Disease Analysis In Deep Learning: A Survey

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Abstract- *The traditional dictionary learning method neglects the relation between the sample and the dictionary atom. This paper produces the new weighted mechanism to connect the sample and the dictionary atom. This paper produces the new algorithm namely greedy deep weighted dictionary learning for mobile multimedia for medical disease analysis. The traditional dictionary learning had caused over-fitting for the patient classification. Over-fitting refers to training the model too well and during training the model learns the noise also and this training negatively impacts on the performance and it also negatively classifies the newly occurring training data. In order to avoid such over-fitting problem this paper adopts l2-norm regularization constraint which realizes the limitation of the model. This paper adopts the layer by layer approach for training so that the local information between the hidden layers can be increased to maintain their own characteristics and also this training approach makes sure that every layer in the network is convergent and it also increases the accuracy of the training. The method proposed in this paper works better with the internet of things and it has better reliability in the field of mobile multimedia for healthcare. The proposed method gives the good classification effect of mobile multimedia for medical disease analysis and in this paper we compare the results of the proposed methods with other existing methods and check for the accuracy.*

Keywords- Dictionary learning, mobile multimedia, deep learning

I. INTRODUCTION

Nowadays the internet of things (IOT) is getting importance among the healthcare stakeholders [1] and healthcare monitoring as a powerful technology. So by implementing the internet of things we can make better classification of patient's diagnosis.

Deep learning is the subfield of machine learning which is based on the learning representation of the raw data and it contains 3 layers input and hidden and output layers. Nowadays machine learning and deep learning are inseparable from people's lives. It is used in almost all the fields such as in medical diagnosis, weather forecasting, recommendation system and object detection etc. Deep learning has formed a mainstream object recognition algorithm based on R-CNN [2], and algorithm is refreshing the higher accuracy. With the promotion of wisdom medical care the medical big data is closely interrelated with the machine learning which is better for the development of the internet medical [3].

This is the era of data and there is a massive amount of data released day by day which has to be maintained properly else we may lose the data but maintaining such large amount of data is very difficult especially in the field of medical data, we are supposed to maintain the patient data properly. Hence to maintain such massive data big data came into picture. The concept of big data slowly began to get prominence in 2008. In the special issue of science the big data is defined as "represents the progress of human cognitive process, the size of the dataset is not in tolerable with current technology, methods and theory to obtain, manage ,deal with[4]". The characteristic of big data is summarized as 4V that is Volume, Velocity, Variety, and Value. In traditional days the doctors for diagnosis of the patient they used to rely on their own knowledge or on clinical symptoms but sometimes this led to diagnostic errors. This has urge to the automated patient classification methods that are conducive for the effective diagnosis. We have studied the changes in activity of various regions of the brain through BOLD techniques and functional magnetic resonance imaging (FMRI) techniques[5][6]. All studies of each patient will be saved and by using internet of things the doctors are able to quickly use the relevant patient information. There are several methods for the classification of diagnosis of the patient. The methods used in this paper assist the doctors for the better treatment of patients through accurate calculation and accurate prediction. In the study of classified medical data from nuclear magnetic resonance imaging, predecessors have extended a series of methods from dictionary learning to make corresponding contributions in this respect. The original dictionary learning was used for signal reconstruction, but later the researchers applied the classification by means of the label information to supervise the learning. The classification methods of dictionary learning are broadly divided into two categories: one is to directly learn the dictionary with recognition and the other is sparse representation. Wright et al [7] proposed sparse representation based classification (SRC) to deal with facial recognition problems, which adopts l1-

norm regularization constraint to ensure the sparsity of coding coefficients. The SRC has a strong robustness to noise on the light and shade. Later, there are many people who offer to learn a self-adapted dictionary for each class in order to improve the previous method . At the same time, for the study of dictionary learning, the researchers began to learn from another point of view in-depth study. This method is to make the sparse coefficient of identification, which only need to train to learn a whole dictionary and do not require each class separately to learn corresponding dictionary. Zhang and Li [8] proposed an improved K-SVD (D-KSVD) based on the K-SVD to construct a dictionary to sparse represent the data and achieved a good representation of the dictionary. Yang et al. [9] proposed the Fisher Discriminant Dictionary Learning (FDDL) distinguishing between different classes by representing the remainder. This method requires the divergence is small in the class and the divergence of interclass is larger. Vu et al. [10] proposed a simple and effective image classification method named discriminant feature oriented dictionary learning (DFDL). This method emphasizes the similarity of intra-class and the direct differences of inter-class.

II. DATASET

We obtained the required data from the Chinese Academy of Sciences Institute of Automation, and used data from depression as training data, then validated the efficiency of our method with a resting-state fMRI database of attention deficit hyperactivity disorder (ADHD). The data were from the ADHD-200 sample for global competition/). In this paper, we choose 30 data sets of depression as a training set. Which get through transforming the pictures that we get from some mobile devices, such as smartphones, PDA, into digital information through a series of tool. In order to rationalize the data distribution and randomness, we select local people and the number of health and patients of each 15. At the same time, the number of health and patients also include eight men and seven women, whose age is random choice at different stages of a random distribution. All the preparations are to eliminate the influence of additional factors on experimental data. Through training of the training set, we use the data set of ADHD to verify our results in detail, to make experimental analysis and draw conclusions.

III. DATASET PROCESSING AND DEEP BOLTZMANN MACHINE

On one hand, the pictures obtained through some mobile multimedia devices are not clear. On the other hand, it might contain some noise that the clinical data we obtained from the Institute of Automation of the Chinese Academy of Sciences, which is not what we want. Meanwhile, the data we get are too complicated, and some interfering data may interfere with the experimental results and affect the results of the tests. In order to ensure data purity and the correctness of the experiment, we have data source processing to exclude irrelevant data. uses a series of processing methods, such as Statistical Parametric Mapping Resting-State fMRI Data Analysis Toolkit to ensure the effectiveness of data.

The construction of deep Boltzmann machine (DBM) on the basis of the Restricted Boltzmann machine (RBM). Unlike the RBM with only one hidden layer, DBM has multiple hidden layer structures. As shown in Figure 1, it is the Boltzmann machine structure with the three hidden layer. RBM is usually an unsupervised learning model, but some researches use class labels to training discriminative Boltzmann machine, and if the hidden layer unit exceeds the corresponding threshold, they will carry on corresponding processing to control the sparseness of learning. Deep Boltzmann machine is a non-directional learning model, this feedback mechanism is conducive to manage the uncertainty of learning model, which is different from those top-down or bottom-up multi-layer network learning architecture. In the unsupervised way to train a number of restrictions Boltzmann machine, and then reached a good classification effect through the composition of the deep confidence network.

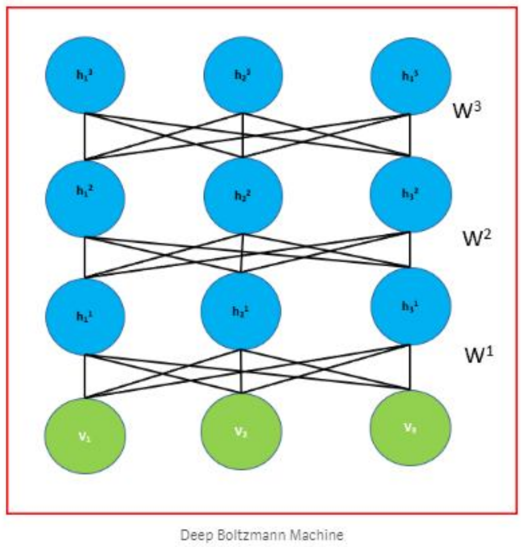

Figure 1 –Deep Boltzmann machine [11]

IV. DICTIONARY LEARNING

Dictionary learning can be simple called sparse coding. We understand the dictionary learning from the perspective of matrix decomposition. In fact, it is equivalent to a given data set X and each column of the matrix X represents a sample. The goal of dictionary learning is to make matrix X decompose into matrix D and matrix K.

$$X=D*K$$

Where D represents the dictionary and K represents the coefficient matrix and it is as sparse as possible.
In practice to carry out the dictionary learning we can directly create the objective function :

$$F= \underset{D,K}{\operatorname{argmin}} \|X-DK\|^2$$

Such that $\|X\|<=L$

Where L is a constant, which is a sparse constraint parameters. It needs to deal with the corresponding to meet the experimental needs when a certain threshold is not satisfied. For the dictionary learning, there are many other methods of research on the original basis.

V. A GREEDY DEEP WEIGHTED DICTIONARY LEARNING

1) OBJECTIVE FUNCTION

After the data-preprocessing, we must extract the data information and the extracted data information is expressed in the form of matrix and it is denoted by $X^t \in R^{m\times n}$ where m represents the number of brain regions and n represents the time code series. In order to better express the training we need to divide the training group into two groups namely disease group (DG) and health group(HG).And the health group is represented by X matrix and disease group is represented by the matrix $X^{\tilde{}}$. By training we are supposed find out the dictionary that is D which contains the sparse representation of health group. And we must find out the dictionary D~ which contains the sparse representation of the disease group, it is represented by figure 3.

$$F = \underset{D,K,\tilde{K}}{\arg\min} \left(\frac{1}{C} \sum_{i=1}^{C} \frac{W_i}{W} \|x_i - Dk_i\|_2^2 - \frac{\rho}{\tilde{C}} \sum_{j=1}^{\tilde{C}} \frac{\tilde{W}_j}{\tilde{W}} \left\|\tilde{x}_j - D\tilde{k}_j\right\|_2^2 \right)$$

Fig 3-objective function

Where c = np is the number of columns of X, D is the sparse representation dictionary for the entire training group, xi is the column vector of X, ki is the coding coefficient of xi , wi is the weight coefficient of xi , W is the sum of each column vector of the weight ratio. Similarly, C˜ = nq is the number of columns of X˜ , x˜j is the column vector of X˜ , k˜ j is the coding coefficient of x˜j , Wj is the weight coefficient of x˜j , ρ is the regularization parameter. The first expression of the objective function emphasizes that the difference in the internal class is small during the classification process, and the second expression emphasizes the difference between the class and the class. The objective function is set up in order to balance the sparseness of the sample, and to better represent the effect of classification. It is to improve the accuracy of the classification using weight, to ensure that the various samples fluctuate within their reasonable range and matches better with real situation.

The matrix decomposition mentioned above is equivalent to a single-layer neural network, and the algorithm proposed in this paper is based on multi-layer dictionary learning, that is, , multi-layer matrix decomposition: X = D1 ∗ D2 ∗ . . . ∗ K . The shallow dictionary learning is a non-convex optimization problem. It will make the problem becomes more complex while increasing the hidden layer, and multi-layer dictionary learning to participate in the parameters greatly increased, and sometimes it easily cause the phenomenon of over-fitting in the limited training samples. Therefore, this paper adopts the study thinking of layer-by-layer training based on the previous study, using a similar approach to the method of SAE and DBN. The objective function is modified on the basis of the original. The layer-by-layer training makes ensure that each layer is convergence and the entire training process is perfect and effective.

In fact, the process of deep learning is the first training to learn the feature K1 and the weighted dictionary D1 of the first layer.

$$X = D1 * K1$$

Then learn we treat the feature K1 learned from training of the first layer as input of the second layer to learn, and then get the second feature K2 and the weighted dictionary D2

$$K1 = D2 * K2$$

And so on, you can achieve deeper dictionary learning. In the whole process of training, in order to ensure more accurate classification, reduce the coupling between class and class, increase the cohesion within the class, better reflect the authenticity of the data, avoid cause problem of the deep neural network error accumulated too long and reduce the error, we hope to get a dictionary each layer can satisfy:

$$Di * Ki = Xi$$

$$Dj * Ki = 0$$

ALGORITHM :

1. Parameter Initialization that is initialize the atoms of Di as the feature vectors of Xi.
2. Input
   Matrix X and X˜, dictionary size r and regularization parameter.
3. core process
   a) While training layer is not the last one do
   b) Update the weight
   c) Fix D, update K and K˜.
   d) Fix K and K˜ and update di.
4. Output
   return to step 3 until the objective function reaches to the optimal solution

VI. CONCLUSION

This paper proposes a novel method of deep learning, GDWDL, which applied to the classification of mobile multimedia for medical diseases. With the help of mobile multimedia technology, we timely follow-up observation to patients and exchange the collected information into data information. It can better and more effectively classify the patients, taking into account the large amount of data on the basis of large data accumulation Complex and difficult. Using the weight method to measure intrinsic relation between the sample and the dictionary atom, we deal with the over-fitting phenomenon for the limited training set through l2-norm regularization constraint. At the same time, we introduce the model of the deep network learning, and make local information between the layers train to ensure that each layer is convergence, layer by layer to promote their own characteristics, in order to achieve the best classification effect. The combination of healthcare and machine learning can play a great role in machine learning, and better improve efficiency in the field of mobile multimedia for healthcare. Although the proposed algorithm is superior to other algorithms such as FDDL and DFDL, this is only the result of experimental verification on depression and ADHD data sets. There are some shortcomings to be further study in the future

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