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Efficiency Comparison of Multilayer Perceptron and SMO Classifier for Credit Risk Prediction

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Abstract: Credit Risk Prediction is an important task in any Banking Industry. Identifying the defaulter before giving loan is a crucial task of the Banker. Classification techniques are used to classify the customer, whether he/she is a defaulter or a genuine customer. Determining the best classifier is a critical assignment for any industrialist. It leads to instil different research works for determining the best classifier for the credit risk prediction. This paper analyzes the efficiency of Multilayer Perceptron Classifier and Sequential Minimal Optimization (SMO) Classifier for the credit risk prediction and compares their efficiency through various measures. The German credit data is taken for credit risk prediction and the classification experiment is done using open source machine learning tool.

Keywords: Credit Risk Prediction, Multilayer Perceptron Classifier, SMO Classifier, Performance Evaluation

I. INTRODUCTION

The huge volume of transactions spins the information processing automation into a vital factor for cost reduction, high quality standards with high speed results. Automation and result of the relevant successes achieved by state-of-the art computer solutions applied have changed the opinions of many sceptics. In past days, people tended to think that financial market analysis entails knowledge, intuition and experience and wondered how this activity could be automated. However, through steadily growing along with the scientific and technological advances, the automation of financial market analysis has been achieved. In modern days, credit risk evaluation and credit defaulter prediction have attracted a great deal of interests from theorists, regulators and practitioners, in the financial industry. In past days, financial institutions utilized the rules or principles built by the analysts to decide whom to give credit. But it is impossible both in economic and manpower terms to conduct all works with the tremendous increase in the number of applicants. Therefore, the credit approval decision process needs to be automated. Automation of credit risk prediction is achieved using a classification technique. Determining the classifier, which predicts the credit risk in an efficient manner, is an important and crucial task. This paper evaluates the credit risk performance of two different classifiers, namely, Multilayer Perceptron Classifier and Sequential Minimal Optimization (SMO) and compares which provide more accurate credit risk prediction.

II. LITERATURE REVIEW

Many researchers have made the credit risk prediction using varied computing techniques. A neural network based system for automatic support to credit risk analysis in a real world problem is presented in [2]. An integrated back propagation neural network with traditional discriminant analysis approach is used to explore the performance of credit scoring in [3]. A comparative study of corporate credit rating analysis using support vector machines (SVM) and back propagation neural network (BPNN) is analysed in [4]. A triple-phase neural network ensemble technique with an un-correlation maximization algorithm is used in a credit risk evaluation system to discriminate good creditors from bad ones are explained in [5]. An application of artificial neural network to credit risk assessment using two different architectures are discussed in [6]. Credit risk analysis using different Data Mining models like C4.5, NN, BP, RIPPER, LR and SMO are compared in [7]. The credit risk for a Tunisian bank through modelling the default risk of its commercial loans is analysed in [8]. Credit risk assessment using six stage neural network ensemble learning approach is discussed in [9]. Modelling framework for credit assessment models is constructed by using different modelling procedures and performance is analysed in [10].

Hybrid method for evaluating credit risk using Kolmogorove-Smirnov test, DEMATEL method and a Fuzzy Expert system is explained in [11]. An Artificial Neural Network based approach for Credit Risk Management is proposed in [12]. Artificial neural networks using Feed-forward back propagation neural network and business rules to correctly determine credit defaulter is proposed in [13]. Adeptness evaluation of Memory based classifiers for credit risk analysis is experimented and summarized in [14]. Adeptness comparison of Instance Based and K Star Classifiers for Credit Risk Scrutiny is performed and described in [15]. This research work compares the efficiency of Multilayer Perceptron classifier and SMO Classifier for credit risk prediction.

III. DATASET USED

The German credit data is taken for credit risk prediction. It consists of 20 attributes, namely, Checking Status, Duration, Credit History, Purpose, Credit Amount, Saving Status, Employment, Instalment Commitment, Personal Status, Other parties, resident since, Property magnitude, Age, Other payment plans, Housing, existing credits, job, Num dependents, Own Phone and Foreign worker. The data set consists of 1000 instances of customer credit data with the class detail. It has two classes, namely, good and bad.

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IV. METHODOLOGY USED

In this paper, two different classifiers namely, Multilayer Perceptron Classifier and Sequential Minimal Optimization (SMO) Classifier are used for efficiency comparison of credit risk prediction.

A. Multilevel Perceptron Classifier

Neural networks, with their remarkable ability to obtain meaning from complicated or inexact data, can be used to extort patterns and detect trends that are too complex to be perceived by human or by computer techniques. A neural network, after training can be considered as an "expert" in the category of information it has been given to scrutinize. This expert can then be used to afford projections given new situations of interest and answer "what if" questions. It includes other advantages like:

- Adaptive learning: An ability to learn how to do tasks based on the data given for initial experience or training.
- Do not make any assumption regarding the underlying probability density functions or other probabilistic information about the pattern classes under consideration.

Multilayer Perceptron (MLP) is a Classifier that uses back propagation to classify instances. This network can be created by an algorithm or built by hand, or both. The network can be observed and modified during training time as well. The nodes in MLP network are all sigmoid.

B. SMO Classifier

Sequential minimal optimization (SMO) is an algorithm for quickly solving the optimization problems. Consider a binary classification problem with a dataset (x_1, y_1)... (x_n, y_n), where x_i is an input vector and $y_i \in \{-1, +1\}$ is a binary label corresponding to it. The dual form of quadratic programming problem solved using support vector machine is as follows:

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j K(x_i, x_j)\alpha_i\alpha_j, \quad (1)$$

subject to:

$$0 \leq \alpha_i \leq C, \quad \text{for } i = 1, 2, \ldots, n,$$

$$\sum_{i=1}^{n} y_i\alpha_i = 0$$

where C is a Support Vector Machine hyper-parameter and $K(x_i, x_j)$ is the kernel function, supplied by the user; and the variables α_i are Lagrange multipliers.

SMO breaks the problem into a series of smallest possible sub-problems, which are then solved analytically. Since the linear equality constraint involving the Lagrange multipliers α_i, the smallest possible problem involves two such multipliers. Then, for any two multipliers α_1 and α_2, the constraints are reduced to:

$$0 \leq \alpha_1, \alpha_2 \leq C, y_1\alpha_1 + y_2\alpha_2 = k, \quad (2)$$

k is the sum of the rest of terms in the equality constraint, which is fixed in each iteration.

The SMO algorithm proceeds as follows:

1. Find a Lagrange multiplier α_1 that contravenes the Karush–Kuhn–Tucker (KKT) conditions for the optimization problem.
2. Choose a second multiplier α_2 and optimize the pair (α_1, α_2).
3. Repeat step 1 and 2 until convergence of multipliers.

The problem has been solved, when all the Lagrange multipliers satisfy the Karush–Kuhn–Tucker conditions within a user-defined tolerance level.

V. MEASURES USED FOR PERFORMANCE EVALUATION

Different measures are used to evaluate the performance of the classifiers.

A. Classification Accuracy

All classification result could have an error rate and it may fail to classify correctly. Classification accuracy can be calculated as follows:

Accuracy = (Instances Correctly Classified / Total Number of Instances)*100 % (3)

B. Mean Absolute Error

MAE is the average of difference between predicted and actual value in all test cases. The formula for calculating MAE is given in equation shown below:

MAE = (|a1 – c1| + |a2 – c2| + … +|an – cn|) / n (4)

Here 'a' is the actual output and 'c' is the expected output.

C. Root Mean Square Error

RMSE is used to measure differences between values actually observed and the values predicted by the model. It is calculated by taking the square root of the mean square error as shown in equation given below:

RMSE = [√ ((a1 – c1)2 + (a2 – c2)2+ … + (an – cn)^2)] / n (5)

Here 'a' is the actual output and c is the expected output. The mean-squared error is the commonly used measure for numeric prediction.

D. Confusion Matrix

A confusion matrix contains information about actual and predicted classifications done by a classification system.

VI. RESULTS AND DISCUSSION

The performance of both Multilayer Perceptron and SMO classifiers are checked using open source machine learning tool. The performance is checked using the Training set itself and using different Cross Validation and Percentage Split methods. The class is obtained by considering the values of all the 20 attributes.

A. Performance of Multilayer Perceptron Classifier

The overall evaluation summary of Multilayer Perceptron Classifier (MPC) using training set and different cross validation methods is given in Table I. The classification summary of MPC for different percentage split is given in Table II. The confusion matrix for each different test mode is given in Table III to Table XII. The chart showing the performance of Multilayer Perceptron Classifier with respect to Correctly Classified Instances and Classification

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Accuracy with different type of test modes are depicted in Fig. 1, Fig. 2 and Fig. 3. Multilayer Perceptron classifier gives 99.3% for the training data set. But for evaluation testing with test data is essential. So various cross validation and percentage split methods are used to test its actual performance. On an average, it gives around 72% to 75% of classification accuracy for credit risk prediction.

TABLE I
MULTILAYER PERCEPTRON CLASSIFIER OVERALL EVALUATION SUMMARY

Test Mode	Correctly Classified Instances	Incorrectly Classified Instances	Accuracy	Kappa Statistic	Mean absolute error	Root Mean Squared Error	Time Taken to Build Model (Sec)
Training Set	993	7	99.3 %	0.9832	0.012	0.0841	80.03
5 Fold CV	724	276	72.4%	0.3403	0.2827	0.4923	79.94
10 Fold CV	716	284	71.6%	0.3199	0.2855	0.4942	79.09
15 Fold CV	733	267	73.3%	0.35	0.2708	0.4803	80.22
20 Fold CV	720	280	72.0%	0.3243	0.2809	0.4903	82.53
50 Fold CV	721	279	72.1%	0.3351	0.2822	0.4917	79.55

TABLE II
MULTILAYER PERCEPTRON CLASSIFIER PERCENTAGE SPLIT OVERALL EVALUATION SUMMARY

Test Mode	Total Test Instances	Correctly Classified Instances	Incorrectly Classified Instances	Accuracy	Kappa Statistic	Mean absolute error	Root Mean Squared Error	Time Taken to Build Model (Sec)
66% Percentage Split	340	251	89	73.8235 %	0.3053	0.2555	0.4627	0.13
33% Percentage Split	670	460	210	68.6567 %	0.2498	0.3117	0.5164	0.28
75% Percentage Split	250	191	59	76.4 %	0.3956	0.2423	0.4468	0.11
80% Percentage Split	200	150	50	75%	0.3893	0.2693	0.4724	0.08

TABLE III
CONFUSION MATRIX – MPC ON TRAINING DATASET

	Good	Bad	Actual (Total)
Good	700	0	700
Bad	7	293	300
Predicted (Total)	707	293	1000

TABLE IV
CONFUSION MATRIX – MPC FOR 5 FOLD CROSS VALIDATION

	Good	Bad	Actual (Total)
Good	564	136	700
Bad	140	160	300
Predicted (Total)	704	296	1000

TABLE V
CONFUSION MATRIX – MPC FOR 10 FOLD CROSS VALIDATION

	Good	Bad	Actual (Total)
Good	561	139	700
Bad	145	155	300
Predicted (Total)	706	294	1000

TABLE VI
CONFUSION MATRIX – MPC FOR 20 FOLD CROSS VALIDATION

	Good	Bad	Actual (Total)
Good	567	133	700
Bad	147	153	300
Predicted (Total)	714	286	1000

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TABLE VII
CONFUSION MATRIX – MPC FOR 15 FOLD CROSS VALIDATION

	Good	Bad	Actual (Total)
Good	578	122	700
Bad	145	155	300
Predicted (Total)	723	277	1000

TABLE VIII
CONFUSION MATRIX – MPC FOR 50 FOLD CROSS CALIDATION

	Good	Bad	Actual (Total)
Good	561	139	700
Bad	140	160	300
Predicted (Total)	701	299	1000

TABLE IX
CONFUSION MATRIX – MPC FOR 66% PERCENTAGE SPLIT

	Good	Bad	Actual (Total)
Good	210	40	250
Bad	49	41	90
Predicted (Total)	259	81	340

TABLE X
CONFUSION MATRIX – MPC FOR 33% PERCENTAGE SPLIT

	Good	Bad	Actual (Total)
Good	367	123	490
Bad	87	93	180
Predicted (Total)	454	216	670

TABLE XI
CONFUSION MATRIX – MPC FOR 75% PERCENTAGE SPLIT

	Good	Bad	Actual (Total)
Good	154	30	184
Bad	29	37	66
Predicted (Total)	183	67	250

TABLE XII
CONFUSION MATRIX – MPC FOR 80% PERCENTAGE SPLIT

	Good	Bad	Actual (Total)
Good	118	31	149
Bad	19	32	51
Predicted (Total)	137	63	200

B. *Performance of SMO Classifier*

The overall evaluation summary of SMO Classifier using training set and different cross validation methods is given in Table XIII. The classification summary of SMO Classifier for different percentage split is given in Table XIV. The confusion matrix for each different test mode is given in Table XV to Table XXIV. The chart showing the performance of SMO Classifier with respect to Correctly Classified Instances and Classification Accuracy with different type of test modes are depicted in Fig. 4, Fig. 5 and Fig. 6. SMO classifier gives 78.4% for the training data set. But for testing various cross validation and percentage split methods, it outperforms than Multilayer Perceptron Classifier. On an average, SMO Classifier gives around 75% of classification accuracy for credit risk prediction.

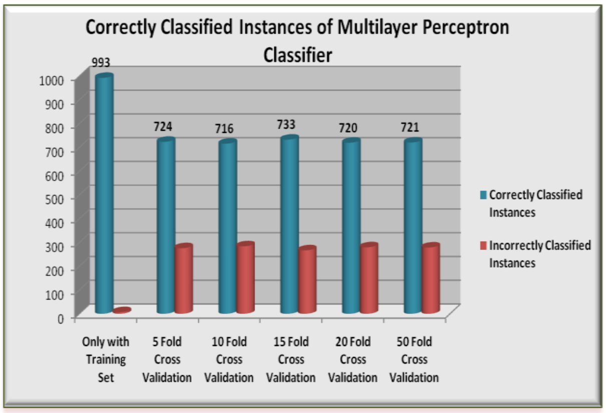

Fig. 1 Correctly classified instances of Multilayer Perceptron Classifier

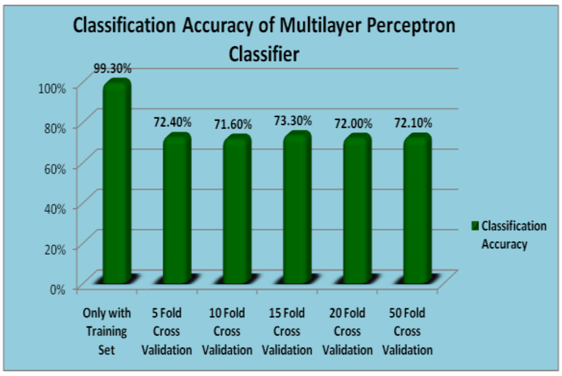

Fig. 2 Classification Accuracy of Multilayer Perceptron Classifier

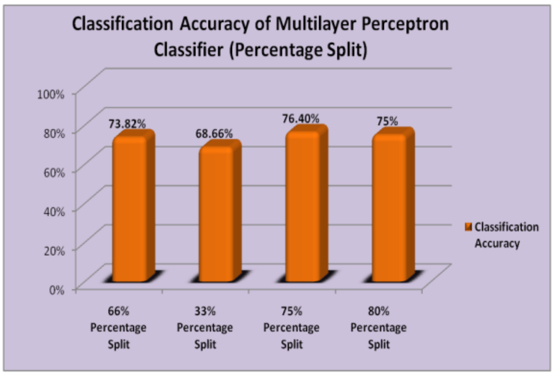

Fig. 3 Classification Accuracy of Multilayer Perceptron Classifier for Different Split Percentage

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TABLE XIII
SMO CLASSIFIER OVERALL EVALUATION SUMMARY

Test Mode	Correctly Classified Instances	Incorrectly Classified Instances	Accuracy	Kappa Statistic	Mean absolute error	Root Mean Squared Error	Time Taken to Build Model (Sec)
Training Set	784	216	78.4%	0.4501	0.216	0.4648	2.44
5 Fold CV	760	240	76.0%	0.3939	0.24	0.4899	2.56
10 Fold CV	751	249	75.1%	0.3654	0.249	0.499	2.66
15 Fold CV	747	253	74.7%	0.3499	0.253	0.503	2.52
20 Fold CV	745	255	74.5%	0.3528	0.255	0.505	2.44
50 Fold CV	745	255	74.5%	0.3435	0.255	0.505	2.38

TABLE XIV
SMO CLASSIFIER PERCENTAGE SPLIT OVERALL EVALUATION SUMMARY

Test Mode	Total Test Instances	Correctly Classified Instances	Incorrectly Classified Instances	Accuracy	Kappa Statistic	Mean absolute error	Root Mean Squared Error	Time Taken to Build Model (Sec)
66% Percentage Split	340	261	79	76.7647 %	0.3695	0.2324	0.482	2.52
33% Percentage Split	670	482	188	71.9403%	0.3031	0.2806	0.5297	2.52
75% Percentage Split	250	196	54	78.4 %	0.4387	0.216	0.4648	2.45
80% Percentage Split	200	155	45	77.5 %	0.4116	0.225	0.4743	2.53

TABLE XV
CONFUSION MATRIX – SMO ON TRAINING DATASET

	Good	Bad	Actual (Total)
Good	626	74	700
Bad	142	158	300
Predicted (Total)	768	232	1000

TABLE XVI
CONFUSION MATRIX-SMO FOR 5 FOLD CROSS VALIDATION

	Good	Bad	Actual (Total)
Good	610	90	700
Bad	150	150	300
Predicted (Total)	760	240	1000

TABLE XVII
CONFUSION MATRIX – SMO FOR 10 FOLD CROSS VALIDATION

	Good	Bad	Actual (Total)
Good	610	90	700
Bad	159	141	300
Predicted (Total)	769	231	1000

TABLE XVIII
CONFUSION MATRIX – SMO FOR 15 FOLD CROSS VALIDATION

	Good	Bad	Actual (Total)
Good	612	88	700
Bad	165	135	300
Predicted (Total)	777	223	1000

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TABLE XIX
CONFUSION MATRIX – SMO FOR 20 FOLD CROSS VALIDATION

	Good	Bad	Actual (Total)
Good	605	95	700
Bad	160	140	300
Predicted (Total)	765	235	1000

TABLE XX
CONFUSION MATRIX – SMO FOR 50 FOLD CROSS VALIDATION

	Good	Bad	Actual (Total)
Good	612	88	700
Bad	167	133	300
Predicted (Total)	779	221	1000

TABLE XXI
CONFUSION MATRIX-SMO FOR 66% PERCENTAGE SPLIT

	Good	Bad	Actual (Total)
Good	218	32	250
Bad	47	43	90
Predicted (Total)	265	75	340

TABLE XXII
CONFUSION MATRIX – SMO FOR 33% PERCENTAGE SPLIT

	Good	Bad	Actual (Total)
Good	389	101	490
Bad	87	93	180
Predicted (Total)	476	194	670

TABLE XXIII
CONFUSION MATRIX – SMO FOR 75% PERCENTAGE SPLIT

	Good	Bad	Actual (Total)
Good	158	26	184
Bad	28	38	66
Predicted (Total)	186	64	250

TABLE XXIV
CONFUSION MATRIX – SMO FOR 66% PERCENTAGE SPLIT

	Good	Bad	Actual (Total)
Good	126	23	149
Bad	22	29	51
Predicted (Total)	148	52	200

C. Comparison of MLP and SMO Classifiers

The comparison between MLP classifier and SMO classifier are depicted in Fig 7, Fig. 8 and Fig. 9 in terms of classification accuracy and Correctly Classified Instances. The overall ranking is done based on the classification accuracy, correctly classified instances, MAE and RMSE values and other statistics found using Training Set results, Percentage Split and Cross Validation Techniques. Based on that, it is observed that SMO classifier performs better than MLP Classifier.

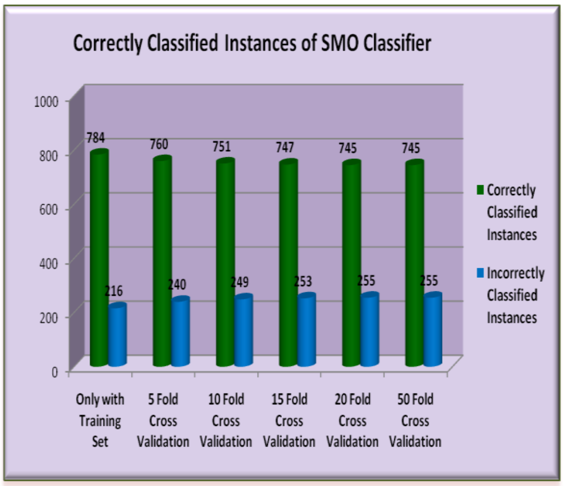

Fig. 4 Correctly Classified Instances of SMO Classifier

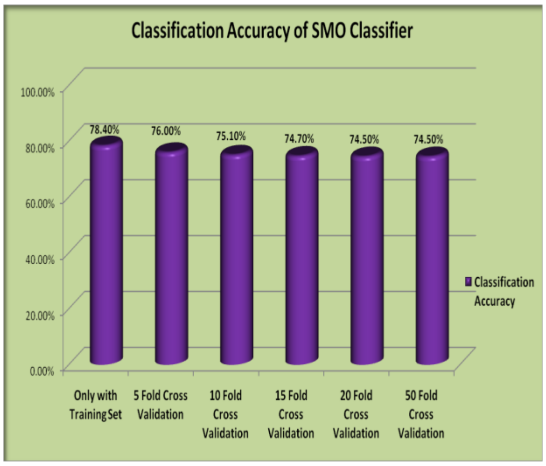

Fig. 5 Classification Accuracy of SMO Classifier

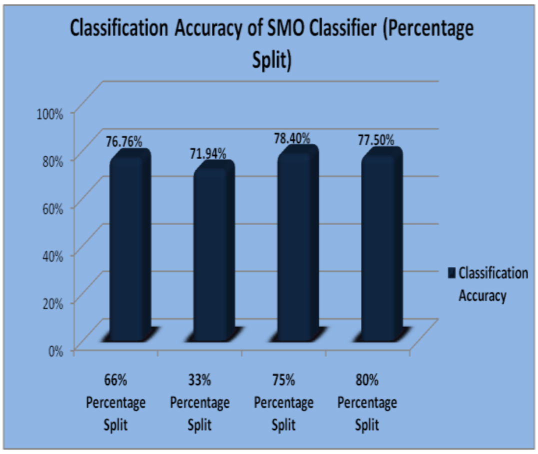

Fig. 6 Classification Accuracy of SMO Classifier for different Split Percentage

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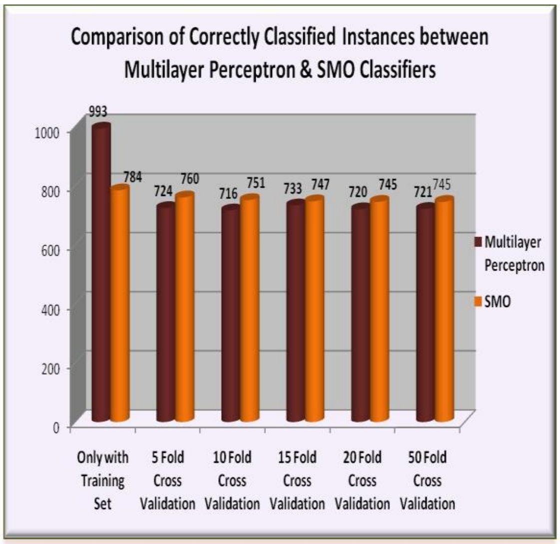

Fig. 7 Correctly Classified Instances Comparison between Multilayer Perceptron and SMO Classifier

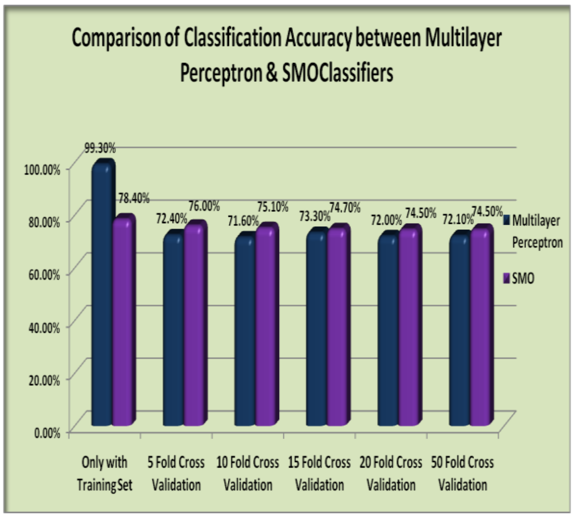

Fig. 8 Classification Accuracy Comparison between Multilayer Perceptron and SMO Classifier

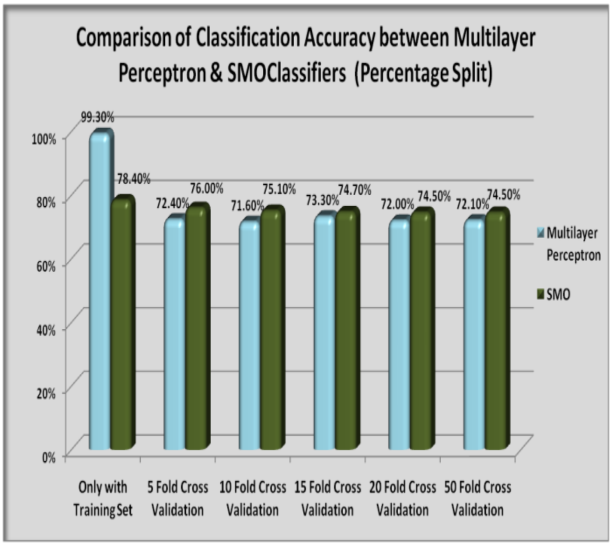

Fig. 9 Classification Accuracy comparison between Multilayer Perceptron & SMO Classifiers for Percentage Split

VII. CONCLUSION

This work investigated the efficiency of two different classifiers namely, Multilayer Perceptron Classifier and Sequential Minimal Optimization (SMO) Classifier for credit risk prediction. Experiment is done using the open source machine learning tool. Efficiency comparison of both the classifiers has been done by considering different measures of performance evaluation. After experiment, it is observed that Sequential Minimal Optimization (SMO) Classifier performs better than Multilayer Perceptron Classifier for credit risk prediction.

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REFERENCES

[1] John C. Platt, “Fast Training of Support Vector Machines using Sequential Minimal Optimization,” 2000.

[2] Germano C. Vasconcelos, Paulo J. L. Adeodato and Domingos S. M. P. Monteiro, “A Neural Network Based Solution for the Credit Risk Assessment Problem,” Proceedings of the IV Brazilian Conference on Neural Networks - IV Congresso Brasileiro de Redes Neurais pp. 269-274, July 20-22, 1999 - ITA, São José dos Campos - SP – Brazil.

[3] Tian-Shyug Lee, Chih-Chou Chiu, Chi-Jie Lu and I-Fei Chen, “Credit scoring using the hybrid neural discriminant technique,” Expert Systems with Applications (Elsevier) 23 (2002), pp. 245–254.

[4] Zan Huang, Hsinchun Chena, Chia-Jung Hsu, Wun-Hwa Chen and Soushan Wu, “Credit rating analysis with support vector machines and neural networks: a market comparative study,” Decision Support Systems (Elsevier) 37 (2004) pp. 543– 558.

[5] Kin Keung Lai, Lean Yu, Shouyang Wang, and Ligang Zhou, “Credit Risk Analysis Using a Reliability-Based Neural Network Ensemble Model,” S. Kollias et al. (Eds.): ICANN 2006, Part II, LNCS 4132, pp. 682 – 690, 2006.© Springer-Verlag Berlin Heidelberg.

[6] Eliana Angelini, Giacomo di Tollo, and Andrea Roli “A Neural Network Approach for Credit Risk Evaluation,” Kluwer Academic Publishers, 2006, pp. 1 – 22.

[7] S. Kotsiantis, “Credit risk analysis using a hybrid data mining model,” Int. J. Intelligent Systems Technologies and Applications, Vol. 2, No. 4, 2007, pp. 345 – 356.

[8] Hamadi Matoussi and Aida Krichene, “Credit risk assessment using Multilayer Neural Network Models - Case of a Tunisian bank,” 2007.

[9] Lean Yu, Shouyang Wang, Kin Keung Lai, “Credit risk assessment with a multistage neural network ensemble learning approach”, Expert Systems with Applications (Elsevier) 34 (2008), pp.1434–1444.

[10] Arnar Ingi Einarsson, “Credit Risk Modelling”, Ph.D Thesis, Technical University of Denmark, 2008.

[11] Sanaz Pourdarab, Ahmad Nadali and Hamid Eslami Nosratabadi, “A Hybrid Method for Credit Risk Assessment of Bank Customers” , International Journal of Trade, Economics and Finance, Vol. 2, No. 2, April 2011.

[12] Vincenzo Pacelli and Michele Azzollini, “An Artificial Neural Network Approach for Credit Risk Management”, Journal of Intelligent Learning Systems and Applications, 2011, 3, 103-112.

[13] A.R.Ghatge, P.P.Halkarnikar, “ Ensemble Neural Network Strategy for Predicting Credit Default Evaluation” International Journal of Engineering and Innovative Technology (IJEIT) Volume 2, Issue 7, January 2013 pp. 223 – 225.

[14] Lakshmi Devasena, C., “Adeptness Evaluation of Memory Based Classifiers for Credit Risk Analysis,” Proc. of International Conference on Intelligent Computing Applications - ICICA 2014, 6-7, (IEEE Explore), March 2014, pp. 143-147.

[15] Lakshmi Devasena, C., “Adeptness Comparison between Instance Based and K Star Classifiers for Credit Risk Scrutiny,” International Journal of Innovative Research in Computer and Communication Engineering, Vol.2, Special Issue 1, March 2014.

[16] Lakshmi Devasena, C., "Adeptness Comparison between Instance Based and K Star Classifiers for Credit Risk Scrutiny," Proc. of International Conference on Intelligent Computing Applications - ICICA 2014, 978-1-4799-3966-4/14 (IEEE Explore), 6-7 March 2014, pp. 143-147.
[17] UCI Machine Learning Data Repository – http://archive.ics.uci.edu/ml/datasets.

BIOGRAPHY

Dr. C. Lakshmi Devasena has completed her Ph.D in Karpagam University, Coimbatore. She has 10 ½ years of Teaching and two years of Industrial experience. She has published 35 papers, in that 24 papers are published in International Journals and 11 are published in National Journals and conference proceedings. She has presented 35 papers in various International and National conferences. Her research interest is Data Mining, Medical Image Analysis, Business Analytics, Algorithm Evaluation, and E-Governance. She is presently working in Operations & IT Area, IBS Hyderabad, IFHE University.