International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-3, September 2019

Deep Neural Networks for the Classification of Bank Marketing Data using Data Reduction Techniques

Chittem Leela Krishna, Poli Venkata Subba Reddy

Abstract: The amount of data belonging to different domains are being stored rapidly in various repositories across the globe. Extracting useful information from the huge volumes of data is always difficult due to the dynamic nature of data being stored. Data Mining is a knowledge discovery process used to extract the hidden information from the data stored in various repositories, termed as warehouses in the form of patterns. One of the popular tasks of data mining is Classification, which deals with the process of distinguishing every instance of a data set into one of the predefined class labels. Banking system is one of the real-world domains, which collects huge number of client data on a daily basis. In this work, we have collected two variants of the bank marketing data set pertaining to a Portuguese financial institution consisting of 41188 and 45211 instances and performed classification on them using two data reduction techniques. Attribute subset selection has been performed on the first data set and the training data with the selected features are used in classification. Principal Component Analysis has been performed on the second data set and the training data with the extracted features are used in classification. A deep neural network classification algorithm based on Backpropagation has been developed to perform classification on both the data sets. Finally, comparisons are made on the performance of each deep neural network classifier with the four standard classifiers, namely Decision trees, Naïve Bayes, Support vector machines, and k-nearest neighbors. It has been found that the deep neural network classifier outperforms the existing classifiers in terms of accuracy.

Keywords – Data Mining, Classification, Attribute Subset Selection, Principal Component Analysis, Deep Neural Networks

I. INTRODUCTION

Extraction of useful information from the data stored in repositories is termed as Data Mining [2]. The hidden information to be uncovered in the form of patterns from the data stored across different locations is referred to as Knowledge [2-3].

Manuscript published on 30 September 2019
* Correspondence Author
Chittem Leela Krishna*, Research Scholar, Dept. of CSE, S.V.U. College of Engineering, S.V. University, Tirupati, India.
Email: chittem.leelakrishna03@gmail.com
Dr. Poli Venkata Subba Reddy, Professor, Dept. of CSE, S.V.U. College of Engineering, S.V. University, Tirupati, India.
Email: vsrpoli@hotmail.com

Thus data mining is one of the steps of the knowledge discovery process, which includes different tasks to be performed based on the type of patterns to be discovered. There is a need to preprocess the data stored in various repositories (warehouses) so as to apply mining tasks effectively. Data Reduction is a data preprocessing technique used in attaining a reduced representation of the original data in terms of size in such a way that the results of the reduced data are similar to that of the original data.

Classification is a data mining task used to distinguish each data object into one of the predefined categorical class labels by following a two-step process [2]. The first step is to build a classifier by analyzing the training data with known class labels i.e., training phase and the second step is to use the classifier to predict the class labels of the test data with unknown class labels i.e., testing phase. During the training phase, different forms of classifiers can be built such as Decision trees, Naïve Bayes, *k*-Nearest neighbors, Backpropagation neural networks, Support vector machines [2-5] etc. Decision tree classifier is similar to a tree structure with the non-leaf nodes indicating attributes of the training data, branches emanating from each node represent the possible outcomes of the node and the leaf nodes indicating the class labels [2-5]. Every internal node of the tree is chosen by applying an attribute selection measure among all the attributes. The attribute that suits best is selected as the tree node that splits the training data into different classes. The popular attribute selection measures used are Information gain, Gain ratio, Gini index [2]. Once the classifier is built, test data is supplied to it for predicting the class label of each tuple by traversing the tree from its root.

Bayesian Classifier is based on the class membership probability of each tuple in the training data defined by Bayes' theorem [2-3]. Naïve Bayesian classifier is built based on the assumption that an attribute value is independent on the values of other attributes for each class label. Bayes' theorem defines the posterior probability of H conditioned on T, P(H|T), for some hypothesis H and a tuple T of the input data based on (1). Once the classifier is built, posterior probabilities are evaluated for each tuple D in the test data conditioned on every possible class. The class label with higher probability will be predicted as the class of D.

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)} \quad (1)$$

Support Vector Machine (SVM) classifier can handle both linearly separable and inseparable data [2].

While building the classifier for linearly separable data, the training data are transformed into a higher dimensional space so as to search for a hyperplane that distinguishes the tuples from one class to the other. The hyperplane with a maximum margin is chosen as the best classifier for predicting the class labels of test data. While building the classifier for linearly inseparable data, a non-linear mapping of the training data to a higher dimensional space is made and then a search for a maximum margin hyperplane to separate the data is made in the dimension.

The dot product of each tuple in the test data and the support vectors is computed to obtain the class label of unknown tuples during the testing phase. *k*-Nearest Neighbor (k-NN) is a lazy learner classifier since it is built only when the test data is supplied. The training data provided earlier is just stored [2-3]. The closeness of each tuple in the test data to *k* training tuples is evaluated by the *k*-NN classifier, named as the *k* nearest neighbors of the test tuple. Euclidean distance is used as one of the measures of closeness [2]. For two tuples $T_1(t_{11}, t_{12}, \ldots t_{1n})$ and T_2 $(t_{21}, t_{22}, \ldots t_{2n})$, the Euclidean distance will be calculated based on (2). The class label of the test tuple will be assigned to the class supplied by the majority of its *k* nearest neighbors.

$$Eucl\_dist(T_1,T_2) = \sqrt{\sum_{i=1}^{n}(T_{1i} - T_{2i})^2} \qquad (2)$$

The paper is organized as follows: Section 2 presents two data reduction techniques, namely Attribute subset selection and Principal component analysis. Section 3 describes the Backpropagation based Artificial neural network. Section 4 presents two variants of bank marketing data set. Section 5 provides related work on data reduction techniques for classification. Section 6 presents a detailed form of proposed work which includes Methodology, Preprocessing and the complete process of classification followed. Experimental results along with the comparison of existing classifiers are provided in section 7. Section 8 concludes the paper with future enhancements.

II. DATA REDUCTION

Data reduction techniques can be applied in attaining a subset of the original data such that the results obtained on the subset are similar to that of the results of original data. In this paper, we have focused on two data reduction techniques, namely Attribute subset selection, a feature selection method [1,2] and Principal component analysis, a feature extraction method [2,15].

A. Attribute subset selection

The process of selecting a subset of relevant attributes, namely dimensions/features by removing redundant or weak attributes from the input data set is termed as Attribute subset selection [1,2]. Among all the possible subsets of attributes, the best subset is chosen by applying one of the below heuristics:

Forward Selection – Determine the best attribute among all and add it to the empty set and repeat the process iteratively until the reduced set of attributes is obtained.

Backward Elimination – Determine the worst attribute among all and remove it from the whole attribute set and repeat the process iteratively until the reduced set of attributes is obtained.

A Mixture of Forward Selection and Backward Elimination – Combine the above two processes such that the best attribute is maintained in the reduced set and the worst attribute will be removed from the set in each iteration.

Decision tree Generation – Construct a decision tree with the internal nodes representing the possible subset of attributes and the leaf nodes representing all the possible classes. One of the measures such as Information gain, Gain ratio, and Gini index is used in choosing the best attribute that can act as the internal node of the tree [2-5].

B. Principal Component Analysis

Dimensionality reduction is classified into either lossless or lossy decomposition depending on the reconstruction of original data from its reduced representations. Principal Component Analysis (PCA) is a lossy dimensionality reduction technique, where an approximation of the original data can be reconstructed from its reduced data. PCA makes use of data encoding techniques and searches among the *n* attributes of the original data set to find *k* orthogonal vectors [2,15]. A reduced data set with *k* dimensions is projected onto a new space such that $k \leq n$. The basic process of PCA is given below:

1. Normalize the input data set so that every attribute falls in the same range i.e., 0-1.
2. Compute *k* orthogonal vectors for the normalized data such that the vectors are perpendicular to each other. The *k* orthogonal vectors will be the Principal components.
3. Sort the principal components in their decreasing order of variance. The component with the highest variance will be the first axis and the component with the second higher variance will serve as the second axis and so on.
4. Obtain a reduced form of original data by eliminating the weaker components in terms of variance.

The process of PCA makes use of measures like Co-variance matrix, Eigen values, Eigen vectors while generating the principal components.

III. BACKPROPAGATION NEURAL NETWORK

Artificial neural network (ANN) is biologically inspired by the human brain, consisting of a set of interconnected processing nodes distributed across several layers [5,22,23]. The processing nodes in an ANN are termed as neurons, spread across different layers viz., input, hidden and output layers. A Multi-layered neural network has one input, one or more hidden and one output layers in which each neuron in layer *i* is interconnected to all the neurons in layer *i+1* through the weights associating them. This work focuses on neural network based classification using Backpropagation [1,15,22]. Once the training data is supplied to the neural network, the learning phase deals with finalizing certain network parameters such as updating the weights and minimizing the error function. The parameters once set are used to predict the class labels of the test data during the testing phase. The process of building a neural network classifier using Backpropagation is given below:

1. Initial the neural network with random weights and set the bias to one.
2. For each tuple in training dataset

3. Propagate inputs forward and
 3.1 Calculate the output of each node in every hidden layer
 3.2 Calculate the output of each node in the output layer
4. Calculate Error function at the output layer
 Error = Expected output value – Actual output value
5. Backpropagate Error function from output to input layers through hidden layers
6. Update all weights between the layers.
7. Repeat step 2 for *n* epochs

IV. BANKING SYSTEM

Banking system stores a huge number of client data on a daily basis. One among such data is related to conduct marketing campaigns by the banking staff to make clients subscribe for various services, offers, deposits offered by banks. In this work, two data sets related to bank marketing campaigns conducted by a Portuguese financial institution are collected from [6]. Banking staff of the institution contacts their clients through phone calls so as to make them subscribe for term deposits within their bank. When seen as a classification problem, the class label indicates whether a client subscribes for a term deposit in the form of a binary variable. The two data sets related to bank marketing data consisting of client details are chosen in such a way that one of them is used for feature selection through attribute subset selection and the other is used for feature extraction through Principal component analysis. The first data set consists of 41188 instances with 21 attributes including a class label and the second consists of 45211 instances with 17 attributes including a class label [1,15]. Tables 1 and 2 lists all the attributes and their type in each data set. The class label (namely Y) is of a binary type which has either yes/no for each client instance where **yes** represents that a client subscribes for a term deposit and **no** indicates that a client does not subscribe for a term deposit.

Table 1. List of Attributes and Type of Data set 1 [1]

S. No.	Attribute	Type
1.	Age	Numeric
2.	Job	Categorical
3.	Marital	Categorical
4.	Education	Categorical
5.	Default	Categorical
6.	Housing	Categorical
7.	Loan	Categorical
8.	Contact	Categorical
9.	Month	Categorical
10.	Day_of_week	Categorical
11.	Duration	Numeric
12.	Campaign	Numeric
13.	Pdays	Numeric
14.	Previous	Numeric
15.	Poutcome	Categorical
16.	Emp.var.rate	Numeric
17.	Cons.price.idx	Numeric
18.	Cons.conf.idx	Numeric
19.	Euribor3m	Numeric
20.	Nr.employed	Numeric
21.	Y (class label)	Binary

Table 2. List of Attributes and Type of Data set 2 [15]

S. No.	Attribute	Type
1.	Age	Numeric
2.	Job	Categorical
3.	Marital	Categorical
4.	Education	Categorical
5.	Default	Binary
6.	Balance	Numeric
7.	Housing	Binary
8.	Loan	Binary
9.	Contact	Categorical
10.	Day	Numeric
11.	Month	Categorical
12.	Duration	Numeric
13.	Campaign	Numeric
14.	Pdays	Numeric
15.	Previous	Numeric
16.	Poutcome	Categorical
17.	Y (class label)	Binary

V. RELATED WORK

Feature selection on bank marketing data set consisting of 1000 instances through attribute subset selection and building a deep neural network classifier to predict the clients subscribe for a term deposit from the featured data was discussed in [1]. Another approach to identify the customers who subscribe for the bank services had been discussed in [7] by achieving two objectives, in which the first objective was to predict the response of each customer and the second was to identify the relevant features using clustering. Improving the outcome of marketing campaigns was proposed in [8] by performing clustering of customers based on similarities and then building a classifier.
Novel algorithms such as SMOTE [9], Rotation Forest (PCA)–J48 [10] were also proposed to improve the outcome of marketing campaigns. Comparison on the performance of the algorithms was made with the existing classifiers [11-12] in terms of several parameters viz., accuracy, mean square error, and the results were analyzed in different studies [13-14].
Principal component analysis on bank marketing data set containing mixed attributes to perform feature extraction so as to build a deep neural network classifier was proposed in [15], where the input data set had 1000 instances and a reduction in dimensions from 16 to 3, with a cumulative variance of 99.99740%. Predicting the closing stock price using two-dimensional PCA had been discussed in [16], where deep belief networks were used to perform classification. Another work including Elman neural network [17] to predict the stock price was presented. Assessment of credit risk in banking sector through PCA based Support vector machines and Fuzzy Support vector machines were discussed in [18-20]. The importance of PCA in reducing the dimensions for loan granting and early-stage lung disease diagnosis had been analyzed in [21].

VI. PROPOSED WORK

A. *Methodology*

The whole process of classification followed in this work is presented in the form of workflow as shown in figure 1. Initially, the bank marketing data set is gathered from the UCI repository. We have performed data preprocessing in two phases i.e., L1 and L2, where L1 preprocessing focused on the elimination of errors and inconsistencies from the input data set and L2 preprocessing focused on the techniques decided by the feature selection/extraction module.

Between the two preprocessing phases, the input data set has been split into training and test data in an 80-20 fashion. The featured training data has been fed as an input to the deep neural network classification algorithm so as to build a classifier/model. Once the classifier is found to be ready, its performance is evaluated by predicting the class labels of the featured test data.

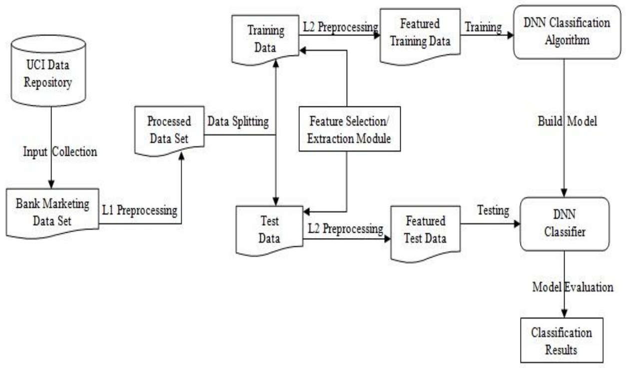

Figure 1. Proposed Workflow process

B. *Data Collection and L1 Preprocessing*

Two variants of Bank marketing data set pertaining to a Portuguese financial institution are collected from the UCI repository [6]. The total number of instances in the first data set is 45211 with 21 attributes as listed in table 1, and the second data set has 41188 instances with 17 attributes as listed in table 2. On the two data sets, initial preprocessing has been done on all the instances which include identification of missing values and other inconsistencies for each attribute and replacement of the values with the attribute's mean, data normalization so as to bring all the attribute values to a range of 0-1 [1,15]. The initially processed data sets are then split into training and test sets in an 80-20 fashion, where the training data comprises of 80 percent of the total instances and test data contain the remaining 20 percent of instances.

C. *Feature Selection/Extraction Module and L2 Preprocessing*

i. Attribute Subset Selection on Data Set 1

The training data set chosen from the first variant of the bank marketing data set is fed as input to the feature selection/extraction module. The module performs Attribute subset selection [1] on the training data set to select the most promising attributes suitable for classification. The attributes selected by the method are termed as features. Attribute subset selection internally evaluates information gain for every attribute and sorts all the attributes in the decreasing order of their information gain results. The attribute set with high information gain is selected as the feature set of the training data.

ii. Principal Component Analysis on Data Set 2

The training data set chosen from the second data set is fed as input to the feature selection/extraction module. The module here performs Label Encoding [15] followed by Principal Component Analysis. During label encoding, all the values of categorical attributes are converted to numeric form. Statistical measures such as Covariance matrix, Eigen values, and Eigen vectors are evaluated for the encoded training data. From the measures, Principal components are extracted and are aligned in the descending order of their variance. The set of principal components with high variance is selected as the feature set of the training data [15].

D. *Deep Neural Network Classifier*

i. Structure of a Neural Network

A Deep Neural Network is an Artificial Neural Network with more number of hidden layers between input and output layers [23]. The structure of the proposed Deep neural network (DNN) consists of twenty hidden layers interconnecting input and output layers. Each hidden layer internally accommodates 25 nodes. Size of the input layer (*inp*) is equal to the number of features returned by the feature selection/extraction module. Since the class label is a binary attribute, the size of the output layer (*out*) is one, where the node indicates one of the two values (yes/no). Thus, the total size of the neural network is *inp*(25*20)*out*. The work uses Rectified Linear Unit [1,15,22] Activation function in evaluating the output values of the nodes at each hidden layer and the output layer.

ii. Deep Neural Network Classification Algorithm

Backpropagation Technique [1,15,22] has been used as the underlying classification algorithm for the deep neural network. The algorithm used in building a Deep Neural Network classifier is given below:

begin BPDNN_Classifier(Data, inp, out)
Data, inp = FeatSel_Ext(Data)
Create a neural network of size *inp**(25*20)**out*
Initialize the network parameters i.e., node and bias weights, momentum and learning rate
For each iteration
For each tuple in *Data*
Calculate Input values of hidden layers
$$\mathrm{I_h} = \sum \mathrm{I_{inp} W_{inp}}$$
Calculate output values of hidden layers
$$\mathrm{O_h} = \mathrm{ReLU(I_h)}$$
Calculate Input values of output layer
$$\mathrm{I_o} = \sum \mathrm{I_h W_h}$$
Calculate output values of output layer
$$\mathrm{O_o} = \mathrm{ReLU(I_o)}$$
Calculate Error at the output layer
$$\mathrm{Err} = \mathrm{ActualClass} - \mathrm{O_o}$$
Calculate Error at hidden layers
Update node and bias weights
Repeat for *i* epochs
end BPDNN_Classifier

VII. EXPERIMENTAL RESULTS

A. *Process of Classification on Data Set 1*

The Bank marketing data set containing 41188 instances of clients' data represented by using 21 attributes is collected from the repository. After L1 preprocessing, data splitting has been performed and the sizes of training and test data are 32950 and 8238 [1].

Retrieval Number C5522098319/2019©BEIESP
DOI: 10.35940/ijrte.C5522.098319
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The processed data set is fed as input to the feature selection/extraction module. Based on the decreasing order of information gain, we have chosen the top 10 attributes as the features for training data to undergo classification. BPDNN_Classifier algorithm is implemented in Python programming language [1,15].

The 10 featured training data serves as input to the algorithm, with randomized initial weights, momentum as 0.15 and learning rate as 0.002. Rectified Linear Unit (ReLU) [1] is used as the activation function in the algorithm. The Deep Neural Network classifier is built by running the algorithm on the featured training data for 500 epochs.

After building the classifier, the 10 featured test data is supplied to the classifier for evaluating its performance in predicting the class labels of the test instances and the results are represented by using a Confusion Matrix [1] as shown below:

Table 3. Classifier Results on Data Set 1

Confusion Matrix		Class
7111	209	no
520	398	yes

Accuracy has been calculated from the confusion matrix which resulted in 91.15% [1]. Finally, we have made a comparison on the performance of the Deep Neural Network classifier with the four existing classifiers viz., Decision Trees, Naïve Bayes, Support Vector Machines and k-Nearest Neighbors in terms of accuracy and the plot is shown in figure 2. From the figure, it is evident that the accuracy of the proposed Deep Neural Network classifier is better to the four existing classifiers.

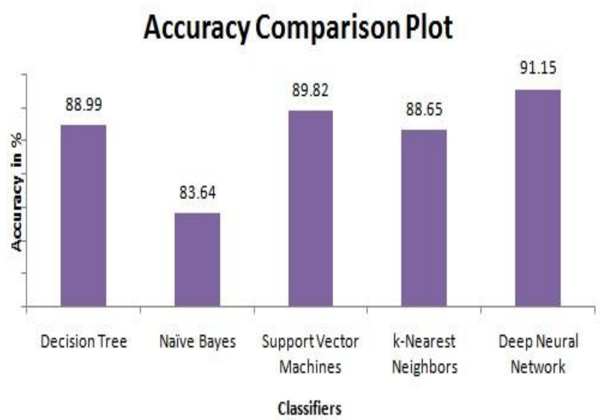

Figure 2. Accuracy Comparison on Data Set 1

B. Process of Classification on Data Set 2

The second variant of the bank marketing data set containing 45211 instances of clients' data represented by using 17 attributes is collected from the repository. After L1 preprocessing, data splitting has been performed with the sizes of training and test data being 36168 and 9043 respectively [15]. The processed data set is fed as input to the feature selection/extraction module. Based on the decreasing order of variance among the principal components (PCs), we have chosen the top three PCs with a cumulative variance of 91.59957% as the features for training data to undergo classification. BPDNN_Classifier algorithm is implemented in Python programming language [1,15]. The three featured training data serves as input to the algorithm, with randomized initial weights, momentum as 0.9 and learning rate as 0.001. Rectified Linear Unit (ReLU) [15] is used as the activation function in the algorithm. The Deep Neural Network classifier is built by running the algorithm on the featured training data for 1000 epochs.

After building the classifier, feature extraction has been performed on the test data and the three featured test data is supplied to the classifier for evaluating its performance in predicting the class labels of the test instances and the results are represented by using a Confusion Matrix [15] as shown below:

Table 4. Classifier Results on Data Set 2

Confusion Matrix		Class
7926	66	no
907	144	yes

Accuracy has been calculated from the confusion matrix which resulted in 89.24% [15]. Finally, we have made a comparison on the performance of the Deep Neural Network classifier with the four existing classifiers viz., Decision Trees, Naïve Bayes, Support Vector Machines and k-Nearest Neighbors in terms of accuracy and the plot is shown in figure 3. From the figure, it is evident that the accuracy of the proposed Deep Neural Network classifier is better to the four existing classifiers.

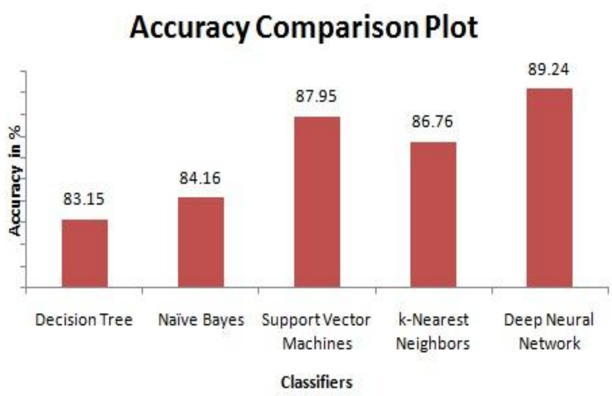

Figure 3. Accuracy Comparison on Data Set 2

VIII. CONCLUSIONS AND FUTURE WORK

This work deals with the classification of Bank Marketing data set belonging to a Portuguese financial institution. The main goal of the task is to predict whether a client subscribes for a term deposit in the bank based on his/her characteristics represented using attributes. To achieve the goal, we have collected two variants of the bank marketing data set with 41188 and 45211 instances from the UCI repository and built a deep neural network using Backpropagation algorithm containing 20 hidden layers interconnected with input and output layers. The first data set has been preprocessed and feature selection has been applied using Attribute subset selection method based on information gain parameter. Among the 20 non-class attributes of the first data, top 10 features have been chosen for building the deep neural network classifier. After building the classifier, the test data set has been supplied to the classifier to predict the class labels.

Finally, a comparison has been made on the performance of the deep neural network with four standard classifiers in terms of accuracy.

The second data set has been preprocessed and feature extraction has been applied using Principal component analysis. Among the 16 non-class attributes of the second data, the top 3 principal components contributing to a cumulative variance of 91.59957% among total attributes have been chosen for building the deep neural network classifier. After building he classifier, the test data set has been supplied to the classifier to predict the class labels. Finally, a comparison has been made on the performance of the deep neural network with four standard classifiers in terms of accuracy.

The two experimental results show that the Deep neural network classifier has outperformed four existing classifiers while classifying the two bank marketing data sets in terms of accuracy.

In future, we shall focus on improving the accuracy of Deep Neural Network classifier by introducing Evolutionary techniques viz., Genetic algorithms for neural network parameter optimization, Different activations at different hidden layers instead of one. We shall also extend the classification of data using Deep neural networks to other real-world domains like Healthcare system.

REFERENCES

1. C. L. Krishna and P. V. S. Reddy, "*An Efficient Deep Neural Network Classifier in Banking System*", International Journal of Research and Analytical Reviews, Vol.6, Issue.2, pp.511-517, 2019.
2. J. Han J. and M. Kamber Data Mining Concepts and Techniques, Morgan Kauffmann Publishers, India, 2006.
3. M. H. Dunhamm, *Data Mining: Introductory and Advanced Topics*, Pearson Education, India, 2006.
4. C. Lin and F. Yan, "*The Study on Classification and Prediction for Data Mining*", Seventh Int'l Conf. on Measuring Technology and Mechatronics Automation, 2015.
5. A. S. Alasadi and W.S. Bhaya, "*Review of Data Preprocessing Techniques in Data Mining*", Journal of Engineering and Applied Sciences, Vol. 12, Issue 6, pp. 4102-4107, 2017.
6. https://archive.ics.uci.edu/ml/datasets/bank+marketing
7. A.J. Frempong and M. Jayabalan, "*Predicting Customer Response to Bank Direct Telemarketing Campaign*", 2017 International Conference on Engineering Technology and Technopreneurship, IEEE, Sept. 2017.
8. M. Mitik, O. Korkmaz, P. Karagoz, H.I. Toroslu and F. Yucel, "*Data Mining based Product Marketing Technique for Banking Products*", 16th International Conference on Data Mining Workshops, IEEE, Dec. 2016.
9. D. Grzonka, G. Suchacka and B. Borowik, "*Application of Selected Supervised Classification Methods To Bank Marketing Campaign*", Information Systems in Management, Vol. 5, Issue 1, pp. 36-48, 2016.
10. P. Ruangthong and S. Jaiyen, "*Bank Direct Marketing Analysis of Asymmetric Information Based on Machine Learning*", 12th International Joint Conference on Computer Science and Software Engineering, IEEE, July 2015.
11. A.H. Elsalamony, "*Bank Direct Marketing Analysis of Data Mining Techniques*", International Journal of Computer Applications, Vol. 85-No 7, Jan. 2014.
12. A.H. Elsalamony and M.A. Elsayad, "*Bank Direct Marketing Based on Neural Network*", International Journal of Engineering and Advanced Technology, Vol. 2, Issue 6, Aug. 2013.
13. A.A. Koc and O. Yeniay, "*A Comparative Study of Artificial Neural Networks and Logistic Regression For Classification of Marketing Campaign Results*", Mathematical and Computational Applications, Vol. 18, No. 3., pp. 392-398, 2013.
14. K. Wisaeng, "*A Comparison of Different Classification Techniques for Bank Direct Marketing*", International Journal of Soft Computing and Engineering, Vol. 3, Issue 4, Sept. 2013.
15. C. L. Krishna and P. V. S. Reddy, "*Principal Component Analysis on Mixed Data For Deep Neural Network Classifier in Banking System*", International Journal of Computer Sciences and Engineering, Vol.7, Issue.5, pp.129-134, 2019.
16. T. Gao, X. Li, Y. Chai and Y. Tang, "*Deep Learning with Stock Indicators and two-dimensional Principal Component Analysis for closing price prediction system*", Seventh IEEE Int'l Conf. Software Engineering and Service Science, IEEE, Aug 2016.
17. H. Shi and X. Liu, "*Application on Stock Price Prediction of Elman neural networks based on Principal Component Analysis Method*", 11th Int'l Conf. Wavelet Activ Media Technology and Information Processing, IEEE, Dec 2014.
18. C.T.J. Ming, M.N. Noor, M.O. Rijal, M.R. Kassim and A. Yunus, "*Lung Disease Classification Using Different Deep Learning Architectures and Principal Component Analysis*", 2nd Int'l Conf. Bio Signal Analysis, Processing and Systems, IEEE, July 2018.
19. W. Feng, Y. Zhao and J. Deng, "*Application of SVM Based on Principal Component Analysis to Credit Risk Assessment in Commercial Banks*", WRI Global Congress on Intelligent Systems, IEEE, May 2009.
20. Z. Min, "*Credit Risk Assessment Based on Fuzzy SVM and Principal Component Analysis*", Int'l Conf. Web Information Systems and Mining, IEEE, Nov 2009.
21. I. Ioniţă and D. Şchiopu, "*Using Principal Component in Loan Granting*", Seria Matematică – Informatică – Fizică, Vol. LXII, pp. 88-96, 2010.
22. P.G. Zhang, "*Neural networks for classification: a survey*", IEEE Trans. Systems, Man, and Cybernetics, Part C (Applications and Reviews), Vol. 30, Issue 4, Nov 2000.
23. C. L. Krishna and P. V. S. Reddy, "An Efficient Deep Neural Network Multilayer Perceptron Based Classifier in Healthcare System," *2019 3rd International Conference on Computing and Communications Technologies (ICCCT)*, Chennai, India, 2019, pp. 1-6.

AUTHORS PROFILE

Mr. Chittem Leela Krishna received his B.Tech degree from SVU Tirupati in the department of Computer Science and Engineering in 2012 and M.Tech degree from JNTU Anantapur in the department of Computer Science and Engineering in 2014. He is currently pursuing his Ph.D as a Full-time Research Scholar in the department of Computer Science and Engineering at S.V. University, Tirupati. He has published articles in three reputed journals and has presented articles in four conferences. His areas of Research include Data Mining, Artificial Intelligence and Machine Learning

Prof. Poli Venkata Subba Reddy is currently working as Professor and Chairman, Computer Science and Engineering, College of Engineering, Sri Venkateswara University, Tirupati, India. He did B.S, SVU, 1984., M.S., SVU, 1986), M.Phill (DBMS) SVU 1988., Ph.D(AI) SVU 1992) in S V University, PDF (fuzzy algorithms) IISc/JNCSR, 1995 and PGDCM&P, CSI 1985. His research interests are Artificial Intelligence, fuzzy Systems and Database systems. He is member in IEEE. He published more than 50 publications in reputed International Journals and Conferences. He visited Taiwan. Hong Kong, Thailand, Malaysia, South Korea and Dubai to present the research papers.