IJFBS Finance & Banking Studies

Finance & Banking Studies

IJFBS VOL 12 NO 1 ISSN: 2147-4486

Available online at www.ssbfnet.com
Journal homepage: https://www.ssbfnet.com/ojs/index.php/ijfbs

Improving Credit Risk Assessment through Deep Learning-based Consumer Loan Default Prediction Model

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ARTICLE INFO

Article history:

Received 1 May 2023
Received in rev. form 2 June 2023
Accepted 3 June 2023

Keywords:

Machine learning, UAE banks, Loans Default, Model

JEL Classification:
O15, E42

ABSTRACT

This study aims to enhance credit risk identification, improve loan borrower review efficiency, and increase default prediction accuracy rate using data mining and machine learning techniques. The study also employs deep learning to develop a consumer loan default prediction model that minimizes credit risks and ensures consistent development. The researchers collected data from a survey of 1000 participants, stratified into local and foreign banks, and selected the top 11 banks based on turnover and customer volume. To construct the machine learning model, Keras, a neural network library that runs on TensorFlow, was utilized. The model predicts loan applicant default likelihood. The study's practical implications demonstrate a noteworthy success rate of customer default prediction, which can significantly benefit banks. The model was evaluated on a test set of 250 records and achieved a test set accuracy of 95.2%, correctly predicting the default state of 238 out of 250 respondents.

Introduction

Bank loan issuance has been steadily increasing in recent years. In order to attract more consumers, several banks now sanction loans manually or semi-automatically with straightforward terms and conditions. So, among the challenges facing the banks are return delays and human interference. In order for the banks to meet their goals, these delays are posing hitherto unheard-of difficulties and hurdles. Time is money, so these delays are the primary obstacle to banks reaching their goals. Bank loans are made available to customers to cover their extravagant needs. The purpose of loans is to offer a means of sustaining both short- and long-term profit cycles. The consumers, however, are frequently unable to repay the loan in accordance with agreed schedule (Zhu, Qiu, Ergu, Ying, & Liu, 2019).

In addition, it can be seen that amount of research to automate and upgrade the sanctioning process in the banks. However, there is a great need to automate the process using supervised and deep learning technologies (Aslam, Tariq, Sohail, & Batcha, 2019). Bayesian networks and Artificial Neural Networks (ANN) for credit risk prediction were compared by Teles et al. in 2022. They studied 1890 data that they had received from a banking institution. The contract value, balance value, collateral value, quantity of collaterals, recovered value, value tx rate, value tx interest rate, value rate overdue, client size, main value delay, seniority level, duration in years, duration in months, duration in days, and delay in days were among the predictor attributes. Two categories—risky and non-risky—were applied to each document. An 81.85% was achieved using a 3-layer neural network (input layer, hidden layer, and output layer).

In Jordanian banks, a model based on neural networks was first put forth much earlier to assess credit applications and support commercial lending decisions (Eletter & Ghaleb, 2010). They had a 94-record training set and a 46-record test set. They used the applicant's attributes, including his age, account type, income, nationality, residency, company type, guarantor, work history, and DBR (a debt balance ratio that gauges the applicant's capacity to repay), as predictor factors. Their NN model consisted of four layers, two of which were hidden. The first hidden layer included 10 neurons, and the second contained 7 neurons. A 95% accuracy rate was attained.

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https://doi.org/10.20525/ijfbs.v12i1.2579

In this research study, we are using deep learning to create a Prediction Model for consumer loan defaults to lower the credit risks and ensure the healthy and steady development, it is crucial to use data mining and machine learning information promptly and effectively, employ intelligent methods to identify credit risk, and increase the review efficiency of loan borrowers and default prediction accuracy rate.

Literature Review

Theoretical and Conceptual Background

The vital role of banking industry in any country towards sustainable development and intermediary role in an economy is enormous. Banks are always playing major role in an economy, intermediaries between public and capital invested in companies (Van Greuning & Bratanovic, 2020). The overall benefits of banking sector including retail and commercial banks are safety of public wealth, extensive availability of loans, propelling the nation's economy etc. It can be seen that traditional banking working hours are not always convenient as per the public needs, however online and mobile banking initiatives have impacted positively in the performance of banking culture (Ghosh, 2016).

In addition, the most important banking role is matching up the creditors and borrowers and essential ways to provide a flow to the domestic and international payments (Amiti & Weinstein, 2019). It is crucial for any such industry to enhance economic growth while building and maintaining financial relationships with all customers and provided financial products and services (Meyer & Shera, 2017).

However, in failure to do so can have key challenges and issues to any economy. There are chances that the bank goes Bankrupt, the risk of robberies or fraud, huge banking loans, variability in the market situations, increasing domain complexity i.e., internal and external, market instability etc. In this research one of our focus discussions is on the risk of debt (Iqbal, et al., 2018).

Literature reveals that probability of default (POD) expresses the expectations or prediction that a borrower will not be able to maintain a smooth financial debt payment as per their schedule (Curi & Lozano-Vivas, 2020). This default probability is represented by two main factors i.e., debt-to-income ratio and credit score. Several research studies shows that borrower not paying back their loans on time is the main reason of credit risk and this is one of the possibilities of losing lenders as well. Consumer credit risk are measured based on capacity to payback, the actual capital, loan terms and conditions, associated collateral and credit history (Ibtissem & Bouri, 2014).

A few studies reveal that the main causes of loan default may vary depending on the situation, regime, improper client's selection, high rate of interest, inadequate loans with lack of proper monitoring etc., thus creating the situation of default risk (Awan, Nadeem, & Malghani, 2015). Default risk may vary based on the company's financial situation. Economic fluxes and reforms can have vital impact on company's revenues and earnings. Default risks and economic reforms may influence company's ability to make interest payments on debt with debt itself (Ntiamoah, Oteng, Opoku, & Siaw, 2014).

Fabio and Ana (2017) researched on defaults in banks loans to SMEs during the financial crises. They have investigated the role of business collateral and personal loan guarantees and enhanced body of knowledge related to the theory of financial economics (Eichberger, Eichberger, & Harper, 2014). In particular they use bank and loan properties, different sector with geographical areas, macro-economic conditions in predicting default at the peak financial crisis. They collected SMEs data through questionnaires and done analysis using SPSS and AMOS. Binary probabilistic model deployed. Research analyses showed that minor loans were granted during financial crises and were secured with collateral. In hypotheses testing, a positive relation between collateral and default with a negative relation among guarantees with default is observed, thus highlighting critical role of personal guarantees to access bank loans (Fábio, P, Gama, & Ghulam, 2017).

In a research report by, National Bureau of Economic Research (NBER) on "Bank Risk Dynamic and Default", structural models related to bank default risks were investigated. Research findings emphases on the importance and modeling bank default risk. Assessment of bank default is vital not only as an investors point of view, but also decision makers & managers analyzing default factors. In this research study, a modification of the Merton Model is proposed, i.e., empirical approximation of modified model by non-linear transformation of Merton Model. A non-parametric regression model is linking the two specified model, thus exploring the expected relationship between risk and default of banks (Nagel & Purnanandam, 2019).

A credit scoring model that empirically evaluates the risks of bank loan default was proposed in a study by Manolis and Dimitris in 2016. According to the research (Kavussanos & Tsouknidis, Default risk drivers in shipping bank loans, 2016), major elements in estimating the likelihood of bank loan defaults are dependent on present and anticipated market conditions. (Kavussanos & Tsouknidis, Default Risk Drivers in Shipping Bank Loans., 2014) Kavussanos and Tsouknidis (2011) construct a credit scoring model for the first time based on secondary data of shipping. With regard to credit theory, this study established a theoretical framework for bank loans. Petersen (2009) and Thompson (2011) used a panel data logit model with a two-way clustered adjusted standard error to assess the likelihood of defaulting on loans. Kavussanos and Tsouknidis (2014) used a dataset of more than 120 bank loans to empirically investigate the theoretical relationship among default risk and potential variables in credit scoring model (Kavussanos & Tsouknidis, 2014).

Awan, Nasir and Falak's study investigated the causes of loan default with its impact on profitability of banking industry. A total of 100 questionnaires respondents using purposive sampling applied and found a few causes such as business management knowledge, monitoring inefficiency, delays in loan approvals, weather condition, bad credit appraisal and unwillingness of public etc., thus negatively effect on the profitability with interest income of commercial banks (Awan, Nadeem, & Malghani, 2015). Before the financial recession, a study by Vasiliki, Athanasios and Bellas (2014) to identify factors affecting the non-performing loans of Eurozone's banking system is done by looking into macro-variables i.e., annual growth rate, public debt, unemployment etc., with micro-variables i.e., deposit ratio of loans, assets return, equity return etc. Research findings reveal a strong correlation between macroeconomic and bank specific factors (Makri, Tsagkanos, & Bellas, 2014). The main purpose of banks and financial institutions in the economy is intermediation, which means collecting deposits and using them in useful investments.

Empirical Review and Hypothesis Development

The focus of the paper is to develop two distinct inquiry lines i.e., seek to develop a model or a framework that can facilitate the prediction of the default and their influence. The other emphasis is to identify financial and operational key factors that can be useful in predicting defaults.

Research and Methodology

Data Collection

To gather information from respondents, the researcher developed a questionnaire, which underwent a pilot test with 35 sample respondents and industry experts. Based on their feedback, the questionnaire was edited. Using the standard deviation test, the researcher determined the appropriate sample size, which rounded off to 1000. The questionnaire was distributed via email and WhatsApp, utilizing Google forms.

Through the questionnaire survey, data was collected from 1000 participants. The survey covered various aspects, such as the frequency of address changes, education level, gender, monthly income, bank borrowing, percentage of debt to income, credit card usage, amount of credit card debt, and loan defaults

This information was stored in the following 10 variables:
Times changing the current address',
'Education',
'Gender',
'Age',
'Monthly Income',
'Borrowed from a bank',
'Percentage of debt to income',
'Do you have credit card',
'Credit card Debt',
'Default'

Descriptive Analysis

We now look at the each of the variables.

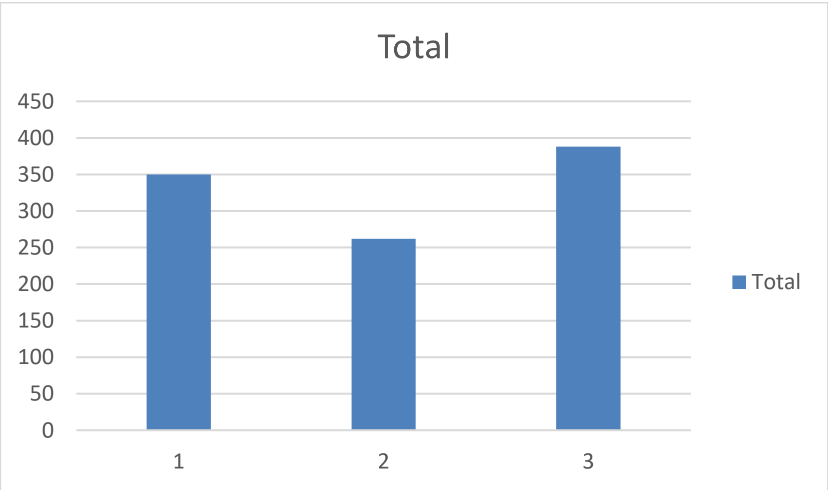

Figure 1: Times changing the current address

350 respondents had changed their address just once, 262 respondents had changed their address twice, and 388 had changed their address three times.

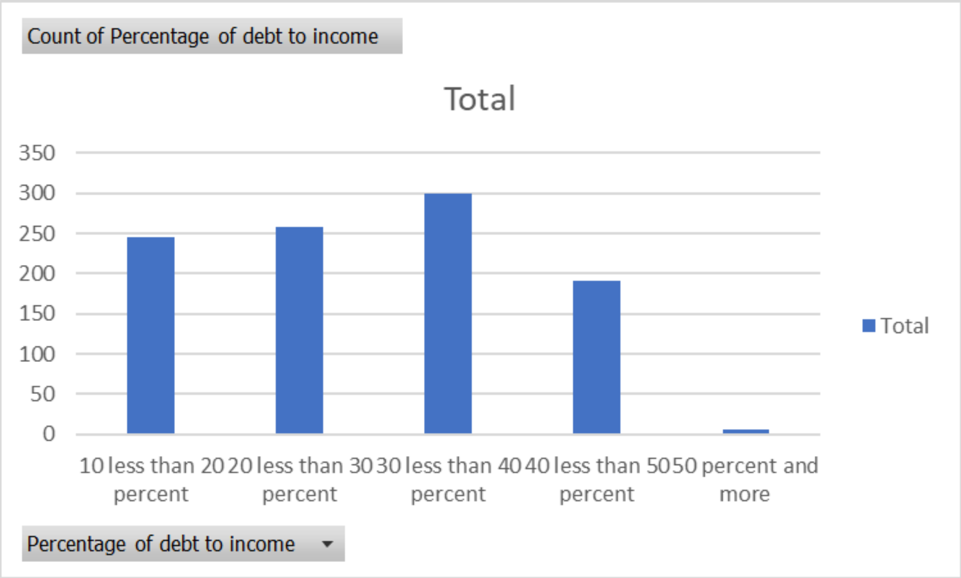

Figure 2: Percentage of debt to income

300 respondents had debt which was between 30 – 40 % of their income. 245 respondents had debt of between 10 and 20% of their income, 258 respondents had debt between 20 and 30% of their for the purpose of building the predictive model, only those respondents who had actually taken a loan from a bank were selected.

Hence the final dataset consisted of 625 records or rows. Of these 625, 352 had defaulted and 273 had not defaulted. In order to make the data suitable for further analysis, all the categorical variable were converted into numeric variables. So, for instance, the variable Credit card debt has 5 categories. After the conversion to numerical variable, the Credit card debt variable is now converted to 5 variables with values of 0 and 1. See the table below:

Table 1: Categorical to Numerical Variable Conversion

Credit card Debt_10000 less than 15000	Credit card Debt_15000 less than 20000	Credit card Debt_20000 less than 25000	Credit card Debt_25000 less than 30000	Credit card Debt_30000 and more
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	1	0	0
0	1	0	0	0

So, after the conversion of all the categorical variables into dummy variables, the number of variables in the dataset become 26. Since we were building a model to predict whether a particular loan applicant will default or not, we separated the Default variable from the rest of the dataset. The variable Default is now the target or the output variable. The rest of the 25 variables are the input variables. We have used a neural network model to predict consumer default. The next section explains the neural network model and its working.

Neural Networks

There are three levels in a multilayer feed-forward neural network: an input layer, one or more hidden layers, and an output layer. There are units in each tier. Data attributes or variables make up the input layer's units. In other words, if our dataset contains 15 attributes or variables, the input layer will also contain 15 units. There are 25 input variables in our baseline consumer dataset. The input layer therefore contains 25 units. One buried layer with 1024 units is present. Unit, the target variable by default, is the only element of the output layer.

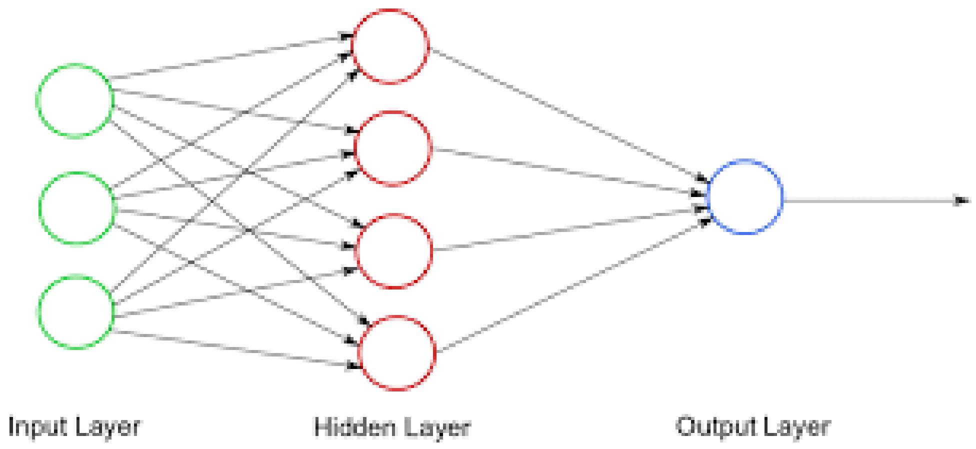

Figure 3: Categorical to Numerical Variable Conversion

Each unit (or node) in each layer is connected to every unit in the subsequent layer. This connection between any two units is represented by weights (or parameters).

So if X1 is one particular unit in the input layer, then the unit it is connected to in the hidden layer will be represented by

$$A1 = ah1X1 + bh1 \qquad (1)$$

Where ah1 and bh1 are the parameters.

That particular unit A1 in the hidden unit is connected to all the units in the previous input layer, each with it its own weights (or parameters). The summed weighted input for each unit in the hidden layer is then transformed into an activation using an activation function. In our model we use the Rectified Linear Unit (ReLU) function for the hidden layer. The rectified linear activation function is a simple calculation that returns the value provided as input directly, or the value 0.0 if the input is 0.0 or less.

This means that a node or unit in the hidden layer is 'fired' only if the input to that unit, (calculated using the weights from the connection with the units in the previous layer) has a positive value.

For the output layer, we have only one node or unit, as this is a binary classification problem. All the nodes in the hidden layer are connected to this output represented by their own weights.

So for the A1 node in the hidden layer connected to the output layer node, that output node will be represented by

$$A2 = ao1A1 + bo1 \qquad (2)$$

Where ao1 and bo1 are the parameters.

The summed weighted input from all the nodes in the hidden layer is then transformed using the Sigmoid activation function. The Sigmoid function converts the input value into a number between 0 and 1. So any value less than 0 is converted into a number between 0 and 0.5 and all positive values are converted into a number between 0.5 and 1. This is useful when we are predicting the probability as an output, since probability exists between 0 and 1.

The final dataset consisting of 625 records was randomly divided into a training set and test set. The training set consisted of 468 records and the test set consisted of the remaining 157 records. The model was trained on the training set and then tested on the test set.

This feed-forward is done for all the 468 records of the training set using an initial value for all the parameters in the model and the output values obtained (either 0 or 1). These output values thus calculated are then compared with the actual output values of the training set to give a measure of accuracy of the model.

This process is repeated for the 468 records a number of times till the peak accuracy is reached, each time the parameters of the model being adjusted by the back propagation method using the 'adam' optimizer. The model had a final accuracy of 97.44% on the training set.

The model was then tested on the test set consisting of 157 records with a single-run of the feed-forward. The model achieved an accuracy of 97.45% on the test set.

Methodology

For the study, the researcher utilized stratified random sampling. The UAE was divided into eight strata based on the research criteria. This included 21 national banks and 27 foreign banks operating in the country. Further stratification was conducted based on the distinction between local and foreign banks. To determine the sample size, the researcher identified the top 11 banks based on their business volume and number of customers. These banks included HSBC, Mashreq, ADCB, Dubai Islamic Bank, Standard Chartered, Abu Dhabi Islamic Bank, Emirates NBD, Commercial Bank of Dubai, First Gulf Bank, RAK, and Noor Bank. Weightage was assigned to each bank based on the number of branches, and data was collected from respondents accordingly (Jumaa, M, 2020).

Table 2: The number of respondents chosen by the researcher from each Emirates.

Bank / Emirate	Al Ain	Ajman	Abu Dhabi	Dubai	Fujairah	Sharjah	RAK	Umm Al Quwain	Total
Number of sample respondents	50	20	225	583	30	87	40	15	1000

Table 2 displays the distribution of respondents across the Emirates. Dubai had the highest number of respondents with 583 participants, while Abu Dhabi had 225 participants. With 118 branches of the selected 11 banks, Abu Dhabi is a large Emirate and the capital of the UAE. In comparison, there are 212 bank branches of the selected 11 banks in Dubai. Other Emirates, such as Sharjah, Al Ain, RAK, Fujairah, Ajman, and Umm Al Quwain, had 87, 50, 40, 30, 20, and 15 respondents, respectively.

To provide ease and flexibility for respondents, a closed-ended questionnaire was utilized. Respondents were required to choose the most appropriate response from a set of options. However, a Likert scale was also incorporated to collect more accurate data about respondents' views, as it is a widely used tool for designing survey questions (Saqib, Zarine, & Noor, 2022).

The questionnaire was designed into two parts; the first part was collecting demographic data and the second part was gathering information on different hypothesized factors affecting consumer loans default.

Findings and Discussions

The data consisted of 1000 respondents to the survey. Out of this 566 had defaulted and 434 had no default. For the purpose of building the machine learning model, the dataset was divided into a training set and a test set. The training set consisted of 750 randomly selected records or rows and the test set consisted of the remaining 250 rows.

The model was trained on the training set and then evaluated on the test set.Python was used as the programming language and tensorflow library was used as the platform for building the machine learning model. Keras, a neural network library that runs on top of tensorflow was used. The model built is used to predict whether a particular loan seeker will default. With the analysis, a training set accuracy of 97.6% was obtained. This model was then evaluated on the test set (250 records). The test set accuracy of 95.2% was obtained. This means that the model correctly predicted default status of 238 out of 250 respondents. Since the dataset consisted of almost comparable number of defaulters and non-defaulters, the precision and recall scores are not critical, but they are provided below:

The precision and recall scores for the model is shown below:

0 – no default
1 – Customer defaulted

The confusion matrix was as follows:

109	5
7	129

This meant that the True Negatives were 109 and False Negatives were 7. True Positive were 129 and False Positive were 5. So out of 114 respondents with no default (0), the model correctly predicted 109 as no default and wrongly predicted the remaining 5 as default. And for the 136 respondents with default (1), the model correctly predicted 129 as defaulted and wrongly predicted 7 as no default.

$$Precision = \frac{TP}{TP + FP}$$

Precision (customer defaulted, 1) = 129/(129+5) = 0.9626

$$Recall = \frac{TP}{TP + FN}$$

Recall (customer defaulted, 1) = 129/(129 + 7) = 0.95

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

F1 Score (customer defaulted, 1) = 2 ((0.96*0.95)/(0.96+0.95)) = 0.95.

Conclusion

The paper illustrated the data collection process, where information was gathered from 1000 participants through a questionnaire survey. The top 11 banks were identified based on turnover and the number of customers. The list of selected banks includes HSBC, Mashreq, ADCB, Dubai Islamic Bank, Standard Chartered, Abu Dhabi Islamic Bank, Emirates NBD, Commercial Bank of Dubai, First Gulf Bank, RAK, and Noor Bank.

The survey collected various data points from the participants, such as the number of address changes, level of education, gender, monthly income, borrowing history, debt-to-income ratio, credit card usage, credit card debt, and loan default status. It is mentioned that only respondents who had actually taken a loan from a bank were selected for the purpose of building the predictive model.

Python was used as the programming language, and the TensorFlow library with the Keras interface was employed as the platform to build the machine learning model. The model's primary objective was to predict whether a loan applicant would default. The high accuracy of 95.2% on the test set indicates that the model successfully predicted loan defaults.

Therefore, the study proposed that UAE banks can seamlessly adopt this predictive model in their loan assessment processes. By incorporating the model into their decision-making procedures, banks can better evaluate the creditworthiness of applicants and make more accurate predictions regarding the likelihood of loan default. This can help mitigate potential financial risks and improve the overall loan portfolio performance of the banks.

Additionally, the statement suggests future research opportunities. It recommends conducting multivariate linear regression analysis and ANOVA analysis to explore research hypotheses concerning the relationships between various study factors. By further investigating these relationships, banks and researchers can gain deeper insights into the underlying dynamics affecting loan default and potentially enhance the predictive model's performance even further.

Acknowledgement

Author Contributions: Conceptualization, M.J., A.T.; Methodology, M.J., M.S.; Data Collection, M.J., M.S.; Formal Analysis, A.T., M.J.; Writing—Original Draft Preparation, M.J., M.S.; Writing—Review and Editing, M.J., M.S.; All authors have read and agreed to the published the final version of the manuscript.

Institutional Review Board Statement: Ethical review and approval were waived for this study, due to that the research does not deal with vulnerable groups or sensitive issues.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Conflicts of Interest: The authors declare no conflict of interest.

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