Zeszyty Naukowe Uniwersytet Ekonomiczny w Krakowie

6(978)

ISSN 1898-6447
e-ISSN 2545-3238
Zesz. Nauk. UEK, 2018; 6(978): 41–60
https://doi.org/10.15678/ZNUEK.2018.0978.0603

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Predicting Bankruptcy at Polish Companies: A Comparison of Selected Machine Learning and Deep Learning Algorithms

Abstract

Insolvency prediction is one of the crucial abilities in corporate finance and financial management. It is critical in accounts receivable management, capital budgeting decisions, financial analysis, capital structure management, going concern assessment and co-operation with other companies. The purpose of this paper is to compare the efficiency of selected deep learning and machine learning algorithms trained on a representative sample of Polish companies for the period 2008–2017. In particular, the paper tested the following popular machine learning algorithms: discriminant analysis (DA), logit (L), support vector machines (SVM), random forest (RF), gradient boosting decision trees (GB), neural network with one hidden layer (NN), convolutional neural network (CNN), and naïve Bayes (NB). The research hypotheses evaluated in the paper state that if one has access to a large sample of companies, the most accurate algorithm (first choice) in bankruptcy prediction will be gradient boosting decision trees (H1), random forest (H2) and neural networks (H3) (deep learning) algorithms. The initial hypotheses were formulated based on the practitioners' opinions regarding the usefulness of various machine learning and artificial intelligence algorithms in bankruptcy prediction. As the results of the research suggest, both deep learning and machine learning algorithms proved to have very comparable efficiency. The new factor introduced in the paper was that the training of the models was carried out on a representative sample of companies (for years 2008–2013) and also the testing phase used a significant number of bankrupt and active companies (validation

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included a completely different set of companies than those used in the training phase: data were taken from a different time period, 2014–2017, and companies in both sets were also completely different).

Keywords: bankruptcy prediction, deep learning, machine learning, corporate finance.
JEL Classification: G33.

1. Introduction

Currently, there is unprecedented growth in the amount of information generated worldwide and on the internet which can be collected, processed and used for prediction purposes. This has led to the creation or reinvention of many big data prediction methods, including machine learning and deep learning algorithms. Machine learning used algorithms to parse data, learn from it and make decisions or predictions about various processes described by this data (Lewis 2017). Deep learning uses a subset of machine learning algorithms. "Classical" machine learning algorithms require some guidance during training (if a machine learning algorithm returns inaccurate predictions, a human must introduce adjustments), while "classical" deep learning algorithms can determine by themselves whether the prediction they produced is accurate or not. Deep learning algorithms are usually based on artificial neural networks, which structure algorithms in layers and make the information processing resemble human-like intelligence.

The development of machine learning methods (including neural networks) has led to the creation of new positions in banks, various financial institutions, companies and ministries. While such enterprises have always employed statisticians, new developments in the field of data processing have created a demand for data scientists, who do statistical analysis as well as use programming languages to create semi-automatic and automatic tools for data analysis and processing. Today, data science (and deep learning) algorithms handle risk management, online trading, insurance underwriting, bankruptcy prediction and speech and text recognition, which are popular research areas at a range of financial institutions (Brynjolfsson & Mcafee 2017, Barboza, Kimura & Altman 2017, Liao *et al*. 2014). In terms of bankruptcy prediction, specialised companies concentrate solely on providing accurate insolvency risk information about various businesses and physical persons to their clients, which include banks, loan companies, insurers and commercial factoring and commercial companies. These specialised bankruptcy prediction companies are on the lookout for better classification algorithms as even the most marginal of improvements in the accuracy of their classification algorithms produces significant cost savings for their clients by reducing unfavorable debt.

Interestingly, the majority of studies that have analysed the accuracy of machine learning algorithms have used relatively modest data samples. This issue led to the research hypothesis of this paper, which tests the usefulness of various machine learning algorithms using a relatively large and representative set of Polish commercial companies. The paper tests the usefulness of the following methods: discriminant analysis (DA), logit (L), support vector machines (SVM), random forest (RF), gradient boosting decision trees (GB), neural network with one hidden layer (NN), convolutional neural network (CNN), naïve Bayes (NB). The research hypotheses tested in the paper state that if one has access to a large sample of companies, the most efficient algorithms (first choice) for predicting bankruptcy are gradient boosting decision trees (H1), random forest (H2) and neural networks (H3) (deep learning) algorithms. This research verifies the accuracy of more algorithms and uses a wider base of companies, especially for the verification phase, than have the author's past papers (Wyrobek & Kluza 2018a, 2018b).

2. Literature Review

2.1. Review of International Publications

Tables 1 and 2 summarise the final accuracy of models presented in research papers on bankruptcy prediction[1]. The accuracy of the models was estimated in

[1] Publications used for the creation of Tables 1 and 2 (abbreviations represent models estimated in the paper): Aktan (2011) – SVM, DT, BN, NB; Alaminos, del Castillo & Fernandez (2016) – CART, DT, BN, SVM, NB; Alfaro, Garciá & Gámez (2008) – DA, DT, NN, (A)DT; Altınırmak & Karamaşa (2016) – SVM; Anandarajan, Lee & Anandarajan (2001) – DA, NN, (Ba)NN; Arieshanti *et al.* (2013) – SVM; Barboza, Kimura & Altman (2017) – DA, LR, NN, SVM, (A)NN, (Rf)DT, (Bg)NN; Blanco-Oliver *et al.* (2015) – LR; Chaudhuri & De (2011) – LR, NB, SVM; Chen (2012) – DT, CART, SVM; Cho, Hong & Ha (2010) – DT, LR, NN; Cho, Kim & Bae (2009) – DA, DT, LR, NN, SVM; Chuang (2013) – LR; Dellepiane *et al.* (2015) – SVM; Ecer (2013) – SVM; Edrogan (2013) – SVM; Fedorova, Gilenko & Dovzhenko (2013) – DA, (A)NN; Geng, Bose & Chen (2015) – DT,NN, SVM; Ghodselahi & Amirmadhi (2011) – DA, DT, LR, NN, SVM, (B)DT, (Bg)NN, (Gb)DT, (Bo)NN, (Bo)SVM; Hauser & Booth (2011) – L; Heo & Yang (2014) – DT, NN, SVM, (A)DT; Hu & Tseng (2007) – DA, LR, PROBIT; Jardin (2009) – DA, DT, CART, LR, (Bo)NN, (Bg)NN, NN, (RS)LR; Jayanthi, Suresh & Vaishnavi (2011) – SVM; Kasgari, Salehnezhad & Ebadi (2013) – LR, NN; Kim & Kang (2010) – DT, NN, SVM, (B)DT, (Bo)NN, (Gb)NN, (Bo)SVM; Kim & Kang (2012) – NN, (A)NN, (Bg)NN; Kim & Upneja (2014) – DT, (A)DT; Ko, Blocher & Lin (2001) – LR, NN; Krichene (2017) – NB; Laitinen & Laitinen (2000) – L; Lee, Jang & Park (2017) – DT, CART, LR, NN, GP; Li *et al.* (2011) – DA, LR, PROBIT, (RS)LR; Li & Sun (2009) – DA, LR; Li & Sun (2010) – DA, LR; Li & Sun (2011) – DA, LR; Liao *et al.* (2014) – DA, DT, (Rf)DT, LR, B; Marqués, Garcia & Sanchez (2012) – DT, LR, NN, SVM, (Rs)SVM, (A)DT, (Bg)NN; Min & Jeong (2009) – DA, DT, LR, NN; Min & Lee (2005) – DA, LR, NN, SVM; Mirzaei, Ramakrishnan & Bekri (2016) – DT, CART, LR; Nagaraj & Sridhar (2015) – LR, NN, SVM,

various ways, with some based on a separate validation sample (in a number of papers the researchers first trained a model on the separate training sample, then tested it on a separate test sample and, finally, validated it on a separate validation sample). In other papers, the model was tested only on a test sample (without a validation sample) while in still other papers the authors used a cross-validation technique (the model was trained several times, each time with one part of the data used as a training sample while another was used as a test sample – in the end, the researchers took the average accuracy of all of the models).

The summary of the publications presented in Tables 1 and 2 shows separately the accuracy of non-ensemble models and ensemble models. Table 1 presents the accuracy of non-ensemble models.

Table 1. Summary of Accuracy Single Machine Learning Methods

Base Classifiers	Average Accuracy	Number of Publications
BN – Bayesian network	86.4	3
CART – classification and regression trees	76.79	4
DA – discriminant analysis	76.1	17
DT – decision trees	75.5	18
GP – Gaussian process classification	85.67	2
LR – logistic regression	74.78	31
NB – naïve Bayes	95.25	3
NN – neural network	76.67	25
PROBIT	85.48	3
SVM – support vector machines	80.15	27

Source: the author's own research.

As can be seen in Table 1, the highest accuracy was found for naïve Bayes algorithms. However, only three papers used this method, so it is uncertain whether the results are reliable and generally representative for insolvency detection. This also applies to the Bayesian network (BN), Gaussian processes (GP) and probit. The algorithms which returned a relatively promising accuracy in the publications analysed were the following: neural networks (NN), with an accuracy of 76.67%; logistic regression (LR), with an accuracy of 74.78%; decision trees (DT), with

BN, (Rf)DT; Nanni & Lumini (2009) – NN, SVM, (Bg)SVM, (Bo)NN, (Bo)SVM, (Rs)SVM; Peña, Martinez & Abudu (2009) – DA, LR, GP, PROBIT, SVM, BN; Ramakrishnan, Mirzaei & Naveed (2015) – DT, NN, SVM; Shin, Lee & Kim (2005) – SVM; Sun, Jia & Li (2011) – DT, SVM, (A)DT; Sun & Li (2009) – LR, NN, SVM, DA, DT; Sun & Li (2012) – SVM; Tsai (2014) – DT, LR, NN; Tsai & Cheng (2012) – DT, LR; Tseng & Hu (2010) – L, (Ba)NN; West, Dellana & Qian (2005) – NN, (Bg)NN, (A)NN; Xiao *et al.* – LR, NN, SVM; Zhou, Lai & Yen (2014) – SVM.

an accuracy of 75.5%; and support vector machines (SVM), with the accuracy of 80.15%.

From a practical point of view, it would seem acceptable to use algorithms with a prediction accuracy exceeding 90% (it was the author's assumption that for both classes a model should prove at least 90% accurate – in similar research the authors only compare the accuracy of different algorithms), so one would make a mistake in only 10 out of 100 cases. The most promising algorithm therefore seemed to be naïve Bayes.

Table 2 presents the average accuracy of ensemble algorithms, which combine basic algorithms into more advanced methods. The most popular and frequently enlisted algorithms are random forest and gradient boosting decision trees, which combine decision trees with majority voting to create the next decision tree to correct the mistakes of the one that preceded it. There are dozens, and potentially hundreds, of such ensemble algorithms, but here only the most popular algorithms are presented.

Table 2. Summary of Ensemble Machine Learning Algorithm Accuracy

Technique	Base Classifiers	Average Accuracy (%)	Number of Publications
AdaBoost	(A)DT	87.92	5
	(A)NN	84.67	4
Backpropagation	(Ba)NN	82.83	2
Bagging	(B)DT	75.63	2
	(Bb)NN	77.65	7
	(Ba)SVM	76.69	4
Gradient boosting	(Gb)DT	74.62	2
Boosting	(Bo)NN	76.52	3
	(Bo)SVM	75.63	3
Random forest	(RF)DT	93.12	3
Random subspace	(RS)LR	83.71	2
	(RS)NN	80.8	2
	(RS)SVM	87.95	2

Source: the author's own research.

Table 2 shows the accuracy of the ensemble methods found more than once in the papers analysed. As can be seen in Table 2, the most accurate algorithm proved to be random forest decision trees. The second best was an algorithm based on SVM, which applied random subspaces applied to SVM. Adaptive boosting algorithm (AdaBoost) applied to decision trees was a close third. All three algorithms

were very close to 90% accuracy. Underperforming when used individually, neural networks finished in fourth place when they were combined with the AdaBoost algorithm (accuracy 85%).

2.2. Review of Publications Concerning Bankruptcy Prediction in Poland

Recent publications dedicated to the application of machine learning algorithms and artificial intelligence for bankruptcy prediction in Polish companies include a paper by B. Pawełek and D. Grochowina (2017), a book by J. Pociecha, B. Pawełek, M. Baryła and S. Augustyn (Pociecha *et al*. 2014) and another by T. Korol and B. Prusak (2009). Each of the three used different data samples and algorithms. B. Pawełek and D. Grochowina used CART, bagging, boosting, random subspaces and random forest approaches. J. Pociecha *et al*. received the best results for neural networks, discriminant analysis and CART methods. T. Korol and B. Prusak used neural networks for different proportions between active and bankrupt companies.

I will first discuss findings from the paper written by B. Pawełek and D. Grochowina (2017). In it, the researchers looked at 7223 Polish manufacturing companies, including 42 bankrupt companies. The data sample covered the years 2013–2015 (it came from the Emis database).

The authors used decision trees (CART) as a basic learning method and then combined it with: boosting (learning of distribution from weak classifiers (weak learners are restricted, smaller models) and adding them to a final strong classifier), bagging (bootstrap aggregation), random subspaces (this method reduces the correlation between variables by training a model based on random subsets of the dataset) and random forest (majority voting ensemble of decision trees). Aggregation of the base models was conducted based on the majority voting technique described by E. Gatnar (2008). Estimation and testing were carried out as follows: the dataset was divided into 10 balanced and 10 unbalanced subsets. Each subset was divided into 9 training sets and 1 testing set (each time different observations belonged to the training and testing sets). Final models were based on the aggregation of partial models trained on subsets. The authors did not use any validation sample, but the testing sample was different for every subsample. The results were presented as the total classification error of the final models. Table 3 shows a small fraction of the results, only for the models with a prediction period of one year prior to the bankruptcy and for the ensemble consisting of 100 base models (but this number of base models produced the best validation results).

In the ensemble methods in Table 3, random subspaces and random forest are presented in 2 columns (4 columns in total). These algorithms were applied in two ways. In the first approach (symbol (1)), the models were simply trained on

16 financial ratios. In the second approach, the models were trained on 8 randomly chosen ratios (symbol (2)).

Table 3. General Error Rates of Models Comprising 100 Base Models (in %) One Year Before Bankruptcy (the Second Approach)

Error Type	Type of Subset	CART	Bagging	Boosting	Random Subspaces 1	Random Subspaces 2	Random Forest 1	Random Forest 2
Total error	balanced	35.5	29.5	34.1	31.9	28.4	29.2	27.7
	unbalanced	27.9	21.8	23.2	22.3	21.6	22.5	21.6
First type error	balanced	34.8	29.1	36.2	31.3	27.9	30.3	28.6
	unbalanced	57.7	61.1	56.6	57.4	61	57.1	56.7
Second type error	balanced	36.1	29.8	32	32.6	28.9	28.1	26.9
	unbalanced	17.9	8.7	12.1	10.6	8.5	10.9	9.9

Source: Pawełek and Grochowina (2017, p. 175).

As can be seen in Table 3, the most accurate non-ensemble algorithm was random forest and random subspaces algorithms for randomly selected ratios. For the balanced sample, the most accurate algorithm was the random forest one also for 8 randomly selected financial ratios (random selection was carried out separately for every base model).

The researchers confirmed dependency between model accuracy and the number of base models (positive relationship) and the most recommended and promising methods turned out to be (for unbalanced sample and random selection of financial ratios for base models) random subspaces, random forest, and bagging.

Another important publication which analyses the accuracy of various machine learning techniques in bankruptcy prediction is the book written by J. Pociecha, B. Pawełek, M. Baryła, and S. Augustyn (Pociecha *et al*. 2014), who used data for 7147 active companies and 182 bankrupt companies and two approaches to test their models: 70%/30% and 60%/40%. They did not use a validation sample. Observations were for years 2005–2009.

Pociecha *et al*. (2014) used the following algorithms: logit, discriminant analysis, decision trees (CART – classification and regression trees), and neural networks (only 3-layer networks: an input layer, one hidden layer, and one output layer). To teach neural networks, the researchers used the BFGS method (Broyden-Fletcher--Goldfarb-Shanno). The researchers tested many different activation functions: linear function, logistic function, hyperbolic tangent, an exponential function and softmax function. Table 4 shows the best models trained on the balanced sample.

Table 4 shows that the most effective algorithm was the 3-layer neural network with proportions between training and test samples from 60% to 40%. The total

Table 4. Ranking of the Best Models in (Pociecha *et al*. 2014) for a Balanced Sample One Year before Bankruptcy (Abbreviations of Variables Used in Each Model Are Omitted)

Ranking	Model Type	Training: Test Proportion	Test Sample		
			Error Type 1	Error Type 2	Accuracy
1	NN (equity + long-term liabilities)/total assets; (operating profit + + depreciation)/total assets; operating costs/ short-term liabilities)	6:4	95.83	83.33	89.58
2	DA (equity + long-term liabilities)/total assets; (operating profit + + depreciation)/total assets; operating costs/ short-term liabilities)	6:4	95.83	75	85.42
3	CART (net profit (loss) × × 100/total assets)	6:4	95.83	70.83	83.33

Note: NN – neural network, DA – discriminant analysis, CART – decision trees.

Source: Pociecha *et al*. (2014, p. 109).

Table 5. Ranking of the Best Models in Pociecha *et al*. (2014) for the Unbalanced Sample (Random Sampling) One Year before Bankruptcy

Ranking	Model Type	Training: Test Proportion	Test Sample		
			Error Type 1	Error Type 2	Accuracy
1	NN ((current assets – inventories – short-term receivables)/current liabilities; (operating profit + depreciation)/total assets)	6:4	100.00	91.67	95.83
2	NN ((operating profit + + depreciation)/total assets; operating profit/ total assets; 2 × net sales revenues/(short-term receivables (t) + short-term receivables (t – 1)); operating costs/short-term liabilities)	7:3	100.00	83.33	91.67
3	CART (net profit (loss) × × 100/total assets)	6:4	100.00	79.17	89.58

Note: NN – neural network, DA – discriminant analysis, CART – decision trees.

Source: Pociecha *et al*. (2014, p. 109).

Table 6. The Accuracy of Korol and Prusak's Models, K1 Approach

Proportions of Training Sample	Number of Hidden Neurons	Proportions of Test Sample								
		1:1 Error 1	1:1 Error 2	1:1 Accuracy	3:1 Error 1	3:1 Error 2	3:1 Accuracy	10:1 Error 1	10:1 Error 2	10:1 Accuracy
1:1	28	0	2.25	98.72	0	2.56	98.08	0	2.56	97.67
3:1	10	15.38	0	92.31	0	0	100	0	0	100
10:1	10	41.02	0	79.49	7.69	0	98.08	0	0	100

Source: Korol and Prusak (2009, pp. 161–162).

Table 7. The Accuracy of Korol and Prusak's Models, K2 Approach

Proportions of Training Sample	Number of Hidden Neurons	Proportions of Test Sample								
		1:1 Error 1	1:1 Error 2	1:1 Accuracy	3:1 Error 1	3:1 Error 2	3:1 Accuracy	10:1 Error 1	10:1 Error 2	10:1 Accuracy
1:1	28	0	5.12	97.44	0	5.12	96.16	0	5.12	95.35
1:1	56	15.38	0	92.31	0	0	100	0	7.69	100
3:1	10	28.2	0	95.9	0	0	100	0	0	100
10:1	28	12.82	12.82	87.18	7.69	12.82	88.47	0	12.82	88.38
10:1	10	30.76	2.56	83.34	15.38	2.56	94.24	0	2.56	97.68

Source: Korol and Prusak (2009, pp. 161–162).

Table 8. The Accuracy of Korol and Prusak's Models, K3 Approach

Proportions of Training Sample	Number of Hidden Neurons	Proportions of Test Sample								
		1:1 Error 1	1:1 Error 2	1:1 Accuracy	3:1 Error 1	3:1 Error 2	3:1 Accuracy	10:1 Error 1	10:1 Error 2	10:1 Accuracy
1:1	8:4:2	15.38	0	92.31	0	0	100	0	0	100
3:1	8:4:2	20.51	0	89.75	7.69	0	98.08	0	0	100
10:1	8:4:2	25.64	0	87.18	7.69	0	98.08	0	0	100

Source: Korol and Prusak (2009, p. 170).

error rate was 89.58%. The second best model was the discriminant analysis model while the third best was a single decision tree. However, only the neural network accuracy was close to a 10% error rate in classification.

Table 5 shows the results for models trained on the unbalanced sample. The most accurate algorithm again proved to be a neural network, though it was based on different ratios than was the balanced sample. Only this model's total error rate was below 10% (4.47%). The second best model, with an accuracy of 91.67%, was also a neural network, but based on a different combination of financial ratios. The third most accurate model was a simple decision tree with a total accuracy equal to 89.58%.

T. Korol and B. Prusak (2009) also analysed bankruptcy detection in Polish companies. The researchers used data for 180 manufacturing companies published in "Monitor Polski B" in the years 1998–2001. The dataset was divided into a training set, consisting of 39 bankrupt companies and 39 active companies, and a test sample including 39 bankrupt companies and 39 active companies. Three different approaches were used: K1 – a model trained on all financial ratios, K2 – a model trained on financial ratios selected based on variance matrix, and K3 – the ratios for training were chosen arbitrarily. T. Korol and B. Prusak used the neural network with one hidden layer and experimented with different numbers of neurons looking for the most efficient combination (which produced the highest accuracy of the model).

The authors also tested different structures of the training sample: either a 1:1 proportion between bankrupt and active companies, a 3:1 proportion (3 active companies for each 1 bankrupt company) and a 10:1 proportion (10 active companies for each 1 bankrupt company). Selected results of the estimated models are presented in Tables 6, 7 and 8.

The results presented in Tables 6–8 show that the accuracy of the network deteriorated as the imbalance of the training sample increased. For a balanced training sample, the model's accuracy was very high for all approaches: K1, K2, and K3. All accuracies were above 90%; some even reached 100%. For unbalanced samples, the classification accuracy deteriorated and for the training sample proportions 10:1 the accuracy was below 90%. The researchers did not use validation samples.

3. The Research Method

Table 9 lists definitions of the financial ratios used in the training of the models. For algorithms like logit, where multicollinearity must be avoided (logit, SVM with linear kernel, naïve Bayes without the PCA application) I used only

variables which were not highly correlated with each other (the correlation had to be below 0.3). For models capable of creating their ratios (algorithms based on the decision trees, neural networks), I also used nominal data from financial statements (but following normalisation). Eight variables (features) were kept in the final model training, and the rest were removed, beginning with the least important one).

Table 9. Construction of the Financial Ratios Included in the Model Training

Symbol	Definition
RSHF	(profit before tax / shareholder funds) × 100
RCEM	(profit before tax + interest paid) / (shareholder funds + non current liabilities) × 100
RTAS	(profit before tax / total assets) × 100
ROE	(net income / shareholder funds) × 100
ROCE	(net income + interest paid) / (shareholder funds + non current liabilities) × 100
ROA	(net income / total assets) × 100
PRMA	(profit before tax / operating revenue) × 100
GRMA	(gross profit / operating revenue) × 100
ETMA	(EBITDA / operating revenue) × 100
EBMA	(EBIT / operating revenue) × 100
NAT	operating revenue / (shareholder funds + non current liabilities)
IC	operating profit / interest paid
STOT	operating revenue / stocks
COLL	(debtors / operating revenue) × 360
CRPE	(creditors / operating revenue) × 360
RDOP	(research & development / operating revenue) × 100
CURR	current assets / current liabilities
LIQR	(current assets – stocks) / current liabilities
SHLQ	shareholder funds / non current liabilities
SOLR	(shareholder funds / total assets) × 100
SOLL	(shareholder funds / (non current liabilities + current liabilities)) × 100
GEAR	((non current liabilities + loans) / shareholder funds) × 100
NatWym	short-term investments / trade liabilities
ZadlAkt	(total assets – shareholder funds) / total assets
ZadlKapWl	(total assets – shareholder funds) / equity
ZadlDlug	long-term liabilities / total assets
PozKoszOp	operating costs / operating revenue

Source: the author's own calculations.

The dataset chosen for the research included the years 2008–2017 and 152 340 companies (with double-sided accounting). The data were downloaded from the database Orbis, which belongs to the Bureau Van Dijk company. The data included the balance sheet (statement of financial position) and elements of the income statement. The data were tested to determine whether the sum of the assets was equal to the sum of equity and liabilities. Moreover, any suspicious or error records or columns were also removed. Finally, a panel of 1526 bankrupt companies and 1561 active companies was selected from the sample. Active companies were randomly chosen, but I tried to match the type of economic activity between each bankrupt company and a "matching" active company. As a status change date, I assumed the year when the company had negative equity for the first time. I assumed that the insolvency application must have been filed one year earlier and that the model should be aware of it one year later.

The data sample was then divided into a training set including the data for the years 2008–2013 (1411 active and 1376 bankrupt companies, of which 10% of the sample was used during each training as a testing set) and a validation (evaluation) set including the companies' data for the years 2014-2017 (150 active and 150 bankrupt companies). The companies selected for each dataset differed from set to set (companies in the validation set did not belong to the training set). After the validity was checked and processed, the collected data were normalised.

To handle the processing, I used the skleran Python library. Training the data sample was divided into 10 parts and for each iteration, 9 parts were used for training and 1 part for testing (cross-validation).

As explained above, the following models were trained (all with skleran library): discriminant analysis (DA), logit model (L), support vector machines (SVM), random forest (RF, 100 trees), gradient boosting decision trees (GB), neural network with one hidden layer (NN, the number of input neurons and in the hidden layer was equal to the number of variables), convolutional neural network (CNN) and naïve Bayes (NB)

The code was written in Jupyter Notebook (Python version 3.6).

For the gradient boosting decision trees model, the number of estimators was assumed to be 100, while the function which measured the quality of the split was mean squared error with improvement score by M. Friedman. The learning rate was 10% and the improvement of the loss function was calculated as the deviation between the value for the out-of-the-bag samples and the value for the previous iteration. The maximum depth of the individual regression estimators was set to 3.

For the NN model, I assumed 100 trees. The activation function used for RF was the scaled exponential linear unit (I also tested ReLU) while the initializer used was LeCun uninform initializer.

CNN was also based on SeLU function and LeCun uninformed initializer and the sigmoid activation function. The loss function was a binary cross-entropy. Random forest assumed 100 decision trees, and the nodes were split based on the Gini criteria.

4. Results and Discussion

Table 10 shows the results of the model training and validation. As can be seen, the accuracies for every training subset were similar. At the bottom, the average accuracies for every method are calculated.

Table 10. Comparison of Accuracy

Training Subset	L	DA	SVM	RF	GB	NN	CNN	NB
1	84.2	82.4	66.9	94.4	95.0	79.9	79.8	69.4
2	82.7	83.2	68.4	94.5	94.5	79.1	79.9	67.6
3	83.8	82.8	66.4	94.5	95.2	81.6	78.2	70.7
4	84.2	82.4	64.5	94.9	94.5	79.6	77.5	71.0
5	84.6	82.9	65.4	94.1	94.2	76.8	77.1	69.8
6	82.9	82.9	67.5	93.9	93.6	77.5	78.2	68.0
7	84.0	83.2	65.8	93.8	94.7	80.1	77.8	70.0
8	84.3	81.8	65.3	94.3	94.3	80.7	79.3	72.1
9	83.8	83.4	64.2	93.9	94.5	77.7	78.9	68.0
10	83.3	82.7	69.2	94.3	94.5	82.6	78.5	68.4
Average	83.8	82.8	66.3	94.3	94.5	79.6	78.5	69.5
Validation sample accuracy	81.2	80.5	64.8	93.7	93.8	78.1	76.3	67.1
Error 1	11.7	11.7	28.9	0	0	14.9	11.7	25.7
Error 2	25.9	27.4	41.6	12.7	12.4	28.9	35.7	40.2

Source: the author's own calculations.

As Table 10 shows, the most accurate method was the gradient boosting decision trees algorithm. The accuracy for the validation sample was 93.8%, which means that for 100 companies the model would make a mistake for about 7 companies. The second most accurate model was random forest decision trees, with an accuracy for the validation sample of 93.7%. In terms of testing 100 companies against the bankruptcy risk, this model would also be inaccurate for about 7 companies.

The rest of the models failed to achieve useful accuracy levels for practical application, although I did not use macroeconomic data, which could significantly improve the quality of the classifications (this is one of the suggestions for further research).

A comparison of the results presented in Table 10 with the results of previous international research (Table 1) leads to the conclusion that four algorithms worked better for the Polish sample: RF, GB, DA, LR. Worse accuracy was observed for NB and SVM. Finally, a similar accuracy was observed for neural networks.

A comparison of the results presented in Table 10 with the results of other Polish researchers shows that I obtained higher accuracy with the GBDT and RFDT algorithms than did B. Pawełek and D. Grochowina (2017). Further, the accuracy was lower for the neural network model (78.1% compared to Pociecha's 89.58%) and the DA algorithm (80.5% compared to Pociecha's 85.42%) than was that of J. Pociecha *et al*. (2014). The accuracy of the DA model in this paper was lower than the accuracy achieved by T. Korol (78.1% compared to Korol's 85.28%). Finally, T. Korol and B. Prusak (2009) obtained a higher accuracy for their neural network.

5. Conclusions

The research presented in this paper was designed to observe the behaviour of various machine learning algorithms when they were trained on a representative sample of companies. GBDT and RFDT proved to be the most effective algorithms. However, the low accuracy of the other machine learning algorithms analysed here must be treated with caution: the numerous variants of these methods could potentially significantly change their accuracy.

Based on the empirical evidence, hypotheses H1 and H2 cannot be rejected. Furthermore, the neural network with one hidden layer did not prove sufficiently accurate to confirm hypothesis H3. However, this may be attributable to the model being insufficiently tuned.

The technical properties of decision tree-based algorithms endows them with a particular advantage. GBDT and RFDT algorithms do not require outliers to be removed. At the same time, they also resist multi-collinearity because both methods put outliers and different variables into different leaves of the decision trees and they do not influence the prediction process. Both methods also handle automatically missing values, so they can learn from the cases which were useless for classical methods. Both algorithms deal well with the independent variables' lack of normal distribution. Random forest algorithm is based on majority voting, so it uses a technique quite popular in the financial analysis, where multiple bank-

ruptcy prediction models are often used to estimate enterprise solvency based on multiple models of different authors taken together.

Another advantage of GBDT and RFDT algorithms was that they used the nominal data taken from financial statements (after normalisation) and there was no need to calculate any financial ratios for them. The algorithms managed to train themselves legitimately automatically from the data given. Both algorithms are also capable of detecting non-linear feature interactions and of adjusting to them. Some feature may achieve very high and very low values for insolvent companies, and the algorithms are capable of recognising this behaviour and adjusting to it.

For a long time, bankruptcy prediction was based on models provided by researchers in the form of linear equations, with given coefficients and financial ratio formulae to use as variables in such a formula. The most famous Altman model survived for more than 50 years and is still in used today. However, due to the significant differences in the accuracy, companies throughout the world are switching to machine learning algorithms, usually by purchasing server access, which offers a commercial credit scoring/bankruptcy prediction system. They prefer to pay a monthly fee and participate in the system, which trains itself using big data, than to risk mistakes and use free non-commercial linear bankruptcy prediction models. Given the differences in accuracy presented in the paper between the DA and L algorithms and RFDT and GBDT, it is safe to say the decision pays for itself.

The second important implication for economic practice is that if one has access to a large enough sample of financial data, training of a model is not very difficult, because the RFDT and GBDT work very well almost out of the box. One need not decide which data should be removed as outliers, thus not only facilitating the training of the model, but also leaving potentially valuable information in the sample. Decision tree-based models may not work very well with time and, moreover, due to their non-linear nature, may not allow a significant extrapolation. But if they are fed regularly with new information, they can learn from it and maintain their high accuracy. While they tend to be rather short-term solutions than long-term prediction models, they are relatively easy to train and tune. Adjustments to the neural network concerning the number of neurons, the number of hidden layers and activation functions can take a very long time, as can the training of the neural network.

Finally, the paper explains that ensemble algorithms generally perform better than non-ensemble algorithms. While this may seem natural, there is a price to be paid for it. Decision tree-based algorithms and neural networks operate like black boxes, making it challenging to understand how exactly the models work. This is a significant disadvantage of these methods as they cannot be shared as easily as logit or discriminant analysis models.

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Prognozowanie upadłości polskich przedsiębiorstw – porównanie skuteczności wybranych metod uczenia maszynowego oraz deep learningu

(Streszczenie)

Poprawne przewidywanie niewypłacalności przedsiębiorstw jest niezwykle istotne z perspektywy zarządzania finansami przedsiębiorstw, gdyż ma ono kluczowe znaczenie w zarządzaniu należnościami, ocenie projektów inwestycyjnych, zarządzaniu kapitałem obrotowym, oceną zdolności do kontynuowania działania, podejmowaniu współpracy i podpisywaniu umów z innymi przedsiębiorstwami. Celem artykułu jest porównanie skuteczności wybranych algorytmów uczenia maszynowego i deep learningu, które zostały zastosowane na reprezentatywnej próbie polskich przedsiębiorstw z wykorzystaniem danych za lata 2008–2018. W artykule podjęto próbę porównania skuteczności następujących algorytmów *machine learning* (uczenia maszynowego): analizy dyskryminacyjnej (DA), funkcji logitowej (L), *support vector machines* (SVM), *random forest* (RF), *gradient boosting decision trees* (GB), sieci neuronowych z jedną warstwą ukrytą (NN), konwolucyjnych sieci neuronowych (CNN) oraz metody naïve Bayes (NB). Zgodnie z hipotezami badawczymi jeśli ma się dostęp do dużej próby firm, najskuteczniejszym algorytmem (pierwszym wyborem) w prognozie bankructwa są algorytmy: *gradient boosting decision trees* (H1), *random forest* (H2) i nierekurencyjne wielowarstwowe sieci neuronowe (H3). Wstępne hipotezy zostały sformułowane na podstawie opinii praktyków dotyczących przydatności różnych algorytmów uczenia maszynowego i algorytmów sztucznej inteligencji w prognozowaniu upadłości przedsiębiorstw. W artykule wykorzystano do uczenia algorytmów bardzo dużą (reprezentatywną) grupę przedsiębiorstw komercyjnych (dane za lata 2008–2013), a do walidacji skuteczności algorytmów również bardzo dużą populację przedsiębiorstw (dane za okres 2014–2018); obydwie populacje obejmowały zupełnie inne podmioty gospodarcze i inne okresy, co pozwoliło na rzetelne porównanie skuteczności badanych algorytmów.

Słowa kluczowe: prognozowanie upadłości, *deep learning*, uczenie maszynowe, finanse przedsiębiorstw.