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Kernelized support vector machines for modified Gabor features facial recognition

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Abstract:

The Gabor-filter approach has been extensively used in the recognition of patterns most especially in the extraction of features during image processing. Gabor filters usefulness explored in face recognition is traceable to its computational properties and biological relevance. Despite all the distinct characteristics of Gabor filters, it suffers from high feature dimensionality. This has led majorly to computational problems in any Gabor-based facial recognition model. The paper presents modified Gabor features for face recognition by introducing a meta-heuristics optimization algorithm using the Ant Colony Optimization Algorithm (ACO) to obtain relevant and optimal features from huge Gabor features. Kernels of Support Vector Machines (SVM); Linear SVM Kernel (LSVMK), Polynomial SVM Kernel (PSVMK), Sigmoid SVM (SSVMK) and Gaussian SVM Kernel (GSVMK) were employed for the classification of face images to either matched or mismatched. Two datasets were used for the evaluation of the system, they include: the Olivetti Research Laboratory (ORL) database and the acquired Africa face image database (ABFI). All the Kernelized SVMs produced an effective output in terms of training time, classification accuracy and error rate. Experimental results showed the lowest training time of 7.3195s was obtained in GSVMK for ABFI face image dataset, non-optimized Gabor feature gave the best accuracy of 90.88% in PSVMK of image size 75x75 for ABFI dataset, the optimized Gabor features recorded the best accuracy of 96.93% in GSVMK of image size 125x125 for ORL image dataset, the lowest error rate of 08.18% was obtained in LSVMK with image size of 150x150 for ORL image dataset

Keywords: Ant Colony Optimization, Feature extraction, Kernelized SVMs, Image processing, Gabor features

1. INTRODUCTION

Effective pattern recognition models such as image processing, text classification, facial recognition and so on are determined by the quality of feature representation (Serey *et al.*, 2023; Kopalidis *et al.*, 2024). The representation of features involves finding and removing discriminant data from an image (Saquib et al., 2010; Banumalar *et al.*, 2023). The most important and distinctive attributes are extracted from facial image during the feature extraction phase (Krishna & Nagamani, 2022). Feature extraction represents the most significant stage of face recognition due to its great influence on the accuracy of facial recognition (Amraee *et al.,* 2022). Several techniques such as Local Binary Pattern (LPB), Local Preserving Projections (LPP), Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Fisher's Linear Discriminant Analysis (LDA) (Chihaoui *et al.*, 2016; Peprah *et al.*, 2017) and Gabor filter approach have been broadly recognised and utilised in the extraction of features in facial recognition applications (Hassan *et al.*, 2021; Luimstra & Bunte, 2022). It has also has been considered as a robust technique for extracting both local and discriminate feature from image regions with high level of similarity compared to the human visual system (Munawar *et al.*, 2021; (Muzaffar *et al.*, 2023). The visual characteristics which includes spatial localization, spatial frequency and orientation selectivity are captured by Gabor filters (Vinay *et al.*, 2015). Numerous domains of application of Gabor filters include texture segmentation, detection of face, edge detection, fingerprint recognition, handwritten numeral recognition (Nur-A-Alam *et al.*, 2021; Li *et al.*, 2021) and medical image analysis techniques (Barshooi & Amirkhani, 2022). Gabor-filter has attracted a lot of interest in areas such as pattern recognition, computer vision, object recognition, and image processing (Rai & Rivas, 2020). Gabor filter has achieved great success and is considered one of the best techniques for face representation (Rizvi *et al.*, 2016). The Gabor technique is a powerful tool for identifying and eliminating irrelevant or redundant features in pattern recognition, leading to a more accurate and efficient classification. (Ouanan et al., 2020; Tallapragada et al., 2023).

The Gabor-filter is a reliable and effective method for feature extraction in image processing, enabling the efficient segregation and differentiation of textures in images. (Al-Kadi, 2017). Despite its numerous advantages, the Gabor-filter technique is hindered by its high dimensionality of features, leading to a computationally demanding process. However, there is a need to employ a dimensionality method, researchers in the past have used different techniques like PCA, Dicrete Cosine Transform (DCT), and Independent Component Analysis (ICA), Discrete Wavelet Transform (DWT) to decrease the feature dimensions (G. Kaur & Kaur, 2015)(Desale & Verma, 2013). These techniques have not taken into consideration how relevant features are before finally classification process.

Additionally, a feature selection approach would be beneficial in reducing the number of features, selecting only the most pertinent ones for classification and reducing computational complexity. A meta-heuristic algorithm needs to be introduced to reduce feature dimensionality. The meta-heuristic denotes a level of complexity above and beyond that of simple heuristics (Behdad, 2022; Kaur et al., 2023). Virtually any metaheuristic method can be utilized for high-probability global optimization (Sabel et al., 2023). The Ant Colony Optimization (ACO) technique was leveraged to address the issue of high dimensionality of features in the Gabor-filter approach. ACO decreased the Gabor feature vectors by a selection of the most discriminant and optimal features, without losing much information in a reasonable time. The remaining section sections of this paper contain the related work, the general approach used to carry out the study, results and discussion on the developed facial recognition system using two image datasets and a conclusion.

2. RELATED WORK

A plethora of research have been conducted to explore the use of Gabor filters for feature extraction, accompanied by different dimensionality reduction methods. Gabor filter has been duly employed for facial feature extraction (Dora, Agrawal, Panda & Abraham, 2017). A groundbreaking software application for facial recognition was developed, incorporating a hybrid biometric approach that could accurately identify individuals despite various uncontrollable environmental factors (Vijaya Kumar & Mathivanan, 2023). The proposed system applied two features namely, Laplace of Gaussian filter-based Discrete Wavelet Transform (LGDWT) and Discrete Cosine Transform Compressed Log Gabor Filter (DCTLGF). A Multiclass Support Vector Machine (MSVM) classifier was trained on a combination of LGDWT and DCTLGF features extracted from face images. This hybrid biometric software application was able to accurately classify individuals even in varying environmental conditions, as demonstrated by its superior performance on a face dataset of 200 images from 25 people, captured using a five-megapixel low-resolution web camera.

In 2022, Fini et al., introduced two innovative Gabor filter banks: the Optimal Gabor Filter Bank (OGFB) and Personal Gabor Filter Bank (PGFB). These techniques showed promise in alleviating the computational burden of facial recognition systems, reducing the computational complexity by approximately 7.5 times for OGFB and 30 times for PGFB. A novel approach for face recognition, termed Square Region of Face (SRoF), was proposed, which takes into account the geometric positions of facial features, such as eyes, nose, and lips. Unlike existing techniques, SRoF is not affected by variations in eyebrow shape, hairstyle, color, or by Islamic veils that cover parts of the face. The new model was tested on multiple datasets, including Caltech, Yale, Feret, and CsetM, and exhibited superior classification accuracy compared to many recently developed face recognition systems.

Singh et al., (2021) proposed a face recognition system that incorporates Support Vector Machine (SVM) for classification. The system addresses various factors that can impact accuracy, such as low image quality, varying facial expressions, use of glasses or beards to disguise the face, and other challenges typically encountered in face recognition systems. The proposed system is divided into

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two main components: detection and extraction, and matching. Gabor filters and SVMs are utilized to identify faces, leveraging the classification capabilities of SVMs, which are analytical models that can identify patterns in data. Augusto et al., (2020) proposed an innovative approach for 3D facial recognition, involving wavelet Gabor filtering, feature extraction, and Support Vector Machine (SVM) classification. The study utilized the BU-3DFE database, which includes 350 3D face models from 50 individuals. The process involved projecting the 3D face models onto three planes, effectively transforming them into 2D images for recognition. Using SVM (kernel cubical), the proposed method achieved an impressive accuracy of 97.3%. Results were compared to those of other recent 3D facial recognition approaches, demonstrating the potential of the proposed method.

3. RESEARCH METHODOLOGY

The kernelized Gabor features facial recognition system used a step-wise approach to build the face recognition. In this study, Gabor filters were used to extract features from the facial region of interest. Subsequently, these features were fed into the Ant Colony Optimization (ACO) algorithm for feature subset selection, and finally, Kernelized Support Vector Machines (SVMs) were employed for classification of the face images. Two face image datasets were applied for the training and testing, Olivetti Research Laboratory (ORL) and the AFI dataset (Acquired Africa Images of Students from the University of Ilorin). This study utilized two datasets, each containing 400 face images, with 70% utilized for training and 30% for testing. All the facial images were captured against a homogenous, dark background with the subjects in an upright and frontal position. Preprocessing of the images included cropping, resizing, and contrast adjustment using Adaptive Histogram Equalization (AHE). The Gabor-filters were applied with 5 scales and 8 orientations to obtain facial features. The optimized Gabor features obtained through the Ant Colony Optimization (ACO) algorithm were used as a template for matching in conjunction with Kernelized Support Vector Machines (SVMs), utilizing four different kernels: Linear SVM Kernel, Polynomial SVM Kernel, Sigmoid SVM and Gaussian SVM Kernel. The framework of the developed facial recognition system is shown in Figure 1.

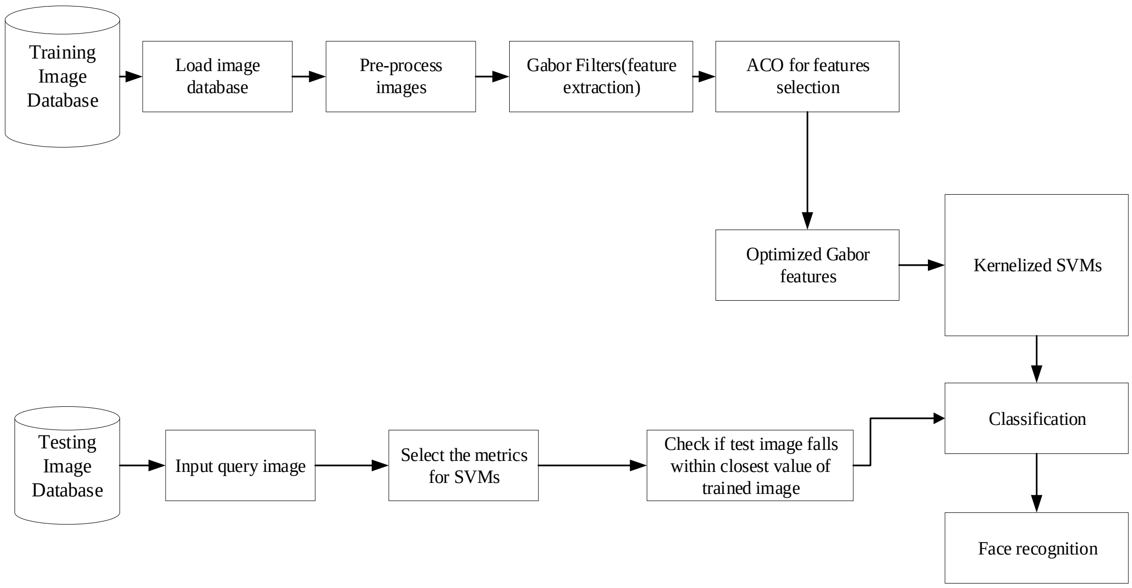

Figure 1: Framework for KACOGF

3.1 Acquisition Face Image Database

The evaluation of the developed KACOGF is necessary and should be carried out with image database. There is a need to create an image database of different people. While various standardized face datasets are available online, they are typically captured in controlled environments and often tailored to meet the requirements of specific algorithms, which may limit their universality. Additionally, the diversity of facial features across races can impact the performance of face recognition systems when benchmarked on different datasets. Therefore, there is a need for a more inclusive and versatile face dataset to address these issues. Facial Images used in this work was acquired from Olivetti Research Laboratory (ORL) Database and locally acquired black faces were captured from student of the University of Ilorin, Ilorin, Nigeria.

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Samples of the face images are shown in Figure 2 and Figure 3.

Figure 2: Sample of ORL Face Image Dataset

Figure 3: Sample of Acquired Black Face Images (ABFI)

3.2 Pre-processing of Face Images

To ensure uniformity among the two face image datasets, preprocessing techniques were employed to standardize the images. The preprocessing techniques focused on improving the quality of the images without altering the head position (tilt) or emotions depicted in the images. Since the locally acquired face images were captured under less controlled conditions compared to the ORL database, extra attention was paid to the preprocessing phase, which included Geometrical Normalization, Image Gray-scale conversion, and Illumination Normalization.

3.3 Feature Extraction Using Gabor-Filter

The face images from ORL and ABFI Database were convoluted separately by applying Gabor-filters as depicted in Algorithm 1.

Algorithm 1: Gabor-Filter
Begin
Step 1: Retrieve a face image from the given image database for processing
Step 2: Face image is converted if not in grayscale format for further processing
Step 3: Prepare the image using pre-processing techniques to improve image quality
Step 4: Design filter-banks (setup parameters for Gabor-filters)
Step 5: Apply the created filter on pre-processed face image by convolution of face image I (x, y) with a filter bank containing filters of different 5 scales (u) and 8 orientations (v)
Step 6: Decompose convolution output $G_{a,b}(a, b)$ into complex values of real and imaginary part as shown in Equation (2) and (3)

$$G_{u,v}(a,b) = I\,(a,b) * g_{u,v}(a,b) \quad (1)$$

$$E_{u,v}(a,b) = Re\left[G_{u,v}(a,b)\right] \quad (2)$$

$$O_{u,v}(a,b) = Im\left[G_{u,v}(a,b)\right] \quad (3)$$

Step 7: Compute the magnitude $A_{u,v}(a,b)$ of filter responses and $\emptyset_{u,v}\,(a,b)$ of phase using Equations (4) and (5) :

$$A_{u,v}(a,b) = \sqrt{E^2 u,v(a,b) + O^2 u,v(a,b)} \quad (4)$$

$$\emptyset_{u,v}(a,b) = \arctan\frac{O_{u,v}(a,b)}{E_{u,v}(a,b)} \quad (5)$$

Step 8: Discard the Gabor phase features
Step 9: Concatenate magnitude of the Gabor responses of convoluted image into face image
End

3.4 Optimization of Gabor Feature Using ACO

A Region of Interest (ROI) was defined within the feature set to focus on features that remain stable over time, such as facial structure. The extracted ROI from Gabor features were passed to ACO for optimal feature selection. The ants move randomly over the Gabor features to construct a pheromone matrix by initialization of ACO parameters α, β, ρ, τ0 K, N, η on the Gabor feature data matrix. Where α = constant value (determine importance of pheromone value), β = constant value (determine the importance of heuristic information), ρ = evaporation rate (pheromone update factor), τ0 = pheromone matrix value, N = number of ants, K = k ants, φ = decay coefficient, η = heuristic desirability. A solution was constructed based on the probabilistic transition rule presented in Equation 6:

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$$P_{IJ}^{K}(t) = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{j\epsilon J^k}[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}} \quad (6)$$

The size of the pheromone matrix for this study varies with different Gabor feature matrix of the image of the cropped image, the heuristic desirability which is the measure of the attractiveness of a feature-based image on the local statistics was obtained. The heuristic desirability is obtained by computing the correlation between pairs of pixels. The construction process of the solution by the ant was carried out by adopting the probabilistic transition rule as discussed in equation (1). Global and Local Pheromone updates were performed as shown in equations 7 and 8 respectively:

$$\tau^{n} = (1-\varphi).\tau^{k} + \varphi.\tau^{n} \quad (7)$$

$$\tau_{i,j}^{k} = (1-\rho).\tau_{i,j} + \rho.\Delta(i,j)^{k} \quad (8)$$

Algorithm 2: Ant Colony Optimization
Begin
Step 1: Create ACO parameters: α, β, ρ, τo, η, φ, K, N,
Step 2: Initialize pheromone matrix on Gabor-filtered image data matrix
Step 3: Construct solution

$$P_{IJ}^{K}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{i,j}]^{\beta}}{\sum_{J\varepsilon J} K[\tau_{i,j}(t)]^{\alpha}[\eta_{i,j}]^{\beta}}$$

Step 4: Find the first update of the pheromone matrix (Global update of pheromone matrix) $\tau_{i,j}^{k} = (1-\rho).\tau_{i,j} + \rho.\Delta(i,j)^{k}$ where $\rho(0<\rho\le 1)$ is the parameter for pheromone update
Step 5: if K ants move over Gabor feature dimensions then Goto Step 6 else Goto Step 2
Step 6: Find the second update of the pheromone matrix (Local update of pheromone matrix). $\tau^{n} = (1-\varphi).\tau^{k} + \varphi.\tau^{0}$
Step 7: if all iterations performed then Goto Step 8 else Goto Step 2.
Step 8: Return optimal feature subsets
End

4 RESULTS AND DISCUSSION

The experimental result for the kernelized Gabor features facial recognition system was given in terms of image normalization size, time taken to extract facial features and accuracy is presented in this section.

The face image normalization was conducted by pre-processing methods that involve geometrical normalization, image gray-scale conversion and illumination normalization as shown in Figure 4 and Figure 5.

4.1 Result of Face Image Normalization

75x75 100x100 125x125 150x150

Figure 4: Samples of Geometrically Normalized ABFI Dataset Images

75x75 100x100 125x125 150x150

Figure 5: Sample of Geometrically Normalized ORL Dataset

4.2 Result of Time Taken for Feature Extraction

In order to extract features using Gabor filters, various sizes of face images were considered to account for the diversity of faces in the dataset and to ensure that the features could be reliably extracted regardless of the image size as shown in Table 1

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Table 1: Features Extraction Time (s)

Image size (Pixel)	AFI Database	ORL Database
75x75	115.2510	117.1320
100x100	118.1642	120.5282
125x125	135.4230	139.5242
150x150	146.1340	151.2780

From Table 1, it was observed that the highest time of 146.1340s was taken to extract features from the AFI database while the highest time of 151.2780s was considered in obtaining the ORL database. It was noticed that the time taken to extract features increases as the image size increases.

4.3 Time Taken for the KACOGF Training Process

The training time taken by each kernelized SVM is shown in Table 2. LSVMK of image 150x150 recorded a very prolonged training time of 9.9892s compared with other classifiers for the ABFI Database. While the GSVMK of 75x75 image gave the lowest training time of 7.3195s of all the classifiers. Also, for the ORL database, the training time for each kernelized SVM classifier is shown in Table 3. LSVMK of image size 150x150 recorded the prolonged training time of 12.4863s and the lowest training time of 7.6854s was obtained in PSVMK classifier of 75x75 image pixel size compared with other classifiers

Table 2: Training Time of the Distance Classifiers (ABFI Database)

Image Size (pixel)	LSVMK(s)	PSVMK (s)	SSVMK (s)	GSVMK (s)
75x75	9.6150	8.2430	7.6164	7.3195
100x100	9.7300	8.4940	7.7043	7.5502
125x125	9.8210	8.6600	7.7419	7.7744
150x150	9.9892	8.6034	7.9238	7.9567

Table 3: Training Time of the Distance Classifiers (ORL Database)

Image Size (pixel)	LSVMK (s)	PSVMK (s)	SSVMK (s)	GSVMK (s)
75x75	13.4309	7.6854	7.8122	7.8342
100x100	12.8622	7.7726	7.9340	7.8534
125x125	12.6743	7.9218	7.9572	7.9123
150x150	12.4863	8.9830	7.9722	7.9689

From Table 2 and Table 3, the performance analysis of the kernelized SVM classifiers for the two image datasets were conducted, the results indicate that the lowest time of 7.3195s was recorded in GSVMK of image size of 75x75 for AFI image dataset compared with lowest training time of 7.6854s of image size 75x75 using PSVMK for ORL image dataset that is higher than the training time of ABFI image dataset.

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4.4 Result of Classification Accuracy for non-optimized Gabor-features

The PSVMK classifier of image size 75x75 yielded the highest classification accuracy of 90.88% for the ABFI Database, while the lowest classification accuracy of 87.120% was obtained by the SSVMK classifier of image size 75x75 for the same dataset, as demonstrated in Table 4. Also, the ORL Database recorded the highest classification accuracy of 90.850% achieved in GSVMK of image size 100x100. The lowest classification accuracy of 87.120% was achieved in LSVMK of image size 75x75 as shown in Table 5.

Table 4. Classification Accuracy for non-optimized Gabor Features (ABFI Database)

Image Size (pixel)	LSVMK (%)	PSVMK (%)	SSVMK (%)	GSVMK (%)
75x75	87.750	88.240	87.120	89.890
100x100	89.320	90.025	89.450	90.250
125x125	90.140	89.890	90.370	88.790
150x150	88.290	90.880	88.590	90.540

Table 5. Classification Accuracy for non-optimized Gabor Features (ORL Database)

Image Size (pixel)	LSVMK (%)	PSVMK (%)	SSVMK (%)	GSVMK (%)
75x75	87.120	89.240	89.180	88.890
100x100	88.450	90.150	88.350	90.850
125x125	89.650	88.850	89.350	88.550
150x150	91.820	91.150	88.950	89.140

Comparing the classification results of the two datasets, the highest classification accuracy of 91.820% was achieved in the ORL dataset using non-optimized Gabor facial features, which outperformed the highest classification accuracy of 90.880% in the AFI dataset, also using non-optimized Gabor facial features for classification.

4.5 Results of Classification Accuracy for KACOGF System

For the ABFI Database, the highest classification accuracy of 95.95% was obtained using the SSVMK classifier with image size 125x125, while the lowest classification accuracy of 92.250% was achieved using the PSVMK classifier with image size 100x100. The results in Table 6 show that GSVMK classifier achieved the highest classification accuracy of 96.93% with image size 125x125. However, the lowest accuracy of 94.150% was achieved with GSVMK and image size 75x75 as shown in Table 7.

Table 6. Classification Accuracy of KACOGF (ABFI Dataset)

Image Size (pixel)	LSVMK (%)	PSVMMK(%)	SSVMK (%)	GSVMK (%)
75x75	93.950	93.150	94.850	93.890
100x100	92.450	92.250	94.290	94.450
125x125	94.210	94.750	95.950	94.160
150x150	94.850	93.850	94.350	95.110

Table 7. Classification Accuracy of KACOGF (ORL Dataset)

Image Size (pixel)	LSVMK (%)	PSVMK (%)	SSVMK (%)	GSVMK (%)
75x75	95.430	94.550	94.290	94.150
100x100	94.860	95.350	95.860	95.510

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125x125	95.250	95.830	96.150	96.930
150x150	94.950	96.710	95.150	95.130

The results from the classification phase of the optimized Gabor facial features revealed that the highest classification accuracy of 96.930% was recorded in the ORL image dataset when compared with the AFI dataset.

4.6 Results of Error Rate for Non-optimized Gabor Features

The error rate is an acceptable performance measure for the comparison of different classifiers used in non-optimized Gabor features given balanced datasets. The highest percentage of an error rate of 12.88% was obtained in SSVMK of image size 75x75, while the lowest percentage of an error rate of 09.12% was achieved in PSVMK of image size 150x150 for ABFI Database as shown in Table 8For the ORL image dataset, the classification error rate peaked at 14.08% using the LSVMK classifier with image size 150x150, while the lowest error rate of 8.18% was achieved using the same classifier with an image size of 150x150.

Table 8. Error Rate of the Non-Optimized Gabor Features (ABFI Database)

Image Size (pixel)	LSVMK(%)	PSVMK(%)	SSVMK(%)	GSVMK(%)
75x75	12.25	11.76	12.88	10.11
100x100	10.68	09.98	10.55	09.75
125x125	09.86	10.11	09.63	11.21
150x150	11.71	09.12	11.41	09.46

Table 9. Error Rate of the Non-Optimized Gabor Features (ORL Database)

Image Size (pixel)	LSVMK(%)	PSVMK(%)	SSVMK(%)	GSVMK(%)
75x75	12.88	10.76	10.82	11.11
100x100	11.55	09.85	11.65	09.15
125x125	10.35	11.15	10.65	11.45
150x150	08.18	08.85	11.05	10.86

From Table 8 and 9, it was observed that the highest error rate of 09.12% was obtained in PSVMK of image size 150x150 in AFI image dataset when compared with the error rate of 08.18% image size 75x75 of SSVMK using ABFI image dataset.

4.7 Results of Error Rate for KACOGF System

The error rate is an acceptable performance measure for the comparison of different classifiers used in the ACOGF system given balanced datasets. The highest error rate of 7.75% was obtained in PSVMK of image size 100x100, while the lower error rate of 4.05% was achieved in SSVMK of image size 125x125, city-block of image size 100x100 for AFI Database as shown in Table 10. For the ORL Database, the highest error rate percentage of 5.85% was obtained in GSVMK of image size 75x75, while the lowest error rate percentage of 3.07% was obtained in GSVMK of image size 125x125 for ORL dataset as discussed in Table 10 and Table 11.

Table 10: Error Rate of the KACOGF System (ABFI Dataset)

Image Size (pixel)	LSVMK (%)	PSVMK (%)	SSVMK %)	GSVMK(%)
75x75	6.05	6.85	5.15	6.11
100x100	7.55	7.75	5.71	5.55
125x125	5.79	5.25	4.05	5.84
150x150	5.15	6.15	5.65	4.89

Table 11: Error Rate of KACOGF (ORL Dataset)

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Image Size (pixel)	LSVMK (%)	PSVMK (%)	SSVMK (%)	GSVMK (%)
75x75	4.52	5.45	5.41	5.85
100x100	5.14	4.56	4.14	4.49
125x125	4.75	4.17	3.85	3.07
150x150	5.05	3.29	4.85	4.87

From Table 10 and Table 11, the experimental results showed that the highest error rate of 7.75%, image size 100x100 was recorded in PSVMK for the ABFI dataset which outperformed the highest error rate of 5.85%, image size 75x75 recorded in GSVMK for ORL dataset.

5. CONCLUSION

Gabor filters are linear filters commonly used in image processing for edge detection, texture classification, feature extraction, and disparity estimation. In this study, the Gabor filtering technique was applied on the decompressed JPEG images to extract the texture characteristics, followed by computation of a first-order statistical parameter histogram. The feature dimensionality of Gabor filtering is determined by the specific values assigned to the various parameters. Despite the numerous advantages of Gabor filters in feature extraction, the high dimensionality of Gabor features is still one of the major problems in any Gabor-based facial recognition system. In this paper, a novel technique for dimensionality reduction of Gabor features was proposed using the Ant Colony Optimization (ACO) algorithm, which was inspired by the natural behaviour of ant colonies. The proposed method was able to reduce the high-dimensional Gabor features into a lower-dimensional subspace while retaining the most relevant and discriminative information. The experimental results of the training time for the two datasets applying Kernelized SVMs classifiers with diverse image sizes revealed that the best results were recorded for the developed KACOGF system.

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