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Personal bankruptcy prediction using machine learning techniques

Magdalena Brygała[1]   Tomasz Korol[2]

Abstract

It has become crucial to have an early prediction model that provides accurate assurance for users about the financial situation of consumers. Recent studies have focused on predicting corporate bankruptcies and credit defaults, not personal bankruptcies. Due to this situation, the present study fills the literature gap by comparing different machine learning algorithms to predict personal bankruptcy. The main objective of the study is to examine the usefulness of machine learning models such as SVM, random forest, AdaBoost, XGBoost, LightGBM, and CatBoost in forecasting personal bankruptcy. The study relies on two samples of households (learning and testing) from the Survey of Consumer Finances, which was conducted in the United States. Among the models estimated, LightGBM, CatBoost, and XGBoost showed the highest effectiveness. The most important variables used in the models are income, refusal to grant credit, delays in the repayment of liabilities, the revolving debt ratio, and the housing debt ratio.

Keywords

- personal bankruptcy
- SVM
- random forest
- AdaBoost
- XGBoost
- LightGBM
- CatBoost
- SHAP

JEL codes: G17, G51

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Introduction

The economies of countries that have not managed to recover from the COVID-19 pandemic have to face another challenge for countries around the world, which is the war in Ukraine. Consequently, the risk of consumer bankruptcy has increased dramatically. Therefore, searching for more precise methods and testing modern solutions for consumer bankruptcy prediction is essential. Before the COVID-19 pandemic, it was hard to imagine the impact it could have on economies worldwide. Some countries very quickly implemented support for companies to minimise the effects of the financial crisis. However, soon, before the COVID-19 pandemic was forgotten, the war in Ukraine began, which also affected countries on different continents. Additionally, forecasting the timing of economic recessions is very difficult (Altman & Kuehne, 2016). It is important to anticipate bankruptcy as soon as possible in order to avoid it. In addition to declaring bankruptcy, consumers have various options to deal with problems associated with paying off liabilities. The later these problems are noticed, the more difficult it is to avoid bankruptcy. This study aims to create a good classification model for predicting bankruptcy. However, developing such models to predict bankruptcy risk with high accuracy is challenging because bankruptcy rates are low, and there are few datapoints on which to base predictions (Garcia, 2022).

Many empirical studies have been developed on predicting the risk of corporate bankruptcy and non-performing loans (Barboza, Basso et al., 2021; Barboza, Kimura et al., 2017; Garcia, 2022; Kovacova et al., 2019; Kovacova & Kliestikova, 2017; Letza et al., 2003; Wang et al., 2022), and few studies concern personal bankruptcy (Brygała, 2022; Korol, 2021; Korol & Fotiadis, 2022; Sahiq et al., 2022; Syed Nor et al., 2019). The small body of empirical research on consumer bankruptcy stems from such factors as limited access to data related to consumer bankruptcy. Due to the fact that very few publications focus on forecasting consumer bankruptcy and that there is a research gap in this area, the main goal of this study is to develop predictive machine learning models of consumer bankruptcy based on data from the United States (Survey of Consumer Finances). To fill this gap in the literature, this study is one of the first literary attempts to develop machine learning models in personal bankruptcy prediction.

The contribution of this study to the literature on forecasting the risk of personal bankruptcies is four-fold. First, our research analysed the performance of six machine learning methods: support vector machine (SVM), random forest (RF), adaptive boosting (AdaBoost), extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), and categorical boosting (CatBoost), which were applied to the problem of personal bankruptcy prediction. Second, it identifies the most important predictors of filing for personal bankruptcy. Third, it compares the machine learning models to the results obtained by other methods in the literature of corporate bankruptcy and default prediction. Fourth, it examines SHapley Additive exPlanations (SHAP) to help interpret machine learning model predictions and explore the importance of various features that affect bankruptcy. Moreover, the authors of this research formulated the following research questions:

1. Which model can obtain the highest total effectiveness and the lowest type I and II errors?
2. What are the main microeconomic predictors of filing for personal bankruptcy?

The paper is organised into five sections. In the introduction, the authors justify the topic, the research objectives, and the study's contribution to the literature. Section 1 provides a review of bankruptcy and default predictive models. Section 2 describes the data used in the analysis and the forecasting methods implemented. Section 3 presents six machine learning models. Section 4 discusses the results obtained from the testing sample. Finally, the conclusion section summarises the research.

1. Literature review

Researchers and practitioners have conducted intensive research on models for predicting company bankruptcy and default on loans, both among enterprises and consumers. Among the algorithms used for prediction purposes are traditional statistical techniques (e.g., discriminant analysis and logistic regression), deep learning (e.g., artificial neural networks), and machine learning models (e.g., support vector machine, bagging, boosting, and random forest) (Shi et al., 2022). Machine learning techniques identify characteristics that differentiate the observations of different groups (Barboza, Kimura et al., 2017). They are used in many fields, such as economics, medicine and engineering.

Machine learning and deep learning models have been very successful in financial applications, with many studies looking at their use in predicting bankruptcy. Both models have advantages over traditional statistical methods when there are a large number of variables, the relationships between the variables are complex, the values of each variable change over time, and when it is more important to understand the correlations between variables than to look for causality (Shi et al., 2022; Syam & Sharma, 2018). The advantages of using machine learning and artificial intelligence include their dynamism, which allows for running background processes and making decisions in real time (Syam & Sharma, 2018). To overcome the limitations of statistical models, research has been developed that actively uses pattern recognition methods in machine learning (Son et al., 2019). In the latest research, the most commonly used algorithms are neural networks, boosting and bagging methods, and logistic regression (Al Daoud, 2019). Al Daoud (2019) noted how research has shown that gradient-boosting algorithms are used successfully and represent a very important strategy. Prior research showed that machine learning models are more suitable for predicting the risk of bankruptcy than statistical models (Garcia, 2022; Machado & Karray, 2022; Son et al., 2019). Carmona et al. (2022) also pointed out how recent research shows that gradient boosting can reduce the weaknesses of traditional models and provide an effective model for predicting business failures. The term "black box" is applied to models where we know the inputs and outputs, but we can say little about what is going on inside (Gramegna & Giudici, 2021). However, machine learning models are often considered a black box due to their complexity and hidden internals (Carmona et al., 2022). Brotcke (2022) stated that the less transparency and explainability of machine learning models compared to traditional regression models may lead to discussions about the compliance of models with fair lending regulations. Black boxes that are more complex are more accurate for the highest predictive performance but are often more challenging to interpret. However, in recent years, researchers have proposed improvements to increase the interpretability of machine learning models. One common approach to explaining machine learning models is the SHAP method (Bussmann et al., 2020), which is often performed to interpret complex models (Bussmann et al., 2020; Jabeur, Mefteh-Wali et al., 2021). Brotcke (2022) also pointed out that machine learning can reduce potential discrimination by limiting discretionary and judgmental decisions. This can be crucial, for example, in the case of using indicators or variables containing discriminatory factors such as age, marital status and gender. Due to the importance of the topic of discrimination, in the United States it is illegal for lenders to discriminate against consumers on the basis of: race, colour, religion, national origin, sex, marital status, age, attendance in a public assistance programme (CFPB, 2022).

In the latest research, Papík and Papíková (2023) analysed studies focusing on gradient-boosting algorithms. They noticed that most studies achieved higher performance with gradient boosting, especially XGBoost. In the research analysed, only one study applied Catboost, which proved to be the most effective algorithm. In two cases, the application of a neural network outperformed gradient boosting. Jabeur, Gharib et al. (2021) developed neural network and machine learning models to overcome the limitations of such initial models like discriminant analysis and logistic regression. Sahiq et al. (2022) examined the usefulness of logistic regression in forecasting consumer bankruptcy. They showed that the key determinants of personal bankruptcy include race, education, employment sector, personal loan, study loan, microfinance, and total outstanding balance. Korol and Fotiadis (2022) proposed artificial intelligence techniques: fuzzy sets, artificial neural networks, and genetic algorithms in forecasting the risk of personal bankruptcy. The fuzzy sets outperformed the other techniques in total effectiveness and with the lowest type I and II errors both for Taiwanese and Polish households. The research also proved that artificial intelligence models outperformed the statistical models estimated in previous research (Korol, 2021) based on the same samples. Research conducted by Shi et al. (2022) showed that most deep learning models outperform classical machine learning and statistical algorithms in estimating credit risk. Moreover, team methods provide greater accuracy compared to single models. Alam et al. (2021) compared deep learning with discrete hazard models. Deep learning performed better than discrete hazard models in predicting corporate failure. Halim et al. (2021) developed deep learning models such as: recurrent neural network, long short-term memory, gated recurrent unit, as well as logistic regression, support vector machine, neural network and decision tree. Their research showed that all deep learning models outperform other widely used methods. Bragoli et al. (2022) found that XGBoost performed better in correctly classifying bankrupt firms. Other methods, such as random forest and neural network, were better at classifying non-bankrupt firms. Machado and Karray (2022) proposed hybrid machine learning algorithms for predicting commercial customer credit scores. They compared the effectiveness of hybrid and individual algorithms (AdaBoost, decision tree, random forest, support vector machine, artificial neural network, and gradient boosting). For hybrid models, data is first grouped using a classifier method (k-Means and DBSCAN), then different machine learning models are applied to each of the obtained clusters to predict a given event. Hybrid models outperformed individual ones.

2. Data and methodology

2.1. Data

The study used microdata from 37,900 surveys conducted between 2001 and 2019 in the Survey of Consumer Finances (SCF). SCF is a survey in the United States, which includes household characteristics such as: demographic, behavioural and financial. Unanswered questions in the survey were covered by the multiple imputation technique. The data include a dependent variable of 1 for households that have filed for bankruptcy in the last five years, and 0 otherwise. The independent variables selected during model preparation include demographic and financial characteristics (Table 1). The data include only consumers who have debt. In the models, the inverse hyperbolic sine transformation (IHS) of income is used, which allows the use of samples with zero and negative values (Berlemann & Salland, 2016; Georgarakos et al., 2014). The formula of IHS applied to income is:

$$\log\left(x+(x^2+1)^{\frac{1}{2}}\right)$$

Independent variables such as sex, age, marital status and race were not used. The application of these variables may be discriminatory to the consumer due to the Equal Credit Opportunity Act in the United States (Brotcke, 2022). The above-mentioned federal civil rights apply to credit cards, car loans, home loans, student loans and business loans (CFPB, 2022). The regulations are designed to protect consumers by prohibiting unfair and discriminatory approaches (Brotcke, 2022).

Table 1. The list of variables used in evaluating models

Variable	Description
children	The number of children.
saving_account	The dummy variable is 1 if the respondent has a saving account.
turndown	The dummy variable is 1 if the respondent applied for a loan and was turned down.
late	The dummy variable is 1 if the household had any past payments due in the last year.
income	The inverse hyperbolic sine transformation of income.
homeownership	The dummy variable is 1 if the respondent owns, e.g., ranch/farm/mobile home/house/condo, 0: otherwise.
education	The variable education is described by four values: no high school, high school, college associate degree, bachelor's degree or higher.
mortgage_asset	It represents the proportion of housing debt to the value of total assets.
consumer_debt	It represents the total non-mortgage and non-revolving consumer debt proportion to the total monthly payments.
revolving_debt	It represents the proportion of revolving debt to the total monthly payments.
house_debt	It represents the proportion of housing debt to the total monthly payments.
income_debt	It represents the proportion of income to the total monthly payments.

Source: own research.

Data were divided to train and test samples to avoid overfitting and bias. Models were assessed for different proportions between the training sample and the testing sample to maximise the training sample. To evaluate the models, 80% of the dataset is used for the learning sample (1531 consumers), while 20% is set aside for the testing sample (383 consumers). The dataset is highly unbalanced and skewed towards consumers who did not decide to go bankrupt (negative class). The proportion of bankruptcies to non-bankruptcies stands at the level of 4.38%. Predicting rare events like bankruptcies is often challenging in view of possible bias in estimating probabilities. Without using methods dealing with an unbalanced dataset, the minority class may be ignored in the prediction. The researchers proposed several methods to deal with this challenge, both at the algorithm level and data level (Yen & Lee, 2009). Among the methods used for such a challenge are: undersampling, oversampling, a combination of undersampling and oversampling methods, choosing a cut-off point, and using class weight. Therefore, in the research, the undersampling method was used to balance consumers who decided to file for bankruptcy and those who did not file for bankruptcy. Moreover, the data were preprocessed using StandardScaler. This is a normalisation technique which normalises the features to create standardised features by removing the mean and scaling to unit variance (Le et al., 2018). Stata and Python software was used in the preprocessing step. Next, the models were implemented using Python software packages. The authors used six methods to forecast personal bankruptcy: SVM, RF, AdaBoost, XGBoost, LightGBM, and CatBoost. Such models were calculated for 1914 consumers: 957 bankrupts and 957 non-bankrupts.

2.2. Machine learning models

2.2.1. Support Vector Machine

SVM (Support Vector Machine) is a machine learning algorithm used both for regression and classification problems. The objective of SVM is to find a hyperplane which can segregate the n-dimensional space into classes. The hyperplane is the boundary of classification between two classes with the highest margin. Support vectors are the datapoints which are closest to the hyperplane and create the hyperplane. The strength of SVM is that despite the significant overlap between different data classes, it finds the decision boundary. The SVM model is then ready to classify the new datapoints on the side of the hyperplane to which they should be mapped. However, SVM is more time-consuming, has high algorithm complexity, and requires large memory capacity (Jabeur, Gharib et al., 2021).

2.2.2. Random Forest

The RF (Random Forest) method was proposed by Breiman (2001). The forest consists of several subsets that generate the same number of classification trees, and responses are combined (Barboza, Kimura et al., 2017; Schonlau & Zou, 2020 ; Wu et al., 2016). In RF, the sample features and the number of samples are selected randomly (Wang et al., 2022). Creating multiple trees instead of one and combining the results gives a more stable prediction than a single tree. Each tree is built on a different bootstrap sample that was created by randomising and returning N objects from all N training samples. The prediction result of RF in classification problems is the largest class among all the prediction results of decision trees (Wang et al., 2022).

2.2.3. Adaptive Boosting

AdaBoost (Adaptive Boosting) is one of the machine learning algorithms proposed by Freund and Schapire (1997). The method involves fitting a sequence of weak classifiers, which are models that are only slightly better than random guessing, to multiple modified versions of the data (Barboza, Basso et al., 2021). By incorporating weak classifiers, AdaBoost constructs a more powerful learning algorithm, enhancing the strength of the classifiers (Heo & Yang, 2014). In AdaBoost, the approach is sequential, and the successive classifiers are closely related. If the resulting classifier achieves higher accuracy compared to the default rule, it means that the classification method has identified certain patterns or structures in the data that allow it to perform better (Alfaro et al., 2008).

2.2.4. Extreme Gradient Boosting

XGBoost (Extreme Gradient Boosting) is a methodology for regression as well as classification. It constitutes the implementation of a gradient boosting framework developed by Chen and Guestrin (2016). XGBoost is an ensemble model based on gradient boosted trees (Mo et al., 2019). XGBoost starts with creating a first weak tree with poor performance, then it builds another tree based on the previous tree in the next stage, trying to predict what the first tree could not have predicted. The algorithm continues to build trees, each of which corrects the previous one, until a stop condition is reached, such as the number of trees to be built. In the objective function, normalisation is used to prevent overfitting, estimate the model more efficiently and minimalise the complexity of the model (Jabeur, Mefteh-Wali et al., 2021). Al Daoud (2019) pointed out that the technique used in XGBoost makes the model faster and more stable during model fitting. In addition, there are several hyperparameters, which can be modified to maximise the power of the model and to prevent the overfitting of the model.

2.2.5. Light Gradient Boosting Machine

LightGBM (Light Gradient Boosting Machine) is the implementation of a gradient-boosted framework proposed by Ke et al. (2017). Research has shown that in the case of the used dataset, LightGBM is faster and more accurate than CatBoost and XGBoost (Al Daoud, 2019). Decision trees in the LightGBM algorithm are grown leaf-wise instead of checking all previous leaves for each new leaf, as with XGBoost (Al Daoud, 2019). LightGBM uses a histogram algorithm to combine exclusive features (Wang et al., 2022). The advantage of the LightGBM algorithm is its high accuracy and model training speed, low memory consumption, and that it is adapted to the use of large datasets (Al Daoud, 2019; Ke et al., 2017). Ke et al. (2017) pointed out that LightGBM, in addition to reducing the training time by more than 20 times compared to the gradient-boosting decision tree, achieved almost the same accuracy. However, having a large dataset affects the model training time. Therefore, the choice between a shorter training time and the model's accuracy is not so obvious, especially when the accuracy is not much higher with a shorter model training time.

2.2.6. Categorical Boosting

CatBoost (Categorical Boosting) also belongs to the gradient-boosted binary trees. This is a new gradient algorithm proposed by Prokhorenkova et al. (2018). CatBoost, like other gradient-boosting implementations, constructs each new tree to approximate the gradients of the current model (Dorogush et al., 2018). The objective of CatBoost is to minimise the loss function of the model by adding weak learners with a gradient-descent-like procedure (Papík et al., 2023). One of the advantages of CatBoost is that this algorithm has the ability to work with categorical variables. Dorogush et al. (2018) noted that CatBoost followed by LightGBM are rivals for the fastest method, while XGBoost is much slower than both methods. This is important for large datasets. Hancock and Khoshgoftaar (2020) pointed out that CatBoost exhibits sensitivity to hyperparameters and emphasized the significance of hyperparameter tuning.

2.3. Evaluation metrics

Some of our models, such as RF, AdaBoost, XGBoost, LightGBM, and CatBoost provide a measurement of the importance of features. Feature importance was also used in selecting variables. The importance is the average for each single decision tree in the model, and it is computed as the amount by which the feature split point improves accuracy, weighted by the number of samples on each node (Son et al., 2019). A higher score for feature importance means that the specific feature will have a greater effect on that model. It determines which features contribute most to the predictive power of the model. The same technique can be used for both feature selection and feature importance. However, feature selection is most commonly used before or during model training to select features, while feature importance measures are used during or after training to explain the trained model (Saarela & Jauhiainen, 2021).

This study will use total effectiveness (S), type I error (E_1), type II error (E_2), and AUC as measurements of performance. A type I error shows false prediction of bankrupts (D_1) among all bankruptcies (BR), while a type II error indicates false prediction of non-bankrupts (D_2) among all non-bankruptcies (NBR). The measurement was calculated using a confusion matrix, which is intended to compare the actual classification with the predicted classification. Total effectiveness shows the probability of an accurate prediction of bankrupts and non-bankrupts. The total effectiveness is calculated as (Korol, 2021):

$$S = \left(1 - \frac{D_1 + D_2}{BR + NBR}\right) \cdot 100\% \tag{1}$$

a type I error is computed as:

$$E_1 = \frac{D_1}{BR} \cdot 100\% \tag{2}$$

and a type II error is calculated as:

$$E_2 = \frac{D_2}{NBR} \cdot 100\% \tag{3}$$

The area under the ROC curve (AUC) is suitable for evaluating a method's performance in imbalanced datasets, as it is insensitive to misclassification costs and imbalanced distributions, with a higher AUC value indicating better classifier performance (Zelenkov & Volodarskiy, 2021). AUC measures the probability that a model will rank a randomly chosen positive instance higher than a randomly chosen negative one (Liang et al., 2016). The combination of these four indicators allows for a thorough analysis of the predictive results, taking into account effectiveness among both bankrupts and non-bankrupts.

2.4. Shapley additive explanation

The SHAP method is an approach based on game theory to explain the output of any machine learning model. It was proposed by Lundberg and Lee (2017).

The SHAP value is calculated to provide interpretable prediction results. It also shows the key factors influencing the predictive results, providing more valuable information to identify potential bankruptcies. To make the model interpretable, SHAP uses an additive feature attribution method, and the output model is defined as a linear addition of the input variables (Mangalathu et al., 2020). In view of the fact that machine learning models are considered black boxes, the SHAP summary plot helps to explain the predictions. SHAP is used to interpret each parameter on a global and individual scale (see Section 3). Each point on the graph represents a person, and the set of points constructs the SHAP value of the attribute. The horizontal axis shows the positive and negative correlation between the characteristic variables and the output scores, while the vertical axis is the absolute value ranking of the attribute values (Zhang et al., 2023). Another important aspect is the colour of a given observation. Blue represents a lower value and red represents a higher value. A higher SHAP value means a higher probability of bankruptcy.

3. Results

Among the five most important variables in the prepared models, where feature importance is possible, the most common features were: income, refusal to grant a loan (turndown), having any past payments due (late), the proportion of housing debt to the total monthly payments (house_debt), and the proportion of revolving debt to the total monthly payments (revolving_debt). Figure 1 shows the ranking of the features using RF, AdaBoost, XGBoost, LightGBM, and CatBoost. The most significant variable for RF, XGBoost and CatBoost was the prior refusal of credit. Income was the most significant variable for LightGBM and AdaBoost and the second most significant variable for CatBoost and RF. In the case of selected variables, having a savings account (saving_account) and owning a house (homeownership) turned out to be the least significant in most of the proposed models.

After developing six prediction models using the learning sample, we performed effectiveness analyses of these models on the testing sample. The classification results are provided in Table 2. From the results obtained, out of the six models, LightGBM, CatBoost, XGBoost, and RF perform significantly better than AdaBoost and SVM. LightGBM achieved a higher total accuracy of 0.78 percentage points, a lower type I error of 1.06 percentage points, and a lower type II error of 0.51 percentage points than Catboost. A type I error is considered more costly than a type II error because it can lead to granting a loan to a person who will encounter problems with repayment. The costs of misclassification should minimise the risk of insolvency but also focus on

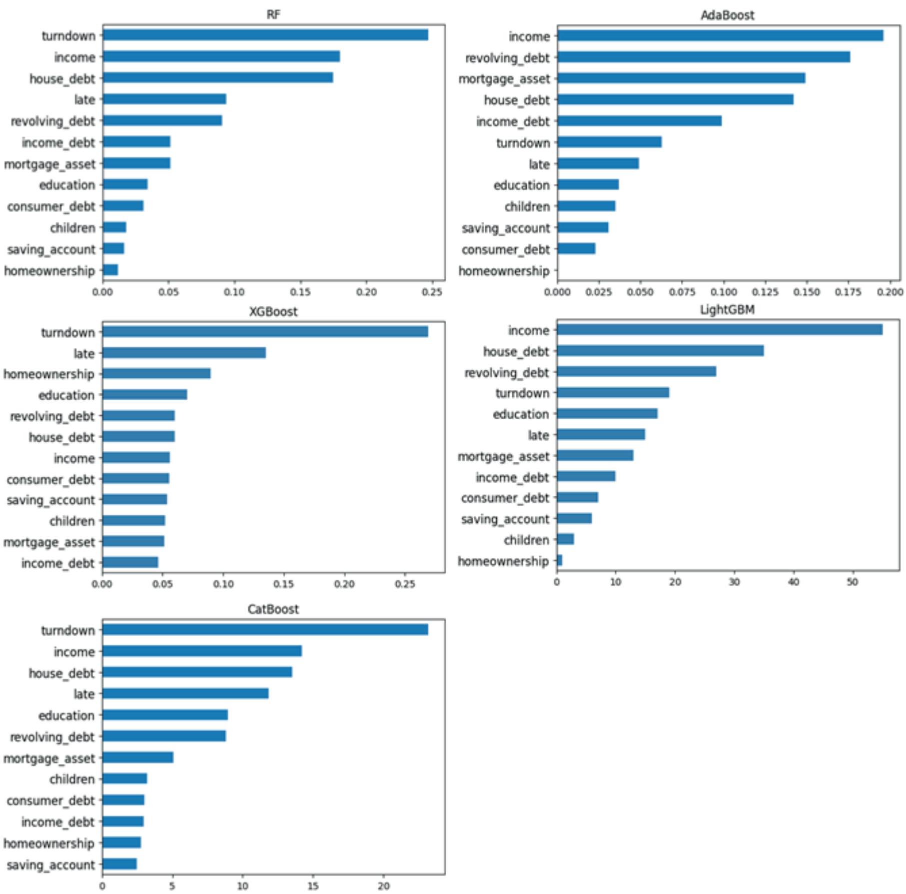

Figure 1. Feature importance

Source: own research.

maximising the number of loans granted, depending on the strategy adopted in this area, because it is profit for banks and financial institutions. The lowest type I error among the proposed models was achieved by LightGBM (21.93%), followed by RF, with a result of 22.46%, and CatBoost (22.99%). The lowest type II error was achieved by XGBoost (27.04%), followed by LightGBM with 28.06%, and then CatBoost (28.57%). The lowest total effectiveness was achieved by AdaBoost (70.76%) and SVM (70.76%). RF is an important alternative to boosting methods, worth verifying in the case of consumer bankruptcy prediction. In terms of AUC, RF and LightGBM showed the best performance, followed by CatBoost and XGBoost.

The study used a small dataset, thus the learning time of the models was not too long. Therefore, it is not required to use this criterion when choos-

Table 2. The results of the effectiveness of models (training and testing sample)

Sample	Model	Type I error (%)	Type II error (%)	Total effectiveness (%)	AUC (%)
Training	SVM	24.55	29.57	72.96	81.73
	Random Forest	23.51	29.30	73.61	81.62
	AdaBoost	27.14	31.14	70.87	78.22
	XGBoost	22.73	28.78	74.27	82.69
	LightGBM	21.30	29.30	74.72	82.61
	CatBoost	24.42	27.22	74.13	82.40
Testing	SVM	25.67	32.65	70.76	77.68
	Random Forest	22.46	31.12	73.11	79.77
	AdaBoost	27.81	30.61	70.76	78.02
	XGBoost	24.60	27.04	73.63	78.63
	LightGBM	21.93	28.06	74.93	79.62
	CatBoost	22.99	28.57	74.15	79.42

Source: own research.

ing an effective model. However, if the dataset was larger, both the indicators showing the effectiveness of the models and the time needed in the model learning process should be considered.

The SHAP summary plots for LightGBM, Catboost, and XGBoost are illustrated in Figures 2, 3, and 4. For the LightGBM model, the income feature provides the highest contribution to prediction, as shown in Figure 2. Consumers who have been turned down in the past (turndown) are more likely to file for bankruptcy. Moreover, a lower proportion of housing debt to total monthly payments (house_debt) leads to a lower risk of bankruptcy.

In Figure 3, for the Catboost model, variables that contribute most to bankruptcy prediction are the refusal to grant a loan (turndown) and the proportion of housing debt to the total monthly payments (house_debt). Additionally, having any past payments due (late) is also one of the most significant factors for the prediction results.

In Figure 4, for the XGBoost model, income, the proportion of housing debt to the total monthly payments (house_debt), and the proportion of housing debt to the value of total assets (mortgage_asset) provide the highest contribution to prediction.

SHAP values can also be used to create an explanation for every observation in the dataset, not only for the global effect presented in the SHAP summary plot. Figures 5, 6, and 7 present explanations of individual predictions

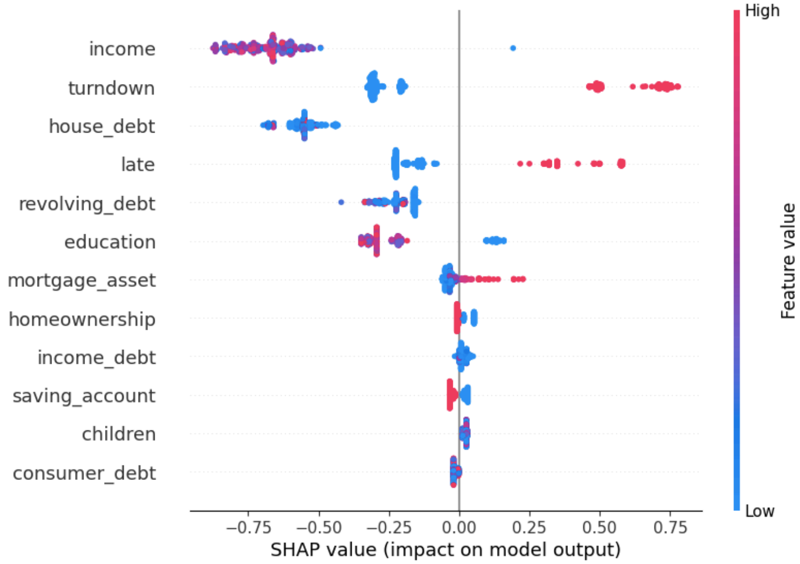

Figure 2. The SHAP summary plot for the LightGBM model illustrates the range and distribution of the impacts of input features

Source: own research.

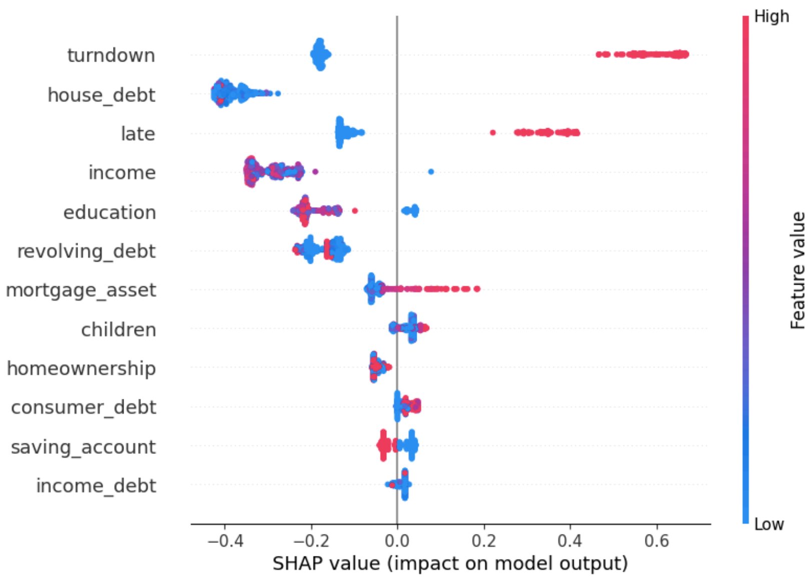

Figure 3. The SHAP summary plot for the Catboost model illustrates the range and distribution of the impacts of input features

Source: own research.

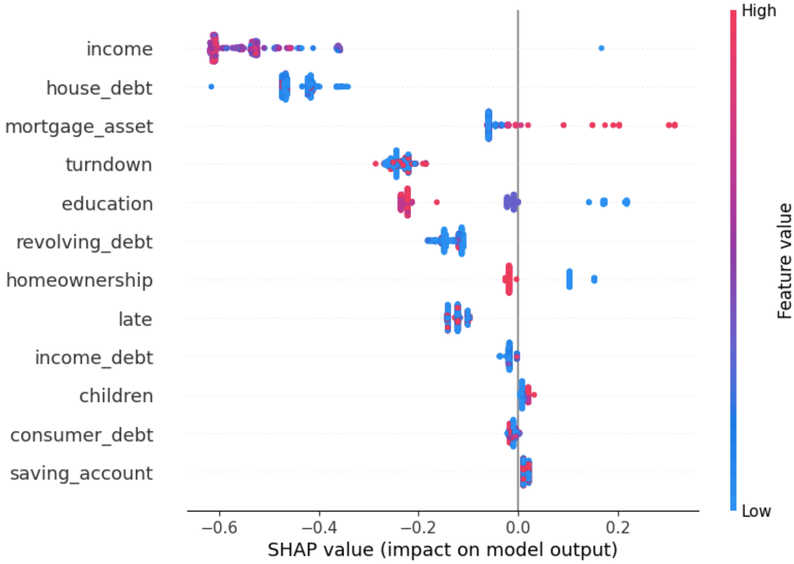

Figure 4. The SHAP summary plot for the XGBoost model illustrates the range and distribution of the impacts of input features

Source: own research.

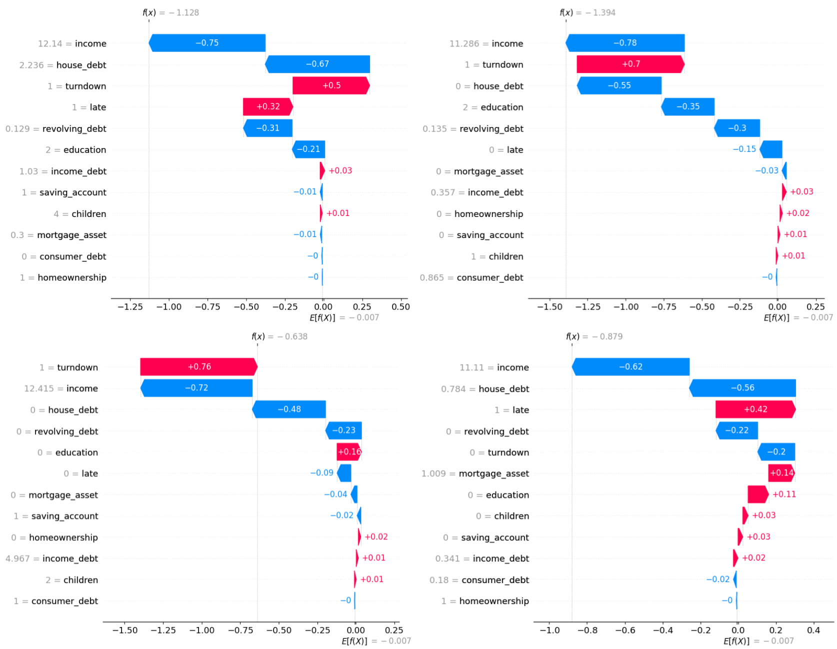

Figure 5. Explanation of individual prediction for the LightGBM model

Source: own research.

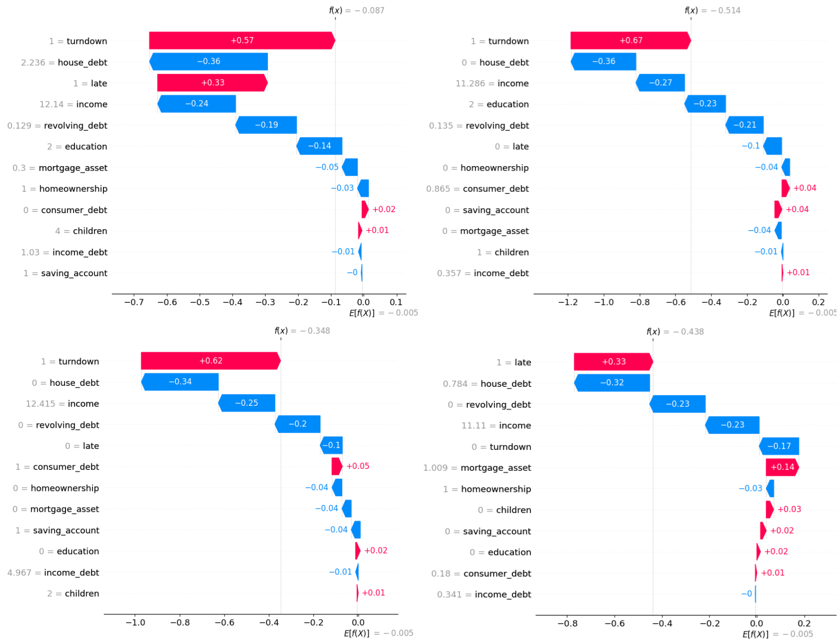

Figure 6. Explanation of individual prediction for the Catboost model

Source: own research.

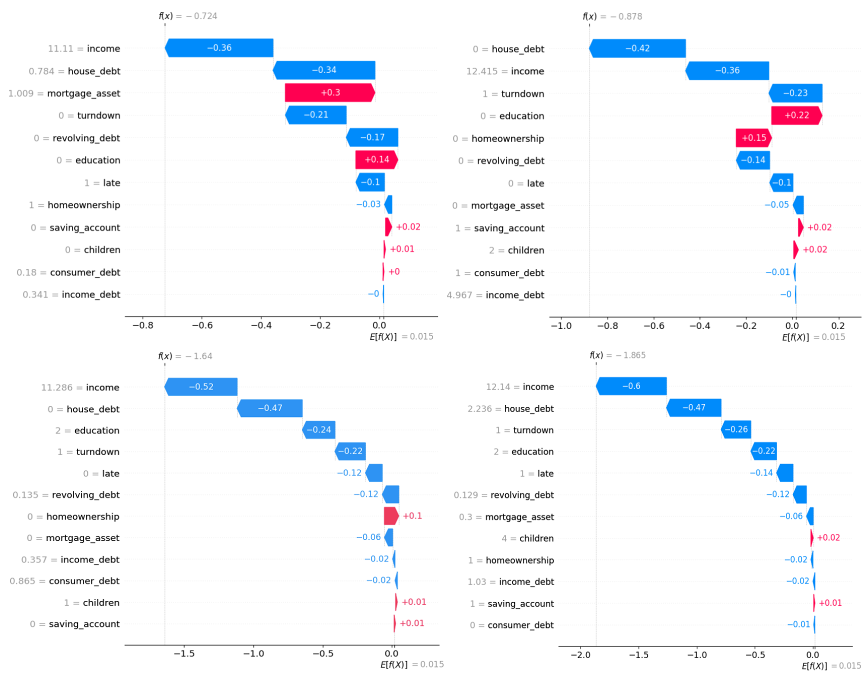

Figure 7. Explanation of individual prediction for the XGBoost model

Source: own research.

for LightGBM, Catboost, and XGBoost for four predictions. The grey values in front of the variables are the values of particular features. The baseline value (E[f(X)]) is displayed below the x-axis and shows the expected value of the model. The value (f(x)) is the model output for each individual, calculated as a sum of the SHAP values for all variables.

4. Discussion

The application of machine learning to financial forecasting is still a relatively new area, but is one worth exploring. The advantage of the effectiveness of machine learning over statistical methods has been confirmed in many studies on both the bankruptcy of enterprises and loan defaults (Garcia, 2022; Machado & Karray, 2022; Son et al., 2019). In comparison to corporate bankruptcy prediction models, it is difficult to compare the effectiveness of consumer bankruptcy prediction models because the literature on this subject contains little research. Existing research mainly focuses on factors affecting consumer bankruptcy rather than predictive models.

Syed Nor et al. (2019) analysed the effectiveness of a decision tree in predicting personal bankruptcy in Malaysia for consumers with terminated or defaulted loans on both an unbalanced and a balanced dataset. The dataset was balanced by the undersampling method. In the case of unbalanced data, despite the higher accuracy (83.29%), by balancing the dataset, accuracy decreased to 70,90%, but specificity (for the minority class) increased from 6.62% to 81.23%, and sensitivity (for the majority class) decreased from 99% to 60.57%. Sensitivity is the probability of the model properly predicting bankrupts (Syed Nor et al., 2019). Despite the higher accuracy, the model for unbalanced data is not effective, due to the large prediction error of the minority class. A more efficient model was presented for a balanced sample. The dataset was obtained from an authorised debt management agency in Malaysia. In the study by Brygała (2022), the results also show that the predictive performance of the logistic regression model based on a balanced dataset is more effective compared to one based on an imbalanced dataset. Two methods of dealing with unbalanced data were used: the undersampling method and the optimal threshold. The research relies on a dataset from the Survey of Consumer Finances from the United States. The total effectiveness of the prediction model on an imbalanced dataset was 95.98%, with a type I error of 99.71% and a type II error of 0%. The total effectiveness of the prediction model on a balanced dataset (undersampling technique) was 69.85%, with a type I error of 29.41% and a type II error of 30.88%. After adjusting the cut-off point to an imbalanced dataset, as one method of dealing with unbalanced data (Mihalovič, 2016), the total effectiveness of the model reached 68.99%, with a type I error of 31.18% and a type II error of 31%. Korol (2021) deployed a decision tree, logistic regression, and discriminant analysis to predict personal bankruptcy on a balanced dataset.

The results show that the highest total effectiveness for European households was achieved by logistic regression (92.70%), followed by discriminant analysis (89.60%) and the decision tree (85.60%). For Far-East Asian households, the highest total effectiveness was also achieved by logistic regression (90.10%), followed by discriminant analysis (87.70%) and the decision tree (83.70%). For the same sample, Korol and Fotiadis (2022) compared fuzzy sets, artificial neural networks, and genetic algorithms in forecasting the risk of personal bankruptcy on a balanced dataset. The dataset was also balanced by the undersampling method. The fuzzy sets outperformed artificial neural networks and genetic algorithms. For Taiwanese households, the fuzzy sets are characterised by 90.60% correct classifications, while for European consumers, it amounts to 93.90%. Artificial neural networks and genetic algorithms obtained a total effectiveness of 89.30% for Taiwanese households and 92.90% for Polish households. The research is based on datasets from Poland and Taiwan. Sahiq et al. (2022) also examined the usefulness of logistic regression in forecasting consumer bankruptcy and compared balanced and imbalanced datasets. The dataset was balanced by the SMOTE technique. The total effectiveness of the prediction model on the imbalanced dataset was 84.82%, with sensitivity (for the majority class) of 100%, and specificity (for the minority class) of 0%. The total effectiveness of the prediction model on a balanced dataset was 73.43%, with sensitivity (for the majority class) of 69.50%, and specificity (for the minority class) of 77.35%. The research relies on a dataset from the Debt Management Programme conducted in Malaysia. The comparison of the personal bankruptcy forecasting models is presented in Table 3.

Comparing the effectiveness of the developed models to the effectiveness of models from the literature related to company bankruptcy and defaults, Bragoli et al. (2022) noted that XGBoost performed better in correctly classifying bankrupt firms, but RF and neural networks were better in classifying non-bankrupt firms. In our study, the lowest type I error was achieved by LightGBM and RF, but the lowest type II error by XGBoost and LightGBM. Al Daoud (2019) compared three algorithms: XGBoost, CatBoost, and LightGBM, in two areas: accuracy and CPU runtime. LightGBM proved to be both faster than other methods used and more accurate. Due to the small dataset in our research, time was not a determinant when choosing a model. However, LightGBM proved to be highly effective in our research, demonstrating higher total effectiveness than other models tested. De Castro, Vieira et al. (2019) compared SVM, bagging, AdaBoost, decision trees, logistic regression, and discriminant analysis in predicting default in a residential mortgage programme. The boosting, bagging, and RF algorithms outperformed other meth-

Table 3. The comparison of the personal bankruptcy forecasting models

Authors	Dataset	Method	Total effectiveness (%)	Type I error (%)	Type II error (%)
Syed Nor et al. (2019)	Imbalanced dataset	Logistic regression	83.29	–	–
	Balanced dataset: undersampling		70.90	–	–
Korol (2021)	Balanced dataset: undersampling (Poland)	Logistic regression	92.70	6.20	8.40
		Discriminant analysis	89.60	8.20	12.60
		Decision tree	85.60	15.80	13
	Balanced dataset: undersampling (Taiwan)	Logistic regression	90.10	10.60	9.20
		Discriminant analysis	87.70	13.80	10.80
		Decision tree	83.70	17.40	15.20
Korol and Fotiadis (2022)	Balanced dataset: undersampling (Poland)	Fuzzy logic	93.90	4.80	7.40
		Artificial neural networks	92.90	5.80	8.40
		Genetic algorithms	92.30	5.80	9.60
	Balanced dataset: undersampling (Taiwan)	Fuzzy logic	90.60	7.80	11
		Artificial neural networks	89.30	8.80	12.60
		Genetic algorithms	89.30	8.80	12.60
Brygała (2022)	Imbalanced dataset	Logistic regression	95.98	99.71	0
	Imbalanced dataset: adjusting cut-off point		68.99	31.18	31.00
	Balanced dataset: undersampling		69.85	29.41	30.88
Sahiq et al. (2022)	Imbalanced dataset	Logistic regression	84.82	–	–
	Balanced dataset: SMOTE		73.43	–	–

Source: own research.

ods. Support vector machines were one of the weaker methods compared to RF, bagging, AdaBoost, and decision trees. In our research, SVM achieved the lowest efficiency with AdaBoost among the methods used, also achieving some of the highest type I and II errors. Furthermore, Coşer et al. (2019) compared RF, logistic regression, LightGBM, and XGBoost to predict loan default. The highest results were obtained for random forest. In the case of our study, RF registered the second lowest type I error but also one of the highest type II errors, which meant that the total effectiveness was not the highest among the models tested.

The dataset was finally divided into 80% of the training sample and 20% of the testing sample, due to the highest efficiency of this division. Previous research (Khare & Sait, 2018; Schonlau & Zou, 2020) has shown that through using a larger training sample, it is possible to obtain higher model efficiency and optimise the size of the training sample. This is especially important for small datasets, a point which was confirmed in our research. It is important to adjust the division of the sample, taking into account the research problem, the proportions between the minority and the majority class, and the size of the dataset.

Conclusions

The application of machine learning models to financial forecasting is still a relatively new area. Moreover, there is a research gap in predicting consumer bankruptcy due to insufficient research in this field. This study is one of the first literary attempts to develop machine learning models in personal bankruptcy prediction. Because machine learning models are considered a black box, the research used SHAP to help interpret and explain model predictions. The use of SHAP offers a meaningful and insightful measure of the importance of each variable in predicting bankruptcy. Increasing the interpretability of models gives the opportunity to use more complex models that may show higher efficiency, but so far, due to less transparency and explainability, they could not be used.

The main objective of this study was to predict personal bankruptcy through machine learning classification algorithms. Six machine learning models (SVM, RF, AdaBoost, XGBoost, LightGBM, and CatBoost) were utilised to predict personal bankruptcy. In summary, the highest total effectiveness was obtained by LightGBM (74.93%), CatBoost (74.15%), followed by XGBoost (73.63%), and RF (73.11%). The lowest type I error was achieved by LightGBM (21.93%), followed by RF, with a result of 22.46%, and CatBoost (22.99%). The lowest type II error was achieved by XGBoost (27.04%), followed by LightGBM, with 28.06%, and then CatBoost (28.57%). The lowest total effectiveness was achieved by AdaBoost (70.76%) and SVM (70.76%). Due to the small dataset in our research, time was not a determinant when choosing a model. However, it is worth noting that CatBoost, followed by LightGBM, are rivals for the fastest method, and XGBoost is slower than these two methods (Dorogush et al., 2018). In the case of financial institutions and banks, where the dataset is large, this can be one of the more important factors when choosing a method. The models were evaluated for varying ratios between the training and testing samples, but an 80% to 20% split was more effective for this dataset. This is in agreement with Schonlau and Zou (2020), who noted that in a small dataset, a 50% to 50% split might reduce the size of the training sample, while a large dataset will not be affected by such a split. Therefore, it is possible to optimise effectiveness on the same dataset by increasing the training sample.

The authors are aware of the limitations of their research. First of all, only data from the United States were taken into account. Having more bankrupts would also make it possible to predict bankruptcy based on data from a shorter period of time.

In the future, the authors will continue to explore the use of other methods, such as deep learning, to predict personal bankruptcy. Moreover, future studies should also explore different feature selection methods, which can be compared with traditional techniques, various common techniques for unbalanced data, such as undersampling, oversampling, a combination of undersampling and oversampling, class weight, threshold tuning, and different techniques increasing the interpretability of machine learning models.

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Aims and Scope

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