Neural Network Classification Algorithm with M-Learning Reviews to Improve the Classification Accuracy

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ABSTRACT
The development of communication technology has led to easy access of information through the internet. Nowadays, the use of mobile devices is increasing rapidly which in turn has popularized the pedagogical methods such as learning through mobile devices. Several mobile learning systems are available and also the user opinions about these systems are aired in the social blogs or review websites. Neural networks have high acceptance ability for noisy data, high accuracy and are preferable in data mining. In Knowledge Discovery in Databases (KDD), Neural Networks are employed in classification process. This research paper develops an opinion mining system for M-Learning reviews, the goal of this system is to extract the opinions and reviews, and determine whether these reviews and opinions are positive or negative. This research works proposes to score the words in the opinion using Singular Value Decomposition; select information gain based attributes, additionally feed forward from input layer to the output layer and presents a novel neural network classification algorithm to improve the classification accuracy.

Keywords: Opinion Mining, Neural network, Classification Accuracy, M-Learning, Information Gain.

1. INTRODUCTION
Opinion mining was first studied by Natural Language Processing (NLP) researchers [1]. It determines an object's positive or negative opinion [2]. For example, book review comments are classified into either positive or negative reviews, by a learning system. Opinion mining is mostly used in the fields of product review related services, business intelligence, augmentation of recommender systems .Opinion mining also known as sentiment classification or sentiment analysis is a computational technique that seeks to understand and explain opinion and sentiment by analyzing large amounts of opinion data in such an efficient way as to assist in human decision making. In Opinion mining, automatic text analysis process is applied for extracting and identifying opinions in wide array of sentiments expressed in the e-learning blogs and forums through which learners are describing their personal opinions and evaluation as regards the services provided [3].

M-Learning means "any sort of learning that happens when the learner is not at a fixed predetermined location or learning that happens when the learner takes advantage of the learning opportunities offered by mobile technologies". Mobile phones, smart phones, Personal Digital Assistants (PDAs), tablet PCs and perhaps laptop PCs, are devices used in Mobile learning [4]. The user reviews of free M-Learning system available are considered. Many methods were suggested as classifiers for opinion mining. Naive Bayesian, Nearest Neighbor techniques, Support vector machine and Decision tree induction were researched with varied modifications.

Neural networks have emerged as an important tool for classification. The recent vast research activities in neural classification have established that neural networks are a promising alternative to various conventional classification methods. The advantage of neural networks lies in the following theoretical aspects. First, neural networks are data driven self-adaptive methods in that they can adjust themselves to the data without any explicit specification of functional or distributional form for the model. Second, they are universal functional approximators in that neural networks can approximate any function with arbitrary accuracy [5]. The neural network considered as an effective classifier uses labeled training segments for classification [6]. Current classification methods rely on parametric or non-parametric multivariate analyses: discriminant analysis, cluster analyses, etc. These methods are often rather inefficient when the data are nonlinearly distributed, even after variable transformation [1].

With the reviews from various researchers, the need for improving the accuracy of the classification is thus contemplated. Therefore, in this research paper a classification method, based on the principles of Artificial Neural Networks (ANN), is proposed. The classification accuracy between existing algorithm and the proposed algorithm is compared. The classification of opinion mining not only based on opinion words but also corpus words which are frequently used in the documents under review are considered. Thus, Input Output Positive Negative Weight Feed Forward Neural Network (IOPNW FFNN) algorithm is proposed to improve the classification accuracy. This paper is organized into the following sections. The overall structure of the research paper is as follows. After the introduction the Section 2 discusses the existing Neural Network classifiers; Section 3 describes the proposed Neural Network classification algorithm; Section 4 describes the results obtained and discusses the same; Finally Section 5 concludes the paper.

2. EXISTING NEURAL NETWORK CLASSIFIERS

An ANN is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system. Neural networks have been successfully applied to a variety of real world classification tasks in industry, business and science, bankruptcy prediction, speech recognition, product inspection, fault detection and medical diagnosis. The concept of existing neural network based classification algorithms are presented as follows.

A. LVQ Algorithm

Learning Vector Quantization (LVQ) is a process of classifying the patterns wherein each output unit represents a particular class. Here, for each class several units should be used. The output unit weight vector is called the reference vector or code book vector for the class which the unit represents. This is a special case of competitive net which uses supervised learning methodology. During training, the output units are found to be positioned to approximate the decision surfaces of the existing Bayesian classifier. Here, the set of training patterns with known classifications is given to the network along with an initial distribution of the reference vectors. When the training process is complete, an LVQ net is found to classify an input vector by assigning it to the same class as that of the output unit, which has its weight vector very close to the input vector. Thus, LVQ is a classifier paradigm that adjusts the boundaries between categories to minimize existing misclassifications [7].

B. Elman Algorithm

Elman Neural Network (ENN) is nonlinear/linear dynamic systems; dynamic Neural Networks are Feed Forward Networks and have dynamic operation ability where Network behavior is based both on current inputs and also on earlier network operations. In ENN, neuron outputs are fed back as inputs to the Network with time delay structures being added. ENN represents time as continuous or discrete time system in neural systems. Signals are represented as real-valued or quantized. ENNs are used as associative memories/ sequence mapping systems [8][9].

C. Feed Forward Neural Network

McCulloch and Pitts [10] proposed a mathematical model of a neuron in 1943 and these abstract nerve cells formed the base for the brain's activities. Rosenblatt [11] also presented a successful neural network system. They titled it as Rosenblatt perceptron, a basic visual system that recognized a limited patterns class which in turn was the foundation for many types of ANN. A perceptron computes a weighted sum of inputs, putting it through a special function known as activation to produce output. Activation is either linear or nonlinear. MLP Networks are FFNNs with one/many unit layers between input and output nodes. Network weights are called Feed Forward as weights flow forward, starting with inputs, and with no weights feed back to earlier or current layers. A FFNN network is shown in Fig 1 [12][13]. Input layers have dummy units distributing inputs to the network. Output layers, with hidden layers between them, equal network discriminant functions.

3. PROPOSED NEURAL NETWORK CLASSIFIER

In this section, the methodology followed in the proposed work is described. As ANN, configured for pattern recognition or data classification, is widely perceived to be accurate to the level of 80% - 90% [14]. In a move to increase classification accuracy there by deducing uncluttered knowledge, neural network based algorithm is designed.

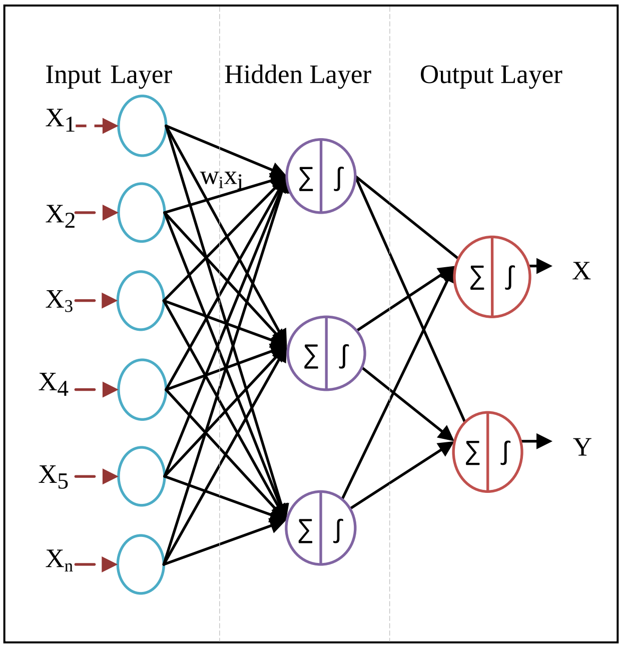

Fig 1: Multi-Layer Perceptron Network

Various sentiment analysis methods relied on opinion words extraction from the opinion text under consideration with a scoring function effectively used by a machine learning algorithm [14]. Both Feature extraction and classification algorithm are important for classification accuracy. This work proposes extraction of opinion words based on its frequent appearance in all documents under study. Eliminating common and uncommon words prepares a word frequency matrix. Extracted features are ranked using Singular Value Decomposition and the dataset obtained is rendered to the existing classifying algorithms. The algorithm based on Neural Network for classifying the features is proposed.
Proposed Neural algorithm consists of two enhancements over the existing FFNN.

- Implementation of additional weights from input layer to output layer.
- An enhanced back propagation algorithm.

In Generalized networks, connections may skip one or more layers as seen in Figure 1. In the proposed IOPNW FFNN, all input layer nodes connect to output layer nodes similar to how it connects from input to first hidden layer. The advantage of IOPNW FFNN algorithm is that it is more efficient than FFNN, which also has a similar number of processing elements.

In the proposed IOPNW FFNN algorithm for increasing the classification accuracy, the preprocessed dataset forms the inputs x_1, x_2,…xn for the IOPNW FFNN architecture. The input weights presented to the input nodes are presented to the Hidden layer with the product of weights and the data in the first epoch. In the Hidden layer, summation and activation function occurs. For performing the activation function, sigmoidal operation is adopted. As the Bias value is set to 0 in the process, the summation of the calculated value with Bias do not make any significant change. The output from the Hidden layer is handed to the output layer. In the Output layer, the calculated values from the Hidden layer with the weights from the Input layer are dispensed. In this scheme, the additional weights are feed forward from input layer to the output layer. The additional, top five positive and top five negative weights are selected with the help of Information Gain. The calculation of entropy E*(s)* for *m* values in each feature is,

$$E(s) = -\sum_{i=1}^{m} p_i \log p_i \quad (1)$$

where *p* is the proportion of positives and negatives, *s* is dataset. For every value in a feature with its corresponding class label, entropy is calculated. At first, the entropy value for the class label is calculated. Subsequently, every feature with respect to the class labels, Information Gain (IG) for *A* feature is calculated using,

$$IG(S,A) = E(S) - \sum_{v \in values(A)} (|S_v|/|S|)\, E(S_v) \quad (2)$$

where, *E(S)* is the entropy of the class label, *S* is the total number of possibilities, S_v is the number of preferred possibilities and *v* is the values in *A* feature. From the obtained IGs, the top five positive and negative values are chosen for further feeding. The summation and activation function are invoked to calculate the values. The process is iterated until the threshold value is encountered or the number of epochs is reached. Parameters used in the IOPNW FFNN algorithm are given in the Table 1.

Table 1. Parameters of the IOPNW FFNN Algorithm

Parameters	Values
Number of neurons in input layer	57
Number of neurons in hidden layer	20
Number of hidden layers	1
Number of neurons in output layer	3
Learning rate	0.1
Momentum	0.5
Number of epochs	500

4. RESULTS AND DISCUSSIONS

The proposed IOFNW FFNN algorithm is operated with M-Learning system reviews as dataset. Learner's opinions about free M-Learning system available are considered. The preprocessed dataset using proposed preprocessing algorithm is applied in IOFNW FFNN algorithm for classification. The classification accuracy obtained from the experiment reaches up to 83.33%. The experiment with the acquired dataset has revealed that the increase of classification accuracy. The same algorithm is also commendable when the existing datasets are used. The comparison of the efficiency among the proposed IOFNW FFNN classifier and the existing ANN classifiers namely, LVQ, Elman and FFNN are performed. The results are tabulated and are shown in Table 2.

Table 2. Comparing Classification Accuracy of IOPNW FFNN with Existing Algorithms

Algorithm	Classification Accuracy %
	M-Learning Dataset
LVQ	56.67
Elman	76.67
FFNN	78.67
Proposed IOPNW FFNN	83.33

From the comparative analysis it is evident to note that the proposed IOPNW FFNN classifier supersedes the existing ANN classifiers. The classification accuracy obtained by IOPNW FFNN measures to 83.33%. The results are shown graphically in Fig 2.

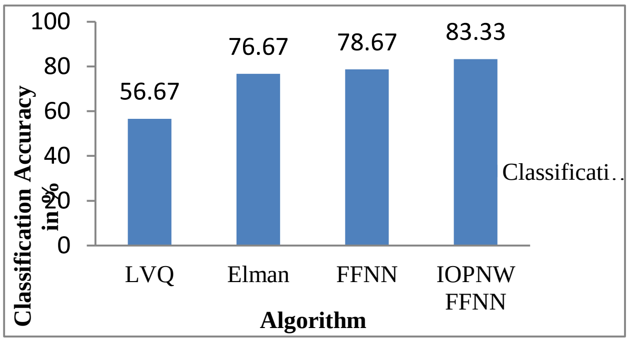

Fig 2: Comparison of IOPNW FFNN with Existing Algorithms

The obtained classification accuracy from the classifiers are validated using Precision, Recall and F-Measure. Precision is the probability that the retrieved document is relevant and Recall is the probability that a relevant document is retrieved in a search. F-Measure is the harmonic mean of Precision and Recall. The Validated measures are shown in Table 3 for the FFNN and the proposed IOPNW FFNN classifiers.

Table 3. Precision, Recall and F-measure of M-Learning Dataset

Algorithm	Precision	Recall	F Measure
	M Learning Dataset		
FFNN	0.667	0.8	0.727
Proposed IOPNW FFNN	0.837	0.826	0.831

The measures of validation are represented graphically in Fig 3, which shows an improvement in the accuracy rate.

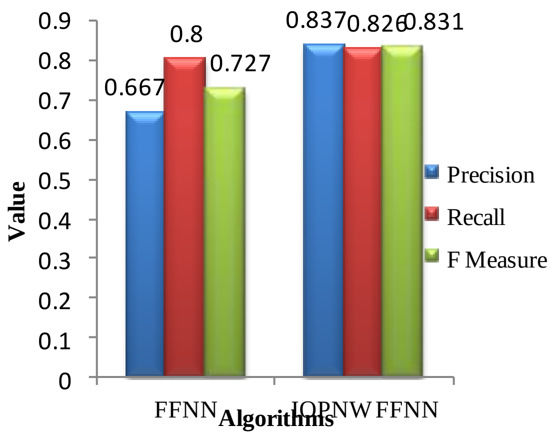

Fig 3: Precision, Recall and F-measure of M-Learning Dataset

Thus the proposed algorithm is validated against the existing ANN classifiers with Precision, Recall and F-Measures.

5. CONCLUSION

The classification accuracy for sentiment/opinion has been evaluated using proposed IOPNW FFNN algorithm. The features were extracted from the dataset and ranked using information gain. The obtained features were employed in the IOPNW FFNN algorithm. ANN based classifiers have been discussed in order to substantiate the proposed algorithm's performance over them. The methodology comprising of the architecture and algorithm have been put forward. The key intervention in the summation and activation function that has brought a difference in the performance has been expounded. The pinnacle and nadir values, calculated through IG, have brought the significant improvement in the classification accuracy. Finally in comparison, IOPNW FFNN algorithm has shown an improvement over the other existing ANN algorithms.

6. REFERENCES

[1] Dave, D., Lawrence, A., and Pennock, D. Mining the Peanut Gallery: Opinion Extraction and Semantic Classification of Product Reviews. Proceedings of International World Wide Web Conference (WWW'03), 2003

[2] Pang, B., Lee, L. and Vaithyanathan, S. Thumbs up? Sentiment Classification Using Machine Learning Techniques. Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing (EMNLP'02), 2002.

[3] Tatemura. Junichi, "Virtual reviewers for collaborative exploration of movie reviews", In Proceedings of Intelligent User Interfaces (IUI), pages 272–275, 2000.

[4] John Traxler, "Defining, Discussing and Evaluating Mobile Learning: the moving finger writes, The International Review of Research in open and Distance Learning, Volume 8, No 2, 2007.

[5] Guoqiang Peter Zhang, "Neural Networks for Classification: A Survey", IEEE Transactions On Systems, Man, And Cybernetics—Part C: Applications And Reviews, Vol. 30, No. 4, pp.451-461, 2000.

[6] Stephen A. Zahorian, Zaki B. Nossair, "A Partitioned Neural Network Approach for Vowel Classification Using Smoothed Time/Frequency Features", IEEE Transactions On Speech And Audio Processing, Volume 7, NO. 4, pp. 414-425, 1999.

[7] S.N. Sivanandam, S.N. Deepa, "Principles of Soft computing", Wiley India(P) Ltd., 2007.

[8] Übeyli, E.D., "Recurrent neural networks employing Lyapunov exponents for analysis of Doppler ultrasound signals", Expert Systems with Applications, Vol. 34, No. 4, pp.2538-2544, 2008a

[9] Übeyli, E.D., "Wavelet/mixture of experts network structure for EEG signals classification", Expert Systems with Applications, Vol. 34, No. 3, pp.1954-1962,2008b

[10] McCulloch, W. Pitts, W. "A logical calculus of the ideas immanent in nervous activity", The Bulletin of Mathematical Biophysics, Volume 5, pp.115-133, 1943.

[11] Rosenblatt, Frank, "The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain", Cornell Aeronautical Laboratory, Psychological Review, volume 65, No. 6, pp. 386–408, 1958.

[12] Mu-Song Chen and M.T. Manry, "Power Series Analyses of Back-Propagation Neural Networks", International Joint Conference on Neural Networks, Volume I, pp.295-300, 1991.

[13] Mu-Song Chen, M.T. Manry, "Nonlinear Modeling of Back-Propagation Neural Networks", International Joint Conference on Neural Networks, Volume II, pp. 899, 1991.

[14] Peter D. Turney, "Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews", Proceedings of the 40th Annual Meeting on Association for Computational Linguistics, pp. 417-424, 2002