International Journal of Innovation, Creativity and Change. www.ijicc.net
Volume 8, Issue 9, 2019

Credit Risk Management and Business Intelligence Approaches of the Banking Sector in Jordan

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Banking is one of the key segments supporting sustainable economic progress in Jordan. Hence, banks in Jordan are tremendously significant financial establishments that pursue profit through financial services through dealing with different risks. Their loan decisions are crucial because they can avert credit risk. However, loan sanction assessment at Jordanian banks is particularly based on credit officers' intuition, and sometimes a combination of their judgment and traditional credit scoring models. Consequently, it is important to assess the riskiness of the banking sector in Jordan. Their clientele data is stored in data warehouses, that can be considered as concealed knowledge assets to be read and exercised via data mining tools. Artificial Neural Networks (ANN) denote a recent development of statistical techniques, and promise tools for data mining and data processing. The current study attempts to develop an artificial neural network model, to support credit evaluation at Jordanian commercial banks, based on applicants' characteristics. The proposed model can help credit officers better decide loan applications. It was developed by using a real world credit application to applications both granted and rejected, by different Jordanian banks. Experimental outcomes showed that artificial neural networks can complement existing classification methods.

Key words: *Credit Risk, Capital market measures of risk, Jordanian banks, Business Intelligence, Artificial Neural Networks, Data Mining, Knowledge Assets, Commercial Banks, Jordan.*

Introduction

The service economy is significant in the progress and social welfare of Jordan as an emerging nation with inadequate natural resources. Jordanian banks loan to individuals, manufacturing and agricultural enterprises, to empower them to precede fruitful investments and consequently, advance the economic progress of Jordan. When banks maintain superior performance, it adds to their profitability and to the economic progress and improvement of the country.

Banks in Jordan are extremely imperative financial organizations that look for profit by giving several services to clienteles, while dealing with different risks. Risk-taking is frequently seen as simply necessary for profitability and financial behaviour. However, credit approval assessment at Jordanian banks is idiosyncratic in spirit. This requires appraising individual loan applications physically, and imposing biases comprising knowledge, personal insights, and instincts of credit executives. This technique has been replaced by a limited number of banks using credit scoring models to take appropriate credit decisions. Conversely, banks warehouse their clientele data, which can be seen as concealed knowledge assets to be read and exercised via data mining instruments. Therefore, the credit management of Jordanian banks is required to progress to more operative models, to progress the predictive accuracy of credit risk judgements.

The current study aims to build up a high performance predictive model, using artificial neural networks (ANN) for Jordanian commercial banks. This model highlights the utmost substantial variables that effect the sanction of individual loan judgements in the Jordanian banking sector. Furthermore, it would upgrade credit judgement and control loan office responsibilities, in addition to saving investigation time and costs.

Credit forms a keystone of the banking sector as credit behaviour influences the success and firmness of a bank. Therefore, loan judgements are significant for financial organisations as they avert credit risk. Olokoyo (2011) emphasises that loaning is at the core of banking business. Often, bank managers can be faced with the problem of exaggerating to upsurge credit volume, while decreasing the possibility of non-payment (Huang et al., 2007). On the other hand, credit scoring models enable bank managers to ascertain those accounts are likely to be credit-worthy and those likely to default (bad credit risks), based on applicants' characteristics in the application form.

Nowadays, the future of the banking business is extremely hooked on risk management subtleties. Banks are looking for more effective risk management instruments and decision support models, supplemented by analytical techniques to survive uncertain business environments. The basis of risk management is to launch a framework that outlines loan approval, a credit risk rating system, a risk-adjusted pricing system, and a comprehensive reporting system (Arunkuma and Kotreshwar, 2006). In addition, Olszak and Ziemba (2006) stress that decision-making is becoming more challenging. It needs to use scattered information assets and engage different parties (stakeholders, suppliers, customers, etc.) to improve decision-making in a scope of global nature. According to the author business intelligence (BI) systems can meet such challenges, to support and increase proactive decision-making. Besides, BI optimizes business process and recourses, leading to increased profits. A BI system is a combined set of tools and technologies, to collect data and analyse information as support for more improved decisions. Therefore, this study will help policymakers decide on the implementation of ANN which is developed as an advanced data mining technique, and mimics the human brain. Moreover, this study helps to contribute to the Jordanian banking sector, by articulating how ANN can minimise missing information, and improve performance. Furthermore, this study will guide future researchers who explore ANN for better credit-risk management output. Few studies have researched it in developed countries. Specifically, very few have done so in underdeveloped and developing countries.

Overview of Jordanian Banking System

The banking industry in Jordan plays a decisive role in the progress of the country. Jordanian banks support economic action, and along with the main providers to the national economy, they play a foremost role in improving national economic progress in the country (Kandah, 2009). According to the Central Bank of Jordan (CBJ) annual report (2018) the number of working banks in Jordan will stand at thirty by the end of 2022. Their services will extend over most of Jordan, with an index of banking density of 9,179 people for each branch at the end of 2022.

The rate of loans and advances to total credit facilities increased from 59.6 percent in 2000 to 86.1 percent projected by the end of 2020 (CBJ, 2018 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 the same period. This is evidence that retail banking is achieving extra base in the acts of banks in Jordan, with an upsurge in economic activity also since the upsurge in the volume of credits was distributed to all economic events. General trade, construction and industry are the main sectors accounting for the biggest part in the volume of credits.

To highlight the significant role of the Jordanian commercial banks, Table 1 shows the percentages of some financial key signals taken from balance sheet items among banks operating in Jordan at the end of 2010. They are total assets, the outstanding credit extended by banks, total deposits, total shareholder equity, and the total capital. As shown, the five percentages affirm the soundness of the commercial banks as they record a three quarter share in each one. Further, 74.87 percent of the total credit facilities extended by banks operating in Jordan are from commercial banks. This indicates the 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.

	% of Total Assets	% of Total Credit Facilities	% of Total Deposit	% of Total Capital	% of Shareholders' Equity
Commercial Banks	77.76	76.69	74.86	76.47	81.66
Islamic Banks	12.79	14.99	16.72	10.97	10.81
Foreign Banks	9.45	8.32	8.42	12.56	7.53

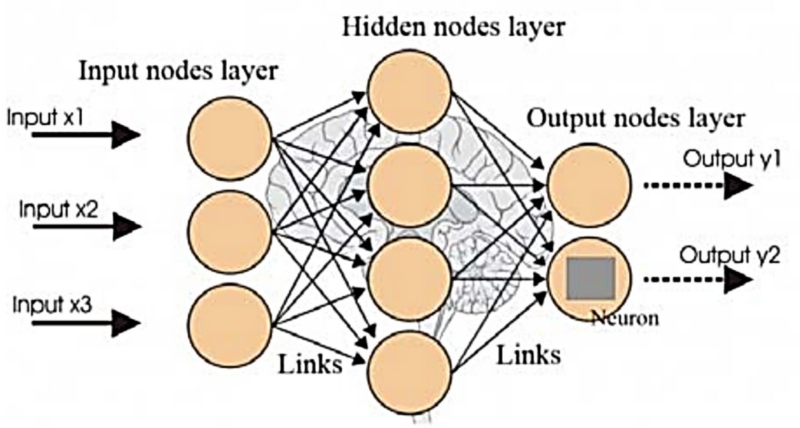
Literature Review

The credit industry has gone through serious progress and development in the last decade. Bank officers have developed some credit scoring models to supplement traditional methods, to classify loan applications as either good or bad, based on the applicant's attributes such as employment history, prior credit history, age, etc. Researchers are constantly searching for new algorithms to increase the accuracy of credit scoring simulations.

According to Ong et al. (2005), a progress even to a fraction of a percent in credit accurateness will lead to substantial savings. Bensic et al. (2005) showed that the probabilistic neural network model achieves the best results. They called for extending the methodology analysis, by adding more neural network algorithms such as unsupervised classifiers, as well as exploring other advanced statistical methods with AI techniques such as genetic algorithms in credit scoring modelling.

Basically, ANNs model the human brain with the simplest definition, and its building blocks are neurons. In the human brain there are approximately 100 billion neurons. Each neuron has between 1,000 and 100,000 connecting points. The information in the human brain is stored in a way that is distributed and, if necessary, we can "parallel extract" more than one piece of that information from our memory. We are not wrong to mention that there are thousands of very, very potent parallel computers in the human brain. There are also cells positioned similarly to the human brain in multi-layer artificial neural networks. Each neuron has certain coefficients linked to other cells. The data is allocated during instruction to these connecting points to enable the network to be taught.

Figure1. Layers of the Artificial Neural Network



A neural network comprises three layers, as illustrated in Figure 1. There is an entry layer, a middle layer, and a yield layer. The red areas are the cells and the arrows are the points of association. The network displays the information collection that is ready for input layer practice. The network gives the activities' weights to the intermediate part of the connecting lines. Not all points should be a value, and certain points could be nullities. A limit between these strata is introduced to ensure that the values of zero are not zero at the link points.

Martens et al. (2002) use rule extraction techniques to create a grouping model. Boguslauskas and Mileris (2009) argue that artificial neural networks and LR are the most efficient and widely used methods for CRM. They describe the rates of CR estimation model accuracy, and counting for the analysis of Lithuanian enterprises' credit risk. They confirm that neural networks models enjoy upper rates of grouping accurateness.

Limsombunchai et al. (2005) developed a loaning decision model and show that Probability Neural Network (PNN) modelling was effective in grouping and screening agricultural loans in Thailand. Huang et al. (2007) state that neural network (NN) models are more accurate, adaptive and robust in predicting bank failure, when compared with other techniques such as discriminant analysis, logistic regression, etc.

Raghavendra and Simha (2010) utilised data mining feature selection algorithms for Australian, German, and Japanese, credit data, to identify the ideal set of attributes for a classification model. The feature selection algorithm and classification accuracy measured the performance of the predictive model, and the neural network classified risk. The classification accuracy, and number of features for selected algorithms with neural networks, 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 executives need to use Machine Learning (ML) techniques to fulfil the growing demand on credit departments, and also to manage huge amounts of credit data, to save time and reduce errors. Thus neural networks are a rewarding alternative business intelligence tool that can apply to credit scoring models, as they classify more accurately. Therefore, the main objective of the current study is to propose a high performance predictive model, capable of assisting credit managers to take sound and safe personal loan decisions.

Data Collection

Data was combined data from both accepted and rejected applications, from different Jordanian banks for 2010-2018. The number of opinions from each bank was hidden, to protect each's privacy. The data is composed of 492 cases. From the sample, 292 (59.3%) applications were credit-worthy while 200 (40.3%) applications were not. In total thirteen variables were used: seven were scale while six were categorical. Also, there were 12 independent variables and one dependent categorical variable with two values, 1 for accepted applications and 0 for rejected ones. All scale variables were standardized to improve network training. SPSS software (Version 22) was employed to perform the analysis.

Methodology

Artificial neural networks are a strong alternative to conventional forecasting and grouping methods, due to their ability to capture nonlinear and complex relationships. According to Cao and Parry (2009), these models have a biologically stimulated competence that mimics processing competences of the human brain. 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 modelling tasks such as predicting share price movements and exchange rate fluctuations. The multi-layer perception (MLP) is the most popular FFNN model used in pattern recognition. Designing an artificial NN model successfully depend on a perfect understanding of the problem, and on determining 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 typical FFNN 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 concealed neuron receives a weighted sum of entire efforts in the input layer, applies a transfer function such as log sigmoid, hyperbolic tangent, soft max to the weighted sum. Similarly, each hidden neuron transfers a weighted outcome to each neuron in the yield layer i.e. each dependent variable neuron (Cao and Parry, 2009). The outcome of the output neuron is the solution of the problem. A learning algorithm finds 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 it is 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: $\Delta = T\text{-}Y$. The training objective is to find the best set of weights that lessens the 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 a multilayer feed-forward (MLFF) algorithm to build a 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 variables 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, nine hidden neurons with hyperbolic tangent function while the output layer represents the dependent variable with soft max 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. Altogether 359 (73%) cases were used for training, 64 (13%) for validation, and 69 (14%) 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
		Total	64	100	100	
Testing	Valid	0	24	34.8	34.8	34.8
		1	45	65.2	65.2	100
		Total	69	100	100	
Training	Valid	0	138	38.4	38.4	38.4
		1	221	61.6	61.6	100
		Total	359	100	100	

Using a 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 to adjust the connection weights in the neural network during the learning phase. A validation set was 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 aims 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	63.29
	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	19.17
	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%
	Overall Percentage	3.6%	62.4%	93%
Testing	0	21	3	87.5%
	1	3	42	93.3%
	Overall Percentage	34.8%	65.2%	91.3%
Holdout	0	29	9	76.3%
	1	2	24	92.3%
	Overall Percentage	48.4%	51.6%	82.8%

Table 5 explains the analysis of the 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. A 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 was the least important. Table 5 also displays 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	0.073	43.8%
Gender	0.029	16.7%
Loan Purpose	0.062	36.8%
TML	0.113	72.3%
Guarantor	0.077	48.2%
DPR	0.163	100%
Amount	0.046	29.4%
Income term	0.071	43.6%
Experience	0.059	36.2%
Nationality	0.127	78.7%
Loan period	0.098	61.3%

Interest rate	0.094	59.9%

Debt income ratio, nationality, and TML seem to have the greatest effect on how the network classifies credit applications. The importance value of debt income ratio, nationality, and TML are 0.163, 0.127, and 0.113 respectively. The normalized importance of debt income ratio, nationality, and TML are 100%, 78.7%, and 72.3% respectively. Gender has the least influence on credit decisions, and the importance value of gender showed in Table 5 is 0.029. The normalized importance percentage shows 16.7%. The importance value of the variables age, loan purposes, guarantor, amount, income term, experience, loan period, and interest rate are 0.073, 0.062, 0.077, 0.046, 0.071, 0.059, 0.098, and 0.094 respectively. Moreover, the normalized importance percentage of the variables age, loan purposes, guarantor, amount, income term, experience, loan period, and interest rate are 43.8%, 36.8%, 48.2%, 29.4%, 43.6%, 36.2%, 61.3%, and 59.9% respectively. The way these variables correlate to the predicted value of the credit decision is not obvious. From common-sense one could guess that a larger amount of DPR points to a greater likelihood of rejecting the credit application. Also, Jordanian applicants can get credit much easier than non-Jordanian applicants. Besides, banks are more flexible in extending credit to applicants working in companies accredited to the bank companies.

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 percentage of 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 it 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. 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 much as possible. The percentage of type I error in the training data was 10.1percent; for the testing data it was 12.5 percent.

Loan approval in the Jordanian banks has been up to the credit officer, mostly or supported by credit scoring based on traditional statistical models. Yet banks can improve loan approval methods by using artificial neural networks. This study proposes a new approach to evaluate loan applications as a decision support model for 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 influence. The results show that multilayer feed-forward (MLFF) neural networks successfully classified loan applications with an accuracy of 91.3 percent. Such methods in Jordanian commercial banks would improve credit decision effectiveness, saving analysis time and cost. This study proposes a further study that compares MLFF neural networks to other types of artificial neural networks with different learning algorithms. Also, a comparison of the classification performance of artificial neural networks against tradition statistical techniques is suggested.

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