Systematic Review of Financial Distress Identification using Artificial Intelligence Methods

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ABSTRACT
The study presents a systematic review of 232 studies on various aspects of the use of artificial intelligence methods for identification of financial distress (such as bankruptcy or insolvency). We follow the guidelines of the PRISMA methodology for performing the systematic reviews. The study discusses bankruptcy-related financial datasets, data imbalance, feature dimensionality reduction in financial datasets, financial distress prediction, data pre-processing issues, non-financial indicators, frequently used machine-learning methods, performance evaluation metrics, and other related issues of machine-learning-based workflows. The study findings revealed the necessity of data balancing, dimensionality reduction techniques in data preprocessing, and allow researchers to identify new research directions that have not been analyzed yet.

Introduction
Predicting the possibility of bankruptcy is considered as one of the key issues of current economic and financial research. The growing importance of corporate bankruptcy prediction as a research subject has been confirmed in recent years by the appearance of various thorough reviews in the literature with the goal of summarizing the important findings of previously published studies (Chen, Ribeiro, and Chen 2016; Matenda et al. 2021). Analysing financial distress and its various forms (insolvency, bankruptcy, etc.) is important because of its essential role in society and economy (Aljawazneh et al. 2021; Chen, Chen, and Shi 2020; Zelenkov and Volodarskiy 2021), energy sector (Ayodele et al. 2019) and social security (Okewu et al. 2019). The prediction of "company survival" is a challenging task due to many numbers of factors, which have to be considered (Veganzones, Séverin, and Chlibi 2021). Relationships (obvious and hidden) between these factors make the task even more difficult (Mora García et al. 2008). Financial distress predictions have become an essential key indicator for decision-makers, such as financial market players, fund managers, stockholders, employees, etc.
(Azayite and Achchab 2018; Zelenkov and Volodarskiy 2021). For these reasons, in empirical and computational finance, the prediction of financial distress has been widely researched, especially in the past decades (Ye 2021; Zelenkov and Volodarskiy 2021), and a large number of academic scholars from across the world have been constructing business bankruptcy prediction models using diverse modeling methodologies.

This study extends previous literature reviews (Bhatore, Mohan, and Reddy 2020; Le 2022; Shi and Li 2019) and we hope will help to under-explored new research fields for further topic development. Previous systematic reviews identified credit risk determinants for conventional and Islamic banks based on 120 research articles from Web of Science (WoS) and SCOPUS (Rosli, Abdul-Rahman, and Amin 2019), analyzed the individuals’ financial behavior associated with credit default based on 108 studies (Çallı and Coşkun 2021), analyzed 30 studies published between 1999 and 2006 in which the authors use neural networks to recognize failing firms (Perez 2006), and analyzed statistical and machine-learning bankruptcy prediction models based on 49 journal articles published between 2010 and 2015 (Alaka et al. 2018). Only the systematic reviews of (Perez 2006) and (Alaka et al. 2018), analyzed the use of artificial intelligence (AI) and machine-learning methods, but the latest study of (Alaka et al. 2018) covered the paper published until 2015. Since then, many new studies have appeared fueled by the explosive growth of AI applications, thus underscoring the need to perform a new systematic review in this research field.

This study seeks to bring knowledge and key insights for further researchers by filling the gaps discussed in previous literature reviews, such as: definitions of “failure,” “bankruptcy,” “insolvency,” “default,” “liquidation” and related terms (Matenda et al. 2021); cost-sensitive learning (Chen, Ribeiro, and Chen 2016); deep learning methods (Bhatore, Mohan, and Reddy 2020); dynamic model applications (Chen, Ribeiro, and Chen 2016; Matenda et al. 2021); financial accounting ratios, e. g. macroeconomics, industries, etc. (Chen, Ribeiro, and Chen 2016; Matenda et al. 2021); AI and machine-learning algorithms (Shi and Li 2019); binary and multi-class classification (Chen, Ribeiro, and Chen 2016); performance validation metrics (Chen, Ribeiro, and Chen 2016; Shi and Li 2019); curse of dimensionality and feature selection methods (Bhatore, Mohan, and Reddy 2020); data preprocessing methods (Bhatore, Mohan, and Reddy 2020); models for private corporations, small-medium enterprises (SMEs), and public corporates (Matenda et al. 2021); tools suitable for different domains of datasets analyses (Bhatore, Mohan, and Reddy 2020); and expert knowledge integration in black-box models (Chen, Ribeiro, and Chen 2016).

This systematic review contributes toward understanding of the role of the AI methods in financial distress identification and prediction, while detailing various elements of the AI based workflow.
The remaining parts of this article are organized as detailed further. Section 2 presents the details of the methodological procedure used for the systematic review. Section 3 presents the analysis of the identified articles identified from the search with keywords: “Bankruptcy” or “Financial distress,” which included 335 articles. The section is further continued with the analysis of the specific problems related to the use of AI methods for bankruptcy prediction, e.g. dimensionality curse, class imbalance, anomaly, etc. The limitations of this study are discussed in Section 4, while the conclusions are presented in Section 5.

Review Methodology

Procedure of the Systematic Review Based on the PRISMA Methodology

The main aim of this study is to identify the context of “Financial distress” and its usage of machine-learning methods, including additional aspects related to it, such as imbalance, dimensionality, etc. Therefore, the systematic review technique is implemented in this study. We gathered relevant studies based on a search query using databases such as Science Direct, Springer, IEEE, Google Scholar, etc. following the guidelines of the preferred reporting items for systematic reviews and meta-analyses (PRISMA) (Page et al. 2021).

Inclusion and Exclusion Criteria

The topic “Financial distress” and “Bankruptcy” is widely analyzed in the literature; therefore, this article seeks to extend and supplement existing systematic reviews (Bhatore, Mohan, and Reddy 2020; Chen, Ribeiro, and Chen 2016; Matenda et al. 2021; Shi and Li 2019) by more relevant context. The inclusion criteria are as follows: (1) The studies that are found with keywords: “Bankruptcy” or “Financial distress;” (2) The studies from 2017 till 2022 February; (3) The studies are published in English; (4) The full text is accessible.

The exclusion criteria selection is related to financial distress barometer creation for SME. The exclusion criteria are: (1) The studies with no companies/enterprises bankruptcy or financial distress data. (2) The studies with no indication of the used data set. (3) The studies with macroeconomic research. (4) The studies analyzing financial sector: banks, insurance, etc. (5) Research with only one class analysis. (6) The traditional Altman method implementation without any new variables or methods comparison. Additional inclusion criteria is selected due to the need of wider analysis in the context of sentiment analysis, dimensionality reduction, imbalance, and outliers. This wider analysis seeks to create knowledge of the variety of methods, their taxonomy, and then the use cases in “Financial distress” context. The additional inclusion
criteria are: (1) The necessity of a return to primary sources. (2) The additional techniques theoretical analyses sources and their usage in “Bankruptcy” or “Financial distress” context.

**Search Query and the Results**

The main search keywords for the specific issue are: “dimensionality reduction,” “feature selection,” “feature extraction,” “anomaly,” “outlier,” “class imbalance,” “imbalance data sets,” and “sentimental analyses,” etc. The boolean model with “and” operator was used for information retrieval with the analyzed topic. The search strategy is based on the keywords “Financial distress” and “Bankruptcy.” Other similar keywords “credit risk,” “credit score,” and “default” have given studies about creditworthiness for customers or risk valuation in the bank sector, due to these reasons, these keywords are not implemented in the main search strategy. If a database search for “financial distress” yields a result with the phrase “credit risk” in the title, this article is examined. Nevertheless, from 2021 the phrase “Financial distress” is used not only in the context of firms but also in the context of human health, so these studies are not included in the analysis. The search query led to Scopus (4455), Web of Science (4049), ScienceDirect (1366), SpringerLink (1148), Emerald (712), IEEE (28), ACM (18), EBSCO (247), Wiley (101), Sage (9), Taylor & Francis (81), Other (58) articles found in databases. Analysis with inclusion and exclusion criteria led to 232 studies (Figure 1). Distribution of articles in different databases is presented in Table 1.

**Domain Taxonomy and Research Questions**

After studying previous systematic research in the financial distress and bankruptcy context, we have made a domain taxonomy (Figure 2), which is the guideline for this study and is related to these research questions:
**Table 1. Distribution of studies.**

| No. | Name of database      | No. of studies | Ratio (%) |
|-----|-----------------------|----------------|-----------|
| 1   | Science direct        | 85             | 36.6%     |
| 2   | Springer              | 41             | 17.7%     |
| 3   | Emerald               | 26             | 11.2%     |
| 4   | IEEE                  | 23             | 9.9%      |
| 5   | ACM                   | 10             | 4.3%      |
| 6   | MDPI                  | 10             | 4.3%      |
| 7   | Ebsco                 | 5              | 2.2%      |
| 8   | Wiley                 | 5              | 2.2%      |
| 9   | Sage                  | 3              | 1.3%      |
| 10  | Taylor & Francis      | 2              | 0.9%      |
| 11  | Other                 | 22             | 9.5%      |
| **TOTAL:** |                        | **232**          | **100.0%** |

**Figure 2.** Domain research taxonomy.

**RQ1:** What is the difference between Financial Distress, Insolvency, and Bankruptcy?

**RQ2:** What indicators are used as financial distress predictors? Its suitability for SMEs.

**RQ3:** What data sources are used?

**RQ4:** What data normalization techniques are used?
RQ5: What non-financial indicators for financial distress prediction are included?

RQ6: What machine-learning models are used?

RQ7: What the addition techniques are important for machine-learning algorithms and which of them are used in financial distress context?

RQ8: What performance metric is used for machine-learning algorithms evaluation in financial distress context?

Analysis of Studies

Conceptual Analysis of Domain Terms: Financial Distress, Insolvency, and Bankruptcy

The concept of financial distress in scientific literature is often related to bankruptcy, insolvency, probability of default, and failure patterns. The common definition of financial distress is a condition of a firm that has difficulties fulfilling its financial obligations (Farooq, Jibran Qamar, and Haque 2018; Yazdanfar and Öhman 2020). In scientific literature is different use cases (interpretation views) of the same financial distress definition. For example, one point of view is financial distress = bankruptcy, and the second point of view is financial distress ≠ bankruptcy.

A common view is that financial distress differs from bankruptcy, it is a distress situation of the company that leads to two possible states: 1) recovery state to become healthy again; 2) bankruptcy state, making reorganization or liquidation of the organization. Bankruptcy is the legal status of the company when creditors take legal actions, so the company cannot repay its debt (du Jardin 2018; Farooq, Jibran Qamar, and Haque 2018; Salehi and Davoudi Pour 2016; Veganzones and Severin 2020). In the context of bankruptcy, the words failure and default can be used as synonyms (Letizia and Lillo 2019; Salehi and Davoudi Pour 2016), contrary to the word insolvency. Insolvency is the middle stage between financial distress and bankruptcy. The main difference between financial distress and insolvency is that in first terminology companies have difficulties paying, or in insolvency used expression is being unable to pay. After insolvency, if legal action is taken, the insolvent firm is declared bankrupt (Farooq, Jibran Qamar, and Haque 2018). Two types of bankruptcy are identified (Lukason and Vissak 2017):
(1) A gradual failure (“chronic”): The financial situation is incrementally declining for the firm some years before its bankruptcy.

(2) An acute failure (“sudden”): The financial situation of the firm rapidly collapses, and sudden bankruptcy occurs. From a year before bankruptcy declared financial statement, there are no indicators about possible companies’ failure.

Most researchers make a separation of the financial distress and bankruptcy concepts. The main difference is that financial distress leads to bankruptcy, which means that firms can recover or become bankrupt. Therefore, there are two classes in bankruptcy, while in the subject of financial distress the researchers choose not only the number of classes but also the method by which the classes will be identified. The choice of class identification method selection is based on the quantity of the available data and the types of firms (public, nonpublic).

Data Sources

Data researchers commonly choose publicly available, e.g. public companies or open data sets. This is evident from the distribution of the data sources from the analyzed articles, which is presented in Table 2. The Private and Other sections are similar due to summarizing different data sources. Nevertheless, the Private section combines data sources, which researchers have given access to data from private sources or specific banks, while the Other section is data sources with a higher probability for other researchers to access such data, e.g. Orbis, Retriever, Thomson Reuters, etc. The Other section summarizes data sources used by the researchers, which are mentioned in the analyzed studies ≤ 2.

If a private database is chosen, researchers choose to analyze public companies and combine more different databases (Compustat, LoPucki’s Bankruptcy Research, New Generation Research, Center for Research in

| No. | Data source                                      | Frequency | %   |
|-----|--------------------------------------------------|-----------|-----|
| 1   | Stock exchange                                   | 69        | 36.3% |
| 2   | Polish                                           | 19        | 10.0% |
| 3   | Compustat                                        | 13        | 6.8%  |
| 4   | Diane                                            | 13        | 6.8%  |
| 5   | Private                                          | 10        | 5.3%  |
| 6   | Taiwan Economic Journal (TEJ)                    | 6         | 3.2%  |
| 7   | Amadeus                                          | 5         | 2.6%  |
| 8   | AIDA                                             | 4         | 2.1%  |
| 9   | Japanese (JPNBDS)                                | 3         | 1.6%  |
| 10  | LoPucki’s Bankruptcy Research                    | 3         | 1.6%  |
| 11  | Other                                            | 45        | 23.7% |
| **Total:** |                                              | **190**   | **100.0%** |
Security Prices, etc. (Darrat et al. 2016)). Eventually, the concepts of bankruptcy and financial distress are important for diverse parties: shareholders, investors, creditors, partners, etc. Furthermore, the beginning of bankruptcy prediction is considered the late sixties with Beaver (1966) and Altman’s (1968) works (Joshi, Ramesh, and Tahsildar 2018; Shen et al. 2020). These authors concentrated on financial indicators as the main historical information holders of the firm. The main of Beaver’s (Beaver 1966) research idea is “finding optimal cutoff point” among healthy and bankrupt firms. The author established that is relevant to use no more than five years’ windows before bankruptcy due to differences between the ratio classes distribution (Beaver 1966). In addition to this, (Altman 1968) created a z-score model, which is used today.

Expanding research on this topic was understood that financial ratios distribution differs from a normal distribution, and covariance matrices in groups are not equal, which leads to logistic regression use in analyses (Wagner 2008). Furthermore, additional features are added to research on financial distress or bankruptcy topic due to technical improvements (software, algorithms functions) and data availability (Chollet 2018). These reasons may lead to better model accuracy and the creation of a more universal model.

Using data normalization or standardization in studies is not common, the information that was applied provided about 16% of analyzed studies. Commonly used functions are normalization: “max-min” with [0,1] (Antunes, Ribeiro, and Pereira 2017; Cheng, Chan, and Sheu 2019; Chou, Hsieh, and Qiu 2017; Hu 2020; Huang and Yen 2019; Letizia and Lillo 2019; Ouenniche, Pérez-Gladish, and Boulah 2018; Qian et al. 2022; Salehi and Davoudi Pour 2016; Xu, Fu, and Pan 2019) or with [−1,1] (Letizia and Lillo 2019; Salehi and Davoudi Pour 2016; Sun et al. 2020; Wang et al. 2017; Zelenkov, Fedorova, and Chekrizov 2017), also function of standardization: Z-score (AghaeiRad, Chen, and Ribeiro 2017; Cheng, Chan, and Sheu 2019; Doğan, Koçak, and Atan 2022; Le et al. 2018, 2018, 2019; Letizia and Lillo 2019; Lin and Hsu 2017; Perboli and Arabnejad 2021). The authors who have applied normalization indicate that it’s necessary for the financial distress prediction model efficiency assurance (Qian et al. 2022) and feature weights alignment for the classification part (Antunes, Ribeiro, and Pereira 2017). Authors (Antunes, Ribeiro, and Pereira 2017) in the data pre-processing part before normalization firstly logarithmized the features due to data distribution uncertainty reduction.

Research on the financial distress and bankruptcy topic is developing in the context of big data, where new features (indicators) are added for greater model accuracy. This leads to higher-dimensional space, which causes the need for data dimensionality reduction before a machine-learning algorithm are used.
Dealing with High Data Dimensionality

The curse of dimensionality claims that the machine-learning algorithm’s cost is exponentially related to dimensions (Kuo and Sloan 2005). The data becomes more sparse when a new feature (dimension) is added. This reason leads to challenges in achieving better model accuracy. There is a common belief that more data is better than less (Altman and Krzywinski 2018). Data pre-processing step is one of the most important tasks for data analytics, which leads not only to simplified model design, but also to the creation of more efficient models. The main problems caused by dimensionality are:

- Data sparsity, e.g. it is used Euclidian distance as a similarity measurement, then a new feature appearance leads to greater dissimilarity, due to increasing distance between classes (points) (Altman and Krzywinski 2018),
- Multiple testing (also known as signal to noise ratio problem), e.g. the ability of pattern detections decreases of the essence inadequate features (Millstein et al. 2020). • Multicollinearity, e.g. if several samples are less than features, this situation leads to redundant feature creation (linear algebra) (Altman and Krzywinski 2018).
- Overfitting (lower model interpretability (Xu et al. 2019)).

Dimensionality reduction methods can be separated to feature selection and feature extraction (Figure 3). Regardless of the method, it is important to perform data preparation techniques such as:

![Figure 3. Dimensionality reduction methods.](image-url)
The feature selection approach is used to find a narrow subset of appropriate features from the initial wide range (Al-Tashi et al. 2020). This approach consists of three steps: method selection, evaluation, and stopping criteria (Wang et al. 2018).

The feature selection approach can be divided into filter, wrapper, embedded, and hybrid models. The first bankruptcy concept researcher - Beaver (1966) used the filter selection technique for healthy and bankrupt firm separation, by comparing the different class ratio distributions. Now in practice are used t-test (Kim, Mun, and Bae 2018), Cohen’s D, $\chi^2$, F-score, information gain ratio, Correlation Feature Selection (CFS), ReliefF, etc. The filter method assumes that features are independent of each other (Wang et al. 2018). The main advantages of this method are a fast, scalable, simple design, easier understanding for other researchers, and working independently from the classifier (Li, Li, and Liu 2017). The last advantage can become a disadvantage if an interaction with the classifier could lead to better performance of the model or could save costs.

The wrapper method uses a classifier in evaluating the features al-(Al-Tashi et al. 2020). This method analyzes features using forward or backward techniques, e.g., forward – begins with one feature subset and adds a new one if accuracy is better than this feature is left in the analysis, otherwise removed, backward – begins with all features subsets and removes by one, if the accuracy is better before removal, the feature is returned to a subset of feature, both algorithms continue until is analyzed all the subset of features. For feature, evaluation is often used accuracy rate or classification error (Cai et al. 2018).

Comparing filter and wrapper feature selection methods for the classificational task, the wrapper method tend to have better performance results (Al-Tashi et al. 2020), but needs much more computational power and time (Cai et al. 2018). The main wrapper methods advantages are: simplicity, interaction with classifier, model features dependencies, disadvantages: overfitting risk, less variety of the classifier which are used, and intensive computation (Li, Li, and Liu 2017). The embedded feature selection method differs from others due to feature selection and classification methods integration into a single process, feature selection becomes a part of the classifier (Wang et al. 2018), e.g., Random Forest, lightGBM, XGBoost, LASSO, and others. This method is less complicated than the wrapper method (Li, Li, and Liu 2017). The hybrid approach combines filter and wrapper methods, firstly using the filter method for primary feature selection, then applying the wrapper method, this combination makes balances the accuracy rate and intensive computation (Wang et al. 2018).
Feature extraction transforms high-dimensional data into a new lower-dimensional space, which has maximum information from the initial data set (Ayesha, Hanif, and Talib 2020). This approach is used not only for mapping but also for class visualization in 2-dimensional or 3-dimensional space, in which the essential data is visualized (Ye, Ji, and Sun 2013). This mapping approach can be divided into linear and non-linear methods. Linear methods attempt to reduce dimensionality by linear functions implementations, which forms new lower dimension feature set (Ayesha, Hanif, and Talib 2020), e.g. Principal component analyses (PCA), Linear discriminant analyses (LDA), Canonical correlation analysis (CCA), Singular Value Decomposition (SVD), Independent component analysis (ICA), Locality Preserving Projections (LPP), Neighborhood preserving embedding (NPE), Robust subspace learning (RSL), Latent semantic analysis (LSA) (for text), Projection Pursuit (PP), etc. Every technique is oriented in some information extraction, for example, PCA extracts global information, LPP extracts local information, and LDA merges the information of classes to the feature set, which means that other information of data is lost (Wang, Liu, and Pu 2019). Nonlinear feature extraction methods have greater performance results than linear due to the reality of the real-world data, which has a higher probability to be non-linear, than linear (van der Maaten, Postma, and Herik 2007). Nonlinear methods are auto-encoders, Kernel principal component analysis (KPCA), Multidimensional Scaling (MDS), Isomap, Locally linear embedding (LLE), Self-Organizing map (SOM), Learning vector quantization (LVQ), T-Stochastic neighbor embedding (t-SNE) (Ayesha, Hanif, and Talib 2020), etc.

Financial distress and bankruptcy concepts tend to expand analyzing indicators for greater model accuracy and new important patterns foundation. This leads to dimensionality reduction issues: data sparsity, multiple testing, multicollinearity, and overfitting, which are solved by feature selection or extraction approaches. In the context of bankruptcy or financial distress this feature extraction technique is used: 1) linear: PCA (Acharjya and Rathi 2021; Adisa et al. 2019; Jiang et al. 2021; Succurro, Arcuri, and Costanzo 2019; Wang, Liu, and Pu 2019; Štefko, Horváthová, and Mokrišová 2021), LDA (Huang et al. 2017; Nyitrai 2019; Veganzones and Séverin 2018; Wang, Liu, and Pu 2019), LPP (Wang, Liu, and Pu 2019), NPE (Wang, Liu, and Pu 2019), RSL (Wang, Liu, and Pu 2019) 2) nonlinear: MDS (Khoja, Chipulu, and Jayasekera 2019; Mokrišová and Horváthová 2020; Štefko, Horváthová, and Mokrišová 2021), tSNE (Zoričák et al. 2020), SOM (Mora García et al. 2008) and autoencoder (Soui et al. 2020). Instead of feature extraction, researchers use feature selection, due to achievable knowledge of the feature’s importance. Frequently used feature selection techniques are: 1) Filter: CFS (Faris et al. 2020; Séverin and Veganzones 2021), ReliefF (Faris et al. 2020; Kou et al. 2021), $\chi^2$ (Azayite and Achchab 2018; Kou et al. 2021); Gain ratio (Kou et al. 2021).
information gain ratio (Faris et al. 2020; Kou et al. 2021), Kruskal – Wallis (Séverin and Veganzones 2021), t-tests (Séverin and Veganzones 2021), 2) Wrapper: Backward (Faris et al. 2020; Perboli and Arabnezhad 2021; Tsai et al. 2021; Zelenkov, Fedorova, and Chekrizov 2017); 3) Embedded: LASSO (Du et al. 2020; Huang et al. 2017; Li et al. 2021; Volkov, Benoit, and Van den Poel 2017), XGBoost (Ben Jabeur, Stef, and Carmona 2022; Du et al. 2020), Tree-based (Azayite and Achchab 2018; Du et al. 2020), Logistic regression (LR) (Doğan, Koçak, and Atan 2022), stepwise LR (Ben Jabeur, Stef, and Carmona 2022), stepwise DA (Ben Jabeur, Stef, and Carmona 2022), partial least squares DA (Ben Jabeur, Stef, and Carmona 2022); CatBoost (Jabeur et al. 2021), f_classif (Du et al. 2020), L1-based (Du et al. 2020), PDC-GA (Al-Milli, Hudaib, and Obeid 2021); and 4) Hybrid (Lin and Hsu 2017; Veganzones, Séverin, and Chlibi 2021). Authors tend to apply 3–5 different feature selection techniques to find the best feature set.

**Dealing with Bias and Imbalance**

The class imbalance occurs when one class’s number of instances is much greater than the other, which is common in real-data set analysis (Le et al. 2018; Lin et al. 2017; Liu, Zhou, and Liu 2019). In the context of financial distress or bankruptcy, the financially successful number of firms is higher than distressed (Sun et al. 2020), which can be expressed as a range of proportion from 100:1 to 1000:1 (Veganzones and Séverin 2018). A firm’s activity sector influence a higher or lower probability of default, e. g. financial distress is more common in the manufactory industry than in transportation (Shen et al. 2020). The most prevailing solution is to add more instances of the minority class. The class imbalance problem is generally related with:

1. Lack of minority data (cannot be found feature patterns due to limited amount of minority class examples);
2. Overlapping or class separability (class examples are mixed up between each other in the feature space);
3. Small disjuncts (intervenes of small groups from minority class in majority classes feature space) (Fernández et al. 2018; Lin et al. 2017).

These problems lead to difficulties in creating an effective machine-learning classification model. In addition to this, researchers dealing with imbalanced data set issue accuracy metrics to consider as inappropriate evaluation measures due to the dominating classes effect, e. g. the classifier can achieve 99% of accuracy without correctly classifying rare examples (Weng and Poon 2008). This measurement is replaced with Precision, Recall, F-scored, the area under the ROC curve (AUC), G-mean, or balanced accuracy metrics (Fernández
et al. 2018; Kotsiantis, Kanellopoulos, and Pintelas 2005; Veganzones and Séverin 2018; Weng and Poon 2008).

Class imbalance reduction methods are used for binary classification issues, however not all methods can be used for multiclass imbalance issues. To use them researchers apply One-vs-One (OVO), and One-vs-All (OVA) strategy schemes, in which multiclass imbalance issue converts to a binary one (Fenández et al. 2018). Methods dealing with class imbalance issues can be separated into data level, algorithm level, and hybrid approach (Figure 4). The \textit{data level approach} is directly related to changes in the data set, it is rebalancing data that its distribution of the classes becomes more equivalent. On the other hand, the \textit{algorithm level approach} is modifying the classifier to the bias of prioritizing minority classes learning (Fernández et al. 2018; Kotsiantis, Kanellopoulos, and Pintelas 2005; Lin et al. 2017). The combination of these two approaches forms \textit{hybrid methodology}, which makes changes to the data and the classifier for specific problem solvation.

The main advantage of the \textit{data-level approach} is independent process creation, which is made separated from the sampling and classifier training process (Lin et al. 2017). From a data modification perspective, there are three possibilities to make modifications: 1) to reduce the majority class, 2) to increase the minority class, or 3) hybrid to combine majority class reduction with minority class increase. Hence, the \textit{data level approach} consists of

\textbf{Figure 4.} Class imbalance reduction methods.
undersampling, oversampling, and hybrids methods. From the undersampling and oversampling methodology perspective the simplest way is to make a random reduction of majority class instances (RUS – random undersampling) or increase of minority class instances (ROS – random oversampling) (Liu, Zhou, and Liu 2019). These random methods are not very efficient due to information loss or overfitting (Kotsiantis, Kanellopoulos, and Pintelas 2005). For this reason, is developing new undersampling models which use clustering, for instance, identification in feature space and majority class instance elimination due to redundancy, distance from the decision border, etc., such as Tomek Links (TL), Undersampling Based on Clustering (SBC), Class Purity Maximization (CPM), Condensed Nearest Neighbor Rule (US-CNN), One-Sided Selection (OSS), colony optimization Sampling (ACOSampling), etc. (Fernández et al. 2018). Synthetic Minority Over-sampling Technique (SMOTE) is the most often used oversampling method (Lin et al. 2017), which generates synthetic instances by using the interpolation method dependent on the required balance of the classes. SMOTE interpolating technique use k-nearest neighbor logic, close examples in the feature space are selected forming a line area in which new synthetic instances are created (Ashraf and Ahmed 2020). The main advantage of SMOTE technique is the improvement of the capacity generalization to the classifier, which leads scientists to create more than 85 different SMOTE technique extensions: Borderline-SMOTE, ADASYN, Safe-Level-SMOTE, DBSMOTE, ROSE, MWMOTE, MDO, etc. (Fernandez et al. 2018). In addition to this, the highest performance of the classifier can be achieved by the combination of the undersampling and oversampling techniques, as hybrid methods I creation: SMOTE +Tomek Link, SMOTE + ENN, AHC, SPIDER, SMOTE-RSB (Fernández et al. 2018). This method maintains weaknesses of both methods: the possibility of important information loss and overfitting.

The algorithm level approach can be divided into the threshold, one-class classifier, cost-sensitive, and ensembles of the classifier’s methods. The threshold method also known as “decision threshold” or “discrimination threshold” makes better classifier label prediction by moving the default threshold (0.5 probability) upper or lower for better special class identification (Zhou and Liu 2006). For example, the financial institution can save costs if the threshold of good credits is 0.8, which means it saves 2 out of 10 cases for creditworthiness tests. The main idea of using this method is to know the boundary that leads to one prior class label identification (Chen et al. 2006). If classes are highly overlapping threshold boundary can not be achieved. Another algorithm level method is one class classifier also known as recognition based learning, this method uses only one specific class example in the training set (Lin et al. 2017), this method is used when there are small disjuncts or noisy instances in the data and can be deviated into 3 types: 1) learning from minority class; 2) learning from majority class; 3) output combination after learning on both.
approaches (Fernández et al. 2018). The method applications lead to a decrease in specificity metrics, one of the methods dealing with this issue is the one-class classifier combination approach (Fernández et al. 2018). Since one-class classifier is trained only on one class instance, other instances are treated as outliers, for this reason, this method is used as one of the outlier’s detection approaches. The cost-sensitive method uses a cost matrix for misclassification of unequal cost between classes creation (Kotsiantis, Kanellopoulos, and Pintelas 2005), it is a penalty treatment for the classifier. In literature two different views are assigning a cost-sensitive method to the class imbalance approach, for one author it is a direct branch of the class imbalance approach (Fernández et al. 2018; Lin et al. 2017; Sisodia and Verma 2018), for others, it is a subclass of the Algorithm level approach (Kotsiantis, Kanellopoulos, and Pintelas 2005; Liu, Zhou, and Liu 2019; Wang et al. 2020). The cost-sensitive method depends on the selected cost, incorrect cost selection leads to impair results of the classifier (Fernández et al. 2018). The main idea of Hybrid method II is to combine different classifier outputs for more accurate final decision creating and this method can involve different algorithm level method combinations (Zhou and Liu 2006). The main difference from the third type of class imbalance – Ensembles of the classifier’s approach, is that the Hybrid methods II do not mix data level and algorithm level approaches outputs. Ensembles of the classifier’s approach allow researchers not only to use a combination of data level and algorithm level approaches but also make their ensembles learning classifiers.

In the financial distress and bankruptcy context class imbalance reduction techniques are used contradictory. The authors (Huang and Yen 2019; Inam et al. 2019; Kanojia and Gupta 2022; Mselmi, Lahiani, and Hamza 2017; Perboli and Arabnezhad 2021; Zelenkov, Fedorova, and Chekrizov 2017) do not use any class imbalance technique instead they chose majority instances depending on the number of minority instances. For example, the authors (Huang and Yen 2019) have 32 financially distressed firms and select 32 non-distressed firms from the same industry. Conversely, authors who adopted class imbalance reduction methods. The commonly used is SMOTE (Al-Milli, Hudaib, and Obeid 2021; Aljawazneh et al. 2021; Angenenet, Barata, and Takes 2020; Choi, Son, and Kim 2018; Faris et al. 2020; Jiang et al. 2021; Kim, Cho, and Ryu 2021; Le et al. 2018; Letizia and Lillo 2019; Roumani, Nwankpa, and Tanniru 2020; Sisodia and Verma 2018; Sun et al. 2021; Veganzones and Séverin 2018; Vellamcheti and Singh 2020; Wang et al. 2018; Zelenkov and Volodarskiy 2021; Zhou 2013), then other oversampling techniques except SMOTE (Aljawazneh et al. 2021; Le et al. 2018; Sisodia and Verma 2018; Smiti and Soui 2020; Veganzones and Séverin 2018; Wang et al. 2018; Zelenkov and Volodarskiy 2021; Zhou 2013), undersampling (Angenenet, Barata, and Takes 2020; Le et al. 2019; Sisodia and Verma 2018; Veganzones and Séverin 2018; Vellamcheti and Singh 2020; Wang et al. 2018; Zelenkov and Volodarskiy
2021; Zhou 2013), ensembles classifiers approaches (Aljawazneh et al. 2021; Roumani, Nwankpa, and Tanniru 2020; Shen et al. 2020; Sun et al. 2020; UlagPriya and Pushpa 2021; Wang et al. 2020), Hybrid I (Aljawazneh et al. 2021; Le et al. 2018; Le et al., 2018; Le et al. 2019), cost-sensitive (Angenent, Barata, and Takes 2020; Chang 2019; Ren, Lu, and Yang 2021; Wang et al. 2018), and threshold (Wang et al. 2018). It is noted that authors (Aljawazneh et al. 2021; Angenent, Barata, and Takes 2020; Le et al. 2018; Sisodia and Verma 2018; Veganzones and Séverin 2018; Vellamchetti and Singh 2020; Wang et al. 2018; Zelenkov and Volodarskiy 2021; Zhou 2013) who use techniques other than SMOTE perform a comparative analysis of these techniques, and compared them with SMOTE. Further, SMOTE is one of the common data preparation steps. Authors (Veganzones and Séverin 2018) have noticed, that the efficiency of the classifier decreases with class imbalance increases, especially if one class instance is less than 20%. This assumption was made only on data level approach application in the research methodology and the maximum performance of the classifier was achieved after SMOTE techniques implementation. Using one classifier technique the class imbalance problem can be seen as anomaly or outlier detection, which is also applied to concepts of financial distress and bankruptcy (Gnip and Drotár 2019; Zoričák et al. 2020).

**Looking from Outliers’ Perspective**

The anomaly is understood as a strong outlier, which is significantly dissimilar to other data instances, on the contrary, a weak outlier is identified as the noise of the data (Aggarwal 2017). It is important to understand, that outlier exists in approximately every real data set due to: malicious activity, change in the environment, system behavior, fraudulent behavior, human error, instrument error, setup error, sampling errors, data-entry error, or simply through natural deviations in populations (Chandola, Banerjee, and Kumar 2009; Hodge and Austin 2004; Wang, Bah, and Hammad 2019). Authors are using different approaches (terminologies), such as outlier detection, novelty detection, anomaly detection, noise detection, deviation detection, or exception mining (Hodge and Austin 2004), which all lead to the same outlier identification problem. The first step to solving this issue is a precise description of normality, but finding the boundary between normality and nonnormality is often fuzzy due to the instances (data points) which are between the boundary, which can be treated as normal or vice versa (Chandola, Banerjee, and Kumar 2009). We identified three types of anomaly/outliers:

(1) **Point anomaly** or **Type I outlier** occurs when is used technique, which is analyzing an individual instance with the rest of the data (Ahmed, Naser
Mahmood, and Hu 2016; Chandola, Banerjee, and Kumar 2009). For example, if a person spends three times more than they used to.

(2) Context anomaly or Type II occurs when it is a structure in the data, for example, seasonality of spending Christmas period. For this type is needed two sets of attributes are: 1) contextual attributes (location, time, etc.); 2) behavioral attributes (noncontextual characteristics of the instance: time interval between purchases) (Bhuyan, Bhattacharyya, and Kalita 2014; Chandola, Banerjee, and Kumar 2009).

(3) Collective anomaly or Type III outlier occurs when is analyzed the sequence of events, in which a separate event is not an anomaly, but the collection of similar events behave anomalously, for example, the sequence of transactions (Aggarwal 2017; Ahmed, Naser Mahmood, and Hu 2016; Chalapathy and Chawla 2019).

We categorize the anomaly detecting methods into six approaches according to literature reviews (Aggarwal 2017; Ahmed, Naser Mahmood, and Hu 2016; Bhuyan, Bhattacharyya, and Kalita 2014; Chandola, Banerjee, and Kumar 2009, 2009; Hodge and Austin 2004; Wang, Bah, and Hammad 2019) in the context of anomaly/outlier detection (Figure 5):

(1) Statistical-based approach is the first algorithms group used for outlier detection (Hodge and Austin 2004), which is splinted into parametric and non-parametric methods. The fundamental idea of this approach is the identification of new instance dependencies to the distribution model (Wang, Bah, and Hammad 2019), e.g. instances are declared as anomalies if has a low probability to be generated from the learning model (Bhuyan, Bhattacharyya, and Kalita 2014). Parametric models use hypothesis testing, if the hypothesis is rejected instance is declared as an anomaly, for hypothesis testing is used $\chi^2$, Grubb’s test, etc. Of course, assuming that data is generated from a Gaussian distribution (Bernoulli (if categorical), etc.) maximum likelihood function can be used as well, where the threshold is applied for the anomaly identification as a distance measure from the mean (Aggarwal 2017; Chandola, Banerjee, and Kumar 2009). A regression model can be applied too. Non-parametric models do not have priory assumption about data distribution, it uses existing data, for example, kernel functions estimate probability density function (pdf) for the data, where instances lying in low probability area are announced as anomalies (Chandola, Banerjee, and Kumar 2009; Wang, Bah, and Hammad 2019). Other often-used non-parametric models are histogram technique, Finite State Machines, PCA, etc. (Chandola, Banerjee, and Kumar 2009). The main advantages of the Statistical based approach are easy implementation, fast processing time, however, this approach has a strong weakness, which is: a)
(2) **Distance, Density-based approach** otherwise known as a **Nearest neighbor-based approach** due to regularly k-NN technique application. The main idea of this approach is that normal data points instance occurs in more dense or nearby neighborhoods, while anomalies are more distant and may form their local dense groups (Aggarwal 2017; Chandola, Banerjee, and Kumar 2009; Wang, Bah, and Hammad 2019). The main advantages of this method are that: a) it can be used during unsupervised learning, b) it is easily scalable in a multidimensional
space, c) has efficient computation, d) does not have a prior assumption about data distribution (Chandola, Banerjee, and Kumar 2009; Wang, Bah, and Hammad 2019). This method is sensitive to parameter settings, which include k-neighbors identification. Also, it relies on the analyzed data, if it is scattered or does not have enough similar normal instances, that leads to a high false-positive rate (Chandola, Banerjee, and Kumar 2009). Method performance decreases due to the course of dimensionality, and it is not suitable for the data stream (Wang, Bah, and Hammad 2019).

3) **Classification-based approach** uses binary classification algorithms to divide instances into the classes: normal instance or anomaly, in which classification boundary can be non-linear (Bhuyan, Bhattacharyya, and Kalita 2014; Chandola, Banerjee, and Kumar 2009). Depending on the availability of data in the testing set of different classes it are used multi-class or one class-based classification technique (Chandola, Banerjee, and Kumar 2009). The main advantages of this approach are a) adoptable threshold setting, and b) flexible pretraining and testing incorporating new information (Bhuyan, Bhattacharyya, and Kalita 2014). The main disadvantages of the model are that: a) the performance of the model depends on the assumptions made by the classifier, b) the new unseen instance is often misclassified, and c) a need for more computational power (Bhuyan, Bhattacharyya, and Kalita 2014; Chandola, Banerjee, and Kumar 2009).

4) A **clustering-based approach** can be used during unsupervised learning, hence pre-label class instances do not require (Ahmed, Naser Mahmood, and Hu 2016). The main method assumption is that normal data instance belongs to the cluster, while anomalies do not or form their own – smaller cluster (Aggarwal 2017; Chandola, Banerjee, and Kumar 2009). Author (Zhang 2013) clustering-based outlier detection algorithms distinguish into seven major categories: Partitioning Clustering methods; Hierarchical Clustering methods; Density-based clustering methods; Grid-based clustering methods. The main advantages of using clustering are a) stable performance, b) no prior knowledge about data distribution is needed, c) adaptable for different data types and data structures d) incremental clustering (supervised) methods are effective for fast response generation (Bhuyan, Bhattacharyya, and Kalita 2014; Chandola, Banerjee, and Kumar 2009). Some cluster categories have additional advantages, for example partitioning clustering is approximately simple and scalable, hierarchical based methods “maintain a good performance on data sets containing non-isotropic clusters and also produce multiple nested partitions that give users the option to choose different portions according to their similarity level” (Wang, Bah, and Hammad 2019). The main clustering-based
approach’s main disadvantages are a) dependence on proper cluster algorithm selection that could capture the structure of normal instances, b) high sensitivity for initial parameters, e.g. clustering is optimized for a prior number of cluster creations not for anomaly detection, hence, identifying the proper number of clusters for normal instances and anomalies is challenging (Bhuyan, Bhattacharyya, and Kalita 2014; Chandola, Banerjee, and Kumar 2009; Wang, Bah, and Hammad 2019).

(5) The information theoretic-based approach’s main assumption is to find out irregularities in the information content, which are caused by anomalies in the data set (Chandola, Banerjee, and Kumar 2009). The information content is analyzed using different information-theoretic measurements, e.g. entropy, relative entropy, conditional entropy, information gain, information cost, (Ahmed, Naser Mahmood, and Hu 2016; Chandola, Banerjee, and Kumar 2009). The main advantages of this approach are that it can be used during unsupervised learning and does not have a prior assumption about data distribution. The main weaknesses are a) performance dependence on the information-theoretic measurement selection; b) date sets application limitation: in most cases used for sequential or spatial data, c) computation time and power resources grow exponentially in more complex data sets, d) it is difficult the information-theoretic measurement output connects with anomaly score or label (Aggarwal 2017; Chandola, Banerjee, and Kumar 2009, 2009).

(6) The combination-based approach otherwise known as Ensemble-based, which the main idea to use several machine-learning algorithms results and combine them using weighted voting, and majority voting techniques (Bhuyan, Bhattacharyya, and Kalita 2014; Wang, Bah, and Hammad 2019). Author (Aggarwal 2017) ensemble-based outlier detection algorithms distinguish into two categories: sequential and independent ensembles. The main idea of sequential ensembles is that is formed sequential algorithms are used dependent on the data, while independent ensembles use a combination of different algorithms voting outputs. The main advantages of this method are a) performance is more efficient, b) predicts results are more stable, and c) applicable for high dimension data, and streaming data. It is difficult to: a) obtain real-time performances, b) select classifiers in the ensemble, and c) interpret a result, which was get during unsupervised learning (it could lead to robust decision making) (Bhuyan, Bhattacharyya, and Kalita 2014; Wang, Bah, and Hammad 2019).

Anomaly detection techniques generate the output, which can be one of two types:
• Labels. Output technique, which assigns labels, e.g. a normal instance or outlier. It generally uses a threshold for conversion from probability score to binary labels (Aggarwal 2017; Chandola, Banerjee, and Kumar 2009).
• Scores. Output technique, which uses direct algorithm outputs as probability score for the outlier, which is ranked (Aggarwal 2017; Chandola, Banerjee, and Kumar 2009).

**Machine-Learning Methods**

Machine-learning is the study of computer algorithms, which have the capability to learn and improve automatically through experience (Helm et al. 2020; Huang and Wang 2019). The machine-learning techniques can be classified into four main groups.

1. **Supervised machine-learning methods** are based on useful information with labeled data (Liu and Lang 2019). It is called the *Task-driven approach* due to it uses a sample of input-output pairs to convert an input to an output (van Engelen and Hoos 2020). Depending on provided data it can be a regression (continuous data) or classification (discrete data) task (Sarker 2021).
2. **Unsupervised machine-learning methods** do not have any provided output and their main task is to map similar inputs to the same class (van Engelen and Hoos 2020). This *Data-Driven approach* is widely used for feature extraction, clustering, association rules detection, density estimation, anomaly detection, etc. (Sarker 2021).
3. **Semi-supervised machine-learning methods** combines Supervised and Unsupervised methods, which seek to improve performance in one of these two tasks by using data that is commonly linked with the other. For example, clustering can benefit from knowing some data points provided output, further classification can be added to additional data points without any output (van Engelen and Hoos 2020). Often used in text classification, fraud detection (Akande et al. 2021; Awotunde et al. 2022), money laundering prevention, data labeling, etc.
4. **Reinforcement machine-learning methods** is based on long-term rewords maximization, which is obtained by imitation of human behavior to take environmental action (by reward or penalty learning).

In financial distress and bankruptcy context, the authors most often apply supervised machine-learning methods, especially popular methods are Logistic regression, Artificial neural network (ANN), and Support vector machine (SVM). Logistic regression is the most popular method due to several reasons: 1) one of the first methods applied in a bankruptcy context (Altman’s z-score model is based on LR); 2) popular in social science for the evaluation of
analyzed variables; 3) one of the main method used in the efficiency comparison with other machine-learning methods. However, LR method performance results is lower comparing with other Machine-learning methods (SVM, Xgboost, ANN, Random Forest, etc.). For this reason, authors extend their research by implementing new methodology for “Financial distress” classification and other machine-learning issues solving such as: dimensionality reduction, imbalance, etc.

A few unsupervised machine-learning methods are applied: One class SVM, Isolation forest (IF), Least-Squares Anomaly detection (LSAD), K-means, and from deep learning methods group – Auto-encoder. For each method, a more detailed description is given in Table 3.

Performance Metrics

The effectiveness of the methods is evaluated by a comparison of different methods’ performance results. In this study, we are interested in evaluating performance metrics suitable for labels. Most of them begin with the confusion-matrix (Altman 1968). In the case of class imbalance, the minority class is presented as negative (Fernández et al. 2018). In the case of financial distress, classes would be presented as follows for positive: Non-Financial Distress|Non-Bankrupt, and for negative: Financial Distress|Bankrupt.

Based on the confusion matrix, many performance measurements can be constructed. For more accurate evaluation of the methods, researchers use three to five measurements. The Figure 6(a) shows that 30.9% of studies used one evaluation metric. The authors use other evaluation metrics, such as $R^2$ or Log-loss, in the regression analyses; therefore, it is common to use 3–5 evaluation metrics. The common evaluation matrix is accuracy and the area under the ROC curve (AUC), then recall, specificity, and type I error (Figure 6(b)). Comparing AUC and ACC ratios, it is observed that studies closer to the present period tend to choose AUC metrics. For AUC calculation is needed ROC curve identification. ROC (the receiver operating characteristic) curve is a graphical evaluation method (Fernández et al. 2018) for the binary classification problems, also called a two-dimensional space coordinate system (Wang et al. 2018), in which Sensitivity (TPR) is plotted on the Y-axis and 1-Specificity (FPR) is plotted on X-axis (Zhou 2013). There is a point in the ROC space for each potential threshold value conditional on the values of FPR and TPR for that threshold (Fernández et al. 2018). Linear interpolation is used to construct the curve. AUC is an average performance metric that helps analysis to compare and contrast different models (García, Marqués, and Sánchez 2019).

Kolmogorov – Smirnov statistic (K-S), Matthews correlation coefficient (MCC), H-measure, and Brier score (BS) have a low number of studies from
Table 3. Machine-learning methods applied in the context of financial distress.

| No. | Method | Definition | Method modification | Source |
|-----|--------|------------|---------------------|--------|
| 1.  | Additive Regression (AAR) | AAR is one of survival analysis Models (an alternative to Cox model). This model can detect changes in coefficient at each distinct survival time due to linear function in the hazard rate estimation. | — | (Zelenkov 2020) |
| 2.  | Accelerated Failure Time Models (AFT) | AFT is an alternative to proportional hazards models. AFT assumes that a covariate effect can become some constant, which accelerate or slow down the progression of a disease. | Weibull Accelerated Failure | (Zelenkov 2020) |
| 3.  | Artificial neural networks (ANN) | The purpose of an artificial neural network (Multilayer perceptron) is to imitate the operation of biological neural systems, which is an example of neuron connectivity architecture design. The neurons are arranged in three completely connected layers: input, output and one or more hidden layers. ANN provides a framework for modeling nonlinear functional mappings between sets of input and output variables. ANN with several hidden layers is also called Deep neural network (DNN). | Time Models (WMF) (Zelenkov 2020) ANN Backpropagation (Almaskati et al. 2021; Kristianto and Rikumahu 2019; Lin and Hsu 2017) Feed-forward neural network (FNN) (Adisa et al. 2019; AghaeiRad, Chen, and Ribeiro 2017; du Jardin 2018) FNN-SOM (AghaeiRad, Chen, and Ribeiro 2017) DGAFLPE (Zhang et al. 2021) DNN (Almazweh et al. 2021; Ben Jabeur, Stefa, and Carmona 2022; Horak, Wbka, and Suler 2020; Jabeur et al. 2021; Li et al. 2021; Smith and Alvarez 2022) GA-MUP (Zhang et al. 2021) MA-DNN (Li et al. 2021) Multi-task Neural Network (MNN) (Zelenkov 2020) Random vector functional-link network (RVFLN) (Lin and Hsu 2017) Rough set NN model (RNN) (Acharjya and Rath 2021) Self-organizing NN (du Jardin 2021a) | (Abdulrah 2021; Acharjya and Rath 2021; Adisa et al. 2019; AghaeiRad, Chen, and Ribeiro 2017; Almazweh et al. 2021; Almaskati et al. 2021; Azyte and Achiab 2018; Barboza, Kimura, and Altman 2017; Ben Jabeur, Stefa, and Carmona 2022; Charalambous, Maltzoukos, and Tsolakis 2022; Cheng, Chan, and Yang 2018; Choi, Son, and Kim 2018; Cleofas-Sanchez et al. 2016; Da et al. 2022; du Jardin 2018, 2021a; Fan, Liu, and Chen 2017; Fan et al. 2020; Garcia, Marques, and Sanchez 2019; Horak, Wbka, and Suler 2020; Hosaka 2019; Hsue 2017; Hajeck 2018; Inam et al. 2019; Jabeur et al. 2021; Kim, Mun, and Bae 2018; Kristianto and Rikumahu 2019; Le et al. 2018, 2018; Letisul and Ullo 2019; Li et al. 2021; Liang et al. 2018; Lin and Hsu 2017; Mora Garcia et al. 2008; Mousavi and Lin 2020; Mieml, Lahiani, and Hamza 2017; Nytrai and Visy 2019; Oz and Yekinci 2017; Perboli and Arabnejad 2021; Qian et al. 2022; Salehi and Davoudi Pour 2016; Salehi, Mousavi Shiri, and Bolandarfar 2021; Salehi, Mousavi Shiri, and Bolandarfar Pasilhan 2016; Smith and Alvarez 2022; Smit and Soui 2020; Soui et al. 2020; Sun et al. 2017; Severin and Voganzare 2021; Tsai et al. 2021; Voganzare and Sekin 2020; Voganzare and Sekin 2021; Vellamchery and Singh 2020; Wagle, Yang, and Bendimane 2017; Ye 2021; Zelenkov 2020; Zelenkov, Fedorova, and Chekrizov 2017; Zhang et al. 2017; Zhou 2013) | (Barboza, Kimura, and Altman 2017; Chen et al. 2021; Chen, Chen, and Shi 2020; du Jardin 2017, 2021a, 2021b, 2021c; Fan et al. 2020; Gnip and Drotop 2019) Random Subspace (du Jardin 2017, 2021a, 2021b, 2021c; Wang et al. 2020) IST-RS (Wang et al. 2018) Bagged-pSVM (Chen, Chen, and Shi 2020) |
| 4.  | Bagging Bootstrap aggregation | An ensemble learning approach is a technique for reducing variance in a noisy data set. Bagging is the process of selecting a random sample of data from a training set with replacement—that is, the individual data points might be chosen many times. Another difference between the boosting and bagging techniques is that weak learners are trained parallel. | Bagging CART (Mousavi and Lin 2020) Balanced Bagging (Gnip and Drotop 2019) Random Subspace (du Jardin 2017, 2021a, 2021b, 2021c; Wang et al. 2020) IST-RS (Wang et al. 2018) Bagged-pSVM (Chen, Chen, and Shi 2020) | (Barboza, Kimura, and Altman 2017; Chen et al. 2021; Chen, Chen, and Shi 2020; du Jardin 2017, 2021a, 2021b, 2021c; Fan et al. 2020; Gnip and Drotop 2019; Keya et al. 2021; Liang et al. 2018; Mousavi and Lin 2020; Qian et al. 2022; Roumian, Nwankpa, and Tamiru 2020; Shen et al. 2020; Siosodial and Verma 2018; Sun et al. 2017; Wagle, Yang, and Bendimane 2017; Wang et al. 2020, 2018; Zelenkov and Vodorskis 2021; Zelenkov, Fedorova, and Chekrizov 2017; Zhou et al. 2022)|

(Continued)
### Table 3. (Continued).

| No. | Method          | Definition                                                                 | Method modification                                                                 | Source                                                                 |
|-----|-----------------|---------------------------------------------------------------------------|-------------------------------------------------------------------------------------|----------------------------------------------------------------------|
| 5.  | Boosting        | An ensemble learning strategy for minimizing training errors by combining a group of weak learners into a strong learner. In boosting technique a group of weak learners are trained in a sequential manner. | AdaBoost (Aljawazneh et al. 2021; Fais et al. 2020; Hosaka 2019; Keya et al. 2021; Le et al. 2019; Qian et al. 2022; Shen et al. 2020; Siadat and Verma 2018; Sun et al. 2017; Wang et al. 2020; Zelenkov and Volodarsky 2021); Zelenkov, Fedorova, and Chekrizov 2017; Zhao et al. 2022; AdaBoost CART (Mousavi and Lin 2020); AdaBoost-SVM (Sun et al. 2017); ADASVM-TW (Sun et al. 2017, 2020); Boosted pSVM (Chen, Chen, and Shi 2020); CatBoost (Jabeur et al. 2021; Zhao et al. 2022); CIBoost (Le et al. 2019); CUSBoost (Du et al. 2020); CUS-GDT (Du et al. 2020); Extreme Gradient Boosting (XGBoost) (Aljawazneh et al. 2021; Du et al. 2020; Huang and Yen 2019; Le et al. 2019; Petboli and Arbabnejad 2021; Qian et al. 2022; Shen et al. 2020; Sun et al. 2017; Zhao et al. 2022) (Ben Jabeur, Stef, and Carmona 2022; du Jardin 2021a, 2021b); C; Jabeur et al. 2021; Smith and Alvarez 2022; Son et al. 2019; Volkov, Benoit, and Van den Poel 2017; GMBoost (geometric mean) (Le et al. 2019); Gradient boosting model (GBoost) (Fan, Liu, and Chen 2017; Gnip and Drotár 2019; Jabeur et al. 2021; Jones 2017; Zelenkov and Volodarsky 2021); LightGBM (Smith and Alvarez 2022; Son et al. 2019); Logit-Boost (Kumar and Roy 2016); NFS-Boost (Kumar and Roy 2016); RobustBoost (Pavlicko, Durica, and Mazanec 2021); RUSBoost (Du et al. 2020; Gnip and Drotár 2019) | (Aljawazneh et al. 2021; Barboza, Kimura, and Altman 2017; Ben Jabeur, Stef, and Carmona 2022; Chen, Chen, and Shi 2020; Du et al. 2020; du Jardin 2017, 2021a, 2021b, 2021c; Fan, Liu, and Chen 2017; Fais et al. 2020; Gnip and Drotár 2019; Hosaka 2019; Huang and Yen 2019; Jabeur et al. 2021; Jones 2017; Keya et al. 2021; Kumar and Roy 2016; Le et al. 2018, 2019; Liang et al. 2018; Mousavi and Lin 2020; Pavlicko, Durica, and Mazanec 2021; Petboli and Arbabnejad 2021; Qian et al. 2022; Roumani, Nwankpa, and Tanniru 2020; Shen et al. 2020; Siadat and Verma 2018; Smith and Alvarez 2022; Son et al. 2019; Soue et al. 2020; Sun et al. 2017, 2020; Vellamcheti and Singh 2020; Volkov, Benoit, and Van den Poel 2017; Wang, Yang, and Benslimane 2017; Wang et al. 2020; Zelenkov and Volodarsky 2021; Zelenkov, Fedorova, and Chekrizov 2017; Zhao et al. 2022) |
| 6.  | Cox’s model     | Cox is essentially a regression model used for association understanding between time and one or more predictor variables, commonly used in medical research. | Cox proportional hazard model (Kanojia and Gupta 2022; Zelenkov 2020) | (du Jardin 2017, 2018; Kanojia and Gupta 2022; Roumani, Nwankpa, and Tanniru 2020; Zelenkov 2020) |
| 7.  | DEA             | DEA is a non-parametric approach, which empirically quantifies the relative evaluations of the efficiency between multiple similar factors inputs and outputs. | DEA - additive model (Almaskati et al. 2021) | (Almaskati et al. 2021) |
| No. | Method | Definition | Method modification | Source |
|-----|--------|------------|---------------------|--------|
| 8.  | Decision tree (C4.5) | Decision tree consists of root, internal/decision node and leaf node. The model has to satisfy the following criteria: 1) The tree must have a single root, which has no entrance and from which the division into branches and leaves begins. 2) Each internal/decision node has only one input. 3) There is a unique path from each leaf node to the root. The splitting for internal/decision node is made by information gain ratio (C4.5), Gini coefficient (CART), $\chi^2$-based test (CHAID), etc. The decision tree pruning techniques are used to deal with overfitting. The decision tree is a nonparametric method, which means that it does not learn the parameters by which to evaluate attributes. The system remembers the main properties of the data. Therefore, even a small change in the data can lead to the formation of a new tree. | AdaBoost CART (Mousavi and Lin 2020); Bagging CART (Mousavi and Lin 2020); Bagging DT (Shen et al. 2020); C4.5 + Boosting (Putri and Dhni 2019); C4.5 + Bagging (Putri and Dhni 2019); C5.0 (Huang et al. 2017; Smiti and Soui 2020); CART (Behr and Weiblait 2017; Hosaka 2019; Jiang et al. 2021; Mousavi and Lin 2020); Nyttai and Vrág 2019; Pavlicko, Durica, and Mazanec 2021); CHAIM (Nyttai 2019; Nyttai and Vrág 2019); J48 (Chen et al. 2021); Keya et al. 2021; Vellamch eti and Singh 2020); Logit regression tree (Andrea et al. 2018) | (Ali-Milli, Hudiaib, and Obied 2021; Almalki et al. 2021; Andrea et al. 2018; Behr and Weiblait 2017; Chen et al. 2021; Cheng, Chan, and Yang 2018; Cho, Son, and Kim 2018; du Jardin 2017, 2018; Faris et al. 2020; García, Marqués, and Sánchez 2019; Hosaka 2019; Hu 2020; Huang et al. 2017; Hajak 2018; Jiang et al. 2021; Keya et al. 2021; Kim and Umejja 2021; Le et al. 2018, 2018; Letizia and Lillo 2019; Liang et al. 2018; Mousavi and Lin 2020; Nyttai 2019; Nyttai and Vrág 2019; Pavlicko, Durica, and Mazanec 2021); Putri and Dhni 2019; Qian et al. 2022; Roumani, Nwankpa, and Tanvir 2020; Shen et al. 2020; Siosadia and Verma 2018; Smilk and Soui 2020; Sun et al. 2017; Tsai et al. 2021; Ulagapriya and Pushpaga 2021; Veganzones, Sèvevin, and Chêbi 2021; Vellamch eti and Singh 2020; Wagle, Yang, and Benslimane 2017; Zelenko, Fedorova, and Chekizov 2017; Zhao et al. 2012, 2013) |
| 9.  | Discriminant analysis (DA) | Linear discriminant analysis (LDA) Multiple discriminant analysis (MDA) | The features combination usage for difference representation between groups, i.e., separating two or more classes. For example, LDA selects a new dimension that gives maximum separation between classes and minimum variance for each class. | PLS-DA (Ben Jabeur, Ste, and Aramona 2022; Mselmi, Lahiani, and Hamza 2017); Quadratic DA (Mousavi and Lin 2020); Zelenko, Fedorova, and Chekizov 2017 |
| 10. | Gaussian processes (GP) | A stochastic process governs the properties of functions (Rasmussen and Williams 2006) | Multivariate Gaussian (Fan, Liu, and Chen 2017); Normalized Gaussian RBF (Cleofas-Sánchez et al. 2016) Dak-GMLPE (Zhang et al. 2021); GA-Fuzzy (Huang and Yen 2019); GA-MLP (Zhang et al. 2021); Genetic programming (GP) (Mora García et al. 2008); Rough set with genetic algorithm (Achariya and Rath 2021) | (Antunes, Ribeiro, and Pereira 2017; Cleofas-Sánchez et al. 2016; Fan, Liu, and Chen 2017) |
| 11. | Genetic algorithm (GA) | The natural selection approach for optimization or search issues. Biological evolution has been driving force of GA, which consists of tree main operations: selection, crossover, mutation. | — | (Achariya and Rath 2021; Huang and Yen 2019); Mora García et al. 2008; Yang and Yang 2020) |
| 12. | Hazard analysis (HA) | Hazard analysis consists of two time functions, which are called survival and default functions. The survival function shows the probability of survival beyond time $t$, while the default function shows probability of failure at time $t$, which means company has survived until that point in time. | — | (Alam, Gao, and Jone 2021; Almalki et al. 2021; Escribano-Navas and Geman 2021) |
| No. | Method                           | Definition                                                                 | Source                                                                 |
|-----|----------------------------------|---------------------------------------------------------------------------|----------------------------------------------------------------------|
| 13  | k-Nearest neighbor (k-NN)        | A non-parametric classifier that determines the class label for each unseen instance by a majority vote of its neighbors. The k is a number of nearest neighbors attended in the voting process. | (Abdullah et al. 2021; Al-Milli, Hudaib, and Obaid 2021; Alijani et al. 2020; Garcia, Marqués, and Sánchez 2019; Hajeck et al. 2018; Jiang et al. 2018; Liang et al. 2018; Maftei et al. 2019; Saieh, Moukhaibo, and Zadeh 2016; Simić and Zadeh 2016; Tobback et al. 2017; Zelenkov, Fedorova, and Chekrizov 2017; Abdullah et al. 2021; Al-Milli, Hudaib, and Obaid 2021; Alijani et al. 2020; Garcia, Marqués, and Sánchez 2019; Hajeck et al. 2018; Jiang et al. 2018; Liang et al. 2018; Maftei et al. 2019; Saieh, Moukhaibo, and Zadeh 2016; Simić and Zadeh 2016; Tobback et al. 2017; Zelenkov, Fedorova, and Chekrizov 2017) |
| 14  | Linear regression (LR)          | The linear approach for relationship modelling between dependent and independent variables. The method usage depends on the number of independent variables used in the model (accordingly one or more than one). | (Aalbers et al. 2019; Boubaker et al. 2020; Dumitrescu, El Hefnawy, and Zakriya 2020; Mathew, Ibrahim, and Archbold 2016; Ye 2021) |
| No. | Method | Definition | Method modification | Source |
|-----|--------|------------|---------------------|--------|
| 15. | Logistic regression (LR) | A logistic function is used to model a binary dependent variable | Kernel ridge regression (KRR) (Shen et al. 2020); Logit regression tree (Andreano et al. 2018); Multinomial logistic regression (Hernandez Timoco, Holmes, and Wilson 2018; Letizia and Lillo 2019); Panel LR (Ali et al. 2021; Oz and Yelkenci 2017; Suçoziro, Arcuri, and Costanzo 2019; Udin, Khan, and Javid 2017); Partial Least Squares LR (Ben Jabeur 2017); Probit model (Balasubramanian et al. 2019; Cooper and Uzun 2019; Oz and Simge-Mugan 2018) | (Ahmad 2019; Ali-Mill, Hudaib, and Obeid 2021; Ali et al. 2021; Almaskati et al. 2021; Andreano et al. 2018; Antunes, Ribeiro, and Pereira 2017; Ashraf, Felix, and Serracquerio 2021; Awwad and Razia 2021; Balasubramanian et al. 2019; Barboza, Kimura, and Altman 2017; Behr and Weinblat 2017; Ben Jabeur 2017; Ben Jabeur, Stef, and Carmona 2022; Bravo-Urquiza and Moreno-Ureba 2021; Cenciarelli, Greco, and Allegrini 2018; Charalambous, Marrzoukos, and Tsoukias 2022; Chen et al. 2021; Chiou, Lo, and Wu 2017; Choi, Son, and Kim 2018; Geóllis-Sánchez et al. 2016; Cooper and Uzun 2019; Ciosato, Domenech, and Liberati 2021; Da et al. 2022; Dararat et al. 2016; Dogan, Köçak, and Arat 2022; du Jardin 2017, 2018; Freitas Cardoso, Piresco, and Barboza 2019; García and Herrero 2021; Hernandez Timoco, Holmes, and Wilson 2018; Mosuka 2019; Hu 2020; Huang et al. 2017, 2019; Jabeur et al. 2021; Jiang et al. 2021; Jinfalí 2020; Kamalirezaei et al. 2020; Kanojia and Gupta 2022; Kim, Cho, and Ryu 2021; Kim, Mun, and Bae 2018; Letizia and Lillo 2019; Li and Fan 2019; Li et al. 2021; Lin and Dong 2018; Mai et al. 2019; Mousavi and Lin 2020; Miselmi, Lahiani, and Hamza 2017; Nyitai 2019; Nyitai and Virág 2019; Olsen and Tamm 2017; Oz and Yelkenci 2017; Park et al. 2021; Perboli and Arabnehzad 2021; Pham Vo Ninh, Do Thanh, and Vo Hong 2018; Putri and Dhini 2019; Qian et al. 2022; Rahayu and Suhartanto 2020; Ravula 2021; Regenburg and Setz 2021; Ren, Lu, and Yang 2021; Richardson, Lantis, and Taylor 2015; Roumans, Nwankpa, and Tanniru 2020; Sayari et al. 2017; Shahwan and Hlabi 2020; Shen et al. 2020; Sisodia and Verma 2018; Smith and Alvarez 2022; Son et al. 2019; Sou et al. 2020; Stef and Zenou 2021; Succurro, Arcuri, and Costanzo 2019; Sun et al. 2017; Séverin and Veganzones 2021; Sivas and Lukisikus 2019; Tsai et al. 2021; Udin, Khan, and Javid 2017; Veganzones and Séverin 2018; Veganzones, Séverin, and Chilibi 2021; Volkov, Benoit, and Van den Poel 2017; Wagle, Yang, and Benslimane 2017; Yazdanfar and Ohman 2020; Zelenkov and Volodarskiy 2021; Zelenkov, Fedorova, and Chekrizov 2017; Zhao et al. 2022; Zhou 2013) |
| No. | Method            | Definition                                                                                                                                                                                                 | Method modification                                           | Source                                                                                     |
|-----|-------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------|--------------------------------------------------------------------------------------------|
| 16  | Naive Bayes       | Classification algorithm that is based on the statistical Bayes theorem, along with the assumption of feature independence. Naive Bayes determines the instance class by the probability calculation for the instance belonging in the certain class. | Gaussian Naive Bayes (Rahayu and Suhartanto 2020)             | (Abdulllah 2021; Chen et al. 2021; Cho, Son, and Kim 2018; Cleofas-Sánchez et al. 2016; Fanis et al. 2020; Hájek 2018; Liang et al. 2018; Mousavi and Lin 2020; Rahayu and Suhartanto 2020; Roumani, Nwankpa, and Taminru 2020; Salehi, Mousavi Shiri, and Bolandasafer Pasikhani 2016; Shen et al. 2020; Wagle, Yang, and Benslimane 2017; Zelenkov, Fedorova, and Chekrizov 2017) |
| 17  | Random Forest (RF)| The type of ensemble estimator method which consist of creating multi-decision trees using various samples from the original data set. Each tree in RF is generated from a bootstrap sample of the data, and a random sample of predictors is inspected at each split. The classification class is determined by the majority voting from the decision trees. | Balanced Random Forest (Gnip and Drotár 2019); Oblique random forests (obRF) (Shen et al. 2020); Random Survival Forest (RSF) (Zelenkov 2020); Rotation forest (du Jardin 2017, 2021b, 2021c; Fais et al. 2020) | (Ajawazneh et al. 2021; Angenent, Barata, and Takes 2020; Barboza, Kimura, and Altman 2017; Behr and Weinblat 2017; Chang 2019; Da et al. 2022; du Jardin 2017, 2021a, 2021b, 2021c; Fan, Liu, and Chen 2017; Fanis et al. 2020; Gnip and Drotár 2019; Huang et al. 2017; Jabeur et al. 2021; Jiang et al. 2021; Jindal 2020; Joshi, Ramesh, and Tahsildar 2018; Keya et al. 2021; Kim, Cho, and Ryu 2021; Li et al. 2018, 2019; Mousavi and Lin 2020; Perboli and Arabnezhad 2021; Qian et al. 2022; Shen et al. 2020; Sisodia and Verma 2018; Smith and Alvarez 2022; Smiti and Soui 2020; Son et al. 2019; Soui et al. 2020; Sun et al. 2017; Veganzones and Sévein 2018; Vellamcheti and Singh 2020; Volkov, Benoit, and Van den Poel 2017; Ye 2021; Zelenkov 2020; Zelenkov and Volkodaviy 2021; Zelenkov, Fedorova, and Chekrizov 2017; Zhao et al. 2022) |

(Continued)
| No. | Method | Definition | Method modification | Source |
|-----|--------|------------|---------------------|--------|
| 18. | Support vector machine (SVM) | SVM uses high-dimensional feature space for class separation by the identification of optimal separating hyperplane (decision boundary line). SVM is applied for linearly (separable by a linear hyperplane) and non-linearly separable data. The SVM approach uses quadratic programming to find unique solutions to the idea of structural risk reduction, which tries to lower the boundaries of misclassification errors by generating an optimal separating hyperplane in a high-dimensional feature space. | ADABoost-SVM (Sun et al. 2017); ADASVM-TW (Sun et al. 2017, 2020); Bagged-pSVM (Chen, Chen, and Shi 2020); Boosted-pSVM (Chen, Chen, and Shi 2020); DBN – SVM (Huang and Yan 2019); DO-SVM (Kim, Mun, and Bae 2018); OS-SVM (Wang et al. 2020); PLS-SVM (Mselmi, Lahiani, and Hamza 2017); Relevance vector machine (RVM) (Lin and Hsu 2017); SMOTE-SVM (Wang et al. 2020); Timeboost-SVM (Sun et al. 2017); US-SVM (Wang et al. 2020) | (Abdullah 2021; Al-Milli, Hudaib, and Obied 2021; Aljawazneh et al. 2021; Antunes, Ribeiro, and Perera 2017; Barbosa, Kimura, and Altman 2017; Ben Jabeur, Stef, and Camrora 2022; Chang 2019; Chen, Chen, and Shi 2020; Cheng, Chang, and Yang 2018; Choi, Son, and Kim 2018; Oeufa-Sánchez et al. 2016; Da et al. 2022; Dogan, Koçak, and Atan 2022; du Jardin 2017, 2018; Horak, Vítková, and Sušer 2020; Hosaka et al. 2019; Hu, 2020; Huang and Yan 2019; Huang et al. 2017, 2017; Hujek 2018; Jabbari et al. 2021; Kim, Cho, and Ryu 2021; Kim, Mun, and Bae 2018; Li et al. 2018; Lin and Hsu 2017; Lu et al. 2014; Mai et al. 2019; Mousavi and Lin 2020; Mselemi, Lahiani, and Hamza 2017; Prak-CHMielewski 2021; Qian et al. 2022; Rahayu and Suhartanto 2020; Ren, Lu, and Yang 2021; Salehi, Mousavi Shiri, and Bolandraftar Pasikhan 2016; Shen et al. 2020; Sisodia and Verma 2018; Smith and Alvarez 2022; Smiti and Soui 2020; Soui et al. 2020; Sun et al. 2017, 2020, 2021; Súevén and Veganzones 2021; Tobback et al. 2017; Tsai and Wang 2017; Tsai et al. 2021; Veganzones and Súevén 2018; Veganzones, Súevén, and Chlíb 2021; Vellamcheti and Singh 2020; Volkov, Benoit, and Van den Poel 2017; Wagle, Yang, and Benslimane 2017; Wang et al. 2020; Ye 2021; Zelenkov, Fedorova, and Chelezenov 2017; Zhao et al. 2022; Zhou 2013; Zoríčák et al. 2020) (Quenniche, Pérez-Gladish, and Boulyah 2018) |
| 19. | TOPSIS | Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) provides ranking alternatives scores, which is known as the positive and the negative ideal solutions, and is based on geometric distance calculation. | - | (Quenniche et al. 2021) |
| 20. | VIKOR | VIKOR is a multi-criteria method created for the ranking a variety of options. VIKOR is designed to choose the compromise solution that is closest to the ideal. | - | (Quenniche et al. 2021) |

**Deep learning models**

| No. | Method | Definition | Method modification | Source |
|-----|--------|------------|---------------------|--------|
| 21. | Convolutional neural network (ConvNet/CNN) | CNN is deep learning architecture that learns directly from data, without additional need for feature extraction. CNN architecture consists of convolution, pooling, and fully connected layers, which are used for automatic and adaptive learn of features for the classification tasks. | Deep Grassmannian Network (GrNet) (Alam, Gao, and Jones 2021); Dependency Sensitive Convolutional Neural Networks (DSCNNs) (Ahmad et al. 2018) | (Aldri et al. 2019; Ahmadi et al. 2018; Alam, Gao, and Jones 2021; Hosaka 2019; Mai et al. 2019; Xu, Fu, and Pan 2019) |

(Continued)
| No. | Method                                      | Definition                                                                                                                                                                                                 | Method modification | Source                                                                 |
|-----|---------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------|------------------------------------------------------------------------|
| 22. | Deep Belief Network (DBN)                   | The strength of DBN is its capacity to recreate both the input and learning feature vectors using a layer-by-layer learning technique. Each layer of a DBN consists of Restricted Boltzmann Machines (RBM). The neurons between different layers are fully connected, and the neurons in the same layer are not connected. |                     | (Aljawazneh et al. 2021)                                              |
| 23. | Deep Boltzmann machines (DBM)               | DBM is comprised of Restricted Boltzmann Machines (RBM). The DBM units in the same layer have no direct connections. The estimated gradient of a variational lower bound on the likelihood goal can be used to optimize the DBM parameters of all layers at the same time. | DBN-SVM (Huang and Yen 2019) | (Huang and Yen 2019)                                                  |
| 24. | Extreme learning machine (ELM)              | The extreme learning machine (ELM) is a single hidden layer feedforward network. The weights between the input and hidden layers are assigned at random using a normal distribution, and the weights between the hidden and output layers are learned in a single step using a pseudo-inverse technique in ELM. During the training, the output weights are solved from regularized least squares. |                     | (du Jardin 2017, 2018; Séverin and Veganzones 2021; Veganzones, Séverin, and Chlibi 2021; Zhang et al. 2021) |
| 25. | Long Short-Term Memory (LSTM)               | LSTM advanced or extension of RNN. LSTM processes information in a sequential manner, but there is a memory cell that remembers and forgets information. Three multiplication units regulate the flow of information in each memory cell: input gate, output gate, and forget gate. The three gates control the flow of information into and out of the cell, and the cell recalls values across arbitrary timestamps. | Bi-LSTM (Li et al. 2021); Dependency Sensitive RNNSA (Abdi et al. 2019) | (Abdi et al. 2019; Aljawazneh et al. 2021; Dai et al. 2022; Kim, Cho, and Ryu 2021) |
| 26. | Recurrent Neural Network                    | An agent learns from interactions with its environment in discrete time steps to update its mapping between the observed state and the probability of selecting possible actions in a reinforcement learning process. Q-learning, as a typical reinforcement learning approach, imitates human behavior by taking actions in the environment to maximize long-term rewards. |                     | (Abdi et al. 2019; Kim, Cho, and Ryu 2021)                             |
| 27. | Recursive deep learning                     | An RNN has feedback connections, which can be between hidden units or from the output to the hidden units. It is able to process the sequential inputs by having a recurrent hidden state whose activation at each step depends on that of the previous steps. |                     | (Abdi et al. 2019)                                                    |

**Unsupervised machine learning methods**

1. **K-means**
   - K-means aggregates data points based on certain similarities (nearest mean, cluster centers or centroid) into k clusters.  
   - Fuzzy C-means (Chou, Hsieh, and Qiu 2017)  
   - (Chou, Hsieh, and Qiu 2017)
| No. | Method                        | Definition                                                                 | Method modification | Source                                                                 |
|-----|-------------------------------|---------------------------------------------------------------------------|--------------------|------------------------------------------------------------------------|
| 2.  | Isolation Forest (IF)         | Isolation Forest assumes that anomaly has two quantitative features: 1) a small minority of examples, and 2) their feature-values are different from a normal class examples. Isolation Forest applies iTree (binary tree) for effective splitting and isolating examples. The anomaly scores generated from the path length of each observed example from root node to node in which the example is isolated are used to create the final model. | -                  | (Fan, Liu, and Chen 2017; Gnip and Drotár 2019; Zoričák et al. 2020) |
| 3.  | Least-Squares Anomaly Detection (LSAD) | LSAD is based on the idea of One-Class SVM, which uses a hypersphere to encompass all the instances. Though, LSAD is used an extended application of the least squares probabilistic classification for a lost function. |                    | (Zoričák et al. 2020)                                               |
| 4.  | One-Class SVM (OCSVM)         | OCSVM aim is to make separation between majority (training) class instances and outliers instances, which are points laying outside captured characteristics of training instances. | -                  | (Fan, Liu, and Chen 2017; Gnip and Drotár 2019; Zoričák et al. 2020) |

**Deep learning models**

| No. | Method | Definition                                                                 | Method modification | Source                                                                 |
|-----|--------|---------------------------------------------------------------------------|--------------------|------------------------------------------------------------------------|
| 5.  | Auto-encoder | An Autoencoder is a neural network type, where the input and the output are the same. The autoencoder consists of: input layer, one or more hidden layers (encoding layers), and output layer (decoding layer). The autoencoder’s primary goal is to lower the dimensionality of the input data by reducing noise. | Stacked Auto-encoder (Soui et al. 2020) | (Smiti and Soui 2020; Soui et al. 2020) |
The application of these methods in the financial distress context was found only in 2021–2022 studies.

**Discussion**

The scope of this study is limited to the period 2017–2022 February, which helps to identify under-explored research fields in financial distress and bankruptcy context. The separation between "Financial Distress" and "Bankruptcy" can be addressed as the "gray" area due to unclear "Financial distress" class indicator. For this reason, author’s results comparison is problematic, because the main class indicator is different. In contrast, the concept "Bankruptcy" has the same understanding as class indicator, but it is too late indication for decision-makers. Analyzing the used data source’s it is noticeable the researchers choose open data sources (Stock exchange, Polish data set). Unfortunately, the authors do not provide data pre-processing steps or present them succinctly, e.g. data were pre-processed, data were normalized, five feature selection methods were used, etc. This information limits ability to identify common data pre-processing steps in Financial distress and bankruptcy context. Therefore, it is needed further analysis in this context.

"Financial distress” topic is challenging for artificial intelligence experts due to existing issues with high data dimensionality, imbalance, sentiment analysis, outliers. These problems author’s analyses separately by combining the most appropriate methodology for their analyzed data. However, at least dimensionality and imbalance pragmatic’s have to be addressed in each study in order to get comparable results.

This study seek to bring knowledge and key insights for further researchers by filling the gaps discussed in previous literature reviews. However, further work can be developed in the directions named by other authors, which were...
not discussed in this article: dynamic models applications (Chen, Ribeiro, and Chen 2016; Matenda et al. 2021); switching from binary classification (Chen, Ribeiro, and Chen 2016); the tools suitable for different domains of datasets analyses (Bhatore, Mohan, and Reddy 2020); users knowledge integration in black-box models (Chen, Ribeiro, and Chen 2016).

Finally, one of the main literature analysis limitations is the lack of dynamic view incorporation in the used methods analysis. For example, to know a timeline, which methods are now at peak, or which are less applicable. Another interesting direction of literature review would be the analysis of ensembles. Studies have shown that the author’s design ensembles of classifiers. In further financial distress scope review would be interesting to know, which methods or their modifications usually fall into voting ensembles.

**Conclusion**

The main aim of this study is to identify the context of “Financial distress” and its usage of machine-learning methods, including additional aspects related to it, such as imbalance, dimensionality, etc. This study analyzed 232 articles, which most of which are Financial distress and Bankruptcy content research from the period 2017 to 2022 February using the guidelines of the PRISMA methodology.

Our main findings are as follows:

1. Data researchers commonly choose publicly available datasets, e. g. public companies or open data sets such as Polish, Spanish, or Japanese. Consequently, the results of the study are difficult to compare due to the different analysis periods and the inclusion of new data (indicators, sources, etc.) in the analysis.

2. Data pre-processing steps in financial distress and bankruptcy context are often forgotten or succinctly present. Information on data normalization provided about 14% of analyzed studies. The commonly used functions are normalization and Z-score.

3. The authors used 27 supervised and 5 unsupervised methods, of which 8 belong to of Deep learning methods subgroup. The most popular method remains in the Logistic regression for the following reasons: 1) one of the first methods applied in the bankruptcy context (Altman’s z-score model is based on LR); 2) popular in social science for the evaluation of analyzed variables; 3) one of the main method used in the efficiency comparison with other machine-learning methods. Other commonly used algorithms are ANN, SVM, Decision tree, Random forest, Boosting (AdaBoost, XGBoost), etc.

4. The most popular data preprocessing are dimensionality reduction and data balancing, which are becoming essential data pre-processing steps.
However, each of these topics contains under-explored research fields for future development.

(5) Lastly, we analyzed evaluation performance metrics suitable for labels. For better evaluation of the methods, researchers use three to five metrics. The common evaluation matrix is accuracy and AUC, then recall, specificity, type I error, etc. The application of K-S, MCC, H-measure, and BS methods in the financial distress context was detected only in 2021-2022 studies.

**Disclosure statement**

No potential conflict of interest was reported by the author(s).

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