Early NPL Warning for SME Credit Risk: An Experimental Study

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Abstract: In credit risk, besides assessing risk of credit applications, it has been very critical to take a proactive decision by foreseeing the risk of non-performing loan (NPL). In Turkey, recent reports demonstrate that among different credit categories such as consumer, corporate, small and medium-sized enterprises (SME) loans, SMEs reflect the highest NPL ratios. This paper focuses on SME credit behavioural scoring to develop an early NPL warning system after the credit is released. Utilizing application scoring features together with behavioural scoring features, an experimental study of classifying SME customers as non-performing or performing is targeted during lifetime of the credit. The proposed system aims to support a warning 6 months ahead to detect NPL state. Random Forest (RF) algorithm is implemented for NPL state classification of active SME credits. Accuracy results of RF algorithm is compared with different machine learning algorithms like Logistic Regression, Support Vector Machine and Decision Trees. It has been observed that accuracy of RF model is increased when different SME credit product features are added to the model. An accuracy ratio of 82.25% is achieved with RF which over performs all other alternative algorithms.

1 INTRODUCTION

Since credit volume in real markets has shown great increase, credit risk analysis (CRA) has become increasingly important for financial institutions and advanced methods that are built using statistical approaches have already started to take place of traditional methods (Huang et al., 2007; Zhou et al., 2010; Derelioğlu and Gürgen, 2011). Credit risk analysis aims to eliminate future losses by assessing credits based on potential risk and can be classified into two categories: application scoring, behavioural scoring. According to definitions in (Thomas et al., 2001), application scoring consists of two snapshots of consumer state at two different dates–the first of their application form information and the second of their creditworthiness which is commonly determined as "good" or "bad" so it is a static event. On the other hand, behavioural scoring is a way of updating consumer risk based on repayment performance of consumer or other performance criteria described by lender. Thus in behavioural scoring, first snapshot is replaced with a time interval but second snapshot still remains the same. However, in behavioural analysis, while some of conducted studies concern with only likelihood of default, others also concern with when default is occurred. In recent years, predicting default date or period in which customers default gains more importance since forecasting 'when' gives insight about default rates over time (Noh et al., 2005). Actually, it has been already used in profit scoring modeling (Thomas et al., 2001) which aims to find customers who will provide better profit to financial institutions due to the fact that lenders will have greater benefit if a customer pays for longer period without default.

1.1 Credit States in Turkey

In Turkey, Banking Regulation and Supervision Agency (BRSA) which checks and balances banks according to banking law publishes annual, quarterly reports to watch financial data of banking sector and structural developments in banking. One of those reports highlights recent changes in credit improvements, market share of credit types and non-performing loan (NPL) ratios of credits with respect to debt owner categories.

In recent years, the worst performing credits are credits lent to SME companies. This situation has several reasons like currency depreciation, supply-chain effect of non-performing loans and changes in macro-economic conditions. Detecting the risk of open SME credits to fall in NPL as early as possible has become crucial for banks. As a result, an experimental study which mainly focuses on early NPL

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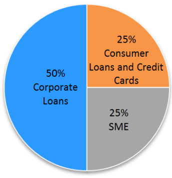
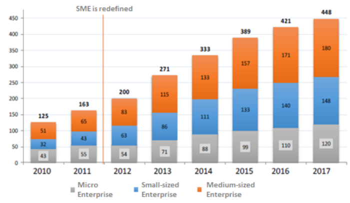


(a)



(b)

(c)

Figure 1: (a) Credit distribution (b) SME credit improvement. (c) NPL ratios.

detection of SME credit is initiated.

In Turkey the ratio of SME credits approaches 25% of total credit distribution which is equal to the ratio of consumer loans and credit cards as presented in Figure 1a. Besides this high ratio of SME credits, year over year trend of total credit capacity in SMEs has been reflecting an increasing trend as shown in Figure 1b. Although credit share of SMEs is increasing, the ratio of SME credits in NPL state is also increasing and demonstrating the highest risk compared to all other credit categories as presented in Figure 1c. 5% of all SME credits are reported to be in NPL in contrast to 4% and 2% ratios for consumer loans and corporate credits respectively.

SMEs are likely to obtain bank loans from multiple banks at the same time thus banks should take precautions as immediate as possible when customers fall in financial distress. Therefore, for a lender, an accurate model for SMEs risk is essential to prevent losses or have greater benefit. As mentioned before, most of the proposed studies can be categorized into two based on the used information types or their aims for the SME credit risk analysis. In application scoring, utilized information types dominantly consist of demographical, risk and financial information while for pure behavioural scoring, only repayment performance is employed. However, using different information types together and forecasting credit status for a specific time interval might give the lender advantages of more accurate model for risk analysis (Sarlija et al., 2009) which can be used for taking necessary steps. With this motivation, we propose an experimental study by forecasting customer status in a period–determined as six months–to maximize profit by restructuring. Therefore, instead of utilizing only features used in pure behavioural scoring which consist of repayment performance of customers (Thomas et al., 2001), features used in two different systems–application scoring, behavioural scoring–are utilized for this study. System is designed to be run each month with new behaviour data along with previously used behaviour data, forecast for next six-month period. According to the outcome, changes to statuses (NPL or PL) of proposals can be adapted. As the first step in this experimental study, it is aimed to explore effects of different machine learning algorithms to obtain a stable model. Moreover, instead of extending behaviour data obtained by shifting the observation point, effects of new information types are investigated. To test performance for period of six months–from April 2016 to October 2016–, observation point is settled on 2016 April and subsequently the model for SME credit risk analysis is trained using Random Forest (RF) (Breiman, 2001). Also we explore effects of feature types on SMEs risk analysis by adding new data associated with SME products to the model incrementally. After the good accuracy rates are achieved, we address the issue of knowledge discovery by using feature selection method. Moreover, in order to evaluate performance of RF on the prediction accuracy, we also compared its performance with Logistic Regression (LR) (Cox, 1958), Decision Trees (DT) and Support Vector Machine (SVM) (Cortes and Vapnik, 1995). Also, to compare obtained results and performance of RF with previously conducted research within the scope of the bank for SME Credit Risk Analysis (Derelioğlu and Gürgen, 2011), Multilayer Perceptron (MLP) is also implemented. Comparative experiments illustrate that RF provides the best prediction performance.

In Section 2, we summarize the proposed studies by categorizing them into two classes. Section 3 looks at SME and also looks at the RF approach for problem solution and summarizes the system design in detail. Section 4 discusses experimental results and comparison of machine learning algorithms based on accuracy performance along with most important features used in building the model. Finally Section 5 concludes the paper, and in section 6, future works will be mentioned.

2 RELATED WORK

Although many researches on quantifying and computing risk have predominantly focused on large corporation's risk or consumer loans, there are very few studies for SME credit risk analysis (Derelioğlu and Gürgen, 2011). Unlike the corporate's risk, SME risk depends not only on financial information but also SME's characteristic properties (Wang, 2012). Therefore, developed models for large corporations or consumer loans might not be proper for SMEs risk. Also, most of the proposed studies attempt to forecast customer status in the future, not in a specific time. As mentioned before, information about status of a credit at a specific period might give a lot of advantages to the lender. Therefore, this study is conducted in the light of all different types of credit risk analysis like application scoring and behavioural scoring.

2.1 Application Scoring

Generally in application scoring, it is aimed to make decision whether to grant credit by forecasting customer defaults by using customer information gathered during application phase. While there are a lot of studies for application scoring which have been conducted for large corporations (Gaganis et al., 2007; Galindo and Tamayo, 2000; Harris, 2015), risk factors for SMEs have been explored in a few studies. Kim and So (Kim and Sohn, 2010) utilized financial ratios and economic indicators along with technology evaluation factors using SVM to grant technology credit to SMEs. They achieved better results (66.16% classification accuracy) by using SVM than results obtained using Back-Propagation Neural Networks(BPNs) and LR. Wang (Wang, 2012) chose to combine credit features of owner and credit capacity features by using LR. Obtained results showed that although credit capacity features are more meaningful for credit default analysis, personal information of the owner–especially age– is also important. Altman & Sabato (Altman and Sabato, 2005) developed a default prediction model on US SMEs dataset by using LR and LR performs better than Multivariate Discriminant Analysis.

2.2 Behavioural Scoring

Unlike application scoring, in behavioural scoring, repayment performance which is gathered during a period is utilized to forecast whether customers are likely to default. To the best of our knowledge, behavioural scoring has not been conducted for SME risk assessment yet. Thus, we benefit from studies conducted for corporation and consumer loans. Researchers in behavioural analysis conduct different studies and develop different models (Sarlija et al., 2009). While some of conducted researches focus on predicting whether customers go into default, others focus on predicting when customers will default or predicting whether customer will default in a specific period. In this experimental study, since we aimed to forecast status of active SME credits in a period, we concentrated on studies for predicting time to default. Thomas (Thomas, 2000) discusses statistical and operational research techniques used for behavioural scoring. The system of (Thomas et al., 2001) utilizes Markov Chain stochastic processes to model delinquency status of consumer and behavioural scores of consumers. In (Sarlija et al., 2009), performances of NN and survival analysis on predicting time to default are compared on data which is collected from January 1 to December 31 and observation point is settled on June. So, it is aimed to forecast customer status in the period of 6 months after the observation point. For NN, 6 different models are trained for samples go into default on different months and they explored that while survival analysis yielded better performance in the first month of survival than NN. In all other five months, NN performed better accuracy than survival analysis. Thomas et all. (Banasik et al., 1999) used LR and survival analysis in behavioural analysis on consumer loan dataset and they found hazard models are competitive with LR for forecasting customers who will default in the first year. Noh et al. (Noh et al., 2005) found that LR and NN are superior to survival analysis in predicting good customers, however for bad customers, survival analysis yielded better performance.

3 MODEL DEVELOPMENT

3.1 Data Preparation

In this section, general properties of SME proposals, generation of dataset and some handicaps that are encountered in data generation will be discussed in detail.

In Turkey, the bank determines a limit which is available for a while for an SME and according to this limit, a proposal which may consist of up to 77 different products such as business card, cheque-book, corporate loan is offered and the total limit is shared among these products based on consumer's needs. In the proposal, each product can have unique patterns such as repayment frequency, interest rate etc. and during lifetime of the proposal, consumers can use any previously determined product whenever they want. If the customer–in this case a SME–misses three consecutive month of payments of one of the used products, status of the customer is determined as NPL (Non-performing loan) otherwise is determined as PL (Performing loan).

The real-life dataset is provided by the bank consists of SME proposals from January 1, 2015 to October 1, 2016. For the first step of this experimental study, an observation point is settled on 2016 April and time interval until the observation point is called performance period and characteristics of the performance in this period are utilized for developing the model. Status of the proposal during the period of six months–from April 1, 2016 to October 1, 2016– which is called outcome period is used to determine whether a customer becomes NPL or not. Representation of the periods are presented in Figure 2. For developing model, proposals, which are offered before the observation point and are still open after the observation point, are selected. While it is required for NPL proposals that close date should be in the outcome period for PL proposals, proposals can be still open during the outcome period. The only condition for PL is that the proposal should be offered before the observation point and customer should not fall in NPL status during the outcome period. However, a customer which is classified as PL can become NPL after the outcome period as shown in Figure 2c. This results in observations that have similar features but different classes (PL and NPL) in the dataset. False positives and negatives that may arise from this situation are considered, and such samples are not eliminated from the dataset, as the predictions in the current outcome period are considered more important in the project than predicting further. The system is designed to be run each month, make predictions about the next six-month period and the algorithm would adapt next month accordingly.

Features utilized for developing SME risk analysis model can be categorized into six different types of information: demographical, application data, financial statements, guarantees, repayment behaviour and credit bureau data as shown in Figure 3. All information types will be explained with examples.

SMEs are more sensitive to changes in economic conditions (Kim and Sohn, 2010), total observed time should not be too long since economic environment may have changed. Therefore, in this experimental study, since the observation point is set to April 2016, behaviour characteristic information of customers between 2014 and 2016 is collected.

Unlike the large corporations, SME depends on owners' credit features since its owner is also its founder. Moreover, better educated and experienced founders can be good at finding opportunities by analyzing the market better (Wang, 2012). Therefore, using owners' personal features or shareholders' features such as age, education level, marital status, etc. can bring a new perspective for analyzing SME credit risk. To represent owner's and shareholder's demographical properties, education levels, age, gender, birth place, net salary, total work year, capital share features are utilized. Also, to get information about customer's risk on other banks, customer reports from the Credit Bureau of Turkey (KKB) are gathered.

If a customer's likelihood to become NPL on one product type increases, it is quite likely the customer will also fall in NPL on other products. Also, for SMEs unlike consumer loans, NPL state of one of the products in its proposal means NPL of the SME customer. Therefore, it is reasonable to assess customers according to their behaviour performance on all of their used products. There are many (77) different types of products offered to SME customers, in order to focus on dominantly used products, most frequently preferred products are chosen in scope of

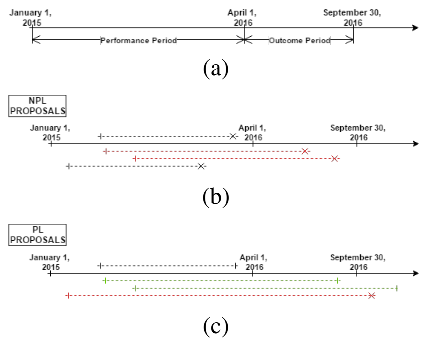


Figure 2: Lifetime of NPL and PL proposals. $(--x)$ and $(--|)$ symbols represent NPL and PL proposals respectively. Green and red arrows are used for included proposals, black arrows are used for proposals that are not included to the dataset since they are closed before the observation point. (a) Representation of the performance period and the observation period (b) Lifetime of NPL proposals (c) Lifetime of PL proposals: Red arrow represents sample which is labeled as PL and falls in NPL status after the outcome period.

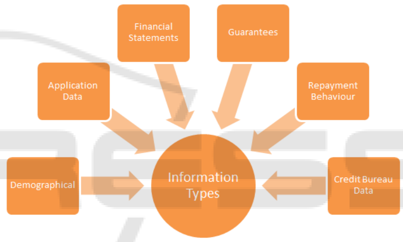


Figure 3: Types of information.

Table 1: Coverage rates of chosen products.

Product Name	Usage Rate
Business Card	20%
Cheque-Book	13%
Corporate Installment Loan	12%
SUM	55%

this experimental study. To evaluate customer performance on remaining less frequently used products, instead of using product specific features, features about delinquency behaviour on all remaining products are preferred. Chosen products and their coverage rate among all products are showed on Table 1. For business card, features of customer's status which represents delinquency rate, doubtful transactions, etc. are collected as well as card features such as card limit, cash limit, maximum withdrawn cash amount. For cheque-book, total risk amount and cheque-book statuses of whether it is granted before expiration features are utilized. For corporate installment loan, delinquency behaviour of installments is included in feature set.

Similar to predicting risk of large corporations, using financial data of the company also highlights risk of SME (Wang, 2012). Therefore, balance-sheet, which presents a company's financial position at a point in time, is used to gain insight about SME's financial status. However, in Turkey, SMEs do not have to provide balance-sheet for credit application if its total revenue is less than 250.000TL. Unsurprisingly, most of SMEs' total revenue are not greater than the limit, and they do not volunteer to provide extra information. This situation causes missing values. However, instead of eliminating these observations, utilizing all available information is preferred. Zero-padding method which fills missing values with zero is utilized for this kind of missing values.

Finally similar to credit scoring applications, application form data which provides knowledge about customer and firm characteristics is also utilized during developing the model. For firm properties, firm's sector, total capital, foundation date and also provided guarantees etc. are gathered.

After choosing proposals according to determined conditions above, class imbalance problem arises since proportion of NPL proposals to PL ones is very close to zero. Class imbalance problem frequently occurs in credit scoring which can affect classification models' accuracy (Menardi and Torelli, 2013). To avoid this situation, class imbalance is decreased by undersampling PL samples by selecting randomly instead of oversampling NPL proposals and equal number of samples from PL and NPL are selected. In total, dataset consists of 3904 samples with 366 features where 1902 samples are NPL and others are PL.

3.2 Proposed Model

After features are determined, some of the features are not suitable for machine learning algorithms therefore some features are converted to numeric or categorical values. For example while birthplace is mapped into a categorical value, birth-date is converted to numeric value to represent age. For experiments, RF–one of the ensemble learning methods–is preferred since ensemble learning methods are widely used in credit scoring modeling and experimental results reveal that ensemble methods can considerably improve the performance (Zhou et al., 2010; Hsieh and Hung, 2010; Wang et al., 2011). Then, data is split into train (80%) and test set(20%) randomly where class distribution is same and algorithms are trained and tested on these datasets.

For further tests, feature size is increased by adding new features to investigate effects of customer behaviour on different products and for each stage, model accuracy is calculated by employing RF. Base dataset with 300 features contains all features except customer repayment performance. 12 features which represent delinquency information for corporate installment loan are added to the dataset and new dataset with 312 features is obtained. Then, while 14 features are added for cheque-book, 25 new features associated with business cards are added to the dataset. Finally, 15 features are utilized for all other products' delinquencies and feature size becomes 366.

After good accuracies are obtained, feature selection method is applied to discover essential features. And also feature selection gives insight into which types of features play an important role for SMEs credit risk analysis.

Other machine learning algorithms (SVM, DT, LR) are applied to compare performance of RF. For SVM, normalization method which is commonly used with SVM is applied to scale feature vector to [-1, +1] during data processing. Finally, MLP which was previously used in the bank for application scoring (Derelioğlu and Gürgen, 2011) is implemented to compare results. It is not possible to compare results with previously conducted researches on open datasets since SMEs' characteristics are directly associated with country's economic situations.

3.2.1 Metrics

In scope of this project, accuracy(acc) and confusion matrix are preferred for performance comparison of machine learning algorithms and result exhibition respectively. Acc, which is between 0 and 1 is obtained by calculating proportion total number of correct predictions to total number of predictions. In confusion matrix, cells mean following meanings: True Negative(TN) is case in which PL customer is predicted correctly. False Positive(FP) is case in which PL customer is misclassified. False Negative(FN) is case in which NPL customers are classified as PL. True Positive(TP) is case in which NPL customers are classified as NPL.

4 EXPERIMENTAL RESULTS

To investigate effects of features of product types and also algorithms, many experiments are conducted. Firstly, to explore effects of features, the dataset is enhanced incrementally and experiments are conducted by utilizing RF. And then, to compare algorithms for credit risk analysis, different algorithms are implemented and obtained results and experiment steps will be discussed in detail in the following section.

4.0.1 Investigating the Predictive Power of Features of Different Products

In order to certify predictive power of customer behaviour on different products, feature size is increased by adding new behaviour data on different products. This lets us to query whether behavioural analysis is powerful for analyzing credit risk. As mentioned before, base dataset consists of 300 features except repayment behaviour. To obtain base results, the dataset is divided into training and test sets. Subsequently, RF algorithm is employed. The resulting algorithm is tested 20 times and obtained max, min, mean and variance of results are shown in Table 2. For further analysis, confusion matrix of one of the test results is presented in Table 3.

Table 2: Base results.

	Mean	STD	MAX	MIN
Base Features	74.65%	1.99%	76.55%	69.83%

As mentioned before, new feature types are added one by one to dataset and experiments are conducted by using RF. After features of repayment performance on a product are added, samples are shuffled and tested 20 times. Each feature set of new product type is added to the previously constructed dataset. Obtained results are shown in Table 4. As it can be seen in Table 4 easily, enriching the dataset by adding customer behaviour data enables us to analyze consumer

Table 3: Confusion matrix of base features.

		PREDICTION	
		PL	NPL
GROUND TRURH	PL	74.9%	25.1%
	NPL	23.8%	76.2%

Table 4: Effects of customer behaviour information on different products.

Product Type	Mean	STD	MAX	MIN
Base Features	**74.65%**	**1.99%**	**77.03%**	**69.83%**
Installment Loan	+0.10%	-0.09%	+0.75%	+1.38%
Cheque-Book	+1.37%	-0.41%	+0.78%	+0.72%
Business Card	+1.68%	-0.16%	+3.46%	+3.89%
Other Products	+2.15%	-0.41%	+0.38%	+2.18%

risk better. Adding customer behaviour data not only increases accuracy but also makes model stable by decreasing standard deviation. To analyze the effects of features on different classes, confusion matrices obtained by using all features and base features are presented in Table 5. As Figure 5 indicates, using customer behaviour data has positive effect on accuracy of both PL and NPL classes. Although the results are calculated by averaging accuracies obtained by testing 20 times on differently shuffled dataset, it is a good approach to compare the effects of feature types obtained by testing on training and test sets which consist of same samples. Hence, the feature types are compared on the same dataset, and obtained results are presented in Figure 4. As Figure 4 illustrates, the results are in line with previous results. Obtained results are discussed with credit experts to check validity of the results, and it is agreed upon that prediction accuracy of the system is enough for the first step of the production deployment.

To be aware of which features play a major role for risk analysis, features are scored using RF and in light of these scores, 15 features with the highest score are determined. The selected features are shown at Table 6. On closer inspection, in the list of the best 15 features, most of them are behaviour features and this indicates that repayment features play a significant role in predicting SMEs which will fall in NPL in period of six months.

Table 5: All features.

ALL FEATURES		BASE FEATURES	
82.9%	17.1%	74.9%	25.1%
18.4%	81.6%	23.8%	76.2%

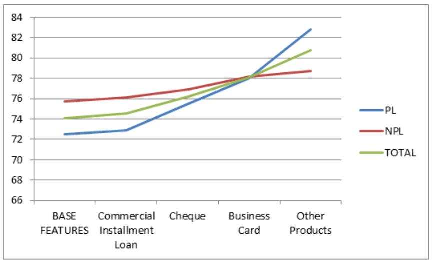


Figure 4: Effects of different information types on same dataset.

Table 6: Types of most important 15 features.

Index	Feature Types
1	Repayment Behaviour on Other Products
2	Repayment Behaviour on Other Products
3	Customer Demographic Information
4	Repayment Behaviour on Other Products
5	Application Form
6	Repayment Behaviour on Business Card
7	Repayment Behaviour on Business Card
8	Repayment Behaviour on Business Card
9	Credit Bureau of Turkey (KKB)
10	Application Form
11	Repayment Behaviour on Other Products
12	Repayment Behaviour on Cheque-Book
13	Application Form
14	Repayment Behaviour on Business Card
15	Repayment Behaviour on Business Card

4.0.2 Investigating the Power of Different Machine Learning Algorithms

Many machine learning algorithms were utilized for customer risk analysis which aims to decide whether customer will become NPL in the future, to the best of our knowledge, there is not so many studies for forecasting customer status in next six-month period. Therefore, other machine learning algorithms which are LR, DT and SVM are also implemented to compare performance of algorithms. All algorithms are trained and tested on the same dataset which consists of all feature types. Obtained results are shown in Figure 5. RF yielded the best performance and it is followed by SVM, DT and LR in order.

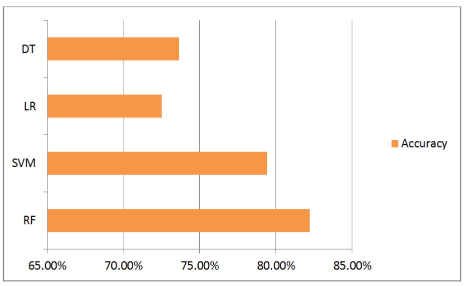


Figure 5: Performance comparison of machine learning algorithms.

Table 7: Comparison of Two Studies.

Study	Maximum Accuracy
(Derelioğlu and Gürgen, 2011)	76.17%
Our result with MLP	80.05%
Our result with RF	**82.25%**

Finally, MLP is implemented which was previously used in scope of the bank for SMEs credit risk analysis. (Derelioğlu and Gürgen, 2011) utilized MLP with one hidden layer on dataset which consists of 512 SME samples with 27 features to forecast customer default. Comparison of results of two different studies and algorithms on our dataset are shown on Table 7. As Table 7 illustrated, our results are better than the previously conducted research, however it cannot prove that our approach is more suitable for credit risk analysis since samples and features in the datasets are different. The experiment is only conducted since it is more sensible to compare the results with previously conducted study in scope of the bank than with other studies on open datasets because of datasets having more similar characteristics.

5 CONCLUSION

We introduced a novel approach to SMEs credit risk by forecasting customer status in the next six-month period instead of in the future. To the best of our knowledge, predicting customer default status in a period, which generally conducted by utilizing survival analysis, has not been aimed for SME credit risk to date by employing machine learning algorithms. We also utilize information of repayment performance along with demographic information, application form data, credit bureau data and so on. To explore performance of customer behaviour on different products, features for each product type are appended to the base dataset incrementally, and the results show that repayment performance on more commonly preferred products gives more information about SMEs credit risk. Then, to compare information types based on effectiveness on credit risk analysis, feature selection algorithm is used and the results show that the most of the selected features is related to customer behaviour. Finally, all feature sets are fed into the machine learning algorithms and experimental results show that RF provides the best prediction performance and it is followed by SVM, DT and LR in order. To compare obtained results with previously conducted study in the bank, MLP is implemented and we obtained better accuracy by using RF. Obtained results indicate that customer repayment behaviour on other products along with other information types need to be investigated further for fully understand the SMEs risk factors.

6 FUTURE WORK

As experimental results indicated, adding behaviour data on frequently preferred products improves performance over using other information types alone. Therefore, as a future work, it is aimed to enhance product based features by adding new product types which will be determined according to their usage rate. Moreover, after information types which play an important role for SMEs risk analysis are determined, it is planned to observe customer behaviour for an interval by shifting the observation point and according to outputs, customer status will be updated. It is expected that, forecasting customers who will fall in NPL on next month is likely to be easier than forecasting customers who will default after 6 months. Therefore, enriching performance data adding behaviour on next months will provide better analysis of SMEs credit risk. It is planned that parameter tuning process for each machine learning algorithm to be implemented at production deployment stage, since up-to-date data in high quantities will only be available on the deployment database.

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