# AN EFFECTIVE CLASSIFICATION APPROACH FOR RECOGNITION OF FACIAL AGE USING FURTHEST NEAREST NEIGHBOR CRITERION

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**Abstract**

**Active learning is a supervised learning method that is based on the idea that a machine learning algorithm can achieve greater accuracy with fewer training labels if it is allowed to choose the data from which it learns. Facial age classification is a technique to classify face images into one of the several predefined age groups. The proposed system applies an active learning approach to facial age classification which allows a classifier to select the data from which it learns. The classifier is initially trained using a small pool of labeled training images. This is achieved by using the bilateral two dimension linear discriminant analysis. Then the most informative unlabeled image is found out from the unlabeled pool using the furthest nearest neighbor criterion, labeled by the user and added to the training set.**

***Keywords*—Active learning, age classification, machine learning, supervised learning.**

## I. INTRODUCTION

### A. *Active Learning*

MCTIVE learning is a strategy that is well-motivated in many modern machine learning problems. It is used in situations where unlabeled data may be abundant or easily obtained, but labels are difficult, time-consuming, or expensive to obtain. Active learning may also be called as "query learning" or "optimal experimental design". The main idea in active learning is that a machine learning algorithm can achieve greater accuracy with fewer training labels if it is allowed to choose the data from which it learns.

For sophisticated supervised learning problems, the labelled instances are very difficult to obtain. Active learning systems attempt to overcome this difficulty by asking queries in the form of unlabeled instances to be labelled by an oracle (e.g., a human annotator). The active learner aims to achieve high accuracy for a given problem using as few labelled instances as possible, thereby minimizing the cost of obtaining labelled data [2].

An active learner begins with a small number of instances in the labelled training set, requests labels for one or more carefully selected instances, learns from the query results, and then uses its new knowledge to choose which instances are to be queried next. Once a query has been made, there are usually no additional assumptions on the part of the learning algorithm. The new labelled instance is simply added to the labelled set and the learner proceeds from there in a standard supervised way.

Pool-based active learning for classification was introduced by Lewis and Gale. A large quantity of unlabeled data will be readily available in most of the classification problems. The active learner has access to this pool of unlabeled data and can request the class label for a certain number of instances in the pool from the human annotator. The main issue with active learning is finding a way to choose good requests or queries from the pool.

### B. *Classification*

In machine learning and pattern recognition, classification refers to an algorithmic procedure for assigning a given piece of input data into one of a given number of categories. An example would be assigning a given email into "spam" or "non-spam" classes or assigning a diagnosis to a given patient as described by the observed characteristics of the patient like gender, blood pressure, presence or absence of certain symptoms, etc. An algorithm that implements classification is known as a classifier.

The term "classifier" sometimes also refers to the mathematical function, implemented by a classification algorithm that maps input data to a category.

The piece of input data is formally termed as an instance, and the categories are termed as classes. The instance is formally described by a vector of features, which together constitute a description of all the known characteristics of the instance. Typically, features are either categorical consisting of one of a set of unordered items, such as a gender of “male” or “female”, ordinal consisting of one of a set of ordered items, such as "large", "medium" or "small", integer-valued, such as a count of the number of occurrences of a particular word in an email or real-valued, like a measurement of blood pressure. Often, categorical and ordinal data are grouped together; likewise for integer-valued and real-valued data.

Classification normally refers to a supervised procedure, i.e., a procedure that learns to classify new instances based on learning from a training set of instances that have been properly labelled by hand with the correct classes. The corresponding unsupervised procedure is known as clustering, and involves grouping data into classes based on some measure of inherent similarity (e.g., the distance between instances, considered as vectors in a multi-dimensional vector space).

In supervised learning, we have training examples and test examples. A training example is an ordered pair <x, y> where x is an instance and y is a label. A test example is an instance x with unknown label. The goal is to predict labels for test examples. The name “supervised” comes from the fact that some supervisor or teacher has provided explicit labels for training examples.

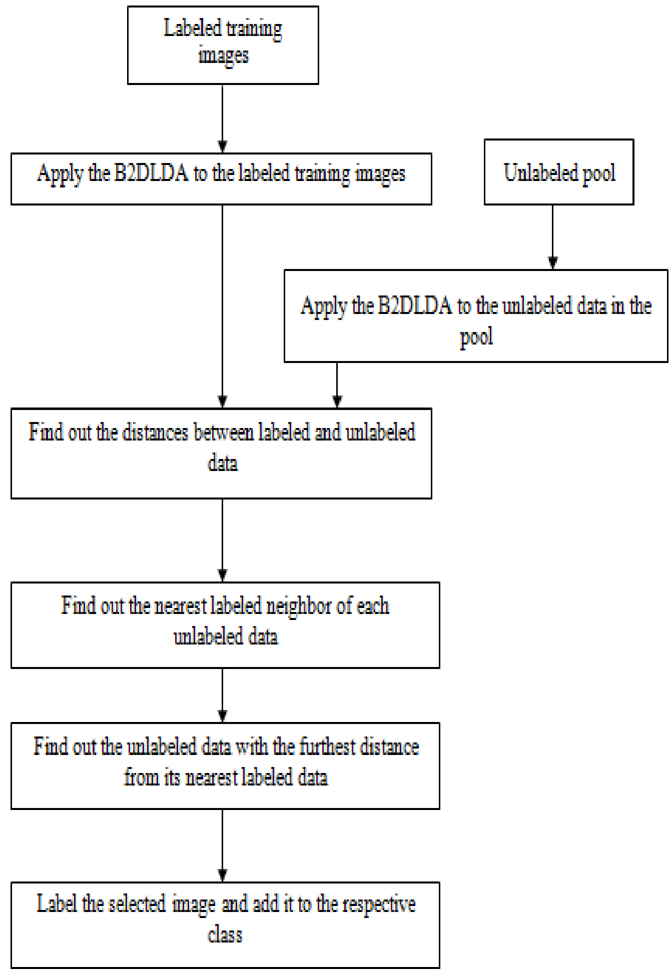


Fig. 1. Overall flow of the system

## II. PROPOSED SYSTEM

The proposed system applies an active learning approach to facial age classification which allows a classifier to select the data from which it learns. The classifier is initially trained using a small pool of labeled training images. This is achieved by using the bilateral two dimension linear discriminant analysis (B2DLDA). Next the most informative unlabeled image is found out from the unlabeled pool using the furthest-nearest neighbor criterion (FNN). The selected image is labeled by the trainer and added to the training set.

### A. *Dimension Reduction*

High-dimensional data that require more than two or three dimensions to represent the data can be difficult to interpret. Hence reduced dimensional representation of the training images has to be prepared. This is done using the bilateral two dimension linear discriminant analysis (B2DLDA). The input to this step is a collection of labeled images belonging to four predefined classes: children, teenager, adult, and senior adult. The outputs are the reduced dimensional representations of input images. Left and right transformation matrices are created by finding out the eigen vectors of the product of between class scatter matrix and the inverse of within class scatter matrix. The reduced dimensional representations are obtained by multiplying original image matrices with these transformation matrices.

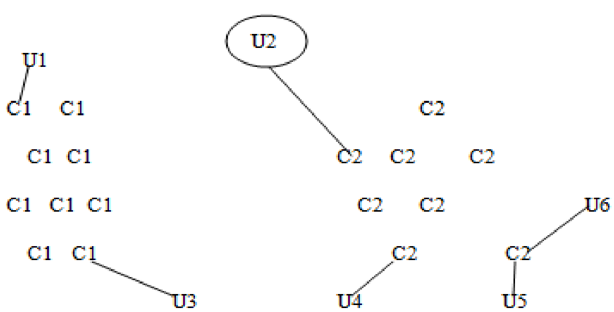


Fig. 2. Data selection using FNN

Let $N$ be the number of classes, $T$ be the total number of training samples and $n_k$ be the number of training images in class $k$. Let $X_i^k$ denote the $i^{th}$ training image belonging to class $k$. B2DLDA computes the set of reduced dimensional representations of input images as follows:

1. Calculate the mean matrix $\overline{X_k}$ of each class $k$, $k=1,2,..,N$.

$$\overline{X_k} = \left({}^{1}/_{n_k}\right) \sum_{i=1}^{n_k} X_i^k \tag{1}$$

2. Compute the global mean $M$ of all the training samples.

$$M = \sum_{k=1}^{N} \left({}^{n_k}/_{T}\right) \overline{X_k} \tag{2}$$

3. Find left between class scatter matrix $S_{bl}$ and left within class scatter matrix $S_{wl}$.

$$S_{bl} = \sum_{k=1}^{N} n_k \left(\overline{X_k} - M\right)^T \left(\overline{X_k} - M\right) \tag{3}$$

$$S_{wl} = \sum_{k=1}^{N} \sum_{i=1}^{n_k} \left(X_i^k - \overline{X_k}\right)^T \left(X_i^k - \overline{X_k}\right) \tag{4}$$

4. Compute the first $m_l$ eigenvectors of $S_{wl}^{-1} S_{bl}$ to get the left transformation matrix $W_l$.

5. Find right between class scatter matrix $S_{br}$ and right within class scatter matrix $S_{wr}$.

$$S_{br} = \sum_{k=1}^{N} n_k \left(\overline{X_k} - M\right)\left(\overline{X_k} - M\right)^T \tag{5}$$

$$S_{wr} = \sum_{k=1}^{N} \sum_{i=1}^{n_k} \left(X_i^k - \overline{X_k}\right)\left(X_i^k - \overline{X_k}\right)^T \tag{6}$$

6. Compute the first $m_r$ eigenvectors of $S_{wr}^{-1} S_{br}$ to get the right transformation matrix $W_r$.

7. Compute the left reduced dimensional representations $LB_i^k$ and right reduced dimensional representations $RB_i^k$.

$$LB_i^k = X_i^k \times W_l \tag{7}$$

$$RB_i^k = \left(X_i^k\right)^T \times W_r \tag{8}$$

### B. *Data Selection*

The data selection is the most important step in the application of active learning principle to age classification. It is used to select an unlabeled sample that will be the most informative sample to improve the classifier. The input to this step is a pool of labeled and unlabeled images. The output is the selected image. The furthest nearest neighbor technique performs the following steps:

1. Find out the distances between labeled and unlabeled samples.
2. Find out the nearest labeled neighbors of each unlabeled sample.
3. Find out the furthest unlabeled sample among those selected in step 2.
4. Give the selected sample to the trainer for labeling.
5. Add the labeled sample to the set of training images.

Fig. 3 Training samples in children class

Fig. 4 Training samples in teenager class

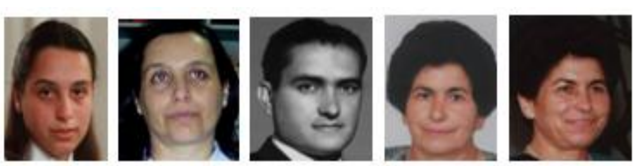

Fig. 5 Training samples in adult class

Fig. 6 Training samples in senior adult class

Fig. 7 Unlabeled samples

The data selection process using furthest nearest neighbor criterion is explained in fig. 2. The labeled training samples belonging to two classes C1 and C2 are shown in the figure. U1 to U6 are the unlabeled instances. Lines are drawn from each unlabeled instance to its corresponding nearest labeled instance. The instance U2 will be selected by the FNN criterion in this case because it is the unlabeled instance which is the furthest from its nearest labeled neighbor.

## III. EXPERIMENTATION

The experiment was carried out using the FG-NET Aging Database. It is an image database containing face images showing a number of subjects at different ages. The images have different illumination, pose, expression, and includes faces with beards, moustaches, spectacles, and hats. The sample images taken in the training set and in the unlabeled pool are shown in the above figures.

. The input is a pool of labeled facial images and a pool of unlabeled facial images. The labeled images belong to four predefined classes- children, teenager, adult, and senior adult.

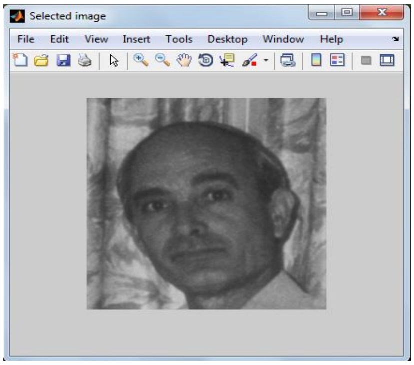


Fig. 8 The image selected by the FNN criterion from the unlabeled pool

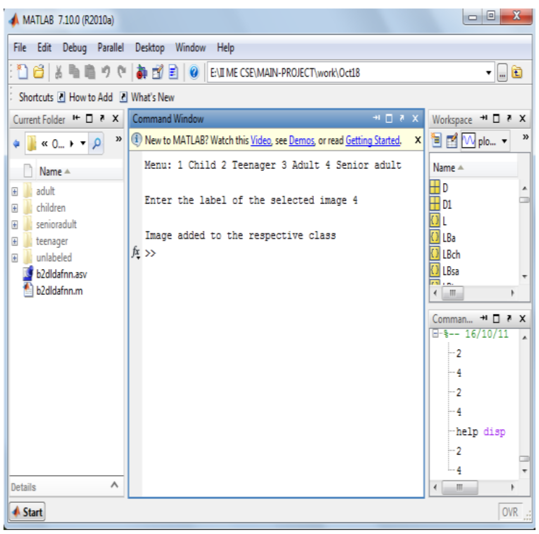


Fig. 9 The labeling of the selected image by the trainer.

The classifier is initially trained with the labeled training images using the bilateral two dimension linear discriminant analysis (B2DLDA). The B2DLDA converts the training images to reduced dimensional representations. The main goal of B2DLDA is to maximize the ratio of the between class distance to the within class distance so that a good separation between the given classes can be achieved. Then the unlabeled images are also reduced using B2DLDA.

The FNN criterion calculates the distances between the labeled and the unlabeled images and finds out the unlabeled image which is the furthest from its nearest labeled neighbor. The image selected in such a way is considered to be the most informative sample to improve the classifier. The image selected from the unlabeled pool using the FNN technique is shown in fig. 9. A menu is displayed to the trainer and the selected image is labeled by the trainer by providing the proper menu option. The labeled image is then added to the respective class in the training set.

## IV. CONCLUSION

The proposed active learning technique using furthest nearest neighbor criterion has been implemented for facial age classification. The bilateral two dimension linear discriminant analysis has been used to convert images to reduced representations. The unlabeled image to be labeled next was selected using the furthest nearest neighbor criterion. It was labeled by the user and added to the training set.

As a future work, the classifier needs to be updated using the samples added during each iteration of active learning. The accuracy of the classifier needs to be evaluated. Support vector machine is a classifier that does not work well in the case of large databases with high feature dimensions. We can try to combine B2DLDA with support vector machine for age classification problem. We can use the B2DLDA for dimension reduction process and support vector machine as the classifier. Such a combination is expected to give better results for high feature dimensions rather than the original support vector machine approach.

 

## REFERENCES

[1] Jian Gang Wang, Eric Sung, and Wei Yun Yau, "Active Learning for Solving the Incomplete Data Problem in Facial Age Classification by the Furthest Nearest-Neighbour Criterion," in *IEEE Trans. Image Process.*, vol. 20, no. 7, pp. 2049-2062, Jul. 2011.

[2] B. Settles, "Active learning literature survey," Univ. of Wisconsin-Madison, Madison, WI, Computer Sciences Tech. Rep.1648, 2009.

[3] T. F. Cootes, G. J. Edwards, and C. J. Taylor, "Active appearance model," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, no. 6, pp. 681–685, Jun. 2001.

[4] S. Tong and D. Koller, "Support vector machine active learning with applications to text classification," *J. Mach. Learning Res.*, pp. 45–66, 2001.

[5] X. Li, L. Wang, and E. Sung, "Multi-label SVM active learning for image classification," in *Proc. IEEE Int. Conf. Image Process.*, 2004, pp. 2207–2210.

[6] P. Jain and A. Kapoor, "Active learning for large multi-class problems," in *Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit.*, 2009, pp. 1–8.

[7] Y. H. Kwon and N. D. V. Lobo, "Age classification from facial images," *Comput. Vis. Image Understanding*, vol. 74, no. 1, pp. 1–21, 1999.

[8] X. Geng, Z. H. Zhou, Y. Zhang, G. Li, and H. Dai, "Learning from facial aging patterns for automatic age estimation," in *Proc. ACMConf. Multimedia*, 2006, pp. 307–316.

[9] A. Lanitis, C. Draganova, and C. Christodoulou, "Comparing different classifiers for automatic age estimation," *IEEE Trans. Syst., Man, Cybernet.*, vol. 34, no. 1, pp. 621–628, Jan. 2004.

[10] N. Ramanathan and R. Chellappa, "Modeling age progression in young faces," in *Proc. CVPR*, 2006, pp. 387–394.

 