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Kernel PCA-enhanced BoVW representation for SIFT-based face recognition using SM

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ABSTRACT

This study proposes a face recognition pipeline that integrates scale-invariant feature transform (SIFT) descriptors, the bag of visual words (BoVW) model, Kernel principal component analysis (KPCA), and support vector machine (SVM) classification. It starts by extracting local keypoint descriptors from preprocessed face images using SIFT. These descriptors are subsequently vector-quantized into a visual vocabulary through MiniBatch K-Means clustering, yielding fixed-length BoVW histograms for each image. Nonlinear dimensionality reduction is achieved by applying KPCA with a radial basis function, addressing the complexity of the feature space. The resulting compact feature representations are subsequently classified using a linear SVM. The proposed method is evaluated on labelled faces in the wild (LFW) dataset with filtered 100 classes, demonstrating notable classification accuracy and reliable generalization across training, validation, and testing splits. Our experimental evaluation confirms that integrating local invariant features, nonlinear feature reduction, and discriminative classification allows the proposed method to exceed state-of-the-art face recognition performance. In addition, this proposed method is particularly suitable for scenarios with limited training data and computational resources, providing a lightweight but robust alternative to deep learning-based models.

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1. INTRODUCTION

Face recognition has become an important tool for a variety of purposes including user authentication, access control and surveillance [1]. In the field of pattern recognition and computer vision, the ability to automatically and consistently identify people from face photographs has attracted much attention. Principal component analysis (PCA) [2] and other comprehensive representation methods are often used in traditional face recognition technology. Although PCA can effectively reduce linear dimensions, it is still hard to capture the complex nonlinear changes observed in real-world face images, such as changes in expression, lighting, and position.

Local feature descriptors with robustness to scale and rotation, such as scale-invariant feature transform (SIFT) [3], have been created to solve these issues. These descriptors enable a fixed-length feature representation of images that is appropriate for classification when paired with the bag of visual words (BoVW) [4] model. However, advanced dimensionality reduction methods are required because of the high dimensionality and nonlinearity of BoVW histograms. Kernel principal component analysis (KPCA) [5] has proven effective in capturing nonlinear structures by extending PCA into a high-dimensional feature space using kernel methods.

This paper proposes a face recognition pipeline that combines support vector machine (SVM) for classification, BoVW histogram representation, KPCA for dimensionality reduction, and SIFT-based feature extraction. The method is evaluated on a dataset containing 100 individuals using a hierarchical training, validation and testing approach. The proposed method is effective in capturing local invariant features and nonlinear relationships in the feature space, thus improving the classification accuracy. It provides a computationally efficient and robust alternative to deep learning model-based methods and is well suited for applications with limited training data and resources.

The remainder of this paper is organized as follows. Section 2 reviews relevant research in the field of facial recognition, covering both classical and modern approaches, and identifies the research gaps addressed by this study. Section 3 introduces the dataset, preprocessing workflow, and the proposed face recognition pipeline, including feature extraction, feature representation, dimensionality reduction, and classification stages. Section 4 describes the experimental settings and results. This is followed by an in-depth discussion interpreting the findings, contrasting them with existing methods to reveal limitations and explore implications. In section 5, we conclude the study and suggest avenues for future work.

2. RELATED WORKS

Recent advances in face recognition technology are mainly driven by deep learning and hybrid approaches that combine traditional feature extraction and modern classification techniques. Deep convolutional neural networks (CNNs) such as ArcFace [6], CosFace [7], and MobileFaceNet [8] have outperformed the state-of-the-art methods on labelled face in the wild (LFW) and MegaFace datasets. Hybrid methods have also achieved promising results by combining deep models with traditional techniques. For example, combining EfficientNetV2-L with KPCA [9] and SVM has proven to be effective in detecting fake faces in the diverse fake face dataset (DFFD). Similarly, the integration of hand-created features such as discrete cosine transform (DCT), Gabor filters, and independent component analysis (ICA) [10] has been shown to improve face recognition performance on the Olivetti Research Laboratory (ORL) dataset.

Among traditional methods, PCA has been extensively used for dimensionality reduction in face recognition pipelines. When its combination with CNNs [11] has demonstrated the potential of fusing manual and deep learning methods on the LFW dataset. PCA has also been successfully applied with K-nearest neighbors (KNN) [12], [13] for face recognition tasks on small-scale datasets. To address the limitations of linear feature extraction, KPCA was introduced as a nonlinear alternative method capable of capturing complex facial patterns. The combined application of KPCA [14], [15] and SVM on the AT&T dataset, as well as a separate application on the FERET dataset, demonstrated an improvement in the class separation capability of KPCA as compared to PCA-based methods. Other dimensionality reduction techniques, such as linear discriminant analysis (LDA) [16], have also been used for face recognition. The use of LDA [17] on the ORL dataset and the CK+ dataset has shown its effectiveness in extracting discriminative features and improving recognition performance.

Besides static image-based face recognition, real-time recognition from video streams remains a relevant research challenge. PCA [18] has been adapted for real-time face recognition, addressing issues arising in dynamic environments. In addition, deep learning also has been applied to niche areas [19] such as facial expression recognition for visually impaired people and sibling discrimination [20] using fusion based face recognition models, reflecting the growing diversity of face analytics techniques.

3. PROPOSED METHOD

This section outlines the complete experimental process of face recognition system implemented in this study. Figure 1 outlines the flowchart of proposed face recognition pipeline. First preprocess data, then extract SIFT features, encode them with BoVW, reduce dimensions via KPCA, and finally classify using SVM. The following subsections provide detailed descriptions.

3.1. Dataset and pre-processing

The experiment was used the labelled faces in the wild (LFW) dataset [21], which contains 13,233 facial photos of 5,749 people. The dataset was unbalanced, so a class subset selection procedure was used. Besides, a total of 100 classes were chosen at random, and only those who had at least five images been kept. Each selected class initially contributed 5 images to the base dataset. To increase generality and prevent overfitting, data augmentation was performed using Keras ImageDataGenerator. Enhancement techniques included horizontal flipping, luminance shifting, scaling, width and height shifting, and rotation. Using

OpenCV's Haar Cascade, face regions were detected and cropped after converting all images to grayscale and resizing to 144×144 pixels. Figure 2 shows a sample of face images after pre-processing.

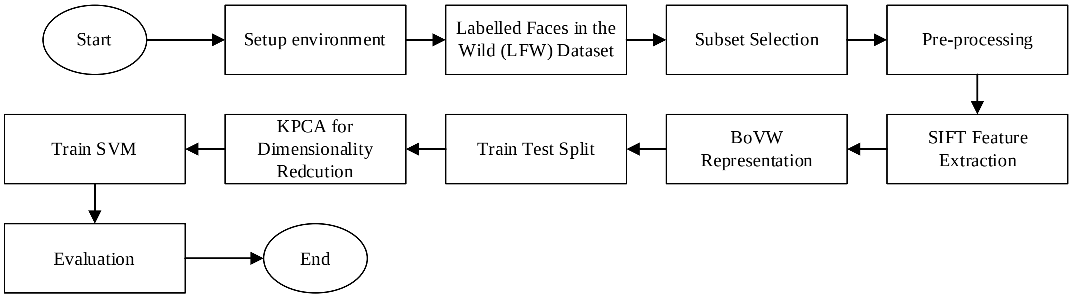


Figure 1. Flowchart of the proposed face recognition pipeline

Figure 2. Sample of face images after pre-processing

3.2. Scale-invariant feature transform

SIFT is to extract local features from each greyscale image. SIFT detects keypoints that represent unique and repeatable patterns in the image, such as edges, corners or blobs. Around each keypoint, a local descriptor is computed that captures the gradient information of the surrounding patches. These descriptors are invariant to scale and rotation and are highly descriptive of local image regions. Depending on the number of detected keypoints, a variable number of 128-dimensional descriptors are generated for each image. These descriptors are collected throughout the dataset and form the basic visual features for subsequent processing. Figure 3 shows the SIFT keypoints detected and visualized on the grayscale face image. SIFT extracts local image features based on gradient magnitudes and orientations that presented in (1). For each pixel, the gradient magnitude $m(x,y)$ and orientation $\theta(x,y)$ are calculated, then aggregated into orientation histograms over local regions. This results in a distinctive 128-dimensional descriptor that is robust to scale, rotation, and illumination changes.

$$m(x,y) = \sqrt{(I_{x+1,y} - I_{x-1,y})^2}, \theta(x,y) = \tan^{-1}\left(\frac{I_{x,y+1}-I_{x,y-1}}{I_{x+1,y}-I_{x-1,y}}\right) \quad (1)$$

Figure 3. SIFT keypoint

3.3. Bag of visual words representation

Variable length SIFT descriptors are converted into fixed length feature vectors suitable for classification using BoVW model. The BoVW model is a widely used method for converting variable-length sets of local image descriptors into fixed-length feature vectors suitable for machine learning models. The descriptors extracted from all training images via SIFT are clustered using an unsupervised algorithm such as KMeans. Each cluster centre is considered as a visual word and forms part of the visual vocabulary. SIFT descriptors for each image are assigned to the nearest visual word, with a histogram representing the frequency of these words. This histogram is a compact summary of the local features of the image. In face recognition, BoVW can represent complex face textures and shapes into a format that can be used by classifiers. Figure 4 illustrates the BoVW histogram and KPCA projection, where the frequency of occurrence of the visual vocabulary is represented as a BoVW histogram in Figure 4(a). In (2), local descriptors $\{x_i\}$ are clustered into a vocabulary $\{c_j\}$ using k-means, and each descriptor is assigned to its nearest cluster center. The final image representation is a normalized histogram $H(j)$ in (3), which counts the frequency of visual word occurrences, providing a compact global description of the image.

$$c_j = \arg\min_j \parallel x_i - c_j \parallel \tag{2}$$

$$H(j) = \frac{1}{N}\sum_{i=1}^{N} \delta(w_i = j) \tag{3}$$

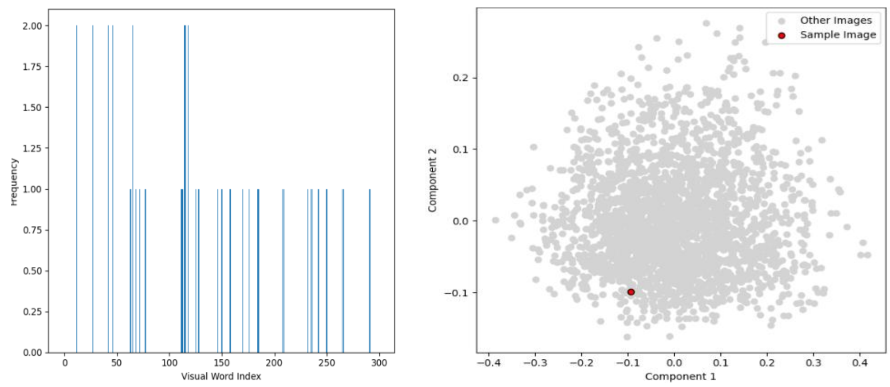
3.4. Dimensionality reduction with Kernel principal component analysis

KPCA was created to facilitate the classification of data whose decision boundary is defined by a nonlinear function. This makes it particularly suitable for face recognition tasks where nonlinearity is a common challenge due to variations in lighting, expression and angle. In this experiment, KPCA is used to perform a non-linear transformation of the data to capture complex relationships that cannot be captured by a linear projection. The use of a radial basis function kernel allows the data to be implicitly mapped into a higher dimensional space where nonlinear patterns can be more easily isolated. This transformation allows linear models to efficiently handle non-linear data distributions, thus contributing to improved classification performance. In Figure 4(b), KPCA is applied to the BoVW histogram to map the high-dimensional data into a 2D nonlinear feature space. The red dot marks the sample image among all dataset images. In (4) KPCA using the RBF kernel $k(x_i, x_j) = \exp(-\parallel x_i - x_j \parallel^2 / 2\sigma^2)$, a centered kernel matrix $\widetilde{K}$ is constructed. Solving the eigenvalue problem yields the principal components, $\widetilde{K}\alpha = \lambda\, \alpha$ in (5), which enables projection of data into a higher-dimensional feature space for improved separability followed as (6).

$$K_{ij} = k(x_i, x_j) = \exp\left(-\frac{\parallel x_i - x_j \parallel^2}{2\sigma^2}\right) \tag{4}$$

$$\widetilde{K}\alpha = \lambda\, \alpha \tag{5}$$

$$y = \sum_{i=1}^{N} \alpha_i\, k(x_i, x) \tag{6}$$



(a) (b)

Figure 4. Representation of visual features: (a) BoVW histogram and (b) KPCA projection

3.5. Classification using support vector machine

The transformed BoVW feature representation is classified into classes using SVM. It is a supervised machine learning method that is popular for classification tasks, especially on high dimensional data, due to its strong generalization performance. SVM generates a decision boundary that maximizes the separation between classes. In this experiment, SVM is applied after transforming the BoVW feature vectors using KPCA, which enables the model to handle non-linear data structures. A linear kernel is used in the final SVM to maintain computational efficiency while still utilizing the discriminative power of the transformed features. This helps the model to accurately classify faces based on patterns captured in the BoVW histogram.

3.6. Experimental setup and evaluation

Table 1 presents the dataset distribution. Stratified sampling was used to split the data into 60% for training, 20% for validation, and 20% for testing, maintaining the class proportions. Table 2 summarizes the hyperparameter settings for each stage of the pipeline. SIFT used default key point detection with three octaves, edge threshold 10, Gaussian blur (σ=1.6) and a contrast threshold of 0.04, to extract multi-scale features. BoVW employed 300 visual clusters with a mini-batch size of 2048 and a fixed seed (42), producing 300-bin histograms. Kernel PCA retained all components with an RBF kernel (γ=0.01) for nonlinear mapping, and the SVM classifier used a linear kernel with (C=1.0) after standardizing features to zero mean and unit variance. All experiments were carried out on a laptop featuring an Intel Core i7-10750H processor, 24 GB memory, and a GTX 1650 Ti GPU.

Table 1. Dataset distribution

Subset	Classes	Total images	Image per class	Percentages (%)
Training	100	1500	15	60
Validation	100	500	5	20
Testing	100	500	5	20

Table 2. Hyperparameters settings

Stage	Parameter	Value/setting	Description
SIFT	Nfeatures	0	All keypoints detected
	Octave layers	3	Multi-scale feature detection
	Contrast threshold	0.04	Keypoint filtering
	Edge threshold	10	Edge response suppression
	Sigma	1.6	Initial Gaussian blur
BoVW	Clusters	300	Size of visual vocabulary
	Batch size	2048	Mini-batch size for KMeans
	Random seed	42	Reproducibility
	Histogram bins	300	Equal to vocabulary size
Kernel PCA	Components	None	All components retained
	Kernel type	RBF	Nonlinear mapping
	Gamma	0.01	RBF kernel width
SVM	Kernel	Linear	For speed and interpretability
	C	1.0	Regularization parameter
	StandardScaler	Mean=0, Var=1	Applied before SVM

3.6.1. Evaluation

Standard classification metrics: accuracy (7), precision (8), recall (9), and F1-score (10), were used to evaluate the system's performance. For this experiment, a classification report and confusion matrix were produced to evaluate the model's overall performance and its accuracy in distinguishing between different facial image classes. It also provides the precision, recall and F1 score for each class, giving insight into the consistent performance of the model across different classes. Figure 5 shows the confusion matrix, it provides a breakdown of true positives, true negatives, false positives, and false negatives, allowing for a detailed analysis of classification errors for all classes.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{10}$$

		Predicted	
		Positive (+)	Negative (-)
Actual	Positive (+)	True Positive (TP)	False Negative (FN)
	Negative (-)	False Positive (FP)	True Negative (TN)

Figure 5. Confusion matrix

4. RESULTS AND DISCUSSION

This section presents the experimental findings of the proposed method and analysis of its performance across various evaluation metrics. A comparative evaluation with other configurations, including PCA-based dimensionality reduction and different classifiers, was performed to validate the advantages of incorporating KPCA. The proposed method achieved a classification accuracy of 82.0% on the test set and 83.2% on the validation set. Figure 6 shows the test set confusion matrix for the proposed method across 100 classes. As observed, most values are clustered along the diagonal, showing correct classifications for most of the test images. With up to 5 samples per category in the test set, many of the diagonal entries show values of 4 or 5, reflecting the high accuracy of each category. The F1 scores for most classes ranged between 0.75 and 0.91, indicating an overall good balance between precision and recall. The macro-mean and weighted mean were both high, with a precision of 0.86 and an F1 score of 0.81.

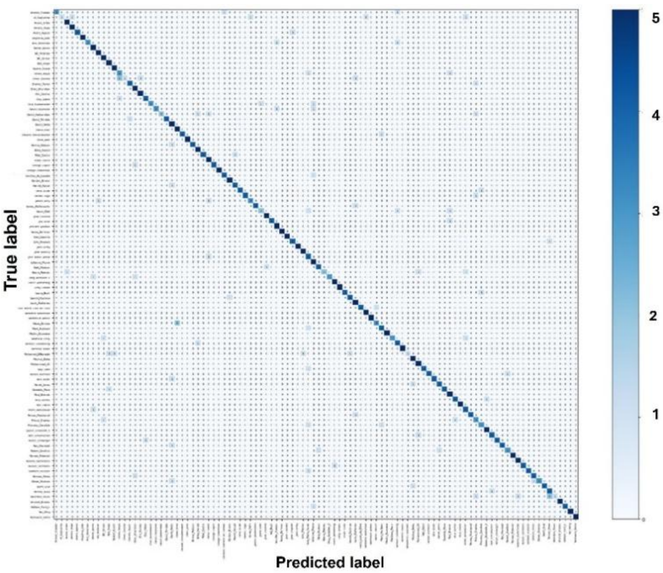


Figure 6. Confusion matrix of the proposed method

Table 3 presents a comparative analysis of our proposed pipeline against both baseline configurations from our experiments and state-of-the-art methods on the LFW dataset. Among classical baselines, PCA with logistic regression achieved only 50.00% accuracy, highlighting the weakness of linear dimensionality reduction when used with simple classifiers. Incorporating KPCA improved performance to 62.00%, while replacing logistic regression with SVM further boosted results, with PCA-SVM and KPCA-SVM reaching 67.00% and 70.00%, respectively. A more advanced baseline, SIFT-BoVW-PCA-SVM, achieved 75.00%, showing the advantage of combining local descriptors with histogram representation. Our proposed method outperformed all these baselines, achieving 82.00% accuracy by leveraging nonlinear feature reduction with KPCA on top of BoVW histograms.

When compared with other existing works, our method also demonstrates strong performance. It surpasses traditional techniques such as SIFT-SVM (65.80%), random forest (74.47%), KNN (74.00%), and approaches the performance of FaceNet (86.00%). Deep learning face recognition models such as DeepFace achieves high LFW accuracy (≈97%) but rely on deep architectures like Inception-ResNet that require significant computational resources and large-scale training data. Compared to existing methods, our pipeline offers an effective compromise between accuracy and efficiency, ensuring robustness even with limited data and computing power.

Table 3. Comparison of the proposed method, internal baseline results, and state-of-the-art methods on the LFW dataset

Year	Method used	Accuracy (%)
2025	PCA-logistic regression	50.00
2025	KPCA-logistic regression	62.00
2025	PCA-SVM	67.00
2025	KPCA-SVM	70.00
2025	SIFT-BoVW-PCA-SVM	75.00
2022	SIFT-SVM [22]	65.80
2025	RF [23]	74.47
2022	FaceNet [24]	86.00
2024	KNN [25]	74.00
2014	DeepFace [26]	97.35
2025	**Proposed method**	**82.00**

5. CONCLUSION

The results indicate that KPCA significantly enhances the discriminative capability of the feature space and improves the generalization of the model compared to other experiment methods like PCA. Furthermore, KPCA showed its strength in preserving important facial structures while reducing noise and redundancy in the feature representation. Overall, this study proved that KPCA is a powerful tool for classical face recognition pipelines, especially when integrated with well-established feature extraction and classification techniques. Although the proposed system achieved a good result, there are several ways for future work to enhance and expand the capabilities of the model. A possible future direction is integrating deep learning architectures, such as CNNs, which have demonstrated strong results in image recognition. These models can automatically extract hierarchical feature representations, potentially removing the reliance on hand-crafted features like SIFT.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Chen-Han Chong	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Siew-Chin Chong	✓			✓	✓		✓			✓		✓	✓	✓
Lee-Ying Chong	✓			✓	✓		✓			✓		✓	✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/atulanandjha/lfwpeople.

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