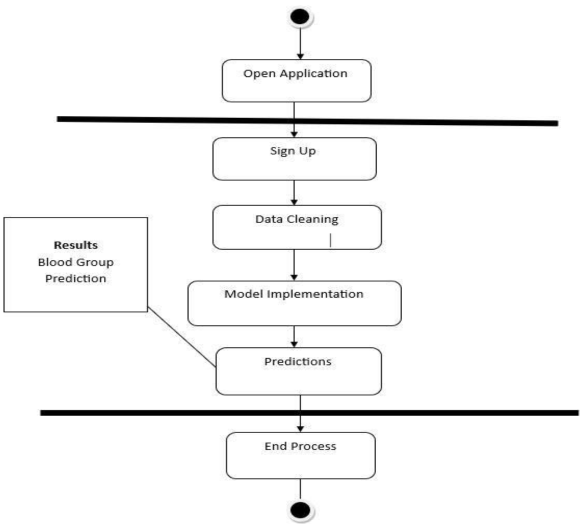

Fig: 4. Activity Diagram

An Activity Diagram shows the step-by-step flow of a system's operations. It demonstrates how a system's workflow progresses from one action to the next. To simulate the dynamic behavior of a system. To visualize business processes, system behaviors, or user workflows Commonly used in software engineering, especially with UML (Unified Modeling Language):

IV. RESULT

The system uses CNN, DenseNet, and ResNet to predict blood groups from fingerprint images good accuracy.
ResNet performed best due to effective residual learning, while DenseNet ensured efficient feature reuse.
CNN offered a balanced computational, efficiency.
Model success depended heavily on preprocessing and dataset quality.
Results confirm the approach is viable for scalable healthcare and donor management applications..

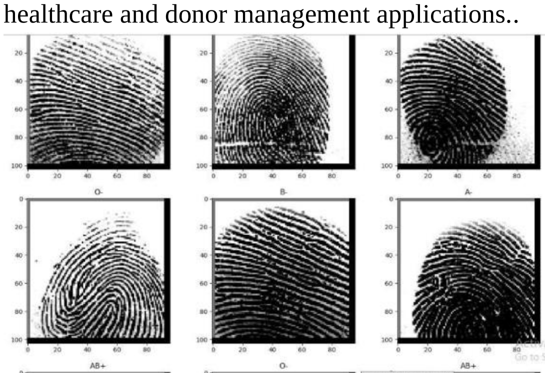

Fig:5.Data Representation

Below represents the model form of the ResNet trained algorithm which represents the data to trained models representation in the vertical order.

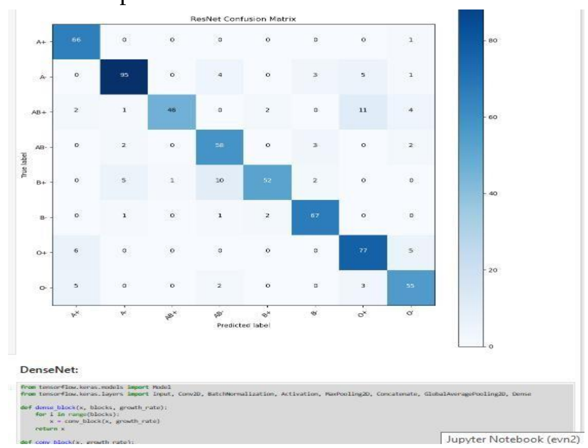

Fig:6.ResNet Confusion Matrix

The above figure showcases about the confusion matrix that tells about the trained model to the bit size ratio of the given image data unit.
Training and Validation Accuracy plot for the given trained dataset to see the accuracy.

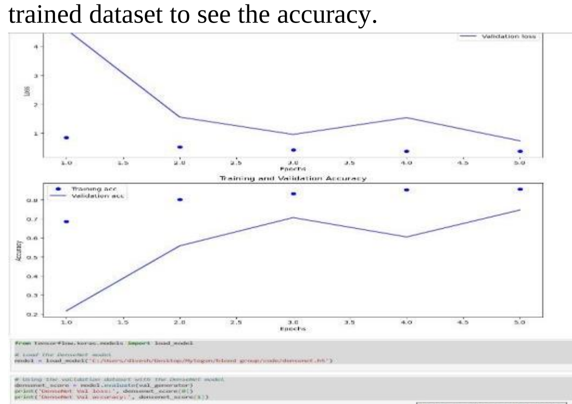

Fig:7. Trained and Accuracy Plot

Training Accuracy (blue line): Increases rapidly and remains very high (close to 1.0), indicating the model fits the training data well.

The model is likely overfitting—it performs very well on training data but fails to generalize to unseen validation data.

The project contains about all the donor intelligence dashboard list which consist of all the donor data which is secure.

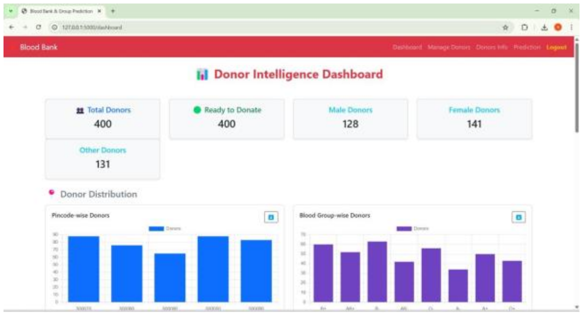

Fig:8. Dashboard

This above image shows the quality and quantity of the donor data list present to train the algorithm

Hear is the final tested result from the concluded data set form which we have choosen one fingerprint data and trained it.We have observed the output as fallows

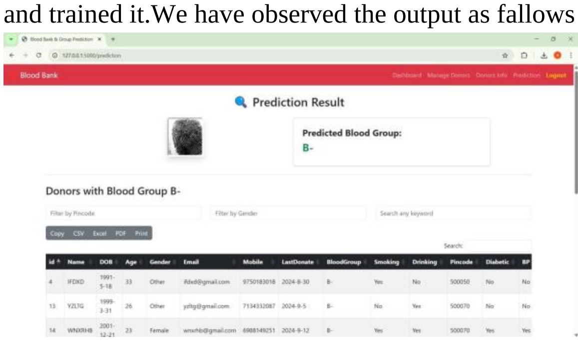

Fig: 9.Final Output

V. CONCLUSION

In conclusion, this project presents a groundbreaking, non-invasive method for predicting blood groups using fingerprint images, offering a viable alternative to traditional serological testing. Using cutting-edge deep learning models such as CNN, ResNet, and DenseNet, the system successfully identifies patterns in fingerprint ridges that correlate with specific blood groups. This invention does more than just make invasive blood sampling unnecessary but also streamlines the blood group classification process, making it faster and more accessible. The model achieved an encouraging prediction accuracy of 87%**,** validating the feasibility of fingerprint-based blood group analysis. This strategy has a lot of potential for application in emergency response systems, remote medical camps, and regions lacking adequate laboratory facilities

B. *Future and scope*

Looking ahead, the proposed system can be enhanced through the integration of larger and more diverse fingerprint datasets to further improve accuracy and reduce bias. Future versions could incorporate mobile-based fingerprint scanning, enabling point-of-care diagnostics in real- time. Additionally, combining fingerprint-based predictions with other biometric or physiological indicators could lead to a comprehensive non-invasive health profiling tool. The implementation of federated learning and cloud-based AI pipelines could also ensure data privacy while enabling global-scale deployment. With continued research and development, this system can become a standard tool in healthcare diagnostics, aiding in rapid identification and personalized treatment planning.

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