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A Comprehensive Method for Fingerprint Classification Based on Gabor Filters and Machine Learning

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ABSTRACT

The fingerprint is a valuable tool for both forensic analysis and community security. State-of-the-art fingerprint classification methods tend to ignore image quality enhancement as well as use high-dimension feature sets resulting in unnecessary computational complexities. To address these issues, this study proposes an efficient fingerprint classification method that combines Histogram of Oriented Gradient (HOG) and Gabor Filter features with Random Forest (RF) and Naïve Bayes (NAÏVE) classifiers. It sequentially preprocesses the input with a series of receiving functions that enhance the image, such as grayscale, morphological, and binary. The method's performance was evaluated on the SOCOFing dataset, and 99% classification accuracy was demonstrated using the Gabor-Naïve approach, surpassing some sophisticated techniques in terms of accuracy and computational efficiency. This work contributes to the field by addressing gaps in image enhancement and feature dimensionality, offering a robust solution for authenticating and distinguishing altered fingerprints. Future research could build on this by examining different classifiers for additional optimization and testing the methodology on a variety of datasets.

1. INTRODUCTION

Biometric systems, or Identity Verification (IV) systems, use biometric traits to automatically identify, assess, and authenticate individuals. These systems are based on the fundamental premise that each individual has unique physical and behavioral characteristics [1]. Currently, Fingerprints exhibit various distinctive attributes that render them a favored option for access authentication when recognizing handprints. Furthermore, fingerprints are employed at incident locations to determine an individual's involvement. One notable attribute is the unwavering constancy of fingerprints, and it is worth noting that fingerprints are unique to each individual, even among twins. According to the previous study [2], fingerprints can be categorized into three distinct types: visible (patent) prints, plastic prints, and concealed (latent) prints. Patent prints are easily visible to the naked eye and do not necessitate the use of a microscope for recognition. These prints are formed when fingers meet colored substances like bodily fluids, liquids, or soil. In contrast, plastic prints are impressions with three-dimensional features that are formed when a finger meets materials like soap, fresh paint, or wax. Latent fingerprints, which cannot be seen with the naked eye, require the application of chemical reagents for detection. Fingerprint images possess specific features that are dependent on the resolution of the acquisition [3].

As illustrated in Figure 1, typically, the image of a fingerprint reveals a recurring arrangement of "delta" to the mix, the distinction between valleys (light sections) and ridges (dark sections) gains prominence.

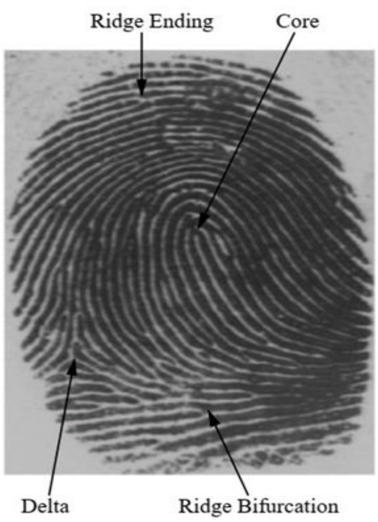

Figure 1. A fingerprint with ridges and delta [3]

Aligning the ridges represents an essential aspect of fingerprint images. Most fingerprint recognition algorithms require the extraction of the orientation as a necessary step. When the image quality is sufficiently high, computing the orientation is relatively straightforward. However, extracting the orientation accurately from poor-quality images still poses an ongoing challenge. Given the remarkable accuracy of fingerprints in criminal identification, perpetrators consistently make efforts to evade fingerprint recognition systems. In response to this, Deliberate classifications are performed by the FBI's Criminal Justice Information Services division. fingerprint modifications based on the specific technique employed for alteration [4]. Figure 2 shows these alterations can be generally categorized into four primary groups: vertical cuts, Z-shaped cuts, burns, and unclassified modifications.

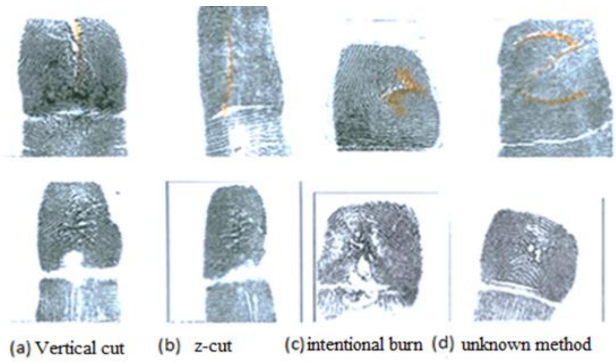

Figure 2. Fingerprint alteration types [5]

The study's key objective is to develop an efficient fingerprint classification method that addresses key limitations in the existing techniques, specifically the dependence on features with high dimensionality and enhancement of insufficient images. The paper's contributions aim to classification accuracy and computational efficiency by leveraging a combination of Gabor filters, HOG features, and machine learning classifiers (Random Forest and Naïve Bayes). Additionally, the study validates the proposed method on the dataset (SOCOFing) and compares its performance against the latest methods.

The remaining parts of this article are structured as follows: Section 2 presents the literature review and previous studies, Section 3 presents the proposed method, Section 4 outlines the results, and Section 5 concludes the study.

2. LITERATURE REVIEW

Extensive research has explored various aspects of fingerprint classification algorithms, including classification, detection, reconstruction, and recognition. A study by Peralta et al. [5] analyzed and categorized minutiae-based fingerprint-matching algorithms, evaluating their accuracy and speed for verification and identification tasks. Singla et al. [6] reviewed the fundamental concepts of latent fingerprinting, as well as recent methods for enhancement, reconstruction, and matching of lifted fingerprints

Various machine-learning techniques and processes for feature extraction are employed in fingerprint classification. Yang et al. [7] developed an image classification technique for fingerprints with 94.7% accuracy (four-class) and 91.5% accuracy (five-class) on the NIST-4 database, effectively handling low-quality fingerprints but with limitations including sensitivity to noise, small block sizes, and unsuitability for certain fingerprint types. Furthermore, Narayanan and Sajith [8] implemented a gender detection system for fingerprints achieving 90.2% accuracy for females and 96.4% for males using a time domain approach and systematic pixel counting, but the method is not suitable for low-quality latent fingerprints. Revathy et al. [9] combined fingerprint ridge orientation with local ridge frequency features for latent fingerprint segmentation. The disadvantage of the proposed work is that they used small and different datasets. Moreover, the proposal needs to add additional features like Ridge types and matching algorithms. Scholars have put forward diverse methodologies leveraging deep learning to classify and detect fingerprints. Saponara et al. introduced a method that utilizes deep learning and sparse auto-encoder algorithms to reconstruct low-resolution or partial fingerprint images, enhancing their quality. The model's robustness was tested on three local fingerprint datasets [10], but the computational complexity of deep learning may limit its scalability for large-scale datasets. In a previous study [11], two models (CNN and transfer learning) were proposed for classifying fingerprint images as real or altered. The CNN model achieved an 81% classification accuracy on the SOCOFing dataset, while the transfer learning model achieved 97.5% accuracy. Transfer learning effectively addressed the insufficient dataset issue, but the CNN model's accuracy was impacted by the lack of image enhancement in the SOCOFing dataset.

Gabor filters are commonly used in fingerprint analysis to enhance and extract features like ridges and minutiae points. In a previous study [12], an authentication technique based on a filter bank-based matching algorithm with Gabor filters. However, the scalability and image quality sensitivity were limited. Moreover, a previous study [13] proposed a two-stage fingerprint classification approach using Gabor filters and twin support vector machines (TWSVM) with a 98% accuracy, but TWSVM limitations such as computational complexity and overfitting should be considered. Görgel and Ekşi [14] proposed a fingerprint identification method using Gabor wavelets and CNN, achieving 91.50% accuracy on the FVC2006 dataset, but with potential limitations of computational complexity and effectiveness depending on image quality and generalization ability of the CNN model.

In a previous study [15], a deep learning strategy utilizing pre-trained CNN and EfficientNetB0 achieves 99.91% accuracy in determining the gender of fingerprints using the SOCOFing dataset and RF classifier.

Through careful literature analysis, two gaps were discovered. Poor use of image enhancement, as well as high-dimension features, are used to build a classification model. To address these gaps, our proposed approach utilizes impactful features and machine learning to classify real and altered fingerprint images. The objective is to improve accuracy, reduce computational complexity, enhance the image database, and increase the efficiency of fingerprint authentication.

3. MATERIALS AND METHODS

This article aims to accurately classify fingerprints as either authentic or altered. This task can be formulated as a two-class classification problem. To achieve this, our proposed method for classifying index fingerprints comprises three primary stages: image enhancement, feature extraction, and classification. The overall process of our approach is shown in Figure 3. Furthermore, Algorithm 1 outlines the proposed steps. Subsequent subsections provide a comprehensive explanation of the method's intricacies and details.

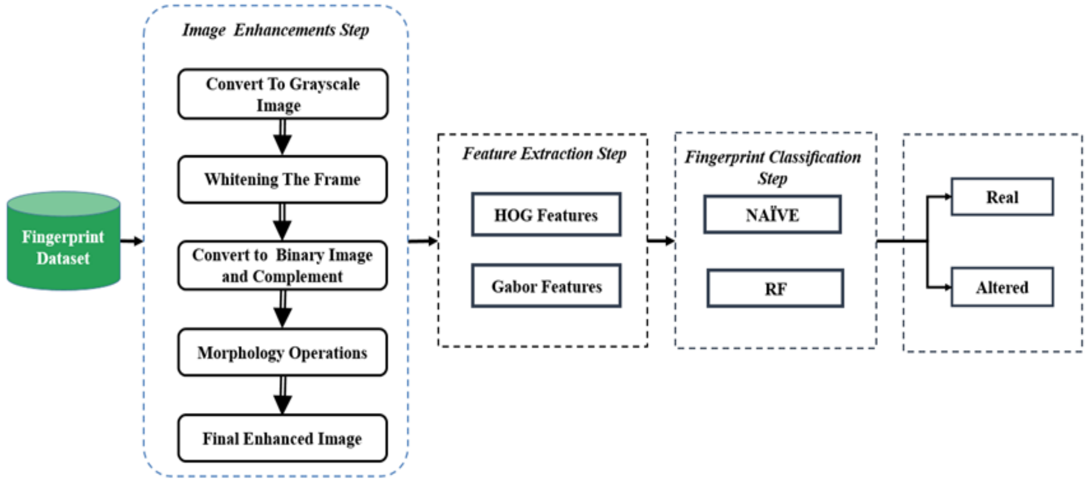

Figure 3. The proposed method block diagram

Algorithm 1: Fingerprint classification utilizing the NAÏVE and RF classifier approach

Begin
For each image:
1. Read the image using the "Imread()" function.
2. Apply enhancement operations:
   2.1. Convert the RGB image to grayscale using the "rgb2gray()" function.
   2.2. Remove any black frames present in the original image.
   2.3. Convert the image to binary.
   2.4. Perform morphology operations.
   2.5. Filter and retain only the most prominent object.
   2.6. Apply additional morphology operations to obtain the final finger mask.
   2.7. Obtain the final enhanced image.
3. Extract HOG features to obtain a 1 × 81-dimensional feature vector.
4. Extract Gabor features:
   4.1. Apply 2D Gabor filters to each enhanced image.
   4.2. Using mean squared energy and mean amplitude as Gabor features, create a 12-dimensional feature vector.
5. Training:
   5.1. Train the RF classifier using the above-mentioned feature vector.
   5.2. Train the Naïve classifier using the above feature vectors.
6. Testing:
   6.1. Test the trained RF model to determine if the image is real or altered.
   6.2. Test the trained Naïve model to determine if the image is real or altered.

End for
End

3.1 Techniques for enhancing images

The purpose of employing image enhancement techniques is to enhance the quality of fingerprint images. Within our dataset, fingerprint images frequently exhibit the presence of noise and unwanted frames, which can effectively impede the extraction of features. To overcome these challenges, we employ a series of image enhancement techniques as outlined below:

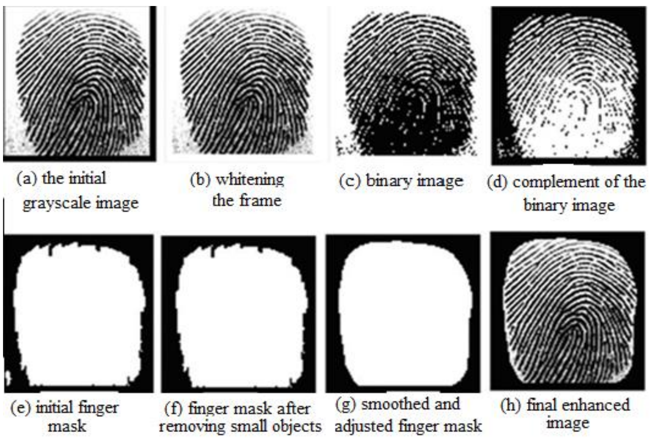

Figure 4. Fingerprint image enhancement steps

Step 1: Initially, we convert the fingerprint image which is an RGB representation into a grayscale image to simplify further processing.

Step 2: In order to eliminate the dark borders evident in the initial image (Figure 4(a)), a technique was employed to alter the pixel values of the first four rows and columns to 255. This adjustment effectively eliminates the undesired frames from the image (Figure 4(b)).

Step 3: Subsequently, the image is transformed into a binary format using a threshold set at a relatively high value to retain all the details of the image (Figure 4(c)). Following this, the image is inverted to create the complementary version as depicted in (Figure 4(d)).

Step 4: Morphological operations, including the removal of tiny objects, gap closure, and hole filling, are executed to generate a comprehensive fingerprint mask (Figure 4(e)).

Step 5: In this phase, we aim to selectively preserve the most significant object (the fingerprint) while eliminating any undesirable noise, we can make use of the size attributes associated with these objects. By identifying the index associated with the largest object, we maintain it within the image and eliminate tiny elements. The outcome of this filtration procedure is illustrated in (Figure 4(f)).

Step 6: To enhance the quality of the ultimate finger mask and achieve smoother edges, we implement an additional series of morphology operations. The mask obtained as a result of this process is presented in (Figure 4(g)).

Step 7: Ultimately, Utilizing the mask acquired from the preceding stage (Figure 4(g)), we superimpose it onto the original image (Figure 4(a)), resulting in the generation of the ultimate enhanced image demonstrated in (Figure 4 (h)).

3.2 Features extraction techniques

Features extraction are distinctive characteristics of the fingerprint that are identified and quantified [16, 17]. These features serve as discriminative attributes that can effectively differentiate between authentic and altered fingerprints. In this stage, the final enhanced image is subjected to feature extraction, wherein the essential features are extracted. A pivotal role is played by the extracted features in the image classification process. In this paper, the features utilized are outlined as stated below.

3.2.1 Histogram of Oriented Gradient (HOG)

In the beginning, the region of interest (ROI) is divided into cells of a predetermined size (e.g., 8 × 8). Next, for each cell, a gradient histogram is calculated. Later, to deal with the problem of illumination variation, the next stage is normalization using histograms of each cell. Finally, for every overlapping block in all blocks, an assembly of HOG features will be obtained. The utilization of HOG features has gained considerable popularity as it can efficiently collect good local image structures. Breaking up the detection window into small cells has an advantage because more points of interest can be identified, and where there are many peaks and troughs in the given area. A similar step in which the direction of edge orientation is divided into different zones is particularly helpful in cases when, for example, one object differs from the other in terms of two patterns. Then, normalization of these histograms will increase the reliability of HOG features even more due to the decrease in the impact of light conditions on image formation. For each block in the image, after collecting HOG features, we get a more detailed idea of its local structure and consequently more reliable parameters for further analysis. The 81 HOG features are computed for finger images based on 1 × 12 feature vectors' dimensions. The process of extracting HOG features involves multiple steps, as depicted in Figure 5.

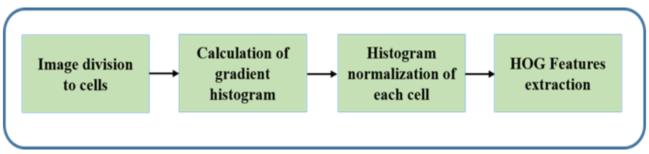

Figure 5. HOG features extraction block diagram

3.2.2 Gabor wavelet filter

Gabor filtering is a linear filter commonly used in image processing and computer vision tasks, and is applied to the fingerprint image to enhance ridges and reduce valleys. It captures both spatial and frequency information, providing precise spatio-spectral information and exhibiting robustness against variations in contrast and brightness. Gabor wavelet filters are commonly employed for texture analysis, edge detection, and various pattern recognition tasks. The Eq. (1) for a Gabor Wavelet Filter is as follows:

$$G(x,y)=\exp\left[-\frac{\left(x'^2+\gamma'^2*\gamma'^2\right)}{2*\sigma^2}\right]*\cos\left(2\pi*f*x'+\varphi\right) \quad (1)$$

- *G(x,y)* represents the Gabor filter response at coordinates (x,y).
- x' and y' are the rotated and scaled coordinates obtained by rotating and scaling the original coordinates (x,y).
- γ is the aspect ratio that controls the ellipticity of the Gaussian envelope.
- σ determines the filter's size by measuring the Gaussian envelope standard deviation.
- f represents the sinusoidal component's spatial frequency.
- φ is the sinusoidal component's phase offset.

Mean Squared Energy and Mean Amplitude are examples of typical Gabor features [18]. These features can be obtained at various scales and orientations. The Mean Squared Energy and Mean Amplitude are feature vectors supplied by Response Matrices. The Mean Squared Energy is calculated by squaring each value in a response matrix. Finally, add these squared values. To calculate the mean amplitude, each matrix value in a response matrix must be determined in absolute terms. Finally, add the following values. Through our experiments, we were able to determine the Mean Squared Energy and Mean Amplitude for orientation 2 and scale 3. The feature vectors measure 1 × 12.

3.3 Classifications

The objective of the study is to employ machine learning as an efficient approach to categorize input images as real or altered fingerprint images, addressing the classification challenge effectively. Various machine learning algorithms have been proposed to learn from training data and make intelligent decisions automatically [2]. In this study, our proposal focuses on two specific machine-learning algorithms: Random Forest classifier (RF) and Naïve Bayes classifier (NAÏVE).

3.3.1 Random Forest (RF) classifier

A Random Forest is a collection of decision trees that are chosen randomly from the input feature set. Utilizing input data, the system trains several models, aggregates predictions from each model, and subsequently utilizes a voting process to determine the optimal option. Random Forests classifier trains fingerprint data and their labels, using features. It constructs multiple decision trees, which collectively classify fingerprints based on majority voting or averaging of their predictions, enabling accurate and robust fingerprint recognition.

3.3.2 Naïve Bayes (NAÏVE) classifier

A Naïve Bayes classifier is a simple probabilistic model that assumes feature independence and uses Bayes' theorem. The model performs admirably in intricate real-world situations and needs minimal training data. With the training set's relative frequencies, model parameters are estimated.

4. RESULT AND DISCUSSION

4.1 Dataset

The dataset includes 600 African people's 6,000 fingerprint images. Ten fingerprints were taken by everyone. To introduce diversity, three types of modifications were employed: "obliteration, central rotation, and z-cut", the generation of synthetic replicas of the authentic fingerprints is underway. All images are presented in a grayscale format; Figure 6 and Figure 7 present images that showcase genuine, straightforward, and complex alterations. The dataset is accessible at the following link: https://www.kaggle.com/ruizgara/socofing. To ensure unbiased results, the prepared dataset was randomly divided into two subsets. The training subset comprised 70% of the total database, while the testing subset consisted of the remaining 30%. To reduce any reliance on specific training or test data, A technique of k-fold cross-validation was utilized with k equal to 10. This approach involved splitting the dataset into ten equal segments, using each segment as the test set once while the remaining nine segments served as the training set. This procedure was repeated ten times to ensure accurate and reliable results.

Figure 6. The caption of a selection of the images of fingerprints from the SOCOFing dataset, including: (a) genuine fingerprint images; (b) modified fingerprint with easy central rotation; (c) modified fingerprint with easy obliteration, and (d) modified fingerprint with an easy z-cut

Figure 7. The caption selection of the images of fingerprints from the SOCOFing dataset, including: (a) images of genuine fingerprint; (b) fingerprint images that have been intentionally modified or manipulated, including central rotation adjustments; (c) fingerprint images that have been intentionally modified or manipulated, including obliteration, and (d) altered images of fingerprint with a hard-altered z-cut

4.2 Performance evaluation measures

The performance of the proposed approach can be evaluated by utilizing the classification accuracy and error measure. The accuracy (Ac) can be determined using Eq. (2) below:

$$Ac = \left(\left(TP + TN\right) / \left(TP + TN + FP + FN\right) \times 100\%\right) \quad (2)$$

Error represents the ratio of the total number of images to the number of incorrectly classified images, as defined in Eq (3).

$$Error = \frac{FP + FN}{TP + TN + FP + FN} \quad (3)$$

In Eq. (3), True Positive (TP) denotes the number of correctly identified altered fingerprint images. False Negative (FN) indicates the number of altered fingerprint images that were misclassified. False Positive (FP) measures the number of genuine fingerprint images incorrectly classified as altered, while True Negative (TN) represents the number of genuine fingerprint images correctly identified.

4.3 Results of the proposed performance evaluation

In order to identify the most efficient classifier, the performance of several classifiers using various features is compared in order to calculate the classification accuracy and error. Tables 1 and 2 illustrate the classification accuracy and error rates of the proposed approach, evaluated using two feature extraction methods and two classifiers on the altered image databases of SOCOFing_Easy and SOCOFing_Hard. Additionally, the method's classification accuracy and error were compared to different feature types, as illustrated in Figures 8-11.

Despite the fact that the classifiers employ identical pattern feature vectors as input, their outcomes vary due to the distinctive characteristics inherent in each classifier. The efficacy of each individual classifier will be thoroughly evaluated and analyzed in the following section.

Table 1. Performance results for features, classifiers, and SOCOFing_Easy database

Classifier	Accuracy (%)		Error (%)	
	HOG Feature	GABOR Feature	HOG Feature	GABOR Feature
RF	74	76	26	24
NAÏVE	83	98	17	2

Table 2. Performance results for features, classifiers, and and SOCOFing_Hard altered images

Classifier	Accuracy (%)		Error (%)	
	HOG Feature	GABOR Feature	HOG Feature	GABOR Feature
RF	69	71	31	29
NAÏVE	80	96	20	4

4.4 Effectiveness of NAÏVE classifier

Based on the results presented in Figure 8 and Figure 10, the NAÏVE classifier demonstrates accuracy rates of 98% and 96% for the Gabor filter. Consequently, it can be concluded that the NAÏVE classifier demonstrates superior performance compared to the RF classifier. The classification error rates for the HOG feature when using the NAÏVE classifier are recorded at 17% and 20% as shown in Figure 9 and Figure 11. These error rates indicate that the NAÏVE classifier achieves a high level of accuracy in classifying data based on the HOG feature. Similarly, the classification error rates for the Gabor are significantly lower at 2% and 4% as shown in Figure 9 and Figure 11, further confirming the effectiveness of the NAÏVE classifier in accurately classifying data using the Gabor.

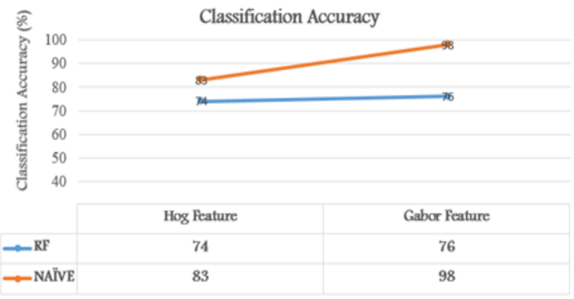

Figure 8. The classification accuracy (NAÏVE and RF) utilizing distinct features in the database of Easy altered images to SOCOFing

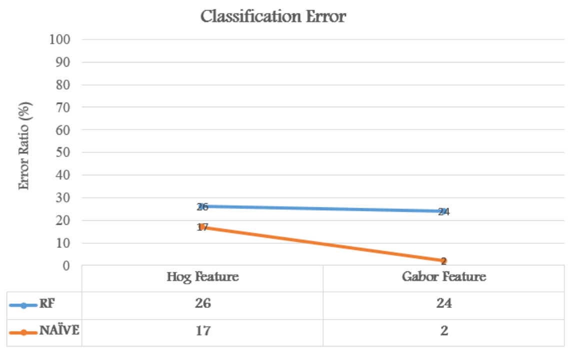

Figure 9. The classification error to both (NAÏVE and RF) utilizing distinct features in the database of easy altered images SOCOFing

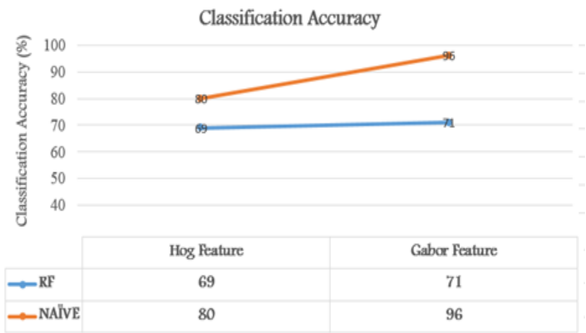

Figure 10. The classification accuracy to both (NAÏVE, RF) utilizing distinct features in the database hard altered images of SOCOFing

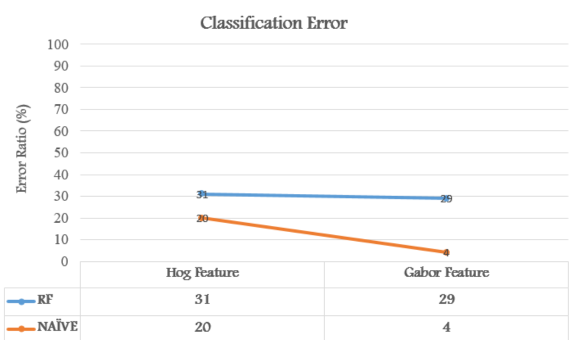

Figure 11. The classification error of (NAÏVE, RF) utilizing distinct features in the database of hard altered images SOCOFing

4.5 Effectiveness of RF classifier

According to the results shown in Figure 8 and Figure 10, the RF classifier demonstrates an accuracy of 74% for the HOG feature and 78% for the Gabor. Based on these findings, it can be concluded that the RF classifier performs second best after the NAÏVE classifier in terms of classification accuracy. Moreover, when utilizing the RF classifier, the classification error rates for the HOG feature are 26% and 24%, while for the Gabor filter, the error rates are 31% and 29% as shown in Figure 9 and Figure 11. This additional information highlights the comparative performance of the RF classifier, demonstrating its accuracy rates as well as the corresponding error rates for both the HOG and the Gabor feature. However, when considering the error rates, it is evident that the RF classifier has higher error rates compared to the NAÏVE classifier. The results unequivocally demonstrate that the Gabor feature surpasses the HOG feature in performance across both classifiers, rendering it the most fitting feature for the classification of fingerprints. Furthermore, the second-highest performance is consistently achieved by the feature of HOG in both classifiers. As a result, a significant enhancement in classification accuracy will be achieved by the adoption of the proposed Gabor-based method. These findings provide strong evidence to support the assertion that the NAÏVE classifier is more effective in accurately classifying the data. The lower error rates achieved by the NAÏVE classifier suggest that it is a reliable and robust classifier for the dataset under consideration.

4.6 Comparison with existing approaches

To assess the performance of the proposed approach, state-of-the-art techniques are used as benchmarks [19, 20]. Table 3 displays the classification results of the proposed method alongside comparisons with other fingerprint classification techniques. A detailed analysis will be carried out to examine the classification accuracy of these approaches [21]. The proposed method surpasses existing fingerprint classification techniques with a detection accuracy of 98% and a small feature vector dimension of 1 × 12, as demonstrated in Table 3. The proposed feature extraction method is computationally faster than most current methods since it uses fewer feature vector dimensions, as seen in Figure 12. The proposed method's accuracy of 99% directly supports the study's objectives of improving classification accuracy and reducing computational complexity. By integrating effective image enhancement and low-dimensional features, the method addresses gaps in noise handling and efficiency identified in prior studies [7, 8].

While the accuracy results of the methods in the previous study [13] may exceed the highest accuracy achieved by the proposed method, it is important to note that these techniques depend on CNN features. Although CNN features are effective, they require large feature vectors, leading to significant computational resource demands. Our method, on the other hand, only required a 1 × 12 feature vector. While the accuracy results of the approach in the previous study [9] may surpass the best accuracy of the proposed method, it is important to note that these techniques rely on manually crafted features, leading to large feature vector sizes. The fingerprint classification methods in the previous studies [8-10, 15, 19] are primarily based on the spatial domain. The feature extraction techniques employ J-divergence entropy, Gabor filter, filter features, HOG and SFTA, and SFTA, respectively. The fingerprint classification approach in the previous study [17] utilizes the transform domain, with Gabor wavelets forming the basis of the method.

Table 3. Comparative results in fingerprint classification between the suggestion method and established algorithms

Ref.	Feature Extraction	Classifier	Feature	Dataset	Accuracy (%)
[2]	J-divergence entropy	SVM	20	NIST-4	91
[3]	Gabor filter	Matching algorithm	320	FVC2000 and DBIT	89
[4]	Filters features	SVM and NAÏVE	135	CASIA 5.0	87
[5]	HOG	-	80	SOCOFing	92
[6]	CNN	CNN	36	SOCOFing ATVS-FFp	81 99
[7]	Gabor wavelets	CNN	28	FVC2006	91
[8]	HOG and SFTA	DCA and GDA	102	SOCOFing	99
[9]	EfficientNetB0	RF	26	SOCOFing	99
Proposed	Gabor filter	NAÏVE	12	SOCOFing	98

However, as shown in Table 3, it is clear that the drawback of these approaches is the excessive time required for execution. The primary justification is the use of the transform domain. Other approaches in the previous studies [15, 19] perform poorly when compared to our proposed strategy. Through the incorporation of Gabor and NAÏVE, the proposed fingerprint classification accuracy increased to 98 percent, outperforming traditional hand-crafted feature approaches, as illustrated in Figure 12.

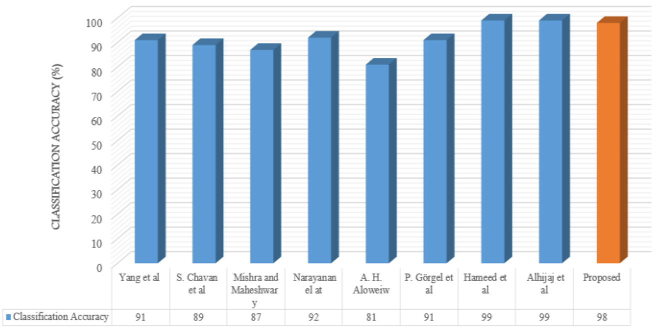

Figure 12. Comparison of performance evaluation techniques for various handcrafted features

5. CONCLUSIONS

This research paper proposed a fingerprint classification approach incorporating Gabor filters, HOG features, and machine learning classifiers (Naïve Bayes and Random Forest). The method demonstrated a classification accuracy of 99%, which is superior to the current methods in terms of both accuracy and computational efficiency. The results confirm the existence of better image quality and utilizing them with low-dimensional features, as a solution to a noise-sensitive and computational-intensive problem. The implications are far-reaching for biometric security and crime scene investigation. Future investigations should include testing the proposed methodology on diverse fingerprint databases to assess its generalizability. Additionally, we will explore the utilization of different classifiers and feature extraction techniques.

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