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# A Novel Approach for Fingerprint Classification using Optimized Support Vector Machine

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**ABSTRACT**

*Individuals can be identified using biometric approaches. With the development of information technology biometric authentication is widely used. Fingerprint is one of the promising authentication technique used. In fingerprint authentication the fingerprint image is processed to extract personalized features and further the extracted features pass through a classification technique. In the classification process takes longer time with large number of users. Whereas, if we categories the users to different category then this classification process becomes much faster because, the individual classification is performed only inside the similar category. Since the search space is reduced to only one category of fingerprints, so the process becomes much faster. In general the fingerprints are classified into five categories: Arch (A), Left loop (L), Right loop (R), Tented Arch(T), Whorl (W). These classification systems are highly dependent on a preprocessing phase that increases the processing time at test stage. Motivated by the recent success of deep learning techniques in many computer vision tasks, the proposed system in this paper consists of a pre-trained Support Vector Machine (SVM) fine-tuned on a subset of the NIST SD4 benchmark database. The SVM architecture contains a VGG16 model. The main contribution of this paper is to show the performance of transfer learning to the problem of fingerprint classification.*

## 1. Introduction

Fingerprint is one of the popular biometric to identify individual persons [1]. Normally the fingerprint verification system consists of two steps. In first step the user's sample are collected and the personalized features are collected from the image. During second step, a new sample is collected and its personalized features are collected and compared to the ftored features to identify a person. The popular features used are the minutiae which are local characteristics of the sample [1]. To increase adaptability among different proposed approaches an international standard for minutiae template has been defined [2]. This standardised representation of is a very compact and does not comprise sufficient information to regenerate the original fingerprint [3, 4]. Therefore, it is necessary to examine the accuracy of a sample reconstruction from the minutiae. Specifically, it is necessary to realise whether such a regenerated sample can dupe 1) a human specialist inspector and 2) an automatic identification system during a masquerade attack. The outcome of such research are certainly related to all the recent applications such as the PIV program [5], and the ILO Seafarers' IdentityDocument [6]

Even if the efficiency and correctness of individual identification is most important parameter of fingerprint identification system, the quickness of the process is also vital in real application. Most of the existing fingerprint recognition system spent a significant amount of time in examining and produces a reliable outcome. Due to these reliable outcomes the automated fingerprint system becomes popular. But most of them ended up being inadequate either regarding time required for calculation or lacking precision of acknowledgment [1]. To speed up the test real-time identification time, it is necessary to classify the whole figureprint space to some predefined classes. In case of identification the figureprint class is identified first and then within the class identification process is applied. As a result, the realtime identification becomes faster.

In recent years SVM is evolved as the most promising technique for classification. In this research work we have applied SVM for figureprint classification. In the literature there are many approaches proposed focusing on figureprint recognition. Recently works on figureprint recognition report the outcomes using publicly available datasets [7, 8].

This paper introduces a novel approach to ckassify fingerprint images using SVM. In general the figureprints are classified into five categories: Arch (A), Left loop (L), Right loop (R), Tented Arch(T), Whorl (W). These classification systems are highly dependent on a preprocessing phase that increases the processing time at test stage. Motivated by the recent success of deep learning techniques in many computer vision tasks, the proposed system in this paper consists of a pre-trained SVM fine-tuned on a subset of the NIST SD4 benchmark database. The CNN architecture contains a VGG16 model. The main contribution of this paper is to show the performance of transfer learning to the problem of fingerprint classification.

## 2. Support Vector Machine

We are given a training dataset of n points of the form where the $y_i$ are either 1 or −1, each indicating the class to which the point $\vec{x}_i$ belongs [9]. Each $\vec{x}_i$ is a $p$ -dimensional real vector. We want to find the "maximum-margin hyperplane" that divides the group of points $\vec{x}_i$ for which $y_i =$

1 from the group of points for which $y_i = -1$, which is defined so that the distance between the hyperplane and the nearest point $\vec{x}_i$ from either group is maximized.

Any hyperplane can be written as the set of points $\vec{x}$ satisfying $\vec{w} \cdot \vec{x} - b = 0$ (1)
where $\vec{w}$ is the normal vector to the hyperplane. The parameter $b / ||\vec{w}||$ determines the offset of the hyperplane from the origin along the normal vector $\vec{w}$. The optimization problem we thus have to solve is stated as:

Given the training sample $\{(x_i, d_i)\}_{i=1}^{N}$, where $x_i \in R^n$ is the i[th] input pattern and $d_i \in \{-1,+1\}$ is the corresponding desired class label, find the optimum values of the weight vector $\vec{w}$ and bias b such that they satisfy the constraints

$$d_i(w^T x_i + b) \geq 1 \quad \text{for } i = 1,2,\dots,N \quad (2)$$

and the weight vector $\vec{w}$ minimizes the cost function

$$\varphi(w) = \left(\tfrac{1}{2}\right) w^T w \quad (3)$$

This problem can be solved by using primal-dual method where the primal problem is to minimize the Lagrangian function:

$$J(w,b,\alpha) = \frac{1}{2} w^T w - \sum_{i=1}^{N} \alpha_i [d_i(w^T x_i + b) - 1]$$
(4)

where $\alpha_i \ \forall \ i = 1,2,3 \dots N$ are Lagrangian multipliers.

Hence, we obtain the following dual problem:

Given the training sample $\{(x_i, d_i)\}_{i=1}^{N}$, find the Lagrangian multipliers $\{\alpha_i\}_{i=1}^{N}$ that maximize the objective function

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j x_i^T x_j \quad (5)$$

subject to the constraints

$$\sum_{i=1}^{N} \alpha_i d_i = 0 \quad (6)$$

$$0 \leq \alpha_i \leq C \quad \text{for } i = 1,2,\dots,N \quad (7)$$

where C is a user-specified positive parameter.

In case of non-linear classification, we use a function $\{\varphi_j(x)\}_{j=1}^{p}$ to denote the set of non-linear transformations from input space to the *p*-dimensional feature space, thus gaining a linearly separable space for classification.

Therefore, we can re-write Eqn. (7) as

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j \varphi^T(x_i)\varphi(x_j) \quad (8)$$

The above equation can be further improved by introducing the *inner-product kernel function* $K(x_i, x_j)$ defined as

$K : X \times X \rightarrow R$ such that

$$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$$
(9)

Thus, computing a kernel function that calculates the inner product between the mapped data samples bypasses the use of a complicated mapping function. This is known as the Kernel Trick.

**3. Fingerprint Classification using SVM**

Fingerprint classification is a pattern recognition problem and the different kinds of patterns in fingerprints can be detected using SVM. Here, SVM is used so as to effectively pre-process the images and transfer learning is used to increase classification performance by introducing kernek SVM. Fingerprint classification is a pattern recognition problem that has received considerable attention for its difficulty, due to the small inter-class variability and the large intra-class variability. Fingerprint classification is a coarse level partitioning of a fingerprint database into smaller subsets. Fingerprint classification reduces the search space of a large database: Determine the class of the query fingerprint. Then, only search templates with the same class as the query. Not all measurements of a fingerprint image remain invariant for a given individual over the time of capture and can be used to discriminate between identities. The first step of fingerprint classification is to find salient features that have low intra-class variation and high inter-class variation. Fingerprint image is an oriented texture pattern that contains ridges separated by valleys and exhibits two levels of feature.

The performance of a fingerprint classification system is usually measured in terms of accuracy or error rate, efficiency or penetration rate, and speed or computational complexity. The measurements of these performance indicators could be quite different on different fingerprint databases. Therefore, the performance comparison of different classification algorithms should be based on the same database. The NIST (National Institute for Standards and Technology) Special Database is the most often used database for the classification performance evaluation. The error rate is computed as the ratio of the number of misclassified fingerprints to the total number of samples in the test set. The error rate of a classification system in general should be reported as a function of the penetration rate that is a performance indicator of the classification efficiency. The classification efficiency is measured by the penetration rate defined as the average ratio of the number of fingerprints in a class to the total number of samples in the database.

For SVM training five class of fingerprints : Arch (A), Left loop (L), Right loop (R), Tented Arch(T), Whorl (W) are considered from NIST SD4 benchmark database.

Fig.1: Sample image of each class of fingerprints

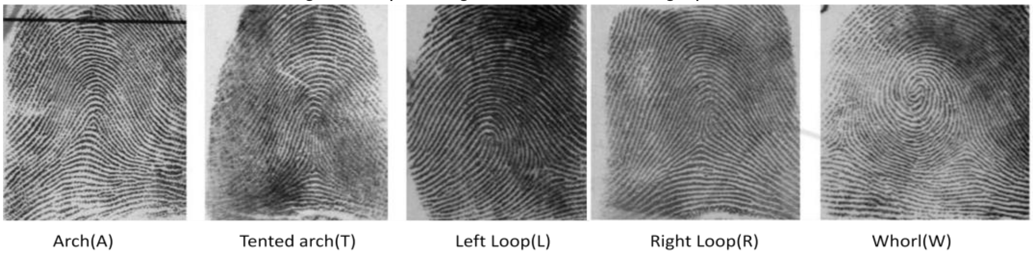



Fig. 2: Fingerprint Classification work flow

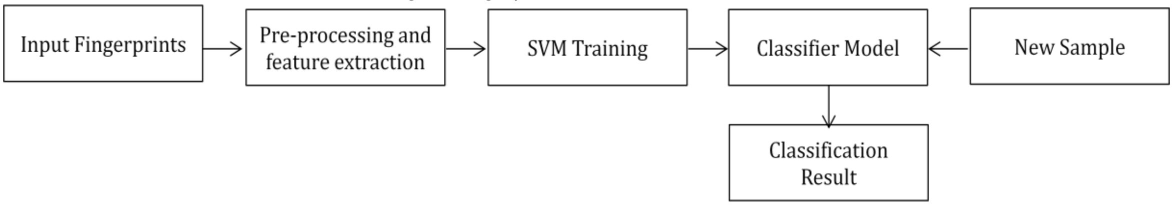
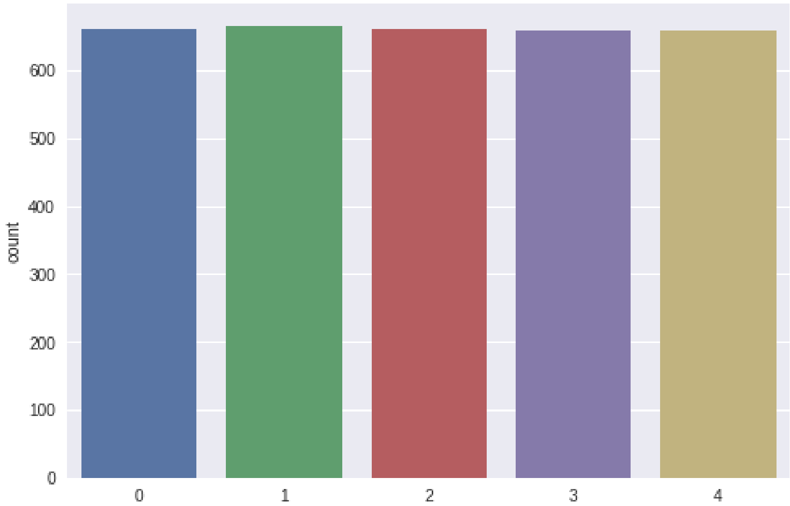



Fig. 3: Data Distribution plot




## 4. Experimental Analysis and Evaluation

The datasets were divided into training and testing datasets(for both X and Y). The testing and training datasets as numpy arrays were loaded. Categorical Y_train data was appended in a list. A data distribution chart (to see the number of values in each class) was plotted in Fig. 3. A data set visualization figure (to get a brief idea of datasets along with labels) was plotted in Fig. 4. The vgg_model was initialized with input shape = (128, 128, 3), pooling = 'max', classes = 5. Layers were added to the model after making it sequential and adding the vgg_model and functions Dense() four times and Dropout() three times along with activation functions 'relu' and 'softmax' were used; also use an efficient optimizer (adam) was used. Fit the model and store it in a variable, say, history. The accuracy graph using history (to determine the accuracy of the model) and the loss graph using history (to determine the loss in building the model) were plotted. Categorical Y_test data is appended in a list. The confusion matrix was plotted which displays datasets along with prediction labels and original class labels. These changes resulted in an accuracy of 89.7% and thus experimentally vgg model proved to be a better option since the same process was carried out using mobileNet which resulted in an accuracy of 76%. Previously, the accuracy was 60%. Required changes were done in the database and the concept of Transfer learning is implemented using the VGG keras model resulting an accuracy of 89.7%.

Fig. 4: Data visualization plot

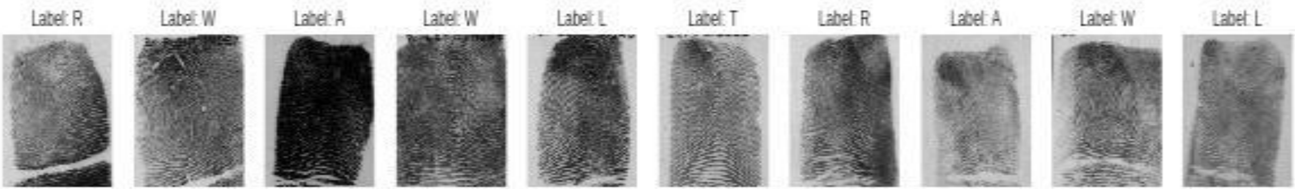
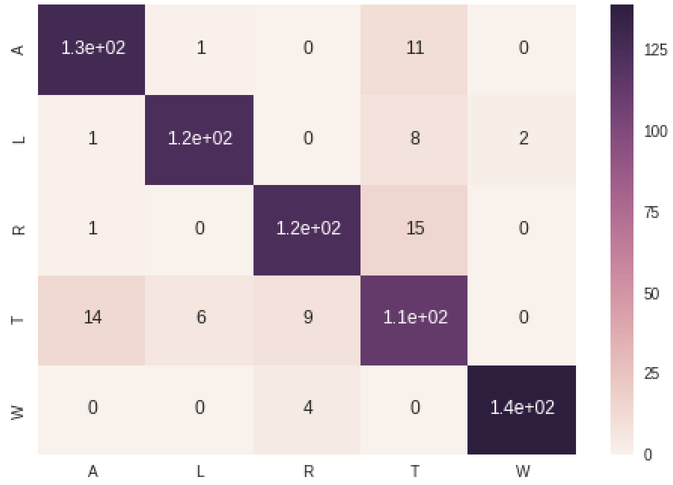


Fig. 5: Confusion matrix




## 5. Conclusion

In this paper, fingerprint classification is implemented using SVM. From the fingerprint samples feature vectors were generated. Several SVM kernels were then used to classify the samples. The accuracy of each varied with change in kernel functions. Whereas, the radial kernel function outperform among others. The specificity and precision of the technique are the best measures of the performance of this technique owing to the intrinsic anomalies of the given dataset. Further improvements in sensitivity of the proposed approach to change detection can be made by using other kernel functions with optimized parameters.

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