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Thumb Fingerprint-Based Blood Group Prediction Using Starfish Optimized Temporal Fusion CNN

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ABSTRACT: Thumb Fingerprint-based Blood Group (TFPBG) prediction is a non-invasive method that blends biometric technology with medical data. This study presents a novel biometric-based framework for predicting blood groups using thumb fingerprint patterns. The Finger Print Based Blood group dataset is given to pre-processing using an Adaptive Gaussian Filter (AGF) to enhance fingerprint quality by reducing noise while preserving critical edge features. Feature extraction is then performed using Rotation Invariant Local Binary Pattern (RI-LBP), a texture descriptor that effectively captures micro-patterns with resilience to rotational variations, ensuring robustness against inconsistent finger placement. The extracted features are subsequently processed by a Temporal Fusion Convolutional Neural Network (TFCNN), which models both spatial and sequential dependencies through multiple convolutional layers to achieve precise blood group classification. Additionally, optimize model, the Starfish Optimization Algorithm (SOA) is employed for hyper parameter tuning, inspired by the regenerative and adaptive behaviours of starfish, enhances the performance. Using Python software, the proposed framework achieved higher accuracy of 95%, F1-score of 95% and recall of 95%, precision of 96% is accomplished when compared to other techniques. The integration of advanced pre-processing, rotation-invariant feature extraction, deep temporal learning, and bio-inspired optimization yields a reliable and accurate system for blood group prediction based on thumb fingerprint.

Keywords: Thumb Fingerprint, Adaptive Gaussian Filter, Rotation Invariant Local Binary Pattern, Temporal Fusion Convolutional Neural Network, Starfish Optimization Algorithm.

1. Introduction

In today's world security and personal identification, biometric systems have emerged as a crucial technology due to their reliability and effectiveness in accurately identifying persons [1]. TFPBG prediction technique use distinctive patterns in a person's fingerprints to identify their blood type, which is a crucial medical point for medical practitioners [2]. Fingerprints are a perfect option for associating particular person with personal medical information, such as blood type, due to their durability and uniqueness. Sweat produced by sweat glands in the ridges and grooves of the fingertips contains proteins or antigens associated with a person's blood type, which are the basis for blood group identification using fingerprints [3]. The ABO and Rh blood group systems are represented by these antigens. One determines a person's blood type by examining the makeup of these antigens in their perspiration [4]. Whereas, conventional blood tests that involve taking blood with needles, TFPBG identification is more pleasant because it

is non-invasive and painless. However, the procedure becomes less intrusive and more convenient using TFPBG detection [5]. These technology supports expedite medical operations, enhance patient care, and speed up emergency medical responses particularly knowing a person's blood type [6]. Fingerprint recognition is widely used in biometric identification, especially in access control and security systems, given the uniqueness and long-lasting stability of fingerprint patterns that are specific to each person throughout their life [7].

The raw images from the original dataset are pre-processed by some of the following techniques. Thumb Fingerprint image is processed using the pre-processing technique such as, Discrete Wavelet Transform (DWT). DWT effectively captures ridge details, edge information, and textural features crucial for distinguishing patterns that correlate with different blood groups. Nevertheless, poor-quality fingerprint images with smudges or incomplete ridge patterns effect in inaccurate extraction [8]. Consequently, Gabor Filter (GF) is utilized to enhance and isolate ridge patterns that correlate with specific blood groups. GF effective for the orientation and frequency characteristics of fingerprint ridges, which are critical for identifying subtle patterns that serve as indicators for blood type. Yet the performance of GF heavily depends on the selection of filter parameters such as frequency, orientation [9].

Additionally, data augmentation in TFPBG is used to expand the dataset by modifying fingerprint images through operations such as rotation, scaling. Models trained on augmented data are better at handling unseen data and variations in fingerprint input. Nevertheless, generating and managing large augmented datasets increase storage needs and processing time during training [10]. Furthermore, to filter the TFPBG the pre-processing technique such as Bloom Filter is utilized [11]. Bloom filter is suitable for handling large-scale biometric databases due to low memory footprint and fast operation. Yet, the accuracy and performance of Bloom filter heavily depend on the choice and number of functions used. To overcome the above limitation proposed AGF based pre-processing technique is utilized to remove unwanted noise and preserve edges from TFPBG for further Processing.

The thumb fingerprints from blood groups are classified by some of the following techniques. In existing method, to classify the thumb fingerprint from the blood group Convolutional Neural Network (CNN) with adaptive interpretable recognition is utilized. The adaptive interpretable recognition enhancement allows the CNN model to dynamically focus on discriminative fingerprint regions and provide its predictions. CNNs have proven effective in classification, and high accuracy in thumb fingerprint-based blood group prediction. Nevertheless, CNNs struggle with noisy, smudged, or partial fingerprints unless carefully pre-processed and augmented [12]. Additionally, incorporates MobileNet with SVM to discriminative fingerprint features from thumbprint images. The output convolutional layer is then passed to an SVM classifier, which performs the final blood group prediction. MobileNet extracts high-quality features from fingerprint images using depthwise separable convolutions, reducing redundancy. Nonetheless, MobileNet sometimes overlook very fine fingerprint details, which affect prediction accuracy for highly similar patterns [13].

Although, finger vein and fingerprint recognition is utilized by non-negative matrix factorization (NMF) and a lightweight deep learning mode. To enhance authentication accuracy and improve resistance against spoofing attacks the cancellable multibiometric method used. NMF decomposes the fingerprint image into a set of non-negative basis components and corresponding weights, producing a compressed, parts-based representation that captures meaningful texture and ridge. Nonetheless, NMF only captures linear relationships and ineffectively represent complex spatial structures

in fingerprint images [14]. Additionally, multimodal fusion method based on a CNN is used to classify the TFPBG prediction [15]. A multimodal fusion method enhances blood group prediction by combining structures from thumb fingerprint images. CNNs absorb hierarchical features from each modality, capturing both local and global patterns effectively. However, handling and synchronizing multiple input modalities increases system, training, and computational complexity. To overcome the limitations of existing classification, a proposed TFCNN, to achieve precise blood group classification.

2. Related work

Sawhney *et al* [16] (2025) have proposed a Siamese network with a modified ResNet50 architecture and multihead attention mechanisms to improve thumb fingerprint matching under such distortions in blood group. Siamese network efficiently compare fingerprint pairings even when there are distortions. Whereas the multihead attention mechanisms concentrate on important fingerprint regions, the improved ResNet50 architecture records intricate ridge patterns. Siamese network is ideal for personalized healthcare systems wherever verifying blood group identity. However, the combination of ResNet50 and multi-head attention significantly increases computational cost during training.

Songara *et al* [17] (2024) have presented a Modified Shark Smell Optimization (M-SSO) with RNN and CNN to identify the blood group in the thumb fingerprint. M-SSO with RNN and CNN effectively searches high-dimensional parameter spaces and avoids local minima when finding the blood group from the thumb finger print. M-SSO mimics this behaviour to search for optimal solutions in complex, multidimensional spaces. Nevertheless, M-SSO is time-consuming, especially when evaluating blood group repeatedly.

Wahab *et al* [18] (2024) have developed a Generative Adversarial Networks (GANs) to redefine Latent Fingerprint Enhancement (LFE) through a structured approach to TFPBG generation. GAN generates improved latent fingerprints with remarkable fidelity to ground truth instances by directly optimizing minute details throughout the creation process. GANs address data scarcity by generating diverse, high-resolution synthetic fingerprint images to enrich training sets. Nonetheless, GAN training requires significant computational resources, especially for generating high-resolution, realistic fingerprint images.

Ipeayeda *et al* [19] (2023) have proposed a Grey Wolf Gravitational Search Algorithm (GWGSA) to detect the TFPBG. The hybrid nature of GWGSA allows it to balance global and local search for superior optimization on blood group prediction. GWO's exploitation with GSA's exploration, improving the search ability and avoid local minima. However, due to its iterative and population-based nature, GWGSA is unsuitable for real-time or embedded biometric systems without simplification.

Ahsan *et al* [20] (2021) have presented a dimensionality reduction algorithm Principal Component Analysis -enhanced Locality Preserving Discriminant Analysis (PCA-LPDA) for accurate thumb fingerprint identification and blood group prediction. PCA removes noisy and redundant fingerprint variations, LPDA ensures ridges and local orientations are unloose. Nonetheless, PCA and LPDA halfly capture non-linear fingerprint features unless kernel versions.

The contribution of this study as follows

- AGF based pre-processing effectively remove noise whereas preserving vital ridge and edge, thus enhancing thumb fingerprint image quality.
- Rotation Invariant Local Binary Pattern (RI-LBP) ensures robust feature extraction from fingerprint textures, the

system resilient to rotational variations and inconsistent finger placement.

- A novel deep learning architecture called TFCNN is developed that captures both spatial and temporal dependencies in fingerprint features. The fusion of short- and long-term representations significantly improves blood group classification accuracy.
- SOA is employed to optimize key hyper parameters dynamically, enhancing model convergence speed and robustness by avoiding local minima through adaptive, nature-inspired behaviour.

3. Proposed work

Figure 1 shows the proposed TFPBG detection framework, designed as a non-invasive and intelligent biometric-medical integration system for accurate blood group prediction.

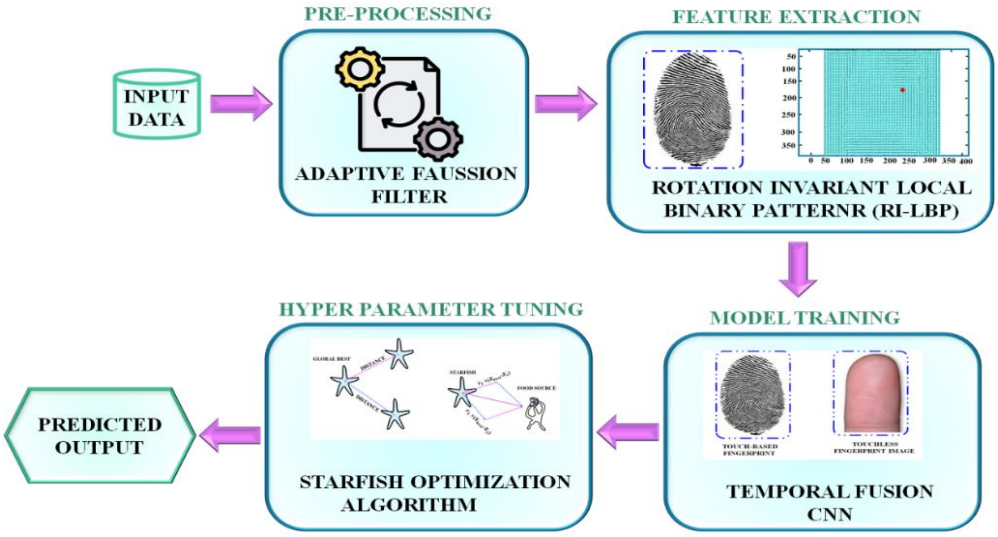

Figure 1: *Block diagram of proposed work*

First, pre-processing using an AGF, AGF filtering technique enhances the quality of thumb fingerprint images by effectively removing noise whereas preserving essential ridge and edge structures, which are critical for reliable feature extraction. Following pre-processing, feature extraction is performed using the RI-LBP feature. RI-LBP is a texture descriptor that captures fine micro-patterns from the fingerprint image, offering robustness against rotational variations and inconsistent finger placement common in real-world biometric acquisition scenarios. The extracted features are then fed to a TFCNN. This deep learning model is designed to capture both spatial and temporal dependencies in the thumb fingerprint image by leveraging a series of convolutional layers. The fusion of spatial texture features with temporal dynamics improves the model's ability to classify complex thumb fingerprint patterns associated with different blood groups. To further enhance model performance, SOA is utilized for hyperparameter tuning. This bio-inspired metaheuristic mimics the regenerative and adaptive behaviours of starfish to explore the solution space effectively. SOA dynamically adjusts parameters such as learning rate, filter size, and network depth, improving convergence speed and serving the model avoid suboptimal solutions during training. "PROVIDE END NOTE"

3. 1 Pre-processing by Adaptive Gaussian Filter for TFPBG prediction

In TFPBG prediction system, the AGF stage is important during the pre-processing step by enhancing image quality whereas preserving essential ridge structures. Unlike the standard Gaussian filter, which applies uniform smoothing, the AGF dynamically adjusts the

degree of smoothing based on local image characteristics such as intensity variance. Figure 2 shows the AGF thumb fingerprint.

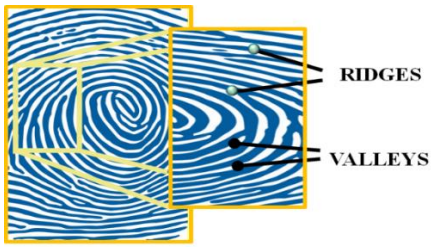

Figure 2: *AGF Thumb fingerprint*

This adaptability ensures that regions with fine ridge details are preserved although homogeneous or noisy regions are smoothed more aggressively. Mathematically, the filter kernel is based on the Gaussian function:

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp(-\frac{x^2+y^2}{2\sigma^2}) \quad (1)$$

Where σ controls the spread of the filter. In the adaptive version, σ is modified locally as:

$$\sigma_{adaptive}\,(x,y) = \alpha.(1+\beta.\frac{Var_w(I(x,y))}{\max(Var)}) \quad (2)$$

Here, $Var_w(I(x,y))$ denotes the local variance in a window around pixel $(x,y)\ and\ \alpha,\beta\ are$ tuning parameters. This adaptive behavior allows the filter to smooth flat areas to reduce noise whereas preserving fingerprint ridges. By improving ridge clarity and reducing background artifacts, AGF significantly contributes to the robustness and reliability of the overall blood group prediction. The processed output is fed to the feature extraction stage by RI-LBP for TFPBG.

3. 2 Feature Extraction by Rotation Invariant Local Binary Pattern for TFPBG prediction

In the TFPBG prediction framework, RI-LBP is used as a robust feature extraction technique that captures fine-grained texture patterns essential for distinguishing biometric traits associated with blood groups. Traditional LBP encodes the local texture around each pixel by thresholding its neighbourhood values against the center pixel, forming a binary code in figure 3.

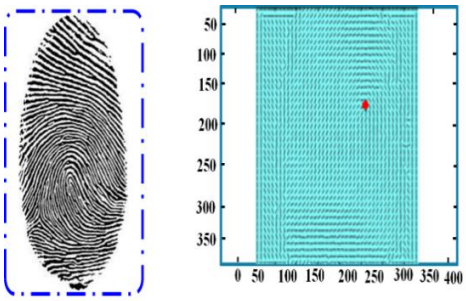

Figure 3: *RI-LBP for TFPBG prediction*

However, it is sensitive to rotation, which is a limitation in real-world fingerprint acquisition. RI-LBP overcomes this by making the binary patterns invariant to rotation, ensuring that features remain consistent regardless of in what way the finger is placed. The basic Local Binary Pattern (LBP) for a pixel is defined as

$$LBP_{P,R} = \sum_{p=0}^{p-1} s(g_p - g_c).2^p \quad (3)$$

Where, g_c is the intensity of the center pixel, g_p is the intensity of the neighbouring pixel p in a circular neighbourhood of radius R, P is the number of neighbours. To achieve rotation invariance, RI-LBP takes the minimum value among all possible circular bitwise rotations of the LBP code:

$$RI - LBP = \min\{ROR(LBP,i) \quad (4)$$

Where, $i = \{1,2,\ldots..p-1\}$, RORROR denotes the circular bitwise right rotation operation. This ensures that similar patterns yield the same descriptor even when rotated. RI-LBP extracts ridge flow, minutiae textures, and pore structures from thumb fingerprint images in a rotation-invariant manner, which is especially useful for improving feature robustness against placement variation. By preserving texture integrity and ensuring consistency across fingerprint orientations, RI-LBP significantly enhances the system's performance. These features are then used as input to deep learning classifiers TFCNN for accurate blood group prediction.

3. 3 Model training by Temporal Fusion Convolutional Neural Network for TFPBG prediction

In the classification of TFPBG prediction system, the TFCNN is a central role in modelling both spatial and sequential dependencies in the extracted thumb fingerprint features. Whereas traditional CNNs are effective at capturing local spatial patterns such as ridges, valleys, and minutiae in fingerprint images, they often fail to consider the temporal or ordered structure that present in sequential fingerprint features extracted using techniques like RI-LBP or time-series-like image patches. Figure 4 shows the basic CNN architecture for predicting the blood group.

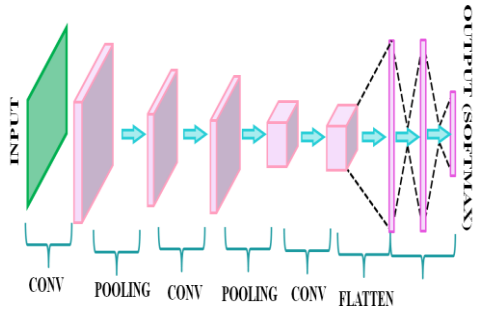

Figure 4: *Basic CNN architecture*

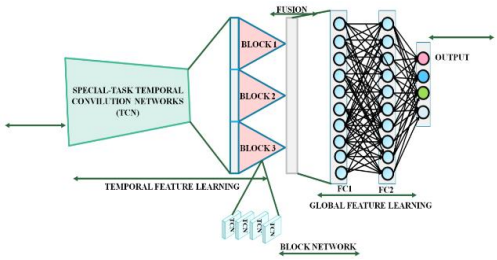

Figure 5 : *Temporal Fusion Convolutional Neural Network*

TFCNN addresses this by integrating temporal fusion layers within the CNN architecture in figure 5, allowing the model to learn feature dependencies across spatial and ordered dimensions, enhancing the fingerprint's representational power for classification tasks such as blood group prediction. Mathematically, the convolution operation in a 2D CNN layer is given by:

$$h_{i,j}^{(k)} = f\left(\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{q=1}^{Q} w_{p,q}^{(k,m)} \cdot x_{i+p,j+q}^{(m)} + b^{(k)}\right) \quad (5)$$

Where, $x_{i,j}^{(m)}$ is the input feature map at location (i,j) in the m^{th} channel, $w_{p,q}^{(k,m)}$ are the convolutional kernel weights for the k^{th} filter, $b^{(k)}$ is the bias, $f(.)$is the activation function (e.g., ReLU), $h_{i,j}^{(k)}$is the output of the convolution. In TFCNN, after a series of convolutional layers, a temporal fusion layer is applied, often implemented using a temporal mechanism or 1D convolution over feature sequences. This fusion captures the temporal evolution or contextual relation of fingerprint features across slices or patches. TFCNN significantly improves the network's ability to classify complex biometric textures. This makes it especially effective in medical-biometric tasks where fine-grained patterns correlate with physiological traits like blood groups.

3. 4 Hyperparameter Tuning by Starfish Optimization Algorithm

SOA is employed as a powerful metaheuristic technique for hyperparameter tuning of the classification model specifically the TFCNN. Figure 6 inspired by the adaptive and regenerative behaviours of starfish in nature, SOA dynamically adjusts critical model parameters such as learning rate, number of filters, filter size, and network depth to maximize classification accuracy and minimize loss.

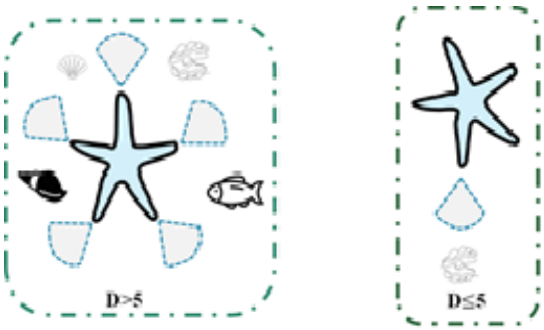

Figure 6 : *Starfish Optimization Algorithm*

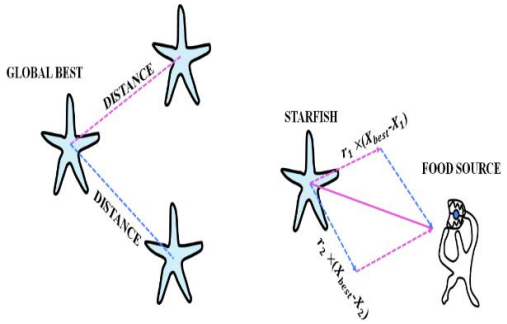

Figure 7: *Starfish best position for food source*

Figure 7 shows the starfish best position for food source and the global best. The algorithm in figure 8 and 9 simulates starfish foraging behaviour and arm regeneration to efficiently explore the solution space and avoid getting trapped in local minima during model optimization. The key update equation in SOA is generally expressed as:

$$X_i^{t+1} = X_i^t + \alpha.(X_{best}^t - X_i^t) + \beta.R_i + \gamma.F_i \quad (6)$$

Where, X_i^t is the position of the i^{th} starfish at iteration t, $X_{best}^t$is the best-known position, R_i represents the random foraging behaviour F_i, simulates regenerative movement or attraction toward other promising solutions (exploitation), α, β, γ are control parameters that balance exploration and exploitation.

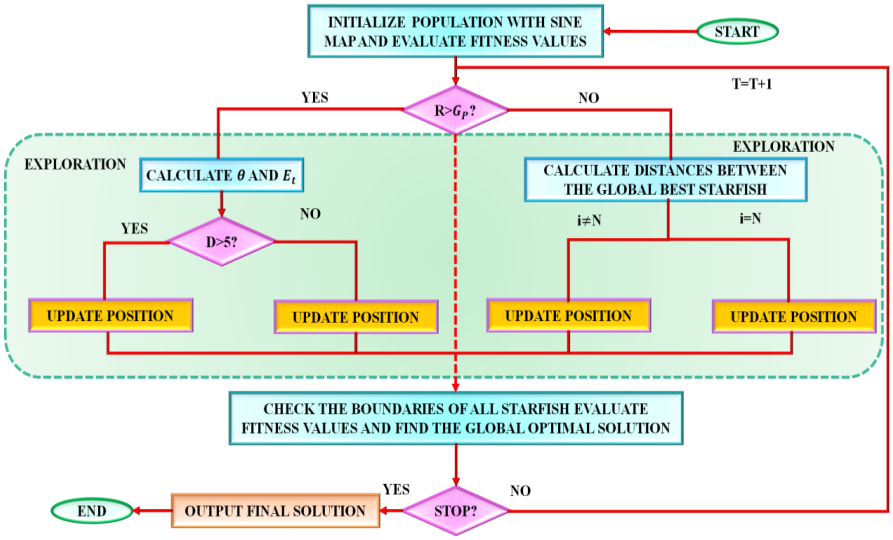

Figure 8: *Flow chart for SOA*

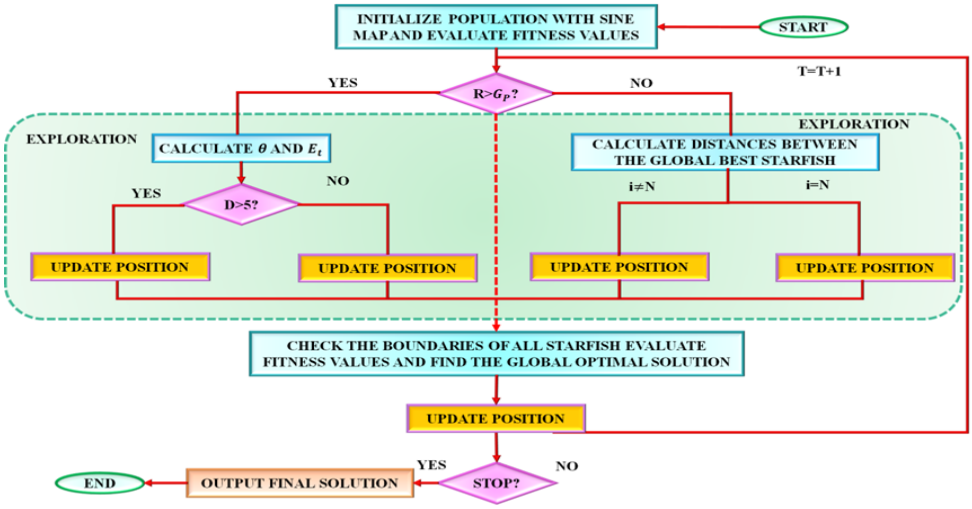

Figure 9: *Flow chart for SOA with update position*

Each candidate solution vector X_i encodes a set of model hyper parameters, and the fitness function is based on validation accuracy or cross-entropy loss from the TFCNN. The starfish

swarm iteratively updates these vectors to find the optimal configuration that yields the best classification performance. By integrating SOA into the system, the model achieves faster convergence, higher accuracy, and improved generalization without exhaustive manual tuning. Its nature-inspired adaptability makes it especially suitable for complex, non-linear optimization tasks in TFPBG prediction.

4. Result and discussion

In result and discussion section the TFPBG is predicted using the proposed for Starfish Optimized Temporal Fusion CNN. Also, the Finger Print Based Blood group dataset is taken from the kaggle.com implemented using Python software. Eight classes of blood groups are in the train image counts and test image counts. For train image counts A+ have 452 images, A- have 807 images, AB+ have 566 images, AB- have 608 images, B+ have 521 images, B- have 592 images, O+ have 681 images and O- have 569 images. For test image counts A+ have 113 images, A- have 198 images, AB+ have 142 images, AB- have 153 images, B+ have 130 images, B- have 150 images, O+ have 170 images and O- have 143 images respectively.

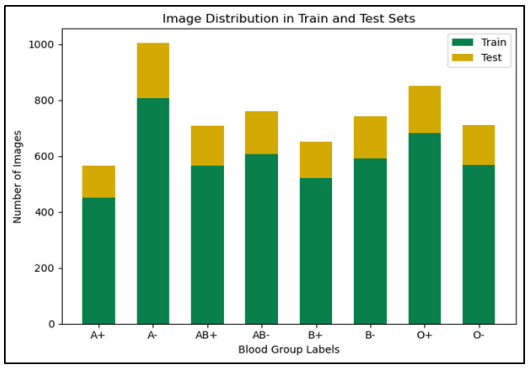

Figure 10: *Image distribution in train and test sets*

Figure 10 shows the image distribution in train and test sets for TFPBG. Figure 10 provides a visual representation of the number of thumb fingerprint images used for training and testing across different blood group categories in a TFPBG prediction system. The X-axis lists the blood group labels $(A+, A-, AB+, AB-, B+, B-, O+, and\ O-)$, wh ereas the Y-axis denotes the number of images. Each bar is split into two segments: the green portion represents the training set, and the yellow portion represents the test set. This layout enables a clear comparison of the Finger Print Based Blood group dataset which is divided for each blood group. Particularly, the $A-$ group have the highest total number of images, followed closely by $O+$, indicating a larger sample representation for these groups.

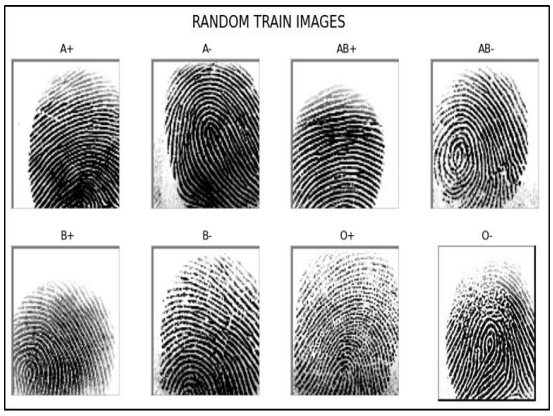

Figure 11: *Random train images*

Figure 11 shows random images in train set for TFPBG. The random images are taken from the Finger Print Based Blood group dataset for further process. Here eight blood groups $(A+, A-, AB+, AB-, B+, B-, O+, and\ O-)$, are taken from the dataset. This visual presentation highlights the intra-class variability and inter-class similarity present in fingerprint patterns, such as ridge flow, curvature, and minutiae distribution. Despite appearing visually similar to the untrained eye, subtle differences in texture orientation, ridge spacing, and structural minutiae are critical for models to distinguish among the classes.

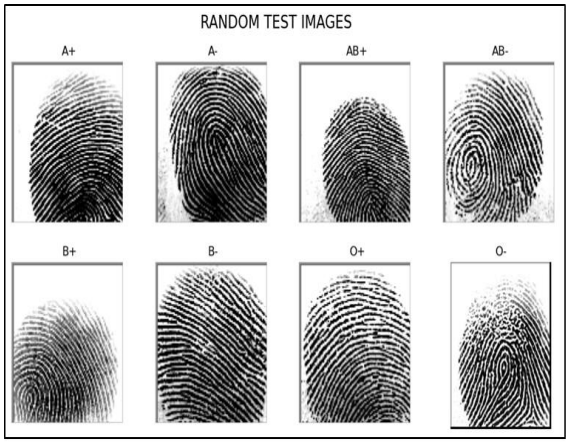

Figure 12: *Random test images*

Figure 12 shows random images in test set for TFPBG prediction. The random images are taken from the Finger Print Based Blood group dataset for further process. Here eight blood groups $(A+, A-, AB+, AB-, B+, B-, O+, and\ O-)$, are taken from the dataset. This visual presentation highlights the intra-class variability and inter-class similarity present in fingerprint patterns, such as ridge flow, curvature, and minutiae distribution. Despite appearing visually similar to the untrained eye, subtle differences in texture orientation, ridge spacing, and structural minutiae are critical for models to distinguish among the classes.

Figure 13: *Original image*

Figure 13 shows the original thumb fingerprint image. The original Image depicts a raw thumb fingerprint sample prior to any pre-processing steps in the blood group prediction. This unprocessed fingerprint image clearly displays the natural ridge and valley structures that form the core of biometric pattern recognition. However, it also exhibits some common issues found in raw image, such as pixilation, uneven contrast, and potential background noise, especially around the edges.

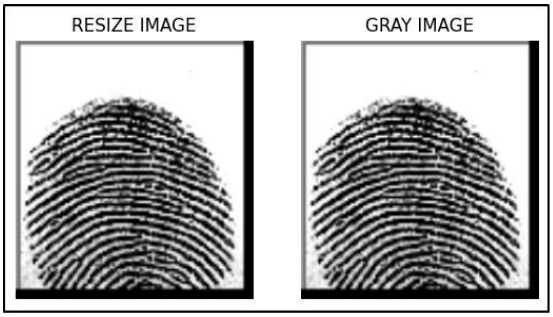

Figure 14: *Resize image in to gray image*

Figure 14 shows the resize thumb fingerprint image in to gray image. Resized image shows how the original fingerprint is scaled to a uniform dimension, ensuring consistency across the dataset. The gray image demonstrates the conversion of the resized image into grayscale format, reducing the image from three color channels (RGB) to a single intensity channel. This transformation simplifies the data by focusing on pixel brightness, which is sufficient for capturing ridge and valley structures in thumb fingerprints. Resizing in to grayscale conversion serve as foundational steps that enhance the quality and consistency of input data, preparing it for further processing.

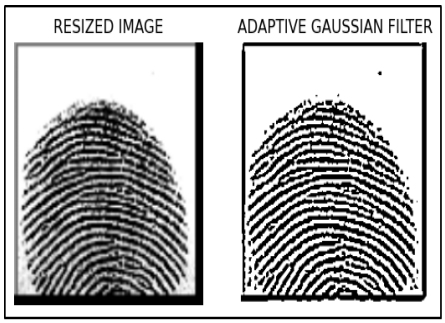

Figure 15: *Resized image in to AGF*

Figure 15 shows the resize in to AGF image .The resized image is the raw fingerprint after it have been scaled to a standard size to ensure uniform input across the dataset. The AGF dynamically adjusts the smoothing intensity based on local pixel variations, effectively suppressing background noise whereas preserving and sharpening ridge structures. As a result, the filtered image shows clearer and more defined

ridgelines, which are essential for accurate extraction of rotation-invariant features such as those captured by RI-LBP.

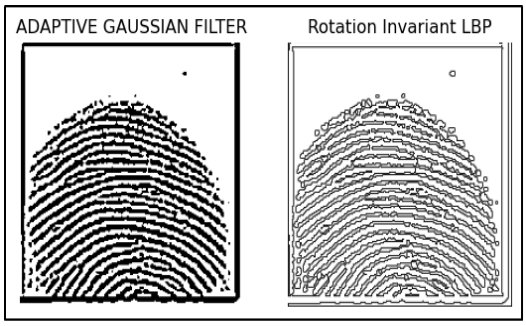

Figure 16: *AGF in to RI-LBP*

Figure 16 shows the AGF in to PI-LBP for TFPBG prediction. RI-LBP processing, transforms the image into a pattern of local binary descriptors. These descriptors encode micro-texture information from each pixel's neighbourhood in a way that is invariant to rotation, creating the system robust against inconsistent finger placement or orientation during scanning. The RI-LBP image emphasizes edge contours and localized patterns whereas discarding irrelevant intensity variations. AGF in to RI-LBP ensure that only the most meaningful and consistent texture features are extracted, forming a reliable input for the classification model used to predict an individual's blood group from their fingerprint.

4.1 Performance metrics for TFPBG prediction

Performance metrics, such as accuracy, sensitivity, and specificity, indicate that the thumb fingerprint are correctly detected and appropriately analysed as the probabilities calculated by Starfish Optimized Temporal Fusion CNN. The performance metrics in this study explained in table 1.

Table 1: *Performance Metrics*

Performance metrics	Values
Accuracy	95%
Precision	96%
Recall	95%
F1-score	95%

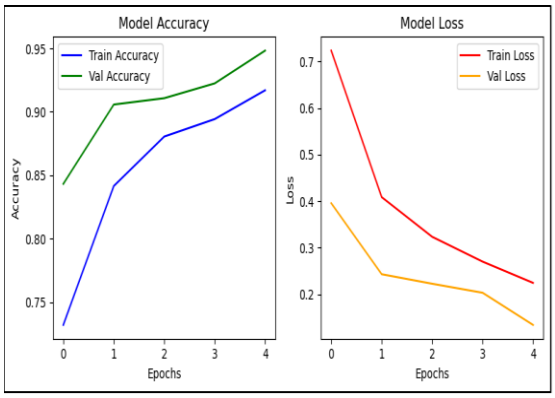

Figure 17: *Model accuracy and Model loss*

Figure 17 shows the training and validation accuracy and loss. The X-axis denotes the epochs and Y-axis denotes accuracy for TFPBG prediction system. The model accuracy graph illustrates increasing accuracy of 95%, with the model achieving high performance and minimal over fitting. For model loss the X-axis indicates the epochs and Y-axis indicates the loss. Training and validation loss is reliably declining in training and validation loss, representing improved learning and reduced error.

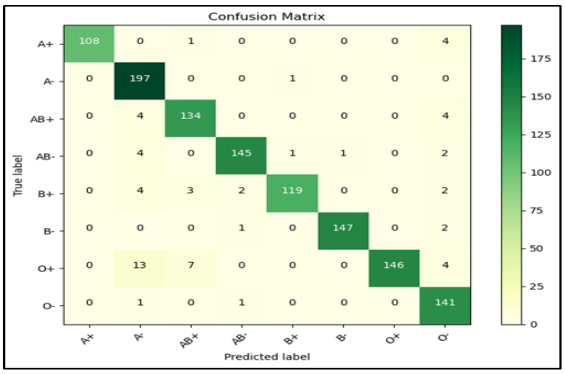

Figure 18: *Confusion matrix for proposed work*

Figure 18 shows the confusion matrix for proposed work. Each row of the matrix corresponds to the true blood group label, whereas each column represents the predicted label by the model. The diagonal elements indicate the number of correctly classified instances for each blood group class. A+ have the matrix of 108, A- have the matrix of 197, AB+ have the matrix of 134, AB- have the matrix of 145, B+ have the matrix of 119, B- have the matrix of 147, O+ have the matrix of 146 and O- have the matrix of 141,respectively.

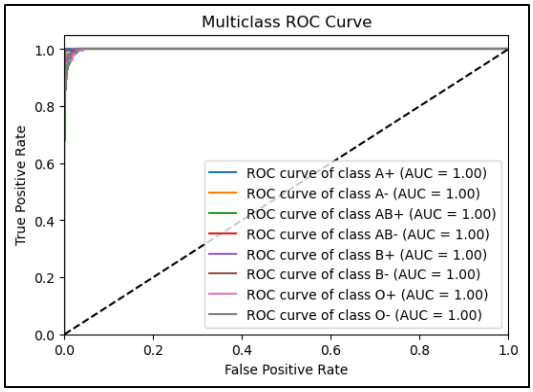

Figure 19: *Multiclass ROC curve*

Figure 19 shows a Multiclass ROC (Receiver Operating Characteristic) Curve. It used to evaluate the performance of a TFPBG classification model across all eight blood group classes (A+, A−, AB+, AB−, B+, B−, O+, O−). Each colour curve represents the ROC curve for a specific class, plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold levels. The closer a curve follows the top-left corner, the better the model's performance. All the curves in the graph closely hug the top-left corner, and the AUC value for each class is 1.00, which indicates perfect classification without any false positives or false negatives. The dotted diagonal line represents the baseline for random classification (AUC = 0.5), and the fact that all curves are well above this line further confirms the model's robustness.

Figure 20: *Predicted output*

Figure 20 shows the predicted output. The models have identified the thumb fingerprint as belonging to an individual with the B positive blood group. The image appears to be pre-processed, showing clear ridge and valley structures an outcome likely achieved through steps such as resizing, grayscale conversion, and AGF. These enhancements help to preserve essential fingerprint features whereas minimizing noise, thereby improving the reliability of the prediction. The successful classification of this fingerprint into the B+ category reflects the effectiveness of the system's feature extraction and learning, particularly the use of RI-LBP for texture encoding and a deep learning classifier such as the Temporal Fusion CNN.

4.2 Comparison for the proposed method

The comparison of the suggested method with existing method is presented in table 2. The GWGSA [19], M-SSO with RNN and CNN [17] have the classification accuracy of 90% and 94.3% [17] and the proposed Starfish Optimized Temporal Fusion CNN have the higher accuracy of 95% compared to the existing method in table 2. The proposed Starfish Optimized Temporal Fusion CNN have better performance for TFPBG prediction.

Table 2: *Comparison for the proposed method*

Method	Accuracy
GWGSA	90%
M-SSO with RNN and CNN	94.3%
Starfish Optimized Temporal Fusion CNN	95%

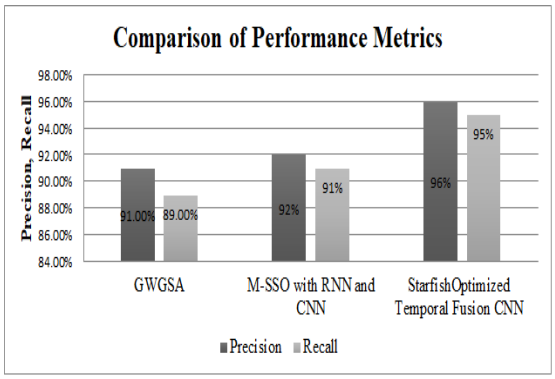

Figure 21: *Comparison for precision and recall*

Figure 21 shows the comparison of performance metrics for precision and recall value of proposed work and the existing work. The GWGSA have precision value of 91% and recall value of 89% [19], M-SSO with RNN and CNN have the

precision value of 92% and recall of 91% [17] and proposed Starfish optimized Temporal Fusion CNN have the precision value of 96% and recall of 95% for identifying TFPBG. The proposed precision and recall value is high compared to the existing method.

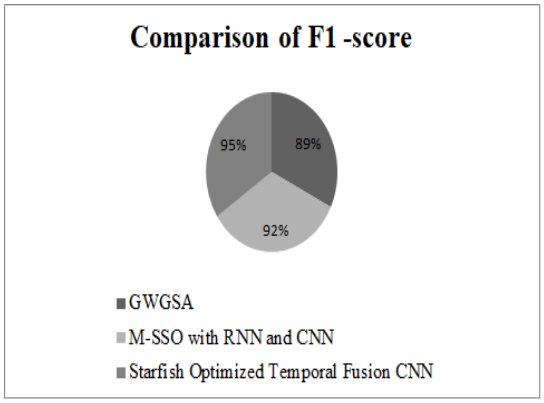

Figure 22: *Comparison for F-1 score*

Figure 22 shows the comparison of F1 score value of proposed work and the existing work. The GWGSA have F1-score value of 89% [19], M-SSO with RNN and CNN have F1-score value of 92% [17] and proposed Starfish Optimized Temporal Fusion CNN have the F1- score value of 95% for identifying TFPBG prediction. The proposed F1 score value is high compared to the existing method.

5. Conclusion

In this study, TFPBG prediction framework demonstrates a promising and innovative approach to non-invasive blood group classification by integrating Finger Print Based Blood group dataset. Utilizing a high-quality thumb fingerprint image, AGF for noise reduction and edge preservation, ensuring clean and analysable input. RI-LBP effectively extracts robust and orientation-independent texture features, crucial for handling variability in finger location. The TFCNN further enhances classification by learning spatial and sequential relationships within the thumb fingerprint patterns, resulting in precise blood group identification. To maximize accuracy and efficiency, SOA is employed for hyperparameter tuning, enabling better convergence and avoiding local minima. The performance evaluation, conducted on the Finger Print Based Blood group dataset, demonstrates the superior capabilities of the Starfish Optimized Temporal Fusion CNN method. The improved accuracy, F1-score, and recall of 95%, precision of 96% is achieved as a greater accuracy and performance in contrast to the existing methods.

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