Object Boundary Tracking In Moving Palm Image For Personal Identification

Hasan Kareem Abdulrahman[1]
[1] Computer Systems Department, Technical Institute Kirkuk, Northern Technical University, Iraq
[1] Hasan.abdulrahman@ntu.edu.iq

ABSTRACT

Famous biometric technique that has been used in recent years for human identification is Palm-print system. the Palm-print includes best features for participating the personal identification. In this work we proposed a new method for palm-print based identification that implemented using famous palm-print dataset named Delhi ver. *IIT* dataset. Our method is to obtain a palm image of each person using a camera placed inside a special box. After that, the area in the center of the palm is determined, and the image is sorted. Deep learning algorithms and algorithms are used to sort and recognize the characteristics extracted from the image of the person's palm. The results shown that our proposed method using Feed Forward Neural Network (FFNN) based palm-print identification system is gives better than other machine learning techniques methods.

Keywords: FFNN, Palm-print, ROI, Pixels, Machine Learning, Supervised Learning.

1 INTRODUCTION

There are many image processing methods were advanced for decades and were come to be crucial to human day by day routine. Security of information is likewise began new level due to generation detection and huge information in the image. Data quantities are dramatically elevated after improvement of recent era cell communique as customers elevated and net and not using a limitations for example face detection or voice detection extensively propagated [1].

The life of robust protection is needed to guard net records in addition to neighborhood server's records hence, the studies pastime on development of protection packages in addition to technology is increased. The first try to guard the net primarily based totally records is the use of the passwords safety in which Technologies for picture processing had been advanced for a completely long term and at the moment are crucial for each day life [2]. As net utilization has improved and era has advanced, information safety has additionally improved. Data volumes have significantly improved with the arrival of next-technology cellular communique due to an growth in customers and the considerable utilization of the net without cables or velocity limitations [2].

As it will become greater essential to defend each on-line information and information stored domestically on servers, studies into greater green safety strategies and apps is growing. The first line of protection for the safety of web-primarily based totally information is password protection, which calls for legal customers to publish their login credentials as a way to get admission to the information [3].

Hidden the passwords keys get greater tough as era advances, specifically with the creation of the net and on-line apps. As dependability rises, passwords frequently encompass unique characters similarly to alphabetic ones, making password prediction greater tough. The frequency of located safety breach tries has expanded because of software program and technical improvements. A new private verification technique have to be advanced due to the fact passwords might also additionally constantly be predicted and guessed [4-5].

The practice of palm recognition has gained popularity as a practical method to safeguard the security of data. It mainly comprises recognizing users based on the palms of their hands and providing them access. Artificial intelligence is quickly overtaking human intelligence as one of the most popular approaches for data protection as palm recognition accuracy increases.

There are numerous times of tries to apply biometric developments for person identity in protection structures with inside the literature. The most customarily used techniques for accomplishing the aforementioned aim are face reputation the use of facial functions and speaker reputation the use of audio characteristics. The following problems with the available recognition technologies have been demonstrated:

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One of the most, astounding ways to verify someone's identity is speaker identification, which uses the human voice as an example. Nonetheless, it could be challenging to identify a speaker if their voice changes for any cause, such the impact of cold weather or a problem with their vocal chords [6].

The age of the applicant has an impact on face recognition; as a candidate gets older, their facial features start to deteriorate and change, necessitating an update to the dataset and retraining of the entire model.

Easiest method of identifying a candidate is to compare them to their individual PIN or password; however, this method suffers from a password guessing issue because several software's may predict the password and get access to the system [7].

The face may often be hidden by a variety of things, including makeup, growing hair, etc. These challenges raise the possibility of mistakes and a sharp decline in the face recognition system's accuracy [8–10].

When updating the dataset day by day this can be crucial if the popularity machine consists of a big pool of candidates, every of whom falls inside a positive age range. This might upload time and cost and be nearly impossible [11–15].

2 PALM DATASET

In spite of efforts on this area depend closely on information accessibility, photo processing has lately attracted loads of attention. Hence, there are procedures to reap information: both via publicly handy datasets produced through a unmarried researcher and made to be had online (respiratory), or via information that can be acquired from the overall public through enlisting volunteers withinside the observe process [16].

Nevertheless, researchers in recent times favor to use pre-current datasets that make the take a look at system greater practical in preference to generating their very own statistics, which takes loads of time and work. Alternatively, if a specific statistics factor is needed for the application, it ought to be acquired via way of means of contacting feasible subject individuals and asking them to take part withinside the take a look at and publish the specified statistics.

Because palm data was required for this investigation, Institute of Technology in Indian They managed a big dataset named Delhi *IIT* palm-print image collection is the most reliable dataset in this regard. With the assistance of many college staff members and students, this dataset was produced in 2006. Each applicant had to place their hand inside a black box, whereupon a smartphone camera captured a colored image of their palm with adequate resolution . The right and left palms of each candidate's hands were clasped together and pointed in the same direction.

3 PRE-PROCESSING

The pre-processing script imports each image one at a time before putting them in the workstation directory by using a marked loop to run through the image names. Each photo has a distinct name, which is crucial to remember for the loop process to function. To lessen the impact of poor lighting and the amount of background objects, a smoothing filter is applied. For the only purpose of color palm detection on particular the region of center of palm-print, the image is converted to binary representation (black and white). The boundary of the palm is then determined by processing the image using Matlab's border function. Even though there are other objects in the image, only the palm object needs to be recognized in order to use the border function. When all item sizes are compared to determine the object of interest, the palm object has the largest size (i.e., the most pixels coordination points). The REGIONGROUPS function, which returns each object together with its centroid, was used to recognize the objects on the image.

The edge of color points that specify for each position in pixel for each point in the palm-print edge and the centroid that specify the middle point in the palm image are not created for each palm image once. Thus images are puts in the pre-processing steps and the palm-print is detected in each of them. The palm must be rotated a specific degree in order to align the photos of all the palms and complete the pre-processing stage (either clockwise or anticlockwise). Three points on the palm plane are used to compute the sway angle. The angle created by the two lines is then used to compute the rotation angle.

Assume that the lengths of X, Y, and Z are represented by the blue, green and red lines, respectively. The triangle formula below can be used to determine the angle indicated by the red circle.

$$\mu = \frac{X}{Y} \quad (1)$$

In order to current the orientation of the palm image, it needs to be rotated by σ angle that producible in the following formula [18]. The palm image must be rotated at a particular angle, which may be determined using the formula below. The best palm image from the dataset's orientation angle was determined using pre-processing, where x is the reference angle. In order to correct each picture rotation in line with equation 2, the angle are considered as the reference angle compared to all the latest angles.

$$\sigma = x - \mu \quad (2)$$

4 CLASSIFICATION

After identifying regions of interest in palm pictures and retouching palm photos, advanced deep learning techniques are used to identify the person using the data from the palm image. In order to identify the owner of a palm tree in this study, feed-forward neural networks are trained using data from the research region. The (FFNN) network gathers data from the palm's-print properties in an effort to correctly identify the owner of the device. For the feed forward neural network model to exploit this information during the learning stage, all of the palm features must be referred to from the regions of interest. The learning stage of this technique, known as supervised learning, uses both the target (the information on palm owners) and the feature information. Matlab was used to create the feed-forward neural network displayed in Table 1.

Table 1: Proposed method parameters configuration for the Feed Forward Neural Network (FFNN).

Parameters of the Networks	Details
Number of Epochs	100
The nodes in each layer	Input layer= 30
	Hidden layer= 10
	Output layer= 1
Total layers	3 layers
Targeted performance (mse)	1 e-200
Learning/ training	Levenberg–Marquardt algorithm (LM)

The essential technology underpinning palm identification is demonstrated using two additional machine learning methods from the unsupervised learning algorithm group [10]. We use the algorithms Random Forest and K-Nearest Neighbor. Comparable photos are categorized into a single class using K-Nearest Neighbor palm picture categorization based on the Euclidean distance between the classes. Using the Random Forest method, which creates a root class from which all other classes will emerge as leaves, the same goal is also achieved [19–24].

It resembles a tree in that the tallest nodes are known as the root nodes and the lowest nodes are known as the primary leaves. Each image is folded beneath a certain leaf after comparing the randomness of each leaf. The class with the lowest randomness will finally receive the image [25].

Neural networks artificial (NNs) are recognized for their cappotential to address difficult issues and provide answers via simplest comprehending (hidden) the essential relationships a number of the input signals [18]. The input vector r and the goal vector T are required for the simple single hidden layer ANN (net) in Figure 2 shows to begin supervised learning. To get the output with the least amount of inaccuracy, weight coefficients between the layers can be modified [10]. You may identify the inaccuracy in Figure 1 by looking at the correlation between the produced vector and the necessary vector [26, 27]. If "r" is a number selected at random:

$$R = net\ (r) \quad (2)$$

$$R = W \times r \quad + b \quad (3)$$

where b is the model bias and R is the put vector. To achieve the best R-T correlation, Net may adjust the W coefficients [28, 30]. Finding the lowest value of Eq. is the goal of learning, in other words (5). The mean square error (MSER), where e is the error vector, serves as a performance measure for training and learning [31-32].

$$e = R - T \tag{4}$$

$$MSE = \frac{\sum_{n=1}^{i} e(n)^2}{i} \tag{5}$$

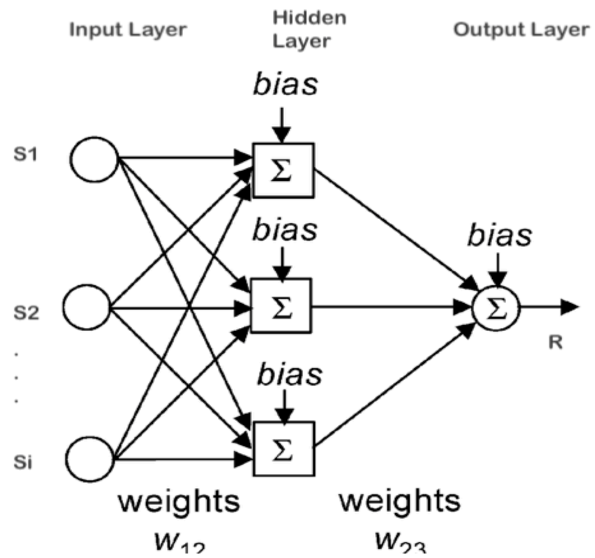

Figure 1: ANN layer structure demonstrating the input, weights/biases and output.

5 Results

The performance metrics uses for, each algorithm presented in the earlier sections has undergone extensive testing (MSER, RMSER, MAER, Accuracy and Times). The results of the performance measurements are shown in Tables 2. According to the results, of proposed FFNN, the most accurate approach for classifying images, has an accuracy of 91.25 in determining who took a palm image. The algorithm's exceptional accuracy is offset by a moderately large latency (see Figures 2 through 6).

Table 2: Comparison metric results Proposed FFNN with other classification technique methods.

Tool	K-Nearest Neighbour	Random Forest Algorithm	Proposed (FFNN)
MSER	849	548.47	484
MAER	33.5	548.48	484.57
RMSER	38.26	31.95	20.33
Accuracy	42.88	33.5	91.25
Time(s)	1.46	4.97	37.22

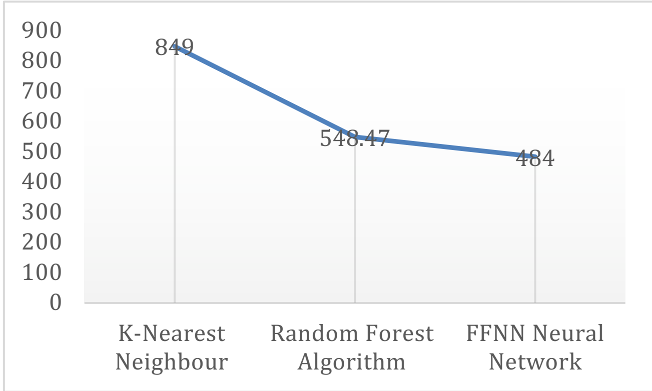

Figure 2: Performance of the proposed FFNN neural network (MSER).

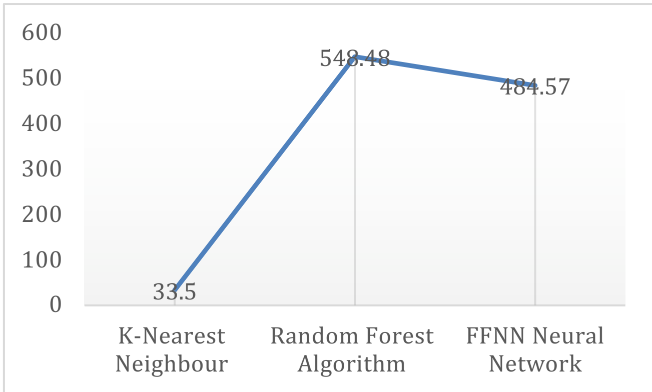

Figure 3: Performance of the proposed FFNN neural network (MAER)

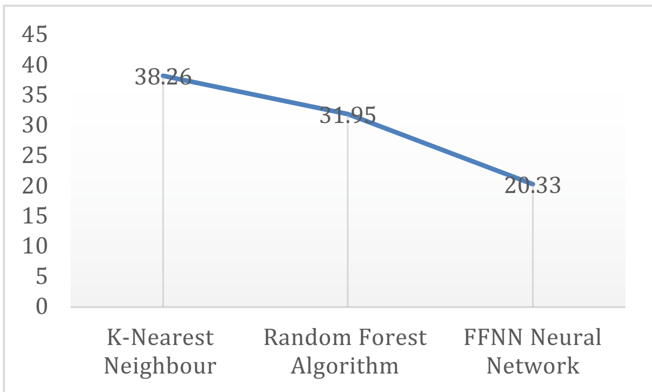

Figure 4: Performance of the proposed FFNN neural network (RMSER).

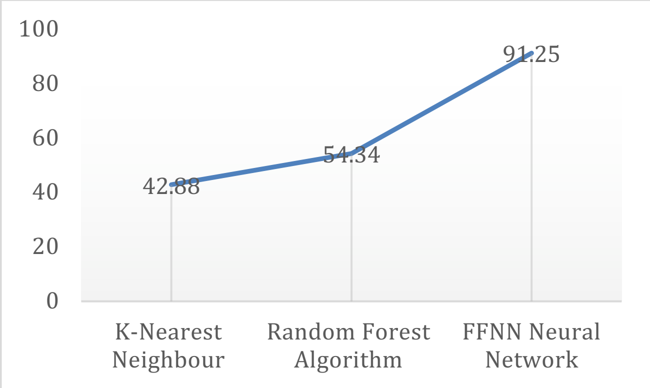

Figure 5: Performance of the FFNN neural network in terms of accuracy.

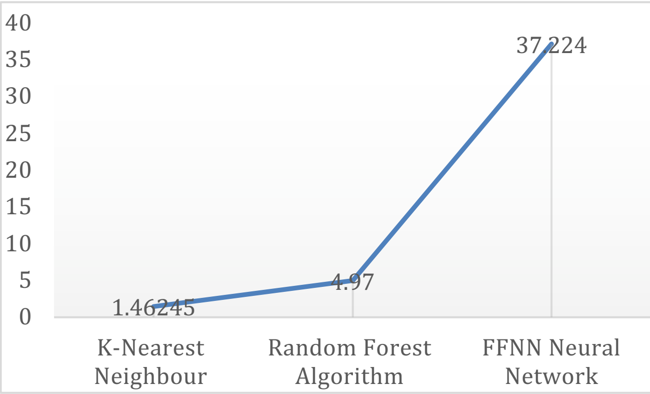

Figure 6: Performance of the FFNN neural network in terms of time (seconds).

6 Conclusion

The concept of palm-based recognition, which considers traits such pronounced lines and wrinkles as well as skin tone, is introduced in this study. Palm images must first be pre-processed to take into account palm orientation and output all the palms with the same coordination before those details can be recovered. In order to pinpoint the precise area of the palm where the distinctive characteristics are showing themselves, a rectangle crop of the region of interest was obtained. The fingers' length, width, and spacing are additional elements that may be significant. Since it had been proven that finger width may vary with body weight, making it challenging to accurately identify people using these traits, these factors were not employed in the study. Three methods for identifying palms were examined after the areas of interest from the palm image were removed. After learning the characteristics of each palm, a supervised learning method called Feed Forward Neural Network is utilized to forecast the individual. K-nearest Neighbors and Random Forest were two further unsupervised machine learning techniques that were used to identify the owners of palm plants. As an illustration, the results demonstrate that the supervised machine learning method (FFNN) outperforms the competition with a prediction accuracy of 91.25%. Also, the proposed (FFNN) obtained good results in terms of time (seconds) than the other classification technique methods.

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