

Identification of Covid'19 Vaccinator by Deep Learning Approach Using Contactless Palmprints

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Abstract

The invention of the first vaccine has also raised several anti-vaccination views among people. Vaccine reluctance may be exacerbated by the growing reliance on social media, which is considered as a source of health information. During this COVID'19 scenario, the verification of non-vaccinators via the use of biometric characteristics has received greater attention, especially in areas such as vaccination monitoring and other emergency medical services, among other things. The traditional digital camera utilizes the middle-resolution images for commercial applications in a regulated or contact-based environment with user participation, while the latter uses high-resolution latent palmprints. This research study attempts to utilize convolutional neural networks (CNN) for the first time to perform contactless recognition. To identify the COVID '19 vaccine using the CNN technique, this research work has used the contactless palmprint method. Further, this research study utilizes the PalmNet structure of convolutional neural network to resolve the issue. First, the ROI region of the palmprint was extracted from the input picture based on the geometric form of the print. After image registration, the ROI region is sent into a convolutional neural network as an input. The softmax activation function is then used to train the network so that it can choose the optimal learning rate and super parameters for the given learning scenario. The neural networks of the deep learning platform were then compared and summarized.

Keywords: Palmprint identification, deep learning method

1. Introduction

Palmprint research has two main branches: online palmprint recognition and latent palmprint identification. Personal authentication has recently emerged as a critical and resource-intensive method at the core of many applications, including security access systems, time attendance systems, and forensics science. Personal identity identification has gained significant research importance as a result of the aforementioned applications [1-3]. Due to the simplicity, safety, and high accuracy characteristics, biometric-based techniques such as fingerprints, faces, iris, and palmprints have lately attracted more interest in efficiently solving such challenges. Due to their uniqueness, non-intrusiveness, and dependability, palmprints and palm veins have gained a lot of attention as biometric identifiers [4]. It has been made possible to classify the vast majority of techniques available in this area into three categories:

1. Line-like feature extraction
2. Subspace feature learning
3. Texture-based coding

On the other hand, their results are poor and leave a huge amount of potential to enhance the existing approaches. Deep neural network architectures that use large training samples to learn higher-level features from those samples have recently received a lot of attention [5-8]. Further, they can also capture many feature engineering representations of corresponding applications. Figure 1 shows the line features present in the infant's palm.

Most palm prints contain three distinct lines: heart, head, and lifeline (or radial artery). Over the course of a person's life, these three types of lines were small and less visible. Palmprint-

based personal identification systems rely on the appearance and placement of fingerprints on the hand to verify the user's identity. Principal lines are thicker and more regular than wrinkles [9-11]. Creases, like fingerprint ridges, are microscopic structures that cover the whole palm. Detecting palm lines using line-based techniques require either the development of new edge detectors or the usage of commercially available ones [12]. Figure 2 provides the sample ROI of palmprint images.

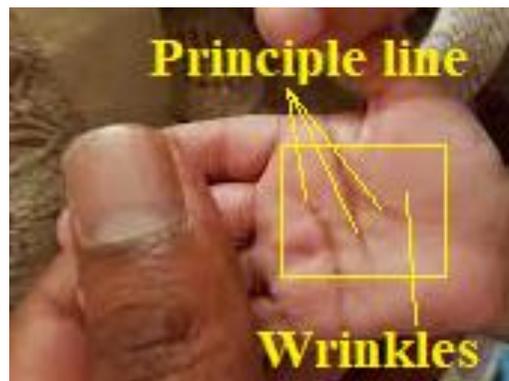


Figure 1. Features from Infant's Palm

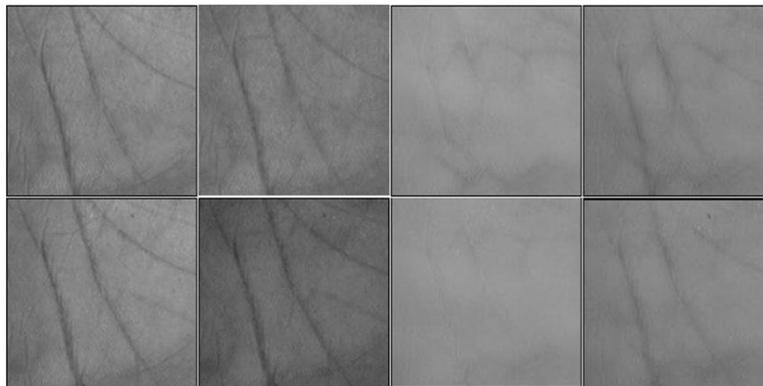


Figure 2. Sample ROI of Palmprint Images

The use of biometric recognition technology has gained importance as a means of enhancing the security and stability of computer systems. Human physiological or behavioral

characteristics are used in biometrics domain to automatically identify people. Biometrics represents a person's unique traits, such as age, height, weight, and gender. Fingerprints, faces, iris, signatures, and voice recognition are just a few of the biometrics that has been utilized. There was no funding for this project in the form of a foundation, a finger vein, or anything else. Meanwhile, Palmprint recognition technology is advancing at a fast pace. This software is excellent for identifying or classifying children or vaccine recipients [13].

2. Motivation of this Research

The palm print has many benefits over other biological traits, and each person's palmprint is unique. The texture and line characteristics of the palm are combined in palmprints, and they remain constant throughout the time. Due to its greater surface area, the gathered palmprint makes it simpler to acquire rich personal information. As a result, palmprints are attracting the attention of more and more researchers owing to their benefits in classifying the vaccine recipients and non-recipients.

3. Organization of the Research

The rest of this paper is organized as follows: Section 4 discusses about the previous research works on palmprint verification. Section 5 details the suggested technique for determining COVID'19 vaccine recipients. Section 6 covers the description of the recognized research findings. The last part summarizes the proposed research and assigns future responsibilities.

4. Preliminaries

A supervised classifier developed by Zhou et al. utilized a random sample of 884 tweets to detect anti-vaccine tweets. The SVM technique, namely the radial basis function kernel was used. Selecting characteristics that could distinguish one class from another has necessitated a

combination of forward and backward elimination. The best performer has achieved an accuracy of 89.8% by just using the tweet's text [14, 15].

An SVM was trained by using 8000 tweets to create a classifier for vaccination attitude, and this was done by Mitra et al. Instead of using all tweets rated equally by all three raters, wherein they only utilized tweets with a projected likelihood higher than 90%. This classifier has an accuracy of 84.7% [16].

Shapiro et al. have carried out another study by using SVM. On the other hand, the categorization was implemented in two stages. So they started with 1,000 tweets that had been manually labelled in order to create a binary classifier that could tell whether or not a tweet was concerned about vaccinations [17].

Du et al. proposed the technique to identify the child care vaccinations that are performed by SVM beat NB and random forest in identifying unfavourable tweets about HPV vaccinations. Totally, 6000 tagged tweets are used to train the SVM models [18].

The method suggested by Shu et al. have used many detection operators to identify palmprint lines from the given images that are available in various directions and further it approximates them with straight line segments to extract characteristics based on the main significant lines of the given input images. These straight-line segment properties are then retrieved from the palmprint such as their endpoints, intercepts, and angles [19].

To extract palm lines, Wu et al. have proposed the edge detection technique to detect the edges of the palm print using the canny edge operator. The edge points were then given as input to four membership functions, each of which is represented as one of the four possible orientations [20].

Dimensionality reduction using the EigenPalm technique presented by Lu et al. globally projects palmprint pictures into a PCA-defined lower-dimensional space. It is observed that PCA considers palmprint representation rather than palmprint discriminating information [21].

Another set of techniques, including texture-based approaches were explored by Kong et al. additionally, it is difficult to classify certain methods of thinking. To extract palmprint characteristics, they utilise a variety of integrated processing techniques [22].

5. Methodologies

Deep learning-based palmprint feature representation frameworks have the potential to improve the accuracy and robustness of contactless palmprint recognition systems, and the proposed study aims to create such a framework. In the literature, such goals have not yet been achieved [23-25]. For the output palmprint pictures, we have divided them into three age groups: those aged 60 to 45, those aged 18 to 45, and those aged under 18. The main goal of this study is to identify the palmprint pictures of people under the age of 18 (U18). A diagram of the suggested framework with a palmnet matching architecture is shown in Figure 3.

5.1 Proposed Training Framework

The PalmNet neural network was used to fine-tune the convolutional kernels of deep networks. During training, all of the weights in the PalmNet neural network are similarly maintained. The framework has been shown in figure 3. For anchor, positive, and negative samples, these convolutional neural networks are parallel linked so that the data and gradients may be propagated in both forward and backward manner.

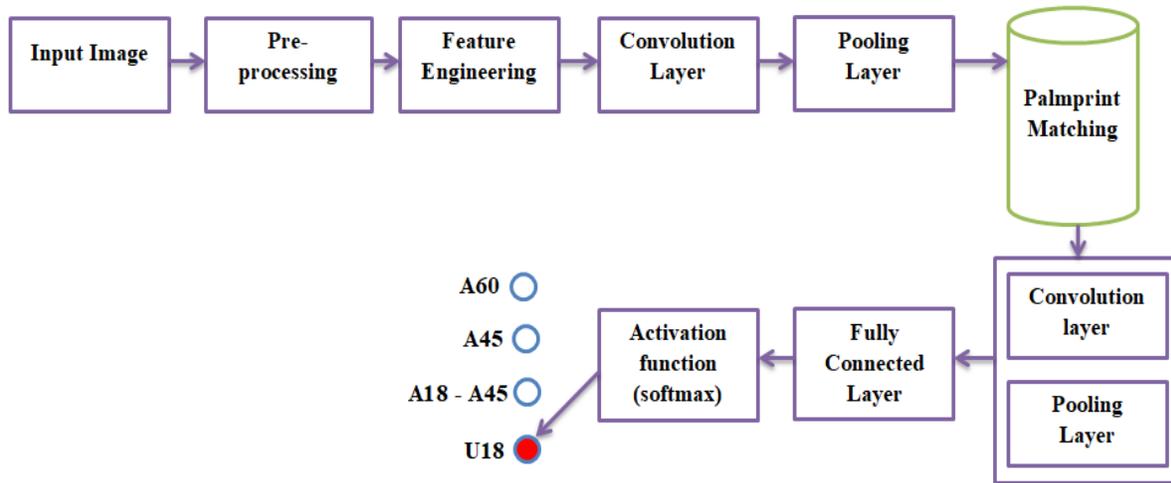


Figure 3. Proposed Framework

5.2 Detection of Palmprint Area

The proposed method has created a method for detecting palmprints in a given picture that is based on the Faster CNN that has been previously presented. It is made up of two modules, which are as follows. The first module contains methods for detecting palmprint areas in images using image segmentation techniques. The second module is a Fast CNN detector, which makes use of the suggested areas to categorize the palmprints in the first module's classification. The whole system is comprised of a single, unified network for performing palm detection, which utilizes the common language of neural networks with "attention" processes to perform the intended operation [26]. The regional area proposal network modules in the system update the Faster CNN module on the particular areas of interest to identify the palm region, which is updated by the regional area proposal network modules. A tensor flow-based implementation of palmprint data and augmentation was integrated into the system. Picture registration was used to enhance the palmprint recognition in the complicated indoor and outdoor environments by aligning the input image with the target image.

5.3 Matching Contactless Palmprint Images

The proposed research study has created a highly optimized deep learning architecture, which is referred to as the residual feature network for correctly matching contactless palmprint pictures, which was used in previous research. In contrast to the residual network, CNN includes completely linked layers to provide pure feature engineering map outputs as a consequence of the findings of the analysis. It is a technique that can maintain a spatial correspondence between palmprint pictures and their surroundings [27-30].

5.4 Loss function

In such architecture, the loss function is anticipated to assist the network in learning to produce feature maps, which may decrease anchor-positive distances while increasing the anchor-negative distances for improving the network's performance. It is creating net loss to allow frequent intra-class changes in the contactless palmprint pictures while learning the feature maps for accurate matching of contactless palmprint images is necessary for accurate matching of contactless palmprint images.

6. Results & Discussion

This research has conducted extensive tests on various aspects of proposed approach's performance by using the freely available data obtained from public sources. Figure 4 shows sample images for palm print examination.

For a variety of reasons, this research study has investigated ROI palmprint pictures for the identification of COVID'19 vaccinated people in well-developed nations, namely in the United States of America. The resulting figures have included palmprint pictures of different age groups, which were used to highlight the feature extraction processing region accomplished by using a

quicker CNN method. The proposed method is carried out by using the palmnet architecture, which has been shown to be more effective in palmprint identification applications.

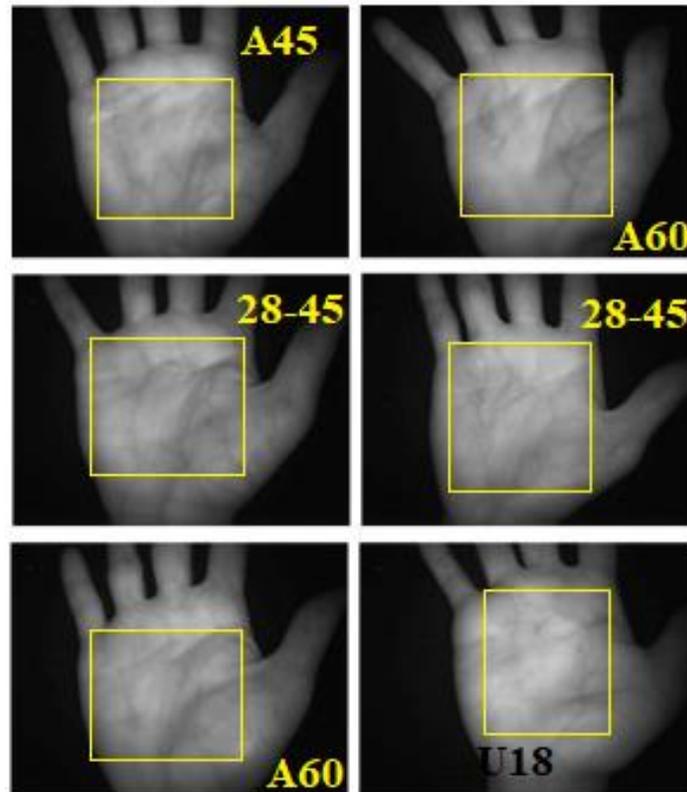


Figure 4. Sample Images for Palm Print Examination

An increase in the number of epochs increases the accuracy and model performance measures, respectively. While the epoch is being extended, the loss is being minimized and it has been shown and illustrated in figure 5.

Finally, the proposed model has shown excellent performance in recognizing or classifying children or older age groups, who are not vaccine recipients. The accuracy also has shown in the figure 6. Besides, table 1 shows the performance metrics of the computed model.

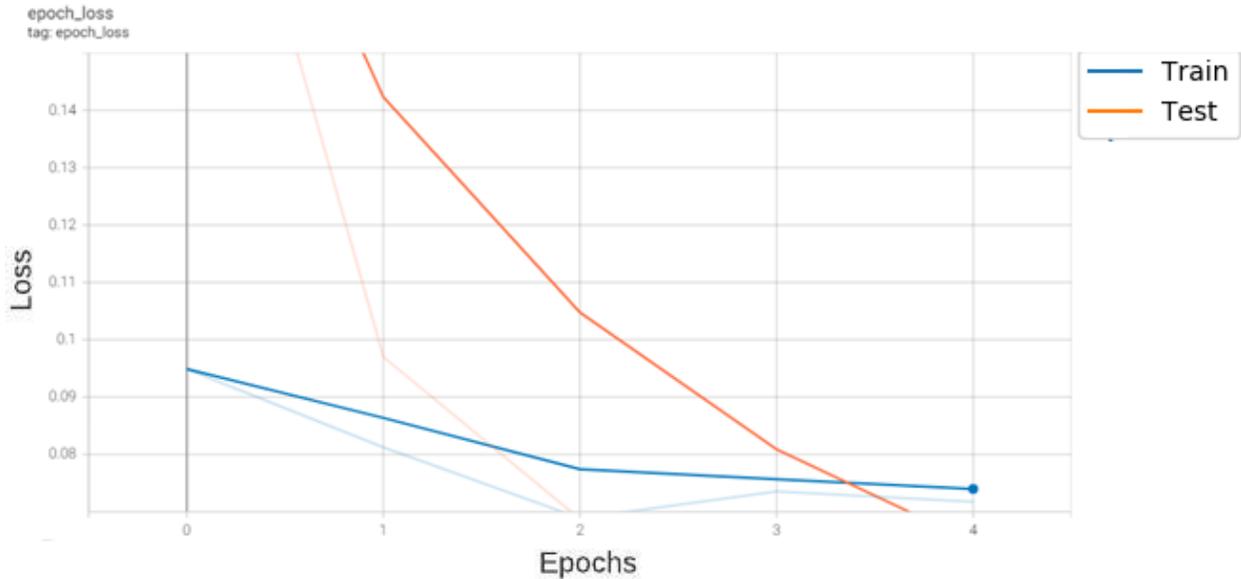


Figure 5. Loss vs. Epoch

Table 1. Computed Performance Metrics

S.No	Method	Accuracy	Sensitivity	Precision	Loss	Average processing Time (s)	Recognition error (%)
1	Image processing by ridge let transforms	82%	80%	78.9%	2.3223	14.4892	0.155
2	SVM	88%	86.92%	85.6%	1.6701	12.3353	0.083
3	Proposed faster CNN	98.6%	96.67%	95.3%	0.0436	9.8138	0.005

Figure 6 shows the overall performance measures of different models. An effective matcher for online palmprint identification also needs a deep learning-based palm detector that can automatically identify palmprints or an area of interest on the hands being presented for scanning and analyzing the data.

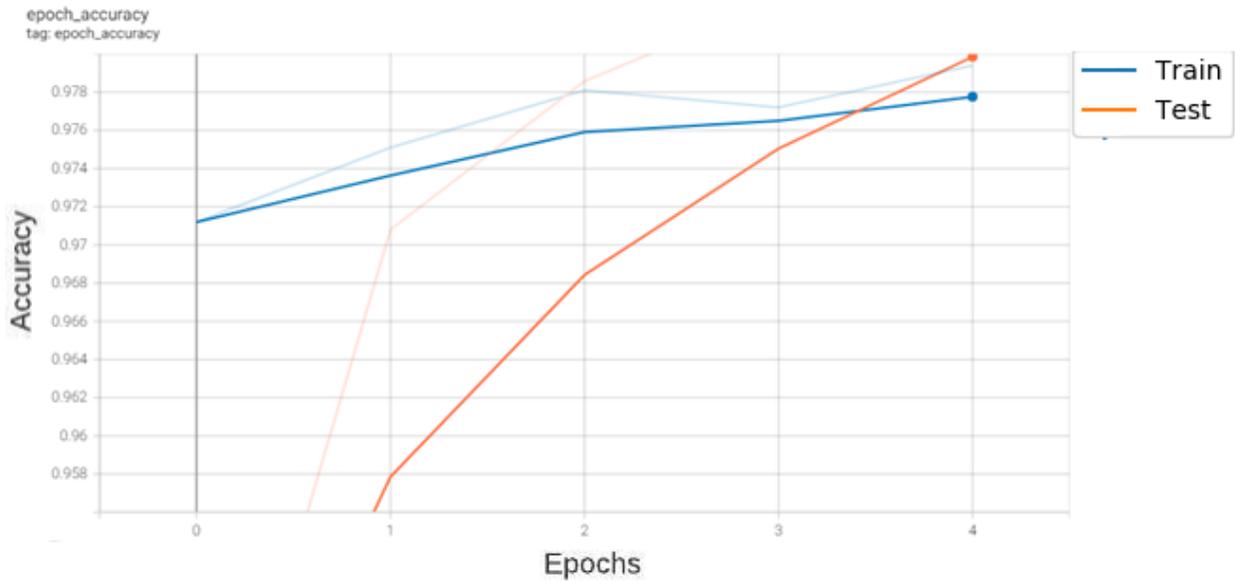


Figure 6. Accuracy vs. Epoch

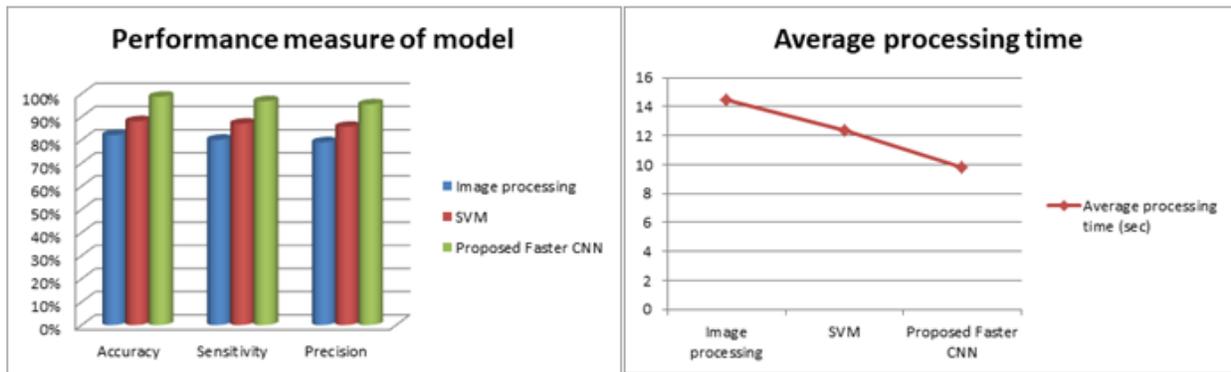


Figure 7. Performance Measures of Different Models

As a result, we created a palm detector that is capable of detecting palmprints on a variety of different surfaces, including some that are difficult to see using traditional techniques of palmprint detection.

7. Conclusion

The main purpose of this study is to create a new deep learning-based contactless palmprint feature representation models, which are capable of providing better matching accuracy and strong generalisation capacity for contactless palmprint pictures. We were able to create contactless palmprint verification by combining a deep learning approach with the CNN method. Using a fully convolutional network, the CNN technique efficiently supervises the learning of complete and spatially matching residual features. When using the traditional palmprint identification technique, you'll have to go through several time-consuming steps, such as extracting and selecting features, as well as narrowing down the classifier possibilities. Convolutional neural networks outperform classical algorithms in nonlinear fitting since they can take an image directly and provide a classification result. Research on benchmark datasets proved that the proposed palmprint recognition method by PalmNet CNN has outperformed the competition. To improve identification accuracy and efficiency, it is highly required to combine palmprint with the advanced version of palm vein analysis in the future.

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