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Deep Belief Network Architecture and Their Applications – A Survey

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***Abstract*—** Deep learning has proven to be beneficial for complex tasks such as classifying the image, pattern recognition, speech recognition, natural language processing, and recommendation systems. Autoencoder, Restricted Boltzmann Machine, Deep belief Network and Convolutional Neural network are four different types of architecture used in deep learning. Deep Belief Network is now the new the state of the art for many fields of machine learning research. The main aim of this survey is to widely cover deep belief network architecture and their practical applications such as computer-aided diagnosis for the dreadful diseases, pattern recognition and also in the field of industry. The proposed work helps to improve the classification performance for breast cancer to a certain extent, which provides a good direction for the future classification of breast cancer. At last, the limitations of Deep Belief network and list of future research information has been given.

***Keywords*—** deep learning, autoencoder, restricted Boltzmann machine, deep belief network, convolutional neural network.

I. Introduction

Machine learning is generally used for image, video and text recognition. In the current trend, it is also used to strengthen the cyber security, ensure public safety and improve medical outcomes. It can also help improve customer service and make automobiles safer. Machine learning can identify patterns the humans tend to overlook or may be unable to find as fast in vast amounts of data. Most of the organizations are making new discoveries, as well as to identify and remediate issues faster by using machine learning. Meanwhile, deep learning, a sophisticated branch of machine learning, is gaining popularity. It requires massive amounts of data and massive processing power. In enormous cases, deep learning is being used in tandem with machine learning to improve products, such as lowering the number of false positives in security breach detection software. Some organizations are using deep learning is to computerize more of the machine learning lifecycle. Machine intelligence and human intelligence are comparatively often paired to overcome the limitations of rule-based systems.

Deep Learning [19] is a subfield of machine learning concerned with algorithms motivated by the structure and function of the brain called artificial neural networks. Since 1980s, Artificial neural networks have been popularly used in wide research areas. The well-known ANNs of predictors can be listed as the multi-layer perceptron, recurrent neural networks, radial basis function networks and many varieties of them. The processes of training the ANNs, gradient descent methods are often used. The most popular supervised learning algorithm is Backpropagation. The main drawback of BP algorithm depends on the size of the training data. If the training data is not big enough, then the NNs will face the problem of over-fitting. As BP is based on local gradient information with a random initial point, the algorithm often gets trapped in local optima. In the way, there are other effective machine learning algorithms such as support vector machine (SVM), Naïve Bayesian, k-nearest neighbour (KNN) and Random Forests adopted to obtain global optimum with lower power consumption.

In order to overcome the drawback, G. E.Hinton [2] introduced Deep Belief Networks. In contrast to perceptron and backpropagation neural networks, Deep Belief Network is unsupervised learning algorithm. Deep Belief Network is an effective method of solving the problems from neural network with deep layers, such as low velocity and the overfitting phenomenon in learning.

In the proposed work, to implement the DBN with Chebyshev function to improve the accuracy of classification of breast cancer after obtaining network weight from the pre-training unsupervised phase. Also, use the PCA to emphasize variation and bring out strong patterns in a dataset.

The content of this paper is organized as follows: In Section II, theoretical basis and the architecture of the DBN are introduced. In Section III, explain the applications of DBN in the various field with the summary of the research papers have been discussed. In Section IV, the outline of the proposed work has been given. Finally, Section V states the conclusion and future research related information.

II. DEEP BELIEF NETWORK ARCHITECTURE

Deep Belief Network is a class of deep neural network which comprises of multiple layers of the graphical model having both directed and undirected edges. It is composed of multiple layers of latent variables namely hidden units, with the connection between the layers, but not between units within each layer [3].

A. The motivation

When trained on a set of examples without supervision, a Deep Belief Network can learn probabilistically to reconstruct its inputs. The layers then act as feature detectors. In the next step, a DBN can be further trained with supervision to perform classification. DBNs [3] can be viewed as a composition of simple, unsupervised networks such as Restricted Boltzmann Machines (RBMs) and autoencoders, where each hidden layer serves as the visible layer for the next. An RBM is an undirected model with a "visible" input layer and a hidden layer and connections between but not within layers. This work leads to speed-up the unsupervised training procedure layer-by-layer, where contrastive divergence is applied to each sub-network in turn; starting from the lowest pair of layers [19].

B. The structure and the algorithm

Deep Belief Networks (DBNs) [3] are the deep architecture that uses the stack of Restricted Boltzmann Machines for the pre-training phase and then a feed-forward network for the fine-tuning phase. Fig. 1 shows the network architecture of a DBN

In the pre-training phase, an unsupervised learning based training is carried out in the down-up direction for feature extraction; while in the fine-tuning phase, a supervised learning based up-down algorithm is performed for further adjustment of the network parameters. The schematic diagram of the model is shown below in Fig. 2

It can be seen from Fig. 2 that in a DBN, every two adjacent layers form an RBM. The visible layer of each RBM is connected to the hidden layer of the previous RBM and the top two layers are not directional. The directed connection between the above layer and the lower layer is in a top-down manner. Different layers of RBMs in a DBN are trained sequentially; the lower RBMs are trained first and then the higher ones. After that features are extracted by the top RBM, they will be propagated back to the lower layers. Compared with a single RBM, the stacked model will increase the upper bound of the log-likelihood, which implies stronger learning abilities.

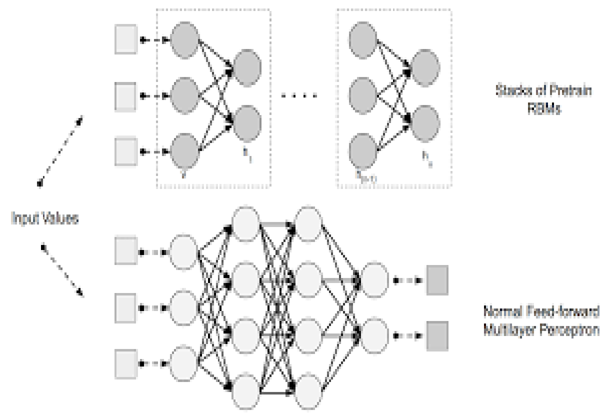

Figure 1. DBN Architecture

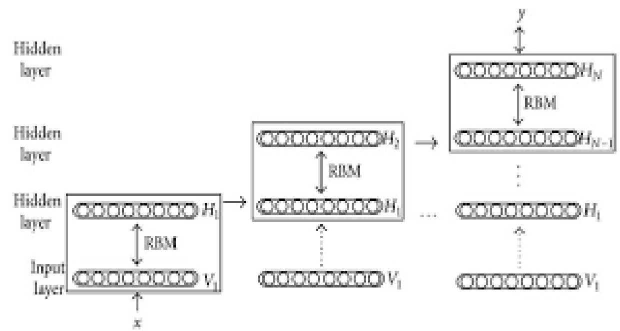

Figure 2. The schematic diagram of the model

In a Restricted Boltzmann Machines, only one layer of hidden units is independently connected with the visible state without connection between hidden units. It is shown in the diagram given below Fig. 3.

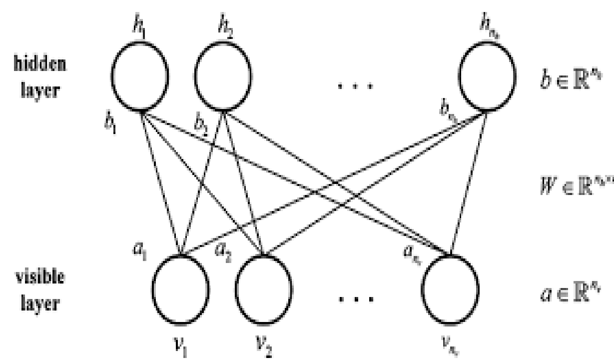

Figure 3. A Restricted Boltzmann Machines model

In the pre-training phase to train an RBM, the Gibbs sampler is adopted. The training process will be more efficient when using the gradient-based contrastive divergence (CD) algorithm. The CD algorithm for RBM training was developed by Hinton in 2002 [20].

1) Take the training dataset, set the states of the visible units to the training dataset.

2) Positive Phase: Update all the hidden units in parallel by using following equation i.e., compute positive statistics for edge E_{ij} Positive (E_{ij}), which is $P(H_i=1/V)$.
   The individual activation probabilities for hidden layer units can be given as
   $P(H_j=1/V) = \sigma\{B_j+\sum_{i=1}^{m} W_{ij}V_i\}$. (1)

3) Negative Phase: Reconstruct the visible units using the similar technique, as given in the following equation i.e., compute negative statistics for edge E_{ij} Negative (E_{ij}), which is $P(V_i=1/H)$.
   The individual activation probabilities for visible layer units can be given as
   $P(V_i=1/H) = \sigma\{A_i+\sum_{j=1}^{n} W_{ij}H_j\}$. (2)

4) Update the weight of edge:
   The updated weight updt (W_{ij}) of edge (having previous weight) W_{ij} can be given as
   $updt(W_{ij})=W_{ij}+L*(Positive(E_{ij})-Negative(E_{ij}))$ (3)
   where 'L' is learning rate.

Repeat with all training example. (Till the required threshold achieved).

The performance, however, is usually unsatisfactory especially when the input data are clamped. In order to overcome this limitation, a greedy layer-by-layer algorithm [3] was introduced which optimizes the weights of a DBN at time complexity linear to the size and depth of the network. In the greedy learning algorithm, the RBMs that constitute a DBN are trained sequentially.

The summary steps of Recursive Greedy Learning procedure for DBN:

1) Fit parameters $W_1$of the first layer RBM to data.
2) Freeze the parameter vector W_1 and use samples "H_1" from $P(H_1/V) = P(H_1/V, W_1)$ as the data for training the next layer of binary features with RBM.
3) Freeze the parameter vector W_2 that defines the 2nd layer of features and use the samples H_2 from $P(H_2/H_1) = P(H_2/H_1, W_2)$ as the data for training the 3rd layer of binary features.
4) Proceed recursively for the next layer.

This training process continues until all the layers are traversed. Since in this algorithm, the approximation of the likelihood function is only required in one step, the training time has been significantly reduced. The under fitting problem that usually occurs in deep networks can also be overcome in the pre-training process.

In the fine-tuning phase, the DBNs are trained with labeled data by the up-down algorithm. To find out the category boundaries of the network, a set of labels are set to the top layer for the recognition weights learning process. The BP algorithm is used to fine-tune the weights with labeled data [21].

The summary steps of Fine Tuning procedure for DBN:

1) Do a stochastic bottom-up pass
   a) Adjust the top-down weights
2) Do a few iterations of sampling in the top-level RBM
   a) Adjust weights in the top level RBM
3) Do a stochastic top-down pass
   a) Adjust the bottom-up weights.

In the simple form, the training process of a DBN includes an unsupervised layer-by-layer pre-training procedure performed in a bottom-up manner and a supervised up-down fine-tuning process. The best initial value for the weights can be obtained through pre-training phase and then used to adjust the entire network by the up-down algorithm. Moreover, the overfitting and underfitting problems can also be avoided [19].

III. APPLICATIONS OF DEEP BELIEF NETWORK

A. Early Detection of Breast Cancer

The early stage of detection of breast cancer will help to improve the treatment in the successful way. For that, they need Computer –Aided Diagnosis (CAD) system in more accurate rate. An accurate classifier is the most important component of any CAD scheme that is developed to assist medical professionals in early detecting mammographic lesion. The use of an accurate CAD system for early detection could definitely save precious lives. In this study, Ahmed M. Abdel-Zaher, Ayman M. Eldieb [1] applied deep belief network in an unsupervised phase to learn input features statistics of the original Wisconsin Breast Cancer dataset. Then, they transferred the obtained network weight matrix of DBN to backpropagation neural network with similar architecture to start the supervised phase. In supervised phase, it has been tested both conjugate gradient and Levenberg-Marquardt algorithm for learning BP neural network. Compared to other classification techniques such as Optimized Learning Quantization methods this performance was 96.7%, Quinlan reached 94.74%, Neuro-Fuzzy techniques obtained 95.06%, Feedforward Artificial neural networks and Back Propagation [14] reached 99.28% and soon on. The highest rate of accuracy was obtained by Deep Belief Network at 99.68%

B. Fingerprint liveliness detection

Fingerprint recognition is one of the biometric authentication methods that have been widely used in forensic, civilian and commercial applications [4]. This method is used to find out a scanned fingerprint is live or fake. In earlier days, fingerprint detection can be done through the hardware-based method which is required more hardware components and specific domain expertise to recognize fake fingerprints. In recent years, researchers have done a lot of work to automate the detection of fingerprint liveliness. With the advancement of image processing technique, researchers proposed different types of deep learning approaches to detect the fingerprint liveliness which gives more accuracy. Soowoong Kim, et al. [5] proposed a method based on DBN. The flowchart of the proposed method is given below.

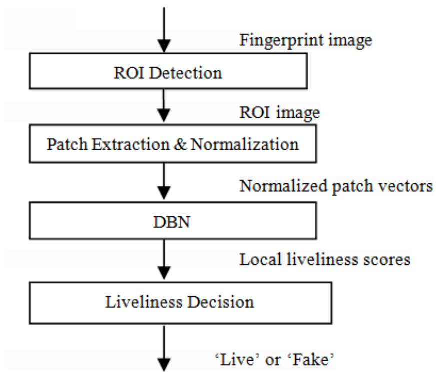

Figure 4. Flowchart of the proposed fingerprint liveliness detection process

A DBN with multiple layers of the restricted Boltzmann machine is used to learn features from a set of live and fake fingerprints and also to detect the liveliness with various sensor datasets. A hypothesis test is set up to determine the liveliness of a given fingerprint based on the outputs of the DBN with multiple patches from the fingerprints. The outputs can be calculated as

$i >= r$: live fingerprint(4)

$i < r$: fake fingerprint

where r is a threshold.

The DBN topology being simple, the computational complexity of the detection method is relatively low.

A. Web spam recognition

The rapid development of the Internet increases the number of web spam gradually, which causes a major problem for the search engine. Any web page content is created to improve search ranking without considering any value for the user is called web spam. Currently, three kinds of web spam are link spam, content spam, and cloaking spam. In last few years, many methods have been developed for detection of web spam and implementation of web spam also increased simultaneously [6]. To overcome the competition requires improving the anti-spam techniques. The present methods [7] have some flaws such as limited expressing and generalization ability, dimension disaster, local optimal and overfitting. Yuancheng Li, et al. [8] proposed a web spam classification method based on the DBN combined with the Synthetic Minority Over-Sampling Technique (SMOTE) and De-Noising Auto-Encoder (DAE) algorithm after the multi-aspect research and consideration. The results showed that the classification method based on DBN improved the classification performance to a certain extent, which provided a good direction for the future classification of web spam.

B. Electricity load forecasting

Electricity load forecasting is of crucial benefit for proper operation, maintenance, and planning of the electric power system. There are four categories of load forecasting according to the time period such as long-term forecasting (1-50years), mid-term forecasting (1month–1year) and short-term forecasting (hour, day or week). The short-term electricity consumption forecasting of at hourly level becomes even more important, especially from the aspect of demand-side management, dynamic integration of renewable energy sources and planning for storage needs [16]. The results of the hourly electricity consumption forecasting may be further used as an input for electricity price forecasting. These predictions may play an important role in decision making for both the power system operators and the market participants.

Electricity load forecasting has proven to be a complex problem, which is non-linear and usually cannot be solved with a simple analytical formulation. Statistical–based models and artificial intelligence based models are used to solve this problem. These methods face the problems such as initialization of the parameters, slow convergence, getting stuck in a bad local minimum.

Hinton G.E., et al. [3] has proposed Deep Belief Network as a solution to these general problems. Aleksandra Dedinec, et al. [9], proposed a DBN made-up of multiple layers of RBM and unsupervised training procedure is followed by fine-tuning of the parameters by using a supervised back-propagation training method. This method [9] has been applied to short-term electricity load forecasting based on the macedonian hourly electricity consumption data in the period 2008-2014. The obtained results are compared with the latest data and also compared with the predicted data obtained from a typical feed-forward multi-layer perceptron neural network. It actually provides superior results than the ones obtained using traditional methods. Using DBN, the mean absolute percentage error is reduced by up to 8.6% for 24h ahead forecasting and for daily peak forecasting is reduced by up to 21%. Also, DBNs are used for load forecasting in the smart gas and water grids.

C. Quality inspection

Traditionally, quality inspection is done by trained experts with different methods through listening to the sound emitted by the product. It is fully dependent on the assessment of the individual expert that brings in the variability in the quality inspection. To overcome this disadvantage many different techniques have been developed. There are signal analysis

Table 1: Summary of Research Work Discussed

Authors	Methods	Performance Metrics
Ahmed M. Abdel-Zaher, Ayman M. Eldieb (2016), (Early detection of breast cancer)	Deep belief network, Backpropagation, Liebenberg Marquardt learning function.	Acc: 99.68%
Paulin F. (2011), (Breast Cancer classification)	Feed-forward artificial neural network, Backpropagation, Liebenberg Marquardt learning algorithm	Acc: 99.28%
Soowoong Kim, Bogun Park, Bong Seop Song, Seungjoon Yang (2016),(Fingerprint liveness detection)	ROI detection, Patch extraction & Normalization, DBN, Restricted Boltzmann Machine	Acc: 97.10%
Yuancheng Li, XiangqianNie, Rong Huang (2018), (web spam recognition)	DBN, Synthetic Minority Over-Sampling Technique, De-Noising Auto-Encoder.	Acc: 95%
Aleksandra Dedinec, Sonja Filiposka, LjupcoKocarev (2016), (Electricity load forecasting)	DBN, Restricted Boltzmann machine, Backpropagation	MAPE: 8.6%
Jianwen Sun, Alexander Steinecker and Philipp Glocker (2014), (Quality inspection for precision mechanism)	DBN, Auto-encoder, Restricted Boltzmann machine, Tilear	MAE: 0.960
Jianwen Sun, Reto Wyss, Alexander Steinecker and Philipp Glocker (2014), (Quality inspection of electromotor)	DBN, Auto-encoder, Restricted Boltzmann machine, Bottleneck layer, Tilear	MAE: 0.935

based methods (SAMS), dynamic model-based methods (DMMs) and knowledge-based methods (KMs) [12]. SAMs and DMMs are used widely by the industry, but it is always necessary to find the best signal feature before starting the threshold comparison. KMs have been studied with the development of machine learning algorithms. A certain amount of fault samples are required to perform the fault type classification. Jianwen Sun, et al. [11] proposed a novel automated fault detection method, namely Tilear, based on a Deep Belief Network (DBN) auto-encoder.

DBN is a probabilistic generative model, composed of stacked RBM layer-wise training methods can perform fast inference and extract the high-level feature of the inputs. By unfolded the stacked RBMS symmetrically, a DBN auto-encoder [11] is examined to reconstruct the inputs as closely as possible. Tilear is structured in two parts: training and decision–making. During training, Tilear is trained with good samples signals which enable to know how to reconstruct signals of good samples. In the next part, comparing the test sample recorded signals and the reconstructed signal allows measuring how well a recording from a test sample matches the DBN auto-encoder model. The possibility of fault detection using Tilear is verified with acquired vibration signal datasets. It is shown that Tilear has comparable performance with the state-of-art technique, support vector machine, using the area under the curve as the performance metric. The experiments in the paper [10] showed the possibility of online fast fault detection for electromotor. It is proven that DBN not only can be used for fault detection but also has the potential in the fault classification area.

IV. PROPOSED METHOD

From the survey, plan to implement the DBN in automate the diagnosis of breast cancer in an effective way. First, extract the features from the dataset. Then using PCA, reduce the maximum feature to minimum numbers without compromising on explained variance. Second, learn the input feature using unsupervised phase in the deep belief network. Then transfer the obtain network weight to backpropagation neural network with similar architecture to start the supervised phase. In final use the Chebyshev function to approximate the non-linear relationship between input and output.

V. CONCLUSION

The latest development of deep belief network has been surveyed in various fields. In the proposed method, provides an effective classification model for breast cancer. Since it is not frequently possible to obtain labeled data in applications, the supervised learning methods can hardly provide satisfactory performance in such cases. Based on deep belief network, unsupervised learning algorithms can be used to process the unlabeled data. So, the flexibility of accuracy and computational complexity can be adjusted. The deep belief network is a very fertile area of research. Now many companies have switched to using DBNs such as google, facebook, Microsoft and soon on. Google used DBNs for android speech recognition. Facebook has launched a new DBN research center. Microsoft has done some amazing research with DBNs with the speech to text, text translation to a new language and text to speech in different languages.
Based on the literature review, some related information for future research is listed as follows.

As an efficient tool for big data analysis, the DBN has achieved great success with huge amounts of unlabeled training data. In case, there is only limited amount of training data is available then it required more powerful models to enhance learning ability. Therefore, it can be considered how to design the models to learn from fewer training data.

Even though DBN can be used for fault detection but also has the potential in the fault classification area. DBN is used for the first time in web spam classification; the performance would be only certain extent. So, the research will focus on the integration of DBN and meta-algorithms and remove the incompatible parts of different algorithms to apply better to the web spam classification. At the same time, find to simplify the model to reduce the time complexity of the algorithm.

- DBNs can be applied to the wider variety of tasks including much larger images, videos, text documents etc.
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Authors Profile

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