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The Classification of Workforce Requirement Planning for Service Oriented Operations

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Abstract:- In today's world of competitive international economy sectors, service industry or service sector oriented businesses, the key point is to maximize the efficiency and sustainability of the business directly related with optimal planning of the workload and distributing them among the employees. Helpdesks and operation centers are one of the fastest developing service area of this sector. This paper compares the machine learning algorithms that can be used for the classification of workforce requirements for a bank operation center which provides support to reduce operational workload of bank branches. Classification of the workload based on the quantity of Money Order and EFT operations within time zones aids in the management of workforce teams and distribution of jobs between team members.

Keywords: *Bank Operations, Workforce Planning, Classification, Machine Learning, ANN, Bayesian Networks, SMO, SVM*

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1. Introduction

Workforce planning and management according to requirements and demand is one of the key issues in service-oriented operations. One major area of service-oriented operations is call center services or specialized operational centers for differentiated operations like banks, stock market and financial institutions. The standard operating procedures are the same for all customer prototypes, however most customers have a unique requirement. The workforce planning and management have two common stages. Stage one involves the analysis of when and how many service operators, namely employees, should be hired or released and the second stage involves how and when employees should work for turnover based fields.Workforce planning and management problems are similar to the common features of general resource allocation problems. [1]

After the Second World War, when the balance between the supply and demand changed in favor of demanders, suppliers began searching for more intelligent and efficient ways of doing their operations. The years of operations research studies started in the earlyfifties and these operations takes the problem of human resource allocation and planning in focus. [2, 3] Actually, in those years the main allocation was the allocation of police officers on the roads and tolls based on traffic volumes, number of toll booths, and grade of service which is still a valid issue withmodern traffic congestion.

If the requirements of the resources can be estimated and forecast with a good classification, then this will solve the planning and allocation of personnel abilities, capacities, processing statistics, the risk of failure and mistakes as well as the need of a supervisor. After this progress, the remaining problem is mostly solved and successfully applied in software packages and even patented algorithms. [4, 5] There are also various studies about staff and personnel scheduling in the literature. [6-10]

2. Machine Learning, Classification and Intelligence

The definitions of machine learning and artificial intelligence are almost nested and inseparable by their nature. Starting from the 19th century when the industry revolutions started, the ultimate target and goal was to find an intelligent machine capable of acting as human workforce wherever and whenever needed. Nearly after a century, the concept of "Industry 4.0" has been introduced and takes its place in the revolution. [11]

Many human mental activities, like doing mathematics, engaging in commonsense reasoning, understanding language, and solving daily problems, are said to demand intelligence. [12] Learning is also a part of this intelligence which includes the gathering of new knowledge, development of skills and abilities through commands or practice, and the discovery of new possibilities, facts, paths and solutions to problems. These parts of this ultimate target are commonly the general aims of artificial intelligence. [13, 14]

However, machine learning progress is most often conflicted with the automation rules and memorization of the process. This is explained briefly in Figure 1based on the nature of the action to be taken. Automation is based on rules which are previously defined like in basic software algorithms in business and industrial PLC's in automation; rules mostly based on "if else then" or "switch cases" and repetitions of these procedures. On the left side, no decision has been made since the rules in a 100% automated system means there is nothing to decide. Vice versa, on the right side no automation and no rules are available except those related with the nature of the process. Decisions are taken without commonsense rules.

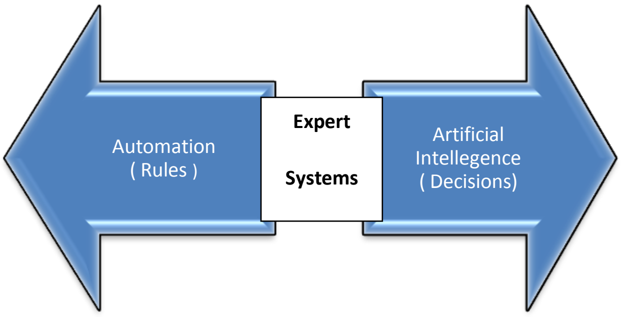

Figure 1. Automation versus Intelligence.

There are various machine learning methods used for classification for many years. [13, 15-20] The popularity of these methods become more important in the field of data mining after the evolution of distributed and parallel computing to cloud computing and various sources and forms of data which creates the modern concept of big data. Velocity, veracity, volume and variety dimensions of this big data make it more valuable if clustered and classified into more meaningful information. These common dimensions with more detailed features or attributes actually form the dataset for machine learning. If the dataset instances are provided with meaningful diversions of corresponding output classes, the learning based on this information or labeled data is a classified learning. If this kind of information or labels is not provided, then this type of learning is known as unsupervised learning. The main focus of the paper is to generate the supervised learning classification based on historical data and predict the future for proper planning by using the obtained classification. Another alternative learning based on the feedback from the environment during the learning process is reinforced learning. However, reinforced and unsupervised learning are not proper for the current dataset and the workforce requirement analysis problem due to their limitations and methodology. Even though there are many other alternatives and variations in machine learning regression and classification methods, the following ones are well known and suitable classification methods for the current research dataset and situation. [18, 19, 21, 22]

2.1 Bayesian Methods

Bayesian methods in classification are based on the probabilistic theory have been used since the 1950's using Bayesian statistics. [23] These methods are used in different applications both in theoretical and practical studies. [24] Bayesian statistics deal with the probabilities of events based on the conditions or properties relevant to the event. In classification, these properties or conditions are the input parameters related with the probability of the input item to the given class. There are different applications and usage of these Bayesian methods and in general they perform well in most classification problems. [25]

2.1.1 Naïve Bayes Classifier

The Naïve Bayes classifier is one of the most effective classifiers, well known for its predictive performance. The algorithm of the classifier is based on the conditional probability of each feature or attribute for the given class label which is calculated from training or previous data resulted in learning. Applying the Bayes' rule to calculate the probability of class C given the input vector allows for predicting the class with the highest posterior probability. [26-28] Bayes' rule gives the posterior probability of A with given B as a function of likelihood, which is the probability of B with given A, multiplied by the prior probability P(A) and divided by the evidence. In another words posterior probability can be thought of as the result of prior probability plus the test evidence.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$$Posterior = \frac{Prior \circ Likelihood}{Evidence}$$

2.1.2 Bayes Network Classifier – Bayesian Networks

Bayesian networks, also called graphical models, are composed of random variables shown as nodes and arcs connecting these nodes as the information of influence between these variables, namely probabilistic dependence or independence. [14, 28, 29]Bayesian networks are regarded as a probabilistic expert system for making the decision within an uncertainty framework. [30, 31]

2.2 Artificial Neural Networks

Artificial Neural Networks (ANN)are computational methodologies inspired from biological neuronsthat perform multifactorial analyses. [32]The first use of computational and practically usable neural networks coincide with the first years of the Bayesian Methods. [33, 34] These computational nodes can operate as nonlinear summing machines which makes a proportional summing of input values and obtains the net value from that sum. Proportional summing can be obtained by weights defined on each interconnection between the nodes. An artificial neural network needs an adaptation, or in other words, a learning process to understand and interpret the information flow according to inputs and outputs. [35] In Figure 2 a basic Artificial Neural Network structure can be seen with the inputs and a summation node connected with the weights and delivers the sum to the activation functions which will delivers the information for classification or regression.

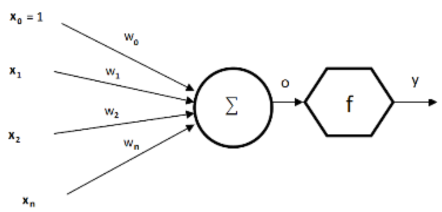

Figure 2. Basic Neural Network Structure

Artificial Neural Networks can be used with different methods for supervised, unsupervised and reinforced learning. There are some recommendations about which type of network and settings to use but in most cases the researcher must perform some trial and error studies depending on the data and the information. There are lots of various usage and applications with examples of classifications with Artificial Neural Networks in the literature.[15, 19, 32, 36-40]

2.3 Logistic Regression

Logistic regression is another predictive analysis derived from a statistical regression model which measures the degree of dependence between the binary or dichotomous dependent variable. Independent explanatory variables used for estimating the probabilities by the use of a sigmoid S shape logistic function curve which makes it different from Multiple Linear Regression or Linear Discriminant Analysis. [41-43] These independent variables are also called covariates. [44] Logistic regression uses the Maximum Likelihood Estimation (MLE) technique for estimation of coefficients. [42]

2.4 Support Vector Machines

Support Vector Machines, or the well-known abbreviation SVM's, is a rather new classification and regression algorithm compared with existing ones derived from pattern recognition and statistical learning theory, Vapnik–Chervonenkis(VC) dimension and margin hyperplanes. [45-49] SVM's is a supervised learning algorithm which builds a classification model based on the training information that can be used both for linear and non-linear classifications by the use of nonlinear kernel functions. [50] SVM's give a sparse solution with the use of simple geometric interpretation and their computational complexity does not depend on the dimensions of the explanatory variables. [51] One major advantage of SVM's over ANN is that SVM's always find a global minimum by the use of simple geometric interpretation and are less prone to overfitting, whereas back-propagation algorithms for ANN can suffer from converging to local optimal solutions.[52, 53] SVM's are good but not perfect, as algorithms with their slowness on large training sets decrease their popularity in big data and large scale applications. Their slowness is due to the algorithm's use of numerical quadratic programming (QP) as an inner loop, and this generates computational complexity.[54]

2.5 Sequential Minimal Optimization

Sequential minimal optimization (SMO) is an improved version of SVM's which makes it easy to implement, operates faster, and has better scaling for recent problems. SMO's use an analytic QP step and break the main problem into a series of the smallest possible optimization problems which generates less computational complexity and without extra matrix storage. [55, 56] SMO's can work in parallel in the training for SVM's which will improve their performance in the enterprise computational environments and cloud computing. [57, 58]

3. Problem Definition

Classification and segmentation of the workloads will improve the workforce assignment and planning for the call and operation centers. Since the abilities and the shifts of the employees differ between the two centers, proper planning should include the evaluation of the requirements and correct job segment matching. Types of jobs and duties also have some expected and officially declared complete timings. As a result of this, a priority dimension should be added to the concerns with the balanced distribution of the workloads between the employees. Distributing and allocating the jobs to resources is another research area based on optimization like the well-known knapsack problem in optimization.

4. Data Set And Operations

This paper compares the propermachine learning classification approaches in order to plan workforce planning by the operation centers.The data being worked on is obtained from the operation center of Is Bankasi which is the first public bank in Turkey and also one of the largest. The data used for the benchmarking of algorithms, collected from the real operational database systems and started from January 2012 to May 2016, include the raw data of hourly started transaction counts and corresponding to 10,000 lines of datafor money transfers and EFT orders. The data involves commercial money transfers from the companies which require extra control and authorization procedures, such as validating customer signature and checking transfer order details on the printed paper. This is unlike personal banking, which can easily be done by online banking systems.

The main aim of the classification is based on quantitative classification based on the types of the job and the quantity of hours and corresponding level zones. Since the precise forecasting of the job data is difficult to obtain, the classification of the requirement levels improves reserving the required amount of employees for the expected workload. Moreover, the average amount of time required to fulfill an assigned job will vary depending on the sub jobs and money transfer orders. Work completion time varies from 2-15 minutes from job to job and employee to employee as shown in Figure 3 from the related work by the authors. [59]

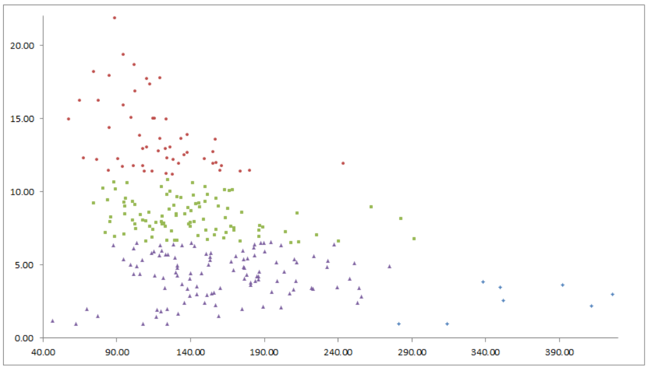

Figure 3. Employee Assigned Work Completion Time Distribution

In order to make proper and efficient planning, dynamic classification is required. In the general management of the operation centers, employees are distributed into teams of 8-10 and managed and controlled by a supervisor. The planning can be done by workload distribution to teams or among the team members. By means of management and control, a team doing a similar type of works performs better and is managed better since the supervisor is controlling similar types of operations.

5. RESULTS AND CONCLUSION

The data analyses have been done in two stages with different classification and regression models. Logistic Regression,Sequential Minimal Optimization (SMO), Support Vector Machines (SVM) with LibSVM, Naïve Bayes, Bayesian Net and Neural Network classification algorithms were applied to the data by using open source optimization software package WEKA. [60]

In the first stage, a simple classification has been made based on the service hours of an operational center starting from official working hours for financial institutions and money transfers from 9:00 to 16:00. As can be seen from Table 1, each hour is separated into proper work load zones with statistical analysis of the data for that time zone. Each hour has a different set of zones depending on the historical data.

Table 1. Hourly Zones and Segments

Hour	Zone1	Zone2	Zone3	Zone4	Zone5
9:00	200	300	400	500	600
10:00	400	550	700	850	1000
11:00	500	675	850	1025	1200
12:00	300	450	600	750	900
13:00	400	550	700	850	1000
14:00	700	900	1100	1300	1500
15:00	700	900	1100	1300	1500
16:00	0	25	50	75	100

The historical data includes the time, the amount of workload and the corresponding job class as from the zones for each hour, the performance comparison of the methods are given in Table 2. The overall outcome of this stage allows making the planning within the team level.

Table 2. Classification Results for Model 1 – 5 Zone Classification

Precision						
Class	**NN**	**Logistic Reg.**	**SMO**	**SVM**	**Naive Bayes**	**Bayes Net**
Zone2	0.727	0.637	0.634	0.583	0.551	0.709
Zone5	0.438	0.2	0	0.667	0	0.5
Zone4	0.639	0.846	0.737	0	0	0.564
Zone3	0.585	0.485	0.531	0.192	0.228	0.373
Zone1	0	0	0	0	0	0
Recall						
Class	**NN**	**Logistic Reg.**	**SMO**	**SVM**	**Naive Bayes**	**Bayes Net**
Zone2	0.949	0.929	0.923	0.047	0.458	0.633
Zone5	0.636	0.364	0	0.182	0	0.364
Zone4	0.354	0.169	0.215	0	0	0.477
Zone3	0.524	0.169	0.41	0.914	0.619	0.657
Zone1	0	0	0	0	0	0

Also, historical data is classified into three different classes as low, moderate and high tomodel the daily total quantity requirements for the workforce planning. This approach is used for preplan the teams and distributing the workload for teamswhereas theprevious approach (classifying into 5 zones)helps to make the employee planning during the day and shifts the employees from one duty to another.

Table 3. Classification Results for Model 2 3 Zone Classification

Precision					
Class	**NN**	**Logistic Reg.**	**SMO**	**SVM**	**Bayes Net**
Low [0-550)	0.897	0.616	0.642	0.882	0.862
Moderate [550-1100)	0.844	0.644	0.678	0.487	0.734
high [1100+)	0.869	0.81	0.842	0	0.818
Recall					
Class	**NN**	**Logistic Reg.**	**SMO**	**SVM**	**Bayes Net**
Low [0-550)	0.924	0.646	0.721	0.146	0.71
Moderate [550-1100)	0.881	0.655	0.67	0.985	0.852
High [1100+)	0.711	0.684	0.65	0	0.768

As can be seen from the table above, Neural Network based classification performs well on both precision and recall models, SMO performs well on small quantities, and SVM works well on moderate classes but not the others. Bayesian Net also works well for both classes and segments.

In conclusion, for workforce assignment and classifications it is better to apply Artificial Neural Networks and Bayesian Networks for proper results.

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7. CONFLICT OF INTEREST

No conflict of interest was declared by the authors.

References

[1] P. De Bruecker, J. Van den Bergh, J. Beliën, and E. Demeulemeester, "Workforce planning incorporating skills: State of the art," *European Journal of Operational Research*, vol. 243, pp. 1-16, 5/16/ 2015.

[2] G. B. Dantzig, "Letter to the Editor-A Comment on Edie's “Traffic Delays at Toll Booths”," *Journal of the Operations Research Society of America*, vol. 2, pp. 339-341, 1954.

[3] L. C. Edie, "Traffic delays at toll booths," *Journal of the operations research society of America*, vol. 2, pp. 107-138, 1954.

[4] P. H. Leamon, "Method and system for skills-based planning and scheduling in a workforce contact center environment," ed: Google Patents, 2005.

[5] Y. Mui, M. Bennett, J. Martin, A. Shukla, and P. Lardin, "Method for enterprise workforce planning," ed: Google Patents, 2001.

[6] I. Blöchliger, "Modeling staff scheduling problems. A tutorial," *European Journal of Operational Research*, vol. 158, pp. 533-542, 11/1/ 2004.

[7] P. Brucker, R. Qu, and E. Burke, "Personnel scheduling: Models and complexity," *European Journal of Operational Research*, vol. 210, pp. 467-473, 5/1/ 2011.

[8] A. T. Ernst, H. Jiang, M. Krishnamoorthy, and D. Sier, "Staff scheduling and rostering: A review of applications, methods and models," *European Journal of Operational Research*, vol. 153, pp. 3-27, 2/16/ 2004.

[9] S. C. Sarin and S. Aggarwal, "Modeling and algorithmic development of a staff scheduling problem," *European Journal of Operational Research*, vol. 128, pp. 558-569, 2/1/ 2001.

[10] J. Van den Bergh, J. Beliën, P. De Bruecker, E. Demeulemeester, and L. De Boeck, "Personnel scheduling: A literature review," *European Journal of Operational Research*, vol. 226, pp. 367-385, 5/1/ 2013.

[11] S. Dais, "Industrie 4.0–Anstoß, Vision, Vorgehen," *Industrie 4.0 in Produktion, Automatisierung und Logistik: Anwendung· Technologien· Migration*, pp. 625-634, 2014.

[12] N. J. Nilsson, *Principles of artificial intelligence*: Morgan Kaufmann, 2014.

[13] R. S. Michalski, J. G. Carbonell, and T. M. Mitchell, *Machine learning: An artificial intelligence approach*: Springer Science & Business Media, 2013.

[14] E. Alpaydin, *Introduction to machine learning*: MIT press, 2014.

[15] B. Heung, H. C. Ho, J. Zhang, A. Knudby, C. E. Bulmer, and M. G. Schmidt, "An overview and comparison of machine-learning techniques for classification purposes in digital soil mapping," *Geoderma*, vol. 265, pp. 62-77, 3/1/ 2016.

[16] D. E. Goldberg and J. H. Holland, "Genetic algorithms and machine learning," *Machine learning*, vol. 3, pp. 95-99, 1988.

[17] G. Holmes, A. Donkin, and I. H. Witten, "Weka: A machine learning workbench," pp. 357-361.

[18] S. B. Kotsiantis, I. Zaharakis, and P. Pintelas, "Supervised machine learning: A review of classification techniques," ed, 2007.

[19] D. Michie, D. J. Spiegelhalter, and C. C. Taylor, "Machine learning, neural and statistical classification," 1994.

[20] J. R. Quinlan, *C4. 5: programs for machine learning*: Elsevier, 2014.

[21] K. Jajuga, A. Sokolowski, and H.-H. Bock, *Classification, clustering, and data analysis: recent advances and applications*: Springer Science & Business Media, 2012.

[22] A. Ozpinar and E. S. Kucukasci, "Use of Chaotic Randomness Numbers: Metaheuristic and Artificial Intelligence Algorithms."

[23] M. West, *Bayesian forecasting*: Wiley Online Library, 1999.

[24] M. Goldszmidt, "Bayesian network classifiers," *Wiley Encyclopedia of Operations Research and Management Science,* 2010.

[25] J. Cheng and R. Greiner, "Comparing Bayesian network classifiers," in *Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence*, 1999, pp. 101-108.

[26] P. Langley, W. Iba, and K. Thompson, "An analysis of Bayesian classifiers," pp. 223-228.

[27] R. O. Duda and P. E. Hart, *Pattern Elesslfication and Scene Analysis*: Wiley, 1973.

[28] N. Friedman, D. Geiger, and M. Goldszmidt, "Bayesian network classifiers," *Machine learning,* vol. 29, pp. 131-163, 1997.

[29] F. V. Jensen, *An introduction to Bayesian networks* vol. 210: UCL press London, 1996.

[30] P. Aguilera, A. Fernández, F. Reche, and R. Rumí, "Hybrid Bayesian network classifiers: application to species distribution models," *Environmental Modelling & Software,* vol. 25, pp. 1630-1639, 2010.

[31] T. D. Nielsen and F. V. Jensen, *Bayesian networks and decision graphs*: Springer Science & Business Media, 2009.

[32] J. Montaño and A. Palmer, "Artificial Neural Networks, opening the black box," *Metodología de las Ciencias del Comportamiento,* vol. 4, pp. 77-93, 2002.

[33] B. Widrow and M. E. Hoff, "Adaptive switching circuits," in *IRE WESCON convention record*, 1960, pp. 96-104.

[34] F. Rosenblatt, "Principles of neurodynamics: Perceptrons and the theory of brain mechanisms. 1962," *Washington DC: Spartan*.

[35] A. Ozpinar and E. Ozil, "Smart Grid and Demand Side Management: Application of Metaheuristic and Artificial Intelligence Algorithms."

[36] J. E. Dayhoff and J. M. DeLeo, "Artificial neural networks," *Cancer,* vol. 91, pp. 1615-1635, 2001.

[37] M. H. Hassoun, *Fundamentals of artificial neural networks*: MIT press, 1995.

[38] G. F. Hepner, "Artificial neural network classification using a minimal training set. Comparison to conventional supervised classification," *Photogrammetric Engineering and Remote Sensing,* vol. 56, pp. 469-473, 1990.

[39] W. Wu, B. Walczak, D. Massart, S. Heuerding, F. Erni, I. Last*, et al.*, "Artificial neural networks in classification of NIR spectral data: design of the training set," *Chemometrics and intelligent laboratory systems,* vol. 33, pp. 35-46, 1996.

[40] G. Zhang, M. Y. Hu, B. E. Patuwo, and D. C. Indro, "Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis," *European journal of operational research,* vol. 116, pp. 16-32, 1999.

[41] D. W. Hosmer Jr and S. Lemeshow, *Applied logistic regression*: John Wiley & Sons, 2004.

[42] S. Menard, *Applied logistic regression analysis*: Sage, 2002.

[43] D. W. Hosmer and S. Lemeshow, *Multiple logistic regression*: Wiley Online Library, 2000.

[44] S. H. Walker and D. B. Duncan, "Estimation of the probability of an event as a function of several independent variables," *Biometrika,* vol. 54, pp. 167-179, 1967.

[45] R. O. Duda and P. E. Hart, *Pattern classification and scene analysis* vol. 3: Wiley New York, 1973.

[46] F. W. Smith, "Pattern classifier design by linear programming," *IEEE Transactions on Computers,* vol. 100, pp. 367-372, 1968.

[47] V. N. Vapnik and S. Kotz, *Estimation of dependences based on empirical data* vol. 40: Springer-Verlag New York, 1982.

[48] V. Vapnik and A. Chervonenkis, "On one class of perceptrons," *Automation and Remote Control,* vol. 25, 1964.

[49] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," in *Proceedings of the fifth annual workshop on Computational learning theory*, 1992, pp. 144-152.

[50] A. Aizerman, E. M. Braverman, and L. Rozoner, "Theoretical foundations of the potential function method in pattern recognition learning," *Automation and remote control*, vol. 25, pp. 821-837, 1964.

[51] C. J. Burges, "A tutorial on support vector machines for pattern recognition," *Data mining and knowledge discovery,* vol. 2, pp. 121-167, 1998.

[52] M. Rychetsky, *Algorithms and architectures for machine learning based on regularized neural networks and support vector approaches*: Shaker, 2001.

[53] J. A. Suykens, J. De Brabanter, L. Lukas, and J. Vandewalle, "Weighted least squares support vector machines: robustness and sparse approximation," *Neurocomputing,* vol. 48, pp. 85-105, 2002.

[54] T. Joachims, "Making large scale SVM learning practical," Universität Dortmund1999.

[55] J. C. Platt, "12 fast training of support vector machines using sequential minimal optimization," *Advances in kernel methods,* pp. 185-208, 1999.

[56] J. Platt, "Sequential minimal optimization: A fast algorithm for training support vector machines," 1998.

[57] L. J. Cao, S. S. Keerthi, C. J. Ong, J. Zhang, U. Periyathamby, X. J. Fu*, et al.*, "Parallel sequential minimal optimization for the training of support vector machines," *IEEE Transactions on Neural Networks,* vol. 17, pp. 1039-1049, 2006.

[58] H.-R. Zhang and Z.-Z. Han, "An improved sequential minimal optimization learning algorithm for regression support vector machine," *Journal of Software,* vol. 14, pp. 2006-2013, 2003.

[59] S. I. SERENGIL and A. OZPINAR, "Planning Workforce Management for Bank Operation Centers with Neural Networks."

[60] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software: an update," *ACM SIGKDD explorations newsletter*, vol. 11, pp. 10-18, 2009.