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Credit Risk Management for the Jordanian Commercial Banks: A business Intelligence Approach

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Abstract: Commercial banks in Jordan are regarded as vitally important and competitive financial organizations that seek profit by providing various financial services to various customers while managing different types of risk. Credit forms a cornerstone of the banking industry as credit behavior stronglyinfluences the profitability and stability of a bank. Therefore, loan decisions for such instuitions are crucialbecause they can avert credit risk. However, loan application evaluation at Jordanian banks is subjective based oncredit officer's intuition and sometimes a combination of credit officer'sjudgment and traditional credit scoring models. On the other hand, banks store data about their customers in data warehouses which can be viewed as hidden knowledge assets that can be accessed and used through data mining tools. Artificial Neural Networks (ANN) represent a recent development of a new family of statistical techniques and promising tools of data mining and data processing. The current study attempts to develop an artificial neural network model as a decision support systemto credit approval evaluation at Jordanian commercial banks based on applicant's characteristics; the proposed model can be utilized to aid credit officers make better decisions when evaluating future loan applications. A real world credit application of cases of both accepted and rejected applications from different Jordanian commercial banks was used to build the artificial neural model. The experimental results show that artificial neural networks area promising addition to the existing classification methods.

Key words: Business Intelligence, Artificial Neural Networks, Data Mining, Knowledge Assets, Commercial Banks, Jordan.

INTRODUCTION

The service economy plays an important role in the growth and social well-being of Jordan as a developing country with limited natural resources. Jordanian banks offer credit to individuals, business firms, service organizations, manufacturing and agricultural enterprises, and the government to enable them to proceed fruitful investments and, therefore improve the economic development of Jordan. When banks sustain good performance, it will add to the profitability of a bank as well to the economic growth and development of a country.

Commercial banks in Jordan are regarded as vitally important and competitive financial organizations that seek profit by providing various financial services to customers while managing different types of risk.Risk taking is often viewed as the basic driver for financial behavior and profitability.However, credit approval evaluation at the Jordanian banks is subjective in nature. This entails reviewing each loan application manually, imposing biases including personal insights, knowledge, and intuition of the credit manager. This method has been replaced in a few banks by credit scoring models or a combination of objective and subjective reviews to make proper credit decisions. On the other hand, banks store data about their customers in data warehouses which can be viewed as hidden knowledge assets that can be accessed and utilized through data mining tools.Therefore,credit managersat Jordanian banks need to develop moreeffectivemodels to improve the predictive accuracy of credit risk decisions.

The purpose of the current study is tobuild up a high performance predictive model using artificial neural networks (ANN) for the Jordanian commercial banks. This model highlights the most significant variables that influence the approval of personal loan decisions in the Jordanian credit industry.Furthermore, itwould improve credit decision effectiveness andcontrol loan office tasks, as well as saving analysis time and cost.

Credit forms a cornerstone of the banking industry as credit behaviorimpacts the profitability and stability of a bank. Therefore, loan decisions are important for financial institutions because they avert credit risk. Olokoyo (2011) points out that lending is at the heart of the banking industry.Often, bank managers are faced with the problem of trying to increase credit volume while decreasing the possibility to defaulting (Huang *et al.*, 2007). On the other hand, credit scoring models enablebank mangersto identify those accounts that are likely to

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be credit worthy (good credit risks) and those likely to default (bad credit risks) based on applicant's characteristics taken from the application form.

Nowadays, the future of the banking industry is highly dependent on risk management dynamics. Banks are looking for more efficient risk management tools and decision support modelssupplemented by analytical tools to survive in uncertain business environments. The basis of risk management is to establish a framework that defines corporate priorities, loan approval, credit risk rating system,risk-adjusted pricing system, loan-review mechanism and comprehensive reporting system(Arunkuma and Kotreshwar, 2006). In addition, Olszak and Ziemba (2006) stress that decision-making is becoming more challenging.Itneeds using scattered information assets and engaging different parties (stakeholders, suppliers, customers, etc) to improve decision-making in a scope of global nature. According to these authors business intelligence (BI) systems can meet such challenges: support and increase proactive decision-making. Besides, BI contributes to optimizing business process and recourses leading to increased profits. A BI system is a combined set of tools and technologies used to collect data and analyze information to support making more improved decisions.

Artificial neural networks (ANN) have emerged as advanceddata mining tools that mimic the human brain on the computer. These techniques are based on parallel distributed processing design. The parallel structure makes neural networks skillful, analyzing problems with many variables (Tafti, 1993; Turban *et al.*, 2011). Scientists have been inspired by the capabilities of the human brain for information processing and problem solving. Therefore, neural network designers strive to put intelligence into these systems in the form of generalized ability to learn and recognize patterns to exhibit similar intelligent functionality like humans (Shachmurove, 2002).

The rest of this paper is structured as follows: Section 2reviews the Jordanian banking system. Section 3introduces literature review. Section 4 describes the theoretical background of neural networks. Section 5 presents data and experimental results. Section 6presents relevant discussion and conclusion.

2. Overview of Jordanian Banking System:

The banking industry in Jordan plays a decisive role in the growth and development of the country.Jordanian banksare the pillar of economic activity as well as key providers to the national economyas they play a leading role in improving economic growth in the country (Kandah, 2009).

The Jordanian Banking System combines the Central Bank of Jordan CBJ, Jordanian commercial banks, Jordanian Islamic banks, non-Jordanian banks, specialized lending institutions (government and joint ownership), money-changing companies and representative offices of foreign banks in Jordan. According to the Association of Banks Annual Report (2010) and CBJ annual report (2010) the number of working banks in Jordan stood at twenty five by the end of 2010. The sector includes thirteen commercial banks, three Jordanian Islamic banks, and nine foreign banks. Their services spread over most regions of Jordan with an index of banking density of 9,179 people for each branch at the end of 2010. Also, the number of branches of licensed banks working inside Jordan was 663 branches (524 of these are commercial) and 81 representative offices. Furthermore, the number of branches,functioning abroad was 153 branches for commercial banks and 13 for representative offices.

Over the past few years,the Jordanian banking sector has been actively supporting economic activities and social development of the country by financing various types of investment projects. Figure 1 shows the development of the overall credit facilities extended by banks working in Jordan in Jordanian Dinars JD. Credit facilitieshave increased since the year 2000 to reach 213 percent by the end of 2010 at an annual growth rate of 11.4 percent.

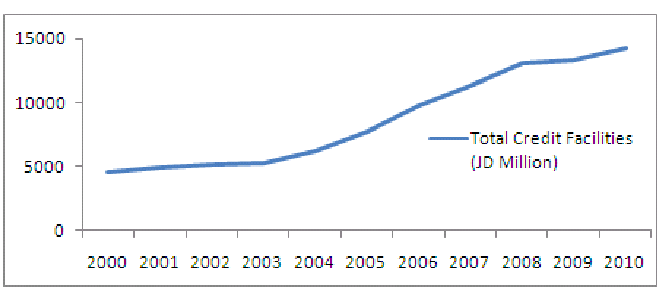

Fig. 1: Total credit facilities extended by banks operating in Jordan (2000-oct.2010).

Figure 2 indicates the percentage of credit facilities to GDP;this wouldverify the significance of the banking sector for the Jordanian economy.

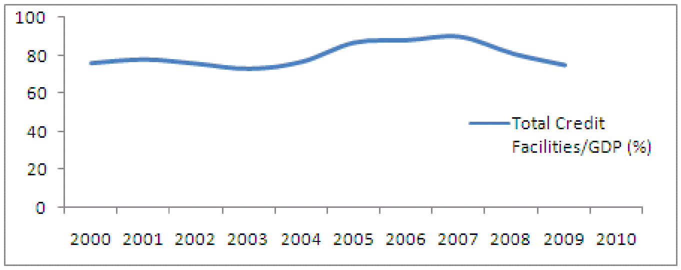

Fig. 2: The percentage of credit facilities to GDP (2000-2009).

The rate of loans and advances to total credit facilities increasedfrom 59.6 percent in 2000 to 86.1 percent by the end of 2010 (Central Bank of Jordan [CBJ], 2010 and figure 3).Simultaneously, the rate of overdrafts to total credit facilities and the rate of bills and discounted to total credit facilities witnessed a decline during same period. This is an evidence that retail banking is gaining more ground in the operations of banks in Jordan with an increase in economic activity as well, since the increase in the volume of credits was allocated to all economic activities.

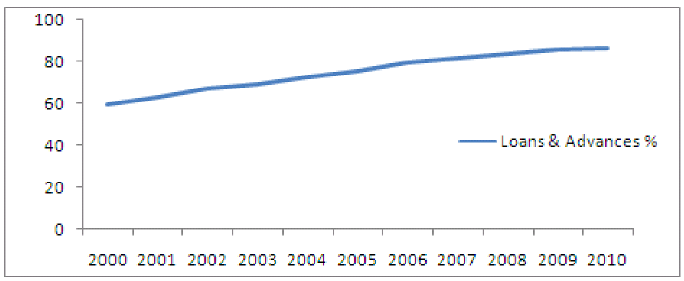

Fig. 3: Development of the percentage of loans and advances to total credit facilities (2000-2010).

Figure 4 shows the spread of credit facilities of banks working in Jordan over the economic sector during the period 2000 to 2010. General trade, construction and industry are the main sectors accounting for the biggest part in the volume of credits. Figure 5 illustrates the development of the credit facilities extended by banks working in Jordan to the main economic sectors during the period 2000-2010.

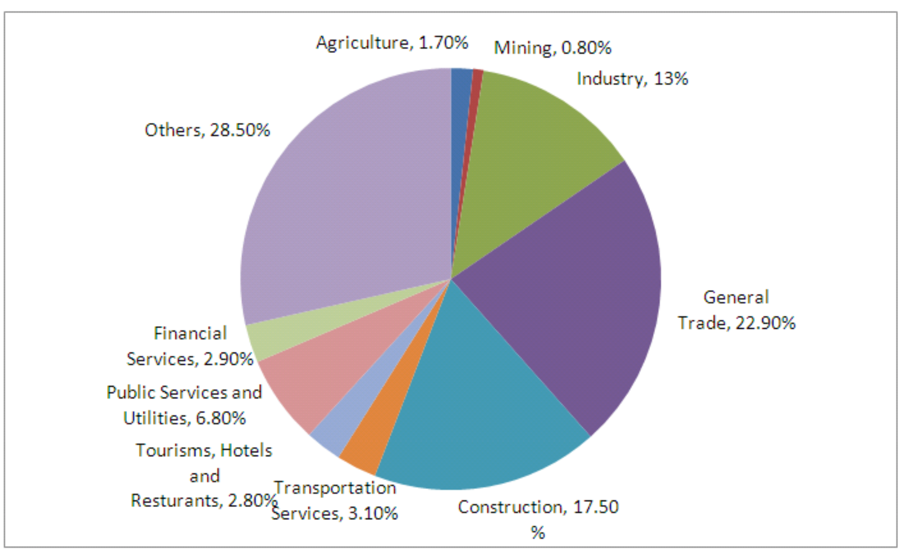

Fig. 4: The distribution of credit facilities of banks operating in Jordan according to the economic activity in (2000- 2010).

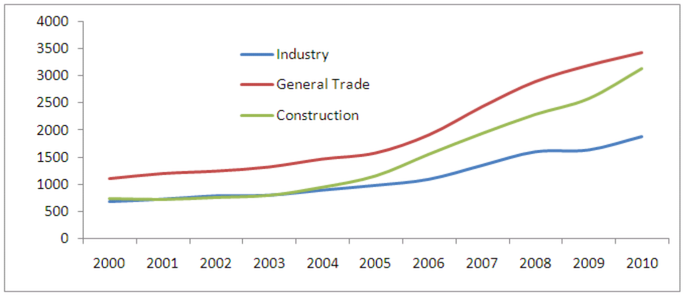

Fig. 5: The distribution of credit facilities over major economic sectors (2010-2010).

To highlight the significant role of the Jordanian commercial banks, table 1shows thepercentages of some financial key signalstaken from balance sheet itemsamong banks operating in Jordan at the end of 2010.They are total assets, the outstanding credit extended by banks, total deposits, the total shareholders' equity and the total capital. As shown,the five percentages affirm the soundness of the commercial banksas they record three-quarter ofshare in each one. 74.87 percent of the total credit facilities extended by banks operating in Jordan are from commercial banks. This indicatesthe role of Jordanian commercial banks as well as their importance in enhancing economic and social development in Jordan.

Table 1: Some financial indicators of banks operating in Jordan in 2010.

	% of Total Assets	% of Total Credit Facilities	%of Total Deposit	%of Total Capital	%of Shareholders' Equity
Commercial Banks	75.9	74.87	73	75.4	78.8
Islamic Banks	12.7	15.56	15.3	11.4	9.8
Foreign Banks	11.4	9.56	11.8	13.3	11.4

Literature Review:

The credit industry has undergone intensive growth and improvement during the last decade. Banks' officershave developed some credit scoring models to supplement traditional methods in order to classify loan applications to either good or bad based onthe applicant's attributes such as employment history, prior credit history, age, etc, etc. Researchers are constantly searching for new algorithms to improve the accuracy of credit scoring models.

According to West (2000) and Ong *et al.* (2005) an improvement even to a fraction of a percent in credit accuracy will lead to significant savings. Bensic *et al.* (2005) compare the performance of using logistic regression (LR), neural network (NN), and classification and regression trees (CART) decision tree models as a credit scoring model for small business lending. Different neural network algorithms have been tested. They show that the probabilistic NN model achieves best results. They called for extending the methodology analysis by adding more NN algorithms such as unsupervised classifiers as well as exploring other advanced statistical methods with artificial intelligence techniques such as genetic algorithms in credit scoring modeling.

Martens *et al.* (2002) use rule extraction techniques to create a classification model. Boguslauskas and Mileris (2009) argue that artificial neural networks and logistic regression are the most efficient, widely used methods for credit risk measurement.They describethe rates of credit risk estimation models accuracy and their calculation for the analysis of Lithuanian enterprises credit risk. They confirm that neural networks models enjoy higher rates of classification accuracy.

Limsombunchai *et al.*, 2005 developed a lending decision model (credit scoring) for the agricultural sector in Thailand. They used logistic regression and ANN to identify critical factors in lending decision process in the agricultural sector and to predict the borrower's credit worthiness (likelihood of a good loan risk). The empirical results show that PNN model was successfully used in classifying and screening agricultural loan applications in Thailand. Huang *et al.*(2007)state that neural network models are more accurate, adaptive and robust in bank failure prediction when compared with other techniques such as discriminant analysis, logistic regression, etc.

Raghavendra and Simha (2010) utilized data mining feature selection algorithms on Australian, German, and Japanese, credit data in order to identify the optimal set of attributes for the classification model. The feature selection algorithm and classification accuracy were used to measure the performance of the predictive model with the neural network for risk classification. Results show that the classification accuracy and number of features selected algorithms with neural network were more efficient when compared with other methods. Lahsana *et al.*(2010) point out that to pursue even a small improvement in credit scoring accuracy, soft computing techniques have to be used to assist existing methods.

Keramati and Yousefi (2011) suggest that credit managers need to employ machine learning techniques to meet the increasing demand on credit departments as well to handle the huge amount of credit data in order to save time and reduce errors. Thus neural networks are a rewarding alternative business intelligence tool that can be applied to credit scoring models as they provide better classification accuracy. Therefore, the main objective of the current study is to propose a high performance predictive model capable of assisting credit managers in taking sound and safe personal loan decisions.

Data Collection and Variables Definitions:

A pooled data of both accepted applications and rejected applications from different Jordanian commercial banks for the 2006-2011periods was used to achieve the objective of the current study. The number of observations from each bank was concealed in order to protect the confidentiality of the banks.The data contentis composed of 492 cases. In the provided sample, 292 (59.3 percent) applications were credit worthy while 200 (40.3 percent) applications werenot.

The dataset contains different variables including applicant's age, gender, total income,DPR (i.e. debt payment ratio measures the applicant's repaying ability: high DPR ratio points to high credit risk, whereas low DPR ratio points to a good credit application), credit history, loan amount, interest rate, loan purpose, period in months with current employer, duration in month, guarantor, nationality, and company's type as well as the credit decision (target).

In total thirteen variables were used:seven of them were scale while sixwere categorical. Also, there were 12 independent variables and 1 dependent categorical variable with two values, 1 for accepted applications and 0 for rejected ones. Categorical variables were converted into numerical values in order to be utilized by neural network model. All scale variables (using the rescaling of covariates option in SPSS) were standardized so as to improve the network training. SPSS software(Version 18) was used to perform the analysis for the current study.

Methodology:

Artificial neural networks are considered a powerful alternative to conventional forecasting and classification methods due to their ability to capture nonlinear and complex relationships. These models have a biologically inspired capability that mimics processing capabilities of the human brain (Cao and Parry, 2009). They have been used successfully in financial applications, a good ability in classification (e.g., credit scoring, corporate failure prediction and bond ratings) as well as in modeling tasks such as predicting share price movements and exchange rate fluctuations. The multi-layer perception (MLP) is the most popular feed-forward neural network (FFNN) model used in pattern recognition. Designing an artificial neural network model successfully relies on a clear understanding of the problem, and on deciding upon most influential input variables.

A typical FFNN model is represented as some processing units called neurons cooperating across several linking layers (Lahsansa *et al.*, 2010). The information flows from origin to destination strictly in one direction through a system of weighted connections, without interconnections between the output of a neuron and the input of another neuron in the same layer or in a preceding layer. The output of each neuron is the outcome after applying the transfer function to the weighted sum of all inputs to that neuron (Limsombunchai *et al.*, 2005).

A typicalFFNN model is usually comprised of a three-layered architecture: input, hidden, and output layers. The input layer feeds the input variables (predictors) to the next layer. Each hidden neuron receives a weighted sum of all inputs in the input layer, applies a transfer function such as log sigmoid, hyperbolic tangent, softmax to the weighted sum. Similarly, each hidden neuron transfers a weighted outcome to each neuron in the output layer i.e. each dependent variable neuron (Ong *et al.*, 2005; Cao and Parry, 2009). The outcome of the output neuron is the solution of the problem. The neural networks learn the desired relationship between the independent and dependent variables by training the net using a representative set of (input, target) pairs.A learning algorithm is used to find the values of the connection weights where the network preserves its knowledge. During training when an input pair is fed to the network, the net calculates a temporary output, Y. Next, the net compares the actual output, Y, with the desired output,T, and if not satisfied then it adjusts the connection weights in proportion to error which is equal to the difference between its output and the target in an iterative process until a desirable result is reached. This is done mathematically by calculating delta Δ, where is:

$$\Delta = T - Y$$

The training objective is to find the best set of weights thatlessensthe mean squared error(Malhotra and Malhotra, 2003). The network model is trained until it is able to recognize the input patterns and classify them to give corresponding outputs.

Furthermore, the current study will use multilayer feed-forward (MLFF) algorithm to builda 3-layer neural network model. The number of neurons in the first layer and the last layer should be set according to the number of independent variables and dependent variable respectively. The middle layer is the hidden layer and the number of neurons in this layer will be set during model implementation using the automatic architecture selection in SPSS. Therefore, the neural network model will consist of three fully connected layers: an input layer, a hidden layer and an output layer in 12-9-1 architecture. Therefore, the input layer has 12 neurons equivalent to the independent variables, 9 hidden neurons with hyperbolic tangent function while the output layer represents the dependent variable with softmax activation function. Next, the training dataset will be used to train the neural network on mixed types of accepted and rejected applications. Throughout the training phase, the net will extract the pattern of accepted applications as well as the pattern of rejected applications. After training the net will classify the training data correctly. Then, the net is ready for testing phase; a testing set (which includes cases that the net has not seen before) will be used to examine the model's predictive power. This study uses the batch training method because it reduces total error more quickly.

Result Analysis:

To build the neural network model, the dataset was divided randomly using a partitioning variable created by SPSS into training, validation and testing subsets.359 (73 percent) cases were used for training, 64 (13 percent) for validation, and 69 (14 percent) for testing. The three subsets contain both accepted and rejected applications as seen in table 2.

Table 2: Screening Data.

Target						
partition			Frequency	Percent	Valid Percent	Cumulative Percent
validation	Valid	0	38	59.4	59.4	59.4
		1	26	40.6	40.6	100.0
		Total	64	100.0	100.0	
testing	Valid	0	24	34.8	34.8	34.8
		1	45	65.2	65.2	100.0
		Total	69	100.0	100.0	
training	Valid	0	138	38.4	38.4	38.4
		1	221	61.6	61.6	100.0
		Total	359	100.0	100.0	

Using training set with the mentioned architecture,the network was able to conduct the training and learn the relationship between input attributes and credit decision. A training algorithm was used toadjust the connection weights in the neural network during the learning phase.Avalidation setwas used during training as well to minimize overfitting. To measure the predictive performance of the developed model, a testing set was used to test the results.All classification results are shown in Table 4.

Furthermore, the gradient descent optimization algorithm was used to estimate the synaptic weights of the neural network with learning rate and momentum 0.7 and 0.1 respectively.Table 3 below displays the training results of the neural network. The training is aimed to reduce the error between the network output and the actual output.As seen from table 3 the percentage of incorrect predictions was 7 percent, meaning the neural model was able to classify 93 percent of training cases correctly. Also, the percentages of false predictions for the testing and validations were 8.7 percent and 17.2 percent respectively.

Table 3: Model Summary

Training	Cross Entropy Error	63.285
	Percent Incorrect Predictions	7.0%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	00:00:00.471
Testing	Cross Entropy Error	19.171
	Percent Incorrect Predictions	8.7%
Holdout	Percent Incorrect Predictions	17.2%

Table 4: Classification Results.

Sample	Observed	Predicted		
		0	1	Percent Correct
Training	0	124	14	89.9%
	1	11	210	95.0%
	Overall Percent	37.6%	62.4%	93.0%
Testing	0	21	3	87.5%
	1	3	42	93.3%
	Overall Percent	34.8%	65.2%	91.3%
Holdout	0	29	9	76.3%
	1	2	24	92.3%
	Overall Percent	48.4%	51.6%	82.8%

Source: output of SPSS package.

Table 5explains the analysis of importance value of independent variables. The importance of an independent variable is a measure of how much the predicted value of the network's model is influenced by different values of the independent variable. Large importance value means the variable has the strongest effect on the credit decision outcome. As seen, debt income ratio (DPR) has the highest concern in the model creation and the predicted value of the model (credit decision) is strongly influenced by the DPR while gender achieved the least importance level. Table 5 also displays the normalized importance which is equal to the percentage of each variable importance value divided by the largest importance value (in this case the DPR's importance value).

Table 5: Independent Variable Importance.

	Importance	Normalized Importance
age	0.071	43.8%
gender	0.027	16.8%
Lon purpose	0.061	37.5%
TML	0.114	70.1%
guarantor	0.076	46.8%
DPR	0.163	100.0%
amount	0.045	27.5%
Income term	0.069	42.4%
experience	0.058	35.5%
nationality	0.126	77.7%
loan period	0.097	59.6%
interest rate	0.093	57.5%

Figure 6 shows the descending order of the normalized importance values shown in table 3.

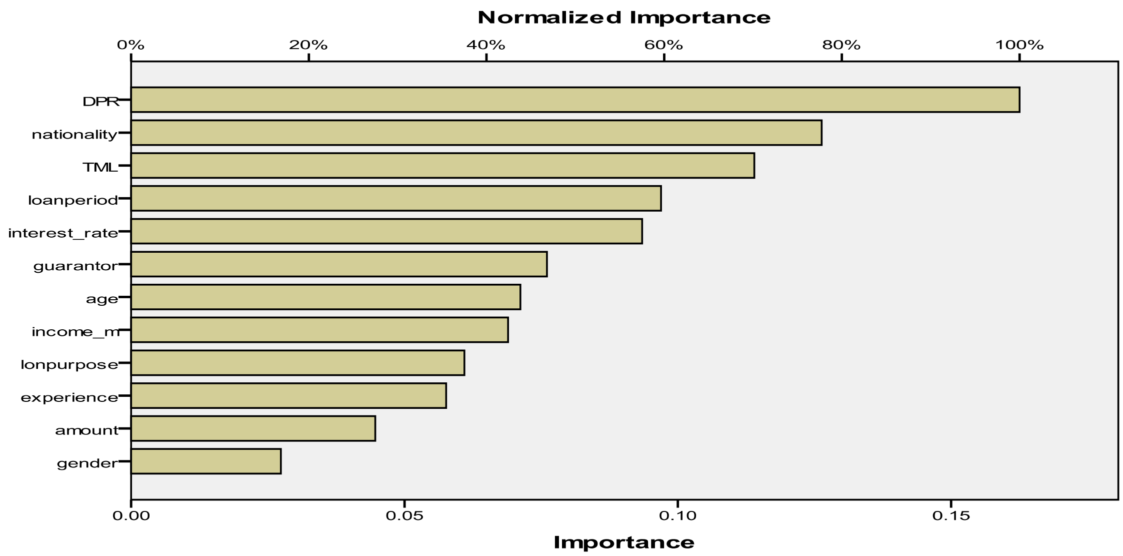

Fig. 6: Normalized independent variable importance.

DPR, nationality, and company's type seem to have the greatest effect on how the network classifies credit applications, whereas gender has the least influence on credit decision. The way these variables are correlated to the predicted value of the credit decision is not obvious. From commonsense, one couldguess that a larger amount of DPR points to a greater likelihood of rejecting the credit application. Also, Jordanian applicants can get credit much easier thannon-Jordanian applicants. Besides, banks are more flexible to extend credit to applicants working in companies accredited to the bank (TML) companies.

Discussion and Conclusion:

The results show the neural model could screen 95 percent of accepted applications correctly, and 89.9 percent of rejected applications correctly in an overall percent, 93 percent. In the holdout sample, classification accuracy level was 92.3 percent for accepted applications and 76.3 percent for rejected applications with an overall percentage of 82.8. Furthermore, testing set classification accuracy of accepted applications was 93.3 while for rejected applications was 87.5 percent with an overall percentage of 91.3.However, type I error occurs when rejected applications are classified as accepted applications.On the other hand type II error occurs when an accepted application is classified as rejected one. For a lending decision, creditors need to look for a classification tool that reduces type I error as much as possible to avoid the cost of default as possible. The percentage of type I error in the training data was 10.1percent; while for the testing data it was 12.5 percent(see Table 3).

Although, loan approval in the Jordanian banks has been up to the credit officer mostly or supported by credit scoring based on traditional statistical models, banks can improve loan approval methods by using artificial neural networks. This study proposesnewapproach to evaluate loan applications as a decision support model to credit officer judgment. The proposed model uses the most important variables in Jordanian credit industry. Debt payment ratio highly influences the loan decision while gender has the least. The results show that multilayerfeed forward (MLFF) neural network successfully classified loan applications with 91.3 percent accuracy level. The benefit of using such method in the Jordanian commercial banks enfold improving credit decision effectiveness, saving analysis time and cost.

Furthermore,this study proposes a further study that compares betweenusing multilayer feed-forward neural networks and other types of artificial neural networks with different learning algorithms.Also, a study thatcompares the classification performance of artificial neural networks against tradition statistical techniques is suggested.

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