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Object Boundary Tracking in Moving Palm Image for Personal Identification

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ABSTRACT

Palm includes enough features for participating the personal identification, one of the encouraging matters of relying on palm features is their resistivity to the age and environmental impacts. In this project, palm based personal identification is implemented based on IIT Delhi palm dataset. Right hand image is being acquired from each candidate using a mobile camera placed inside a black color box. Region of interest was accurately cropped from each palm image and hence deep learning and machine learning algorithms are used for palm classification. Results shown that Feed Forward Neural Network based palm recognition model is outperformed over the other machine learning technologies.

Keywords: FFNN, palm, ROI, pixels, machine learning, supervised learning

INTRODUCTION

Image processing technologies have been developed for many years and have been become vital to human daily routine. Security of data is also begun new stage because of technology revelation and large extension of internet. Data amounts are dramatically increased after development of new generation mobile communication as users increased and internet with no obstacles e.g. (wires or speed) widely propagated [1].

The existence of strong security is required to protect web data as well as local server's data hence, the research activity on improvement of security applications as well as technologies is increased. The first attempt to protect the web based data is using the passwords protection where Technologies for image processing have been developed for a very long time and are now essential for daily life. As internet usage has increased and technology has advanced, data security has also improved. Data volumes have greatly increased with the advent of next-generation mobile communication as a result of an increase in users and the widespread usage of the internet without cables or speed limitations [1].

As it becomes more crucial to protect both online data and data kept locally on servers, research into more efficient security techniques and apps is growing. The first line of defence for the security of web-based data is password protection, which requires authorised users to submit their login credentials in order to access the data [2]. [3].

Passwords get more challenging as technology advances, especially with the introduction of the internet and online apps. As dependability rises, passwords often include special characters in addition to alphabetic ones, making password prediction more challenging. The frequency of observed security breach attempts has increased as a result of software and technical improvements. A new personal verification method must be developed because passwords may always be anticipated and guessed [4]. [5].

The practise of palm recognition has gained popularity as a practical method to safeguard the security of data. It mainly comprises recognising 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 several instances of attempts to use biometric traits for user identification in security systems in the literature. The two most often used methods for attaining the aforementioned goal are face recognition using facial features and speaker recognition using audio characteristics. The cost of adaptation and the variety of these technologies are two of the greatest problems they present. 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 as 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 softwires 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].

Updating the dataset daily may be essential if the recognition system includes a large pool of candidates, each of whom falls within a certain age range. This would add time and cost [11–15] and be almost impossible.

PALM DATASET

Although efforts in this field rely heavily on data accessibility, image processing has recently attracted a lot of attention. Hence, there are two approaches to obtain data: either through publicly accessible datasets produced by a single researcher and made available online (respiratory), or through data that may be obtained from the general public by enlisting volunteers in the study process [16].

However, academics these days prefer to use pre-existing datasets that make the study process more realistic rather than producing their own data, which takes a lot of time and work. Alternatively, if a particular data point is required for the application, it must be obtained by contacting possible field participants and asking them to participate in the study and submit the required data.

Because palm data was required for this investigation, the Indian Institute of Technology IIT (Delhi) palm photo 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 coloured 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.

PRE-PROCESSING

The pre-processing Matlab 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 contour detection for the palm region, 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 recognised 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 recognise the objects on the image.

The boundary (contour) points that provide each position in pixel format in point in the palm boundary and the centroid that provides the middle point in the palm image are not created for each palm picture once the images are processed in the pre-processing stage and the palm is found 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 A, B, and C are represented by the red, blue, and green lines, respectively. The triangle formula below can be used to determine the angle indicated by the red circle.

$$\tan^{-1}\alpha = \frac{A}{B} \tag{1}$$

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 [18]. 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, this angle will serve as the reference angle and be compared to all the other angles.

$$\sigma = x - \alpha \tag{2}$$

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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 feed forward neural network gathers data from the palm's 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: Configuration parameters of the feed forward neural network

Parameter	Details
Number of epochs	One hundred (100)
Nodes per layer	Input layer: 30
	Hidden layer: 10
	Output layer: 01
Total number of layers	(3) Three
Targeted performance (mse)	1 e-200
Learning/ training	Levenberg–Marquardt (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 categorised 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 [19–25].

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 rabdomancy will finally receive the image.

Artificial neural networks (ANNs) are recognised for their ability to take on difficult issues and provide answers by only comprehending the fundamental (hidden) relationships between 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 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:

$$R = \text{net}\ (r) \tag{2}$$

$$R = W \times r + b \tag{3}$$

where b is the model bias and R is the putput vector. To achieve the best R-T correlation, Net may adjust the W coefficients [28, 29]. Finding the lowest value of Eq is the goal of learning, in other words (5). The mean square error (MSE), where e is the error vector, serves as a performance measure for training and learning [30].

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

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

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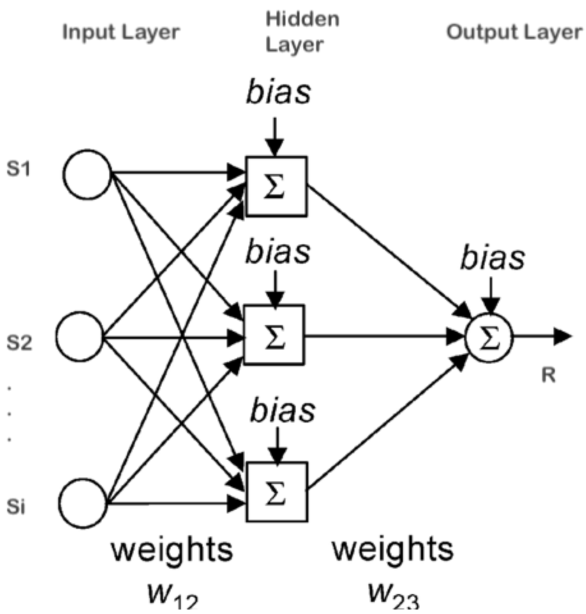

Figure 1: ANN layer structure demonstrating the input, weights/biases and output.

RESULTS

Using performance metrics, each algorithm presented in the earlier sections has undergone extensive testing (MSER, RMSER, MAER, Time and AC). The results of the performance measurements are shown in Tables 2. According to the results, FFNN, the most accurate approach for classifying images, has an accuracy of 80.15 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: MSER metric results for the three classification techniques

Tool	MSER	MAER	RMSER	Accuracy	Time (s.)
K-Nearest Neighbour	849	33.5	38.26	42.88	1.46245
Random Forest Algorithm	548.47	548.48	31.95	54.34	4.97
FFNN Neural Network	484	484.57	20.33	91.25	37.224

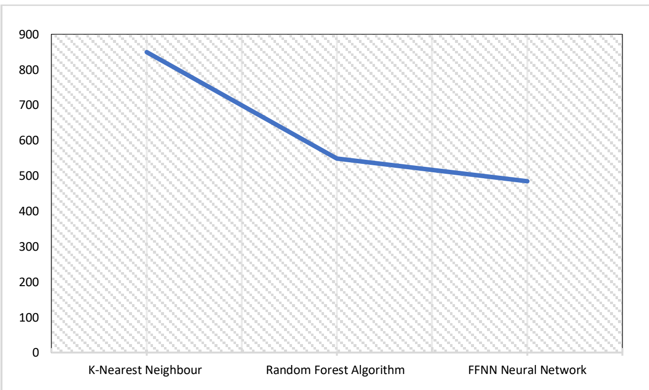

Figure 2: Performance of the FFNN neural network in terms of mse

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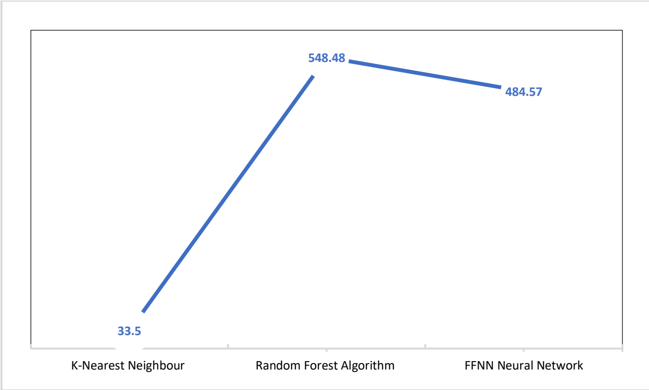


Figure 3: Performance of the FFNN neural network in terms of mae.

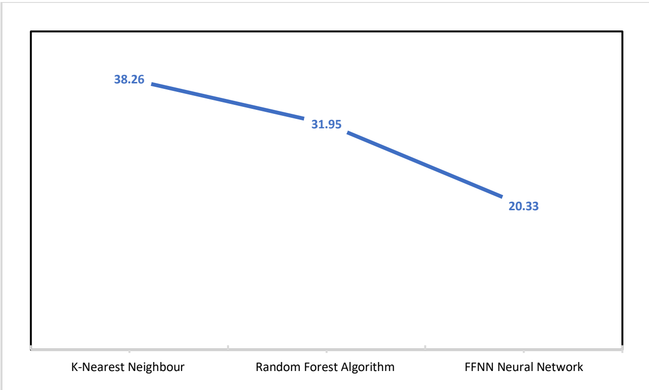
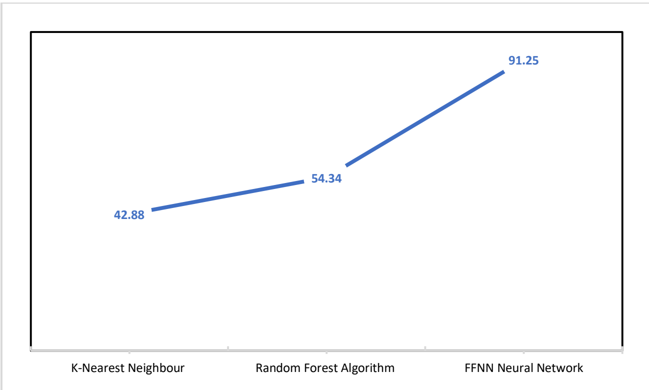


Figure 4: Performance of the FFNN neural network in terms of rmse.



Performance of the FFNN neural network in terms of accuracy.

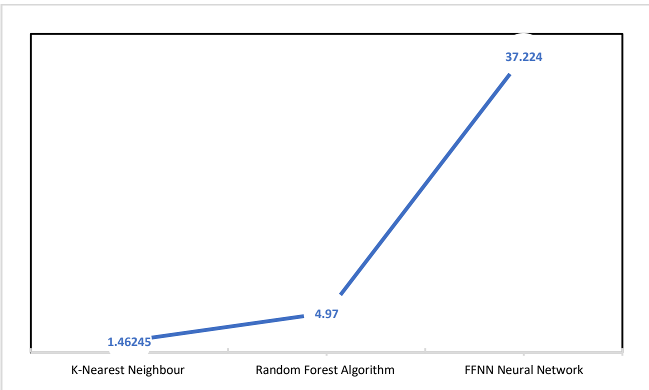


Figure 6: Performance of the FFNN neural network in terms of time (seconds).

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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 produce all the palms with the same alignment 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 utilised 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 81.5%.

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