Deep Nearest Class Mean Model for Incremental Odor Classification

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Abstract: In recent years, more and more machine learning algorithms have been applied to odor recognition. These odor recognition algorithms usually assume that the training dataset is static. However, for some odor recognition tasks, the odor dataset is dynamically growing where not only the training samples but also the number of classes increase over time. Motivated by this concern, we proposed a deep nearest class mean (DNCM) model which combines the deep learning framework and nearest class mean (NCM) method. DNCM not only can leverage deep neural network to extract deep features, but also well suited for integrating new classes. Experiments demonstrate that the proposed model is effective and efficient for incremental odor classification, especially for new classes with only a small number of training examples.

Index terms: incremental classification, nearest class mean, odor recognition, deep neural network, feature extractor.

1. Introduction:

Odor recognition with electronic nose (E-nose) plays an important role in many applications, such as detection and diagnosis in medicine \cite{43, 44, 45}, searching drugs and explosives \cite{46, 47}, quality control in food producing chain \cite{3, 48}, and locating the gas source \cite{49}. One of the difficulties in the E-nose system is that gas sensor is sensitive to physical environment (e.g. temperature, humidity and pressure), gas concentration and abnormal odor. So the data measured by gas sensor may include signal noise, shift, drift, etc. These inaccurate attributes of gas sensor seriously hinders the application of E-nose in real environment. To solve this problem, deep learning algorithms may be appropriate choice. Because the deep learning can extract deep feature, which improve discriminative aspects and suppress the irrelevant variations of raw data \cite{8}. So that they could reduce or eliminate the signal noise, shift and drift of gas sensors, then improve the accuracy of odor recognition. This characteristic of deep learning has been proved this in many other area such as speech recognition \cite{9, 10}, visual object recognition \cite{11, 12}, object detection \cite{13} and natural language understanding \cite{14, 15}.

Some of the odor recognition applications, like classification of Chinese herbal medicines or tea quality evaluation \cite{3}, where acquisition of training data is time consuming and expensive. For example, Chinese herbal medicines recognition with E-nose, there are many kinds of herbs; even the same type herb has different origins. It is not possible to collection all kinds of them at once, and only one or a few kinds of them became available over a period of time. For such scenarios, the number of both samples and classes in training dataset gradually increases. The standard deep learning methods cannot be directly used for this situation, because the effective of deep learning depends on two conditions. First, an off-line setting is assumed that means the complete data set is entirely available before training session. Second, for deep neural network has numerous parameters, it need large amount of training data to fine-tune the parameters.

In this paper, we try to extend deep neural network so that it can seamlessly integrate new classes rather than retraining the classifier from scratch at each dataset update (such would be
necessary for standard deep learning models). We refer to this problem as incremental deep learning which is a particular case of incremental learning [16, 21, 22, 23]. The difference between traditional and incremental learning is show in fig. 1.

In the machine learning community, incremental learning is relative unexplored problem. As a baseline for incremental learning, one could for instance consider model-free classifier such as k-nearest neighbor (KNN) and nearest class mean (NCM) classifiers. KNN is a highly nonlinear classifier that has ability to achieve accuracy rate comparable much more complex methods for classification [17, 18, 19]. It integrate new classes by just simply adding new training samples (of new classes) to the database which can be used for classification directly. The cost of the simple processing is that it not only need to store all training samples, but has large computational burden for predicting. This prevent KNN applied in many real situations. Contract to the KNN method, NCM is an efficient classifier [20]. But NCM is just a linear classifier it cannot handle the nonlinear boundary of classes.

To overcome the limitation of NCM, T. Mensink et al. proposed a metric learning algorithm for NCM, named NCMLM, where samples are enforced to be closer to their class mean than other class mean in the projected space [21]. M. Ristin et al researched a new type of random forests based on NCM, Nearest Class Mean Forests (NCMF), where the decisions at each node are formed by a small random subset of class means observed at that node. They also introduced strategies for updating forest structure in order to integrate new classes [22, 23]. Although, these approaches both using NCM method for incremental learning. They are introduced for large image dataset, such as “ImageNet” [24], where the number of initial classes or training samples of new classes is relative large. But, the number of initial classes and training samples is relatively small for odor recognition. Because an odor measurement equipment, electronic nose, is usually much more expensive than a camera and odor measurement time is longer than take a picture.

To address the sensitive of gas sensor and the small amount of training samples in incremental odor recognition, we propose a deep nearest class mean (DNCM) model which combines deep neural network and nearest class mean classifier. Inspired by transform learning [25, 26, 27], we divided deep neural network into two parts: a deep feature extractor and a softmax classifier, then connect the deep feature extractor to a nearest class mean classifier. The whole training procedure is divided into two steps. First, DNCM is trained on initial dataset where the parameters of feature extractor is learned in this stage. Second, when new samples (of new class) is available, the raw (measurement) vector would be transformed to feature vectors by trained feature extractor. Then the relevant class means will be recomputed. We illustrate the DNCM model in Fig. 2 and explain it in more detail in section IV.

The main idea of this paper are summarized as three points. First, DNCM is proposed to extend deep learning model. It can continue integrating new classes over time, rather than retrain the model from scratch. The second is a new type of link way between the feature extractor and classifier in proposed model. The link way between feature extractor and the classifier is the distance measurement between feature vector (output of feature extractor) and classes mean, see fig.2. Third,
an loss function is introduced for minimizing the intra-class compactness and simultaneously maximizing the inter-class distance in feature space.

Fig. 2 The upper part is a standard neural network which can be divided into a deep feature extractor and a softmax classifier. The lower part is the proposed DNCM model which inherits the feature extractor and replaces the original classifier by a NCM classifier. In the DNCM model, the yellow concentric circles represent mean of classes that have already been integrated into model, not neuron of network. The green concentric circles represent the mean of new class that will be integrated into model. The yellow dotted lines are not the same as the connections in network, which means that the distance between the output of feature extractor (feature vector) and each class mean.

The rest of this paper is organized as follows. Section II show some related work; Section III describe the detail of proposed model; Section IV present an experimental results, analyzing the influence of parameters on the proposed DNCM and comparing them to the current state-of-art in incremental odor recognition problems. Finally, we give our conclusion in Section V.

II Related work

Odor recognition by machine with E-nose is a challenge task for pattern recognition since gas sensor is sensitive to physical environment. Especially, some odor classification task is based on dynamic incremental dataset. Below we discuss various work about odor classification and incremental learning.

A. Odor Classification

With the development of artificial intelligence, more and more machine learning algorithms were proposed for odor recognition. L. Zhang et al. proposed discriminative subspace learning which target at odor recognition across multiple E-nose [1] and extreme learning machine based self-expression for abnormal odor detection [2]. Tudu et al. proposed an incremental fuzzy approach to evaluate black tea quality, which can incremental learn new types of tea [3]. Rodriguez et al. use support vector machine (SVM) for the calibration of gas sensor arrays [4]. Dixon et al. [5] compared the performance of five pattern recognition in odor recognition: Euclidean Distance to Centroids (EDC), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Learning Vector Quantization (LVQ) and Support Vector Machines (SVM). In machine olfaction community, there are some valuable reviews which summarized the pattern classification and signal processing methods for E-nose [6, 7].

B. Deep Learning

Conventional machine learning divide the process of learning into two separate parts: feature extractor and classifier. Feature extractor which transformed the raw data (for example the signal of multiple sensors) into a suitable feature vector was normally designed artificially. It required careful
engineering and considerable domain expertise. The quality of the feature extractor is the key point influencing the performance of the whole learning system.

Deep learning is multiple levels represent learning which allow machine to be fed with raw data and to automatically discover the features needed for detection or classification. Deep learning comprise multiple non-linear layers that each transform the representation at one level (starting with the raw input) into a higher, more abstract level [8]. With the composition of enough such layers, higher levels of representation amplify aspects of the input that are important for discrimination and suppress irrelevant noise. The key difference of deep learning from conventional learning is that these layers of features are not designed by human experts, they are learned from data using a general-purpose learning procedure [8]. In general, the learned features are better than artificial designed. So this is the reason that deep learning is making major advance many application area such as face recognition[33], speech recognition[10] and image classification[11]. In this paper, we leverage this advantage of deep learning method to extract features for incremental learning.

C. Incremental Learning

One vs. rest [40] framework are basic frameworks for incrementally learning a dynamically growing number of classes. Its strategy involves training a single binary classifier (e.g. SVM) per class, with samples of the class as positive sample and all other samples as negatives. Suppose a model have already accommodated N classes, when adding a new class N+1, it trains one new one vs. all classifier and updates their N previous trained classifiers. The computational cost of training a new classifier and update the N trained classifier is high [19]. Another method of this research line is one vs. one [41] framework which trains \(N(N-1)/2\) binary classifier for \(N\)-way multi-class classification problem. To extend model to the N+1-th class, it should train N new binary classifier. When the number of class is large, for example N equals 1000, it need maintain 1 million classifiers, and add new 1000 binary classifiers for add one new class. So one vs. one is only suitable for the number of classes very few.

Model-free methods are another incremental learning methods. Different from model-based methods which first learn models from training samples and then predict test sample by the learned model [34, 35], model-free methods do not have training stage. When new data (new samples and new classes) appear, model-free methods just add them to existing dataset near zero cost. So, Model-free methods naturally can handle dynamic datasets. The classic model free methods includes K-Nearest Neighbor (KNN) [17], Kernel Density Estimators (KDE) [36], the nearest class mean classifier (NCM)[20] and so on. KNN conducts classification tasks by first calculating the distance between the test sample and all training samples to obtain its nearest neighbors then conducting its class. KNN has difficulty to deal with large dataset, such as ImageNet [24] (millions of images and thousands of classes. One reason is that it needs large storage space to save all samples. Another is that although no efforts for training, conducting the classification come with a large computational burden for each test sample. The nearest class mean classifier (NCM) can be seen as a variant of KNN, instead of save all samples, it just represents classes by mean of their samples. Compared to KNN, NCM needs little amount of storage and computation. But it is a linear classifier, not fit for highly non-linear classification tasks like image classification, odor recognition and so on.

Decision tree [37] can be used as a multi-class classifier that uses a tree-like graph or model of decisions and their possible consequences. At each node of tree, the data arriving at that node is divided by a binary classifier such as axis-aligned function [38], NCM classifier [22, 23] and SVM classifier[39]. Multiple decision trees can be clustered into a random forest which are archetype of hierarchical classifier. In [22], Marko Ristin et al. added NCM and the incremental learning mechanism into random forest models. They proposed four approach for incrementally learning an NCM Forest which involves: 1) update leaf statistics, 2) Incrementally grow tree, 3) Re-train
subtree and 4) Reuse subtree. While the first three methods work with general type of node classifier, the last one uses the advantage of NCM for incremental learning. In addition to the above four methods, in [23], Marko Ristin et al. further proposed node sampling for partial tree update which prefer to update subtrees with poor performance. Random forest like other ensembles framework is simple, flexible predictive model, while the number of trees is a difficulty choice. More accurate random forest requires more trees and more node binary classifier, and then more data is required. When the amount of training samples is not enough, the accurate of random forest will drop significantly.

D. Transfer Learning

Some idea of this paper is inspired by transfer learning which use the methods that extract knowledge from one or more source tasks and apply the knowledge to a target task. The most relevant approach is feature representation transfer which aim at finding “good” feature representation to minimize domain divergence and classification model error [25]. According to the data of source domain is labeled or not, the feature representation transfer approach can be divided into supervised and unsupervised feature construction. The key idea of supervised feature construction is learn a feature representation that is shared across related tasks. Argyriou et al. proposed an optimization problem for find the common features in multitask learning [28]. The optimization problem estimates the low dimensional representations and the parameters of the model at the same time. The basic idea of unsupervised feature construction is learning higher level features. Raina et al. proposed a two steps methods by applying sparse coding to learning higher presentation [29].

Deep learning seems well suited for transform learning because it focus on learning representation and particular “abstract” representations, that ideally disentangle the factors of variation present in the input [30]. W. Ge et al. used a subset of training image from the original source learning task whose low-level characteristics are similar to those from the target learning task, and jointly fine-tune shared convolutional layers from both tasks [31]. Y. Wu & Q. Ji [32] introduced a constrained deep transfer feature learning method to perform simultaneous transfer leaning and feature learning by performing transform learning in a progressively improving feature space iteratively. Furthermore, they exploit the target domain knowledge to constrain the process of transfer learning in order to ensure the transferred data satisfying certain properties of the target domain.

III Deep Nearest Class Mean (DNCM)

In this section, before introducing the model of Deep Nearest Class Mean (DNCM), we briefly describe the concept of deep neural network (feature extractor) and NCM classifier, and how to apply them on odor classification, respectively.

A. Deep Neural Network (DNN)

Deep Neural Network, also often called deep network, or multi-layers perceptions (MLPs), are the typical deep learning models. Differentiating from conventional machine learning methods design feature extractor by domain expert, DNN using an expressive hierarchical structure, i.e. multiple layers. Each layer contains multiple neurons which connect with the neurons of its neighbor layers’ neurons. The output $\alpha_i$ of the $i$-th layer is the nonlinear transform of the linear composition of previous layer’s output $\alpha_{i-1}$:

$$
\alpha_i = \phi_i(W_{i-1} \times \alpha_{i-1})
$$

(1)

which $\phi_i(\cdot)$ is non-linear function of the $i$-th hidden layer. Different network type have different choice of $\phi_i(\cdot)$. And $W_i$ is the weight matrix connects $i$-th hidden layer and $(i+1)$-th hidden layer.
The simple but non-linear layers transform the representation at one level (start with the raw input) into a representation at a deeper, slightly more abstract level.

DNN can be decomposed into a feature extractor \( f(\cdot) \) and a softmax classifier \( g(\cdot) \), (see the upper part of fig.2). The feature extractor involves from first up to the last hidden layer. With an odor being represented by a \( d \)-dimensional measurement vector \( x \) which is measured by gas sensor.

The output of feature extractor is feature vector \( v \),

\[
v = f(x) = \phi_h(W_{h-1} \times \phi_{h-1}(\cdots \phi_1(W_0 \times x)) \cdots)
\]  

(2)

The feature vector \( v \) will be input to softmax classifier. And the output of the softmax classifier is probability of input odor belong to each class.

\[
u = [u_1, \cdots, u_m] = W_h \times f(x) = W_h \times v
\]  

(3)

\[
g(u) = \frac{[e^{u_1}, e^{u_2}, \ldots, e^{u_m}]}{\sum_i e^{u_i}} = [z_1, \cdots, z_K] = z
\]  

(4)

Using a set of training dataset \( \mathcal{D} = \{(x_1, y_1), \cdots, (x_n, y_n)\} \), the training procedure is searching parameters \( W = [W_0, \ldots, W_h] \) for the following optimization problem:

\[
\argmin_W \mathcal{L}(\mathcal{D}) = - \sum_{i=1}^{n} \sum_{k=1}^{K} t_{ik} \log z_{ik}
\]  

(5)

Where \( z_i \) is the output of \( g(u_i) \), and \( g(u_i) = W_h \times f(x_i) \), \( z_{ik} \) is the \( k \)-th element of vector \( z_i \), and \( t_{ik} \) is \( k \)-th element of vector \( t_i \) which is a one-hot vector (only the \( y_i \)-th element equal one) corresponding to \( y_i \). The function \( \mathcal{L}(\mathcal{D}) \) is called loss function.

B. Nearest Class Mean classifier (NCM)

Nearest class mean classifier have been applied to large scale image classification [21]. The key idea of NCM is that each classes is represented by their mean feature vector of its elements [20].

First classes mean or center \( c_k \) is computed for each class \( k \):

\[
c_k = \frac{1}{N_k} \sum_{i \in \text{class } k} v_i
\]  

(6)

Where \( v_i \) is a \( d \)-dimensional feature vector which represents an odor, and \( N_k \) is number of samples in class \( k \).

For a new testing feature vector \( v_i \), NCM assigns it to the class \( k^* \) with the closest mean:

\[
k^* = \arg\min_{k \in \{1, \cdots, K\}} d(v_i, c_k)
\]  

(7)

Where \( d(v_i, c_k) \) is the distance between \( v_i \) and class mean \( c_k \).

The success of the NCM critically depends on whether we can find a feature space which can separate the difference classes and make the elements from the same class gather together.

C. Combining DNN and NCM

In this section, we propose to combine a variant of NCM with DNN and we name the resulting model deep nearest class mean (DNCM). It have two different aspects with standard deep neural network. First, the original softmax classifier is replaced by a NCM classifier (see fig. 2). Second, the feature vector, output of DNN’s feature extractor, is directly sent to a set of distance functions, not be weighted sum to a neuron. NCM classifier is also modified where the hard class label output of NCM is translate into probability of each classes. The probabilities will be used in the loss function.

More specifically, we perform the following procedure to predicting a new odor \( x_i \) with an existing DNCM. First \( x_i \) will be input to the deep network feature extractor \( f(\cdot) \) (defined in formula (2)) then a feature vector \( v_i \) will be got:

\[
v_i = f(x_i)
\]

Then we will compute the distance \( d_{ik} \) between \( v_i \) and each classes mean \( c_k \)

\[
d_{ik} = d(v_i, c_k)
\]
where \( d(v_i, c_k) \) is distance function between \( v_i \) and \( c_k \). The distance \( d_{ik} \) will be translated into probability \( p_{ik} \):

\[
p_{ik} = \frac{e^{-d_{ik}}}{\sum_{m} e^{-d_{im}}}
\]  

(8)

DNCM will assign the odor \( x \) to the class \( k^* \in \{1, \cdots, K\} \) with the largest probability.

\[
c^* = \arg\max_{k \in \{1,\cdots,K\}} p_k
\]

From this we can define the loss function of DNCM:

\[
\mathcal{L}(\mathbb{D}) = -\sum_{i=1}^{n} \sum_{k=1}^{K} t_{ik} \log p_{ik}
\]  

(9)

Where \( \mathbb{D} = \{(x_1, y_1), \cdots, (x_n, y_n)\} \) is the training dataset, and \( t_{ik} \) is \( k\)-th element of vector \( t_i \) which is a one-hot vector (only the \( y_i\)-th element equal one).

**IV Incremental Learning Strategies for DNCM**

As discussed in Section II, deep learning has been studied for many pattern recognition applications such as face recognition [33], speech recognition [10] and image classification [11]. Their works usually have a hypothetical condition where the number of classes is static during training phase. In this paper, we focus on incremental adding new classes in context of online odor recognition. The common way of standard deep learning model deal with a new class is retraining the model on the changed training dataset from scratch. This method has two serious drawback. First, since the structure of deep neural network become more and more complex, retraining a network would need consume a lot of computing resource. Second, the total training dataset must be stored for retraining. These two condition is difficulty implemented in portable odor recognition device which has not strong computing power and large storage space. Below we describe the training method for DNCM which exploit the nature of NCM for incorporate the new classes at near zero cost, and the ability of DNN to extract feature. The learning procedure can be divided into two phases: initial training and updating training.

**A. Initial training**

We assume already existing initial training dataset \( \mathbb{D}^\Delta = \{(x_1^\Delta, y_1^\Delta), (x_2^\Delta, y_2^\Delta), \cdots, (x_n^\Delta, y_n^\Delta)\} \) which is composed of \( n \) labeled samples \( (x_i^\Delta, y_i^\Delta) \) where \( x_i^\Delta \) is a signal of gas sensor of an odor at one moment, and \( y_i^\Delta \) is a class label which denote the class that \( x_i^\Delta \) belonged. \( y_i^\Delta \in \{1, 2, \cdots, k\} \). The whole training procedure is to iterate the following three steps:

1) First, the all sample \( x_i^\Delta \) from training dataset will be transformed to feature vector \( v_i^\Delta \) by feature extractor.

\[
\tilde{\mathbb{D}}^\Delta = f(\mathbb{D}^\Delta) = \{(v_1^\Delta, y_1^\Delta), (v_2^\Delta, y_2^\Delta), \cdots, (v_n^\Delta, y_n^\Delta)\}
\]

where \( v_i^\Delta = f(x_i^\Delta) \), and \( f(\cdot) \) is the feature extractor defined in formula (2).

2) The class mean (center) is computed in the feature space by formula (6)

3) Leveraging the loss function \( \mathcal{L}(\mathbb{D}^\Delta) \) (defined in formula (9)) and standard deep learning optimization to fine-tune the parameters of feature extractor.

The specific implementation of initial training is summarized in Algorithm 1.

**B. Updating training**

After finish the initial training phase, the feature extractor are fixed from this point onwards and shared. This idea is inspired by transfer learning [31, 32] and k-shot learning [42]. The trained feature extractor can extracted deep feature vector from new training data (see fig. 2). The “new” means that samples from new classes or new samples from existing classes. The new training data become available in an open-ended fashion, \( \mathbb{D} = \{(x_1, y_1), (x_2, y_2), \cdots\} \). For each \( x_i \), it will be inputed into feature extractor to get its feature vector \( v_i = f(x_i) \), then the \( v_i \) will be used to update \( c_i \), the mean of class \( y_i \). The algorithm is summarized in Algorithm 2.
In this section, we experimentally evaluate our proposed Deep Nearest Class Mean Model (DNCM) which compared with related incremental algorithms under various experimental settings.

In the following, we first describe the data sets and the experimental setup used in our experiments. Then, we compare the proposed model to others mainly in four aspects: 1) accuracy comparison; 2) efficiency comparison; 3) impact of dimensionality of the feature; 4) impact of number of the categories.

A. E-nose system and Experimental Setup

All experimental data developed in this paper were measured by a portable electronic nose system named pen3 in our laboratory. The pen3 E-nose system is based on a 10 different semi-conductive metal-oxide gas (MOS) sensor array positioned into a very small chamber. It operates with filtered, ambient air as a carrier-gas at a flow rate of 100-200 mL/min, sample-chamber temperature of 15-25 °C, humidity 40%-80% and sensor-array operating temperature of 200-500 °C. During the measurement, gas sensors’ response output will be recorded every second. For each measurement, the steady sensor response value is extracted, and as a result, a 10-dimensional raw data vector is recorded.

B. Experimental Data

In this paper, to verify the effective of our proposed model in incremental classification, we divided the benchmark dataset have to two parts: initial datasets and incremental dataset.

1) Initial Dataset: This dataset is a static and reasonable large dataset, which is used for training the deep feature extractor. It includes ten classes, which each has 500 samples.

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**Algorithm 1: DNCM initial training algorithm**

**Input:**
the training dataset $\mathbb{D}^\Delta = \{(x_1^\Delta, y_1^\Delta), (x_2^\Delta, y_2^\Delta), ..., (x_n^\Delta, y_n^\Delta)\}$
where $x_i^\Delta \in \mathbb{R}^D$ is a signal of gas sensor of an odor,
$y_i^\Delta \in \{1, \cdots, K\}$ is the class label

**Initial:**
parameter of feature extractor: $W = [W_0, \cdots, W_{n-1}]$
learning rate: $\delta \in (0,0.1)$
momentum: $\gamma \in (0,1)$
velocity: $t = 0$

**Procedure:**
while epoch $<$ max_epoch do
1) Compute feature vectors of training samples
   for $i=1$ to $n$
do $\hat{v}^\Delta_i = f(x_i^\Delta)$ ($f(\cdot)$ defined in (2))
2) Compute the class mean in feature space
   for $k=1$ to $K$
do $c_k^\Delta = \frac{1}{N_k^\Delta} \sum_{i \in \text{class } k} \hat{v}^\Delta_i$
3) Using stochastic gradient descent method for fine-tune the parameter $W$
   for mini_batch $\mathbb{B}$ in $\mathbb{D}^\Delta$
do $t = \gamma \cdot t + \delta \cdot \frac{\partial L(\mathbb{B})}{\partial W}$ ($L(\cdot)$ defined in (9))
   $W = W - t$
4) if stop condition is satisfied then
   break
output: parameter $W$
2) Incremental Dataset: Totally 3 types (Chinese herbs, fruits, textile), 25 specific classes odor were collected in incremented dataset. The detail description of the initial dataset is presented in Table I. For verifying the effective and efficiency of our proposed model, during the experiment, we will use this dataset to simulate a dynamic dataset. In other words, we consider the data in this dataset is dynamically increasing, where not only the amount of odor samples, but also the number of odor classes increases over time.

For intuitive observing, the scatter points of three classes among the initial and incremental datasets respectively are show in Fig. 3(a) and Fig. 3(d), from which we observe that in both datasets, data points from different classes are almost clustered. In this paper, the proposed model try to training a feature extractor on initial dataset, then using it to data of increasing new class which never encountered before.

C. Parameter of DNCM

The proposed DNCM is composed of two parts. The deep feature extractor can be view as a deep neural network which has multiple layers. In experiments, we set the feature extractor have 3 full connected layers, the number of neurons in the three layers is 64, 32, 20 respectively. The active function of each neuron is uniformly Rectified Linear Unit (ReLU). Although more advanced network structure maybe improve the results, the design and evaluation of network structure is not the focus of this paper. In NCM classifier, we choose the Euclidean distance to measure the difference of two feature vectors.

D. Training Protocol

DNCM can continue incorporating information from new class, but not need retrained from the scratch. The training process of DNCM is divided into two phase. Initial training phase: The output of this phase is a deep feature extractor. The incremental dataset is not available in this phase. That is, the proposed DNCM model is trained only on initial data. 70%, 10% and 20% of the initial dataset were used as training, validation and testing dataset which were randomly choose 50 times, and the performance is measured using average result. The training algorithm for neural network is Stochastic Gradient Descent (SGD), mini-batch size is 16. The initial learning rate is 0.001, which is decayed by 0.5 for 15 iterations. Momentum is set to 0.9. Training algorithm is iterated 100 times. DNCM updating phase: In this phase, the new class data from the incremental dataset will continue valid in sequence, one sample at a time.

E. Compared methods

To show the effectiveness and efficiency of our proposed model, we compared it with baseline NCM and k-nearest neighbors (KNN) method, and the two current state-of-the-art incremental

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**Algorithm 2: DNCM updating training algorithm**

**Input:**
The incremental dataset $\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \ldots\}$, where $x_i \in \mathbb{R}^D$ is a signal of gas sensor of an odor, $y_i \in \{K + 1, \ldots\}$ is the class label.

**Initial:**
- Mean of classes: $c_k = 0$
- Number of samples of classes: $N_k = 0$

**Procedure:**

for each $x_i$ in $\mathcal{D}$ do

1) compute the feature vector $\mathbf{v}_i$ of $x_i$

$\mathbf{v}_i = f(x_i)$ ($f(x_i)$ is defined in (i))

2) updating the mean of class $y_i$

$c_{y_i} = \frac{N_{y_i}}{N_{y_i} + 1} c_{y_i} + \frac{1}{N_{y_i} + 1} \mathbf{v}_i$

$N_{y_i} = N_{y_i} + 1$

**Output:**
The mean of new classes: $\{c_{K+1}, c_{K+2}, \ldots\}$
learning methods which including NCMML [21] (NCM + Metric Learning), and NCMF [23] (NCM + Forest). For the compared approach, the parameters were optimized by cross-validation on initial dataset.

![Image](image1.png)

Fig. 3. We randomly choose data points of three classes from initial dataset and incremental dataset respectively. For visualization, the dimension of data points is reduced to 2 by PCA methods. (a), (b) and (c) show that data points in the initial dataset transformed by nothing, half and full trained DNCM respectively. So do (d), (e) and (f), except a different dataset — incremental dataset. The half (full) trained DNCM means that the DNCM finish half (full) training iterations. From (a) to (c) show that by training DNCM with these data points (initial dataset), we can find a feature space in which data points of different classes can be separated. Compared original data space, in this feature space, the accuracy of classification is higher by the same classifier. From (d) to (f) show that DNCM can produce the same effect on data points in incremental dataset, although these data points have never been used to train the DNCM.

**F. Results**

In this section, the experimental results on initial dataset and incremental dataset are reported to evaluate the proposed DNCM method.

We first observe the intuitive results in fig. 3 which plots the scatter feature vector of three different classes from initial and incremental dataset respectively in three stage of the feature extractor. Fig. 3 (a), (d) show that the raw feature vectors of both datasets are cluster, then is not easy to classify them from each other. Fig. 3 (a) to (c) show that data point of different classes from initial dataset can be separated in new feature space by using trained deep network to extract features. Fig. 3 (d) to (f) show that this feature extractor can produce the same effect on data from new class, although these data are not used to train the extractor as the data from initial dataset. This qualitatively verifies the deep feature extractor which trained on already existing dataset could produce the same effect on data in new classes.

In fig. 4 we analyze the odor classification accuracy and testing time with respect to different number new class from incremental dataset. In real odor classification applications, such as Chinese herbs classification by odor, when we need classify a new herb, probably it is unable to collect large samples for training. So the number of samples in new classes is set to be relatively small, just 10. Fig. 4(a) shows that when the number of new class is less than 10, our proposed model DNCM has little higher accuracy than other models except baseline NCM. With the number of new classes increases, the DNCM’s advantage in term of accuracy become more apparent. When the number of
new classes equal 25, the DNCM achieves 75.7% accuracy, which is almost 8-10% improvement over NCMML and NCMF, and 3.5% improvement than KNN. For NCM, NCMML, NCMF and DNCM, training on new data is only update its' original model. We show the testing time in Fig. 4(b). The DNCM, NCMF, NCMML, baseline NCM only related the number of classes $K$, their time complexity is $O(K)$. So their test time has grown very low. The testing time of KNN method relates 2 components: the number of samples: $N$ and the number of classes: $K$. Its time complexity is $O(N \times K)$. Because $N \gg K$, its testing time grow rapidly as the number of class increase.

As described in previous paragraph, in some situations, it is difficulty to collect many training samples. When fixing $K = 25$, we discuss the impact of $N_k$, the number of samples in each new class, as shown in fig. 5. From $N_k = 10$ samples down to 3, DNCM significantly outperform other methods in term of accuracy, especially the $N_k$ is close to 3, as shown in fig.5 (a). The accuracy of DNCM archives 71.39%, the following is NCMML 59.98%, NCMF 59.36%, and KNN, NCM respectively is 55.75%, 52.98%. So DNCM is almost 12% improvement in comparisons. As the reason mentioned in previous, the testing time of KNN has grown much faster respect to the number of samples than other methods.

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**Fig. 4.** Measurements at variable number of new classes for an incremental learning start with ten initial classes. DNCM achieves 75.7 percent of accuracy at 25 new classes, this is advantage to other NCM based methods. The accuracy of KNN is closed to DNCM, but its testing time increase rapidly with the number of classes. However, the testing time of DNCM, likes other NCM based model, just increases very slowly.

**Fig. 5.** Measurements at variable number of training samples of each new classes. (a) shows that DNCM outperforms other methods in terms of accuracy on different number of training samples. Especially, when the number of samples equals 3, the recognition accuracy achieves 71.39%, which is 10% improvement in comparisons. DNCM and other NCM based methods are less sensitive to the decrease in the number of training samples than KNN. The accuracy of KNN dropped most significantly. (b) shows that testing time of KNN increases linearly with the number of samples.
The detailed performance of the DNCM on incremented dataset is showed in Table I. We can see that the DNCM has advantage. This is because the deep extractor which was trained on initial dataset can be generalize to the new classes that it never see. We just leverage this characteristic of deep neural network to propose DNCM.

G. Effect of Parameters

In the proposed DNCM model, there are two important parameters of training dataset: the number of classes ($K$) of initial dataset and number of samples ($N_k$) in each class of incremental dataset. To observe the accuracy with respect to the two parameters, we show the results of the different configuration of them, in Fig. 6. We can see two phenomena. First, the accuracy of DNCM will increase as $K$ and $N_k$. This is consistent with the common sense of machine learning, the more training data the more accurate the model. Second, when the number of initial classes $K$ is small ($K \leq 4$), the accuracy of DNCM varies widely among different number of new classes $N_k$. However, when $K$ is large ($K \geq 8$), the accuracy of DNCM varies slightly among different number of new classes $N_k$. This means that increasing the number of classes in initial dataset can prevent, to some extent, a reduction in the prediction accuracy due to an increase in the number of new classes.

![Accuracy variation curves of different number of new classes with respect to the number of initial classes by frozen the number of training samples. (a) ~ (h) show the results of 6~20 training samples, respectively.](image)

H. Discussion

In this paper, we evaluate the algorithms from two aspects: testing time and classification accuracy. From the results shown in Fig. 4(a), Fig. 5(a), we observe that the accuracy of DNCM advanced the two current state-of-the-art incremental learning methods. Although, in some parameter setting, the accuracy of KNN is close to DNCM, KNN has some inherent disadvantages. It have to store all of training data and compute the distance between testing sample and each training sample. So it need large storage space and long test time which is shown in Fig. 4(b) and Fig. 5(b). Because of these characteristics, KNN is not suitable for some real incremental classification applications, such as embedded classification chip, real time classification equipment and so on. Conversely, DNCM don’t need store all training samples. While a new class appears, it just need store the mean of this new classes. So it requires only a small amount storage space and short test time while maintaining accuracy. DNCM is suitable a wide range of real incremental classification applications.

VI Conclusion

In this paper, we have proposed an incremental deep neural network model, namely deep nearest class mean (DNCM) model for incremental multiclass odor classification. The proposed
incremental deep learning model presents a new framework that combines standard deep learning model with nearest class mean (DNM) classifier for handling the number of classes grow over time. The core idea of DNCM includes two aspects. One is that using deep neural network to find a feature space where different classes’ samples is separated in this space. This feature space is valid not only for the data (initial dataset) already used for training, but also for new and untrained data (incremental data). Another, to overcome the limitation that standard deep neural network (DNN) can only deal with static training dataset, we extend DNN to an incremental learning model by integrated NCM to DNN.

| TABLE I | Comparison of recognition accuracy on incremental dataset with 20 training samples and 10 initial classes |
|---------|--------------------------------------------------------------------------------------------------|
| Type    | New Classes | DCM | NCMML | NCMF | NCM | KNN |
| Chinese herbal | Musk         | 99.85% | 81.71% | 68.89% | 67.78% | 93.89% |
|          | Centella     | 66.11% | 46.29% | 75.56% | 40.00% | 71.11% |
|          | Microcos     | 78.89% | 57.71% | 72.22% | 71.67% | 85.56% |
|          | sand ginger  | 98.89% | 84.00% | 75.56% | 81.67% | 87.22% |
|          | Cardamom     | 73.89% | 69.71% | 65.00% | 66.11% | 71.11% |
|          | Cucumaria aromatica | 84.44% | 81.71% | 71.11% | 78.33% | 80.00% |
|          | Orthosiphon aristatus | 82.78% | 95.43% | 92.78% | 91.11% | 93.33% |
|          | Bombax ceiba | 66.11% | 84.00% | 87.22% | 83.89% | 86.67% |
|          | Eriobotrya japonica | 62.22% | 30.29% | 64.44% | 28.33% | 53.89% |
|          | Leonurus artemisia | 71.67% | 40.00% | 48.89% | 28.89% | 53.89% |
|          | Rabdosia serra | 88.33% | 74.29% | 66.67% | 68.33% | 80.00% |
|          | Atractylodes lancea | 94.44% | 88.57% | 78.89% | 82.22% | 86.67% |
|          | Paederia foetida | 95.56% | 83.43% | 73.89% | 68.33% | 85.00% |
| Fruit   | Dragon fruit  | 70.00% | 75.43% | 59.44% | 54.44% | 70.00% |
|          | jujube        | 58.89% | 49.71% | 58.33% | 55.56% | 47.78% |
|          | Mango         | 79.44% | 29.71% | 59.44% | 25.00% | 71.67% |
|          | nectarine     | 78.89% | 61.14% | 61.67% | 54.44% | 67.22% |
|          | Melon         | 58.33% | 56.00% | 32.22% | 57.78% | 60.56% |
|          | orange        | 94.44% | 86.29% | 89.44% | 53.89% | 82.78% |
|          | lemon         | 76.67% | 54.86% | 79.44% | 56.11% | 88.33% |
|          | banana        | 70.00% | 98.86% | 56.11% | 86.11% | 86.11% |
|          | tomato        | 79.44% | 72.57% | 75.00% | 76.11% | 81.11% |
|          | Mixed         | 61.67% | 46.86% | 47.78% | 53.89% | 47.22% |
|          | Cotton        | 81.11% | 74.29% | 68.89% | 72.78% | 89.44% |
|          | Wool          | 80.00% | 71.43% | 46.67% | 71.11% | 67.22% |
|          | Average       | 78.09% | 67.77% | 68.69% | 62.96% | 75.51% |

Finally, our experiments on the odor dataset show the proposed DCM compared with traditional NCM, KNN, and state-of-the-art incremental learning methods: NCM+Metric Learning (NCMML) [21], NCM Forest (NCMF) [23].

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