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IMAGE CLASSIFICATION USING MANIFOLD LEARNING

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Abstract**—**This paper describes fast image categorization or classification on an animal dataset using various classification algorithms in conjunction with various learning algorithms. The paper will compare the impacts of multiple non-linear dimensionality reduction algorithms on the speed and accuracy of various classification algorithms. It investigates how various learning algorithms can achieve better classification processing speed by reducing the number of features in image vector representation while maintaining highly accurate results.

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

I INTRODUCTION

Every day, a large number of images such as digital photos, medical images, and satellite images are produced due to the advancement of imaging technologies and the widespread use of images in various fields. Image mining has become a hot topic among experts in computer vision, machine learning, and artificial intelligence [1] due to the need for extraction, analysis, and processing of these images.Two of the most important image classification statistics are accuracy and speed. It is also a complicated process in which many factors can affect accuracy and speed. As a result, maintaining a balance between accuracy and speed is critical in classification.

PCA(Principal component analysis)[4],LDA(linear discriminant analysis LDA)[6]and [9] manifold learning are some of the Various dimensionality reduction methods that have been used in this experiment. The accuracy and speed of varying image classification algorithms are Compared with the different manifold learning classification algorithms and examined, and the results are noted in the experiment. This research used a dataset of animals for image classification.

II. DESCRIPTION OF THE DATA

The KTH-animal dataset [10] used in this paper contains 1740 images from 19 different animal classes.TableI contains detailed information about the number of images and their classes. Figure 1 shows an illustration of a dataset image. The images are in JPEG format and feature an animal in the foreground and various natural objects in the background.

Fig. 1: An example of a sample animal dataset

III METHODS

The classification algorithms can only run on numbers, all of the images in the dataset are transformed into vector-based representations. This is where embedding comes in; embedding is the process of running an image through a previously trained deep neural network. We use one of the best deep neural networks, Google's Inception v3 with 2048 nodes, in this study. Inception v3 converts images into vector-based representations, yielding 2048 features for each image. However, classifying data with such a large number of features can take a long time, especially in large datasets.
This research focuses on lowering the amount of features while retaining accuracy that is comparable to the original 2048 featured data. The visual data consists of intricate shapes placed in a variety of ways. With linear-based dimensionality reduction methods like PCA, they cannot be employed effectively. Before applying classification techniques, the number of features is minimized using based non-linear dimensionality reduction approaches based on manifold learning[2].

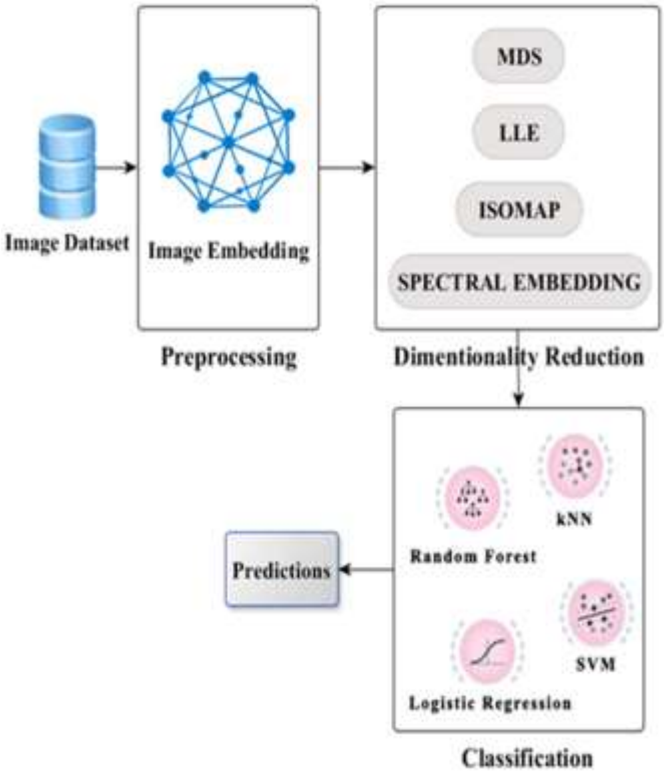

Fig. 2. The diagram of the model used in this study

In the dimensionality reduction stage, this research uses four distinct manifold learning methods. Multi-dimensional scaling, locally linear embedding, isomap, and spectral embedding are among them.

Multi-Dimensional Scaling
By evaluating the initial high-dimensional space, a multi-dimensional scaling method is utilized to identify a low-dimensional representation of the data.MDS is a technique for evaluating how similar and dissimilar pairs of objects are when they are differentiate as distances between their points in a low-dimensional multidimensional space.

Locally Linear Embedding
Locally linear embedding (LLE) is an unsupervised learning technique for computing low-dimensional data projections that keep distances in the local neighbourhood constant. LLE can be considered as a set of PCAs that are compared globally to find the best nonlinear embedding.It converts the input to fewer dimensions with a system of single global coordinate.

ISOMAP
One of the first non-linear dimensionality reduction techniques was isomap. This method is same as kernel PCA or MDS extension. It is extremely efficient and can be applied to a wide variety of data formats. Furthermore, Isomap is used to find lower-dimensional embeddings that keep distances between all points constant.

Spectral Embedding
one of best linear embedding calculation technique is spectral embedding. It utiliszes Laplacian Eigenmaps, which seek a low-dimensional representation of data through the use of a spectral decomposition of the Laplacian graph. The resulting graph can be thought of as a discrete approximation of a lower-dimensional manifold in a higher-dimensional space. To ensure that feature points are close to one another across the manifold and a cost function based on the graph is minimized for feature points, that are mapped closer to one another in a low-dimensional space while maintaining local distances.

In the classification stage, this study uses four traditional machine learning methods: Random Forest, kNN, Logistic Regression, and SVM.

Random Forest (RF), also known as random decision forests, is a method of ensemble technique. It's a mixture of tree predictors. Each tree is built from a bootstrap sample of training data. A random subset of attributes is drawn while constructing individual trees, from which the best attribute for the split is chosen. The final model is based on the majority of votes cast by individually constructed forest trees.

K-Nearest Neighbors (kNN) is a nonparametric classification and regression instance-based learning method that only approximates the function locally and defers all computation until classification. Despite being one of the simplest machine learning algorithms, kNN is a highly competitive and efficient algorithm .

Support Vector Machine
Regression and pattern detection are both accomplished using the Support Vector Machine (SVM). It is a supervised machine learning technique that divides attribute space with a hyperplane to maximize the margin between instances of different classes.

Logistic Regression
Another image classification technique that separates data into discrete outcomes is logistic regression (LR). A variable's value is predicted by binary logistic regression as one of only two possible outcomes. In multi-class logistic regression, the normal logistic regression classification approach is expanded by enabling the variable to predict to have more than two values
Figure 2 depicts a graphical representation of the model developed and used in this study.

IV. EXPERIMENTAL OUTCOMES

The experiments in this study used the four mentioned above manifold learning and classification algorithms. These experiments were carried out on a computer equipped with an Intel(R) Core i3 2.53-GHz microprocessor, 6-GB RAM, and a 64-bit Windows operating system. The following are the test statistics for model performance.
The AUC of a parameter is a measure of how well it distinguishes between two or more classes. Classification accuracy (CA) is a metric for determining how accurate classification results are.The F-1 score is a counter-intuitive mean of recall and precision.
Precision is defined as the fraction of relevant cases among the cases that were recovered or the ratio of true positives to positive categorized instances.Precision is quantified by the ratio of correct positive to positive categorized cases. The proportion of true positives to all other positive conditions in the data is known as recall. The amount of time required for the classification algorithms to finish their prescribed procedure is called time.

TABLE II. classification result before applying manifold learning

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 II shows the results of classification algorithms on the original data before applying manifold learning algorithms. With a classification accuracy of 0.98, logistic regression produces the best results. After logistic regression, SVM and kNN algorithms are ranked second. The random forest algorithm achieves the lowest accuracy score while ranking first in terms of processing speed.Although random forest is an ensemble learning algorithm composed of many decision trees, it produces faster results than other algorithms. This could be because other algorithms use intensive mathematical operations. SVM produced the slowest result in terms of processing speed.

Table III displays the classification technique results following the application of multiple learning dimensionality reduction algorithms. The classification results of using the MDS algorithm are as follows. SVM ranks first in classification accuracy with 0.936 and last in speed with 3.687 seconds.kNN is first in terms of speed, taking 0.471 seconds, and second in classification accuracy, scoring 0.933 seconds. The classification accuracy of random forest is the lowest of the four. It ranks third in terms of execution time, taking 1.061 seconds. Logistic regression ranks second in execution speed (1.046 seconds) and third in classification accuracy (0.910).

TABLE III. Results of classification prior to using manifold learning

Method		AUC	CA	F1	Precision	Recall	Time (sec)
MDS	SVM	0.999	**0.936**	0.930	0.930	03.687	0.3687
	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	0.997	0.940	0.964	0.979	0.950	02.654
	LR	0.985	0.997	0.910	0.923	0.900	01.046
	kNN	0.985	**0.955**	0.980	0.990	0.970	**00.434**
	RF	0.998	0.734	0.930	0.930	0.930	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	0895	0.940	**00.451**
	RF	0.989	0.879	0.951	0.933	0.970	00.907

The classification results obtained after employing the Isomap algorithm are as follows. kNN is the most efficient and accurate of the four classification algorithms. It has a 0.955 classification accuracy and 0.434 seconds of execution time.. The SVM algorithm is the slowest of the four. 2.654 seconds are required. It ranks third in terms of classification accuracy with 0.94.

In terms of classification accuracy, In this experiment, the Logistic regression algorithm has 0.91 accuracies and it ranks last compared with another classification algorithm. It is the third fastest, taking 1.046 seconds to execute. Random forest is the fastest, with an execution time of 0.987 seconds. Random forest score of 0.946 ,ranks second in classification accuracy.

The classification results obtained by using the LLE algorithm are as follows. With a classification accuracy of 0.734, random forest is the most accurate of the four algorithms. It is the third fastest, with an exaction time of 0.89 seconds. The fastest algorithm is kNN, which takes 0.483 seconds to execute. It ranks second in classification accuracy with a score of 0.720. Logistic regression has the lowest classification accuracy of 0.321. the execution time of Logistic regression becomes0.622 seconds and it comes in second place in terms of speed. SVM is the slowest of the four, taking 6.873 seconds to execute. With a score of 0.418, it ranks second worst in classification accuracy.

The classification outcomes of the research while utilizing the spectral embedding technique are as follows. kNN is the best in terms of classification accuracy and speed. It has a classification accuracy score of 0.888 and an execution time of 0.451 seconds.Random forest is ranked second in classification accuracy, with a score of 0.879. With an execution time of 0.907 seconds, it ranks third in terms of speed. The classification accuracy for logistic regression is 0.795. It is the second fastest, with an execution time of 0.799 seconds. compared to the four algorithms, SVM is the slowest because its execution time is 3.216. With a score of 0.874, it ranks third in classification accuracy.

V. CONCLUSION

This paper concludes that prior to classification, using manifold learning with dimensionality reduction algorithms can significantly increase classification speed while maintaining high classification accuracy. According to the experiment statistics, the best results are obtained when the Isomap manifold learning dimensionality reduction algorithm is combined with the kNN classification algorithm.

Comparing the results of the kNN algorithm on original data with the results of the kNN algorithm on data after using the Isomap algorithm. The execution time decreases from 45.695 seconds to 0.434 seconds, representing a 100-fold increase in speed. While the accuracy of categorization has only dropped by 0.015. The findings of the studies presented in this study show that deep learning platforms can be used to construct more powerful image processing models. As a result, it may now be utilized on more complicated digitized image.

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