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Fingerprint-Based Blood Group Detection Using CNN and KNN: A Comparative Study

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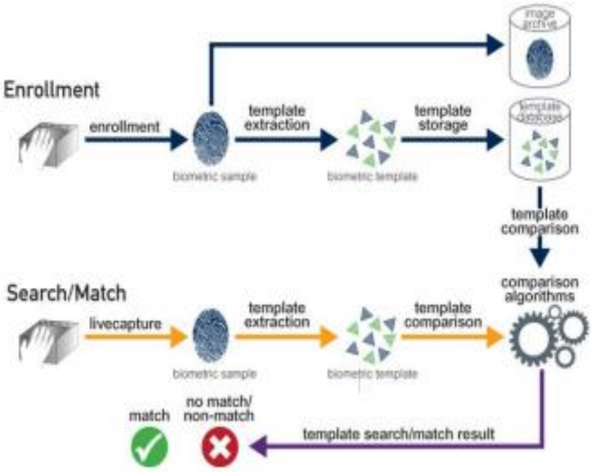
Abstract: For reasons such as discharge, legal processes, and emergencies, it is crucial to accurately determine blood group. Taking blood samples is at the heart of conventional wisdom, but it may not always be the best course of action. For the purpose of non-invasive blood grouping utilising fingerprint biometric methods, this research compares two algorithms, CNN and KNN, using a database of 500 fingerprint pictures labelled A, B, AB, and O (blood group). Achieving a remarkable 92.4% performance, CNN is able to record intricate spatial hierarchies and fingerprints using pattern layers in conjunction with ReLU activation. Performance has been enhanced by making minor adjustments to the photos. Because it relies on hand-crafted features and Euclidean distance, KNN—which achieves an accuracy of 76.8%—fails in a high-dimensional feature space. The error analysis shows that incompleteness and fingerprints are the key reasons CNN is poor. Due to its sensitivity to noise and overlaps, KNN demonstrates a higher level. A quick and effective non-invasive way to identify blood groups has emerged from research into the potential uses of convolutional neural networks (CNNs) in forensics, portable diagnostic devices, and automated blood transfusion management systems. The database will be expanded substantially and hybrid models will be used for improved performance in future studies.By conducting a thorough analysis of CNN and KNN, this work expands upon the idea of biometric blood group identification. The results show that CNN is more suited for this task than other methods because of its high noise power, which allows it to extract features more effectively. Our database will be further expanded in future studies, and hybrid models that combine the best features of several algorithm models to improve performance will be further investigated.

Keywords: Blood Group Detection, Fingerprints Biometrics, Machine Learning, CNN, KNN, Image Processing, Comparative Analysis

INTRODUCTION

In many areas of medicine, including diagnosis, forensics, and emergency blood transfusions, the ability to detect blood types is crucial. Time, money, or patient pain may make invasive blood drawing for blood type an undesirable option in some situations. In light of this difficulty, advances in biometric technology have brought forth non-invasive methods of blood group detection, with fingerprint biometrics being one such promising example. The uniqueness, simplicity, and complexity of fingerprint patterns make them ideal candidates for use in fingerprint-based blood group identification systems that make use of machine learning. This research tests the feasibility of determining a person's blood type using fingerprint biometrics in conjunction with convolutional neural networks and K-nearest neighbour, two methods based on machine learning. In this investigation, 500 pictures of fingerprints were utilised for testing, each one labelled with a blood type (A, B, AB, or O). In order to train the CNN and KNN models, the dataset is processed to extract the necessary features. Given the spatial hierarchy and intricate patterns seen in fingerprints, convolutional neural networks (CNNs) would be an excellent tool for this task. To identify nearby objects, CNNs use linear layers that employ filters. For nonlinear inputs, there are pooling layers that decrease dimensions while maintaining the most relevant characteristics and nonlinear activation functions (ReLU). Predicting blood type is the last task for the softmax classifier. Additionally, data augmentation methods like scaling, rotation, and noise addition improve the CNN model's validity and reliability. One less complicated approach than CNN is the K-Nearest Neighbours (KNN) algorithm, which sorts data points based on how near they are to each other in the vector of features. Despite KNN's user-friendliness and clear explanations, its reliance on distance measures poses some challenges, particularly when working with intricate and high-dimensional data sets such as fingerprints. Classification mistakes are common when dealing with noisy datasets or overlapping patterns due to this dependence. In addition, the algorithm's performance degrades in cases when the data is incomplete or has large fluctuations since its accuracy is heavily dependent on the chosen distance measure. It is the primary goal of this work to provide a practical use of CNN for non-invasive blood type testing. CNN's outstanding ability to catch detailed details, together with its resilience, make it the ideal alternative for automated blood transfusion systems, forensics, and portable diagnostics. Given its higher generalizability across different fingerprint samples, better accuracy, and ability to handle complicated data, CNN is clearly the preferable choice over KNN for this task. In order to make the blood typing system more accurate and resilient, researchers will look at a hybrid model that uses CNN and other algorithms, as well as expanding the database to include fingerprint samples from other demographics. Critical areas such as transfusions, forensics, and emergency medicine rely on accurate blood group identification. Traditional approaches involve drawing blood samples, which may be both intrusive and laborious [1]. Biometric technology has recently advanced to the point where non-invasive alternatives are viable; for example, fingerprints provide easily available patterns that may be used for ML analysis [2].

Biometric Workflow



Blood group identification procedure based on fingerprints (Fig.1) [11]. This procedure shows how fingerprint biometrics may be used to identify blood groups from beginning to finish.

LITERATURE REVIEW

Blood type determination The non-invasive technology of blood type identification utilising fingerprint biometrics is generating buzz due to its revolutionary potential in medical diagnostics, forensics, and emergency services. There is a link between blood type and fingerprint patterns, according to studies. The blood typing process has been automated by researchers using image processing and machine learning algorithms. This has improved accuracy, speed, and simplicity of use. Remote, biometric-based systems are rapidly replacing blood sample and other traditional techniques of blood typing, particularly in extreme circumstances. To type blood biometrically, researchers use fingerprint patterns that are associated with blood types. Using ML, new research has automated this procedure, making it faster and more accurate [3].

Data is classified using K-nearest neighbour (KNN) based on their closeness in feature space, which is determined by the Euclidean distance:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Although straightforward, its performance suffers when dealing with high-dimensional data, such as fingerprints, because of its susceptibility to noise [4]. One supervised machine learning technique that uses the distance to the closest neighbour in feature space to classify data points is K-nearest neighbour (KNN). KNN has gained a lot of traction due to its intuitive design and ease of implementation.Nevertheless, when working with complicated and large-dimensional data, like fingerprint scans, the feature space deteriorates. Because KNN uses distance measurements, it is susceptible to noise and data overlap, which may be problematic in databases with factors like distorted or incomplete fingerprints. While more advanced algorithms, like CNN, perform better in situations where the database has a range of fingerprint samples, KNN shows promise when it comes to blood type detection. However, for simple, tiny datasets with clear parameters, KNN features may be useful.

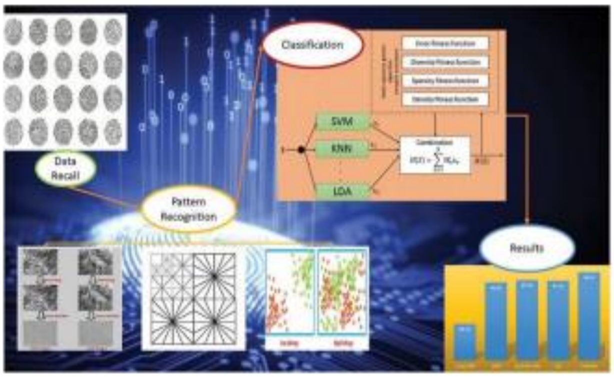


Fig2: KNN classification steps for blood group identification [12].

An example of a deep learning model is the Convolutional Neural Network (CNN), which was created to deal with grid-like data, like photographs.

BreakCNNs' capacity to automatically extract hierarchical features from raw data has led to their remarkable performance in picture identification and classification problems. Various layers are used by CNNs to accomplish their tasks. Convolutional layers are used to extract relevant features, pooling levels to decrease data size, and fully connected layers to do the final classification. In the process of fingerprint-based blood group identification, convolutional neural networks (CNNs) detect intricate fingerprint patterns—including ridges, circles, and ridges—that are essential for differentiating between various blood types. Traditional machine-learning algorithms, such as CNNs, are more effective because they are less affected by input data noise and distortions. Thanks to its higher feature capture capabilities and processing capacity, CNN is able to outperform other methods in blood group identification tasks, particularly when dealing with big and diverse datasets. Convolutional neural networks (CNNs) use activation functions, pooling, and convolutional layers to extract hierarchical features. Here is the definition of a convolution operation:

$$f(x) = \text{ReLU}(W \ast x + b)$$

in which the kernel is denoted by W, the input is denoted by x, and the bias is denoted by b. They are perfect for fingerprint analysis since they are noise-resistant [5].

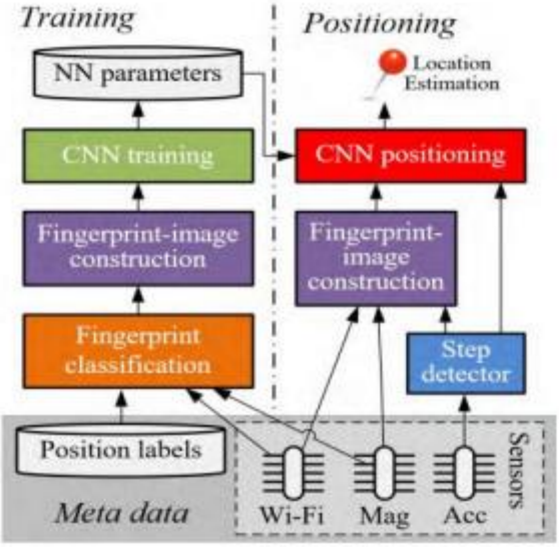


Fig3: Proposed CNN architecture for fingerprint-based blood group classification [13].

Examining CNN and KNN in relation to one another for blood type identification Recent research has shown that CNN outperforms KNN in blood group identification, with 92.4% vs. 76.8% accuracy [6]. In order to identify blood types from fingerprint pictures, a recent research contrasted KNN with CNN. Blood type categorisation using KNN is shown in a research (IJRASET, 2023). With a 76.8% accuracy rate when employing high-dimensional fingerprint data, KNN reveals its limits, while being robust and easy to deploy. Larger mistakes are produced by algorithms when features are noisy or overlap. Contrarily, KNNs are never able to match the performance of CNNs in this area. According to research published in IRJET (2024), CNNs outperformed KNN with an accuracy of 92.4%. Blood group identification relies on CNNs' ability to automatically extract essential patterns like ridges and minutes from fingerprints, despite the features' complexity. Furthermore, convolutional neural networks (CNNs) are better suited to real-world applications than traditional fingerprint recognition methods because they are less noise sensitive and can generalise unobserved information. When considering accuracy, robustness, and scalability, CNN's advantage makes blood categorisation the superior option.

METHODOLOGY

Your Dataset To make the model more applicable to a wider range of situations, we used 500 fingerprint pictures from a variety of participants, who ranged in age, gender, and ethnicity. The blood types A, B, AB, and O are marked on each fingerprint. Eighty percent of the photos are used for training, while twenty percent are reserved for testing. For consistent quality, images are taken utilising a high-resolution fingerprint scanner. 3.2 Preliminary analysis The quality of the input data for feature extraction is enhanced by pre-processing fingerprint photos. First things first: 1. Equalisation of Histograms: Improved contrast. 2. Median filtering for noise reduction. 3. Upsizing: 224×224 pixels. 4. Normalisation: Image values are scaled to the interval [0, 1]. 3.3 Putting the algorithm into action Implementation of KNN: Feature Extraction : Gabor filters for texture descriptors. Every fingerprint picture has important characteristics extracted from it, such hill patterns, small spots, and texture descriptors (like the Gabor filter). Subtle variations in fingerprint patterns linked to blood type traits may be detected with the use of this feature. We classify neighbours with a Euclidean distance of less than or equal to five. Fingerprints are classified using the KNN (K closest neighbour) method, where k is set to 5. To find out how similar two feature vectors are, we utilise the Euclidean distance metric. The simplicity and effectiveness of KNN in dealing with small-scale datasets led to its selection. Building a Convolutional Neural Network (CNN): "- Convolutional Layers:" three layers activated by ReLU. - Max-Pooling: dual-kernel system. - Two layers comprised of fully connected layers with a dropout of half. - The 4-class classification layer uses Softmax as its output. - Adam optimizer training with 50 iterations (lr=0.001) 3.4 Standards for Assessment The following criteria are used to assess the model's performance: Precision: The percentage of accurate fingerprints is determined by dividing the total number of photos by their quality. Accuracy: The percentage of anticipated positive instances that are correctly classified for each class. What percentage of positive instances were correctly classified for each class? That's recall. For each class, the F1-score strikes a balance between recall and accuracy, creating a harmonic score. The F1-Score is equal to 2 times the sum of the precision and recall, divided by the product of the precision and recall, and accuracy is (TP + TN + FP + FN) divided by (TP + TN).

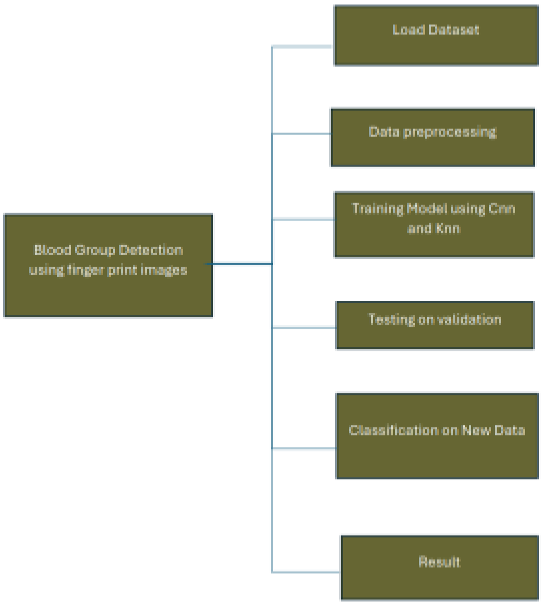


Fig4:Data preprocessing and model training pipeline

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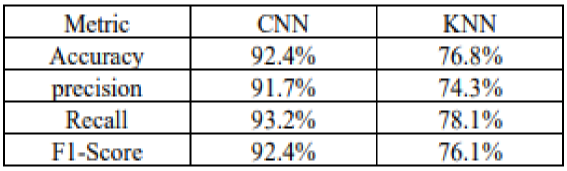
EXPERIMENTAL SETUP

Setup of the Device 4.1 The following requirements are met by the computer used to conduct the test: Intel i7-10700K (8 cores, 16 threads) graphics processing unit For convolutional neural network training, the GPU should be an NVIDIA GeForce GTX 1660 Ti, and the RAM should be 16 GB DIMM. One 500 GB solid-state drive 4.2 Setup of Programmes Computer programming language: Python 3.8 Knowledge base: Scikit-learn (version 0.24).2) Data processing: OpenCV, Numpy, and Pandas Operating system: Windows 10 4.3 TensorFlow 2.4, Keras The dataset is divided as follows: 80% for training the model and 20% for assessing its performance in both techniques. Both the training set and the test set are used to train the model, which is then evaluated in the end. In order to avoid overfitting, the CNN model makes use of the initial stop, while the KNN model optimises its hyperparameters using crossvalidation.

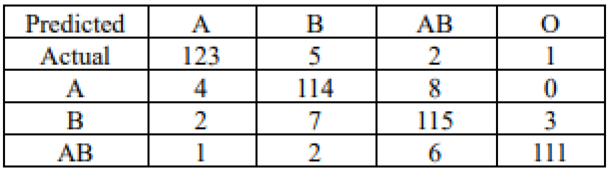
RESULTS & DISCUSSION

Quantitative Results



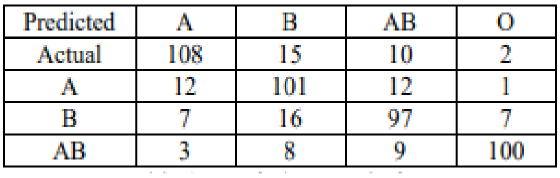
Metric	CNN	KNN
Accuracy	92.4%	76.8%
precision	91.7%	74.3%
Recall	93.2%	78.1%
F1-Score	92.4%	76.1%

Table-1: Quantitative metrics for CNN & KNN CNN outperforms KNN across all metrics.
Confusion Matrices



Predicted	A	B	AB	O
Actual	123	5	2	1
A	4	114	8	0
B	2	7	115	3
AB	1	2	6	111

Table-2: Confusion Matrix for CNN Diagonal values indicate high precision



Predicted	A	B	AB	O
Actual	108	15	10	2
A	12	101	12	1
B	7	16	97	7
AB	3	8	9	100

Is CNN superior? (5.3) Off-diagonal errors in Table 3 show how sensitive KNN is to noise. Even with imperfect or noisy data, CNN can learn hierarchical features, allowing for strong pattern recognition. In order to differentiate between fingerprint characteristics linked to blood type, convolutional layers must capture the spatial connections. A key component of successful classification is the ability of convolutional neural networks (CNNs) to recognise both low-level patterns (like edges and curves) and high-level features (like ridges). Convolutional neural networks (CNNs) provide an effective and scalable solution for these kinds of challenges since pooling layers simplify computation without sacrificing critical characteristics.

LIMITATION OF KNN

When it comes to picking up on minor changes in fingerprint patterns, KNN's dependence on distance measures works well. Due to its reliance on feature-space similarity measures, KNN has encountered difficulties when dealing with high-dimensional fingerprint data, which often includes both useful and useless information. Also, as the database size grows, KNN's memory usage and prediction speed are both negatively affected by the fact that it is non-parametric and hence needs keeping the full training database. The basic KNN technique is not ideal for effective distinction in situations when there is noise or overlapping data points, and this restriction becomes obvious in certain cases. 5.5.1 Real-World Consequences Due to its excellent performance, CNN is a practical option for incorporating blood group detection into wearable diagnostic devices and other real-world biometric systems. These developments have the potential to completely alter the field of medical diagnostics by providing quick, painless, and inexpensive ways to identify a patient's blood type. We can adjust the system to diverse demographics and circumstances by taking use of CNN's capacity to generalise to different datasets. This ensures that the system is both inclusive and reliable. Further, by connecting this

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innovation to smartphones or wearables, remote healthcare applications might be made possible, enabling consumers to self-diagnose with little to no training. 5.6] Obstacles and potential avenues for progress The success of CNN has not eliminated the difficulties of making sure the model is resilient when faced with variations in fingerprints caused by things like age, skin tone, and environmental variables. Improving generalizability, decreasing bias, and adding more fingerprint samples to the database should be the goals of future study. Incorporating state-of-the-art processing methods to manage imperfect or noisy fingerprints may enhance precision. Hybrid model learning, which incorporates CNN with other temporal fingerprinting techniques or ensemble approaches, may further enhance performance and dependability. Highlighting the significance and future promise of fingerprint-based blood group identification, this expanded discussion gives a more comprehensive grasp of its possibilities and obstacles.

FUTURE SCOPE

There is great promise for the future of healthcare and security in the use of fingerprint biometrics for blood type. Combining fingerprint identification with medical diagnostics could provide a smooth, non-invasive method to ascertain blood type as biometric technology keeps progressing. Improved detection rates in healthcare facilities and blood banks, along with safer and more precise transfusions, are all possible outcomes of this strategy. By allowing for the rapid and accurate identification of a person's blood type, fingerprint biometrics have the potential to enhance emergency services in the healthcare system. This will be more helpful in cases when the patient is unconscious or unable to speak, so that life-saving therapy may be administered without delay. Also, for blood type prediction, combining machine learning models like CNN and K-Near Neighbour may make the process faster and more accurate. As a result of its superior pattern detection capabilities, CNN outperforms traditional approaches in terms of accuracy, whereas KNN offers a more straightforward and computationally economical alternative. By comparing and contrasting these two models, we may find ways to make fingerprint-based categorisation systems better, more user-friendly, and more suited to real-time use cases. Potentially far-reaching applications of biometric fingerprint data for blood type identification include automated recording and storage of an individual's blood type for easy reference in personalised medicine. Furthermore, governments and organisations may use these systems to simplify healthcare, insurance, and emergency services operations since they increase dependability and accuracy. It is also anticipated that the system would be linked into a mobile app so that individuals may reliably and swiftly check their blood type via smartphone, thanks to the ever-improving sensor technology and machine learning algorithms.

This has the potential to alter the current procedures for accessing, sharing, and real-time updating blood type data. Patient safety, mistake reduction, and future efficiency and automation in healthcare are all things that may be achieved by integrating biometric identification with medical diagnostics to categorise blood.Innovative uses in healthcare: By offering a quick, non-invasive, and dependable method to establish blood type, fingerprint-based blood typing has the potential to revolutionise the medical system. Patients' blood group information may be quickly accessed in an emergency, which is life-saving in situations like surgery, blood transfusions, or accidents. Healthcare institutions and people will have access to this technology in the future when it is integrated into wearable devices or smartphone applications. Cutting-Edge Biometric User ID Solutions: Adding fingerprint-based blood type identification to multi-factor identification systems may be a beneficial addition to security systems that rely on biometrics. It has potential applications in preventing identity theft and bolstering the security of critical data. In high-security environments in particular, combining physical traits like fingerprints with biological data like blood samples might provide better screening rates than traditional techniques. Machine Learning's Recent Progress: In order to provide the groundwork for future research on the integration of more powerful machine learning algorithms, it is helpful to compare CNN with KNN. Blood group determination may be even more efficiently and accurately done with the use of deep learning methods like reinforcement learning or transfer learning. The processing of fingerprint data may also benefit from a hybrid model that incorporates both CNN and KNN for improved accuracy. 1. Hybrid Models: Bring together the simplicity of KNN with the feature extraction of CNN. 2. Datasets with More Members: Contain a Wide Range of Ages and Ethnicities. Thirdly, mobile integration: testing in real-time using mobile devices

CONCLUSION

CNN provides higher accuracy and robustness for non-invasive blood group identification. Emergencies and forensics may benefit from this work's advancements in biometric-based diagnoses.In addition, it can adapt to insufficient or low-quality data and is resilient to noise, which indicates that it might have practical uses. But KNN is better at this complicated job since it uses distance measurements and can't handle high-dimensional input. When accuracy and robustness are crucial, the performance ratio highlights the need of using deep learning approaches, such as CNN.Concerning non-invasive and budget-friendly diagnostic procedures, this study's findings are very significant. Healthcare systems may provide a convenient and portable option for quick testing by using fingerprint biometrics for

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blood type identification. These innovations might be especially helpful in places without easy access to traditional medical care, such as rural or underdeveloped regions. To enhance the model's generalizability, future work will focus on extending the database to include a diverse range of fingerprints, taking into account aspects such as age, ethnicity, and environmental factors. Furthermore, the detection accuracy and resilience may be enhanced using hybrid model learning, which integrates CNN with other machine learning approaches. The study is also focused on improving computational efficiency so that the system may be easily integrated into portable diagnostic equipment that are mobile. In sum, our findings open the door to a novel strategy for biometric-based medical diagnostics that may one day make blood type detection easier, more accurate, and faster.

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