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DETECT INTEREST REGION OF FINGER VEIN BASED ON K-MEANS CLUSTERING

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Abstract- In our life, biometric technology has become indispensable. A new Finger vein recognition using biometric technology has several advantages. In recent years, A valid biometric has been demonstrated using finger veins for identifying an individual. However, finger form, detailed backgrounds, picture translation, orientation, scale, scattering, scaling, uneven illumination, and collection posture all readily impact finger vein images. These elements could lead to an incorrect region of interest definition, impairing the finger vein recognition system's effectiveness. In these studies, Researchers describe a technique for localizing a finger vein region of interest that is very effective and resistant to the causes above to address this issue. The proposed approach includes three steps for precisely localizing the region of interest: segmentation, orientation correction, and region of interest detection using Gaussian blur (GB). When unlabeled grouping data, the K-means clustering approach investigates label uncertainty and high-density regions, accurate finger region segmentation used flood fill and accurate calculation of orientation can work together to increase the localization accuracy of an area of interest. The first time used the dataset in this topic, and numerous tests ran on the database of finger vein images; 20 times were collected from each finger in two sessions by NUPT-FPV from 140 people, yielding 840 finger information and 33600 images of finger veins. They were produced to confirm the robustness of the proposed approach. The segmentation accuracy for the suggested system is (98.35%). Theoretical analysis and experimental findings support the suggested approach's suitability and accuracy and indicate that it may help enhance the finger vein recognition system's functionality.

Keywords: Finger Veins, Region of Interest (ROI), Flood Fill, Gaussian Blur (GB), K-Means Clustering.

1. INTRODUCTION

In recent years, biometric technology has advanced significantly on both the technological and application levels. It is extensively utilized in a variety of industries, including security, e-commerce, and electronic equipment. As a new biometric method, finger vein recognition has attracted considerable interest [1]. Finger vein recognition has numerous advantages over more established biometrics like fingerprint, face, and iris identification, including living detection, non-contact, difficult forgery, and low cost. As a result, it has promising future applications across a variety of industries [2]. A biometric identification method called "finger vein recognition" gathers images of the finger veins using near-infrared light and identifies the subjects using the traits that were extracted from the finger veins. The primary benefit of the finger vein feature over more popular biometrics like the face or fingerprint is that it is internal to the body. Additionally, while digital vein information is easy to gather and identify quickly, identification must be performed in-person and is quite secure. Following years of research and development, finger vein recognition has found widespread use in intelligent security, intelligent housing, intelligent transportation, and other domains [3].

There is an urgent need for a practical and safe identification mechanism in light of the major international health security challenges that the COVID-19 epidemic has brought to light in recent years. Finger vein recognition has received a lot of interest because it is a second-generation biometric technology and offers such a high level of ease and security [4]. The ability of finger vein recognition technology to identify veins accurately without contact or constraint is impressive. As a result, it can achieve identification while ensuring public health safety. But noncontact and unrestricted digital vein picture capture will invariably add a number of elements that have a bigger impact on recognition ability, such as movement, deformed fingers, and uneven lighting. Only the image's background noise is removed when the finger region is used as the ROI, it is unable to address how finger displacement, deformation, and other factors affect recognition ability. A more reliable and effective ROI extraction method for images of finger veins is needed to lessen the effect of these factors on recognition performance [5].

The main contribution of this research is a strong finger vein ROI localization approach, which we describe. For the initial coarse finger region segmentation, two extended edge operators are used. The confirmed result is faster speed than those wearing the masks [6].

Extensive binarization is suggested for the atypical case photographs to eliminate the fake backdrop brought on by influences from uneven illumination, scattering, and poor collecting. For this, the expanded image is processed using extended edge operators to remove the effects of inappropriate collection, it is then followed by a single linkage clustering method to fix the middle edge points caused by the effects of uneven lighting and scattering [7]. After that, orientation correction is performed using the determined orientation angle. To obtain a more precise finger region, the elimination of fictitious backdrops and estimated corrected orientation angle might serve as guidelines for one another. The reference line in the second knuckle of the finger is searched as the last step of an extended ROI detection technique. In order to lessen the impact of uneven lighting and changes in finger width, the reference line is made from a block picture that has been segmented or otherwise corrected for orientation by flooding segmentation [8].

The suggested method has a segmentation accuracy of 96% and is extremely practical and resilient for the influences of translation, scale, scattering, finger gesture, orientation, and lighting. Results of experiments on our existing database (NUPT-FPV) 140 volunteers provided 840 finger information, which was used to create 33600 fingerprint and finger vein images. Each finger was gathered 20 times over the course of two sessions [9]. The remaining sections of this article are as follows: The finger vein picture and state-of-the-art technology for ROI localization are covered in Section 2. The specifics of the dataset suggested in this paper are presented in Section 3. Section 4 provides a thorough explanation of the suggested method. Section 5 discusses experimental findings and a thorough analysis. Section 6 provides a summary of this paper's conclusions and suggestions for more research.

2. RELATED WORKS

Several academics expressed interest in finger vein recognition systems. The following list includes some published works that relate to the goals of this study:

X. Meng et al. presented a gray level grouping model based on a single finger vein picture improvement (GLC). The primary technique used to improve the pictures of finger veins is Gabor filtering. The experimental findings demonstrate the effectiveness of this method's circular Gabor filter, which enhanced the image for the recognition phase accuracy to 94.68% [10].

K. Shaheed to improve the contrast of the generated image, a histogram equalization method was suggested. Additionally, an easy fuzzy-based multitargeted method that takes into account the peculiarities have been developed of the skin region and vein patterns. The algorithm also improves the vein patterns' contrast with the background accuracy 91.47% [11].

A. Bedari, et al. Finger vein image analysis tools and a classification strategy based on the K-Nearest Neighbor (KNN) algorithm for finger vein recognition have been proposed and developed.

To assess and determine the efficacy of the recognition system, numerous generalized features are retrieved from photographs of finger veins, they rely on the KNN. In experiments, the finger vein verification method built on KNN produced accuracy 93.21% [12].

A. Khan, et al. suggested a maximum edge position detection-based finger vein recognition system. The suggested method is based on displaying and utilizing variations in gradient feature values in different directions by employing the sign and magnitude of the finger vein margins as a stage of feature collection. Maximum values suggested for the finger vein margins, depending on different gradient directions, demonstrate indicating the classifier's accuracy has reached 90.47% and its error rate has almost reached 13.48% [13].

I. Boucherit, et al. suggested an embedded system for classifying and recognizing finger veins for human authentication. The suggested approach is based on a cutting-edge system for identifying finger vein images. The suggested algorithm is built on the distance minority for classifying finger veins and on a Gabor filtering for extracting finger vein features. The outcomes of the trial demonstrated that reliable finger vein recognition has improved easier and accuracy was 93.5% [14].

3. THE DATASET

The proposed system uses an open access dataset called "NUPT-FPV," which is multimodal and based on finger-prints and Identical finger veins [15]. Each finger was gathered 20 times (in two sessions) by NUPT-FPV from 140 individuals, yielding 840 finger information and 33,600 fingerprint and finger vein images. The Nanjing University of Posts and Telecommunications (NJUPT) are collecting the dataset. The average age of these participants, 108 males and 32 females, the average age was 19.3 years. The range of the ages was 16 to 29. The respondents were told to place their fingers into the collection device while sitting between 0.2 and 0.5 meters away from it. A collection equipment was mounted on a 1 m high table. Table 1 presents the statistical information of the NUPT-FPV dataset.

Table 1. NUPT-FPV Dataset Statistical Details

Data	Subject	Finger	Repetitions	Session	Total
Finger-print	140	6	10	2	16800
Finger-vein	140	6	10	2	16800

4. THE PROPOSED METHOD

Our suggested approach enhances the finger vein image by segmenting it, correcting the orientation, and determining the ROI using Gaussian blur (GB), K-Means clustering, and segmented by flood fill. For a finger veins recognition system, a successful finger veins picture segmentation algorithm is crucial, as is a reliable finger vein ROI localization technique. This section describes the suggested technique, which is seen in Figure 1. The following diagram illustrates the specifics of each phase.

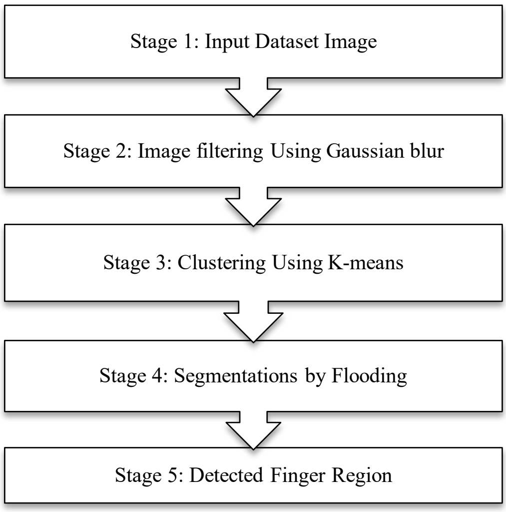

Figure 1. Block diagram illustrating the suggested technique

4.1. Preprocessing of the Image

Preprocessing was needed before using the finger collection device's original image for recognition [16]. The first image the finger collecting apparatus recorded frequently included more superfluous information, like the photo frame, the background, and bright spots. An effectiveness of the recognition system would be more affected by various preprocessing techniques, on the other hand. To concentrate on the finger recognition task and design unbiased test environments for future researchers, to minimize interference and redundant data, we preprocessed the acquired raw photos [17].

In the beginning, we checked to see if the original gray-scale images remained accessible of the finger vein and fingerprint; if not, we converted the images to gray-scale. The unnecessary information outside the finger is then cut from the fingerprint and finger vein photos (delete data outside the scope of the collection, not for extract the image's ROI) [18]. A cropped image is then subjected to Normalization of the size and pixels. Following a data preprocessing phase, we manually examined each image to make sure the appropriate there included information about the finger vein and fingerprint. Satisfy be aware that given that some studies employ context as a characteristic for recognition, the community dataset that we made accessible lacks a ROI for obtaining finger vein images.

4.2. Image Enhancement

To enhance clarity from the image of a finger vein at this phase, a Gaussian blur filter technique was applied. The background layer can also be produced using Gaussian Blur (GB), which appears to be a more natural way [19]. Since the finger vein texture is the high-frequency component and the background intensity distribution may be thought of to get rid of the finger vein texture and simply keep the backdrop layer, GB can be used as a low pass filter as the low-frequency components. The series of meticulous contrast tests on the efficiency of GB for identifying finger veins.

An example of a picture-blurring filter is the Gaussian blur, which uses the Gaussian function to determine the adjustment to be made to each pixel in the image; this is also how the normal distribution in statistics is described [19]. Summarizes the primary traits of the Gaussian function used in the image-enhancing procedure, as shown in Equation 1:

$$(x) = 1/\sqrt{2\pi\sigma 2}e - x2 / 2\sigma 2 \tag{1}$$

Given that $G(x)$ is the final image and is a distribution's standard deviation, has a big influence on how it behaves. The distribution's mean is taken to be zero.

Algorithm 1. The Gaussian Blur algorithm's pseudo-code

Algorithm 1: Gaussian Blur
Input: input image Output: image Gaussian Blur
Step1: Load image Step2: Create a Gaussian filter with a specified standard deviation; The filter is a two-dimensional array of weights. Step3: For each pixel in the image, perform the following steps. a. Multiply the values of the filter with the corresponding values of the pixels in the image. b. Sum the resulting values and store the result in a temporary variable. c. Set the value of the corresponding pixel in the blurred image to the value stored in the temporary variable. Step4: Repeat steps 3a-3c for all pixels in the image. Step5: Normalize the blurred image by dividing each pixel value by the sum of the filter value to ensure that the image values remain within the 0-255 range. Step6: return image

4.3. Clustering of Images Using K-Means Clustering

In our suggested strategy, the five obtained features from each local block are grouped using K-means in the finger vein separating the foreground from the busy background in the image: an energy spectrum, variance, and difference in means, gradient coherence, and the orientation of the ridges. The typical extraction vector for each block [20]. On the one hand, data clustering is a popular application of the K-means algorithm, an unsupervised machine learning model. The ideal result for each iteration is determined via an adaptive method as specified by K means. The required number of clusters is then determined.

To utilize this type of clustering, the data points must be divided into K groups; smaller groupings with a higher K indicate greater specificity. It is more likely that there will be a rise a low K value in the number of clusters. The algorithm creates as a result, labels. Each piece from information is categorized using the K categories. The centroid of each group is identified by the K-means clustering. The points that are closest to their centers are gathered by the centroids and included in the beating heart of the cluster. This approach employs an integration method to lower the total number of clusters using a distance measure (iteration after iteration). Ultimately, we require a massive cluster including each object. Let $[z_1, z_2, z_3 ... z_q]$ be a collection of vector data (samples). These vectors have the following notation.

$$Z = | z_1 \; z_2 \; z_3 \; ... \; z_n | \tag{2}$$

Algorithm 2. Provides the K-Means algorithm's pseudo-code

Algorithm 2: K-Means algorithm
Input: input image Output: image segment images
Step1: Load image Step2: Resize the image to a smaller size. Step3: convert the image to array and flatten it into a 1D array of color values Step4: Select K initial centroids randomly from the color values in the image. These centroids will be used to represent the K clusters in the image. Select K = 3, K show the cluster's number. Assign pixels to clusters: Based on the Euclidean distance between each pixel's color value and the centroid, assign each pixel in the image to the centroid that is closest to it. Recomputed centroids: The centroids should be recalculated using the average color value of all the pixels allocated to the same cluster. Step5: Repeat steps 4a and 4b until the centroids no longer change or a maximum number of iterations have been reached. Step6: Assign a color to each cluster: Assign a unique color to each cluster to visualize the segmented image. Step7: Reshape the image: Convert the 1D array back into a 2D array to form the segmented image. Step8: Select coordinate center image and get value coordinate call value-color. For each pixel in the image Check value is equal value-color then calculation sum. Calculation percentage by sum dive no of pixel in image. Step9: Repeat steps 8c, 8d and 8e until percentage > 60 % Step10: For each pixel in the image Step11: check value of pixel is equal value-color then value of pixel is while else value of pixel is black Step12: Repeat steps 10, 11 for all pixels in the image. Step13: return image

4.4. Flooding Segmentation

Since the algorithm considers that the image is positioned in the image's center, seed flooding segmentation is then carried out from that location [21]. A connection condition is met during the recursive process of seed flooding segmentation, which fills the image with the color assigned to the foreground from a seed point. The center pixel of the image serves as the seed point in this scenario, and the connectivity requirements are based on the intensity differences between the image vein pixels. Assuming once more that the image is centered, a sub region is chosen as the image vein seed from the center of the image that has been transformed to the target in order to determine the connectivity criteria. The intensity difference between the present pixel and one of its neighbors that truly belongs to the image segment is then set as a connection criterion, and it must not be more than the intensity difference between neighboring pixels in the target [22]. The seed point is added to the segmentation cluster, and an eight-connected neighborhood is used to evaluate the connectivity requirements for each neighboring pixel.

The segmentation cluster is expanded by any neighbors who meet the connectivity requirements, and the method is then iterated recursively. Formally, the color associated with the image segment fills out a pixel [23]. The use of (flood fill) helped or contributed significantly to the success of the process of isolating the critical region (the finger vein) from the background in the dataset used in the search. And as we know that in the event of taking a fingerprint, as usual, the finger is placed in the middle of the area designated for scanning in the device to take the fingerprint, so the idea was that by choosing a point in the middle of the image and comparing it with the values specified by the previously chosen cluster (k-means) and determining which cluster this point belongs to it. Thus, we take all the ends adjacent to this selected point that have the same color tone. Then a different color is projected on all the pre-determined points: red. Then we isolate that area, but after determining its percentage in the image, is it 60% or more, it is what is required; it will be necessary, but if the result is less than 60% (and since the noise is present, the finger movement is not fixed, and the data set is diverse and takes more than one case. In this case, we will move the point (left, right) by increasing the location coordinate each time the calculation is made. If the percentage is 60% or more, then that is required.

We linked the ROIs in the prevent shots with 20 labeled samples from ROIs in the post-event images using K-means clustering. Following flood detection technique. In other domain adaptation techniques, after using the pre-event picture ROIs for training, the learned model was adjusted to recognize flood in the target domain using a few labeled samples extracted from post-event photographs. The purpose of this experiment was to determine whether there would be any benefit to using pre- and post-event labeled samples in succession.

Algorithm 3. Provides an illustration of how the Flood-Fill method is applied to the finger-vein image to protect the vein region

Algorithm 3: Determine Vein Region based on Flood –Fill
Input: image segment images Output: Flood-Fill image
Begin Step1: load image and state the starting pixel Step2: determined threshold value to decide which neighboring pixels in the filled region should be included 2-1 Threshold range [100 -128] Step3: initialize an empty stack data structure to store the pixels that will be included in the ROI Step4: add the starting pixel to the stack Step5: While the stack is not empty Step6: pop-item= pop the top pixel from the stack Step7: Check if (the pop-item intensity value is within the threshold range) Then mark it as part of the ROI and add (pop-item) neighboring pixels to the stack. Else delete pop-item Step8: Repeat steps 5-7 until the stack is empty Step9: return image End Algorithm

4.5. The Region of Interest Detection (ROI)

The biometric device displaces a user's finger when it is inserted; therefore this revision suggests the region of interest discovery approach for gather reliable and useful information about vein charm [24]. We have to determine a ROI. For that, we apply a closing on this image and erosion. With the flood fill, we allow the use of ROI, as seen in Figure 2.

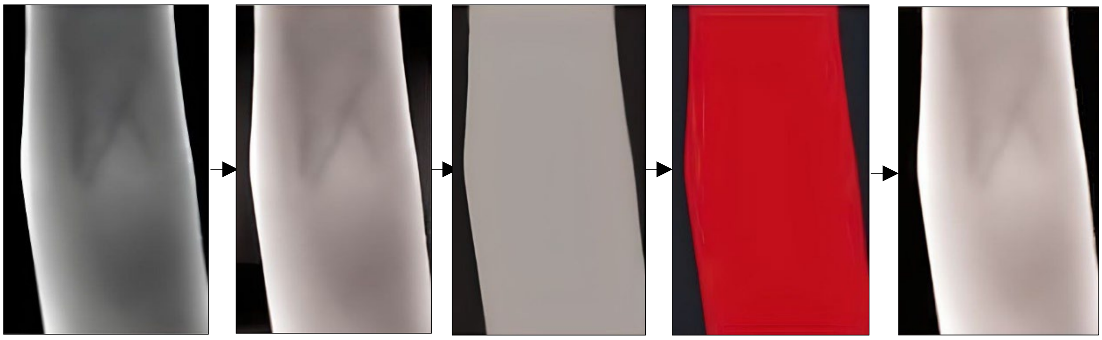

Figure 2. Methods for detecting ROI in finger veins

5. THE EVALUATION

Several applications in the field of image processing depend on objective, numerical assessments of image quality. Any source can distort an image, including those caused by blurring, noise, compression, inadequate sensors, and other factors. The use of a reference image with flawless quality is frequently necessary for objective image quality assessment models. Computing models that can forecast human image quality observations are used for objective evaluation. robust connections with arbitrary observations are crucial for constructing a decent objective quality approach since they allow for the prediction of the typical human observer's perception of image quality [24]. No matter if we're talking about an entire learning model or just one image, there are appropriate quality requirements. Some of them are examined:

5.1. Accuracy

Accuracy is one factor to consider when evaluating categorization models. Accuracy is the proportion of forecasts that our model successfully predicted. The official definition of accuracy says given in Equation (3) [24].

$$Accuracy = TP + TN / TP + TN + FP + FN \tag{3}$$

where, *TP*, *TN*, *FP* and *FN* stand for True Positives, True Negatives, and False Positives, respectively.

6. EXPERIMENTAL RESULTS

This section evaluates the usefulness considering the proposed multimodal fingerprint and finger vein dataset NUPT-FPV and the efficiency of the suggested benchmark technique FPV-Net. On a computer with a 32GB RAM, an NVIDIA GTX 1081Ti GPU, and an Intel i7 8700k CPU running at 3.7 GHz, all techniques are evaluated. The experiment uses the segmentation methods below to more effectively verify our algorithm: K-means. The K-means clustering algorithm; sequential processing. Processing a lot of data in a sequential context takes a long time. *K* mean clustering technique is used in a parallel processing environment to solve this issue. The accuracy of the *K* means clustering parallel approach is increased, and processing large volumes of data takes much less time. Due to these factors, a k mean parallel clustering algorithm is presented in the current study to be used for grouping the characteristics of the finger vein image. Beginning with the data that we are working on NUPT-FPV, due to their poor quality, we should thus enhance these photographs and display the process's benefits include preparing the data for extraction of the necessary patterns from the finger area ROI, which allows us to know the enhanced images as a result of preprocessing. The image was enhanced using a Gaussian filter, which combined multiple techniques to get a better image.

As we execute the improvement process to extract the crucial information and data from the image using a Gaussian filter, we observe that the veins' appearance has darkened from what it was in the original image, as shown by a subjective result in Figure 4, Based on image clustering, an unsupervised learning approach is applied. Here, an advanced picture segmentation method must be utilized to separate the finger vein image from its background. Using fixed starting cluster centroid values rather than random initialization values is the basic tenet of the K-mean optimization. In order to complete this stage, we presume a distribution of intensity is shown as (i;d), where I represents the distribution of intensity and the intensity levels. I stand for a various intensity range between various photos, which are depicted as "$I1$, 2," "In," and "L," respectively. Each pixel in these images has an intensity value of "x (1)," "x (2)," or "x (L"), with L standing for the highest intensity value. Each Cluster center (starting center) is denoted by the numbers 1, 2, and so on up to K, where K is the specified fixed number of clusters. Each group (cluster center) is primarily assigned to each pixel based on x (1), $U1$, x (2), $U2$..., x (n), thus in this instance, each center (cluster center) is selected using a step size that is fixed and gradually increased in accordance with the various intensity values. In this case, the [0-255] range of 256 intensity levels is not appropriate. Comparing this algorithm's effectiveness to that of other Clustering methods, a basic idea from algorithm 2 is to get a finger region ROI from the backdrop. The newly created K-mean algorithm differs from a conventional in contrast to the K-mean technique; we employed a predetermined number of centroid locations. To address the instability and randomness issues that the conventional algorithm faces.

The article (Finger Vein) of the first proposed model's Image Clustering stage is regarded as its core. Obtaining a ROI to separate the finger area from the backdrop is the aim of this stage. A technique was used to select about 100 photographs from a database and compare this technique with original image without determine ROI. The purpose of this study was to see how defining the region of interest (ROI) affected the accuracy of personality recognition in a system that used transfer learning methods. To accomplish this goal, we examined the various transformation learning algorithms utilized in the system and compared the results achieved with and without the identification of the ROI. The transfer learning algorithms that are used in this paper are VGG16 [25], VGG19 [26], and ResNet-50 [27]. The loss and accuracy for both training of three transfer learning algorithms, with and without ROI, are depicted in Figures 3-8.

The performance of VGG16 with and without ROI is shown in Figures 3 and 4. With ROI, the highest accuracy value of 0.98352 and the validation value of 0.81845, the best accuracy and validation values are obtained. The loss value is the lowest for both training and validation, which are 0.00001 and 0.00004, respectively. The accuracy and validation values of the VGG16 algorithm without ROI, on the other hand, were 0.97336 and 0.49405, respectively, with the training and validation loss are 0.00004 and 0.00010, respectively. The performance of VGG19 with and without ROI is presented in Figures 5 and 6. With ROI, the highest accuracy value of 0.98018 and the validation value of 0.82738, the best accuracy and validation values are obtained. The loss value is the lowest among training and validation, which are 0.00002 and 0.00005, respectively. The accuracy and validation values of the VGG19 algorithm without ROI, on the other hand, were 0.97300 and 0.52976, respectively, with the loss values of the training and validation being 0.0001 and 0.00012.

The performance of ResNet-50 with and without ROI is presented in Figures 7 and 8. With ROI, the highest accuracy value of 0.97999 and the validation value of 0.81250, the best accuracy and validation values are obtained. The loss value is the lowest among training and validation, which are 0.00002 and 0.00004, respectively. The accuracy and validation values of the ResNet-50 algorithm without ROI, on the other hand, were 0.96199 and 0.51190, respectively, with the loss values of the training and validation being 0.0003 and 0.0009. Based on the analysis of Figures 3-8, it can be concluded that region of interest (ROI) in the finger vein identification algorithm leads to the best performance among all transfer learning algorithms. These results suggest that identifying the region of interest based on based on K-means clustering is an essential step in optimizing the accuracy and efficiency of finger vein identification systems.

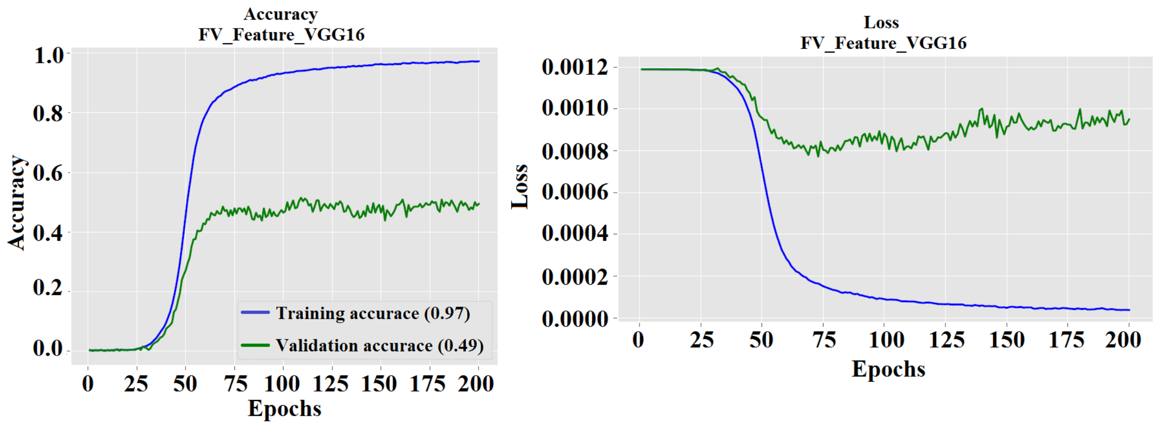

Figure 3. Accuracy and Loss of the VGG16 Transfer Learning Algorithm with Epoch Number =200, Accuracy and Loss of the VGG16 without ROI

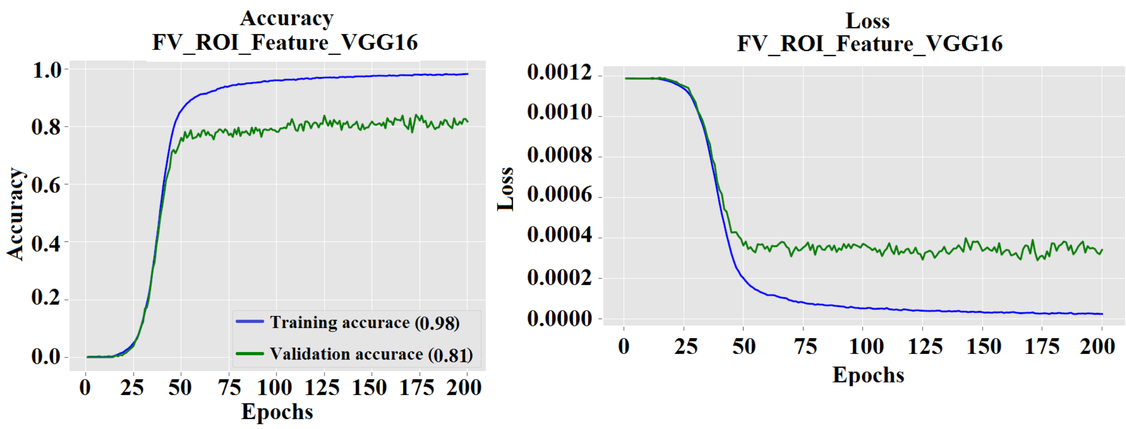

Figure 4. Accuracy and Loss of the VGG16 Transfer Learning Algorithm with Epoch Number =200, Accuracy and Loss of the VGG16 with ROI

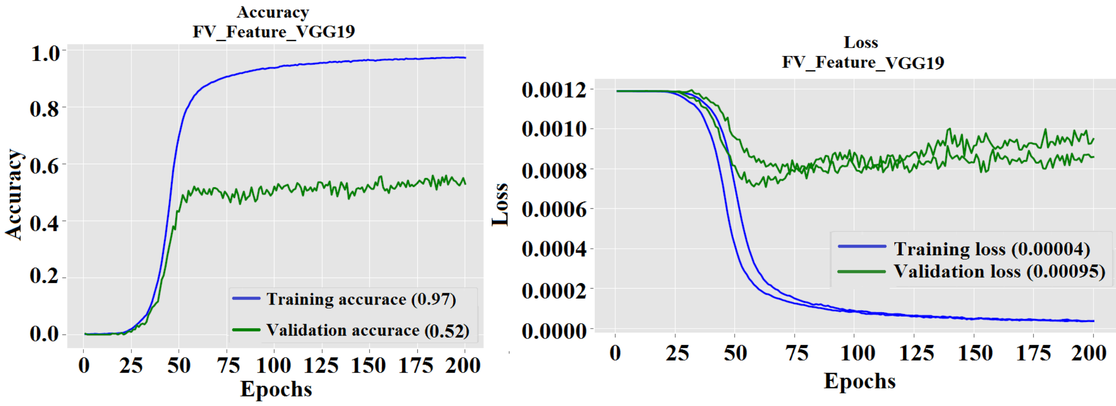

Figure 5. Accuracy and Loss of the VGG19 Transfer Learning Algorithm with Epoch Number =200, Accuracy and Loss of the VGG19 without ROI

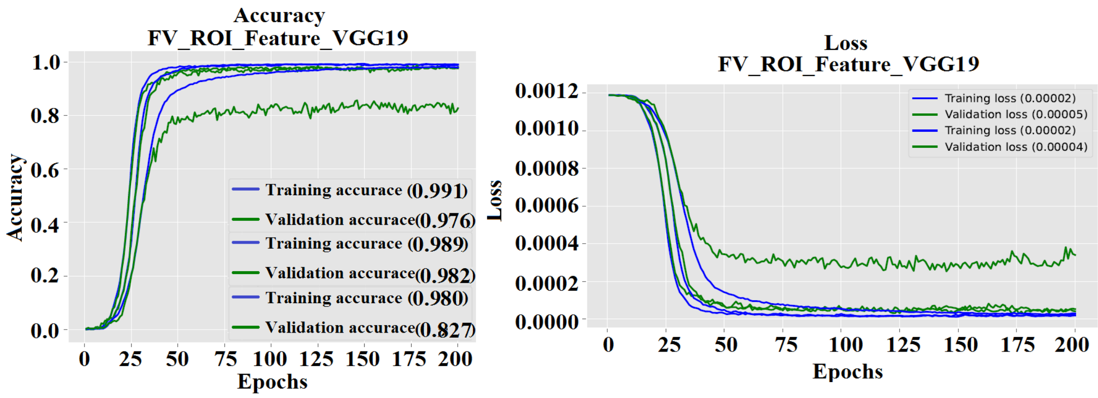

Figure 6. Accuracy and Loss of the VGG19 Transfer Learning Algorithm with Epoch Number =200, Accuracy and Loss of the VGG19 with ROI

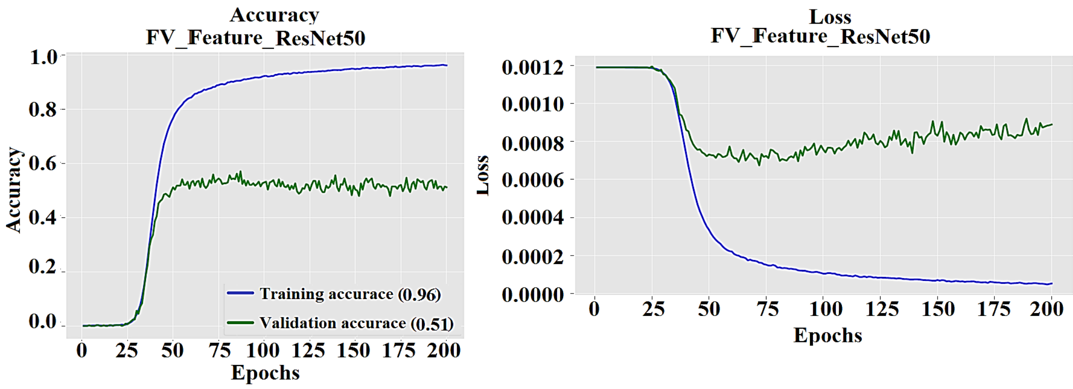

Figure 7. Accuracy and Loss of the ResNet-50 Transfer Learning Algorithm with Epoch Number =200, Accuracy and Loss of the ResNet-50 without ROI

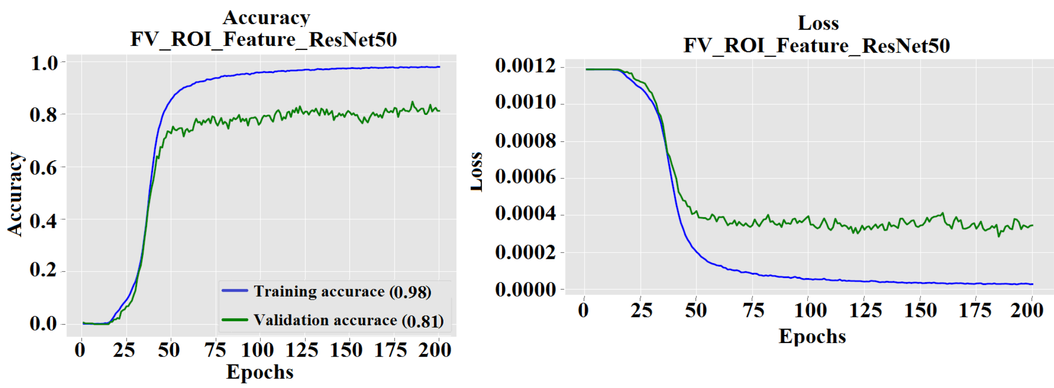

Figure 8. Accuracy and Loss of the ResNet-50 Transfer Learning Algorithm with Epoch Number =200, Accuracy and Loss of the ResNet-50 with ROI

Table 2 presents a precision, recall, and F1-score results of the three transfer learning algorithms. The results of the experiments clearly indicate that the performance of VGG16, VGG19, and ResNet-50 is significantly better when the region of interest (ROI) is identified in the finger vein image, compared to when the original image without any specific region is used.

Table 2. Transfer Learning Algorithms Results with and without Determine ROI in Finger Vein Image

Transfer Learning Algorithms	Metrics	Determine ROI based on K-means clustering	Without ROI
VGG16	Precision	0.9849	0.9709
	Recall	0.9838	0.9691
	F1-scor	0.9836	0.9688
VGG19	Precision	0.9844	0.9729
	Recall	0.9831	0.9709
	F1-scor	0.9830	0.9708
ResNet-50	Precision	0.9824	0.9652
	Recall	0.9811	0.9623
	F1-scor	0.9807	0.9620

Figure 9 offerings a comparison between the three transfer learning algorithms based on their precision, recall, and F1-score results. The comparison aims to prove the positive impact of determine the ROI in finger vein images using K-means clustering on the accuracy of these algorithms, and to identify the algorithm with the best performance.

A Comparison Between the Three Transfer Learning Algorithms Based on Precision, Recall, and F1-Score Results, demonstrates that the VGG16 algorithm with K-means clustering produces highest results in comparison to rest transfer learning algorithms. The precision value of VGG16 is close to 0.9849, the recall value is close to 0.9838, and the f1-score value is close to 0.9836. These results indicate that the proposed K-means clustering algorithm improves the accuracy and performance of transfer learning algorithms.

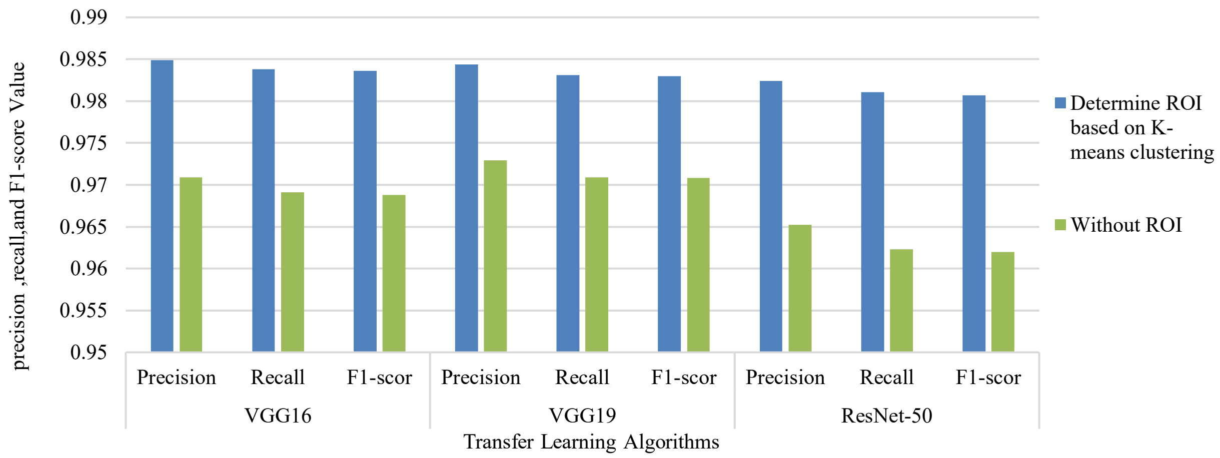

Figure 9. A comparison between the three transfer learning algorithms based on precision, recall, and F1-Score results

7. CONCLUSION

The multimodal finger dataset NUPT-FPV that we suggest in this research is the first publicly available dataset to contain both a fingerprint and a finger vein. The planned NUPT-FPV has 33600 photographs in 840 categories, and the subjects finish the collection in an entirely calm state. The comprises detailed data taken throughout two sessions to investigate the difficulty of feature change using time. This dataset will advance multimodal finger recognition technology. Additionally, we present a technique, an image enhancement method of finger vein combining Gaussian Bluer filter and K-means clustering. The proposed system shows that the performance of different classifiers with other datasets with a different number of instances, after using the K-means clustering technique to group the finger vein images, the high-quality images are blurred using either Gaussian or average filters of various widths. The flooding segmentation for ROI is only obtained using the finger region employing the most recent representative ROI extraction techniques, which also only eliminate the image's background noise.

However, elements like finger movement and finger shape in ROI extraction might negatively impact future recognition performance. As a result, we suggest a gradient operator with a broad receptive field. One the one hand, we can successfully address the issue of a large-scale grey gradient in the joint cavity imaging procedure to actualize the joint cavity's accurate localization. The finger region is further divided by the acquired vertical reference line, and the ROI is limited to the region between the two finger joint cavities, eliminating the influence of factors like finger location and shape on the recognition performance. The ROI generated by our suggested method has improved matching performance, as demonstrated by the trials on three publicly accessible datasets. It is more reliable and consistent with real-world uses. Since the current pandemic has brought public health security to a new level, Contactless and the unrestricted acquisition will move toward finger vein recognition. Further research will be done on the joint cavity extraction operator's shape, and as deep learning advances, it will be a good option for finger vein ROI localization. However, experimental results show that the proposed method is reliable for personal authentication and that the finger vein picture quality is significantly improved. Future scenarios requiring more complicated application situations would benefit greatly from our improved ROI extraction technique.

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