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Delta Ruled Fully Recurrent Deep Learning for Finger-Vein Verification

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Abstract; Finger-vein verification is a significant problem to be resolved in image processing because it provides high security in many practical applications. Few research works have been designed in conventional works using different machine learning techniques. However, the verification accuracy of existing algorithms was not sufficient. Also, the amount of time required for verifying the input finger vein image was more. In order to overcome such limitations, Delta Ruled Fully Recurrent Deep Learning (DRFRDL) technique is proposed. The DRFRDL technique comprises of three main layers namely input, hidden, output layer for accurate finger-vein authentication. The input layer in DRFRDL Technique takes a number of finger vein images as input and then sent it to the hidden layer. The designed DRFRDL technique used numbers of hidden layers in order to deeply examine the input finger vein images. The result of the hidden layer is feeding back into the network along with the inputs in order to find outs the vein features that exist in a given image. Followed by, the extracted vein features at hidden layers are transmitted to the output layer. In DRFRDL technique, output layer applies Gaussian activation function that calculates the features matching score via determining the association between extracted vein features and the vein features that are already stored in the database. After estimating the matching score, the output layer returns the verification result. If the output layer result is 1, then vein features are matched and the user is considered as authorized person. Otherwise, vein features are not matched and the user is considered as unauthorized person. Thus, DRFRDL technique increases the authentication performance of finger-vein with higher accuracy and minimal time. The simulation of DRFRDL Technique is conducted using metrics such as verification accuracy, verification time and false positive rate with respect to a different number of finger-vein images. The simulation results depict that the DRFRDL Technique is able to improve the accuracy and also reduces the amount of time needed for finger-vein verification when compared to state-of-the-art works.

Keywords: Delta Rule, Features matching score, Finger-vein, Gaussian activation function
Input layer, Hidden layer, Output layer, Recurrent Behavior.

I. INTRODUCTION

Finger vein verification is a new physiological biometric for human identification. Finger vein verification system employs vascular pattern underneath the skin of the finger palmar side to validate the personal identity.

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Compared with the existing biometric traits, finger-vein patterns reveal some excellent benefits in a real application. Each finger vein contains a unique vein pattern, which is found inside the body and is extremely not easy to forge. Many research works have been introduced for authenticating finger vein images. But, the verification performance of conventional techniques was not enough. In addition, the time taken for authenticating the finger vein image is also higher when increasing the number of input images. Therefore, DRFRDL technique is proposed in this paper by combining the delta rule concepts in a fully recurrent deep neural network for effective finger-vein authentication.

Convolutional Neural Network (CNN) was employed in [1] for feature extraction and Finger-vein authentication. However, the ratio of number of finger vein images that are wrongly verified was higher. The lightweight deep-learning framework was employed in [2] for finger vein verification. But, time complexity using this method was very higher. A novel method was presented in [3] to enhance the verification performance using finger-vein images with high quality. However, verification accuracy using this method was not enhanced. Finger-vein extraction approach was presented in [4] to find the valley-like structures using the curvatures and thereby increasing the accuracy of the finger-vein verification. But, computational complexity involved during the verification process remained an open issue.

A novel method was designed in [5] based on finger vein patterns through employing region of interest extraction and oriented elements feature extraction scheme. However, verification performance was poor. Bi-layer restoration method was developed in [6] to handle skin scattering and obtain better visibility of finger vein images. But, the false-positive rate was not reduced. An iterative deep belief network (DBN) was introduced in [7] to extort vein features depends on the initial label data and thereby achieve robust vein verification. However, the time required for vein verification process was higher. Finger-vein recognition system was presented in [8] by employing binary robust invariant elementary features. But, the ratio of number of finger vein images that are correctly authenticated using this system was lower. An optimized matching was performed in [9] to create pixel-based 2D displacements that correspond to deformations and thereby finding finger veins. However, the verification time was not minimized. Multi-Features Fusion was carried out in [10] by using the Scale Invariant Feature Transform (SIFT) matching method to get better performance for finger-vein recognition. But, the error rate involved during the finger-vein recognition process was more.

To resolve the above mentioned conventional method issues, DRFRDL Technique is introduced in this research work. The main contributions of DRFRDL Technique are described in below,

- To decreases the time complexity of finger vein verification as compared to state-of-the-art works, the Delta rule is applied in DRFRDL technique which is a gradient descent learning rule that is used to update the weights of the inputs to artificial neurons in a fully recurrent deep neural network structure. The Delta rule utilizes an error function to perform gradient descent learning in DRFRDL technique. Hence, delta rule employs the derivative of the network's weights along with the output error to adjust the weights and thereby provides better finger-vein authentication results with a lower amount of time consumption when compared to existing works.
- To improve the performance of finger vein authentication with higher accuracy and minimal false positive rate, Fully Recurrent Neural network (FRNN) is employed in DRFRDL technique on contrary to conventional deep leanings. Because Fully Recurrent Neural network is a most general type of recurrent network in which all neurons are fully interconnected. As a result, the finger vein verification performance of proposed DRFRDL technique is not affected due to any structural constraints. As a result, DRFRDL technique significantly increases the accuracy of finger vein authentication as compared to conventional works.

The organization of the paper is described as follows: Section 2 describes the literature survey .The proposed DRFRDL technique is explained in Section 3 with help of the architecture diagram. Section 4 presents the simulation evaluation. Simulation Results of DRFRDL technique are analyzed with various metrics in Section 5.Section 6 concludes the work.

II. LITERATURE SURVEY

A finger vein ROI extraction method was presented in [11] that robust to finger displacement and rotation. Singular value decomposition-based minutiae matching method was introduced in [12] for finger vein identification. The deep learning-based method was designed in [13] by combining a Convolutional Auto-Encoder (CAE) with a support vector machine (SVM) for finger vein authentication. A personalized subset of features was extracted in [14] using Pyramid Histograms of Gray, Texture, and Orientation Gradients (PHGTOG) in order to increases the recognition performance with lesser computational complexity. Finger-vein authentication was accomplished in [15] with the support of deformation-tolerant feature-point matching. A novel local binary learning feature for finger vein images called personalized binary code (PBC) was presented in [16].

Enhanced maximum curvature descriptors were employed in [17] to achieve minimal time complexity for finger vein verification. A novel examination of the soft biometric trait was presented in [18] to improve the accuracy of finger vein recognition. A correlation coefficient based template matching algorithm was used in [19] to identify the identity of a person using the match-scores with finger vein images stored in the database. Accurate ROI localization and hierarchical hyper-sphere model was introduced in [20] for finger-vein detection. An efficient finger vein based personal authentication system was presented in [21] to minimize the error rate of verification. A micro-control capture images technology was employed in [22] for the finger vein detection through adaptive image segmentation.

Local binary pattern (LBP) descriptors were designed in [23] to minimize the feature vector dimensionality of finger vein discovery. K-nearest neighbor and sparse representation based classifiers (KNN-SRC) was employed in [24] for personal authentication using finger vein pattern. A survey of different techniques developed for veins based personal identification using different data mining algorithms was analyzed in [25]. Field Programmable Gate Array (FPGA) based finger vein recognition was introduced in [26] for personal authentication. A complete and fully automated finger image matching framework was designed in [27] using the finger surface and finger subsurface features. Contact-Free Palm-Vein Recognition was implemented in [28] with the help of local invariant features. Efficient minutiae matching method was developed in [29] for attaining higher finger vein recognition accuracy. A Novel Approach was introduced in [30] for finger vein authentication by using self-taught learning. A robust method based on Bag-of-Words (BoW) was presented in [31] for achieving higher accuracy for finger vein verification.

Blocked Filtering Method was designed in [32] to increase the reliability of personal authentication. Computational Intelligence Techniques was constructed in [33] to increase the processing speed of the finger vein authentication system. Novel finger-vein recognition was performed in [34] by using an image quality assessment. Local discriminative feature learning method was designed in [35] for finger vein recognition using multi-directional pixel difference vectors. Two Parallel Enhancement Approaches based Fuzzy Histogram Equalization was presented in [36] for finger vein identification. Super pixel-based finger vein recognition method was presented in [37] to improve the recognition performance.A finger vein recognition method was implemented in [38] by application of a personalized best bit map (PBBM).A finger vein recognition algorithm was designed in [39] with the help of gradient-correlation. A systematic review of different finger vein recognition techniques was analyzed in [40]. To diminishing the vanishing gradient problem , to update the weight on pruned cascade [42] and recurrent cascade neural learning [43] to reached the best accuracy on the image classification on Cifar-100 data set.

III. DELTA RULED FULLY RECURRENT DEEP LEARNING TECHNIQUE

The Delta Ruled Fully Recurrent Deep Learning (DRFRDL) technique is developed with the objective of improving the performance of finger-vein verification with higher accuracy and minimal time complexity. On the contrary to conventional works, DRFRDL technique is proposed by applying delta rule concepts in a fully recurrent deep neural network. The designed DRFRDL technique includes an input layer, three hidden layer, and output layer.

An input layer in DRFRDL technique is fully associated with the output layer by means of adjustable, weighted links. The input layer acquires a number of vein images as input. Also, the DRFRDL technique contains a number of hidden nodes to discover the vein features that are presented in input images. Hidden nodes in DRFRDL technique also operate as a secondary, dynamic memory of the system. In addition to that, DRFRDL technique comprises of unit-delay feedback connections which are fed back into its input layer to effectively authenticate input finger vein images. The combination of dynamic, context-based memory with the recurrent behavior, feedback connections formulates the proposed DRFRDL technique for accurately generating the finger vein verification results. Finally, the output layer gives the authentication result. The architecture diagram of DRFRDL technique is depicted in below Figure 1.

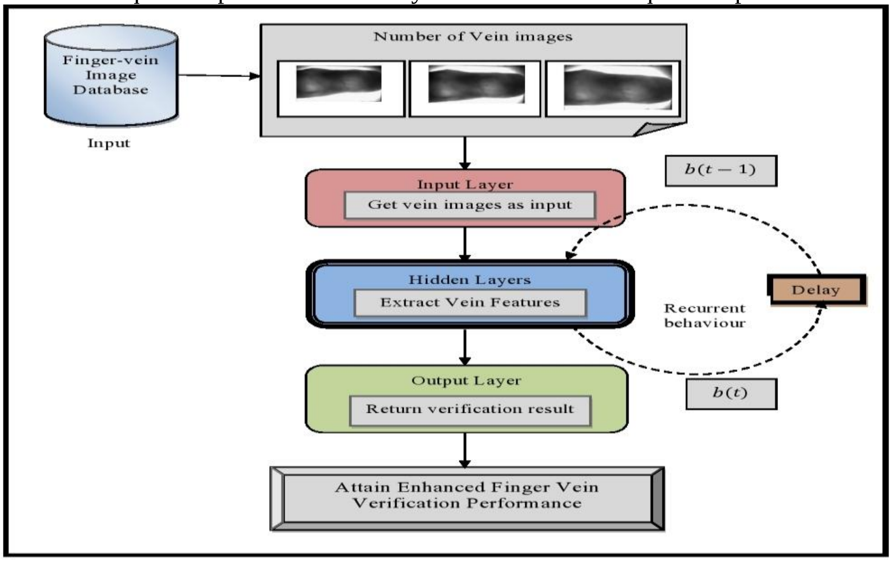

Figure.1. Architecture Diagram of DRFRDL Technique for Finger Vein Authentication

Figure 1 presents the flow processes of DRFRDL technique for effective finger vein verification. As shown in above Figure 1, DRFRDL technique initially gets the finger-vein image database (i.e. SDUMLA-HMT Database.) as input which contains a many numbers of vein images represented as '$\mu_i = \mu_1, \mu_2, .., \mu_n$'. Each user vein images is fed into input layer for verifying their identity. Each input vein image to the input layer is then sent to the nodes in hidden layers. The DRFRDL technique employs one or more hidden layers to deeply learn the input vein image and thereby take out significant vein features for verification. After that, hidden layers sent the discovered vein features to the output layer. In DRFRDL technique, output layer utilizes Gaussian Activation Function that computes feature matching score through finding the relationship between extracted vein features and the vein features that are already stored in the database. The output of hidden layer is feeding back into the network along with the inputs in order to only extract significant the finger-vein features. Finally, the output layer generates a verification result of input vein images. The structure of DRFRDL technique is demonstrated in below Figure 2.

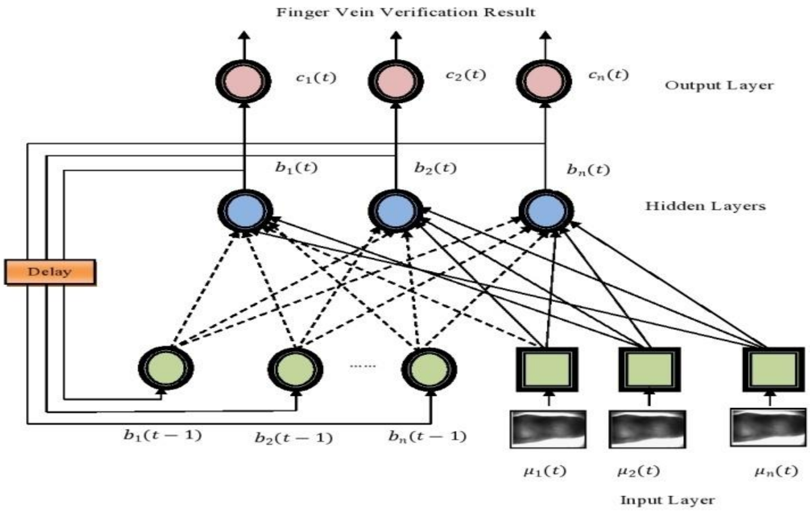

Figure .2 .Structure of DRFRDL for Finger Vein Verification

The structure of proposed DRFRDL technique is depicted in above Figure 2 for accurate finger vein verification. Let us consider an input finger-vein image database comprises a large number of vein images denoted as '$\mu_i = \mu_1, \mu_2, .., \mu_n$'. Here '$\mu_i$' indicates the input vein images. At the beginning, DRFRDL technique initializes the neural network with arbitrary weights. In DRFRDL technique, input neurons are denoted as 'a', the hidden neurons are designated as 'b' and the output neurons are indicated as 'c'.

Input layer is constructed by combining current input vein images '$\mu_i(t)$' and weight 'w_{ab}' and output from neurons in the hidden layer at a time '$t-1$'.

Hence, input layer is mathematically described as follows,

$$a(t) = w_{ab}\mu_i(t) + b(t-1) \quad (1)$$

From the above expression (1), '$a(t)$' denotes the neurons process in input layer at time't'. For each input vein images 'μ_i' of a user, DRFRDL technique updates activities of every neurons at a different time and then generates output. In hidden layer, the action of neuron at a time 't' is mathematically obtained as follows,

$$b(t) = \sum_{i \in b \cup a} w_{ab}\, \mu_i(t) \quad (2)$$

From the above mathematical representation (2), 'w_{ab}' signify a weight between input and hidden layer and '$\mu_i(t)$' point out the activity of neuron 'i' in a hidden layer at time 't. In the same way, the activity of neuron ' i' in hidden layers at a time '$t+1$' is mathematically expressed as follows,

$$b(t+1) = \sum_{i \in b \cup a} w_{ab}\, \mu_i(t+1) \quad (3)$$

From the mathematical formulation, '$\mu_i(t+1)$' indicates the activity of neuron ' i' at a time '$t+1$'. For each time instance of input vein image, the previous output of hidden unit activations is feeding back into network with inputs. Accordingly, recurrent behavioral of DRFRDL technique is mathematically represented as follows,

$$b(t) = \; w_{ab}\, \mu_i(t) + w_b\, b\,(t-1) \quad (4)$$

From the mathematical expression (4) and (5), '$b(t)$' denotes an output of the hidden layer at the time instance 't' and '$b_i\,(t-1)$' signifies the previous hidden layer output. Here, 'w_b' symbolizes a weights of hidden layers. By using the equations (2), (3) and (4), hidden layers detects the vein features in input images for effectual user authentication. The identified vein features are then transmitted to the output layer. From that, the activity of neuron ' i' in output layers at a time '$t+1$' is mathematically determined as follows,

$$c(t) = F(w_{bc} b(t)) \quad (5)$$

From the above mathematical equations (5), '$c(t)$' denotes the verification output whereas 'w_{bc}' signifies the weight between the hidden and output layer. Here 'F' signifies the activation function. The DRFRDL technique used Gaussian function as activation function in order to obtain higher finger vein verification accuracy. Thus, Gaussian activation function is mathematically expressed as follows,

$$F = \frac{1}{\sqrt{2\pi v}} e^{\frac{-(\mu_i - m)^2}{2v^2}} \quad (6)$$

From the above mathematical formula (6), 'μ_i' represent input vein image with their extracted features at a hidden layer. Here, 'm' and ' v' denotes mean and variance value of vein features. Consequently, the output of Gaussian activation function is presented in below Figure 3.

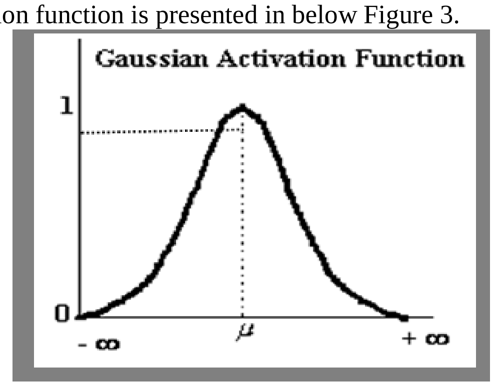

Figure .3. Gaussian Activation Function Output

Figure 3 portrays the result of Gaussian activation function in DRFRDL technique to validate the finger vein of an input image. As presented in the above diagram, the Gaussian activation function is a bell-shaped curve. The Gaussian activation function determines feature matching score in terms of class membership such as '0' or '1' based on how close the extracted vein feature of an input image is to a vein features already stored in a database. The outcome of the Gaussian activation function value is either '0' or '1'. If the extracted vein features of an input image are matched with vein features is already stored in the database, then Gaussian activation function returns matching score as '1'. Otherwise, Gaussian activation function returns feature matching score as '0'. Thus, the verification result at the output layer is mathematically obtained as follows,

$$c(t) = \begin{cases} 1, \; vein\, features\, are\, matched \\ 0, \; vein\, features\, are\, not\, matched \end{cases} \quad (7)$$

From the above mathematical expression (7), '$c(t) = 1$' indicates that extracted vein features of an input image are matched with vein features is stored in the database. Hence, DRFRDL technique considered that the user is an authorized person. Besides to that, '$c(t) = 0$' represents that extracted vein features of an input image are not matched with any vein features is stored in database. Thus, DRFRDL technique considered that the user is not an authorized person.

For all the trained input vein images, then DRFRDL technique measures error rate ' $\tau(t)$' using below mathematical formula,

$$\tau(t) = T_i - A_i \quad (8)$$

From the above mathematical equation (8), DRFRDL technique calculates error rate for each verification result obtained at the output layer. Here, 'T_i' signifies a target output whereas 'A_i' is an actual output. Followed by, DRFRDL technique updates the weights according to estimated error. On the contrary to conventional works, delta rule is used in DRFRDL technique to update the weights of inputs to artificial neurons. For a neuron 'i' with activation function, the delta rule for updating weight is mathematically expressed as follows,

$$\Delta w_{ab} = x(T_i - A_i)\mu_i \quad (9)$$

From the above mathematical representation (9), 'Δw_{ab}' symbolizes an updated weight, 'x' represents a small constant i.e. learning rate. Here, 'μ_i' indicates an actual input (i.e. finger vein image of a user). The delta rule is applied in DRFRDL technique with aiming at minimizing the error function in the output of the neural network using gradient descent. Accordingly, DRFRDL technique determines the partial derivative of error function according to each weight 'Δw_{ab}' using below mathematical formula,

$$\frac{\partial \tau}{\partial w_{ab}} = \left(\frac{\partial(\frac{1}{2}(T_i - A_i)^2)}{\partial w_{ab}} \right) \quad (10)$$

Subsequently, the chain rule is employed in DRFRDL technique to partition the above equation into two derivatives as follows,

$$\frac{\partial \tau}{\partial w_{ab}} = \left(\frac{\partial(\frac{1}{2}(T_i - A_i)^2)}{\partial w_{ab}} \right) \frac{\partial A_i}{\partial w_{ab}} \quad (11)$$

By using the above equation (11), weight between input and hidden layer 'w_{ab}' is updated with respect to error function 'τ'. In the same way, the weights of hidden layer and output layer is updated as follows,

$$\frac{\partial \tau}{\partial w_b} = \left(\frac{\partial\left(\frac{1}{2}(T_i - A_i)^2\right)}{\partial w_b}\right)\frac{\partial A_i}{\partial w_b} \quad (12)$$

$$\frac{\partial \tau}{\partial w_{bc}} = \left(\frac{\partial\left(\frac{1}{2}(T_i - A_i)^2\right)}{\partial w_{bc}}\right)\frac{\partial A_i}{\partial w_b} \quad (13)$$

By using the above mathematical expressions (12) and (13), the weights on the hidden layer and output layer are updated. After updating all weights, DRFRDL technique applied gradient descent which is a first-order iterative optimization algorithm. The gradient descent is employed in DRFRDL technique adjusts weights based on the error function. Thus, the error rate of finger vein verification is optimized as follows,

$$c(t) = \sum_{i=1}^{n} arg\ min\ \tau(t) \quad (14)$$

From the above formula (14), '$c(t)$' signifies a final output where '$arg\ min$' helps for DRFRDL technique to discover minimal error function for accurately verifying the finger vein images. The processes of DRFRDL technique is repeated until the error function is very lower for efficiently performing finger vein verification process. The algorithmic processes of DRFRDL technique is explained as follows,

Delta Ruled Fully Recurrent Deep Learning Algorithm
Input: Finger-vein Image Database '$\mu_i = \mu_1, \mu_2, .., \mu_n$' , TC: Termination Condition,
Output: Improved finger vein verification performance with minimal time complexity
Step 1: Begin
Step 2: Initialize network with random weights
Step 3: **While ('**TC**'** is reached**) do**
Step 4: **For** each input image 'μ_i' at the input layer
Step 5: Input layer sent obtained images to hidden layers using (1)
Step 6: Hidden layers extract vein features in an image using (2), (3) and (4)
Step 7: Hidden layer forwards extracted features to the output layer
Step 8: Output layer applies Gaussian activation function 'F'
Step 9: Measure feature matching score using (6)
Step 10: Output layer generates verification result '$c(t)$' using (5)
Step 11: **End for**
Step 12: Calculate error '$\tau(t)$' using (8)
Step 13: Update weight 'Δw_{ab}' , 'Δw_b', '$\Delta \varphi w_{bc}$' using (11), (12) and (13)
Step 14: Find minimum error using (14)
Step 15: **End while**
Step 16: **If** $(c(t) = 1)$ **then**
Step 17: Vein features are matched and the user is authorized
Step 18: **Else**
Step 19: Vein features are not matched
Step 20: **End If**
Step 21: End

Algorithm 1 Delta Ruled Fully Recurrent Deep Learning

Algorithm 1 shows the step by step process of DRFRDL technique. As explained in the above algorithmic process, DRFRDL technique at first defines network with random weights. For each input finger vein images get at the input layer is forwarded to the hidden layer. Then, the hidden layer in DRFRDL technique deeply analyzes and extracts important vein features in input images with the help of their recurrent behavior. Followed by, hidden layer transmits identified vein features of an image to the output layer. Finally, the output layer in DRFRDL technique computes feature matching score with aid of Gaussian activation function by matching the discovered vein features of an input image with pre-stored vein features in database and returns verification result. For each obtained result, then DRFRDL technique determines the error and consequently updates all the weights on the network and thereby finds outs the minimal error to exactly verify finger vein images with lower time utilization. Thus, DRFRDL technique enhances the finger vein verification performance and also reduces the time required for verifying finger vein images when compared to state-of-the-art works.

IV. SIMULATION SETTINGS

The DRFRDL technique is implemented in MATLAB simulator by using SDUMLA-HMT Database [41] to measure the performance. The SDUMLA-HMT is a finger vein database which contains 3,816 images with 320×240 pixels in size. To conduct the simulation work, DRFRDL technique considers a various number of finger vein images in the range of 25-250 from SDUMLA-HMT Database. The efficiency of DRFRDL technique is measured in terms of verification accuracy, verification time and false-positive rate. The simulation result of DRFRDL technique is compared with conventional Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2].

V. RESULTS

In this section, the simulation result of proposed DRFRDL technique is presented. The effectiveness of DRFRDL technique is compared with conventional Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2] with the assist of parameters such as verification accuracy, verification time and false-positive rate.

5.1 Measure of Verification Accuracy

Verification Accuracy '(VA)' determines the ratio of a number of finger vein images that are correctly verified to the total number of finger vein images.

The verification accuracy is measured in terms of percentages (%) and mathematically computed as follows,

$$VA = \frac{n_{CV}}{n} * 100 \qquad (15)$$

From the above equation (15), the accuracy of finger vein authentication is estimated. Here, 'n' denotes the number of finger vein images considered for performing simulation process whereas 'n_{CV}' represents the number of correctly verified finger vein images.

Sample Mathematical Calculation for Verification Accuracy

- **proposed DRFRDL technique:** Number of finger vein images accurately verified is 21 and the total number of the finger vein images is 25, then the verification accuracy is calculated as follows,

$$VA = \frac{21}{25} * 100 = 84\ \%$$

- **Existing CNN:** Number of finger vein images exactly verified is 17 and the total number of the finger vein images is 25, then the verification accuracy is obtained as follows,

$$VA = \frac{17}{25} * 100 = 68\ \%$$

- **Existing lightweight deep-learning**: Number of finger vein images perfectly verified is 19 and the total number of finger vein images is 25, then the verification accuracy is computed as follows,

$$VA = \frac{19}{25} * 100 = 76\ \%$$

To determine the accuracy of finger vein verification, DRFRDL technique is implemented in MATLAB simulator by considering the different number of finger vein images in the range of 25-250. When performing the experimental evaluation using 175 finger vein images, proposed DRFRDL technique obtains 95 % verification accuracy whereas state-of-the-art works Convolution Neural Network (CNN) [1] and a lightweight deep-learning [2] attains 79 % and 82 % respectively. Thus, verification accuracy using proposed DRFRDL technique is very higher as compared to other works. The performance result analysis of verification accuracy is presented in below Table 1.

Table I Tabulation for Verification Accuracy

Number of finger vein images (n)	Verification Accuracy (%)		
	DRFRDL	CNN	lightweight deep-learning
25	84	68	76
50	86	72	78
75	93	79	83
100	91	77	79
125	90	78	84
150	92	78	81
175	95	79	82
200	92	77	81
225	94	80	83
250	97	82	86

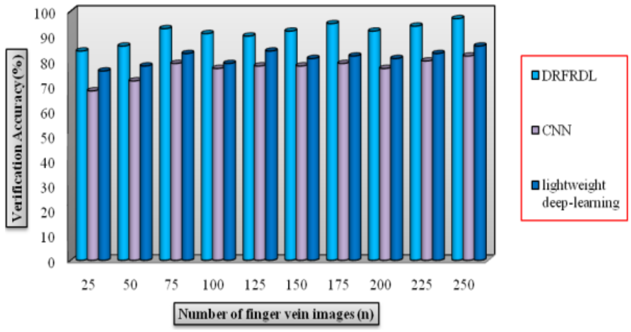

Figure.4. Comparative Result Analysis of Verification Accuracy versus Number of Finger Vein Images

Figure 4 demonstrates the impact of verification accuracy based on a various number of finger vein images using three methods. As presented in the above graphical figure, proposed DRFRDL technique gives higher accuracy to validate the finger vein image of each user as compared to Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2]. This is owing to the application of fully recurrent deep neural network in proposed DRFRDL technique on the contrary to existing algorithms. By using the recurrent characteristic, proposed DRFRDL technique deeply observe and mine the key vein features that present in input images without using any manual feature extraction techniques.

With the help of extracted vein features, then proposed DRFRDL technique evaluates matching score to efficiently perform the verification process with higher accuracy. Moreover, Gaussian activation function is utilized in the proposed DRFRDL technique accurately estimates matching score between extracted vein features and vein features stored in the database. This supports for proposed DRFRDL technique to enhance the ratio of a number of finger vein images that are properly verified as compared to other existing works Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2]. Therefore, the proposed DRFRDL technique increases the verification accuracy by 19 % and 12 % as compared to Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2] respectively.

5.2 Measure of Verification Time

The Verification Time (VT) measured as the amount of time needed for verifying the finger vein images. The verification time is computed in terms of milliseconds (ms) and calculated mathematically as follows,

$$VT = n * Time(VSI) \qquad (16)$$

From the above expression (16), the time utilized for authenticating the finger vein image of a user is determined. Here, 'n' denotes the total number of finger vein images whereas '$Time(VSI)$' indicates the amount of time consumed for verifying a single finger vein image.

Sample Mathematical Calculation for Verification Time

- **Proposed DRFRDL:** total number of finger vein images are 25 and the time needed to authenticate the single finger vein image is 1.1 ms, then verification time is determined as follows,

$$VT = 25 * 1.1\, ms = 28\, ms$$

- **Existing CNN**: total number of finger vein images are 25 and the time required to validate the single finger vein image is 1.4 ms, then verification time is evaluated as follows,

$$VT = 25 * 1.4\, ms = 35\, ms$$

- **Existing lightweight deep-learning**: total number of finger vein are 25 and the time utilized to verify the single finger vein image is 1.6 ms, then verification time is measured as follows,

$$VT = 25 * 1.6\, ms = 40\, ms$$

In order to measure the time complexity of finger vein authentication, DRFRDL technique is implemented in MATLAB simulator with the varied number of finger vein images in the range of 25-250. When conducting the experimental process using 225 finger vein images, proposed DRFRDL technique gets 68 ms verification time whereas conventional works Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2] takes 77 ms and 86 ms respectively. As a result, verification time using proposed DRFRDL technique is very minimal when compared to other works. The comparative result analysis of verification time is depicted in below Table 2.

Table -II Tabulation for Verification Time

Number of finger vein images (n)	Verification Time (ms)		
	DRFRDL	CNN	lightweight deep-learning
25	28	35	40
50	35	40	45
75	42	45	53
100	47	50	58
125	55	59	65
150	63	60	69
175	56	67	74
200	64	74	80
225	68	77	86
250	75	80	90

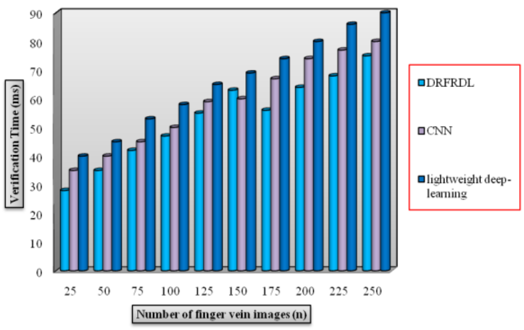

Figure.5. Comparative Result Analysis of Verification Time versus Number of Finger Vein Images

Figure 5 presents the impact of verification time along with a diverse number of finger vein images using three methods. As shown in the above graphical diagram, proposed DRFRDL technique provides a lower amount of time consumption in order to accurately authenticate the finger vein image of each user when compared to Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2]. This is because of application of delta rule concepts in proposed DRFRDL technique on the contrary to conventional algorithms where it is employed to update the weights of the inputs to artificial neurons in a fully recurrent deep neural network structure. In the proposed DRFRDL technique, delta rule utilizes the derivative of the network's weights together with the output error to adjust the weights. Thus, the proposed DRFRDL technique quickly finds the minimum error function to provide better finger-vein authentication results as compared to existing works. This helps for proposed DRFRDL technique to minimize the amount of time needed for verifying the finger vein images when compared to other existing works Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2]. Hence, the proposed DRFRDL technique reduces the verification time by 9 % and 20 % as compared to Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2] respectively.

5.3 Measure of False Positive Rate

The False Positive Rate '(FPR)' calculates the ratio of a number of finger vein images that are incorrectly verified to the total number of finger vein images. The false positive rate is estimated in terms of percentages (%) and mathematically obtained as follows,

$$FPR = \frac{n_{IV}}{n} * 100 \qquad (17)$$

From the above mathematical representation (17), false-positive rate of finger vein authentication is determined. Here, 'n' point outs the total number of finger vein images used for the simulation process and 'n_{IV}' refers to the number of inaccurately verified finger vein images.

Sample Mathematical Calculation for False Positive Rate

- **Proposed DRFRDL:** Number of finger vein images mistakenly verified is 4 and the total number of the finger vein images is 25, then the false positive rate is estimated as follows,

$$FPR = \frac{4}{25} * 100 = 16\,\%$$

- **Existing CNN:** Number of finger vein images imperfectly verified is 8 and the total number of the finger vein images is 25, then the false positive rate is obtained as follows,

$$FPR = \frac{8}{25} * 100 = 32\,\%$$

- **Existing lightweight deep-learning**: Number of finger vein images inexactly verified is 6 and the total number of finger vein images is 25, then the false positive rate is determined as follows,

$$\text{FPR} = \frac{6}{25} * 100 = 24\,\%$$

For evaluating the false positive rate of finger vein verification, DRFRDL technique is implemented in MATLAB simulator by taking a diverse number of finger vein images in the range of 25-250. When accomplishing the simulation process using 200 finger vein images, proposed DRFRDL technique achieves 8 % false-positive rate whereas existing works Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2] obtains 23 % and 20 % respectively. Accordingly, false-positive rate of finger vein authentication using proposed DRFRDL technique is very lower as compared to other works. The tabulation result analysis of false-positive rate is shown in below Table 3.

Table 3 Tabulation for False Positive Rate

Number of finger vein images (n)	False Positive Rate (%)		
	DRFRDL	CNN	lightweight deep-learning
25	16	32	24
50	14	28	22
75	7	21	17
100	9	23	21
125	10	22	16
150	8	22	19
175	5	21	18
200	8	23	20
225	6	20	17
250	3	18	14

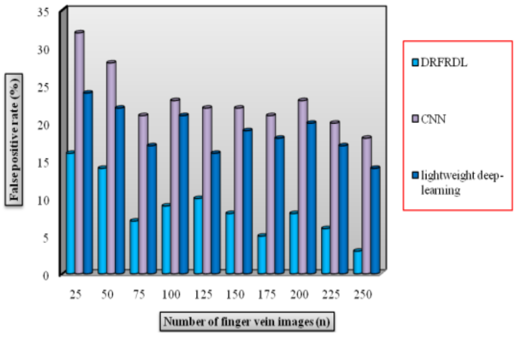

Figure.6. Comparative Result Analysis of False Positive Rate versus Number of Finger Vein Images

Figure 6 portrays the impact of false-positive rate of finger vein authentication with respect to a different number of finger vein images using three methods. As illustrated in the above graphical figure, proposed DRFRDL technique gives minimal error rate in order to correctly validate the finger vein image of each user when compared to Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2]. This is due to the application of fully recurrent deep neural network in proposed DRFRDL technique on the contrary to existing algorithms where all neurons in network structure are fully interconnected. Therefore, the verification performance of proposed DRFRDL technique is not impacted by any structural constraints.

From that, DRFRDL technique considerably increases the accuracy of finger vein verification as compared to conventional works. This assists for proposed DRFRDL technique to decrease the ratio of a number of finger vein images that are incorrectly verified when compared to other existing works Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2]. Thus, proposed DRFRDL technique lessens the false positive rate of finger vein verification by 64 % and 56 % as compared to Convolutional Neural Network (CNN) [1] and a lightweight deep-learning [2] respectively.

VI. CONCLUSION

The DRFRDL technique is proposed with the goal of enhancing the finger-vein verification performance with higher accuracy and lower time. The goal of DRFRDL technique is obtained with the application of delta rule concepts in a fully recurrent deep neural network. The proposed DRFRDL technique improves the ratio of a number of finger vein images that are accurately verified with support of fully recurrent deep neural network when compared to other existing works. Further, the proposed DRFRDL technique reduces the amount of time needed for authenticating an input finger vein images with help of delta rule concepts as compared to state-of-the-art works. Accordingly, the proposed DRFRDL technique attains enhanced finger-vein authentication performance as compared to conventional works. The proposed DRFRDL Technique carried outs simulation evaluation using parameters such as verification accuracy, verification time and false positive rate with respect to a diverse number of finger-vein images. The simulation result reveals that the proposed DRFRDL Technique presents betters performance with an improvement of finger vein verification accuracy and minimization of finger vein verification time when compared to state-of-art methods.

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