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Impostor Detection Based Finger Veins Applying Machine Learning Methods

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Abstract- *Finger veins are different from other biometric signs; it is a special characteristic of the human body. The challenge for an imposter to explore and comprehend it, since the veins are below the skin, it is impossible to tell which one is, and which one stands out because the person has more than one finger to examine. Impostor recognition based on applying three machine-learning methods will be presented in this article, and then there is a discussion at preprocessing, Linear Discriminant Analysis (LDA) for feature extraction, and k fold cross-validation as an evaluation method. These measures were carried out on two different datasets, which are the Shandong University Machine Learning and Applications - Homologous Multi-modal Traits (SDUMLA-HMT) Dataset and the University of Twente Finger Veins (UTFV) dataset. The classifier with the best results was Support Vector Machine (SVM) and Linear Regression (LR) had the lowest classifier accuracy.*

Index Terms— *Machine learning, Finger Veins, Impostor, Support Vector Machine, Liner Regression, One Rule.*

I. INTRODUCTION

Biometric identification methods are increasing and widely applied in various purposes for recognition purposes, in difference to the traditional recognition tools such as Personal Identification Number (PIN) or password, which are constantly in risk of being forgotten or stolen, biometric identification advances great advantage for the user [1]. As it is well-known, many biometric techniques such as voice recognition, iris identification, finger veins recognition and face identification are used for objective identification and verification in different domains [2]. Newly, the domain of images pattern recognition with its various applications became an attractive and important research domain [3]. Finger vein recognition system is estimated more strong, secure, and emerging biometric characteristics, because of its unique characteristics such as real-time detection and anti-falsification [4]. A finger-vein recognition method allows a secured identification process that is reliable, simple and very accurate. *Fig.* 1 shows finger vein identification method [5].

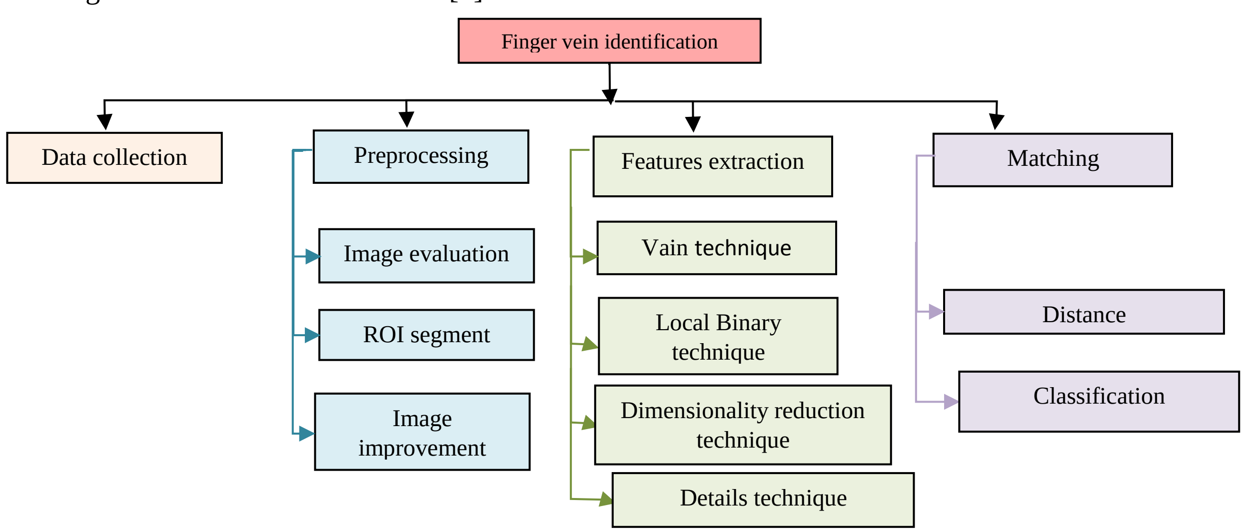

FIG.1. FINGER VEIN RECOGNITION METHOD

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Biometrics signs, which lead to the detection of somebody based on their behavioral or physiological properties. Physiological characteristics combine forms of hands or fingers, facial traits, plus iris verification. Behavioral characteristics are features, which are learned or gained [6]. Finger veins have been attracting more and more researchers in the last four decades. Because of poor image quality and low permeability of the Finger veins, most Finger veins detection systems suffer from the drawbacks associated with the extraction of meaningful features. Poor infrared radiation regulation, weak brightness requirements, as well as spreading in the tissues that coat the vein structure to be photographed can all contribute to poor image quality. The four stages of a biometric technique focused on finger veins are image obtainment, preprocessing of image, feature extraction, in addition to conformity of characteristic. Infrared light (near-infrared) ; the first is light reflection, and the second is light refraction, all of which are used to capture images. The importance of a reliable image acquisition operation is critical; otherwise, preprocessing will be needed. Several current finger vein detection concepts work well with a tidy and clear image. Changes are required even if the picture is of poor quality and the finger positioning is perverted or corrupt. It is critical to preprocess a vein image after obtaining it to increase the accuracy of the image. There are two methods for extracting image features. The first is to consider an image as a whole, which can be referred to as image-level feature extraction by some thoughtful feature extraction algorithms in the area processing of an image. The second method is to remove the image's vein shapes, and then extract features from vein-level function extraction is the process of extracting the simple vein shapes. Table1 shows the survey for main biometric signs [7].

TABLE 1. SURVEY OF MAIN BIOMETRIC SIGNS

Biometric characteristics	Key Advantage	disadvantage	Safety Level	Cost
Voice	Natural and comfortable	Noises	Medium	Low
Face	Remote capturing	Lighting requirements	Medium	Low
Iris	High accuracy	Glasses	Very Good	High
Fingerprint	Extensively implemented	Skin	Good	Low
Finger -veins	Large-safety level	Disease	Very Good	Low

II. LITERATURE REVEIW

Finger vein recognition has been widely established since the beginning of the twenty-first century. This segment would explore some early literature correlated to this research provided the recognition of finger veins using convergent techniques to the proposal that has been used in this paper:

In 2014, suggested Cross-correlation matching and Sobel detector, enhancement filter and a binarization process to prepare the vein pattern, edge detection, ROI extraction and smoothing filter, the accuracy rate had reached 72.44 percent [8]. In 2014, presented two techniques for features extraction, the first used ridge let, and the second discrete algorithms based on Unequally Spaced Fast Fourier Transform (USFFT), choose USFFT coefficients in a different scale to represent various varieties of image information. Moreover, used corresponding processing technique for the feature in various scales, after that all the modified features were linked to an integrated feature. The classifiers were SVM; the recognition accuracy was reached 91.89 percent [9]. In 2015, the researcher proposed Euclidean Distance techniques, preprocessed images with image enhancement, Region Of Interest (ROI) detection, and resizing, and used the Kekre Wavelet Transform (KWT) method for feature extraction, with an accuracy of 86.3 [10]. In 2015, presented Template matching method to recognize finger veins, preprocessing was used ROI extraction and Brightness normalization. For features extracting applying Local Entropy Thresholding (LET),

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Morphological Dilation and Morphological filtering, the accuracy obtained from was 90.9 percent [11]. In 2015, suggested Curve Analysis method for finger vein recognition. Applied pre-processing by Compute grey-threshold and Binary Conversion. For features extraction used Combination of minutiae extraction. It achieved an accuracy of 92 percent [12]. In 2015, discussed a technique for finger-vein image features extraction using 2-D Rotated Wavelet Filters (RWF) and Discrete Wavelet Transform (DWT). The 2-D RWF and DWT jointly employed for the decomposition of a finger vein image ROI. The standard deviation and energy of all sub band from every decomposition stage are applied for the creation of features vector. Then Canberra Distance (CD) classifier employed for the classification of finger vein images. The achievement of this approach has evaluated on the Shandong University Machine Learning and Applications - Homologous Multi-modal Traits (SDUMLA-HMT) dataset, and the accuracy result was 92.33 percent [13]. In 2016, presented a template matching method by different techniques of the Local Directional Pattern (LDP) to make finger vein recognition reliable. LDP is applied to compute the edge response in all eight directions and considering each pixel position. The performance is evaluated on the (SDMULA-HMT) dataset. The achieved result accuracy of 86.16 percent [14]. In 2019, used Discriminant Analysis (DA) and the K-Nearest Neighbor (KNN) classifier to recognize finger veins. The accuracy of the features of the finger vein images was tested and calculated using the KNN classifier. Using the (SDUMLA-HMT) dataset, the accuracy obtained from KNN is 55.84 percent, while the accuracy gained from discriminant analysis is 92.21 percent [15]. In 2019, presented a feature method named as Straight Line Approximator (SLA) for extending the feature space of vein pattern using The Dempster-Shafer (DS) and General Weighted of the Average Rule (GWAR). The SDUMLA-HMT dataset was examined. Used the Extreme Learning Machine (ELM) and Support Vector Machine (SVM) classifier in different kernels. Then, used the combination rules to enhance the performance of the system. The result of the suggested method reached an accuracy of 87 percent [16]. In 2021, as an improvement to the k-Nearest Centroid Neighbor (kNCN) classifier, added an adaptive k-Nearest Centroid Neighbor (akNCN) to the equation. On the finger-vein database of Malaysian Polytechnic University (FV-USM) image database, used Principle Component Analysis (PCA) for features extraction. The classification rate is 85.64 percent, which is promising [17].

III. FINGER VEINS AUTHENTICATION PROPOSED (FVA)

The Finger Veins Authentication (FVA) proposed is based on a machine-learning algorithm. Finger veins images, dataset definition, pre-processing, feature extraction, K-fold cross-validation, classification levels, and post-processing level are all common features. *Fig*. 2 depicts the proposed device architecture.

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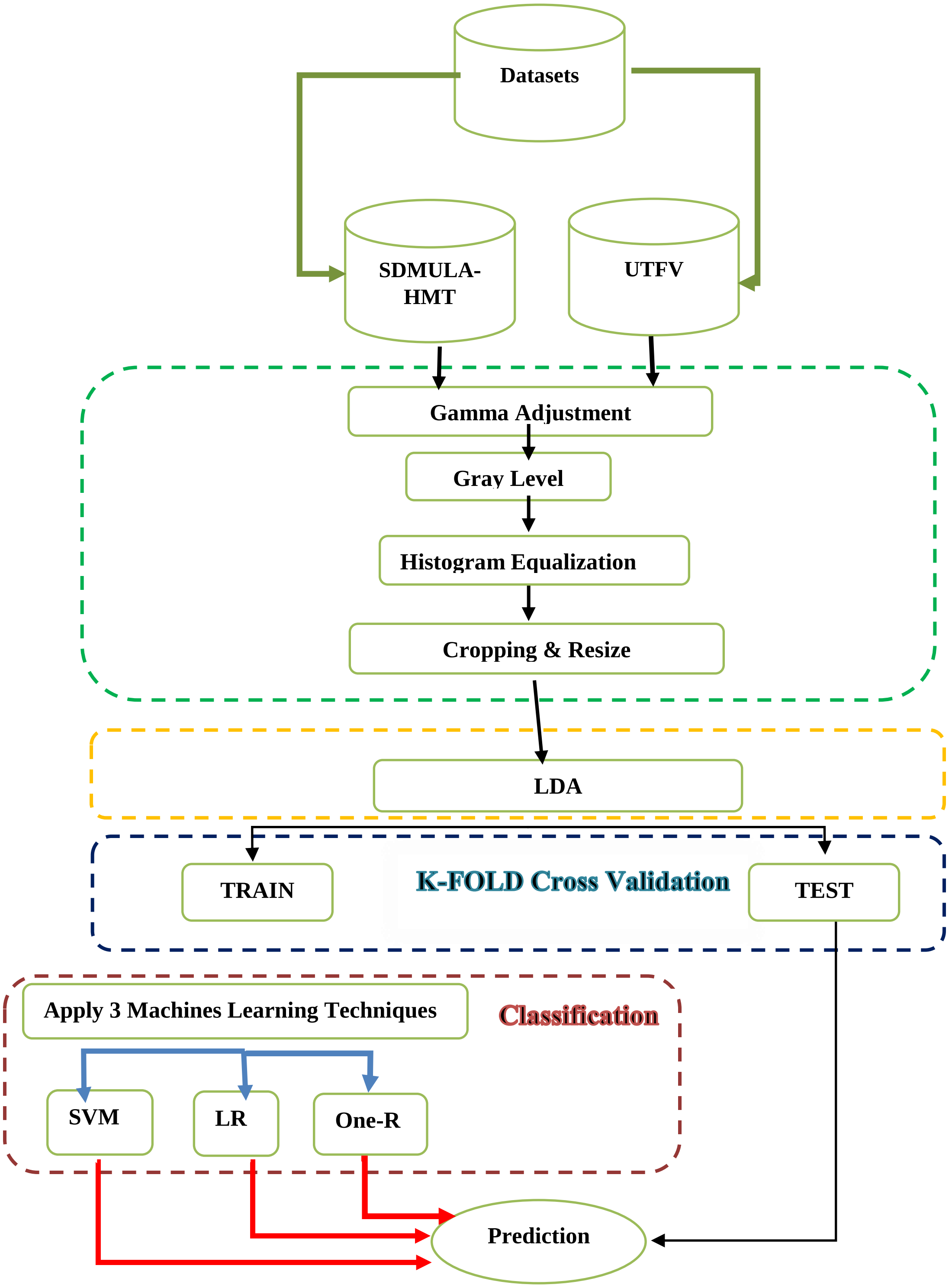

FIG. 2. FLOWCHART OF THE FINGER-VEIN AUTHENTICATION METHOD

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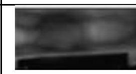
A. Dataset Specification

Table 2 shows the datasets details.

TABLE 2. DATASETS FOR THE SYSTEM'S FINGER VEINS [1]

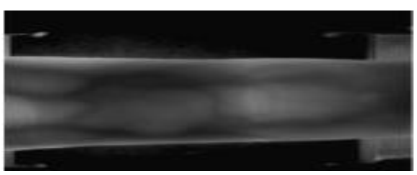
Dataset	Number of images	Number of persons	Finger number per person	Image No. per Finger	Image resolution	Format	Typical Image
SDMULA -HMT	3816	106	6 (Index, ring, middle, of both hands)	6	320x240pxl	. Bmp	
UTFV	1440	60	6 (Index, ring, middle, of both hands)	4	672x380pxl	. Png	

B. Preprocessing

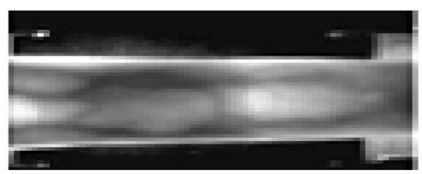
The preprocessing phase's key benefit is that it organizes the data and producing identification assignment simpler. Both activities that work with photographs are referred to as "preprocessing".

1. Gamma Correlation for Boost Contrast

The finger image was dark and faint after it was taken; the next step is to enhance its brilliance with Gamma correction. The productive region of pixel organizations can be expanded by using a nonlinear method to pixel regulation. It helps with less co-event network correlation. The aim of this approach is to put the most significant distinctions to the forefront and increase their visibility. It greatly improves picture quality by controlling traditional image brilliance in a novel way. Its effect is shown in the *Fig*.3.



Primary image from (SDMULA-HMT) Database



Primary image after **Gamma Correlation**

Primary image from (UTFV) Database

Primary image after **Gamma Correlation**

FIG. 3. IMAGE GAMMA CORRELATION

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2. RGB to gray level image applying Grayscale Image

Because just a single channel is sold within the grayscale field rather of tripartite as in RGB (Red, Green, and Blue), changing a color image to the grayscale domain decreases data and advances processing speed. A weighted average system was employed to convert the RGB colored image to a gray image; this method was preferred because it presents a purer image in which the colors are not equally weighted. Because pure green is lighter than pure blue and pure red, it has a bigger weight. Its effect is shown in *Fig*.4.

(SDMULA-HMT) after **Color to Gray level** (UTFV) after **Color to Gray level**

FIG. 4. IMAGE COLOR TO GRAY LEVEL

3. Contrast improvement using Histogram Equalization

The main objective of Histogram Equalization is to level the probability intensity function of the input image and redistribution the grey levels to build a treated image with improved contrast. Its important advances is that the average brighbess of the processed image with interest to the original image. It also includes noise and density congestion effects which appear in a loss of image features and give the appearance of the processed image unnatural. Its effect is shown in the *Fig*.5.

(SDMULA-HMT) after Histogram Equalization (UTFV) after Histogram Equalization

FIG. 5. HISTOGRAM EQUALZATION FOR IMAGE

4. Resizing and Cropping (R&C)

The most widely used picture editing techniques are: (R&C). Both would have undergone extensive testing because they have the potential to impair image quality. When an image is resized, its proportions

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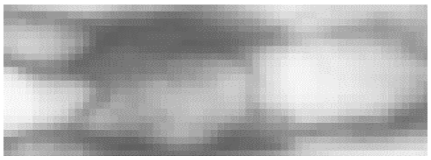
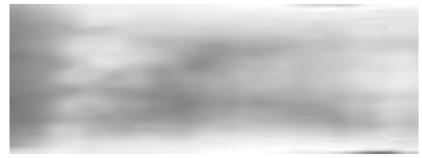
are altered, resulting in greater file size (and, thereby, image quality). Cropping also includes raising a serving of the unique image, which causes pixel loss. Its effect is shown in the *Fig*.6.



SDMULA-HMT after (R&C)



(UTFV) after (R&C)

FIG. 6. IMAGE RESIZING AND CROPPING

C. Linear Discriminant Analysis for Feature Extraction

Linear Discriminant Analysis (LDA) is a well-known method of analysis. It uses linear sequences of variables to differentiate between classes, resulting in linear decision limits. The methodology searches for a linear transformation that maximizes class reparability in a low-dimensional field. A characteristic imperative that merges linear features, defines axes that maximize volatility, and merges linear features can be used to reduce the number of dimensions.

D. Classifiers of Proposed System

This is a classification issue because of the machine-learning Technique, including feature extraction method, it is needed to assess the overall efficacy of the Finger Veins identification model. As a consequence, the following supervised classification machine learning algorithms can be applied:

1. Support Vector Machine (SVM)

The SVM can wield categorical and continuous variables. In addition, the SVM model runs well on regression and classification intricacies for data mining. The SVM is a classification algorithm that performs the hyperplanes for all class labels in the multidimensional area by applying the margin values. The SVM aims to maximize the margins among various classes by optimally distributing hyperplanes. The hyperplane is a data case of the given dataset used by the support vectors. Margin is the maximum distance between the support vector and the hyperplane.

2. One Rule (One-R)

One-R, short for "One Rule," is a one-regular decision tree-generating classification algorithm applied for data mining. From a set of cases, (One-R) can derive normally simple, yet specific classification rules. (One-R) can also work with missing values and numeric attributes, presenting its versatility- despite its simplicity. The (One-R) algorithm generates one rule for all attribute in the training data and takes the rule with the lowest error measure as its "one rule".

3. Linear regression (LR)

Linear regression is a statistical method centered on mathematics. It is estimated that the aim function F is linear and that it is dependent on the input features. View all input attributes to be real numbers and record the present results most significantly. ai is obtained by minimizing the sum of the

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error squared value (squared difference between the actual value and the received built function). The approach is based on minimizing the Euclidean distance between the actual results vector and the vector obtained via regression recovery.

IV. IMPLEMENTATION OF PROPOSED (FVA)

This method is divided into two stages, which are as follow:

A. Training Phase

The suggested method's first step is to split the two datasets using K fold cross-validation. Following that, the models are related to Finger veins that were entered using k fold cross-validation with a value of k = 6. The datasets will be preprocessed applying a Gamma correlation, after which the images will be transformed from RGB to Gray Level, then preprocessed with Histogram Equalization before being cropped and resized. The classification algorithms are built on top of the LDA-extracted functionality. The mixed features are preserved as root templates during the training phase.

B. Testing Phase

This process of the proposed method is the next step. As previously mentioned, the reminder data will be checked later using the same pre-processing measures as the training data. The recommended method structure is given in Algorithm (A) below.

Algorithm (A), Suggested (FVA) implementation

Input -: Finger veins datasets

Output: - Best classifier performance

<u>Begin</u>

1: Load dataset (SDMULA-HMT), (UTFV) **// Input //**
2: Increase Contrast using Gamma Correlation
3: Color to gray level using Grayscale Image for (UTFV) Dataset
4: Contrast enhancement using Histogram Equalization
5: Resizing and Cropping

Pre-processing Phase (steps 2–5)

6: Dimensionality Reduction using LDA

Feature Extraction Phase (step 6)

7: Shuffle the dataset randomly and divide it into (6) groups using Cross-Validation, a (k –1) sub-instances were applied for training
8: The remaining data single sub-instance will be applied as the validation data for testing
9: Classify instances based 3 Classifiers

K fold Cross-Validation (steps 7–9)

10**:** Classifiers Evaluation
11: Best Classifier performance (Accuracy measurements, Error measurements) **Output**

<u>End</u>

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V. PROPOSED SYSTEM EVALUATION

Certain parameters are used to evaluate a model's actions when assessing its output. The findings are influenced by the size of the training data, the consistency of the files, and, most importantly, the type of machine-learning algorithm used. The efficacy of the models is evaluated using the following parameters [18]:

- **Accuracy (Acc):** The percentage of examples correctly classified out of all those given. It is determined as follows[18]:

$$\text{Accuracy} = \frac{a+b}{a+b+c+d} \qquad (1)$$

Where

a = True positives are the number of samples that were expected to be positive but turned out to be positive.

c = False positives: the number of samples that were expected to be positive but turned out to be negative.

b =True negatives are the number of samples that were expected to be negative but turned out to be negative.

d=False negatives: the number of samples that were expected to be negative but turned out to be positive.

- **Precision (Pre):** For all those classified as class x, the percentage of true x-class instances. It is determined as follows [18]:

$$\text{Precision} = \frac{a}{a+c} \qquad (2)$$

- **Recall (Rc):** The proportion of examples classified as class x out of all examples classified as class x. It is determined as follows[18]:

$$\text{Recall} = \frac{a}{a+d} \qquad (\mathbf{3})$$

- **F- measure:** precision and recall have a harmonic mean. It's worked out as follows[18]:

$$F_1 = 2 * \frac{Pre * Rc}{Pre + Rc} \qquad (4)$$

Error Rate (ER): An error is basically a misclassification, a case is presented to the classifier, and it incorrectly classifies the case, as shown in Eq. (5) below[18]:

$$\text{Error Rate} = 1 - \text{accuracy} \qquad (5)$$

- **Specificity:** Also called True Negative Rate (NTR). The tendency of a test to be negative when the un present condition is measured. It is also referred to as the false-positive rate, accuracy, Type I error, error, commission error, or null hypothesis [18].

$$\text{Specificity(NTR)} = \frac{b}{b+c}\ 100\% \qquad (6)$$

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- **KAPPA Cohen's** The kappa coefficient can be applied to determine how well two standard nominal classifications agree. When using Cohen's kappa to measure classification agreement, the distances between all nominal categories are considered identical, which makes sense if all nominal categories represent different types of "presence". The weighted kappa coefficient is calculated as follows[18]:

$$\boldsymbol{K} = \frac{\boldsymbol{O-E}}{\boldsymbol{I-E}} \qquad (\mathbf{7})$$

Mean Absolute Error (MAE) and Root Mean Square Error (RMSE): These measures are commonly used to assess the accuracy of a recommender system, and they are calculated as shown in Eq. (9) and (8) [18]:

$$\text{MAE} = \sum |\text{r}^{\text{n}} - \text{rn}|\text{N n} - 1/\text{N} \qquad (8)$$

$$RMSE = \sqrt{} \sum(\text{r\^{}n} - \text{rn})\text{N 2 n} - 1/\text{N} \qquad (9)$$

Where, $r \wedge n$ means the prediction rating; rnmeans the true rating in testing data set;

N is the number of rating prediction pairs between the testing data and prediction result

VI. EXPERIMENTAL FINDINGS

Use (One-R, LR, SVM) classifiers to evaluate the datasets in this experiment. Table 1 shows the effects by applying the Finger veins datasets (SDMULA-HMT and UTFV) as information (2). Table (3) and Figs numbered from (7-15) show that the (SVM) classifier has the highest accuracy measurements, while the (LR) classifier has the lowest accuracy measurements. In terms of error measurements, the results were the same, with the (LR) classifier producing the highest error rate and the (SVM) classifier producing the lowest error measurements among the other classifiers.

TABLE 3. RESULTS OF MACHINES LEARNING CLASSIFIER

	One-R		**LR**		**SVM**	
	SDMULA-HMT	UTFV	SDMULA-HMT	UTFV	SDMULA-HMT	UTFV
Total instances	3816	1440	3816	1440	3816	1440
Total correct	3224	1408	2183	489	3710	1419
Total incorrect	592	32	1633	951	106	21
Accuracy	84.48	97.77	57.20	33.95	87.18	98.54
Precision	91.34	97.98	57.39	40	90.61	98.61
Recall	84.48	97.77	57.20	33.95	87.18	98.54
F- measure	85.79	97.79	56.83	34.06	87.15	98.54
Error rate	15.52	2.23	42.80	66.05	12.82	1.46
Specificity(NTR)	99.85	99.96	99.59	98.88	99.87	99.97
KAPPA	84.33	97.74	56.79	32.83	87.06	98.51
M.ABS.E	0.01	0.02	0.008	0.030	0.005	0.004
RMSE	0.08	0.11	0.08	0.12	0.04	0.003
Execution Time	6.6 sec	2.44 sec	2.42	2.21 sec	2.1	1.01sec

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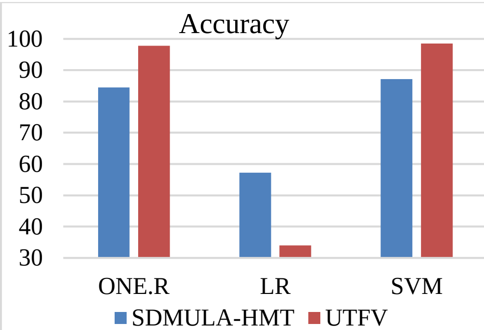

FIG. 7. ACC. FOR CLASSIFIER

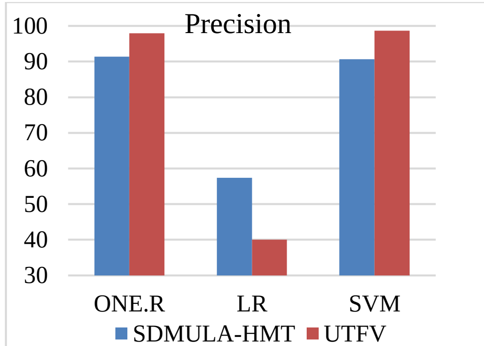

FIG. 8. PRE. FOR CLASSIFIER

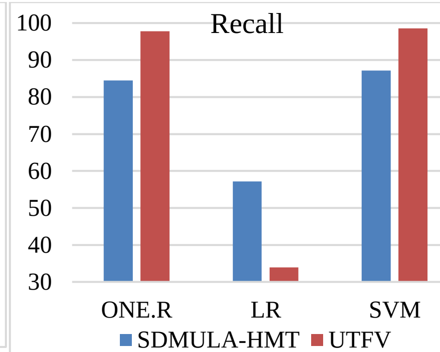

FIG. 9. REC FOR CLASSIFIER

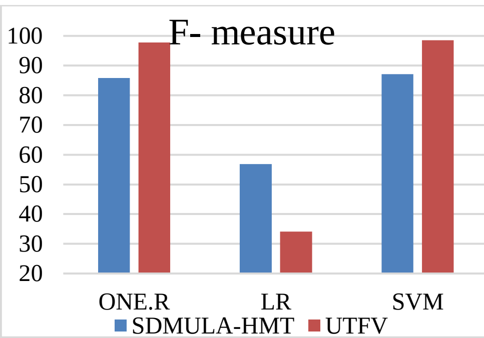

FIG. 10. F-MEASURE FOR CLASSIFIER

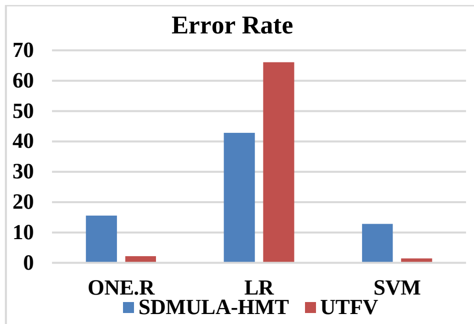

FIG. 11. ER FOR CLASSIFIER

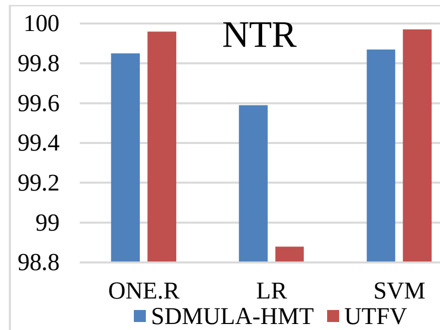

FIG. 12. TNR FOR CLASSIFIER

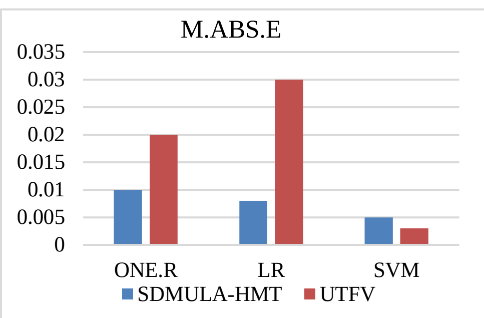

FIG. 13. M.ABS.E FOR CLASSIFIER

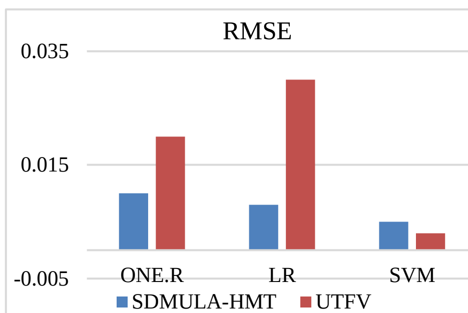

FIG. 14. RMSE FOR CLASSIFIER

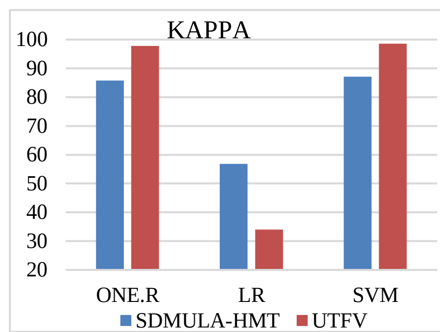

FIG. 15. KAPPA FOR CLASSIFIER

According to the results in (Table 3), (SVM) had a simple superiority over the other algorithms, led by the One-R algorithm, and the LR algorithm had the worst score.

VII. COMPARISON RESULTS WITH RELATED WORK

The following table compares the best two outputs of the suggested device algorithms to the relevant work. For the two classifiers (SVM, One-R), Eq. 10 measures the average accuracy of the proposed:

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$$Average\ accuracy = \frac{accuracy\ of\ dataset1 + accuracy\ of\ dataset2}{2} \qquad (10)$$

TABLE 4. RESULTS AND TECHNIQUES COMPARISON

Reference number	Suggested Date	Features extraction	Technique used	Accuracy
Ref. [8]	2014	ROI extraction	Cross-correlation	72.44%
Ref. [9]	2014	USFFT	SVM	91.98%
Ref. [10]	2015	KWT	Euclidean Distance	86.30%
Ref. [11]	2015	LET	Template matching	90.90%
Ref. [12]	2015	Combination of minutiae	curve analysis	92%
Ref. [13]	2015	DRWF & DWT	Canberra Distance	92.33%
Ref. [14]	2016	LDP	Template matching	86.16%
Ref. [15]	2019	DA	KNN	92.21%
Ref. [16]	2019	DS & GWAR	SLA	87%
Ref. [17]	2021	PCA	AkNCN	85.64%
Proposed	**2021**	**LDA**	**SVM**	**93.17%**
Proposed	2021	LDA	(One-R)	91.13%

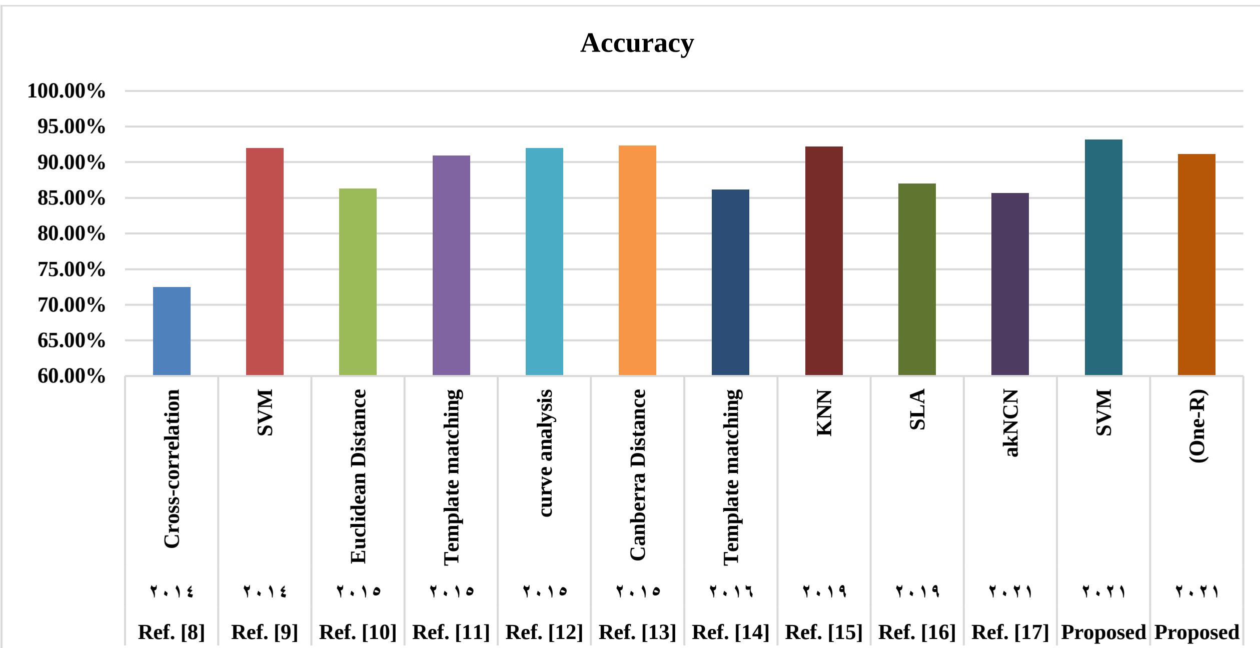

FIG. 16. COMPARISON RESULTS WITH RELATED WORK

The findings show that the proposed scheme outperformed the overall Literature Survey methods in terms of average precision of finger veins detection using the (SVM) algorithm, as seen in Table 4 and *Fig.* (16).

VIII. CONCLUSIONS

Finger veins turn out to be one of the most difficult biometric features for an Impostor to obtain and prevent. Choosing two datasets in different formats to improve the system's accuracy efficiency. Images are preprocessed to eliminate noise, boost accuracy, rotate, and crop them. The extraction of features is a crucial step. Applying the LDA technique for features extractions. For data splitting phase applying K fold cross-validation, the value of k = 6 was chosen, because when increasing the value of k to 10, it is noticeable

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that the accuracy does not increase, and increasing the value of k causes a loss in time and cost. Machine-learning methods were used to obtain a variety of results, with (SVM) achieving the maximum average accuracy of 93.17 percent and requiring the least amount of time for execution, followed by (One-R) with an outcome of 91.125 percent. As a result, explored and evaluated the findings in most areas.

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