A Survey: Blood Group Detection Using Fingerprint Images

Authors: Sukanya Bhaskar, Rajeshwari Golande, Yash Jahagirdar, and Rohit Kandelkar *Under Guidance of Prof. Anandkumar Birajdar , PCCOE, Akurdi*

ABSTRACT: Fingerprint pattern is the most consistent and distinguishing aspect of human identification. The fingerprint pattern cannot be modified and remains the same until the individual dies. Fingerprint verification is still considered the most crucial piece of evidence in the case of an event, even in the court of law. Each individual has a unique minutiae pattern, and the chances of resemblance are extremely low, around one in sixty-four thousand million. Even twins exhibit unique patterns. The ridge pattern is also unique, and has not changed since the birth of an individual. The method described in this work involves matching minutiae feature patterns obtained from fingerprints for a person identification system. Blood grouping has also been studied using fingerprints. Fingerprint matching was performed using ridge- frequency estimation. The spatial features were retrieved using a Gabor filter. The fingerprint scanner-based work reported here demonstrates great efficiency in image processing activities, such as image- to- binary conversion and thinning for fingerprint pattern correction and normalization.

Keywords: Machine Learning, Deep learning, Blood Groups, Fingerprints, Fingerprint Map Reading, Image Processing.

1. INTRODUCTION

The study demonstrated the value of fingerprint-based work and the fact that it has been around for several centuries. The most common use for fingerprints is pattern recognition for identity verification. Fingerprint-based biometric identification is employed in the majority of Indian enterprises; gender and age identification are also important application modalities [1].

The basic idea underlying fingerprint technology is "you are your own key," which runs counter to the idea of tokens or passwords. Ever since the research, fingerprint-based matching techniques dating back to the 16th century have been in use. The work has demonstrated how distinctive and singular fingerprints are. It introduced the present fingerprint-based identifying method.

A survey conducted significant fingerprint analyses in the 1800s and asked for fingerprints based on simple models such as circles, whorls, and curves. The articulation of dermal perspective diagrams at the digits "Dermatoglyphics (derma ¼ skin, glyphic ¼ turns)" of arms and the confirmation that the point course of development is no longer settled but rather guided by heredity or unavoidable impact that produces weight continuously of their progression sometimes of fatal life is credited to Cummins.

Even though there have also been documented instances of dietary and occupational modifications in later life. Blood tests are used to identify and diagnose most disorders in the human body. Blood is essential for maintaining the health and vitality of the human body. Biometrics, or a person's physical and behavioral traits, are employed in computer security for identification and authentication [1].

Computers are now utilized for a variety of functions, including identification, authentication, and other forms of security. In addition to being inexpensive and small in size when compared to other biometric sensors, fingerprint sensors differ and are easy to get, which contributes to their variable performance when compared to other biometric approaches. The method of biometric verification allows for a person's unique identification [2].

The first section includes the introduction of the study Blood group detection using fingerprint images mainly through ridge frequency, GLCM. Section second includes all the related works of study matching to the topic including base paper. The third section consists of gap analysis from papers which thoroughly covers the algorithm, parameters and future work. The fourth section covers observation and key issues regarding the study. Last section gives overall conclusion through field of study.

2. RELATED WORK

A literature survey consists of different learning techniques to retrieve ontology from data as follows: In this study, a unique method for determining a person's blood type using fingerprint patterns is presented. It analyses minute details in fingerprints and correlates them with blood types by utilizing machine learning techniques. Using image processing methods such as Gabor filters, the study examines fingerprint patterns such as loops, whorls, and arches. The suggested approach, which makes use of multiple linear regression, produces predictions with an accuracy of roughly 62%. Future research with a bigger sample size and more fingerprint characteristics, according to the scientists, might increase accuracy. This technique might provide a non-invasive substitute for conventional blood group testing techniques [1].

The study discusses an inexpensive method for determining blood types using fingerprints. The approach for extracting features from fingerprint images includes GLCM (Gray Level Co-occurrence Matrix), wavelet transforms, texture feature extraction, and minutiae feature extraction. These traits are subsequently classified using a Back Propagation Neural Network (BPNN). The method identifies the blood group by comparing fingerprint traits to a pre-existing database, with an accuracy of roughly 80%. This technology seeks to give a faster and less invasive alternative to existing blood group testing techniques [2].

The study covers the creation of a low-cost, automated system for detecting human blood types through image processing techniques. The technology uses a CCD camera to capture images of blood samples combined with specified serums. By analyzing these photos with specialized software (IMAQ Vision), the device detects agglutination, which determines blood type. This method provides a quick and effective means to establish blood type, making it useful in emergency circumstances where time is important. The authors propose developing a portable, low-cost gadget based on this technology [5].

The study describes two recent genetic technologies used for blood group genotyping. It describes how single nucleotide variant (SNV) mapping with DNA microarrays and massively parallel sequencing (MPS) improves accuracy in predicting blood group antigen phenotypes. The research discusses the advantages of employing SNV mapping for common blood groups while also addressing its drawbacks, such as its inability to detect novel or rare alleles. MPS, on the other hand, has a greater throughput and can detect previously unknown genetic variations, but it requires more resources and produces massive data sets that necessitate extensive bioinformatics analysis. The research continues by examining the potential for these technologies to improve transfusion safety by offering more thorough blood group typing. While SNV

microarrays are currently more practicable, MPS may become the method of choice in the future [13].

The study describes a system for automating blood type detection with image processing technology. In emergency scenarios where quick and accurate blood group identification is critical, this technology enables the simultaneous testing of several blood samples, decreasing human error and increasing efficiency. Blood samples are mixed with certain antigens, and photos of the reactions are captured using a camera. The photos are then analysed to identify blood type based on agglutination. The suggested technology enhances the speed and precision of blood type identification, making it perfect for high-demand situations like blood transfusions and roadside emergencies. The use of image processing ensures little human interaction, reducing errors and requiring specialized professionals [12].

The study describes a unique approach for detecting human blood groups that employs image processing and deep learning techniques. The system uses Scale-Invariant Feature Transform (SIFT), Orientated FAST, and Rotated BRIEF (ORB) algorithms for feature extraction and Convolutional Neural Networks (CNNs) for classification. This method improves the accuracy and efficiency of blood group detection by automating the process, minimizing human error, and optimizing image quality. The algorithm is trained on blood group picture datasets and has a high accuracy in classifying blood types. The suggested method is particularly useful in medical diagnostics, as it improves transfusion management and patient care by analyzing blood samples quickly and automatically. It also gives robustness to differences in image quality, resulting in dependable forecasts. Future advances will entail integrating this system with electronic health records and expanding its capabilities to anticipate new blood-related features

The study covers a method for detecting blood groups using machine learning classifiers, with a particular emphasis on image processing approaches for analyzing blood samples. It describes the picture acquisition, segmentation, and gray conversion steps that simplify the analysis of blood samples containing specified chemicals. The study emphasizes the benefits of automated technologies in decreasing human error and enhancing the quality of blood banking findings. Furthermore, it reviews alternative approaches from earlier research, emphasizing the potential for speedy and precise blood type detection. Future developments are expected to use GSM technology for effective

communication with lab technicians [9].

The study offers a novel approach to blood group categorization that employs artificial intelligence and image processing techniques. It describes a methodical methodology for collecting blood samples, capturing pictures, and processing them using MATLAB to obtain accurate categorization. The procedure includes segmentation, feature extraction, and comparison with predefined images in a dataset, all of which lead to automatic blood group determination. This novel approach aims to increase the efficiency and accuracy of blood type testing, which is critical for safe transfusions and illness identification, resulting in a considerable improvement over standard testing method [6].

The study provides an innovative blood group determination method based on fingerprint analysis, which takes use of fingerprints' unique and unchangeable character. It emphasizes the potential of sweat from fingerprints, which contains proteins and antigens linked to blood types, notably the ABO and Rh systems. To extract and classify features effectively, the system uses advanced image processing techniques such as Gabor filters and Convolutional Neural Networks (CNN). The device is designed to offer quick and accurate blood typing results, making it especially useful in emergency situations where traditional procedures are timeconsuming. The study underlines the significance of consistent association establishing a fingerprint patterns and blood groups, with future research focusing on enhancing accuracy expanding the dataset for more complete analysis [8].

The study provides an automated blood type determination approach based on image processing techniques, with an emphasis on the examination of agglutination in blood samples. It describes the processes of dilatation and erosion in morphological procedures, which are critical for improving image quality and retrieving useful features. The technology incorporates color plane extraction, pixel intensity quantification, and the use of HSL luminance to accurately classify blood types. The findings illustrate the proposed system's efficiency in providing quick and reliable blood type identification, with future plans to improve portability and add GSM technology for better communication in laboratory settings [5].

The study proposes the implementation of a type of spectrophotometric method to create a tiny, low-cost, portable system for blood typing in emergency scenarios. The system's goal is to overcome the limitations of current human and automated approaches by using optical analysis of blood agglutination to determine ABO and Rh types. The

study analyses the problems with current blood typing systems, particularly their subjectivity and time limits in emergencies, and suggests an automatic approach that can provide speedy, accurate findings outside of clinical laboratories. The device automates the procedure with light-based detection and electronic components, decreasing human error and increasing portability. Initial tests proved the feasibility of employing spectrophotometry, with future work concentrating on system calibration and real-time application [3].

The study offers a novel, non-invasive method for estimating human blood component levels such as hemoglobin, glucose, and creatinine using fingertip video data acquired by a smartphone. The method makes use of photoplethysmogram (PPG) signals obtained from fingertip videos illuminated by nearinfrared (NIR) light-emitting diodes (LEDs). The study estimates blood component levels by extracting 46 typical features from the PPG signal, its derivatives, and Fourier analysis using deep neural network (DNN) models. The models use genetic algorithms to optimize feature selection and reduce overfitting, resulting in high accuracy hemoglobin, glucose, and creatinine estimates. The findings indicate that the technology could be used as a simple, non-invasive alternative to traditional blood sample for real-time health monitoring [11].

3. GAP ANALYSIS

Table 1. Summary of related work / gap analysis:

	=	=	
	Parameter	Algorithms	Limitat
R			ion and
ef			Future
N			work
0.			
1.	1)	1) Fingerp	1) Accur
	Fingerprint	rint	acy
	features	matching	about
	2) Blood	2) Preprocessin	62%
	Group	g	2) Sam
	Data	3) Multi	ple
	3) Dataset	ple	size
		Linear	with
		Regression	features
			scope
			3) Advan
			ced
			Machine
			Learning

Level Crocurrence process of sample size 2) Buck propagation 3) Blood sample cuty 2) Optical Density (OPS) 3) Light source and detector 4 Density source and detector 5 Density source and detector 4 Density source and detector 4 Density source and detector 5 Density source and detector 4 Density source and detector 5 Density source and detector 4 Density	2.	1)Gray-	1) Ima	1)				4) Accuracy
3. 1) Blood samples 2) Optical Density Spectrum (OPS) 3) Light detector 1) Optical density 2) Light emitting diodes (LED) 3) Test samples with antibodies will antibodies 1) Thresholding for agglutination 3) Reagents 1) Image processing 2) Treat sample collection 2) Image segmentation 2) Trea		· -	ge	Limitation				
3. 1) Blood samples 2) Optical Density Spectrum (OPS) 3) Light source and detector density 2) Light emitting floods (LED) 3) Test samples with antibodies with antibodies 2) Threshold for feature processing processing processing 2) Threshold for feature 2) Threshold for feature and processing or detection 3) Image segmentation 4. In J. Specific spec		occurrence	process	of sample				
1) Blood samples 2) Optical Density Spectrum (OPS) 3) Light source and detector 2) Submility source and detector 2) Tight source and developed partial processing of countered and and source and developed partial processing and luminary 2) Tight source and detector 2) Tight sourc			_	size				-
1) Blood sample 2) Optical Density Spectrum (OPS) 3) Light source and detector and			· ·					
1) Blood samples 2) Optical Density Spectrum (OPS) 3) Light source and detector of detection (OPS) 3 Light source and detector of detection (OPS) 3 Light source and detector of detection (OPS) 4) Dependence affecting accuracy 3) Experiment the system variation detection (OPS) 4) Dependence affecting accuracy 3) Experiment the system variation of computer and object of the computer of			propagation		0	1)	1) C 1 FT	
Sample 2) Optical Density Spectrum (OPS) 3) Light source and detector detection detect	3.	1) Blood	1)Spectrophotom	1) Blood	0.		· ·	
2) Staglatination detection Density Spectrum (OPS) 3) Light source and detector 4. 1) Optical density 2) Light emitting diddek (LED) 3) 3) Test sample with antibodies 5. 1) Il Image processing 2) Threshold for angletination 3) Image processing 2) Threshold for angletination 3) Image segmentation 4. 1) Disample contexting and and deep learning extraction 2) Blood group classification 3) Image segmentation 3) Imag			etry	Sample				
Spectrum (OPS) 3) Light source and detection affecting accuracy 3 incorporating detection detector 4. I) Optical density 2) Light emitting disoles (LED) 3) Test samples with antibodies 2) Tresting disoles (LED) 3) Reagents 2) Tresting 2) Tresting disoles (LED) 3) Reagents 2) Tresting 2) Tresting distact 3) Tour all processing 2) Tresting distact 4) Clinical Tresting 2) Tresting distact 4) Contrast optimization 1 Tresting 2) Tresting distact 4) Contrast optimization 2) Tresting 2) Tresting distact 4) Contrast optimization 2) Tresting distact 4) Contrast optimization 2) Tresting distact 4) Contrast optimization 3) Tresting distact 4) Contrast optimization 2) Tresting 2) Tresting 2) Tresting 2) Tresting 2) Tresting 2) Tresting			2) Agglutination					-
OPS 3) Light source and detector Advanced affecting accuracy 3) Stability issues affecting accuracy 3) Experiment the system variation 4. 1) Optical density 2) Light emitting diodes (LED) 3) Test samples with antibodies 1) Image processing pipelines 2) Time shold for all pipelines 2) Pisch value classification 3) Reagents 1) Image processing pipelines 2) Road feature 2) Road group classification 3) Test sample segmentation 1) Image processing pipelines 2) Road group classification 3) Test sample segmentation 1) Image processing pipelines 2) Road group classification 3) Test sample segmentation 1) Image processing pipelines 2) Road group classification 3) Test sample segmentation 1) Image processing pipelines 2) Road group classification 3) Test sample segmentation 2) Image 2) Road group classification 3) Test sample segmentation 4) Image 4) Ima			detection				Networks	·
source and detector Advanced CNN Advanced CNN		(OPS)		_		Anagens	(CNN)	dependency
detector Advance Adva		_						
accuracy 3) Experiment the system variation 4. 1) Optical density 2) Light entiting diodes (LED) 3) Test samples with antibodies viit antibodies 5. 1) Image processing 2) Threshold for agglutination 3)Reagents 2) Pixel value classification 3) Regression 3) Regression 6. 1) Blood sample collection 2) Blood group classification 3) Linear Regression 3) Linear Regression 7. 1) Sample simages 2) Color plane extraction with and and extraction 4) Image techniques 2) Region grocessing 1) Image processing for feature 1) Image processing 2) Thresholding and complex 3) Linear Regression 3) Linear Regression 3) Linear Regression 4) Countriation 2) Proprosessing and complex 3) Image segmentation 3) Linear Regression 4) Countriation 2) Proprocessing and complex 3) Image segmentation 3) Linear Regression 3) Linear Regression 4) Proprocessing for feature 4) Linitations architecture 4) Linearing features extraction 2 (A) Clinical traction 2) Regression 3) Complex 3) Test sing data 4) Contrast optimization human interference 2) Time reconsuming and complex 3) Linear Regression 3) Linear Regression 4) Crival 4) Deep learning learning (Inexposed features) 1) Image extractions 4) Clinical Tresting 4) Clinical Tresting 4 Clinical Tresting 4 Clinical Tresting 4 Clinical Tresting 4) Clinical Tresting 4 Clinical Tresting 4 Clinical Tresting 4 Clinical Invariant feature extraction 2) Thresholding and complex 3) Test sing 4 Clinical Tresting 4) Contrast optimization human from the deciron and diverse dataset 2) Deep learning 7 (Mean, Standard 4) Clinical Tresting 4) Contrast optimization from 6 (A) Clinical Tresting 4) Contrast optimization 7 (A) Contrast optimization 8 (A) Contrast optimization 9 (A) Contr								
A. 1) Optical density 2) Light entiting dods (LED) 3) Test samples with antibodies 1) Image processing 2) Threshold for agglutination 3) Reagents 1) Image processing 2) Threshold for agglutination 3) Reagents 1) Image processing plipelines (2) Pisting data 4) GSSM (Clettion 2) Pistory and popularisification 3) Image segmentation 1) Image segmentation 1) Image processing or collection 2) Blood group classification 3) Linear Regression 4) Limitation of computer and deviation and deviation detection 2) Earning data 4) Clinical Tresting 4) Computation and deviation and deviation detection 2) Earning data 4) Clinical Tresting 4) Computation and deviation and deviation and deviation and deviation and deviation and deviation and extraction 3) Results and the processing plipelines 2) Non classification 3) Results and the processing plipelines 2) Non classification 3) Test and the processing data 4) Clinical Tresting data 4) Clinical								
Experiment the system variation 4 (a) Dependence density 2) Light emitting diodes (LED) (3) Test samples with antibodies 2) Tresting 2) Threshold for agglutination 3) Reagents 2) Processing 2) Threshold for collection 2) Blood group classification 3) Image segmentation 4 (a) Diagrage segmentation 4 (b) Diagrage segmentation 4 (b) Diagrage segmentation 4 (c) Diagrage segmentation 5 (c) Diagrage segmentation 4 (c) Diagrage segmentation 5 (c) Diagrage segmentation 5 (c) Diagrage segmentation 6 (c) Diagrage segmentation 6 (c) Diagrage segmentation 7 (c) Diagrage segmentation 8 (c) Diagrage segmentation 9 (c) Diagra				3)			-	
the system variation 4) 1) Optical density 2) Light emitting dodes (LED) 3) Test samples with antibodies 2) Testing antibodies 2) Testing 2) Tireshold for agglutination 3)Reagents 5. 1) Image processing 2) Tireshold for agglutination 3)Reagents 5. 1) Image processing 2) Tireshold for agglutination 3)Reagents 1) Il load sample collection 2) Blood group classification 3) Linear Regression 3) Linear Regression 3) Linear Regression 3) Linear Regression 2) Tiresholding images 2) Tiresholding images 2) Color plane extraction 4) Clair and deep learning techniques 2) Tiresholding images 2) Color plane extraction 4) Clair and deep learning techniques 2) Region Morphological techniques 3) 3) Variable in high morphological techniques 3) 3) Variable and morphological techniques 3) 3) Variable in high morphological techniques 3) 3) Variable and morphological techniques 3) 3) Variable in high morphological every 2) Color dense density and the processing processing processing processing of feature 2) Picci value and and complex 4) Contrast optimization 4) Complex 4) Contrast optimization 4)				Experiment			_	
4. 1) Optical density 2) Ligh emitting antibodies (LED) 3) Test samples with antibodies of processing 2)Threshold for agglutination 3)Reagents Processing 2) Pixel value classification 3)Reagents Sample sample cextraction 2) Blood group classification 3) Inage segmentation 3) Linear Regression 2) Logistic 2) Time regression 3) Linear Regression 2) Complex 2) Time regression 3) Linear Regression 2) Logistic 2) Time regression 3) Linear Regression 2) Logistic 2) Complex 3) Linear Regression 2) Logistic 2) Time regression 3) Linear Regression 2) Logistic 2) Pixel value classification 3) Linear Regression 3) Linear Regression 3) Linear Regression 3) Sample techniques 2) Pixel value classification 2) Logistic 2) Time regression 3) Linear Regression 3) Linear Regression 3) Sample techniques 2) Complex 3) Linear Regression 3) Sample techniques 3) Linear Regression 3) Linear Regression 3) Sample techniques 3) Linear Regression 3) Sample techniques 3) Linear Regression 4) Limitation deviation, entropy) detection (binary) Limitation deviation, entropy) and detection 3) CNN creations and deviation, entropy) and detection 3) CNN creation 3) CNN complication and deviation, entropy) and deverse and deviation, entropy) and detection 3) CNN creation 3) CNN creation 3) CNN complication and deviation, entropy) and detection 3) CNN creation 4) Contract 4) Limitations of complex 3) CNN creation 4) Limitation 4) Complex 4) Contract 4) Contract 4) Complex 4) Contract 5) Complex 4) Contract 5) Complex 4) Contract 6 Complex 4) Contract 6 Complex 6) Complex 6) Complex 6) Complex 6) Complex 6) Comp				-			_	-
4. 1) Optical density 2) Light emitting diodes (LED) 3) Test samples with antibodies of processing 2) Threshold for agglutination 3)Reagents 2) Pixel value classification 3)Reagents 2) Pixel value classification 3) Tests ample some agglutination 3)Reagents 2) Pixel value classification 3) I limage processing 2) Pixel value classification 3) I limage processing 6 collection 2) Blood group classification 3) Linear Regression 3) Linear Regression 2) Complex 3) Linear Regression 3) Sample techniques 2) Pixel value classification 2) Logistic 2) Time consuming and Regression 2) Pixel value chaiques 2) Pixel value classification 2) Logistic 2) Time corrowable device deviction (binary) 2) Preprocessing for feature extraction 2) Logistic 2) Time corrowable device deviction, entropy) detection (binary) detection (binary) 2) Preprocessing and diverse data 4) Complex 3) CNN complexity consumes time and space and complex 3) CNN linear data 4) Contrast optimization and complexity consumes time and space and diverse data 4) Contrast optimization and complexity consumes time and space and diverse data 4) Contrast optimization and complexity consumes time and space and diverse data 4) Limitations in fibre optics in detection (binary) 1) Large and data 4) Contrast optimization and complexity consumes time and space 3) CNN linear data 4) Contrast optimization and complexity consumes time and space and diverse data 4) Contrast optimization and complexity consumes time and space and diverse data 4) Limitations of the centropy and data 4) Contrast optimization and complexity consumes time and space and diverse data 4) Limitation (binary) 1) Large and data 2) Deep learning and complexity cons					9.	1)Gray-Scale		1)Limitation
4. d) Optical density emitting diodes (LED) 3,7 Test samples with antibodies vith antibodies 2) Testing learning 2) Threshold for agglutination 3; Reagents 2) Pixel value classification 3; Inage segmentation 3; Inage segmentation 4 Classification 3) Linear extraction 2, Dinear extraction 2, Dependence measurement 2) Light (and the processing processing processing placing and data 4) GSM technology classification 3) Linear extraction 2, Dinear extraction 2, Dinear extraction 3) Linear extraction 2, Dinear extraction 3) Linear extraction 2, Dinear extraction 3, Dinear extraction 3, Dinear extraction 2, Dinear extraction 2, Dinear ext				· · · · · · · · · · · · · · · · · · ·			acquisition	of computer
4. 1) Optical density 2. Light metric measurement 2.) Dependence metric diodes (LED) 3.) Test samples with antibodies of processing 2.) Threshold for agglutination 3.) Reagents Processing 2.) Threshold for agglutination 3.) Reagents Processing 2.) This plant of the collection 2.) Blood group classification 3.) Linear Regression 3.) Linear Regression 3.) Linear Regression 2.) Complex 2.) Complex 2.) This plant of the complex and deep learning and Regression 3.) Linear Regression 3							· ·	
density 2) Light emitting diodes (LED) 3) Test samples with antibodies with antibodies with antibodies 2) Testing antibodies 2) Testing 2) Threshold for agglutination 3) Reagents 2) Fixed value classification 4) Reagents 2) Fixed value 2) Fixed valu	4.	1) Optical	1)Spectrophoto					
Complexition Complex							, ,	*
diodes (LED) 3) Test samples with antibodies 5.			measurement 2)	_				
3) Test samples with antibodies with antibod		C	Light	Environmen			· ·	
antibodies with antibodies Testing 5.			-	1				-
5. 1) Image processing 2)Threshold for agglutination 3)Reagents 6. 1) Blood sample collection 2) Blood group classification 3) Image segmentation 3) Image segmentation 4. In Sample images 2) color plane extraction 5. In Sample images 2) color plane extraction 6. In Sample images 2) color plane extraction 7. In Sample images 2) color plane extraction 8. Intervention 2) Region Morphological techniques 3) Variable Quantification 9. Va			-				classification	3)
1) Image processing 2) Threshold for agglutination 3) Reagents 1) Image pipelines (2) Pixel value classification 3) Reagents 1) Image pipelines (2) Pixel value classification 3) Reagents 1) Image pipelines (2) Pixel value classification 3) Testing data 4) GSM technology 1) Image processing for feature extraction 3) Image segmentation 1) Image processing for feature extraction 2) Logistic 2) Time regression 3) Linear Regression 3) Linear Regression 1) Improving AI and deep learning techniques 2) color plane extraction 4) Sample images 2) color plane extraction 5) Sample images 2) color plane extraction 6) Sample images 2) Sample images 2) color plane extraction 6) Sample images 2) Sample images 2) Sample imag		antibodies	with antibodies				(binary)	_
processing 2)Threshold for agglutination 3)Reagents 6. 1) Blood sample collection 2) Blood group classification 3) Image segmentation 3) Linear Regression 7. 1) Sample images 2) color plane extraction 2 (2) Complex 2) Region specific thresholding 3) Variable images 3) Cyantification 2) Region specific thresholding 3) Variable in high	5	1) Image	1) Image					-
2)Threshold for agglutination 3)Reagents 6. 1) Blood sample collection 2) Blood group classification 3) Image segmentation 3) Linear Regression 7. 1) Sample images 2) color plane extraction A 1) Sample images 2) color plane extraction A 2) Pixel value 2) Non portability 3) Testing data 4) GSM technology 1 Manual errors and human interference 2) Time consuming and complex 3) Improving AI and deep learning and complex 3) Improving AI and deep learning segmentation 7. 1) Sample images 2) color plane extraction Morphological techniques 3) Variable in high A 2) Pixel value 2) Non portability 3) Testing data 4) (Computation and diverse dataset 2) Deep learning (ata 4) (Dontrast optimization and diverse dataset 2) Deep learning (ata 4) (Contrast optimization and space 3) CNN Normalization 3) CNN Sensitivity of input image quality 4) Integration with electronic health record (EHR) system 7. 1) Sample images (2) Computation and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast optimization by improving and diverse dataset 2) Deep learning (ata 4) (Contrast	J.		-	_	10	1)0 1	1)	
2) Pixel value classification 3)Reagents 6. 1) Blood sample collection 2) Blood group classification 3) Image segmentation 3) Linear Regression 2) Computation and space plearning extraction 4) Improving AI and deep learning techniques 2) Computation and space and human extraction 4) Integration with electronic health record (EHR) system 7. 1) Sample images 2) Color plane extraction 4) Thresholding techniques 2) Region specific thresholding 3) Variable in high				_	10.	,	<i>'</i>	
6. 1) Blood sample processing for feature plooper classification 3) Image segmentation 3) Linear Regression 3) Linear Regression 2) color plane extraction 4) Thresholding images 2) color plane extraction 4) Thresholding and data 4) GSM technology and techniques 2) Region Sylvariable in high			2) Pixel value	2) Non		feature		
6. 1) Blood sample collection 2) Blood group classification 3) Image segmentation 3) Linear Regression 2) Complex 4) Contrast optimization nat space segmentation 3) Image segmentation 4. The complex segmentation 5 and deep learning and complex 3) Linear Regression 2) Complex 3) Linear Regression 2) Complex 3) Linear Regression 2) Complex 3) Linear and deep learning and complex 3) Linear and Regression 2) Complex 3) Linear Regression 2) Complex 3) Linear and deep learning and complex 4) Contrast optimization by time and space and s			classification			,		
6. 1) Blood sample collection 2) Blood group classification 3) Image segmentation 3) Linear Regression 2) Consuming AI and deep learning and complex 3) Improving AI and deep learning and complex 4) Contrast optimization by the consuming and complex 4) Contrast optimization by the consuming and consuming and space 3) Sensitivity of input image quality 4) Integration with electronic health record (EHR) system 2) color plane extraction 4 (EHR) system 2) color plane extraction 4 (EHR) system 2) color plane extraction 4 (EHR) system 2) Region Sy Variable techniques 3) Variable quantification in high 1 (EHR) size 4							2) Deep	Computatio
6. 1) Blood sample collection 2) Blood group classification 3) Image segmentation 3) Linear Regression 2) Consuming and complex 3) Linear Regression 2) Re				·		3)		nal
6. 1) Blood sample collection 2) Blood group classification 3) Image segmentation 3) Linear Regression 3) Linear Regression 2) Color plane extraction 2) Logistic reduction 2 (EHR) system 2) color plane extraction 4 (EHR) system 2) color plane extraction 4 (EHR) system 2) color plane extraction 4 (EHR) system 2) Quantification 4 (EHR) size mades and space 3) Sensitivity of input image quality 4) Integration with electronic health record (EHR) system 2) PPG signal generation 2) Feature extraction 3) Feature 4) Additional Factors 4 (EHR) size mades space 3) Sensitivity of input image quality 4) Integration with electronic health record (EHR) system 2) PPG signal generation 2) Feature extraction 3) Feature 4) Additional Factors 4 (EHR) size mades space 3) Sensitivity of input image quality 4) Integration with electronic health record (EHR) system 2) PPG signal generation 2) Feature extraction 3) Feature 4) Additional Factors 4 (EHR) size mades space 3) Sensitivity of input image quality 4) Integration with electronic health record (EHR) system 2) PPG signal generation 2) Feature extraction 3) Feature extraction 3) Feature extraction 3) Peature extraction 3) Feature extraction 3) Feature extraction 4 (EHR) size mades and space 3) PPG signal generation 2) PPG signal generation 2) PPG signal generation 2) Feature extraction 3) PPG signal generation 2) PPG							3) CNN	
sample collection 2) Blood group classification 3) Image segmentation 7. 1) Sample images 2) color plane extraction 2) Morphological techniques 3) Morphological techniques 3) Quantification 4 Quantification 4 Page 1 Processing for feature extraction 2) Logistic 2) Time consuming and consuming and plant feature extraction 4 human interference 2) Time regression consuming and consuming and plant feature extraction 4 human interference 2) Time regression consuming and plant feature extraction 4 human interference 2) Time regression consuming and plant feature extraction 4 human interference 2) Time regression consuming and plant feature extraction 4 human interference 2) Time regression consuming and plant feature extraction 4 human interference 2) Time regression consuming and plant feature extraction 4 human interference 2) Time regression consuming and plant feature extraction 4 human interference 2) Time regression consuming and plant feature extraction 4 human interference 2) Time regression consuming and plant feature extraction 4 human interference 2) Time regression 2) High data size extraction 3 preature extraction 2 pr	6.	1) Blood	1) Image					
collection 2) Blood group classification 3) Image segmentation 7. 1) Sample images 2) color plane extraction Morphological techniques 3) Variable Quantification 3) Isample images 3) Variable Quantification feature extraction 2) Logistic 2) Time consuming and consuming and consuming and consuming and consuming and complex 3) Sensitivity of input image quality 4) Integration with electronic health record (EHR) system 1) Input data 2) PPG signal 3) Feature extraction 3) Feature extraction 3) Feature extraction 3) Feature extraction 3) Feature 1) Input data 2) PPG signal 3) Feature extraction 3) Feature extraction 3) Feature extraction 3) Feature		sample		, , , , , , , , , , , , , , , , , , ,				
classification 3) Image segmentation Regression 3) Linear Regression 3) Linear AI and deep learning techniques 2) color plane extraction Morphological techniques 3) Wariable Quantification AI and deep learning techniques 4) Intervention 2) Region AI and deep learning techniques 2) Region 3) Region 3) Variable in high AI and deep learning techniques 4) Intervention 2) Region 3) Feature Additional Factors Sensitivity of input image quality 4) Integration with electronic health record (EHR) system 1) PPG signal generation 2) Feature extraction 3) Feature Variability of input image quality 4) Al and deep learning techniques 2) Region Al and deep learning techniques 2) Region Al and deep learning techniques 3) Region Al and deep learning techniques 4) Intervention 2) Region Additional Factors Feature Extraction 3) Feature President Additional Factors Feature Extraction 3) Feature Feature Extraction 3) Feature			feature	human				
3) Image segmentation Regression 3) Linear Regression 3) Linear Regression 3) Improving AI and deep learning techniques 2) color plane extraction Morphological techniques 3) Variable in high Quantification Logistic regression 2) Time consuming and complex 3) Linear Regression 3) Linear Regression 3) Linear Regression 4) Integration with electronic health record (EHR) system 2) Region Specific thresholding 3) Variable in high 11. 1)Input data 2) PPG signal generation 2) Feature extraction 3) Features 4) Additional Factors 11. 1)Input data 2) PPG signal generation 2) Feature extraction 3) Feature extraction 4)			· ·					*
3) Linear Regression 4) Integration with electronic health record (EHR) system 2) Color plane extraction Morphological techniques 2) Region Morphological techniques 3) Variable in high 1) Integration with electronic health record (EHR) system 2) PPG signal 3) Features 4) Additional Factors Feature extraction 3) Feature 2) High device		3) Image		· ·				_
Regression complex 3) Integration with electronic health record (EHR) system 2) color plane extraction Norphological techniques 3) Variable Quantification Regression Complex 3) Integration with electronic health record (EHR) system 2) PPG signal 3) Features 4) Additional Factors Regression 1) Integration with electronic health record (EHR) system 2) PPG signal 3) Feature variability extraction 3) Feature Peature extraction 3) Feature Peature extraction 3) Feature Peature extraction 3) Feature extraction 3) Feature		segmentation	_	_				_
7. 1) Sample images 2) color plane extraction Morphological techniques Morphological techniques 3) Improving AI and deep learning techniques 2) Region Morphological techniques 3) Variable Quantification 3) Integration with electronic health record (EHR) system 1) Integration with electronic health record (EHR) system 1) Integration with electronic health record (EHR) system 1) Integration with electronic health record (EHR) system 2) PPG signal generation 2) Feature extraction 3) Feature extraction 3) Feature 4) Integration with electronic health record (EHR) system 2) PPG signal generation 2) Feature extraction 3) Feature extraction 3) Feature								
The sholding techniques 7. 1) Sample images 2) color plane extraction Morphological techniques The sholding techniques 2) Region Morphological techniques Thresholding techniques 2) Region Morphological techniques Thresholding techniques 2) Region Morphological techniques Thresholding te			110510001011	_				
7. 1) Sample images 2) color plane extraction Morphological techniques 3)				· · · · · · · · · · · · · · · · · · ·				_
7. 1) Sample images 2) color plane extraction Morphological techniques 4) Morphological techniques 3) Variable Quantification in high learning techniques 4) Quantification learning techniques 4) Manual Intervention 2) Region 2) Region 4 Morphological techniques 4) Additional Factors health record (EHR) system 2) PPG signal 3) Features 4) Additional Factors Feature extraction 3) Feature device				_				
7. 1) Sample images 2) color plane extraction Morphological techniques 3)				_				
images 2) color plane extraction 2) Region Morphological techniques 3) 3) Variable Quantification 2) Region 3) Variable Quantification 1) Input data 2) PPG signal 3) Features 4) Additional Factors 11. 1) Input data 2) PPG signal 3) Feature 4 Additional Factors 11. 1) Input data 2) PPG signal 3) Feature 4 Additional Factors Feature extraction 3) 2) High device		1) 0	1/101 1 1 1	_				record
2) color plane extraction 2) Region Morphological techniques 3) Variable Quantification 2) Region specific thresholding 3) Variable in high 2) Region specific thresholding 3) Variable in high System 11. 1)Input data 2) PPG signal generation 2) 3) Feature 4) Additional Factors Feature extraction 3) Feature device	7.			· · · · · · · · · · · · · · · · · · ·				(EHR)
extraction Morphological techniques 3)			_			41.7		
techniques thresholding 3) Variable Quantification in high Quantification thresholding 3) Features 4) Additional Factors Feature variability 2) High extraction 3) Feature extraction 3) Feature device					11.			
3) Variable Quantification in high Quantification in high Additional Factors Feature variability 2) High device				_			-	
Quantification in high Factors Feature device			_			Additional		-
3.4.			Quantification	-		Factors	· ·	
Selection acpetitueite				conditions			selection	dependence

networks (6P) (DNN) 3) Computatio nal complexity 4) Cloud based integration 12. 1)Blo 1)Preproces- od sing ual sampl 2)Segmenta- es tion n 2) 3)Feature introduct es tion introduct Antige extraction ion 2) n 4)Calssifica- reactio tion process n 3) Pi camara 4) Raspberr y Pi Microcontr oller de			4) Deep Neural	(NEXUS
(DNN) (DNN) (Computational complexity 4) Cloud based integration 12. 1)Blo 1)Preproces-1)Man ual sampl 2)Segmentates tion n introduct ion 2) (Computational complexity 4) Cloud based integration 12. 1)Blo 1)Preproces-1)Man ual sampl es tion n introduct ion 2) (Computational complexity 4) Cloud based integration 13. 1)Feature introduct ion 2) (Computational complexity 4) Cloud based integration (Computational complexity 4) Cloud based integration (Computational complexity 4) Cloud based integration 2) (Computational complexity 4) Cloud based integration 2) Manual integration of integration ion of ion of ion			_	,
Computatio nal complexity 4) Cloud based integration 12. 1)Blo 1)Preproces- 1)Man ual sampl 2)Segmentates tion n introduct ion 2) 3)Feature es tion introduct ion 2) n 4)Calssification reactio tion process n 3) Pi camara 4) Raspberr y Pi Microcontr oller			(DNN)	
12. 1)Blo 1)Preproces- 1)Man ual sampl 2)Segmenta- introduct ion 2) 3)Feature es tion n introduct ion 2) Testing process n 3) Pi camara 4) Raspberr y Pi Microcontr oller Mapping le PCR nucleo tide variant (SNV) Sequencing lel sequen cing Microcontr didardardardardardardardardardardardardard			, ,	*
12. 1)Blo 1)Preproces- 1)Man ual sampl 2)Segmenta- antige es tion n 2) 3)Feature introduct ion 2) n 4)Calssifica- Testing process n 3) Pi camara 4) Raspberr y Pi Microcontr oller Mapping ion of Accuracy 13. 1)Genoty ping Mapping le PCR nucleo tide 2)Massively parallel sequen cing Migh level testing laft le sequen cing Migh loptimizatio (large input) (large i				
12. 1)Blo 1)Preproces- 1)Man ual sampl 2)Segmenta- antige es tion n introduct ion 2) Antige extraction ion 2) Testing process n 3) Pi camara 4) Raspberr y Pi Microcontr oller Mapping ion of platforms 2) Sing Multiplex PCR nucleo tide variant (SNV) 3) paral lel sequen cing Messample level testing large l				complexity
12. 1)Blo od sing ual antige tion 2)Segmentaes tion n interduct ion 2) 3)Feature extraction ion 2) 1 4)Calssification process n 3) Pi camara 4) Raspberr y Pi Microcontr oller 2)Sing platforms 2)Sing platforms 2)Sing platforms 2)Sing platforms 2)Sing paral lel variant (SNV) 3) paral lel sequen cing (MPS) analysis less the first sequen cing (large input) 4) High Optimizatio				4) Cloud
12. 1)Blo od sing ual sampl es tion n introduct ion 2) Antige extraction ion 2) Antige extraction ion 2) n 4)Calssification process ific equipm ent 4) Enhan ced Accuracy 13. 1)Genoty ping Mapping ion of platforms contide variant (SNV) sparal lel sequen cing (large input) (large in				based
od sing ual antige res tion n introduct ion 2) Antige extraction ion 2) n 4)Calssification process n 3) Pi camara ific equipm ent 4) Enhan ced Accuracy 13. 1)Genoty ping Mapping ion of platforms introduct ion 2) 13. 1)Genoty ping Mapping ion of platforms introduct ion 2) 13. 1)Genoty ping Mapping ion of mapping ion ion specific platforms ion mapping ion mapping ion ion mapping ion mapping ion ion mapping ion mapping ion mapping ion ion mapping ion ion mapping ion mapping ion ion ion mapping ion ion mapping ion				integration
sampl es tion 2) Segmenta- tion 2) 3)Feature introduct Antige extraction n 4)Calssifica- reactio tion process n 3) Spec ific equipm ent 4) Raspberr y Pi Microcontr oller 13. 1)Genoty ping platforms 2)Sing le nucleo tide variant (SNV) 3) paral lel Sequen cing (MPS) le sequen cing MPS 2)Segmenta- introduct ion 2) Testing process 3) Spec ific equipm ent 4) Enhan ced Accuracy 1) Integrat ion of MPS 2) Populat ion specific platforms 3) High level testing (large input) 4) High Optimizatio	12.	1)Blo	1)Preproces-	1)Man
es tion 3)Feature introduct introduct introduct introduct introduct introduct into 2) n 4)Calssifica- Testing process 3) Spec iffic equipm ent 4) Raspberr y Pi Microcontr oller ced Accuracy 13. 1)Genoty ping Mapping ion of platforms : MPS 2)Sing Multiplex per le nucleo tide 2)Massively variant (SNV) sequencing tel (SNV) sequencing 1) Data sequen cing (large input) analytics introduct introduct introduct introduct ion 2) High level testing (large input) 4) High Optimizatio		od	sing	ual
2) 3)Feature introduct ion 2) n 4)Calssification process n 3) Pi camara 4) Raspberr y Pi Microcontr oller 13. 1)Genoty ping Mapping ion of platforms 2)Sing Multiplex pCR nucleo tide variant (SNV) sequencing tel (SNV) 3) paral lel sequen cing le sequen cing 3) Feature introduct ion 2) Testing process 3) Spec ific equipm ent 4) Enhan ced Accuracy 11. I) SNV pint ion of MPS 2) Populat ion specific platforms 3) High level testing (large input) 4) High Optimizatio		sampl	2)Segmenta-	antige
Antige a cxtraction a cy and and a cy and and a cy and a		es	tion	n
n a d)Calssification process n a 3) Pi camara diffic equipm ent d) Raspberr y Pi ent Microcontr oller dear dear dear dear dear dear dear de		2)	3)Feature	introduct
reactio n 3) Spec ific equipm ent 4) Raspberr y Pi ent Microcontr oller Ced Accuracy 13. 1) Genoty ping Mapping ion of platforms : MPS 2) Sing Multiplex le PCR nucleo tide variant (SNV) sequencing tel sequen cing 1) Data analytics input) (Iarge input) (Antige	extraction	ion 2)
n 3) Pi camara 4) Raspberr y Pi Microcontr oller 13. 1) Genoty ping platforms 2) Sing nucleo tide variant (SNV) 3) Spec ific equipm ent 4) Enhan ced Accuracy 1) Integrat ion of MPS 2) Populat ion specific platforms 2) Massively parallel variant (SNV) sequencing 3) paral lel sequen cing (MPS) lesting (large input) 4) High Optimizatio		n	4)Calssifica-	Testing
3) Pi camara 4) Raspberr y Pi Microcontr oller 13. 1) Genoty ping platforms 2) Sing nucleo tide variant (SNV) 3) paral lel sequen cing le sequen cing 3) Pi camara 4) Raspberr ent 4) Enhan ced Accuracy 1) Integrat ion of MPS 2) Populat ion specific platforms 3) High level testing (large input) 4) High Optimizatio		reactio	tion	process
4) Raspberr y Pi Microcontr oller 13. 1) Genoty ping platforms le nucleo tide variant (SNV) sequencing lel sequen cing 3) paral lel sequen cing 4) Enhan ced Accuracy 1) SNV 1) Integrat ion of MPS 2) Populat ion specific platforms 3) High level testing (large input) 4) High Optimizatio		n		3) Spec
y Pi Microcontr oller 13. 1)Genoty ping platforms 2)Sing le nucleo tide variant (SNV) 3) paral lel sequen cing le sequen cing Square sequen cing Square Squ		3) Pi camara		
y Pi Microcontr oller 13. 1)Genoty ping Mapping Platforms 2)Sing Multiplex le PCR nucleo tide 2)Massively variant (SNV) sequencing 3) paral lel 3) Data lel sequen cing (MPS) sequen cing (large input) 4) High Optimizatio ent 4) Enhan ced Accuracy 1)Integrat ion of MPS 2)Populat ion specific platforms 3) High level testing (large input) 4) High Optimizatio		4) Raspberr		equipm
oller ced Accuracy 13. 1)Genoty ping ping Mapping platforms 2)Sing le nucleo tide variant (SNV) 3) paral lel sequen cing le sequen cing Accuracy 1) Integrat ion of MPS 2) Populat ion specific platforms 3) High level testing (large input) 4) High Optimizatio		y Pi		
13. 1)Genoty ping Mapping ion of platforms : MPS 2)Sing Multiplex PCR ion specific platforms 2)Massively variant (SNV) sequencing lel 3) paral lel sequen cing sequen cing cing MPS 1) Integrat ion of MPS 2) Populat ion specific platforms 3 High level testing (large input) 4) High Optimizatio		Microcontr		4) Enhan
13. 1)Genoty ping Mapping ion of platforms : MPS 2)Sing Multiplex PCR ion specific platforms ide 2)Massively variant (SNV) sequencing lel 3) paral lel sequen cing cing (large input) 4) High Optimizatio		oller		ced
ping Mapping ion of MPS 2)Sing Multiplex 2)Populat ion specific platforms tide 2)Massively parallel 3) High level (SNV) sequencing lel 3) Data (large sequen cing cing 4) High Optimizatio				Accuracy
platforms 2) Sing Begin Multiplex PCR Discreption For tide PCR Discreption For tide PCR Discreption For tide PCR Discreption Amplification Specific Discreption Specific Platforms Parallel PCR Discreption Specific Platforms Parallel Polymarsively Parallel Parallel Polymarsively Platforms Platform	13.	1)Genoty	1) SNV	1)Integrat
2) Sing le Multiplex PCR ion specific platforms yariant (SNV) sequencing lel 3) Data lel sequen cing sequen cing cing PCR ion specific platforms 3) High level testing (large input) 4) High Optimizatio		ping	Mapping	ion of
le nucleo Amplification 2)Massively platforms 2)Massively platforms 3) High (SNV) sequencing 3) paral (MPS) testing lel 3) Data (large sequen cing analytics input) 4) High Optimizatio		platforms	:	MPS
le nucleo Amplification specific platforms 2)Massively parallel 3) High level (SNV) sequencing lel 3) Data (large sequen cing cing 4) High Optimizatio		2)Sing	Multiplex	2)Populat
tide variant variant (SNV) sequencing lel sequen lel sequen sequen sequen sequen analytics specific platforms 3) High level testing (large input) 4) High Optimizatio		_	-	_
variant (SNV) sequencing lel sequen analytics input) variant (SNV) sequencing level testing (large input) cing 4) High Optimizatio		nucleo	_	specific
(SNV) sequencing level 3) paral (MPS) testing large sequen analytics input) cing 4) High Optimizatio		tide		platforms
3) paral (MPS) testing lel 3) Data (large sequen cing 4) High Optimizatio		variant		3) High
lel 3) Data (large input) cing 4) High Optimizatio		(SNV)		level
sequen analytics input) cing 4) High Optimizatio		3) paral	1	testing
cing 4) High Optimizatio		lel		(large
Optimizatio		sequen	analytics	input)
Optimizatio		cing		4) High
n				
· · · · · · · · · · · · · · · · · · ·				n

4. OBSERVATION AND FINDING

A. Key issues and insights

Image Clarity: One challenge mentioned is improving image quality in order to improve accuracy.

Accuracy: Although the suggested system beats earlier systems, there is still potential for development, particularly in terms of error rates and accuracy [1].

The paper covers the use of fingerprint patterns, which are unique and consistent throughout a person's life, for personal identification and medical needs such as blood group determination [2].

The primary focus is on a non-invasive method for establishing blood types via fingerprint analysis, which eliminates the need for traditional blood tests that need needles. Sweat released by fingerprint ridges and grooves contains blood group-related proteins or antigens [2].

The blood group detection technology has potential uses in healthcare (rapid blood group determination in an emergency), forensics (victim identification in mass casualty situations), and disaster management. [2].

The study evaluates fingerprint patterns and associates them with blood types using machine learning techniques such as convolutional neural networks (CNNs) and other image processing algorithms. Feature extraction is accomplished utilizing techniques such as the Gabor filter, ridge frequency, and minutiae detection.

The system obtained a 62% accuracy utilizing machine learning methods such as Multiple Linear Regression with Ordinary Least Squares. Future research involves increasing the dataset and using more advanced models to increase accuracy [5].

Ongoing research in sensor technology, data analysis, and feature extraction is required to improve this method. Improvements in these areas may expand the use of fingerprint-based blood group detection in practical applications.[8].

B. Findings

When it came to determining blood types from spectroscopic images, the trained machine learning and deep learning model performed 95% of the time accurately [1].

The Scale-Invariant Feature Transform (SIFT), Oriented FAST, and Rotated BRIEF (ORB) algorithms were used successfully to extract different features from spectroscopic images. These enhancements significantly improved the model's accuracy and interpretability.

The suggested system utilizes spectroscopic imaging to provide a non-invasive solution for blood group identification, which can be used in place of existing blood typing procedures.

The system demonstrated robustness to fluctuations in image quality while maintaining excellent accuracy, making it appropriate for a variety of real-world medical contexts.

The machine learning and deep learning technology can be connected with electronic health records (EHR) to simplify patient care and improve clinical decision-making [2].

The machine learning and deep learning model's decision-making process is transparent, which gives

healthcare professionals more confidence in using the system for blood group prediction [2].

The machine leaning and deep learning technology has the potential for extensive use in medical diagnostics, notably in transfusion management, by automating and enhancing the accuracy of blood group detection [11].

This blood group detection using fingerprint images

approach could be expanded to predict other bloodrelated features, such as antibody screening and Rh factors, hence increasing its clinical relevance [6].

5. CONCLUSION

The research study examines various methods for detecting blood groups using fingerprint scans, emphasizing advances in machine learning, image processing, and biometric identification. Fingerprint-based blood group testing is a promising non-invasive alternative to established procedures that require blood samples. This strategy is based on the uniqueness of fingerprint patterns that remain consistent throughout a person's life. Machine learning methods, such as Convolutional Neural Networks (CNN) and multiple linear regression, have showed promise, but are currently constrained by accuracy, dataset size, and the need for more complex models.

While the proposed methodologies provide a low-cost and speedy solution for blood group detection, more research is needed to increase accuracy, reduce reliance on high-quality sensors, and broaden datasets. Future developments should concentrate on improving machine learning models, increasing fingerprint image quality, and connecting with electronic health record systems. This method could transform blood group detection in emergency situations and routine medical diagnostics, providing a speedier, less invasive procedure with applications in healthcare, forensics, and disaster management.

7. REFERENCE

- [1] Vijaykumar, Patil N., and D. R. Ingle. "A Novel Approach to Predict Blood Group using Fingerprint Map Reading." 2021 6th International Conference for Convergence in Technology (I2CT). IEEE, 2021.
- [2] D. Siva Sundhara Raja and J. Abinaya, "A Cost- Effective Method for Blood Group Detection Using Fingerprints," International Journal of Advance Study and Research Work, vol. 2, no. 3, pp. 1-10, March 2019, doi: 10.5281/zenodo.2591955.

- [3] S. Pimenta, G. Minas and F. Soares, "Spectrophotometric approach for automatic human blood typing," 2012 IEEE 2nd Portuguese Meeting in Bioengineering (ENBENG), Coimbra, Portugal, 2012, pp. 1-4, doi: 10.1109/ENBENG.2012.6331340.
- [4] Pimenta S, Soares F, Minas G. Development of an automatic electronic system to human blood typing. Annu Int Conf IEEE Eng Med Biol Soc. 2012; 2012:2712-5. doi: 10.1109/EMBC.2012.6346524. PMID: 23366485.
- [5] Ferraz, Ana. "Automatic system for determination of blood types using image processing techniques." 2013 IEEE 3rd Portuguese meeting in bioengineering (ENBENG). IEEE, 2013.
- T. Gupta, "Artificial Intelligence and Image [6] Processing Techniques for Blood Group Prediction," 2024 **IEEE** International Conference Computing, Power and on Communication Technologies (IC2PCT), Greater Noida, India, 2024, pp. 1022-1028, doi: 10.1109/IC2PCT60090.2024.10486628.
- [7] Ravindran, G., et al. "Determination and classification of blood types using image processing techniques." International Journal of Computer Applications 157.1 (2017): 12-16.
- [8] T. Nihar, K. Yeswanth, and K. Prabhakar, "Blood group determination using fingerprint," MATEC Web of Conferences, vol. 392, p. 01069, 2024, doi: 10.1051/matecconf/202439201069.
- [9] Dannana, S., & Prasad, D. Y. V. (2022). "Blood group detection using ML classifier". International Journal of Health Sciences, 6(S1), 4395–4408.

https://doi.org/10.53730/ijhs.v6nS1.5830

- [10] J. Sai Ganta, M. Rishitha, Y. Jaya Surya Pulivarthi, and M. Roopa, "Blood Group Detection Using Image Processing and Deep Learning," International Research Journal of Engineering and Technology (IRJET), vol. 11, no. 4, pp. 97-103, April 2024, doi: 10.17148/IJARCCE.2015.4123
- [11] M. R. Haque, S. M. T. U. Raju, M. A. -U. Golap and M. M. A. Hashem, "A Novel Technique for Non-Invasive Measurement of Human Blood Component Levels from Fingertip Video Using DNN Based Models," in IEEE Access, vol. 9, pp. 19025-19042, 2021, doi:10.1109/ACCESS.2021.3054236.

- [12] Banu, A. N., & Kalpana, V. (2018). An Automatic System to Detect Human Blood Group of Many Individuals in a Parallel Manner Using Image Processing. International Journal of Pure and Applied Mathematics, 118(20), 3119-3128.
- [13] Rhiannon S. McBean, Catherine A. Hyland, Robert L. Flower, Approaches to Determination of a Full Profile of Blood Group Genotypes: Single Nucleotide Variant Mapping and Massively Parallel Sequencing, Computational and Structural Biotechnology Journal, Volume 11, Issue 19, 2014, Pages 147-151, ISSN 2001- 0370, https://doi.org/10.1016/j.csbj.2014.09.009.