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Detection Change on Fingernail Biometric using Machine Learning

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Abstract: *This study focuses on detection change on fingernail biometric using Machine Learning, analysis of fingernail image for person that capture, monitored, and photographed for 90 days. It used an image processing system which includes image segmentation, color threshold, and shape analysis. The fingernail database used are classified using (Statistics and Machine Learning Toolbox™) on the extracted features. The proposed detection accuracy training in the machine learning (0.9545 at first day, 0.7333 at eight days and 0.2267at 90 days). It was matched with the support our hypothesis which said that the fingernail is transient biometric trait that is change during three months.*

Keywords: *Fingernail, Biometric, detection change, image processing system, Machine Learning, detection accuracy.*

1. Introduction

Common non-biometric recognition systems confirm a subject's identity based on what a subject knows e.g password or possesses access card. Such systems have the inherent risk of disclosure of the recognition token or theft of the possession. Such risks are largely mitigated when biometric recognition systems are employed, as they offer the possibility of confirming a subject's identity based on their own biometric characteristics, rather than what they know or carry. Biometric recognition systems thus offer protection from theft of access data, as well as convenience of use since access data does not have to be remembered or carried. Recent biometric research has produced compelling results in terms of distinctiveness, universality and performance [1, 2]. However it has also concentrated on permanent biometric features, such as the iris, face or fingerprint. Individuals fearing the misuse of their permanent biometric data and are often unwilling to provide such data to any biometric solution, especially so for noncritical applications. Thus, the benefits granted by biometric technology (i.e. password and device free access to resources), cannot be fully exploited. Research on cancelable biometrics [3,4] concentrates on the acceptability issue. It pre-transforms the biometric information before a biometric signature is extracted. As such a transformation is irreversible, the possibility of exploiting any stolen information is restricted by the fact that the exploiter has no access to the original biometric information. An extra security layer is provided as the transformation can be changed at any given time. Nevertheless, cancelable biometrics has to identify the theft of biometric information in order to change the transformation. Last but not least, a subject still has to entrust the biometric capture point with their permanent biometric information. The Bioelectrical characteristics of a fingernail are used as a biometric signature in [5]. This patent work presents a RFID chip glued over the fingernail. This embedded system measures the subjects' capacitance, which is claimed to be unique, thus creating a biometric solution based over the fingernail region. The use of fingernail images as biometric data has been the topic of few different lines of research. The skin under a nail plate, called nail bed, is unique for each individual [5,7and8]. A special acquisition system has been designed to acquire images of the nail bed. Such images use the grooves of the nail bed for recognition purposes [6]. The fingernail surface has also been explored for a biometric authentication system [9, 10 and 11]. This work segments the fingernails as regions-of-interest (ROI) from a hand image using a contour segmentation algorithm. The hand is photographed while resting on a white surface. This segmentation methodology works but the employed dataset was biased with respect to the subjects' skin tones.

2. Experimental

The object of this study including the results of fingernail image for five person that capture, monitored, and photographed for 90 days .And used Matlab software programmer (Training Machine Learning) to analysis samples. This experiment's shows how to extract learned image features from a pertained convolutional neural network, and use those features to train an image classifier. Feature extraction is the easiest and fastest way to use the representational power of pertained deep networks. For this experiment's, was train a support vector machine (SVM) using (Statistics and Machine Learning Toolbox™) on the extracted features.

3. Results

After capture, monitored, and photographed for 90 days of fingernail image used Machine Learning to detection change on fingernail biometric.

Training in the First Day Images using Machine Learning**:**

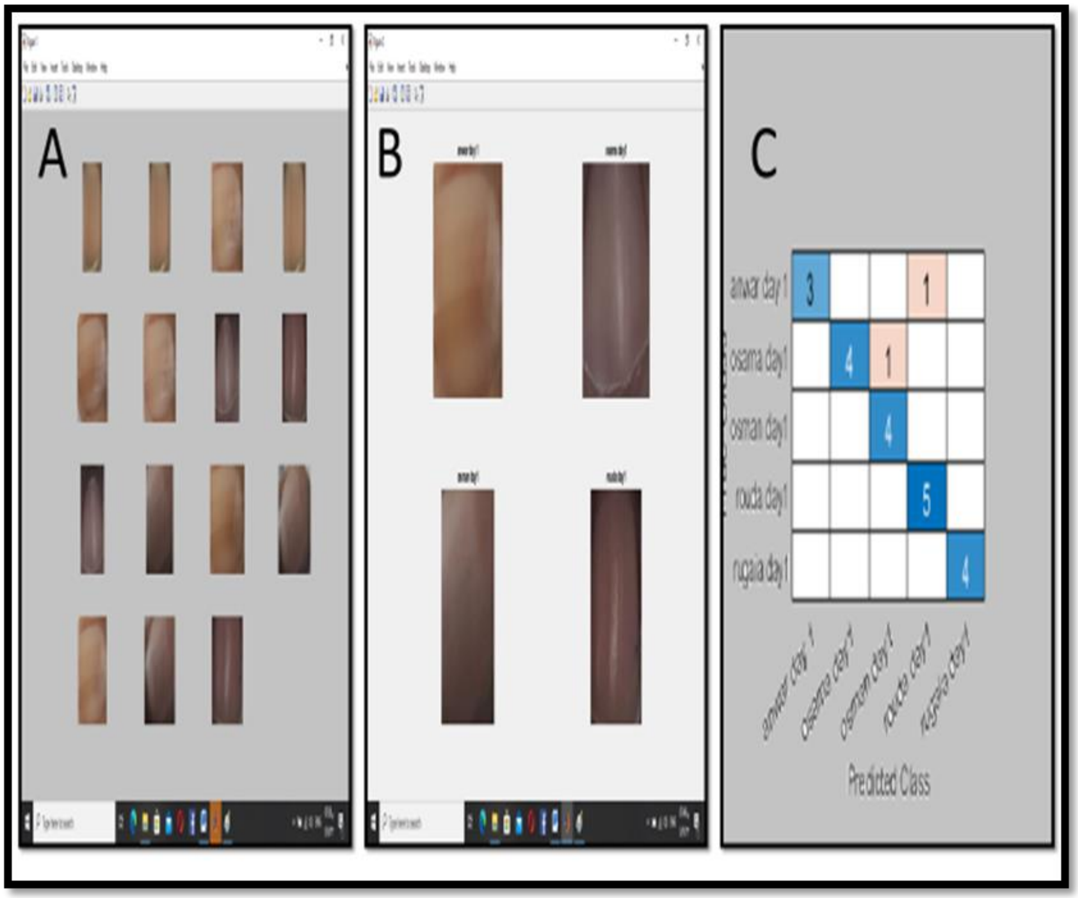

Figure (1) (A) Display some sample images for first day images to 90 days (B) Display some sample images for first day images (C) confusion matrix first day images.

The accuracy when extracted poo5 layers feature and use the features extracted from the training images as predictor variables and fit a multiclass support vector machine (SVM) using fitcecoc is 0.9091and when extract features from an earlier layer in the network and train a classifier on those features. Earlier layers typically extract fewer, shallower features, have higher spatial resolution, and a larger total number of activations. Extract the features from the 'res3b_relu' layer. This is the final layer that outputs 128 features and the activations have a spatial size of 28-by-28. The accuracy is 0.9545.

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Training in First Day and Eight Day Images:

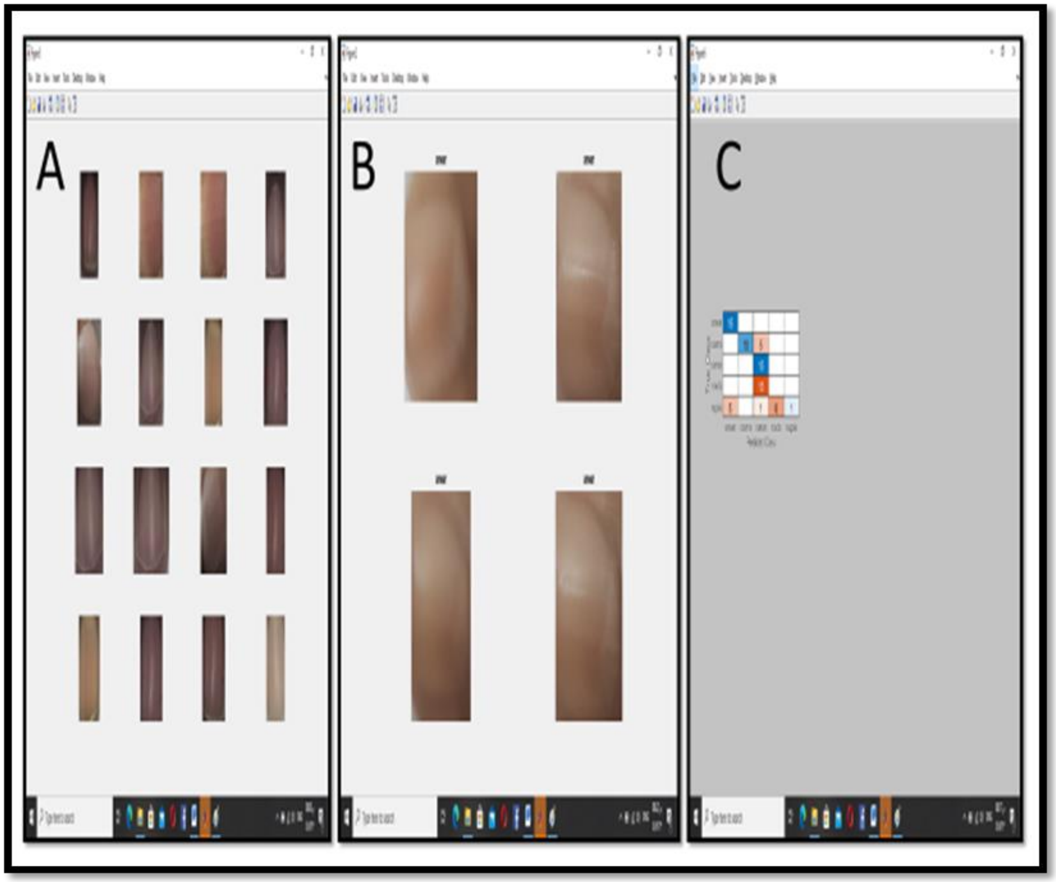

Figure (2) (A) Display some sample images for first day and eight day (B) Four sample test images with their predicted labels for first day and eight day day's images when taring using machine learning (C) confusion matrix for day1 and day8 images

The accuracy when were are extracted poo5 layear feature and Use the features extracted from the training images as predictor variables and fit a multiclass support vector machine (SVM) using fitcecoc is 0.5467and when extract features from an earlier layer in the network and train a classifier on those features. Earlier layers typically extract fewer, shallower features, have higher spatial resolution, and a larger total number of activations. Extract the features from the 'res3b_relu' layer. There are final layer that outputs 128 features and the activations have a spatial size of 28-by-28. The accuracy is 0.7333.

Training in after 90 Days images:

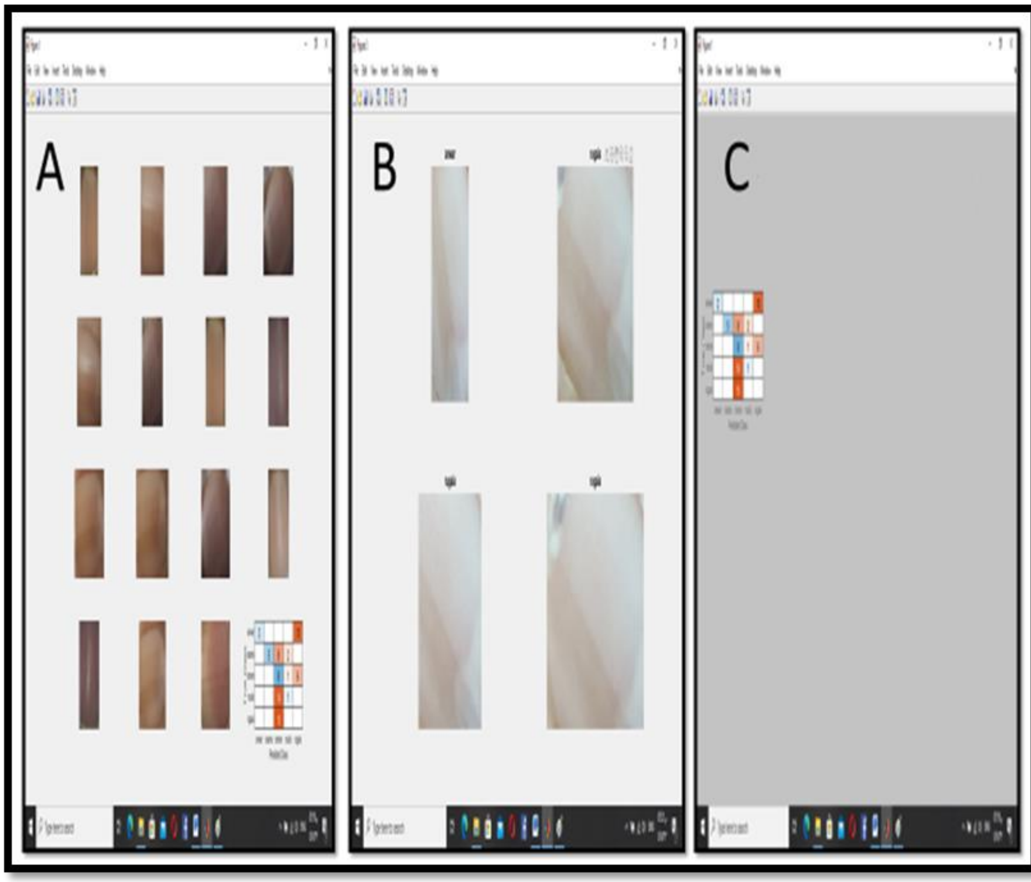

Figure (3) (A) Display some sample images for after 90 days images (B) Four sample test images with their predicted labels for after 90 days images (C) confusion matrix for after 90 days images

The accuracy when were are extracted poo5 layear feature and Use the features extracted from the training images as predictor variables and fit a multiclass support vector machine (SVM) using fit cecoc is 0.2133 and when extract features from an earlier layer in the network and train a classifier on those features. Earlier layers typically extract fewer, shallower features, have higher spatial resolution, and a larger total number of activations. Extract the features from the 'res3b_relu' layer. There are final layer that outputs 128 features and the activations have a spatial size of 28-by-28. The accuracy is 0.2267.

5. Conclusions

The accuracy training in the first day images using machine learning to be 0.9545, when at training in the eight day images using machine learning the accuracy equal 0.7333, but at 90 days the accuracy of training images using machine learning equal 0.2267.

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