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Artificial Intelligence Techniques to Identify Individuals through Palm Image Recognition

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Abstract

Artificial intelligence (AI) is entering many fields of life nowadays. One of these fields is biometric authentication. Palm print recognition is considered a fundamental aspect of biometric identification systems due to the inherent stability, reliability, and uniqueness of palm print features, coupled with their non-invasive nature. In this paper, we develop an approach to identify individuals from palm print image recognition using Orange software in which a hybrid of AI methods: Deep Learning (DL) and traditional Machine Learning (ML) methods are used to enhance the overall performance metrics. The system comprises of three stages: pre-processing, feature extraction, and feature classification or matching. The SqueezeNet deep learning model was utilized to resize images and feature extraction. Finally, different ML classifiers have been tested for recognition based on the extracted features. The effectiveness of each classifier was assessed using various performance metrics. The results show that the proposed system works well, and all the methods achieved good results; however, the best results obtained were for the Support Vector Machine (SVM) with a linear kernel.

Key words and phrases: Palm print, Random Forest, Support Vector Machine, k-NN, SqueezNet, Machine Learning.
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1 Introduction

Biometric recognition uses unique and immutable human characteristics to improve security. Among various biometric modalities, palm print recognition stands out for its compelling advantages. More importantly, palm print recognition can be achieved through non-invasive and contactless methods, improving user comfort and hygiene, particularly in security-sensitive environments. Despite its strengths, extracting the most relevant features and developing robust algorithms for efficient analysis remain active research areas [1]. This is where Machine Learning (ML) comes in. ML has significantly impacted various fields as in [2][3][4][5]. Its success in detection, prediction, and classification tasks further underscores its potential to enhance palm print recognition. The use of ML in biometric technologies has been reported, and the research community is developing new approaches, methods, and technologies.
Deep Learning (DL), an Artificial Neural Network (ANN) type, has shown promising outcomes in numerous data fields, such as data classification, clustering, and rule mining. Unlike other methods, DL concentrates on automatically drawing out features from data representations, mimicking the structure of the human nervous system [6].
This paper explores the hybridization of SqueezeNet deep learning (for both image resizing and feature extraction) with different ML classifiers: ANN, k-Nearest Neighbour (kE-NN), Random Forest (RF), and Support Vector Machine (SVM) with linear, Radial Basis Function (RBF), and polynomial kernels to identify individuals from palm print image. To the best of our knowledge from previous work, only traditional ML or DL methods have been used. Integration of DL with ML has significantly improved the performance of the suggested method.

2 Research Methods

In this section, we discuss the layout of the proposed method and its main stages in details. Our aim is to develop an accurate approach to identify individuals from palm print images. In this work, we use Orange software for ML and data analysis through Python scripting and visual programming [7].

2.1 The Pre-processing

This is vital for the recognition process, as it repairs the data to ensure that it can be employed in feature extraction and hence the classification stage. SqueezeNet resizes the input palm print image at this stage to shorten processing time.

2.2 The Feature Extraction

This is a crucial stage in ML and data analysis, as it focuses on the most relevant information and improves the performance of the model. Here, the SqueezeNet model is used for feature extraction, at increasing levels of abstraction, that has already been trained. The extracted features were standardized to have zero mean and unit variance to ensure consistency among different features. The result will be a vector of 1000 extracted features.

2.3 The classification/feature matching

This is typically done to classify the input pattern or to identify it as a particular object or entity. The matching process aims to compare the feature vector of the test image with the stored templates of the training set to generate match scores. Match scores show how similar two palm prints are: the higher the score, the more alike they are. The features extracted from the previous stage are fed into different ML classifiers, which are:
A) ANNs: in this work, 100 neurons in its hidden layer were used, activated by the ReLU function, which is used to increase the nonlinear properties of the decision function, by replacing the negative values of each pixel in the activation map with zero. ADAM was chosen to calculate the adaptive learning rates for each parameter so that there is no need to tune the learning rate to achieve the best results using the same default value.
B) RF: for this work, a forest of 41 decision trees, mirroring the 41 classes within the database and the Gini index, was used, which collaborated to vote on the most probable identity, improving robustness, and mitigating overfitting.
C) k-NN: in this work, the Euclidean distance (ED) metric was used to calculate the distance between the feature vector of the test palm print and all the feature vectors of the training set. The value of k is determined by the user, where $k \in \{1, 3, 5, 7, 9, ...\}$. In our experiments, $k = 3$ was a preferable choice. A detailed analysis of the impact of varying k values is presented in the subsequent results and discussion section.

D) SVM used with the familiar kernel types: Linear kernel: works well for linearly separable data. Polynomial kernel: useful for more complex data, but prone to overfitting. RBF kernel: widely used for nonlinear data, offering a good balance between performance and complexity.

2.4 Palm print database

The Birjand University Mobile Palm Print Database (BMPD) has been used for this work for both training and testing. This publicly available database contains 1640 colored labeled images collected from the left and right hands of 41 Iranian women. Images taken in two sessions: 6 images for session 1 and 16 images for session 2. Each image in the database is named as follows: Number_Session_Hand_Age.jpg [8]. An example of the images in this database appears in Figure 1.

Figure 1: Examples of palm images from BMPD [8]

3 Results and Discussions

In this section, we evaluate and discuss the performance of the suggested method using the BMPD database. A three-fold cross-validation has been used. The database is divided into three parts and the model is trained and tested three times. Each time, training is done by using two different parts, and the rest are used for testing. AUROC, accuracy, F1 score, precision, and recall have been used to evaluate palm print recognition. The extracted features are classified using k-NN with different values (3, 5, and 7) as shown in Table 1.

Table 1: Classification performance metrics of k-NN with various values of k

K Value	AUROC'%'	Accuracy '%'	F1score'%'	Precision '%'	Recall '%'
3	99.3	97.9	97.9	98	97.9
5	99.5	97.2	97.2	97.4	97.2
7	99.6	95.8	95.8	96.1	95.8

In Table 2, SVM with three types of kernel have been examined.

Table 2: The classification report of SVM with different kernels

Kernel	AUROC'%'	Accuracy '%'	F1score'%'	Precision '%'	Recall '%'
Linear	100	98.8	98.8	98.8	98.8
Polynomial	100	98.7	98.7	98.8	98.7
RBF	100	98.6	98.6	98.7	98.6

Table 3 shows the performance metrics for ANN and RF.

Table 3: ANN and RF performance metrics

ML Method	AUROC'%'	Accuracy '%'	F1score'%'	Precision '%'	Recall '%'
ANN	100	98.5	98.5	98.6	98.5
RF	99.8	95.6	95.6	95.7	95.6

Tables 1, 2, and 3 show that SVM has an excellent performance with the three different kernels, compared to the other ML used. All models achieved high AUROC scores greater than (99'%'), indicating excellent discriminatory power in distinguishing between classes. SVM with linear, polynomial, and RBF kernels, as well as ANN, achieved near-perfect performance in all metrics. The best accuracy obtained was 98.8‘%‘.

4 Conclusion

This work has successfully demonstrated the effectiveness of the hybridization of SqueezeNet deep learning with various ML classifiers to highly accurately identify individuals through palm image recognition. The process involves three main stages: pre-processing, feature extraction using SqueezeNet, and classification/matching using different ML methods. The effectiveness of the suggested method is evaluated in BMPD, a publicly available database.
For future work, the use of other databases with more subjects, age groups, and palm poses would improve the generalizability of the proposed approach.

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