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An Innovative Non-Invasive Blood Group Detection Using Fingerprint Images

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Abstract

The determination of blood types is a crucial step in transfusion and diagnosis in the health sector. In this paper, imaging techniques coupled with deep learning algorithms are employed to automatically recognize blood groups. Connective Embedded with Scale Invariant Feature Transform (SIFT), Directional BRIEF and Rotated BARF (ORB) and spatial correlation of fingerprints using Gabor filters are applied to identify the distinguishing features of blood group as well as fingerprints images. The extracted features are then classified by Convolutional Neural Networks (CNNs). Also, fingerprint features are supplemented with ridge frequency and spatial features to further improve the determination of blood group. The framework consists of contrast enhancement and denoising techniques for image quality improvement, making it robust to image quality fluctuations. To increase model effectiveness and generalizability, transfer learning with VGG, ResNet, and DenseNet as base models is employed. Tested against different datasets, the method shows a good level of accuracy, consistency, and rate of success in recognizing blood types and discriminatory marks. This novel technique is fully automated. It could revolutionize the process of blood group and transfusions by allowing fast and accurate management of blood transfusions and patients.

Keywords: Determination of Blood Type; Image Recognition Systems; Deep Learning CNN Architectures; SIFT; ORB; Gabor Analysis; Fingerprinting; Models of Transfer Learning; VGG; Resnet; Densenet; Image Cropping and Scaling; Image Processing; Blood Transfusion Processes; Automatic Interpretation; and Treatment of Patients

Abbreviations

AI: Artificial Intelligence; CNNS: Convolutional Neural Networks; SIFT: Scale-Invariant Feature Transform; DL: Deep Learning; ML: Machine Learning; MATLAB: Matrix Laboratory; FAST: Face, Arm, Speech, Time BRIEF: Binary Robust Independent Elementary Features); ORB: Object Request Broker; AUC-ROC: Area Under The Receiver Operating Characteristic Curve; NIST-DB4: National Institute of Standards and Technology-Data Base 4.

Introduction

Identifying blood groups is an integral part of, for example, transfusion practices and emergency treatment procedures. There exists sufficient evidence to support the fact that

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manual assessment of blood samples is time consuming, requires surgical procedures and is still reliant on the possibility of making mistakes [1]. Development and incorporation of artificial intelligence (AI) techniques gained foothold in translational medicine especially the aspects of treatment and diagnosis more than a decade ago. It aimed at providing state of the art technologies that are both driven by ideas of automation and new approaches to the problem solving Pimenta S, et al. [1] and Fernandes et al. [2]. Medical image analysis in particular makes extensive use of Convolutional Neural Networks (CNNs) which are a part of deep learning in the recognition of complex patterns [3]. More so when combined with Scale-Invariant Feature Transform (SIFT), Oriented FAST and Rotated BRIEF (ORB) and Gabor filters, these models are good at recognizing and classifying blood groups from the images Phad AS, et al. [4]. Moreover, the analysis of a person's fingerprint can also be used to establish blood groups making it non-invasive and more accurate through the use of writing patterns and the composition of sweat antigens for blood typing Raja DSS, et al. [5] and Fathima S, et al. [6]. This could change the entire health industry since it allows for faster, more automated, less prone to errors and precise blood group classification.

Machine learning is usually classified into three categories: supervised, unsupervised and semi-supervised learning. Supervised ML is based on training algorithms for tasks such as classification and regression, with the aid of labelled datasets [7]. Supervised learning is mainly associated with neural networks and various tasks, such as text categorization or image identification, price prediction or spam detection [8]. On the contrary, unsupervised ML works with unlabelled sets of data that are employed to devise means to cluster and associate the given data, which is very useful in market segmentation, image compression, and even recommendation systems Saqer A, et al. [9]. Semi-supervised learning takes advantage of both labelled and unlabelled data to improve the models, particularly when the labelled data, e.g. about pneumonia detection, is difficult to source Araj A, et al. [10]. Self-training and consistency regularization are some examples of strategies that improve the efficiency of the model in important tasks such as chest X-ray analysis, when adequate labelled data is not possible to obtain Massri A, et al. [11] and Madhoun A, et al. [12].

Deep learning (DL), the new generation of machine learning (ML), handles data automatically by feature extraction using multiple hidden layer's perceptron, outperforming standard ML in tasks such as remote sensing images classification and autonomous driving Mubayyed OM, et al. [13]. Despite the fact that DL models use large amounts of computational resources, they are able to permit the extra training time on complex applications Shawwa M, et al. [14]. CNNs, a family of deep learning models is highly suitable for image and language related tasks. CNNs are applied to an unprocessed image; therefore they do not require considerable preparation, making them suitable for age and gender classification and medical image interpretation [7,8].

The combination of semi-supervised learning and deep learning seems to be quite helpful in the fight against pneumonia. The review of semi supervised methods by targeting the chest X rays is said to be effective in improving them, while, with CNN, the medical imaging is feasible with little or no pre-processing steps [7,11]. Models based on such architecture have to be appraised on parameters such as precision, sensitivity, AUC-ROC or similar ones so as to ensure that the model performance has a reasonable value when applied in practice Mobayed AA, et al. [15]. As a result, while utilising semi supervised and deep leaning algorithms to develop the area of medicine's diagnosis, it is not necessary to deal with quantitative and qualitative issues encountered with labelled datasets.

Materials and Methods

The materials and methods for the study on blood group detection using fingerprint images combine hardware, software and laboratory techniques. The materials comprise high resolution fingerprint sensors that capture fingerprint images and some reagents like anti A, anti B and anti D sera for conventional blood typing when needed [1]. Spectrophotometers or microfluidic devices are employed for agglutination detection based on optical properties [1,2]. A raspberry pir or another microcontroller type is used for coupling hardware parts and for data handling tools for analysis of information such as Python, MATLAB and ML tools like TensorFlow or PyTorch Phad AS, et al. [4]. Albeit being important for ensuring the performance of the model, the fingerprint images containing blood groups indicated on them were critical for training and testing the model [2,5].

The process starts with capturing fingerprint pictures via fingerprints scanners which are of sufficient quality for feature extraction purposes Ali MMH, et al. [16]. The obtained images go through some image pre-processing techniques like histogram equalization, noise suppression and edge enhancement to improve quality [3,4]. Ridge density, minutiae, and wavelet transforms are all considered while using image processing techniques [4]. The features are then utilized to train machine learning models such as convolutional neural networks (CNNs) or Siamese neural networks for the purpose of blood type classification [2,17]. For more efficient analysis microfluidic devices are used to depurate the blood sample, agglutination is then detected by spectrophotometers through transmission measurements at determined wavelengths [1,18].

Using metrics like accuracy, precision and recall model is trained and tested on annotated datasets [3]. The proposed system is tested to provide a real-time blood group detection method proven by the accuracy and reliability as compared with versatile conventional methods [1,5]. The approach combines novel image-processing and machine learning approaches with conventional spectrophotometric methods to devise an automated, low cost technique of blood group detection [1,2].

Blood group detection is significantly improved by incorporating the techniques of machine learning, image processing, and feature extraction. Techniques like CNNs have been heavily in use for the blood group categorization with feature extraction techniques such as oriented FAST, rotated BRIEF (ORB) and scale-invariant feature transform (SIFT) for efficiency and accuracy purposes Mansi K, et al. [19]. It serves as a novel method for blood group detection. Gabor filters analyse unique ridge patterns for obtaining an estimate of ridge frequency. It enhances the chances of fingerprint matching Odeh N, et al. [20]. Such methods overcome the shortcomings of the traditional methods like automatic identification of blood groups, reducing the error rate, and thus it becomes reliable Banu N, et al. [21].

The proposed approaches depend on pre-processing techniques such as enhancing the image quality using contrast and noise removal operations. Then, it exploits the discriminative features obtained through algorithms like SIFT and ORB from these models of CNNs in correct classification of images Talukdar M, et al. [22]. The hybrid approach improves transfusion management and patient care with the speedy and accurate analysis of blood groups Keerthana D, et al. [23]. Moreover, with this evolution, it has become possible to automate the process of identifying blood types, thus saving precious time in emergencies, and avoiding universal donor transfusions and risks associated therewith Ferraz A, et al. [24].

Fingerprint-based blood group detection is a non-invasive approach to traditional methods. From antigens present in sweat, it is possible to make an inference of the individual's blood type, especially useful for sensitive populations towards needle-based procedures Alshehri H, et al. [25]. Latent fingerprint recognition using deep learning is another example of the applicability of CNNs, showing exceptional accuracy even when dealing with incomplete datasets [26]. Deep learning is fundamental towards the enhancement of a classification's accuracy and robustness regarding fingerprint images. 95.9% on NIST-DB4 achieves CNN classification accuracy according other innovations in this area include applying Siamese neural networks in fingerprint recognition for issues of algorithmic complexity and cross-platform compatibility. This has already reached a maximum accuracy of up to 92% [17]. Wavelet transforms are also implemented in the enhancement of the quality of fingerprint images, and gender and blood group prediction is feasible with pixel calculation [27]. The adoption of MATLAB programming and advanced image compression techniques enhances the quality of results, enabling reliable detection to Shrei JM [28].

More developments also occur in the form of applying Siamese neural networks in fingerprint recognition to overcome some complexities in the algorithm and its compatibility with cross-platform; it can attain up to 92% accuracy, according to Zihao Li, et al. [17]. Wavelet transformations are further used in quality improvement on the fingerprint images with capabilities for gender and blood group predictions using pixel calculations, as described in Mondal M, et al. [27]. The use of MATLAB programming combined with advanced compression on images results in high-quality output with reliable detection.

Finally, the integration of machine learning with intelligent image processing techniques has led to automated systems that can achieve very high accuracy in blood group detection. These systems are adaptive across the varied image datasets and have been shown to be capable of improved transfusion practices and diagnostic reliability [29]. Such technologies will revolutionize medical diagnostics as they come with speed, precision, and scalability in blood group determination.

Results and Discussion

Novel techniques of this nature have shown several pertinent advances in the identification process of blood groups. Spectrophotometric methods have had high utility in the analysis of agglutination because they are very specific and allow for the full automation of the blood typing processes, reducing human error during this process and being convenient for laboratory use [1,2]. With cost-effective and portable solutions such as Raspberry Pi-based systems and basic image processing techniques, blood typing can be made accessible even in resource-limited settings, enhancing outreach in healthcare [4]. Methods of image processing have also shown great potential in the analysis of blood samples with high accuracy when combined with artificial intelligence models like convolutional neural networks [3,6]. These methods have streamlined the process, speeding it up and making it accurate. The latest of the non-invasive prediction techniques for blood groups includes fingerprint analysis.

Several studies have established a correlation between fingerprints and blood groups, and therefore, it is feasible to conduct preliminary screening based on this relationship [30,31]. Other advanced techniques, which include minutiae matching and fingerprint image enhancement, have also enhanced the reliability of these systems [16,32]. Some applications of deep learning include the use of Siamese neural networks and autoencoders that enhance the precision and reliability in predicting blood group from fingerprints [17,32]. Novel techniques of this nature have shown several pertinent advances in the identification process of blood groups. Spectrophotometric methods have had high utility in the analysis of agglutination because they are very specific and allow for the full automation of the blood typing processes, reducing human error during this process and being convenient for laboratory use [1,2].

Even though these technologies have much to offer in revolutionizing the process of detecting blood groups, research goes on for fine-tuning these systems to make sure that they are applicable for people from diverse populations and for getting over the limitations that are present. The cumulative findings pave the way to more accessible, accurate, and efficient blood typing methodologies both in clinical and non-clinical settings [1,29].

Future Prospects

Blood group detection and related technologies possess great promise for the future. This is particularly with imaging and artificial intelligence as well as cost-effective technologies. More so, their future offers a lot of promise because studies such as those from Fernandes J, et al. [1] and Pimenta S, et al. [2] suggest that automatic blood typing combining spectrophotometry with image processing can be developed to increase speed and accuracy. Further, application of machine learning, specifically models like deep learning-CNNs and Siamese networks, would be expected to revolutionize the accuracy of blood group prediction even using information like fingerprints [17,32-39]. It will therefore lead to the development of more sophisticated and efficient diagnostic apparatuses which can identify not only blood groups but health information as well.

Future costs will also be dominated by cost-effective solutions. Even in low-resource settings, blood typing will be possible. Low-cost technologies are promising, for example, Raspberry Pi-based systems. Further miniaturization may make such devices available for use in everyday situations [4]. As these systems evolve, they could lead to portable, self-contained blood typing kits that integrate AI and sensor technologies to provide fast, accurate results in emergency or remote settings. More importantly, cross-applying fingerprint recognition with health data opens exciting possibilities for personalized health monitoring where one device can assess blood type, monitor health status, and predict potential risks [29].

The future is in reliability-enhanced fingerprint and image-matching techniques, universal blood typing devices in which several types of sensors are embedded, and AI in real-time diagnostic systems. These are all aimed at the enhancement of accuracy in blood typing, making it accessible, affordable, and versatile, changing the medical diagnostics landscape and the practice of personalized health management [1,2].

Conclusion

The deep learning and image processing technology-based blood group identification systems have represented a big leap in non-intrusive diagnostic methods. Advanced feature extraction techniques, such as SIFT, ORB, and CNNs, proved highly efficient for the accurate determination of blood types from spectroscopic images and provide an alternative for the traditional blood typing method. The intuitive design of the system, ease of integration with laboratory information systems, and potential for future enhancements make this a valuable tool to health professionals; hence, there's seamless workflow integration as well as improved management of data. Future developments in this area will include adding predictions for blood-related traits such as screening and detection of the Rh factor that transform the system into an overall blood analysis tool. Interconnection with HER would further expand the clinical decision-making and improve the management of patients' information, thus making it easy to refer to and update blood type to the patient's total medical history.

This would improve the interpretability of the CNN model while improving transparency in its decision-making process, thus increasing trust and confidence among doctors in collaboration with the system. As time advances, more contribution from the system in relation to better patient outcomes, better healthcare decisions, and further insight into blood-related diseases and traits is quite apparent.

Another layer of innovation for this technology is provided by the deep learning technique of fingerprint and blood group correlation, especially CNNs. Some of the examples of increased applications in machine learning include algorithms like fingerprint matching for blood group detection. Deep learning and data integration enhance the overall effectiveness of identification technologies of blood groups, as well as system interpretability.

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