

Performance Evaluation of Touchless Fingerprint Recognition: A Comparative Study of SVM VS Decision Trees

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ABSTRACT

Since the encounter of COVID-19 pandemic, different aspects of daily life in early 2020 had got considerably impacted. To control the rate of newly introduced viral infections a range of various measures were recommended worldwide such as the use of facial masks, face shield, enhanced hand hygiene practices etc helped to decrease the spread of pathogens in social gatherings. Nevertheless, these specific measures were creating difficulties in ensuring the reliability of biometric recognition methods, such as voice, facial, and hand-based biometrics. To avoid problems associated with contact/touch – based Biometrics, in this work we have designed an algorithm for touchless fingerprint recognition using HOG features and Machine Learning classifiers. Performance of recognition is evaluated for SVM vs Decision Tree algorithms. The integration of "HOG features with SVM" proves to be more effective in Touchless Fingerprint Recognition domain.

Keywords: Touchless Fingerprint, Machine Learning, Biometrics, HOG, SVM, Decision Trees

INTRODUCTION

During the COVID-19 Pandemic, public contact and physical interaction were restricted by the guidelines from Government organizations. Biometric attendance system which utilizes scanning of fingerprint or hand signature involves physical touch of biometric trait could be risky as it may lead to spread of infectious viruses and causing severe health issues. Hence to avoid getting infected by corona virus in COVID-19 pandemic, a better way is to use methods based on touch/contact -less biometric recognition. Such method includes recognition of touch-less fingerprint, face, palm print and knuckle print. To reduce the chance of spreading COVID-19 and provide safe environment, these touch/contact -less technologies can be adopted in the universities, schools, companies, factories and offices [20].

Conceptually, biometric systems work by individual data acquisition, feature extraction, and then template comparison. They are secured trusted systems for individual identifications depending on several behavioral and physiological human characteristics such as iris, gait, and keystroke. The covid-19 social distancing scenarios have harmed the majority of biometric systems. Many of these required a long capture time or surface contact, resulting in rapid virus dissemination [30].

A range of preventive strategies has been adopted globally to slow the transmission of the coronavirus and reduce the likelihood of new infections. Two widely adopted practices include wearing protective face masks and enhancing hand hygiene through frequent use of disinfectants like hydroalcoholic gel or regular handwashing. These preventive steps have significantly affected daily routines. For example, wearing a face shield or mask that covers the mouth, nose, or eyes can interfere with the effectiveness of face recognition technologies in smartphones and other biometric systems. COVID-19-related impacts and the operational prevalence briefed in Table 1. in the context of most commonly used biometric traits [27].

TABLE I. IMPACT OF COVID19 ON BIOMETRIC TRAITS

Biometric trait	Operational Prevalence	Impact of Covid19
Face	Broad	Intense
NIR Iris	Broad	Minimal
Voice	Broad	Moderate
Touchless Hand Vein	Minimal	Minimal
Touch-based Hand Vein	Minimal	Minimal
Touchless Fingerprint	Minimal	Minimal
Touch-based Fingerprint	Broad	Minimal

As the spread of coronavirus is a big concern, hygiene practices has become an important factor. However in touch based biometric recognition such as fingerprint, contact between surface of the sensor and the finger skin is needed to scan the image. Touch based fingerprint recognition faces problems e.g. distortion caused due to contact, hence in order to avoid such issues and maintain hygien practices to prevnt the spread of Covid19, the idea of touch- less fingerprint recognition can be useful [23].

Histogram of Oriented Gradients (HOG) is a commonly used feature extraction technique has specific attributes that represent the image gradients and their corresponding angles [24]. The HOG algorithm works as follows:

1. Divides an image into small cells
2. Computes each cell's gradient orientation and magnitude
3. Aggregates the gradient information into a histogram of oriented gradients.

We have used open source database [15] as mentioned in Table II.

TABLE II. DATABASE DETAILS

Database	Capturing Device	Subjects	Samples
IIT Bombay Touchless Fingerprint Database	Lenovo vibe K5 plus smartphone	200	800

In this paper, two different classifiers i.e. SVM and Decision Trees are used for fingerprint image recognition and performances of these methods are compared.

RELATED WORK

Several studies have reviewed different biometric technologies used during the COVID-19 pandemic. These include methods like palm recognition, face recognition, face mask detection, iris scanning, and attendance monitoring systems. Other research focused on challenges faced during the pandemic and the emerging opportunities for biometric systems. Some researchers explored situations where traditional fingerprint systems couldn't be used, especially when gloves were required. In these cases, alternative methods such as Keystroke dynamics and multimodal Touchscreen swipe patterns were tested for authentication. Various classifiers, including k-NN, SVM, and fuzzy logic, were employed to improve authentication accuracy. Additionally, other work has highlighted the evolving role of biometric systems and technologies in the post-pandemic world [20, 27, 28, 30].

Various studies have explored methods to improve fingerprint recognition systems, both for touch-based and touchless biometric approaches. One study introduced a contactless fingerprint enhancement technique that improves image quality by combining color-grayscale enhancement with local ridge orientation, leading to better minutiae detection and higher recognition performance. Other research evaluated the compatibility between fingerprints from touch-based systems and "fingerphotos" from touchless systems, using advanced minutiae-based matchers. To bridge the gap between touch-based and touchless systems, a method was proposed for making these systems more compatible. In addition, the use of smartphones for touchless fingerprint recognition was investigated. One study developed a smartphone-based system with feature matching modules and compared the performance of touch-based and

touchless systems. Another study examined the reliability of fingerprint comparison when one image was captured with a fingerprint scanner and the other with a smartphone camera. Further, a contactless multimodal biometric system combining palmprints and fingerprints was proposed, with advanced texture descriptors used for feature extraction. Performance evaluations were conducted using publicly available datasets. Other work compared touchless and touch-based fingerprint acquisition methods, discussing technical challenges and trade-offs. Clustering techniques were also explored for fingerprint verification, showing promising results when tested on a touchless fingerprint database [5, 6, 7, 13, 14, 15, 16, 17, 21, 22, 23].

Various studies have explored the use of Histogram of Oriented Gradients for extracting features in biometric systems. One study employed HOG in combination with Support Vector Machines (SVM) for detection of human in images. Another focused on the application of HOG for fingerprint recognition, showing that it significantly improved accuracy, achieving a perfect recognition rate of 100%. Additionally, HOG features were used for matching in fingerprint systems, with SVM proving effective in extracting these features. Another approach integrated Local Interpretable Model-agnostic Explanations (LIME) with HOG to distinguish between counterfeit and genuine fingerprint scans, further enhancing fingerprint verification accuracy [1, 2, 24, 31, 32].

Different machine learning algorithms have been explored for fingerprint recognition, focusing on minutiae-based and texture-based features. A touchless fingerprint verification system was developed using minutiae features, with classification performed using GMM and SVM. Several studies evaluated the performance of algorithms like Naïve Bayesian, MLP, RBF, and Random Forest for automatic fingerprint recognition. Advanced SVM variants were introduced and compared based on optimization techniques, while different classifiers, e.g Decision Trees, Naive Bayes, and SVM, were assessed for classification accuracy. Performance enhancement methods incorporating K-NN, Linear Discriminant Analysis, MG-SVM, Bagged Tree Ensemble classifiers were explored. Additionally, classifiers like K-NN, SVM, and Deep Neural Networks were used for fingerprint recognition, and SVM and Logistic Regression were applied to level 3 fingerprint features. Comparisons of image classification performance between SVM and CNN were made. Reviews on the applications and challenges of SVM, as well as an in-depth analysis of decision trees, were provided. In a study, a lightweight, efficient touchless fingerprint identification system utilizing SSIM and Random Forest classifiers was proposed [3, 4, 8, 9, 10, 11, 12, 18, 19, 25, 26, 29].

METHODOLOGY

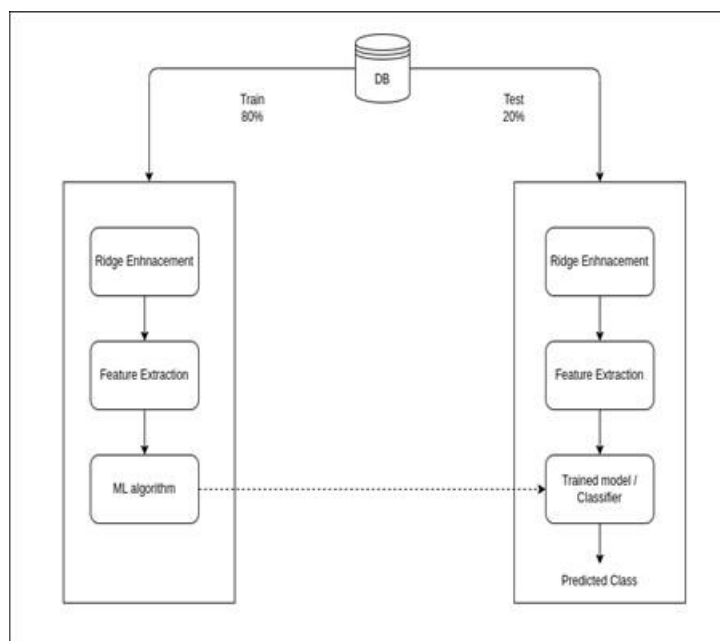


Fig. 1. Outline of the Touchless Fingerprint Recognition

A. Data augmentation

This process was carried out to increase number of images enough for training and validation.

B. Data split

In Machine Learning classification, data is split into Train (80%) and Test (20%).

C. Ridge Enhancement

- **Resize:** After data acquisition, all images in the databases may or may not be of identical shape, hence we need to resize images to make it of same size, shape and resolution.
- **Sharpening:** Image sharpening is used to highlight edges and fine details in the image.
- **Clahe:** Contrast limited adaptive histogram equalization (Clahe) amends the local contrast of an image, while also limiting excessive amplification by regulating the contrast enhancement process [5, 21, 34].
- **Segmentation:** The process involves distinguishing the foreground regions of a fingerprint image from the surrounding background. The foreground area, which contains valleys and ridges, is the main focus, while the background area outside the fingerprint's border usually lacks valuable information. If feature extraction algorithms are applied to these background regions, they might produce noisy and inaccurate results. To avoid this, segmentation is used to remove the background areas, ensuring that feature extraction is more accurate and reliable.
- **Normalization:** The segmented image is then normalised. Image normalization employed to bring the grey level values into a certain range that is good enough for improving brightness and contrast of the image.
- **Ridge Orientation Estimation:** It is a crucial process that captures the natural pattern of ridges and valleys in fingerprint images. This process analyzes pixel intensity in small blocks to determine the ridge direction in a local area, providing essential angular information about the ridges.
- **Ridge Frequency Estimation:** Ridge frequency estimation calculates the average distance between ridges in fingerprint images. This metric helps in understanding the regularity and spacing of the ridges, which is vital for accurate fingerprint analysis.
- **Gabor Filtering:** Gabor filtering is used to clean up fingerprint images by removing noise and artifacts. The process utilizes the structured pattern of parallel valleys and ridges in the fingerprint that exhibit distinct frequencies and orientations. By tuning the Gabor filter to match these patterns, noise is minimized while the essential ridge and valley structures are preserved. Gabor filters are particularly effective because they can target specific orientations and frequencies, making them ideal to enhance the clarity as well as details of fingerprint images.
- **Binarization:** The Gabor filtered image is then binarized which makes it more suitable for extraction of features .

D. Feature Extraction

We extracted two features from Fingerprint images

1. Fingerprint Pattern (Level 1)
2. HOG of Fingerprint Pattern

The Binarized image obtained from Ridge Enhancement stage is nothing but the Fingerprint Pattern. We extracted Histogram of Oriented Gradients (HOG) feature from enhanced Fingerprint Ridge Pattern.

The HOG is a method employed for detecting image objects. HOG is a feature descriptor that captures the distribution of edge directions and intensities in an image. It operates by splitting the image into tiny regions and computes the magnitude and gradient orientation of each pixel within those regions, and subsequently grouping these gradients into histograms (see Figure 1). These histograms are then normalized to account for variations in lighting and contrast. HOG has achieved remarkable success in computer vision and image processing applications by solving previously challenging problems. It is beneficial in object detection tasks, such as pedestrian detection, where it has shown superior performance compared to other feature descriptors [31].

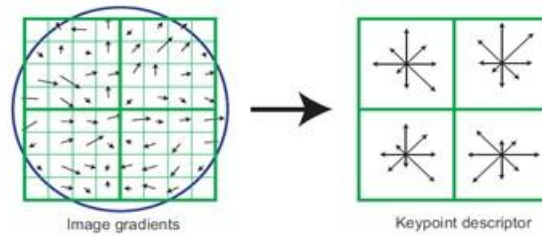


Fig. 2. Image Gradients and Orientation Histogram [31]

E. Machine Learning Classifiers

Two supervised machine learning algorithms were used to train models for classification

1. Support Vector Machine
 2. Decision Trees
- SVM

SVM is a well liked method for addressing classification problems, initially introduced by Vapnik, Boser, and Guyon in 1992. SVM is a linear classifier that efficiently predicts and classifies data by considering all relevant factors. It is commonly applied in diverse fields such as pattern classification, due to its capacity to provide tailored solutions for specific problems. SVM is easy to train and works well with high-dimensional data. It also provides a clear way to balance the complexity of the classifier with the error rate. However, its performance depends on selecting an appropriate kernel function [31].

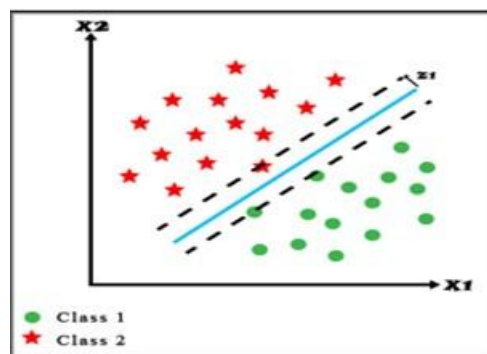


Fig 3. SVM Mechanism [31]

SVM is known for minimizing classification errors while maximizing the geometric margin, earning it the name as Maximum Margin Classifier which is based on Structural Risk Minimization principle. SVM transforms input data into a space of higher dimensions that constructs a decision boundary (hyperplane) to segregate the data. Two additional boundaries are placed on either side of the main separating hyperplane. The goal is to enlarge the gap, or margin, between these boundaries, as a broader margin tends to improve classifier's capacity for generalization. Consider a collection of data points represented as $\{(j_1, k_1), (j_2, k_2), \dots, (j_n, k_n)\}$ where $k_n = 1$ or -1 , indicating the category to which the corresponding point x_n is belongs. Every j_n is a vector in a p -dimensional space. The equation $m \cdot j + c = 0$ defines the separating hyperplane involves a scalar value c , with m being a p -dimensional vector that is orthogonal to the hyperplane. Modifying c helps to increase the margin, thereby enhancing the performance of the classifier. For linearly separable data, the parallel hyperplanes are represented by the equations $m \cdot j + c = 1$ and $m \cdot j + c = -1$. The distance between these hyperplanes is $2/|m|$, meaning that minimizing $|m|$ serves to maximize the margin. To guarantee correct classification of all data points, we require that either $m \cdot j_i - c \geq 1$ or $m \cdot j_i - c \leq -1$ for each i , which can be written as $k_i(m \cdot j_i - c) \geq 1$ for all $1 \leq i \leq n$ [19, 33].

- Multi-Class SVM problem

It is essential to recognize that the standard SVM classification method is designed specifically for binary classification. In cases where there are multiple classes, such as in fingerprint systems, alternative techniques need to be employed. Researchers have developed several approaches to simulate the SVM mechanism for more than two classes, including

One-vs.-One, One-vs.-All, and Error-Correcting Output Coding (E-COC). In this paper, we chose One-vs-All approach to solve the multi-class problem. This approach treats each person as a separate class [31].

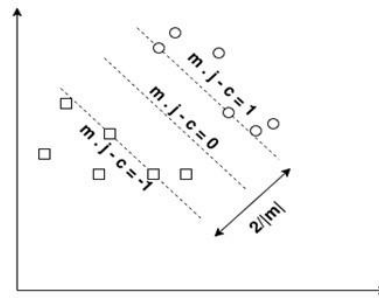


Fig 4. Binary classification

SVM [33]

- Decision Trees

Decision trees are commonly employed in image processing, pattern recognition, machine learning etc. They form a step-by-step model that efficiently merges a sequence of basic checks, with each check comparing a numerical feature to a set threshold. The rules in decision trees are easier to formulate than the numerical weights in neural networks. Decision trees are mainly used for classification tasks and are a common choice in data mining for this purpose. A decision tree consists of branches and nodes, with each node representing a characteristic to be categorized, and each branch indicating a possible value of that characteristic. Decision trees are popular because they are easy to understand and offer high accuracy across different types of data.

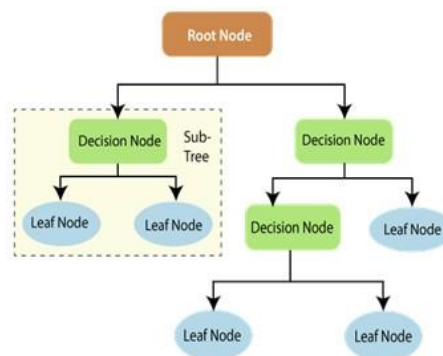


Fig. 5. Decision Tree [25]

RESULT ANALYSIS

The results visualization of Fingerprint operations is as shown in Fig. 6.

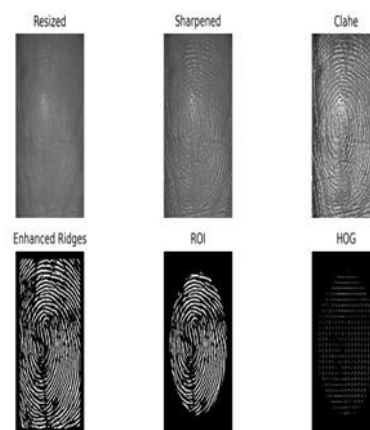


Fig 6. Visualization of results

Table III. below summarizes the results obtained.

TABLE III. RESULT SUMMARY

Sr. No.	Classifier	Feature	Accuracy (%)
1	Support Vector Machine (SVM)	Pattern (Level1)	43.40
		HOG of Pattern	100
2	Decision Trees (DT)	Pattern (Level1)	21.80
		HOG of Pattern	67

Fig 7 shows the bar plot for comparison of accuracies obtained from different feature-classifier combinations.

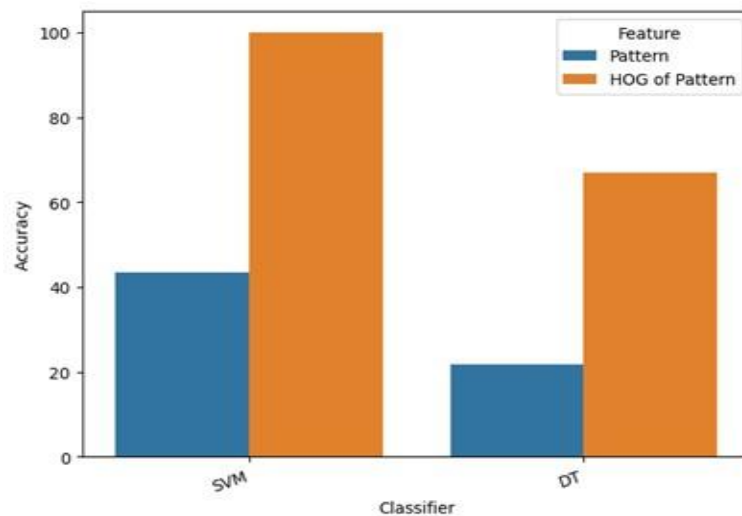


Fig 7. Barplot for accuracy comparison: SVM vs DT

TABLE IV. COMPARISON WITH STATE OF THE ART METHODS

Paper	Features extracted	Method implemented	Accuracy
Deepika, K. C., and G. Shivakumar [29]	Minutia	Classification by SSIM	90.02%
	GLCM	Classification by Random Forest	94.72%
Proposed method	HOG	Decision Trees	66.04%
		SVM	100%

CONCLUSION

We have designed and implemented an algorithm which has three stages: 1. Ridge enhancement 2. Feature Extraction 3. Classification. We have evaluated the performance of Fingerprint Recognition for SVM vs Decision trees. Based on the empirical data, we have observed that Touchless Fingerprint Recognition performance drastically improved using HOG feature. SVM provides 43.40% and 100% accuracy whereas Decision Trees provides 21.80% and 67% accuracy using Fingerprint Pattern and Hog respectively. Hence the combination of “HOG feature + SVM” outperforms within the scope of Touchless Fingerprint Recognition. All the operations have been implemented in Python programming language (Version 3.10).

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