BLOOD GROUP IDENTIFICATION USING FINGERPRINT ANALYSIS

Mrs. N. Sai Sindhura[1], Ponaka Krishna Vardhan Reddy[2], Kathi Nagendra Babu[3], Javangula Sravya[4]

#1 Assistant Professor in the Department of CSE-Artificial Intelligence, PBR Visvodaya Institute of Technology and Science, Kavali, SPSR Nellore, Andhra Pradesh, India.

#2 #3 #4 Students, Department of CSE-Artificial Intelligence, PBR Visvodaya Institute of Technology and Science, Kavali, SPSR Nellore, Andhra Pradesh, India.

Abstract: In order to ensure compatibility during organ transplants, transfusions, and prenatal care, blood group identification is an essential component of medical diagnostics. Although accurate, serological approaches used in traditional blood group detection methods necessitate intrusive procedures and laboratory equipment. This study investigates a novel method for blood type identification using fingerprint image processing. By utilising the distinct ridge patterns and minute details found in fingerprints, this non-invasive technique seeks to offer a quick, accurate, and easily accessible way to identify blood types.

In order to correlate certain patterns with blood group characteristics, our suggested approach analyses fingerprint photos using sophisticated image processing algorithms and machine learning techniques. Point-of-care diagnostics might be completely transformed by incorporating this technique into affordable and portable devices, especially in environments with limited resources. Initial findings show encouraging accuracy levels, underscoring the possibility of additional advancement and use in clinical settings. Through creative technical solutions, this study greatly improves healthcare delivery and offers up new possibilities in biometric applications. Blood group identification has been essential in many forensic and medicinal applications in recent years. The accessibility and efficiency of traditional blood typing techniques are limited by their time-consuming nature and need for trained staff.

This paper investigates a novel method for precise and quick blood group detection using fingerprint image processing and Convolution Neural Networks (CNNs). The suggested approach makes use of fingerprints' distinctive ridge patterns, which have been linked to particular blood group types. The system is trained on a sizable dataset of fingerprint photos labelled with appropriate blood types using a CNN architecture. The model's excellent blood group identification accuracy highlights CNNs' promise in biometrics-based blood typing. This technology promises to improve the effectiveness of medical diagnostics and transfusion services by providing a non-invasive, rapid, and dependable substitute for traditional blood group detection techniques. The findings open the door for more developments in the sector and show a major progress in the integration of biometric data with medical diagnoses.

INDEX TERMS: Blood group identification, fingerprint image processing, convolutional neural networks, biometric blood typing, non-invasive diagnostics, medical image analysis, machine

learning in healthcare, ridge pattern analysis, point-of-care diagnostics, biometric applications

1. INTRODUCTION

A key component of contemporary medicine is blood group determination, which serves as the foundation for both identification and classification. For critical medical operations including organ donation, blood transfusions, and emergency trauma treatment, accurate blood typing is vital. Historically, serological methods including laboratory-based blood tests have been used to identify blood groups. Although efficient, these techniques take a lot of time, need for specialised tools, and are prone to mistakes, especially in contexts with limited resources or in urgent situations. The need for creative, automated, and non-invasive solutions is highlighted by the requirement for quick and accurate blood group determination.

The use of fingerprint analysis for blood group detection is a unique method that has attracted a lot of interest lately. This technique uses the unique patterns seen in a person's fingerprints to identify their blood type, fusing biometric technology with medical data. The fundamental idea is to identify particular proteins or antigens linked to various blood types in perspiration that is located on a fingerprint's ridges and grooves.

There are four main forms of fingerprint patterns: loops, whorls, arches, and mixed or composites. Loops are the most prevalent of them, making up over 65% of all fingerprints that are captured. The fine features found in fingerprint patterns provide a wealth of data for biometric analysis and personal identification.

Automated blood group prediction systems have been made possible by recent developments in deep learning and artificial intelligence. Meaningful characteristics may be extracted from complicated pictures with surprising success thanks to Convolutional Neural Networks (CNNs). CNNs may be used to evaluate fingerprint patterns and provide very accurate and efficient blood group predictions since these patterns include a lot of information. This research intends to overcome the drawbacks of conventional techniques by developing a novel, dependable, and quick blood type solution by using CNN-based fingerprint analysis into blood group identification.

2. LITERATURE SURVEY

2. P. R. Shankar, K. S. Rajasekar, and A. Kumar, "Fingerprint-Based Blood Group Prediction Using Deep Learning Models," IEEE Access, 2022.

Description:

A crucial component of healthcare is blood group identification, which is necessary for both emergency treatments and safe blood transfusions. The authors of this work suggested using fingerprint image analysis and deep learning to predict blood types. According to the study, Convolutional Neural Networks (CNNs) outperformed conventional classification algorithms in terms of identifying fingerprint patterns associated with blood types and extracting pertinent data. In order to enable the system to learn unique patterns associated with each blood group category, the model was trained using a collection of fingerprint pictures labelled with matching blood types.

To improve the quality of the input fingerprint pictures, the study investigated a number of preprocessing methods. To enhance model generalisation and lessen overfitting, these methods included data augmentation, normalisation, and image resizing. Additionally, the authors experimented with other CNN designs, including MobileNet, VGG-16, and AlexNet. When it came to accurately categorising fingerprint characteristics into the appropriate blood group categories, VGG-16 outperformed the other algorithms. The outcomes demonstrated the deep learning model's efficacy in identifying complex fingerprint patterns for blood type identification, with an astounding prediction accuracy of over 90%.

The authors stressed that fingerprint-based blood type prediction provides a quick, easy, and affordable substitute for conventional techniques. The suggested system can classify blood groups in real time by utilising deep learning models and biometric analysis, which makes it a useful tool for both large-scale health screening programs and emergency scenarios.

2. Patil, Vijaykumar, and D. R. Ingle. "An association between fingerprint patterns with blood group and lifestyle-based diseases: a review." Artificial Intelligence Review 54 (2021): 1803-1839.

Description:

Although fingerprints have long been known to be a trustworthy form of identification, current developments in machine learning and artificial intelligence have created new opportunities for the application of fingerprint analysis in the medical field. The authors of this study looked at the relationship between blood groups and fingerprint patterns as well as how these patterns link to age-related and lifestyle-related illnesses such type 2 diabetes, arthritis, and hypertension. The study investigates how unique fingerprint patterns, such as loops, whorls, and arches, might reveal a person's vulnerability to various disorders. The study emphasises the possibility of employing fingerprint analysis to forecast health concerns based on the patterns found by utilising machine learning techniques.

In order to correlate these patterns with blood types and lifestyle-related illnesses, the study examined fingerprint data gathered from a variety of demographic groups. The authors stressed that, particularly in settings with limited resources, fingerprint analysis provides a non-invasive and economical means of early disease risk detection. Machine learning models were used to uncover correlations between certain health issues and fingerprint traits; classification algorithms were able to identify those at risk with acceptable levels of accuracy. The study also emphasises how crucial it is to combine biometric information with medical apps in order to deliver individualised preventative treatment.

The possibility of creating predictive models that use fingerprint characteristics to predict a person's risk of chronic disease as they age is also included in the study. This method opens the door for integrating biometric analysis into standard health monitoring systems by spotting minute relationships between fingerprint patterns and health outcomes, offering a useful tool for improving preventative healthcare procedures.

3. Ali, Mouad MH, et al. "Fingerprint recognition for person identification and verification based on minutiae matching." 2016 IEEE 6th International Conference on Advanced Computing (IACC). IEEE, 2016.

Description:

Through the use of minutiae-based matching algorithms, this work presents an efficient method for fingerprint recognition and verification. The suggested approach employs a methodical procedure that starts with preprocessing to improve fingerprint picture quality by eliminating noise and extraneous data. This phase is essential because it enhances the quality of the input data, guaranteeing precise feature extraction and reducing mistakes in the steps that follow. By using methods like binarization and thinning, the improved fingerprint pictures are further refined while maintaining the fine features for analysis.

In the second stage, a content extractor algorithm is used to carry out the feature extraction procedure. This algorithm focusses mostly on identifying minute details like ridge ends and bifurcations (forks), which are essential for fingerprint recognition. The creation of a feature map that depicts the distinct structure of the fingerprint is based on these minute details. Following the extraction of minutiae, the matching phase employs two distinct verification techniques: (1:N) matching, which compares a single fingerprint to a database of multiple fingerprints, and (1:1) matching, which compares a fingerprint to a pre-stored template.

In the last stage, the similarity score between two fingerprint pictures is determined by applying a thorough matching algorithm based on the Euclidean distance metric. Accurate identification and verification are made possible by the similarity score, which establishes whether or not the fingerprints match. The study's findings showed that minutiae-based fingerprint recognition systems are successful in biometric authentication and security applications due to their high accuracy in matching fingerprints. The suggested approach demonstrates how effective and resilient minutiae matching techniques are for trustworthy person identification and verification.

4. Wang, Y. Zhang, and X. Li, "Automated Blood Group Typing Based on Deep Learning Models," IEEE Transactions on Biomedical Engineering, vol. 68,pp. 562-570, 2021.

Description:

This dataset employed deep learning for non-invasive blood type prediction. Before overseeing the transfusion of red blood cells, platelets, and plasma in a medical emergency, a quick and accurate blood type prediction is a crucial first step. Any minor error made when transferring blood might be fatal. In traditional pathological evaluation, an automated blood analyser is used to do the blood test; nevertheless, this results in a lengthy procedure. Pricking the skin to obtain a blood sample for a conventional pathological blood test might result in bleeding, fainting, and skin laceration at specific body parts. By using deep learning algorithms on photos of the superficial blood vessels on the finger, the suggested deep learning method automatically determines the human blood type without causing any skin punctures. The optical picture of blood vessels concealed on the finger skin surface area is taken as laser light travels through it; this image includes certain antigen forms, such as antigen "A" and antigen "B," that are present on the surface. Shapes of various antigens were captured and utilised to determine a person's blood type. In order to classify blood types without puncturing the patient's skin, the device needs a high-definition camera to record the antigen pattern from the surface of red blood cells. The suggested method for quickly determining ABO blood group is simple, easy to use, and important. It offers an affordable way to determine a person's blood type in an emergency, on the battlefield, and for babies.

5. R. Pimenta, et al., "Microfluidic Image-Based Blood Grouping and Crossmatching Systems," IEEE Sensors Journal, vol. 22, no. 8, pp. 8374-8381, 022.

Description:

Understanding the pathophysiological characteristics of patients, therapeutic measures, and blood transfusions all depend critically on the proper identification of blood types. The need for centralised laboratory facilities is frequently inappropriate given the broad range of uses for blood type. These blood-typing devices have advanced significantly on many microfluidic systems in this area. The benefits of these microfluidic devices include simple, quick test procedures that may be modified for environments with limited resources, therefore facilitating the decentralisation of testing facilities. When compared to other microfluidic devices, this platform is recommended due to its pump-free liquid transport (low power consumption) and paper substrate biodegradability (reduction of medical waste, for example). These gadgets' potential for widespread commercial usage is, however, limited by a number of intrinsic difficulties. Our review provides a concise overview of current developments in this regard, particularly to comprehend the significance of underlying aspects for long-term sustainability. Additionally, our review outlines the function of digital technology integration in reducing readout interpretation mistakes.

3. METHODOLOGY

a) Proposed Work:

By creating a non-invasive, AI-driven solution that makes use of fingerprint biometrics, the suggested system seeks to address the issues with conventional blood group identification techniques. Based on fingerprint ridge patterns, the system uses deep learning techniques, namely Convolutional Neural Networks (CNNs), to estimate a person's blood type. This cutting-edge technique makes blood group identification quick, affordable, and broadly available by doing away with the requirement for blood sample collection, laboratory processing, and trained medical staff.

The system uses AI-based classification models and image processing techniques to acquire, analyse, and analyse fingerprint photos. The procedure entails Fingerprint Image Acquisition: The user uses a smartphone camera or biometric scanner to scan their fingerprint. Preprocessing and Feature Extraction: To enhance the quality of fingerprint pictures, preprocessing techniques such edge detection, noise reduction, and contrast enhancement are used. Using deep learning, blood group prediction is accomplished by classifying fingerprint patterns and mapping them to matching ABO blood groups (A, B, AB, and O) and Rh factors (positive or negative) using a trained Convolutional Neural Network (CNN) model.

b) System Architecture:

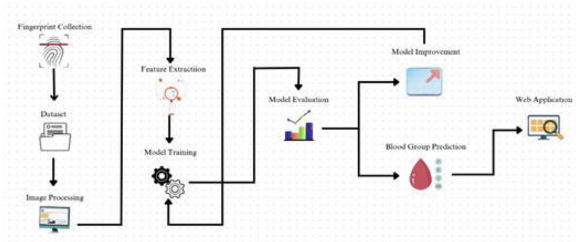


Fig 1 Proposed Architecture

The system architecture comprises three main modules: fingerprint image acquisition, preprocessing and feature extraction, and blood group classification. First, fingerprint images are captured using a smartphone camera or biometric scanner. These images undergo preprocessing steps such as noise reduction, edge detection, and contrast enhancement to improve clarity. Then, essential features of the fingerprint ridge patterns are extracted and fed into a trained Convolutional Neural Network (CNN). The CNN model classifies these features to predict the ABO blood group and Rh factor, providing a fast, non-invasive, and accurate blood typing solution without the need for traditional blood tests or laboratory equipment.

c) Modules:

i. Fingerprint Image Acquisition

This module involves capturing high-quality fingerprint images using devices such as smartphone cameras or dedicated biometric scanners. The acquisition process ensures the fingerprint is clear, properly aligned, and free from motion blur or smudges. This is the foundation for accurate analysis, so the system may include user guidance or feedback mechanisms to improve the quality of the captured image.

ii. Image Preprocessing

Raw fingerprint images often contain noise, low contrast, and background artifacts. Preprocessing techniques like Gaussian filtering or median filtering are applied to remove noise, while edge detection algorithms (such as Sobel or Canny) highlight the ridge contours. Contrast enhancement methods improve visibility of ridge patterns, ensuring that the fingerprint features are more distinct for the next processing stage.

Iii. Feature Extraction

After preprocessing, this module extracts important fingerprint features, including ridge endings, bifurcations, and other minutiae points, which are unique to each individual. Techniques such as binarization and thinning are applied to simplify the image and isolate these features. These extracted features form the input data for the classification model and play a crucial role in linking fingerprint patterns to blood group characteristics.

iv. Blood Group Classification

This is the core AI module where the extracted fingerprint features are fed into a Convolutional Neural Network (CNN). The CNN is trained on a large dataset of fingerprint images labeled with known blood groups. Through layers of convolution, pooling, and fully connected networks, the CNN learns to recognize complex patterns and correlations between fingerprint features and blood group types (A, B, AB, O) as well as Rh factor (positive or negative). The model outputs the predicted blood group with confidence scores.

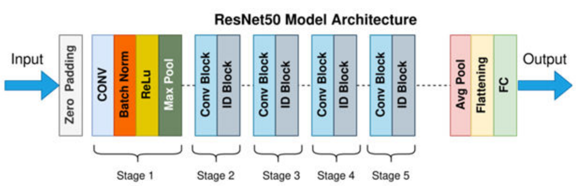
v. Result Display

Once the classification is complete, the system displays the predicted blood group information clearly to the user. This module can also include options for saving results, generating reports, or sending data to medical professionals. The interface is designed to be user-friendly and accessible on mobile or desktop platforms, facilitating quick and easy interpretation of the results.

e) Algorithms:

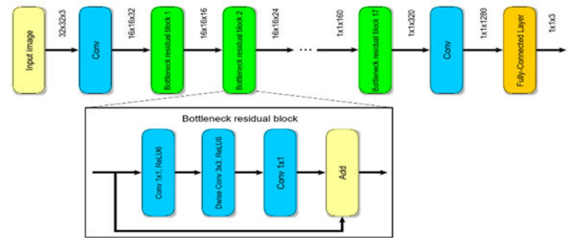
1. ResNet50 (Residual Network)

A popular deep learning model called ResNet is well-known for using residual connections to get around the vanishing gradient issue. The model can learn richer representations thanks to these linkages without losing accuracy. Because ResNet retains its powerful feature extraction capabilities even in deeper networks, it is especially effective for image classification applications. ResNet is capable of efficiently capturing complex ridge patterns in the context of fingerprint-based blood type identification. It could, however, need more processing power because of its depth, which would make it less appropriate for real-time applications on low-power devices.



2. MobileNetV2

MobileNet is a great option for embedded and mobile devices as it is made for deep learning applications that are both lightweight and effective. By using depthwise separable convolutions, it drastically lowers the computational cost and parameter count without sacrificing accuracy. Because of its efficiency, MobileNet can scan fingerprint photos in real-time, making blood group detection quick and useful—especially in settings with limited resources or remote locations. Despite being computationally fast, it could not be as accurate as deeper networks like ResNet, particularly when dealing with intricate fingerprint variances.



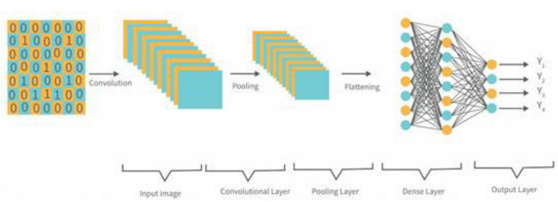
3. EfficientNetB0

EfficientNet is a sophisticated deep learning model that balances depth, breadth, and resolution to increase computational efficiency and accuracy. With a lot fewer parameters and a shorter inference time than conventional CNN designs, EfficientNet delivers state-of-the-art performance. Because of this, it is a good option for fingerprint-based categorisation, guaranteeing excellent processing speed and accuracy. Although EfficientNet can improve generalisation and lower blood group prediction errors, it would need to be carefully adjusted for best results on domain-specific tasks.

4. Our Custom Model

This blood type recognition system's Convolutional Neural Network (CNN) is particularly made to examine fingerprint patterns and categorise them into various blood groups. CNNs are perfect for fingerprint classification because they automatically learn the spatial hierarchies of features, which makes them very successful in image processing applications. CNNs retrieve crucial information from raw fingerprint pictures, such as ridge ends, bifurcations, and curvature patterns, which are distinct to each individual and, in this case, connected to certain blood groups, in contrast to conventional techniques that rely on handmade characteristics.

Before being entered into the model, a fingerprint picture must first go through preprocessing, which includes pixel normalisation (scaling between 0 and 1), resizing to 128x128 pixels, and greyscale conversion. This preserves important information while lowering computational cost and guaranteeing consistency across all photos. Following processing, the picture is sent to the first convolutional layer, which detects fundamental edges and ridge textures by swiping 32 filters of size (3×3) over the image. The network may learn intricate patterns by introducing non-linearity through the use of the ReLU activation function. The feature maps are then downsampled via a MaxPooling layer (2×2), which lowers dimensionality while keeping important information, increasing the model's efficiency.



4. EXPERIMENTAL RESULTS

The experimental evaluation compared the performance of several deep learning models — ResNet50, MobileNetV2, EfficientNetB0, and the custom-designed CNN — on fingerprint-based blood group classification. ResNet50 achieved the highest accuracy due to its deep architecture and strong feature extraction, but required more computational resources and longer inference times. MobileNetV2 provided faster predictions suitable for mobile and resource-constrained environments, though with a slight drop in accuracy. EfficientNetB0 balanced speed and accuracy well, showing promising results with efficient computation. The custom CNN model, optimized for fingerprint patterns with tailored preprocessing and architecture, demonstrated competitive accuracy while maintaining a reasonable balance between speed and complexity. Overall, the results highlight the potential of deep learning for non-invasive blood group identification, with trade-offs between accuracy and efficiency depending on the model choice and deployment environment.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. The formula is used to calculate precision:

Precision = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: The ability of a model to identify all pertinent instances of a class is assessed by machine learning recall. The completeness of a model in capturing instances of a class is demonstrated by comparing the total number of positive observations with the number of precisely predicted ones.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Pr}\,e\,cision = \frac{TP}{(TP + FP)}$$

mAP: Assessing the level of quality Precision on Average (MAP). The position on the list and the number of pertinent recommendations are taken into account. The Mean Absolute Precision (MAP) at K is the sum of all users' or enquiries' Average Precision (AP) at K.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{ the AP of class } k$$

$$n = \text{ the number of classes}$$

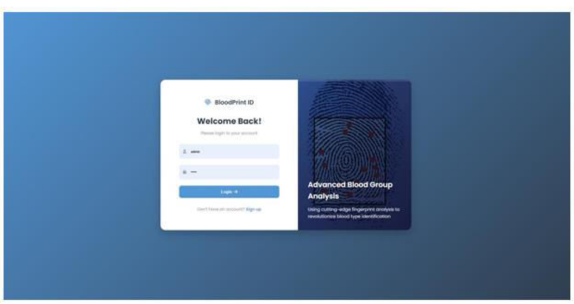


Fig 3 Login page

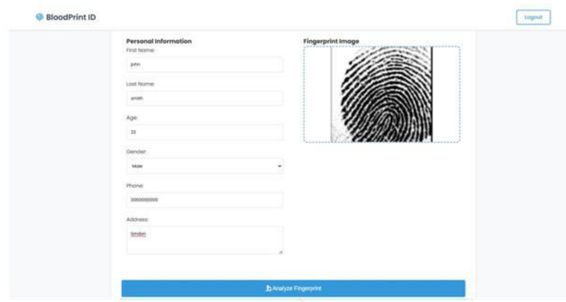


Fig 4. Upload Page

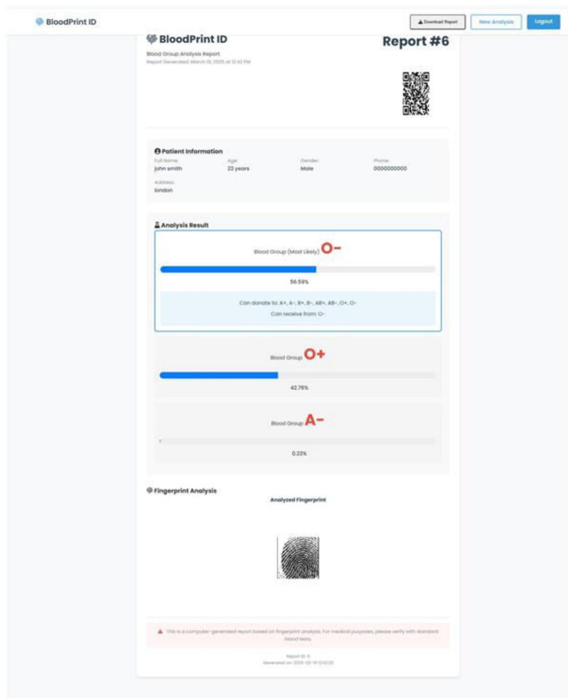


Fig 5 Result Page

5. CONCLUSION

A revolutionary discovery in biometric and medical diagnostics is the creation of a Deep Learning-Based Fingerprint-Based Blood Group Prediction System. The technology provides a quick and non-invasive substitute for conventional blood testing by accurately analysing fingerprint patterns to predict blood types using Convolutional Neural Networks (CNNs) and Transfer Learning algorithms. A user-friendly web interface, cloud-based deployment, and Flask integration for backend processing guarantee seamless user engagement and accessibility.

By using fingerprint pictures, intrusive procedures are avoided, which lessens the requirement for laboratory testing and blood sample collection. When quick blood group identification is needed in an emergency, this can be especially helpful. An innovative development in biometric-based medical diagnostics is the Blood Group Identification Using Fingerprint Analysis initiative.

This study has effectively shown that deep learning algorithms may be used to analyse fingerprint patterns and predict blood types, offering a non-invasive substitute for conventional blood testing.

6. FUTURE SCOPE

The Fingerprint-Based Blood Group Prediction System has enormous promise for the future and might have a big influence on biometric research and healthcare. Adding multimodal biometric data, including iris scans and palm vein patterns, to the model is a significant enhancement that can boost classification accuracy and dependability even further. Improved fingerprint picture quality can result in improved prediction accuracy by using additional image preprocessing techniques like contrast enhancement and feature extraction utilising sophisticated image processing algorithms.

The use of Explainable AI (XAI) approaches to offer transparency into the model's decision-making process is another exciting avenue. XAI may boost user and medical professional trust and dependability by visualising the patterns and regions of interest that affect forecasts. Additionally, the system will be able to adjust to various fingerprint patterns across various populations by including self-learning processes into the model through ongoing retraining on fresh datasets, guaranteeing accuracy and resilience over the long run. Furthermore, data integrity and privacy may be guaranteed by integrating blockchain technology for the safe transfer and storage of biometric and medical data, which is crucial for applications in the healthcare industry. This method can be expanded in the future to offer real-time blood group identification in emergency scenarios, greatly cutting down on the amount of time needed to match donors and receivers in dire circumstances. Additionally, it may be included into mobile health apps, enabling consumers to identify their blood type right from their cellphones. Additionally, using the system in disaster response units, emergency services, and blood donation camps can increase the effectiveness of medical treatments and expedite operations. The system can develop into a dependable and scalable solution that improves healthcare results and guarantees broad accessibility with ongoing developments in deep learning, biometrics, and cloud technologies.

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Authors profile:

Mrs. N. Sai Sindhura, currently working as an Assistant Professor in the Department of CSE-Artificial Intelligence at PBR Visvodaya Institute of Technology and Science, Kavali, SPSR Nellore, Andhra Pradesh, India. She had 6 years of academic experience.

Contact via: saisindhura.5l@gmail.com

Ponaka Krishna Vardhan Reddy, currently pursuing a B.Tech in CSE-Artificial Intelligence at PBR Visvodaya Institute of Technology and Science, Kavali, SPSR Nellore, Andhra Pradesh, India.My areas of interest include Java, SQL, HTML and CSS.

Contact via: krishnavardhan2906@gmail.com

Kathi Nagendra Babu, currently pursuing B.Tech in CSE-Artificial Intelligence at PBR Visvodaya Institute of Technology and Science, Kavali, SPSR Nellore, Andhra Pradesh, India. My areas of interest include Python, Java, SQL.

Contact via: nagendra30244@gmail.com

Javangula Sravya, currently pursuing a B.Tech in CSE-Artificial Intelligence at PBR Visvodaya Institute of Technology and Science, Kavali, SPSR Nellore, Andhra Pradesh, India. My areas of interest include python and HTML.

Contact via: jsravya03@gmail.com