DOI: http://dx.doi.org/10.26483/ijarcs.v8i7.4373

ISSN No. 0976-5697

Volume 8, No. 7, July – August 2017

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

NEURAL NETWORK BASED DEEP LEARNING AND ENSEMBLE TECHNIQUES FOR DATA CLASSIFICATION

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Abstract: In this paper, four neural network architectures are proposed for data classification. The four neural networks are constructed based on deep learning and ensemble architectures. Supervised and unsupervised learning paradigms are adopted. Stack of Supervised Neural Network (SSNN), Stack of Unsupervised Neural Network (SUNN), Ensemble of Supervised Neural Network (ESNN), and Ensemble of Unsupervised Neural Network (ESNN) are the proposed neural network classifiers. Australian credit approval data set from the University of California, Irvin is used to evaluate the classifiers. Supervised neural networks have produced more accurate classification results than unsupervised networks. Stack architectures are comparatively better than ensemble architectures. It is found from this research that the combination of supervised learning method and stack architecture leads to better performance.

Keywords: Data Classification, Deep Learning, Ensembles, Neural Networks, Supervised and Unsupervised Learning.

I. INTRODUCTION

In the recent decades soft computing techniques have grabbed more attention of the researchers. Artificial neural networks, fuzzy logic and genetic algorithms are notable soft computing techniques and they are applied to solve various kinds of problem irrespective of domains. They are biologically inspired machine learning techniques. Supervised learning and unsupervised learning are the two significant paradigms of this soft computing approach. Deep learning neural networks and ensemble of neural networks are the advanced versions of regular methods. Deep learning can be achieved through the stack architecture and a high amount of training is required [1]. Deep neural networks are successfully applied to classification problems. Hierarchical fuzzy deep neural networks are applied for image categorization, financial data prediction and MRI segmentation of brain [2]. To improve the efficiency of deep neural networks, weight matrix parameterizing and low rank factorization are applied [3]. Diagnosis and classification of faults in semiconductor manufacturing process can be carried out by neural networks [4]. Deep convolutional features of neural network classifiers are used for classifying remote sensing images [5]. The effectiveness of deep learning in classification process is proved on remote sensing image data of lands and crops [6]. Extreme learning machines are built by stack architecture for solving various type of classification problems [7]. The complexity of deep learning neural network classifiers are discussed in the literature [8].

Application of the neural network based ensemble methods for classification problems are found better in terms of decreasing the error rate [9]. Ensembles of neural networks are applied for classification of seismic signals [10] and medical image classification [11]. Linear combination of multiple neural networks has improved the performance of classifier [12]. A combination of multiple neural networks for online pattern classification is attempted [13]. Hybrid methods such as Neuro-Fuzzy ensembles are producing better results in classification [14] [15]. Multilayer perceptron based ensembles can be used as classifiers [16] [17]. Clustering based classification is a novel approach to solve classification problems in some select domain [18]. When analyzing the literature, ensemble methods seemed better classifiers and they are applied on data related medical diagnosis also [19].

II. PROPOSED METHODS AND EXPERIMENTS

Australian credit approval data set is a bench mark data set provided by the UCI repository. It contains 690 records, 14 attributes and two classes. It is used here to evaluate the performance of proposed neural network architectures. The overall structure of the proposed approach is represented in Figure.1. Stack of Supervised Neural Network (SSNN), Stack of Unsupervised Neural Network (SUNN), Ensemble of Supervised Neural Network (ESNN), and Ensemble of Unsupervised Neural Network (ESNN) are the proposed neural network classifiers.

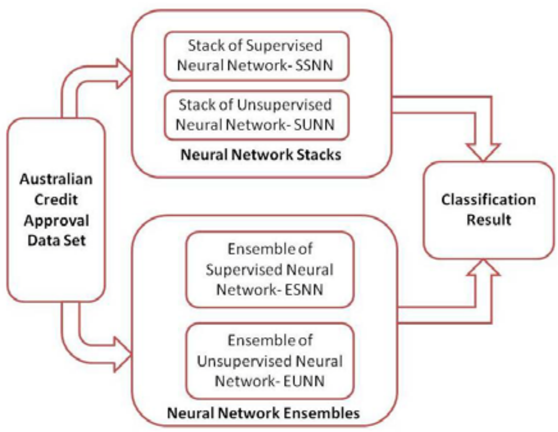

Figure.1. Functional Diagram of Proposed Approach

The proposed methods are implemented in Python language with the specifications mentioned below.

A. *Stack of Supervised Neural Network (SSNN)*

Network Type : Feed forward multilayer network
Learning Method : Supervised deep learning
Number of Layers: Six layers & completely interconnected
No. of Neurons in the input Layer : Eight neurons
No. of Neurons in the hidden Layers: Eight neurons
No. of Neurons in the output Layer : One neuron
Description of layer wise task : Input weights vectors are fed into the first layer and in the second layer, the Euclidian distance among the weights is calculated to get better grouping. Perceptron learning rule is applied repeatedly in the third, the fourth and the fifth layers in order to enrich the training of the classifier. The final classification result is derived through the output layer.

B. *Stack of Unsupervised Neural Network (SUNN)*

Network Type : Feed forward multilayer network
Learning Method : Unsupervised deep learning
Number of Layers: Six layers & completely interconnected
No. of Neurons in the input Layer : Eight neurons
No. of Neurons in the hidden Layers: Eight neurons
No. of Neurons in the output Layer : One neuron
Description of layer wise task : Input weights vectors are fed into the first layer and in the second layer, the Euclidian distance among the weights is calculated to get better grouping. Maxnet activation function is applied repeatedly in the third, the fourth and the fifth layers in order to produce the accurate classification. The final classification result is derived through the output layer.

C. *Ensemble of Supervised Neural Network (ESNN)*

Network Type : Feed forward multilayer network
Learning Method : Supervised ensemble learning
No. of Classifiers in the Ensemble : Three
Number of Layers: Four layers & completely interconnected
No. of Neurons in the input Layer : Eight neurons
No. of Neurons in the hidden Layers: Eight neurons
No. of Neurons in the output Layer : One neuron
Description of layer wise task : Input weights vectors are fed into the first layer and in the second layer, the Euclidian distance among the weights is calculated to get better grouping. Perceptron learning rule is applied in the third layer. The final classification result is derived through the output layer. The consolidate result is produced by the ensemble at the end.

D. *Ensemble of Unsupervised Neural Network (EUNN)*

Network Type : Feed forward multilayer network
Learning Method : Unsupervised ensemble learning
No. of Classifiers in the Ensemble : Three
Number of Layers: Four layers & completely interconnected
No. of Neurons in the input Layer : Eight neurons
No. of Neurons in the hidden Layers: Eight neurons
No. of Neurons in the output Layer : One neuron
Description of layer wise task : Input weights vectors are fed into the first layer and in the second layer, the Euclidian distance among the weights is calculated to get better grouping. Maxnet activation function is applied in the third layer. The final classification result is derived through the output layer. The consolidate result is produced by the ensemble at the end.

III. EXPERIMENTAL RESULTS

The classification accuracy and mean squared error (MSE) rate are calculated as follows.

$$\text{Accuracy} = (TP+TN)/(TP+FP+TN+FN)$$

Where, TP = True Positive Classification, TN = True Negative Classification, FP = False Positive Classification, and FN = False Negative Classification.

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{X}_i - X_i\right)$$

Where $\hat{x}_i$ is a vector of classifications, and x_i is the vector of observed values corresponding to the inputs to the function which generated the classifications.

The Figure.2. represents the performance accuracy of all the four neural network classifiers. The Figure.3. represents the mean squared error rate of all the four neural network classifiers.

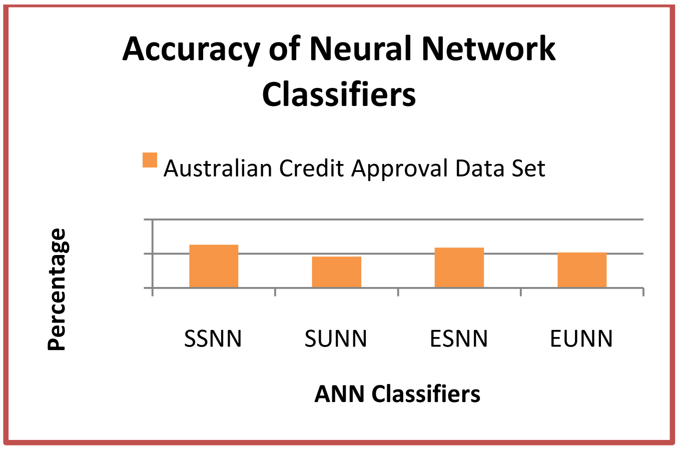

Figure.2. Accuracy of proposed classifiers.

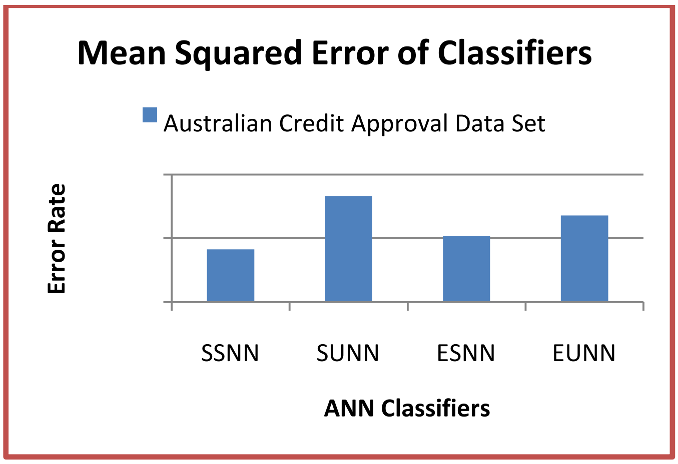

Figure.3. Error rate of proposed classifiers.

IV. CONCLUSION AND FUTURE SCOPE

The obtained classification accuracy of the proposed SSNN, SUNN, ESNN and EUNN are 86.3%, 84.6%, 85.9% and 85.2% respectively. The error rate of SSNN, SUNN, ESNN and EUNN are 0.1365, 0.1533, 0.1408, and 0.1472 respectively. Results indicate that among the proposed techniques, supervised methods are more efficient in classification when compared with unsupervised neural network. In future researches, hybrid soft computing techniques such as Neuro-fuzzy, Neuro-genetic, fuzzy-genetic may be applied to improve the performance of classifiers.

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