Principal Component Analysis in Image Classification: A review

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***Abstract*—Principal component analysis (PCA) is considered as an important technique for dimension reduction of the data in various artificial intelligence/machine learning applications. One of the most important application is computer vision or image classification. Owing to the benefits and importance of PCA in image classification it is used not only for reducing dimensions, but also used to find important/dominant features hidden inside the data set having high dimensions. That makes PCA as one of the best techniques that helps in image classification yielding highly accurate results. This paper reviews some of the recent studies of application using PCA in image classification. The article covers different datasets having different properties and information of images. Moreover, the paper contributed in listing details of evaluation matrices, datasets, objectives, and possible improvements to increase the accuracy with reduced computational time of included articles.**

***Index Terms*—Image classification, principal component analysis**

I. Introduction

Visual recognition and evaluating computer vision has been a topic of interest for over a decade for researchers. Images contain huge amount of information and can also be used in hiding information inside them. In recent years, computer vision is divided into many fields based on the targeted task they perform. Such as, image classification [1], detection and semantic segmentation of images [2], [3]. One of major development in image classification is dependent upon artificial intelligence (AI). It is a mechanism of developing an intelligent system perceiving information from animals and humans and implementation them on machines.

Image classification is a task of extracting information, features, or specific classes from image. It is the core of computer vision and basis of image recognition. Hence, image classification is the basis for the development of computer vision. Data prepossessing, feature selection, feature extraction, and further classification techniques are applied based on the tasks or information required from the images. The classification techniques can be supervised e.g., conventional neural networks (CNN) or unsupervised such as K-means. Furthermore, it is important to choose the right metrics for evaluating the mechanisms of image classification. Similarly, it is equally crucial to choose right techniques for improving the values of evaluation metrics. Such as, regularization, adding dropout, changing batch norm, data augmentation, and etc. One of the most important technique to improve the final results is principal component analysis [4].

Principal component analysis (PCA) is a technique of dimension reduction of a data set. It is a multivariate technique of extracting the dominant patterns related to improving score and plots of the results from data set. This paper focuses on;

1) The importance of principal component analysis in image classification in Section II
2) Collecting recent articles to study the impact of using PCA for image classification in Section III
3) Enlisting objectives, datasets, matrices, and possible improvements in Section IV. Moreover, a comparison of results before and after application of PCA is also presented.

II. Background

Image classification methods have been modernized and developed alot over the past two decades. Optimal weighted sum based linear observation model, reduction of noise, and dimension reduction can be done learning from the type and task to perform on the chosen image [5]. Such as, from among several types of images with different spectral resolutions can be choosen, i.e., multispectral images and hyperspectral images [6]. Image classification in machine learning is based on the features extracted in the form of certain categories using appropriate methods. Image classification involves image acquisition (gathering images/finding dataset for image processing), image pre-processing (removal of noise, transformation, etc), and feature extraction from the dataset (extracting required/important characteristics). Whereas, there is another method that can enhance the accuracy of image classification is PCA. The focus of this paper, is to compare the results of latest developments proposed for dimensional reduction using PCA in image classification. PCA is based on the “approximately” gaussian (the scatter plot can be fitted by the hyper-ellipsoid) assumption [7]. Whereas, a collection of PCAs is used to fit the data, when distribution is not gaussian [8]. Furthermore, for classification problems, each class is fitted by a PCA model [9]. Principal component analysis significantly reduces a number of non-dominant features statistically from high-dimensional data. It transforms the correlated set of features

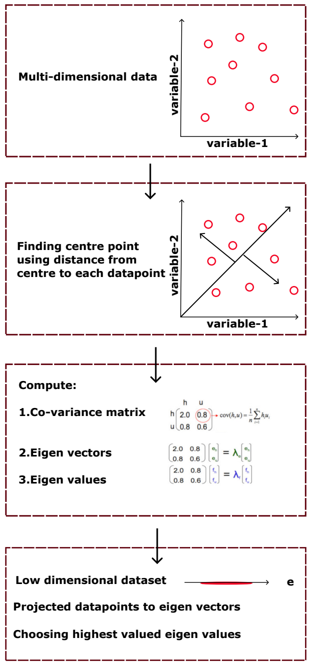

Figure 1: Steps of principal component analysis

from one dimensional space onto the smaller set of uncorrelated features without losing significant features from the data set. Suppose, the data set is N dimensional and has to be transformed into I dimensions. The steps for this dimensional transformation includes finding I eigen-vectors from N dimensions. As shown in Figure 1, data is represented based on two different features/variables on x and y dimensions, i.e., $variable-1$ and $variable-2$. After finding the centre point of the dataset, distance from the centre point is calculated to each data point. Co-variance and eigen vectors are used to find projection of data-points onto eigen values for reduced dimensions of the data.

III. Literature Review

This section illustrates comprehensive review of gathered papers regarding image classification using PCA.

M. Ahmad *et al.* proposed a compact hybrid Convolutional Neural Networks (CNNs) [10]. The proposed mechanism helps to compute classification of hyperspectral image in less computational time. Authors have used PCA, incremental PCA (iPCA), sparse PCA (SPCA), Singular Value Decomposition (SVD), Independent Component Analysis (ICA), and hybrid CNN to overcome the spectral mixing effects. Moreover, inter-class similarity and intra-class variability are caused due to spectral mixing. The proposed mechanism was implemented on data-sets gathered from Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) and Reflective Optics System Imaging Spectrometer (ROSIS), i.e., Indian Pines, Salinas Full Scene, and Pavia University dataset. Furthermore, the results of different data-sets were compared using precision, recall, F1 score, overall, average, and kappa. The results showed that the proposed mechanism performed significantly good compared to other commonly used state-of-art CNN models.

Y. Sun *et al.* the proposed classification mechanism that includes data pre-processing, feature extraction, data stitching, dimension reduction using PCA, and testing these techniques on CNN and support vector machine (SVM) [11]. The sample picture from data set is divided into R, G and B. Authors used Scene15, MIT Indoor, and Caltech256 datasets to test the proposed mechanism with five layerd CNN with feature extraction, image matrix, and convolution kernel. Moreover, a supervised SVM was used to for classification of images. Results showed that proposed mechanisms outperformed in MIT indoor data set.

L. Shi *et al.* proposed a robust complementary method of hyper-spectral image classification [12]. Authors focused on reducing the information loss during feature extraction using spectral-spatial information. Furthermore, the proposed process of feature extraction included two stages, i.e., pre-processing (adaptive cubic total variational smoothing method) and edge-preserving filtering in the post-processing stage. The probability map was gained using pixel-level classifier and were integrated by decision fusion rules. Also, to enhance the differentaion of the of pixels of species, the kernel principal component analysis was used. The results were tested on ten datasets, i.e., University of Pavia dataset, China, and Houston 2013 data set, and etc. The results showed that proposed mechanism was effective in differentiating different land cover areas and could be applied to practical applications.

H. Chen *et al.* used grey wolf optimization technique and principal component analysis to improve accuracy and generalization of hyperspectral image classification [13]. The local spatial features of these images were extracted using low computational local binary pattern method. After that, grey wolf optimization algorithm was used to build a model to optimize the kernel extreme learning machine‘s parameters. The proposed technique was used to classify the images in Indian pines, houston, Pavia University, and WHU-Hi-LongKou datasets. The results showed that the technique classified images effectively with higher accuracy.

Y. Yang and C. Guan proposed an improved three-layered CNN with dimension reduction for image classification [14]. The mechanism replaced pooling with PCA to calculate eigen values/vectors to have reduced dimensions of MNIST, MNIST small, and 1584 kaggle datasets. To avoid over-fitting of the model, authors used two dropout layers in their experiments. The results showed an improved accuracy of $\sim$99% for test and train datasets.

S. Mei *et al.* solved the problem of classification computational time for hyper-spectral images using network compression [15]. A novel step quantization technique to limit the incoming data in the CNN layers was proposed to represent the integers having low-bits. To represent integer operations a non-linear uniform quantization was used to do the task of limiting the input. CNN used feature extraction for spectral features using PCA. The back-propagation used a constant and tanh functions to avoid the problem of vanishing gradient and occurrence of noise. Moreover, the datasets used were gathered from Reflective Optics System Imaging Spectrometer and Airborne Visible Infrared Imaging Spectrometer. The results showed that the proposed model increases in saving and speeding up memory and computational time by 13.6 and 10 times.

A. N. Abbasi and M. He proposed a deep learning based spectral reduction technique for hyperspectral image classification [16]. The technique has a pre-processing and batch normalization at every layer of the network. Normalization used spectral reduction in the pre-processing phase using PCA. Whereas, batch normalization with 25% and 50% dropouts were used to avoid over-fitting. To validate the proposed model, authors used Indian pines and University of Pavia datasets. The datasets acquired higher percentages of accuracy of ∼99%.

K. K. GV and G. M. Reddy proposed a classification technique for whole slide images cervical cell clusters using PCA feature interpretation methods [17]. This involves classification without extraction of single cell patches using segmentation-free classification. Moreover, PCA was used to provide interpretability and transparency to the model by visualizing and analyzing the features. The proposed model was validated on the SIPaKMeD and Herlev dataset. The developed classification technique showed a high accuracy and F1 score classified instances within less computational time.

X. Xie *et al.* proposed feature extraction mechanism based on dimension reduction for hyperspectral images [18]. First, PCA is used for data dimension reduction and the reduced dimensional data was than feature extraction is done. Multiregion piecewise gaussian pyramid downsampling method and resnet network was used to generate multiscale data and extract spatial information from it. These extracted features were based on spectral and spatial information were fed into connected layers for classification. The validation was done using three datasets, i.e., Houston, University of Pavia, and Xiong-An. The results showed improved accuracy and higher performance rates for given datasets.

A. I. Champa *et al.* worked on hyperspectral image classification using feature selection and extraction [19]. PCA was used for feature extraction whereas normalized Mutual Information was used for feature selection. For classification HYDICE and AVIRIS datasets were used to validate proposed technique on Support Vector Machine (KSVM). Moreover, the results showed higher classification accuracy of HYDICE dataset as compared to AVIRIS.

G. Y. Chen developed a novel algorithm using PCA for hyperspectral image classification [20]. PCA was used for dimensional reduction of hypersecteral image data cube. The reduced data is used for performing spatial CNN spread over three filters. The output of these filters were then classified to improve the accuracy using SVM on Indian Pines and Pavia University datasets.

Md. R. Haque and S. Z. Mishu proposed a hybrid approach dimension reduction technique for CNN to separate spectral and spatial features in classification [21]. As existing CNN methods consider spatial kernel for exploring spatial information. Therefore, dimensional reduction and extracted spatial features were used for hyper-spectral image classification. Indian pines data set was used for validation of proposed technique.

L. Sun *et al.* proposed a spectral spatial feature tokenization to extract features, i.e., spectral and high-level semantic [22]. This low-level feature extraction was done using 2, 3 dimensional convolution layers, and principal component analysis. Moreover, another tokenizer with gaussain weighted feature was used that form the basis for feature representation and learnings. That was then used to gain the sample label. Indian Pines, Pavia University, and Houston 2013 datasets were used for evaluating the impact of proposed technique in terms of accuracy and computational time. Furthermore, the technique provides high level semantic features.

M. Mateen *et al.* proposed a diabetic retinopathy using the fundus images for classification of retinal disease found in diabetic patients [23]. The proposed systematic solution was a resultant of gaussian mixture, singular value decomposition, segmentation using softmax, principal component analysis, and visual geometry group network. Moreover several features were also collected and selected yo get highly accurate classification of fundus images. The proposed solution classified the images in KAGGLE data set over fully connected layers to achieve high accuracy.

A tensor-based robust PCA was proposed by Y. Wang *et al.* for hyperspectral image classification in [24]. Tensor based robust principal component analysis has locality preserving graph and frontal slice sparsity using a laplacian graph. This graph is used for preserving the local structures while denoising the low-rank part of the hyperspectral images. The principal component analysis was used to minimize the redundant information to yield good accuracy in classification process. The datasets such as Indian Pines, Pavia University, and Salinas were used to study the proposed scheme.

Q. Li *et al.* proposed spectral-spatial based feature extraction for hyperspectral image classification [25]. Indian Pines, Pavia University, and Salinas data sets were used to reduce their dimensionality using PCA. The resultant data is then processed to do feature extraction and reduce noise. This was done using adaptive total variation filtering. Lastly, the principal components, filter, and ensemble empirical mode decomposition was used to get the final results. The proposed algorithm showed high performance rates.

R. Zeng *et al.* proposed an extension of principal component analysis network, called quaternion principal component analysis network for image classification [26]. The proposed model helps in overcoming the problem of classification of colored images by utilizing the information of the spatial distribution of RGB. First quaternion features were extracted using quaternion convolutional layer, filters, and constructing non-linear layer, adding pooling layer. UC Merced land use dataset, Georgia Tech face, CURet texture, Caltech-101 object datasets were used to validate the proposed model. Moreover, the accuracy for texture classification was measured on various benchmarks (i.e., RGB SIFT, RGB LBP), among which the proposed model stands out with highest accuracy.

Principal component analysis is a dimension reduction technique that works on unified projection using hyperspectral images. This technique was very effective and efficient to reduce data dimensions. However, if spectral features were diverse PCA is not appropriate to reduce dimensions. J. Jiang *et al.* proposed superpixelwise PCA that learns intrinsic low-dimensional features of hyperspectral images [27]. This technique incorporates spatial context of the data into unsupervised dimensionality reduction using superpixel segmentation to improve the classification performance on Indian Pines, Pavia University, and Salinas data sets.

R. Vaddi and P. Manoharan proposed a data normalization for remote sensing hyper spectral image classification [28]. This scheme had low computational power and storage capacity for normalizing the images by reducing the scalar values. This was done using principal component analysis and gabor filtering for extracting spectral and spatial features, respectively. These features were then used for CNN framework on Indian Pines, Pavia University and Salinas data sets. The proposed method has many real world applications, i.e., food industry, forestry, and agriculture.

Waste management with growing environment challenges was a difficult task nowadays. A. P. Puspaningrum *et al.* proposed waste classification mechanism based on images and types of wastes [29]. This classification of waste materials was technological advanced and does the sorting faster and in efficient way. For this, a Scale Invariant Feature Transform-Principal Component Analysis was used to first extract the related features from Trashnet dataset and to reduce their dimensions. Afterwards, SVM classifier was used that showed 62% accuracy.

IV. Discussion

This section discusses the literature review in detail for all the included articles. The articles included in this study have applied PCA as a dimension reduction technique to have better results for image classification. Table I and II shows the details of articles included in this review. The table clearly states the objective /motivation of the proposed techniques, datasets and evaluated matrices authors used to validate the proposed technique. Moreover, the tables also show the improvements that can be done in the field of respective research. OA, AA, Kappa, and accuracy are mostly used parameters evaluated for proposed models. Kappa is a measure of total observed and predicted/inferred classes in testing a dataset. Accuracy is ratio of correctly predicted observations to the total observations

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

Whereas, Overall accuracy (OA) is ratio of correctly predicted values whereas, average accuracy (AA) is the average of correctly predicted values per class. Furthermore, execution time is the total time of execution of code to get classification results. For hyper-spectral image classification, Indian Pines and Pavia University are mostly used datasets. From the result analysis of aforementioned articles, it is clear that dimension reduction actually increases the feature learning by removing noise, redundant features, and irrelevant data from the used dataset. The analysis of the included articles show that accuracy of the proposed techniques increases using PCA. Authors in [10] used PCA dimension reduction and got higher accuracy for indian pines ($\sim 96\%$), salians ($\sim 99\%$), pavia university ($\sim 58\%$, $\sim 99\%$) as compared to singular value decomposition and independent component analysis. [11] used PCA for image classification and got higher accuracy for all datasets, i.e., for scene 15 dataset obtained $\sim 85\%$ accuracy as compared to all mentioned datasets in the article. [12] used PCA and got $\sim 91\%$ for OA, AA, and Kappa as compared to other models, e.g., SVM. Similarly, for [13] higher values for OA, AA, and Kappa $\sim 97\%$ were gained compared to all discussed models. Furthermore, [14] used PCA to gain $\sim 99\%$ accuracy for MNIST datasets using CNN. [16] increased the accuracy to ~99% for pavia university and indian pines. Moreover, [17] used PCA to improve Sens, Spec, H-Mean, accuracy, and F-score to $\sim 99\%$ compared to provided benchmarks in their paper. Similarly, all the papers included in this review validate that the values of evaluated metrics are better when PCA is applied, but computational time also gets higher as a limitation.

Figure 2 shows the datasets used in image classification for the articles included in this survey. Pavia and Indian Pines are very frequently used datasets among the researchers for classification of hyper-spectral images. Also, kaggle datasets were used such as “Standard kaggle dataset”, which is manually labelled dataset. For manually labelled datasets measures must be taken to ensure data security, without which the chances of human error can increase error rate or introduce unforeseen outcomes to the model. For Figure 2, the “Others” datasets included are WHU-Hi-LongKou, Data acquired from Reflective Optics System Imaging Spectrometer, Airborne Visible Infrared Imaging Spectrometer, SIPaKMeD, Herlev, HYDICE, AVIRIS, UC Merced land use, Georgia Tech face, and CURet texture.

Figure 3 shows the evaluation matrices used for checking the validity of the proposed mechanisms. Accuracy was the mostly used evaluation matrices, however it does not takes false positive measurements into the account. Therefore, accuracy should be measured with recall and precision to give the reader an idea of correct and in-correct classified images. Moreover, out of all included papers only five papers computed the execution time for classification of images. For system robustness and efficiency, future research works must consider to measure the execution time and work to maintain equilibrium to achieve high accuracy in least time. The “Others” term indicates the count of Sensitivity, specificity, and H-Mean.

V. Conclusion

This paper presented a review to highlight the importance of dimension reduction using PCA. The analysis showed that applying PCA not only improves the evaluated matrices, however increases the computational time in majority of cases, validated by included articles. Authors should work not only

Table I: Taxonomy of Review

Article	Objective	Dataset used	Evaluated Metric	Comments
[10]	Hyperspectral Image Classification	Indian Pines, Salinas Full Scene, Pavia	Kappa, Overall, Precision, Recall, F1 Score, and Average accuracy	Batch normalization and data augmentation could be applied to improve results
[11]	Image classification with image depth views	Scene15, MIT Indoor, and Caltech256	Performance and accuracy	More evaluation metrics could be used (i.e, precision, recall).
[12]	Spectral-Spatial Method for Hyperspectral Image Classification	University of Pavia dataset, China, and Houston 2013	Computational time, Performance, Mean square error, Peak signal to noise ratio	Mechanism needed to automatically tune and select the parameters. Moreover, optimizing the resultant of combined weights from adjusted spectral adaptive weight and spatial domain pixel adaptive weight.
[13]	Hyperspectral image classification using an improved kernel extreme learning machine algorithm (PLG-KELM)	Indian pines, Houston, Pavia University, and WHU-Hi-LongKou	OA, AA, and Kappa	Work needs to be done to improve the operation efficiency of the PLG-KELM
[14]	Image classification using Convolutional neural network	MNIST, MNIST small, 1584 kaggle dataset	Accuracy, Loss	The paper neither provided any comparison with benchmarks nor any other evaluation metrics except accuracy and loss
[15]	Decreasing computational time/accelerating the CNN model for hyperspectral image classification	Data acquired from Reflective Optics System Imaging Spectrometer and Airborne Visible Infrared Imaging Spectrometer	OA, AA	Network compression and acceleration can be done using different weight quantification strategies.
[16]	Spectral reduction technique for hyperspectral image classification	Indian pines and University of Pavia	Accuracy and computational time	More evaluation metrics and benchmarks could be used for results comparison
[17]	Automatic classification of Whole slide pap smear images	SIPaKMeD and Herlev	Sensitivity, specificity, H-Mean, accuracy, computational time, F-score	Comparison of matrices are done using different models leaving room of improvement to compare the results with other articles
[18]	Hyperspectral image classification using feature extraction and spectral imaging	Houston, University of Pavia, Xiong-An	Accuracy, OA, Kappa, AA	Improvements in proposed algorithm can further reduce the errors and increase the accuracy as compared to several benchmarks mentioned in paper.
[19]	Hyperspectral image classification with hybrid subspace detection	HYDICE and AVIRIS	Accuracy	Experiments could be evaluated on more evaluation matrices, and comparison with already proposed techniques could highlight the importance of proposed technique
[20]	Multiscale filter-based hyperspectral image classification	Indian Pines and Pavia University datasets	Accuracy	A comparison of different evaluation matrices is important to get count of false positives and false negative classification using proposed technique, and comparison with already proposed techniques
[21]	Hyperspectral image classification using CNN	Indian pines	Accuracy	Evaluation matrices could help in validity of proposed technique
[22]	Spectral–Spatial Feature Tokenization Transformer for hyperspectral image classification	Indian Pines, Pavia University, and Houston 2013	OA, AA, Kappa values, Accuracy	Area of exploring the joint fusion and classification of hyperspectral and light detection and ranging data
[23]	Fundus image classification VGG-19	Standard KAGGLE dataset	Accuracy	Kaggle data sets are manually labelled datasets, the proposed models could be tried with other fundus image classification datasets

Table II: Taxonomy of Review

Article	Objective	Dataset used	Evaluated Metric	Comments
[24]	Tensor-based robust PCA with locality preserving graph and frontal slice sparsity for hyperspectral image classification	Indian Pines, Pavia University, Salinas	OA, AA, Kappa values, Accuracy	Improvement can be done by adjusting the parameters and also preserving local low-rank structures for more stable results
[25]	Ensemble empirical mode decomposition feature extraction for hyperspectral image classification	Indian Pines, Pavia University, and Salinas data sets	AA, OA, Kappa, Accuracy, Execution time	Improvements can be done to lower the execution time of proposed mechanism
[26]	Color image classification	UC Merced land use, Georgia Tech face, CURet texture, Caltech-101 object	Accuracy	The proposed model had higher accuracy and performed well
[27]	Unsupervised Feature Extraction of hyperspectral imagery	Indian Pines, Pavia University, and Salinas	AA, OA, Kappa, Computational time	Proposed technique significantly improved the results using PCA
[28]	Hyperspectral image classification with spectral and spatial features integration	Indian Pines, Pavia University and Salinas	OA, AA, Kappa values, Accuracy	Improvements should be done to reduce running time of the architecture
[29]	Waste classification	Trashnet	Confusion matrix, Accuracy	Higher accuracy could be achieved using more tuning of parameters

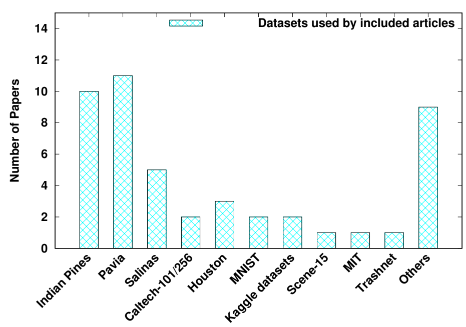

Figure 2: Datasets used

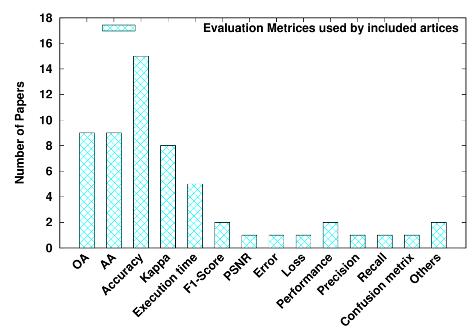

Figure 3: Evaluation Matrices used

to increase the accuracy but also devise a model that computes the values of matrices in short time.

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