Image Classification using Manifold Learning Based Non-Linear Dimensionality Reduction

Ainuddin Faaeq
Information System Engineering
Mugla Sitki Kocman University
Mugla, Turkey
ainuddinfaaeq@posta.mu.edu.tr

Hüseyin Gürüler
Information System Engineering
Mugla Sitki Kocman University
Mugla, Turkey
hguruler@mu.edu.tr

Musa Peker
Information System Engineering
Mugla Sitki Kocman University
Mugla, Turkey
musa@mu.edu.tr

***Abstract*—This paper presents fast categorization or classification of images on an animal dataset using different classification algorithm in combination with manifold learning algorithms. The paper will focus on comparing the effects of different non-linear dimensionality reduction algorithms on speed and accuracy of different classification algorithms. It examines how manifold learning algorithms can improve classification speed by reducing the number of features in the vector representation of images while keeping the classification accuracy high.**

***Keywords*—Image classification, manifold learning, dimensionality reduction, image mining, machine learning**

I. INTRODUCTION

With the advancement of imaging technologies and the heavy use of images in different fields, a vast number of images such as digital photos, medical images, satellite images are produced every day. The need for extraction, analysis and processing of these images has turned image mining into a hot topic among experts in computer vision, machine learning and, artificial intelligence [1-3].

Accuracy and speed are two of the most important metrics in the image classification. It is also a complicated process in which the accuracy and speed may be affected by many factors. Therefore, keeping a balance between accuracy and speed is very important in classification.

Over the years, numerous studies have been carried out on dimensionality reduction in image classification intended to optimize the classification execution time. In this regard, various dimensionality reduction methods such as principal component analysis (PCA) [4-6], linear discriminant analysis (LDA) [7- 9] and manifold learning [10-12] has been utilized.

This paper provides a comprehensive comparison on effects of four different manifold learning algorithm on accuracy and speed of different classification algorithms. The experiments are carried out on an animal dataset.

II. THE DATA DESCRIPTION

The KTH-animal dataset [13] utilized in this paper consists of 1740 images in 19 classes of different animals. The detailed information regarding the number of images and their classes can be seen in Table I. Fig. 1 shows a sample of dataset images. The images are in JPEG image format with animal in the foreground and different natural objects in the background.

III. METHODS

The images in the dataset are all transformed into their vector-based representation since the classification algorithms are able to run only on numbers. That is where embedding comes in; embedding is the process of putting an image through an already trained deep neural network. In this study, we use one of the best deep neural networks, Google's Inception v3 with 2048 nodes. Inception v3 transforms the images into their vector-based representation giving 2048 features for each image. However, classifying data with such huge number of features can be very time consuming especially in big datasets.

Therefore, in this paper, we are focused on reducing the number of features while maintaining similar accuracy to the original 2048 featured data. The image data consists of complex shapes in variant positions. The vector-based representation of them cannot be efficiently utilized with linear based dimensionality reduction algorithms like PCA [14]. To overcome this problem, manifold learning based non-linear dimensionality reduction algorithms used to reduce the number of features before classification algorithms are applied.

Fig. 1. Sample of dataset images.

978-1-5386-1501-0/18/$31.00 ©2018 IEEE

TABLE I. THE DESCRIPTION OF THE KTH-ANIMAL DATASET

No.	Classes	Number of Images
1	Bear	105
2	Cougar	100
3	Cow	97
4	Coyote	100
5	Deer	100
6	Elephant	100
7	Giraffe	84
8	Goat	99
9	Gorilla	83
10	Horse	100
11	Kangaroo	90
12	Leopard	100
13	Lion	98
14	Panda	97
15	Penguin	80
16	Sheep	68
17	Skunk	62
18	Tiger	100
19	Zebra	77

This study utilizes four different manifold learning methods, in the dimensionality reduction stage. Those are Multi-dimensional scaling, locally linear embedding, Isomap, and spectral embedding.

Multi-dimensional scaling (MDS) is a method used to find low dimensional representation of data in respect to the original high dimensional space. MDS is a measure of analysis of similarity and dissimilarity among pairs of objects as distances between points of a low dimensional multi-dimensional space [15, 16].

Locally linear embedding (LLE) is an unsupervised learning technique used in computing low dimensional projection of data that maintains distances in local neighborhood. LLE can be perceived as a series of PCA globally compared to compute the best nonlinear embedding. It maps the input into a single global coordinate system of lower dimensionality [17, 18].

Isomap is one of the earliest non-linear dimensionality reduction techniques. Isomap can be considered as an extension of Kernel PCA or MDS. It is highly efficient and generally applied to a wide range of data formats. Moreover Isomap is used to find lower dimensional embedding that maintains distances among all points [19].

Spectral Embedding is another linear embedding calculation approach. It uses Laplacian Eigenmaps, which seeks a low dimensional representation of data utilizing a spectral decomposition of the Laplacian graph. The generated graph may be viewed as discrete approximation of a lower dimensional manifold in a higher dimensional space. To ensure that points are near each other on the manifold and mapped closer to one another in a low-dimensional space, maintaining local distances, minimization of a cost function based on the graph is applied [20, 21].

This study utilizes four different machine learning algorithms, namely Random Forest, kNN, Logistic Regression, and SVM in the classification stage.

To briefly introduce **Random Forest (RF)** or random decision forests is an ensemble learning technique. It's a combination of tree predictors. Every tree is constructed from a bootstrap sample from training data. While constructing individual trees, a random subset of attributes is drawn, from which the best attribute for the split is selected. Final model is founded on the majority of votes from individually constructed trees of the forest [22].

K-Nearest Neighbors (kNN) is a nonparametric classification and regression instance-based learning method where the function is only approximated locally and all computation is deferred until classification. Despite being one of the simplest algorithms in machine learning, kNN is a highly competitive and efficient algorithm [23].

Support Vector Machine (SVM) is developed for the purpose of pattern recognition and regression. It's a supervised machine learning technique that separates attribute space with a hyperplane, which maximizes the margin among instances of different classes [24].

Logistic regression (LR) is a method for classifying data into discrete outcomes. Binary logistic regression predicts the value of a variable to be one of the only two possible outcomes. Multi-class logistic regression extends the standard logistic regression classification method by letting the variable to predict to have more than two values.

Fig. 2 shows graphical representation of the applied model developed and used in this study.

IV. EXPERIMENTAL RESULTS

The experiments performed in this study using the four manifold learning and the four classification algorithms mentioned above. A computer with Intel(R) Core i3 2.53-GHz microprocessor, 6-GB RAM, and 64-bit windows operating system has been used to perform these experiments. Test statistics for the model performance is described as below.

Area under ROC (AUC) is a measure of how well a parameter differentiate two or more classes. Classification accuracy (CA) is the measure of accurate classification results. F-1 score is a sub-contrary mean of recall and precision. Precision is the ratio of true positives outcomes among positive classified instances. Recall is the proportion of true positives among all positive instances in the data. Time is referring to the execution time for the classification algorithms.

Table II represents the results of classification algorithms on the original data before manifold learning algorithms applied. In terms of accuracy, logistic regression produces the best results with 0.98 classification accuracy. SVM and kNN algorithms comes second after logistic regression. The lowest accuracy score is obtained by random forest algorithm while coming first in terms of speed. Although random forest is a kind of ensemble learning algorithm, formed by the combination of many decision trees, it achieves a faster results than other algorithms. This may be due to intensive mathematical operation in other algorithms. In terms of speed, SVM produced the lowest result.

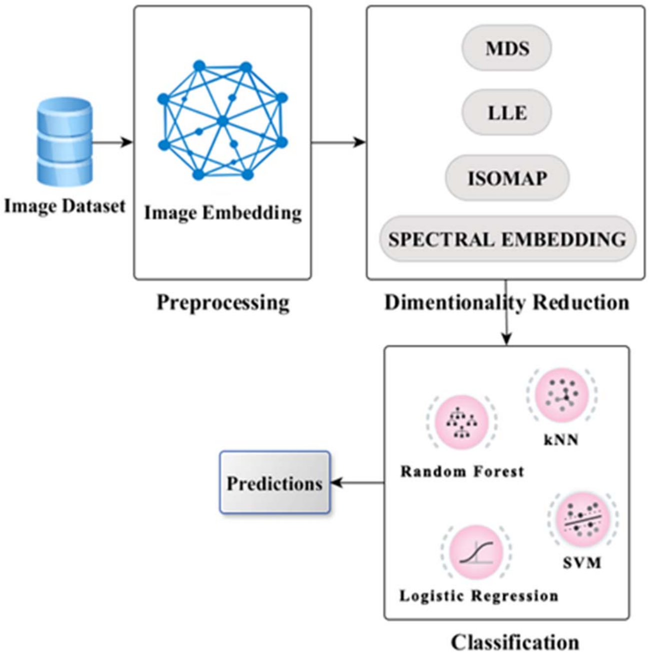

Fig. 2. The diagram of the model used in this study.

TABLE II. CLASSIFICATION RESULS OF ORIGINAL DATA

Method	AUC	CA	F1	Precision	Recall	Time (min:sec)
SVM	1.00	0.97	0.95	0.92	0.98	06:49.878
LR	0.99	0.98	0.97	0.98	0.97	02:54.664
kNN	0.99	0.97	0.96	0.99	0.95	00:45.695
RF	0.98	0.92	0.92	0.93	0.92	00:22.760

Table III represents the results of classification algorithms after manifold learning with dimensionality reduction algorithms applied. When MDS algorithm applied the classification results are as follows. SVM comes first in classification accuracy with 0.936 while coming last in speed taking 3.687 seconds. kNN comes first in terms of speed taking 0.471 seconds while coming second in classification accuracy with score of 0.933 seconds. Random forest's 0.906 classification accuracy is the lowest of all four. It comes third in execution time taking 1.061 seconds. Logistic regression comes second in execution speed taking 1.046 seconds while coming third in classification accuracy scoring 0.910.

After applying Isomap algorithm the classification results are as following. The fastest and the most accurate of all four classification algorithm is kNN. It has a classification accuracy of 0.955 and execution time of 0.434 seconds. The slowest of all four algorithms is SVM. It takes 2.654 seconds. Its 0.94 classification accuracy place it third on accuracy ranking. Logistic regression comes last in terms of classification accuracy with a score of 0.91. It ranks third in speed with 1.046 seconds execution time. Random forest comes second in terms of speed with an execution time of 0.987 seconds. It is second best in terms of classification accuracy with a score of 0.946.

While applying the LLE algorithm the classification results are as follows. Random forest is the most accurate of all four algorithms with a classification accuracy of 0.734. It ranks third on speed with a 0.89 seconds exaction time. The fastest algorithm is kNN with 0.483 seconds execution time. It comes second on accuracy with 0.720 classification accuracy score. Logistic regression is the worst in terms of classification accuracy scoring 0.321. It coming second in terms of speed with 0.622 seconds execution time. SVM is the slowest of all four with 6.873 seconds execution time. It is second worst in terms of classification accuracy with a score of 0.418.

TABLE III. CLASSIFCAIOTN RESULTS AFTER MANIFOLD LEARNING DIMENTIONALITY REDUCTION APPLIED

Method		AUC	CA	F1	Precision	Recall	Time (sec)
MDS	**SVM**	0.999	0.936	0.930	0.930	0.930	03.687
	LR	0.997	0.910	0.923	0.947	0.900	01.046
	kNN	0.988	0.933	0.910	0.910	0.910	00.471
	RF	0.991	0.906	0.887	0.874	0.900	01.061
Isomap	**SVM**	0.999	0.940	0.964	0.979	0.950	02.654
	LR	0.997	0.910	0.923	0.947	0.900	01.046
	kNN	0.985	0.955	0.980	0.990	0.970	00.434
	RF	0.998	0.946	0.960	0.951	0.970	00.987
LLE	**SVM**	0.967	0.418	0.098	0.273	0.060	06.873
	LR	0.934	0.321	0.583	0.470	0.770	00.622
	kNN	0.984	0.720	0.913	0.880	0.950	00.483
	RF	0.989	0.734	0.930	0.930	0.930	00.890
Spectral Embedding	**SVM**	0.998	0.874	0.925	0.929	0.920	03.216
	LR	0.992	0.795	0.901	0.945	0.860	00.799
	kNN	0.988	0.888	0.917	0.895	0.940	00.451
	RF	0.989	0.879	0.951	0.933	0.970	00.907

When spectral embedding algorithm applied the classification results are presented as follows. kNN ranks first both in classification accuracy and speed. It has 0.888 classification accuracy score and 0.451 seconds execution time. Random forest comes second in terms of classification accuracy with a score of 0.879. It ranks third in speed with an execution time of 0.907 seconds. Logistic regression has the lowest classification accuracy scoring 0.795. It comes second in terms of speed with execution speed of 0.799 seconds. SVM is the slowest of all four algorithms with 3.216 seconds execution time. It comes third in classification accuracy with score of 0.874.

V. CONCLUSION

This paper concludes that applying manifold learning with dimensionality reduction algorithms before classification can significantly increase the classification speed with a high level of classification accuracy. Based on the experiment statistics above the best results are produced when Isomap manifold learning dimensionality reduction algorithm is used in combination with kNN classification algorithm.

Comparing the classification results of kNN algorithm on original data and results of kNN algorithm on data after Isomap algorithm is applied. The execution time drops from 45.695 seconds to 0.434 seconds which represent more than a 100 times faster execution time. While the classification accuracy has a mere drop of 0.015.

The results of experiments performed in this paper exhibits potential for developing more powerful image processing models specially if combined with deep learning platforms. Therefore, making it possible to be used on more complex image datasets.

REFERENCES

[1] W. Hsu, M. L. Lee, and J. Zhang, "Image mining: Trends and developments," J. Intell. Inf. Syst., vol. 19, no. 1, pp. 7–23, 2002.

[2] P. G. B. Enser, "Visual image retrieval," Annu. Rev. Inf. Sci. Technol., vol. 42, no. 1, pp. 1–42, 2008.

[3] X.-J. Wang, W.-Y. Ma, G.-R. Xue, and X. Li, "Multi-model similarity propagation and its application for web image retrieval," in Proceedings of the 12th annual ACM international conference on Multimedia, 2004, pp. 944–951.

[4] J. Xia, J. Chanussot, P. Du, and X. He, "(Semi-) supervised probabilistic principal component analysis for hyperspectral remote sensing image classification," IEEE J. Sel. Top. Appl. earth Obs. Remote Sens., vol. 7, no. 6, pp. 2224–2236, 2014.

[5] S. Das, M. Chowdhury, and M. K. Kundu, "Brain MR image classification using multiscale geometric analysis of ripplet," Prog. Electromagn. Res., vol. 137, pp. 1–17, 2013.

[6] F. Ye, Z. Shi, and Z. Shi, "A comparative study of PCA, LDA and Kernel LDA for image classification," in Ubiquitous Virtual Reality, 2009. ISUVR'09. International Symposium on, 2009, pp. 51–54.

[7] X. Liu, L. Zhang, M. Li, H. Zhang, and D. Wang, "Boosting image classification with LDA-based feature combination for digital photograph management," Pattern Recognit., vol. 38, no. 6, pp. 887–901, 2005.

[8] V. P. Rathi and S. Palani, "Brain tumor MRI image classification with feature selection and extraction using linear discriminant analysis," arXiv Prepr. arXiv1208.2128, 2012.

[9] X.-Y. Jing, Y.-Y. Tang, and D. Zhang, "A Fourier–LDA approach for image recognition," Pattern Recognit., vol. 38, no. 3, pp. 453–457, 2005.

[10] Y. Fu and T. S. Huang, "Human age estimation with regression on discriminative aging manifold," IEEE Trans. Multimed., vol. 10, no. 4, pp. 578–584, 2008.

[11] L. Ma, M. M. Crawford, X. Yang, and Y. Guo, "Local-manifold-learning-based graph construction for semisupervised hyperspectral image classification," IEEE Trans. Geosci. Remote Sens., vol. 53, no. 5, pp. 2832–2844, 2015.

[12] L. Ma, M. M. Crawford, and J. Tian, "Local manifold learning-based k-nearest-neighbor for hyperspectral image classification," IEEE Trans. Geosci. Remote Sens., vol. 48, no. 11, pp. 4099–4109, 2010.

[13] H. M. Afkham, A. T. Targhi, J.-O. Eklundh, and A. Pronobis, "Joint visual vocabulary for animal classification," in Pattern Recognition, 2008. ICPR 2008. 19th International Conference on, 2008, pp. 1–4 - KTH-animal dataset, https://www.csc.kth.se/~heydarma/Datasets.html.

[14] A. Ghodsi, "Dimensionality reduction a short tutorial." Department of Statistics and Actuarial Science, Univ. of Waterloo, Ontario, Canada, 37, p.38, 2006.

[15] I. Borg and P. J. F. Groenen, "Modern multidimensional scaling: Theory and applications," Springer Science & Business Media, 2005.

[16] I. Borg, P. J. F. Groenen, and P. Mair, Applied Multidimensional Scaling. Springer Berlin Heidelberg, 2012.

[17] X. Zhang, H.-M. Ma, Y.-S. Liu, and C.-X. Gao, "An extension of locally linear embedding for pose estimation of 3D object," Machine Learning and Cybernetics, 2007 International Conference, vol. 3, pp. 1672–1677, 2007.

[18] Y. Zhang et al., "Light-field depth estimation via epipolar plane image analysis and locally linear embedding," IEEE Trans. Circuits Syst. Video Technol., vol. 27, no. 4, pp. 739–747, 2017.

[19] X. Geng, D.-C. Zhan, and Z.-H. Zhou, "Supervised nonlinear dimensionality reduction for visualization and classification," IEEE Trans. Syst. Man, Cybern. Part B, vol. 35, no. 6, pp. 1098–1107, 2005.

[20] M. Filippone, F. Camastra, F. Masulli, and S. Rovetta, "A survey of kernel and spectral methods for clustering," Pattern Recognit., vol. 41, no. 1, pp. 176–190, 2008.

[21] M. Belkin and P. Niyogi, "Laplacian eigenmaps for dimensionality reduction and data representation," Neural Comput., vol. 15, no. 6, pp. 1373–1396, 2003.

[22] A. Bosch, A. Zisserman, and X. Munoz, "Image classification using random forests and ferns," in Computer Vision, 2007. ICCV 2007. IEEE 11th International Conference on, 2007, pp. 1–8.

[23] L. Chen, S. Kapoor, and R. Bhatia, "Emerging Trends and Advanced Technologies for Computational Intelligence," Springer, 2016.

[24] L. Gao et al., "Subspace-based support vector machines for hyperspectral image classification," IEEE Geosci. Remote Sens. Lett., vol. 12, no. 2, pp. 349–353, 2015.