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Deep Learning for Repayment Prediction in Leasing Companies

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Abstarct:

Purpose: *This paper aims to improve repayment prediction in leasing companies using a deep learning model.*
Design/Methodology/Approach: *In this work, we prepare some deep learning models and compare them with other solutions based on artificial intelligence like, multiple regression, decision tree, random forest, and bagging classifier.*
Findings: *The developed model enables automatic analysis of large amounts of data that changes quickly and is often unstructured. Additionally, the input vectors consist of specific attributes related to leasing. The results of experiments allow us to conclude that the prediction accuracy of the developed model is higher than reference models used currently in leasing companies.*
Practical Implications: *The developed model has recently been implemented in the Decision Engine system (a system used by leasing companies in Poland) developed by BI Technologies Sp. Z o.o. Company.*
Originality/Value: *Financial institutions automate and simplify credit procedures, eliminating the analyst from the process and replacing him with automatic decision-making processes based on a scoring or similar models. However, to automatically analyze the significance of phenomena occurring in the environment of organizations that affect the assessment of customer's repayments, it is necessary to use artificial intelligence tools.*

Keywords: *Repayment prediction, deep learning, Fintech, leasing companies, multi-layer neural networks.*

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1. Introduction

Financial institutions automate and simplify credit procedures, eliminating the analyst from the process and replacing him with automatic decision-making processes based on a scoring or similar models (Grima and Thalassinos, 2020). Those, in turn, are based on financial and economic data describing the client and the transaction (Noja *et al.*, 2021). On the other hand, scoring models are focused on credit risk assessment. They are often prepared based on the results of statistical analysis of the impact of various customer characteristics and transactions on the probability of their inability to satisfy required repayments on time. However, these models are insufficient to analyze large amounts of fast-changing, often unstructured data. Financial institutions have access to data from internal sources (organization's information systems database) and external sources (databases of financial supervision institutions, data from cyberspace).

To automatically analyze the significance of phenomena occurring in the environment of organizations that affect the assessment of customer's repayments, it is necessary to use artificial intelligence tools. Nowadays, deep learning technology is used for repayment predictions more and more often. However, recent works are related to bank products (credits, loans, debit cards, etc.) (Han, 2019; Jiang, 2018). Only one publication is explicitly dedicated to leasing prediction (Perera, 2019) based on decision trees. The existing general solution for repayment prediction can be, however, insufficient in case of leasing problems. These problems differ from credits, loan repayment prediction because the subject of leasing is always some fixed asset (e.g., a car, a machine). Therefore, additional features (attributes) can be considered in the prediction model (e.g., a feature of fixed assets), which are not considered in repayment perdition models, for example, for debit or credit cards). Using a decision tree for repayment prediction by leasing companies is also insufficient due to limited capabilities for generalization.

This paper aims to improve repayment prediction in leasing companies using a deep learning model. In this work, based on collected and available data, we prepare some deep learning models and compare them with other solutions based on artificial intelligence like: multiple regression, decision tree, random forest, or bagging classifier. We will try to demonstrate that advanced prediction methods are beneficial for practical use.

The remaining part of this paper is organized as follows: the related works and research methodology are presented in the next section. Next, the model development, including data description and preparation, deep learning model specification, and research experiment for the model's accuracy verification. The last part presents conclusions.

2. Background

The repayment prediction (also considered as customer risk or customer scoring, fraud prediction) is performed using different data and methods-Paper (Natasha (2019) presents a comparison of different machine learning methods for classifying consumer risk. The 988 rows and 17 attributes (variables) are used for model building. The attributes are mainly related to personal information about a customer (e.g., Age, Gender, Number of children). The accuracy of the considered models was between 0.61 and 0.70. The convolutional neural network is used in Kim (2019) for repayment prediction in Peer-to-Peer Social Lending. The 855500 rows and 63 attributes are used (such as loan amount, payment amount, and loan period). The accuracy was 0.76.

The same problem is considered in accuracy as shown in the works of Xu (2017), Ouzineb (2019), Kim, (2017; 2018), Han (2019), Tomczak (2015), Fu (2017), Zhang (2017), and Jiang (2018). Paper by Eweoya (2019), in turn, presents using Support Vector Machine. The 5000 rows and nine attributes were used. The accuracy level equals 0,81. The logic regression and XGBoost algorithm are used for credit risk prediction in loan companies. Fifty thousand rows and 700 attributes have been used. The large number of attributes resulting from data augmentation of main attributes (e.g. for principal balance main attribute, the sum, count, avg, Std, min, max aggregates were calculated and treated as input variables). The AUC value between 0.83 and 0.88 was achieved. A bagging ensemble learning-based method for credit risk scoring is presented in Abedini (2016). One thousand rows and 20 attributes were used. The accuracy level was 0.78.

Similar works have been presented in Song (2019), Chen (2020), Arora (2020), Mehrotra (2017), and Björkegren (2017). The accuracy is also similar. A Deep Genetic Hierarchical Network of Learners for Prediction of Credit Scoring is presented in the paper of Pławiak, (2019). One thousand rows and 20 attributes were used. 0,95 accuracy level was achieved. Paper by Torvekar (2019) presents Multilayer Perceptron and k-Nearest-Neighbor for predicting a credit score for credit card defaulters. Thirty thousand rows and 24 attributes were used. The accuracy was between 0.76 and 0.82.

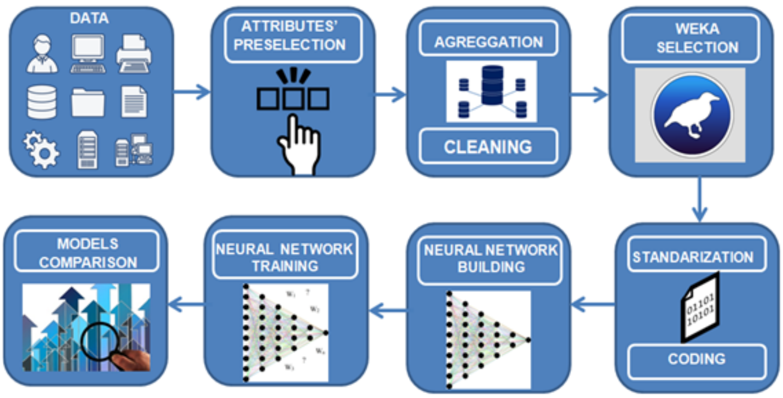
Similar works have been presented in Li (2019), Shichao (2014), Serrano-Cinca (2016), Okur (2019), Geng (2015), and Castellanos (2018). The accuracy is also similar. Considering the application of machine learning in leasing companies the article by Zhang (2019) mentions leasing companies in the context of collecting user data via a public bicycle service system. Once the shared cycling data is obtained, important information in the data is separated. The management of urban transport systems faces many optimization problems. The paper presents the performance of several data mining tasks based on real data sets to solve unsustainable bicycle use problems.

We explored different scientific databases (google scholar, IEEE Explore, Scopus, Science Direct, SpringerLink, and others), and we found only one work-related to repayment prediction in leasing companies. The work by Perera (2019) presents a model based on a decision tree for predicting the credit risk of leasing customers in Sri Lanka. The accuracy level was 0.92, but the AROC value was only 0.63. Therefore the model is precarious. The decision tree also has limited possibilities of generalization, in relation, for example, to deep neural networks. Therefore, it is an interesting research problem. Of course, there are publications related to repayment prediction in financial institutions, but the models are based on general data (loan agreement data, company data, credit payment history). They do not take into consideration attributes that are essential for leasing companies (e.g., year of vehicle production, the market price of a vehicle, vehicle supplier data), and they not take into consideration many important data from different public registers (e.g., young people on the board, number of months since address change, startup, the risky activity of customer). Therefore, there is a need to develop a new deep learning model, which will consider the above issues. Such a model can allow for improving repayment prediction by leasing companies.

3. Methodology

The general idea of the assumed research methodology is presented in Figure 1.

Figure 1. *General Idea of research methodology.*



Source: *Own elaboration.*

The first stage relied on preparing data for further analysis and their preliminary analysis to find statistically significant relationships that affect a customer's creditworthiness. Firstly, a human expert's pre-selection of the proper attributes was made in the economic and credit field. Next, data was aggregated and cleaned by deleting repeating attributes. Polish characters were replaced with equivalents from the English alphabet. The most important attributes that could affect the final decision were selected for further analysis using WEKA software. The evaluation criterion was set to the default attribute, where: 0 means that the customer has fulfilled the contract and one means that the customer has stopped paying. Some attributes needed to be coded by using dummy variables. The following formula standardized continuous data:

$$x = \frac{x - mean(x)}{stand.devation(x)} \quad (1)$$

Such prepared and selected data were used to build the deep learning model.

The second stage depends on building neural network models. These tasks consist of selecting the structure of a neural network, the number of hidden layers, activation functions, and the output of classifier output. These works have been based on literature review and by applying previous experience on neural network construction. Several dozens of configurations of different structures of deep neural networks have been tested. In our work, we have assumed that the results of the output neuron are in the range [0,1]. If the value is closer to one, we have assumed that the leasing will be completed. Otherwise, we will be expecting a default. The next step required choosing a proper learning algorithm to determine the model parameters (neuron weights). In our work, we have used SGD (Stochastic Gradient Descent) algorithm with the adam optimize and the loss function as binary_crossentropy. The values of the hyper-parameters of the model were determined by experimental research. All available records have been split randomly in ratio 70:30 for training and testing samples, respectively. For assessing the effectiveness of the proposed model for default detection, a specific measure called accuracy has been used. The accuracy is the proportion of accurate results among the total number of cases that had been examined.

In the last stage, the effectiveness of the deep learning model has been compared with other approaches. This research references model based on multiple regression models, decision tree classifier, bagging classifier, and random forest classifier.

4. Model Development

4.1 Data description and Preparation

As a dataset used for developing the model, we worked with accurate data from a leasing company due to the model itself being applied in this institution. Previous to the research done for this paper, an analyst from the institution had determined around 50 attributes describing the client to predict his repayment. A manually constructed algorithm based on those attributes had been used for many years, with the error margin increasing each year due to changes in market structure. For this research, we have omitted all the information about the previous algorithm and started afresh with raw data.

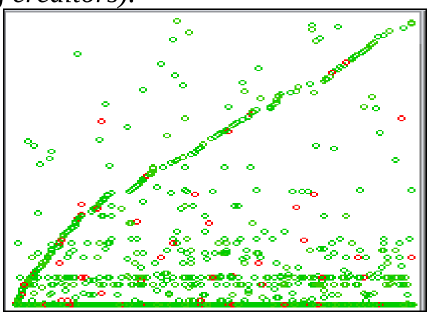
Initially, we were provided with all data about clients that were accessible to the company. As an unnormalized database, this consisted of 53.000 clients (rows) described by 220 attributes (columns). The clients could be grouped into three categories:

- -1 – clients disqualified by previous algorithm
- 0 – clients that paid back credits
- 1 – clients that did not pay back leasing (defaulted).

Thus the task of the model in this research was to correctly classify clients as "good" ones (class 0) and "bad" ones (class 1 and -1), while minimizing mainly the number of "bad" clients (it is more costly for a company to have a non-paying client, than not to have a paying client). The clients were also described with several other attributes that were created based on their specific contracts, e.g., the country-wide credit rating was provided, but for historical data (2012), this was filled with current information (2019) – not paying a specific contract could be the reason for the credit rating. These could not be used in the dataset and were immediately removed.

The next step of data pre-processing was manual attribute pruning and integration, which lead from 200 initial attributes to 60 very distinct and possibly important ones. The attributes related to the areas: contract details, applicant's finances, legal forms, accounting data, historical data on the applicant's operations, management structure, administrative data]. The selection of attributes for different purposes was made by a group of non-financial experts, with consultations with the problem domain experts. Specifically, it was essential to select attributes significant from an analyst's point of view and differentiate them. We also looked for attributes that could be correlated (to remove them) or connected (to integrate them) with each other.

Figure 1. *Visualization of company shares number against its creation date (Red dots mark the defaulting creditors).*

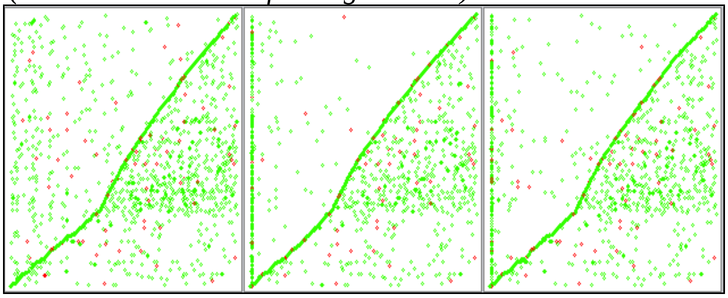


Source: *Own elaboration.*

Attributes may be merged into one if their visualization against other ones is very similar, e.g., Figure 3 presents the company creation date against three initially distinct financial measures (which are shown to be very similar). An integration of these parameters, as well as a specific formula for integration, needed to be provided by a domain expert.

As a helpful tool for this step, we used Visualize functionality in WEKA (Russel and Markov, 2017). This helped to select attributes for further in-depth analysis, based on the following reasoning: Attributes *may* be correlated if there is a visible linear grouping of points, e.g., in Figure 2 presents the number of shares a company has against its creation date (which *may* be correlated from common sense point of view). These *potential* correlation were later verified with mathematical methods.

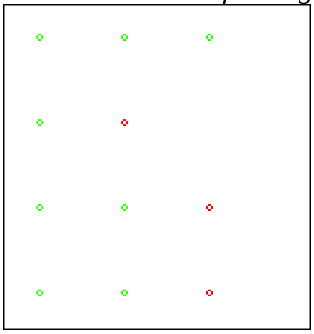
Figure 2. *Visualization of company creation data against three different financial parameters (Red dots mark the defaulting creditor)s.*



Source: *Own elaboration.*

Combinations of enumeration type attributes need to be taken into account if the default state depends on more than one of them, e.g. Figure 4 presents the number of risky areas of economic activity against the currency of the credit. All arguments from such combinations are selected for use in the model.

Figure 3. *Visualization of the number of risky areas of economic activity against the currency of the credit (Red dots mark the defaulting creditors).*



Source: *Own elaboration.*

All attributes marked by the consulting experts as important were also selected.

4.2 Deep Learning Model

The developed model is a binary classifier. The classifier is based on deep neural networks. The model consists of six neural networks connected to a common one. Each of the six neural networks (where the number of output neurons was determined experimentally) is the input to the shared neural network – the whole network has only one output neuron. The output neuron assumes values in the range from 0 to 1. The result is interpreted as follows: if its value is close to 0, we assume that the leasing contract will be completed; if its value is close to 1, the leasing contract will be discontinued (called "default" by leasing companies)
Input vector

$$X = \left\langle \begin{matrix} X^{PKD}, X^{Continous}, X^{ConctractType}, X^{LegalForm}, X^{Boolean} X^{Department}, \\ X^{Branch}, X^{Object}, X^{Scoring}, X^{Categorical} \end{matrix} \right\rangle \tag{2}$$

Where:
X^{PKD} - the symbol of classification of business activity (in our research - Polish Classification of Business Activity – PKD) - type of values: string
$X^{Continous}$ - continuous attributes' values (16 attributes, such as: Incomes, Initial contract value, Initial fee, Margin, etc.) - type of values: double
$X^{ConcractType}$ - type of contract, type of values: string
$X^{LegalForm}$ - type of legal form of business activity, type of values: string
$X^{Boolean}$ - boolean attributes (15 attributes, such as: Is an authorized supplier, Is leaseback, Additional transaction security, etc.), type of values: boolean
$X^{Department}$ - department, where the transaction was signed, type of values: string,
X^{Branch} - a branch of activity, type of values: string
X^{Object} - a name of the contract subject, type of values: string
$X^{Scoring}$ - the scoring attributes (57 attributes, such as: Number of people on the management board, Number of company owners, New client, New supplier etc., type of values: integer
$X^{Categorical}$ - categorical data (322 attributes, such as: Postal codes, Clients region, Virtual office, etc.).

The model has a multi-mixed architecture. The output is defined as follows:2

$$y = f(y^1, y^2, \ldots, y^L) \tag{3}$$

Where:
y^l denotes a layer in which $l = 1, 2....L$ (L denotes a number of layers),
$f()$ denotes the output activation function.

Let *dense* denote the layer composed of a certain number of neurons, *flatten* denote a flatten layer (flatten layers are quite simplistic and are used in order to extract a feature vector from the output of the other layers (Xie *et al.*, 2017)), *embedding* denotes embedding layer (embedding layers compress the input feature space into a smaller one (Xie *et al.*, 2017)), *neurons* denotes a number of neurons, *relu* denotes rectified linear unit activation function defined as follows
(Aghdam, 2015):

$$relu(z) = \begin{cases} z, & \text{if } z \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

and *batch* denote normalization performed across mini-batches and not the entire training set (Bjorck *et al.*, 2018)
The first layer comprises a concatenation of sub-networks and is defined as follows:

$$y^l \begin{cases} concatenate(\mathrm{y}^{PKD}, y^{Continous}, y^{ConcractType}, y^{LegalForm}, \\ y^{Boolean} y^{Departmen}, y^{Branch}, y^{Object}, y^{Scoring}, y^{Categorical}), l = 1 \\ \mathrm{dense}(\mathrm{y}^{l-1}, \mathrm{neurons}^{l-1}, \mathrm{relu}^{l-1}, \mathrm{dropout}^{l-1}), \mathrm{l}>1 \end{cases} \tag{5}$$

where:

$$y^{PKD} = dense(flatten(embedding(X^{PKD})), neurons^{PKD}, relu)$$

$$y^{Continous} = dense(batch(dense(X^{Continous}, neurons^{Continous}, relu)), neurons^{bath}, relu)$$

$$y^{ConcractType} = dense(flatten(embedding(X^{ConctactType})), neurons^{ConctactType}, relu)$$

$$y^{LegalForm} = dense(flatten(embedding(X^{LegalForm})), neurons^{LegalForm}, relu)$$

$$y^{Boolean} = dense((dense(X^{Boolean}, neurons^{Boolean}, relu)), neurons^{\overline{Boolean}}, relu)$$

$$y^{Department} = dense(flatten(embedding(X^{Department})), neurons^{Department}, relu)$$

$$y^{Branch} = dense(flatten(embedding(X^{Branch})), neurons^{Branch}, relu)$$

$$y^{Object} = dense(flatten(embedding(X^{Object})), neurons^{Object}, relu)$$

$$y^{Scoring} = dense(flatten(embedding(X^{Scoring})), neurons^{Scoring}, relu)$$

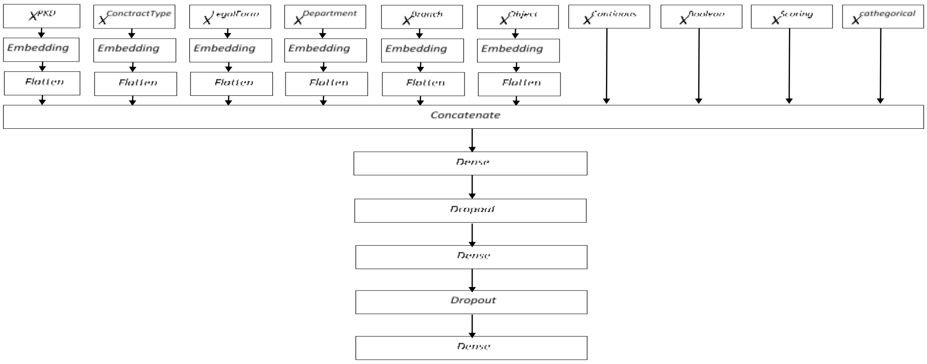
$$y^{Categorical} = dense((dense(X^{Categorical}, neurons^{Categorical}, relu)), neurons^{\overline{Categorical}}, relu)$$

The visualization of the model is presented on Figure 5.

5. Results

The experiment tested several models for accuracy in predicting defaults and non-default and the combined accuracy of both. We used neural networks and several classifiers but mainly focused on neural networks. Our datasets were the same for each experiment and contained 5000 data rows (leasing clients) in the training set and 1714 data rows in the validation set. The experiment was divided into five parts. The first experiment concerned a perceptron. The perceptron was characterized by a constant batch size of 20 and a varying number of epochs. We checked the results separately for 100, 150, 200, and 300 epochs. The results have been presented in Table 1. There is an overall accuracy (mean average between default and non-default accuracies) and a separate accuracy for finding defaults and non-defaults.

Figure 4. *Visualization of the model*



Source: *Own elaboration.*

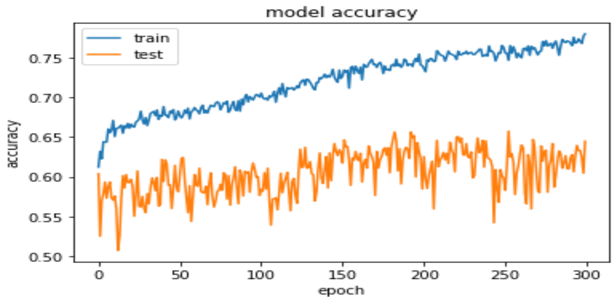
Table 1. *Perceptron's accuracy results*

Number of epochs	**Overall Accuracy**	**Accuracy for Default=1**	**Accuracy for Default=0**
100	0.610851809	0.486581097	**0.73512252**
150	0.597432905	0.508751459	0.686114352
200	0.630105018	**0.686114352**	0.574095683
300	**0.644690782**	0.65344224	0.635939323

Source: *Own elaboration.*

The results were quite unstable, as can be seen in Figure 6. As expected for such a simple model, it did not show an increase in the test sample relative to the accuracy of the learning sample. The results of this experiment were unsatisfactory in terms of learning time.

Figure 5. *Model accuracy by each epoch for perceptron with 300 epochs*



Source: *Own elaboration.*

The second experiment focused on the use of a deep learning model. The experiment was carried out for a model containing 5,10,15, and 20 epochs and a constant batch size of 50. The results were better than in the case of the perceptron and have been presented in Table 2.

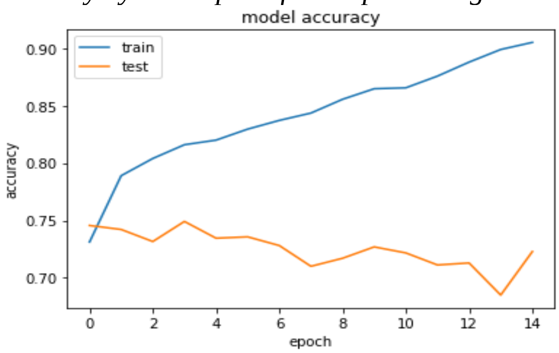
Table 2. *Deep Learning accuracy results*

Number of epochs	**Overall Accuracy**	**Accuracy for Default=1**	**Accuracy for Default=0**
5	0.70070012	0.488914819	**0.912485414**
10	0.70361727	0.613768961	0.793465578
15	**0.72287048**	0.691948658	0.753792299
20	0.6831972	**0.787631272**	0.578763127

Source: *Own elaboration.*

The model learning achieved the best results with 15 epochs. It showed a lower percentage of non-default detection than other amounts of epochs, but it was still within tolerance. On the other hand, it did much better with defaults, which affected the model's overall accuracy. The accuracy of the learning sample is much greater than the accuracy of the test sample, as seen in Fig. 7. This indicates that the model has been overfitting.

Figure 6. *Model accuracy by each epoch for deep learning model with 15 epochs.*

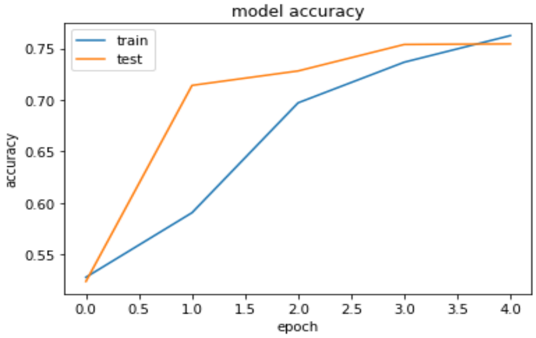


Source: *Own elaboration.*

The third stage of the experiment was supposed to prevent overfitting. For that purpose three additional Dropout Layers were added. They turned off 50% of neurons in the next layer. This operation solved the problem of overfitting (Figure 8).

This model increased general accuracy compared to the one without dropouts (Table 3). An additional change in the model was the reduction in the number of batch size from 50 to 20.

Figure 7. *Model accuracy by each epoch for deep learning, dropouts-including model with 5 epochs*



Source: *Own elaboration.*

Table 3. *Deep Learning model with dropout accuracy results*

Number of epochs	**Overall Accuracy**	**Accuracy for Default=1**	**Accuracy for Default=0**
5	**0.75437573**	**0.756126021**	0.752625438
10	0.74795799	0.718786464	0.777129522
15	0.74212369	0.700116686	0.784130688
20	0.72753792	0.704784131	**0.78529755**

Source: *Own elaboration.*

The fourth stage of the experiment was to compare 4 classification methods. The following methods have been selected:

- Multiple regression
- Decision Tree Classifier
- Bagging Classifier
- Random Forest Classifier.

Hyperparameters in all models were used with the default settings. The results have been presented in Table 4. The Bagging Classifier achieved the highest accuracy. In the last stage, models from each part of the experiment were selected to compare the accuracy of corresponding methods. The AROC (Area Under The Curve) was implemented as an additional comparative measure. Table 5 shows cumulative results.

Table 4. *Classifier models accuracy results.*

Classifiers	**Overall Accuracy**	**Accuracy for Default=1**	**Accuracy for Default=0**
Multiple regression	0.63786234	0.4857495	**0.7574987**
Decision Tree Classifier	0.66336056	0.545308741	0.620985011
Bagging Classifier	**0.730455076**	0.77746077	0.692003949
Random Forest Classifier	0.712368728	**0.781733746**	0.670720299

Source: *Own elaboration.*

The deep learning model achieved the highest accuracy and highest AROC value with dropouts. Although the developed model achieved a lower accuracy than the model presented in (Perera, 2019), it is more stable due to a higher AROC value. In addition, the developed model has higher capabilities of generalization than the model presented in (Perera, 2019). It should also be emphasized that the accuracy of the existing model (using in Polish leasing companies based on expert system) is about 0.65 (based on information from BI Technologies sp. z o.o. – the developer of decision support systems for leasing companies). The bagging classifier achieved higher accuracy than networks without dropouts. It may result from the overfitting of neural networks without dropouts. The lowest accuracy was achieved by perceptron.

Table 5. *Cumulative results*

Model	**Overall Accuracy**	**Accuracy for Default**	**Accuracy for Non-Default**	**AROC**
Bagging Classifier	0.730455076	**0.777461**	0.692003949	0.806518901
Deep learning model without dropouts	0.72287048	0.691949	**0.753792299**	0.759553761
Deep learning model with dropouts	**0.75437573**	0.756126	0.752625438	**0.818234486**
Perceptron	0.644690782	0.653442	0.635939323	0.613892864

Source: *Own elaboration.*

6. Conclusions

The main result of the presented research is the experimental model of the automatic repayment prediction in leasing companies. It enables automatic analysis of large amounts of data that changes quickly and is often unstructured. Input data comes from internal sources (databases of information systems of an organization) and external ones (databases of financial supervision institutions). Additionally, the input vectors consist of specific attributes related to the leasing contract (such as fixed asset features). The results of experiments allow us to conclude that the prediction accuracy of the developed model is higher than reference models (which are currently used by leasing companies in Poland).

We obtain the highest accuracy using the deep learning model with dropouts. Our algorithm detects potential problems with customer repayments in more than 75% of cases. It results with practical significance, as it outperforms the previous method used by the company providing the dataset. In addition, it should be noted that the algorithm rejects only less than 25% of good customers who can pay back but do not get funds for leasing. Our algorithm offers a good balance between profit (from provisions) and loss (from default). The developed model is more precise than the model developed for Sri Lanka (Perera, 2019). The developed model can be used for automatic decision-making by leasing institutions. It may serve as a substitute for manual and time-consuming decision-making processes performed by humans (analysts). The developed model has recently been implemented in the Decision

Engine system (a system used by leasing companies in Poland) developed by BI Technologies Sp. Z o.o. Company.

Our future work will focus on developing deep learning models and their application in other financial problems like detecting fraud, calculating credit scores, or predicting profits on the FOREX market.

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