Neural Networks for Financial Stability of Economic System

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Abstract

In the present economic landscape, securing the monetary steadiness of economic structures, augmenting their financial efficacy, and competitiveness necessitates the scrutiny of the financial state of enterprises, along with predicting their future progressions utilizing contemporary technologies and models. In acquiring information regarding the fluctuations of significant financial hazards, machine and deep learning techniques can offer more precise projections founded on vast-dimensional datasets, authorize the employment of unbalanced datasets, and preserve all accessible information.

The aim of this investigation is to construct a neural network-driven model for assessing the financial stability of economic systems. The study employed financial and economic activity data from 12,573 enterprises and opted for specific financial ratios that generate a significant set of indicators suitable for forecasting the financial stability of economic systems. Both feedforward neural networks (FNN) and recurrent neural networks (RNN) were utilized in the model development. The constructed models were evaluated using established data science techniques.

Keywords

Financial stability, bankruptcy, company, neural network, financial ratios

1. Introduction

In "Society 5.0," advanced technologies such as robotics, artificial intelligence, cloud computing, blockchain, and high-speed networks are utilized across all aspects of social life, not solely for the purpose of attaining economic advantages, but also to ensure the well-being of every citizen. This approach aligns with the European Commission [1] priority of a people-centered economy, which entails adopting a human-focused approach to digital technologies.

The rapid expansion of financial technology has not only provided numerous conveniences for individuals in their production and daily lives but also engenders significant risks to corporate and individual finances. Despite increasing the adaptability and inclusiveness of financial systems, financial technologies can hasten the propagation of financial risks and pose major challenges to financial security. Therefore, more researchers are utilizing machine learning techniques to forecast the financial stability of economic systems. It is important to use efficient models for evaluating the financial stability of economic systems based on machine learning, particularly deep learning, to prevent financial risks.

Bankruptcy forecasting is a significant research task that provides essential information about a company's financial health, identifying the risk of bankruptcy. The accurate prediction of a company's likelihood of bankruptcy is essential for investors, creditors, and financial analysts in investment

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decisions, assessing credit risks, and complying with regulatory requirements. Additionally, early detection of financial risks can prevent companies from facing bankruptcy by implementing corrective measures.

Bankruptcy forecasting models assess the financial impact of various factors on a company's health and help in making investment, lending, and regulatory compliance decisions. Furthermore, the increasing complexity of business operations resulting from globalization has led to the evolution of financial risks faced by companies. Therefore, continued research is necessary to develop more precise and reliable bankruptcy prediction models that can adapt to the changing economic environment. Consequently, bankruptcy forecasting is a critical area of research that provides vital information about a company's financial well-being and influences important business decisions, especially in today's economic climate.

Neural networks are effective in bankruptcy prediction as they can learn the complex relationships and patterns among variables, employing them to make accurate predictions. In particular, when combined with vast datasets, neural networks can identify sophisticated patterns and relationships that other models may overlook.

Furthermore, neural networks are adaptable and can learn from different types of data, making them useful in a variety of contexts. They are also able to learn from past data and adjust their predictions when new data becomes available.

In general, the ability of neural networks to learn complex relationships between variables, adapt to different types of data, and adjust their forecasts based on new data makes them an effective tool in predicting the financial stability of economic systems.

2. Related Works

This research is located at the intersection of finance and machine deep learning technologies. Currently, there are different approaches to determining the financial stability of economic systems, namely using machine learning or deep learning, and comparing these tools. There are many methods available to measure the financial health of a business.

The construction of the CART decision tree for forecasting the financial stability of economic systems is presented in the works [2]; [3], and has reached an increasingly high level of complexity and accuracy: in such approaches as Multiple Additive Regression Trees (MART) [4], and Random Forest [5].

Altman's Z-indicator is a reliable tool for predicting the possibility of bankruptcy of a production organization. Multiple discriminant analysis (MDA) is a useful tool in such situations [3]. Article [6] presents the results of applying various Z-score models and calculating the probability of bankruptcy on a sample of agricultural companies listed on the Belgrade Stock Exchange in 2015-2019.

Standard approaches are usually unable to fully understand the dynamics of financial risks in economic systems in which structural relationships interact in a non-linear and state-dependent manner. Today, more and more researchers are using more complex network approaches to determine the financial stability of economic systems. The paper [7] compares a set of machine learning methods with network approaches, showing that machine learning models mostly outperform logistic regression in out-of-sample predictions and forecasts. The authors [8] have developed a self-organizing map of financial stability, where countries can be placed depending on whether they are in a pre-crisis, crisis, post-crisis, or calm state. They also show that this tool performs better or as well as a logit model in classifying in-sample data and predicting global financial crisis out-of-sample.

The authors [9] presented a classification of the authors' research according to the adopted experimental models, and then reviewed the research achievements of machine deep learning for predicting bankruptcy by category. They reviewed several classical models, such as multivariate discriminant analysis, logistic regression, ensemble method, and support vector machines, as well as basic deep learning methods, such as Deep Belief Network and Convolutional Neural Network. The use of linguistic systems for risk identification and control is discussed in works [10]; [11], which can be useful in an indicative assessment of the stability of economic systems. To build a neural network for predicting financial stability, the authors [12] – [14] use different programming languages. The advantages of using Python to create a neural network for detecting the financial stability of economic systems are described in works [14] – [19].

Another important task in the process of building a neural network model is to determine the input data of the study. The works [2]; [11]; [13]; [15] consider various statistical data used to build a neural network model for determining financial stability.

Particular attention is paid to the organizational aspects of building a neural network, namely, the stages of creating a neural network to identify the financial stability of economic systems [14]; [16] – [19], as well as the purposes of its use [15]; [20] – [29].

3. Bankruptcy prediction models based on neural networks

Bankruptcy prediction models are statistical data-driven models that analyze a company's financial data to predict the probability of its bankruptcy in the future. These models can be useful for various purposes [15]; [20]; [21]; [30]:

1. Early warning: bankruptcy prediction models can provide early warning of potential financial instability. Vulnerability risks identify companies with a high risk of insolvency, and stakeholders such as investors, creditors, and suppliers can take appropriate measures to minimize their risks [22].

2. Credit risk assessment: Lenders can use bankruptcy prediction models to assess the creditworthiness of potential borrowers. By analyzing a company's financial data, lenders can make more informed decisions about whether to grant a loan and on what terms [23]; [24].

3. Investment management: investors can use bankruptcy prediction models to make investment decisions. By identifying companies with a high risk of bankruptcy, investors can avoid investing in these companies or take short positions to profit from their potential fall [25].

4. Restructuring and recovery planning: companies facing bankruptcy can use bankruptcy prediction models to identify the root causes of their financial problems and develop a restructuring or recovery plan [15]; [26].

5. Compliance: regulators can use bankruptcy prediction models to identify companies that are in financial distress and take appropriate measures to protect consumers, investors and other stakeholders [15].

6. Supply chain management: companies can use bankruptcy prediction models to determine the financial condition of their suppliers and mitigate risks in the supply chain. By monitoring the financial stability of suppliers, companies can take proactive measures to mitigate potential disruptions in their operations [27]; [28].

7. Mergers and acquisitions: bankruptcy prediction models can be used to assess the financial condition of target companies during mergers and acquisitions. By analyzing the financial data of the target company, buyers can make more informed decisions about whether to proceed with the transaction and what the terms of the acquisition should be [29].

The selection of tools for building models depends on the goals of financial stability forecasting. Depending on the input data and output results, it is necessary to choose a programming language and configure all things properly to obtain the highest efficiency. There are several programming languages that can be used to develop neural networks for bankruptcy prediction [12]; [13]; [14], in particular:

1. Python: has many libraries and frameworks specifically designed for the development of neural networks, such as TensorFlow, Keras and PyTorch.

2. R: used for statistical analysis and has many packages for building neural networks, such as caret and nnet.

3. MATLAB: has a set of tools for developing and analyzing neural networks, including the Neural Network Toolbox.

4. Java: has several libraries and frameworks for building neural networks, such as DeepLearning4J and Neuroph.

5. C++: can be used to develop efficient neural network models, especially for large data sets.

3.1. Python

The choice of programming language depends on several factors, including the specific requirements of the project, the preferred development environment, and the availability of appropriate libraries and frameworks. However, Python is a popular choice for neural network development due to its simplicity, readability, and the availability of many high-quality machine learning libraries and frameworks [16].

Building a neural network to predict bankruptcy in Python is a complex process that requires a deep understanding of both machine learning and financial analysis [14]. The general steps to create a neural network to detect the financial stability of economic systems are as follows:

1. Data preparation: It starts with collecting data on enterprises, including their financial performance for the previous year and information on which ones went bankrupt. This data will need to be cleaned, pre-processed, and transformed into a format suitable for machine learning.
2. Feature selection: identifying the most relevant features for predicting bankruptcy. This usually involves the use of financial ratios such as liquidity, profitability, and solvency. The selection of features can be done using statistical methods such as correlation analysis or principal component analysis [17].
3. Splitting the data into training and test sets: allows you to train a neural network on a subset of the data and evaluate its performance on a separate subset.
4. Building a neural network: using Python machine learning libraries such as TensorFlow or Keras to build a neural network for bankruptcy prediction. The architecture of the neural network will depend on the specific problem, but a common approach is to use a deep learning model with multiple layers [14].
5. Training the neural network on training data using an appropriate optimization algorithm, such as stochastic gradient descent, allows you to track the performance of the neural network on training data and adjust hyperparameters if necessary [18].
6. Evaluation of the model on test data: it is necessary to calculate such indicators as accuracy, precision, recall, and F1 to determine how well the model performs.
7. Model optimization: techniques such as cross-validation, hyperparameter tuning, and functional engineering to optimize the neural network performance allow for optimizing the model's performance.
8. Prediction: the generated neural network can be used to make predictions based on new data to predict the bankruptcy of companies that have not been seen before [19].

Overall, building a neural network for bankruptcy prediction in Python is a complex process that requires a deep understanding of both financial analysis and machine learning. However, with careful data preparation, feature selection, model building, and optimization, a highly accurate bankruptcy prediction model can be developed that can be used by investors and financial institutions to make better investment decisions [14].

3.1.1. Feedforward neural networks (FNN) та recurrent neural networks (RNN)

This research utilized feedforward neural networks (FNNs) and recurrent neural networks (RNNs) due to their distinctive features and benefits expounded by other authors [31] – [34]:

1. Feedforward neural networks (FNNs) are a type of neural network that transmits input data through multiple layers, with each layer comprising a set of neurons that perform linear or nonlinear transformations on the input data. FNNs are well-suited for bankruptcy prediction tasks as they can learn complex, nonlinear relationships between inputs and outputs, specifically the probability of bankruptcy. This versatility is beneficial for modeling a range of factors that may impact bankruptcy risk, such as financial ratios, economic activity, and non-financial data [35].
2. Recurrent neural networks (RNNs) are a type of neural network capable of processing sequential data where each input signal is dependent on the preceding one. RNNs are particularly suitable for bankruptcy prediction tasks because they can learn temporal relationships between inputs, which can be valuable when analyzing time series data such as financial data over time. Furthermore, RNNs may also be useful for predicting the bankruptcy of companies with a history of financial difficulties or financial performance that changes over time [36].

The selection of the appropriate neural network type depends on the specific task requirements, such as type of input data and the desired level of model complexity. In addition, RNNs can be extended with long short-term memory (LSTM) and closed recurrent units (GRU). They are widely used in natural language processing, speech recognition, and time series analysis. Both LSTM and GRU networks are designed to solve the vanishing gradient problem that can occur when training RNNs on long data sequences.

LSTM networks were introduced to solve the problem of vanishing gradients in RNNs by adding "memory cells" that can remember information over a long period of time. The LSTM unit consists of several gates and memory cells that control the flow of information. "Gates", including input and output gates, regulate the flow of information into and out of a memory cell. The input gates control how much new information is added to the memory cell, the forgetting gate determines how much information is removed from the memory cell, and the output gates regulate how much information is used for prediction. This architecture allows the LSTM network to selectively remember or forget information over time, which is especially useful when processing long data sequences. LSTM networks have proven to be effective in a variety of applications, including speech recognition, natural language processing, and time series forecasting [36]; [37].

Gated Recurrent Unit (GRU) is another type of RNN that is similar to LSTMs but has a simpler architecture. Unlike the multiple gates in LSTMs, GRU units contain only two gates: an update gate and a reset gate. The refresh gate controls the amount of new information that is added to the hidden state, and the reset gate controls the amount of old information that is forgotten from the hidden state. The simpler architecture of GRUs allows for faster learning and inference compared to LSTMs, while remaining effective at detecting long-term dependencies in input data. GRU networks have been successfully applied in various fields, including language modeling, machine translation, and image captions.

In general, LSTMs and GRUs are two types of recurrent neural networks that are effective at capturing long-term dependencies in input data, with LSTMs being more complex and capable of more accurate memory management, while GRUs have a simpler architecture and are faster to train and execute. The choice of network type will depend on the specific requirements of the task and available resources [37].

4. Experiment

4.1. Dataset Description

Forecasting bankruptcy involves analyzing a large number of financial and non-financial variables to identify companies at risk of financial distress. Traditional statistical methods often face the complexity of these datasets, as there may be many interdependent variables that affect the financial condition of a company [14]; [20].

An analysis of publications on the development of a neural network for predicting bankruptcy [11] – [15] allowed us to summarize several types of input data that can be used to build a model, in particular:

1. Financial ratios are often used as inputs in bankruptcy prediction models because they allow for a quantitative assessment of a company's financial condition. The most common financial ratios include liquidity, solvency, profitability, and efficiency ratios [2]; [13].

2. Market data, such as stock prices, trading volumes and other market indicators, can also be used as inputs to bankruptcy prediction models. These data can provide insight into how the market perceives the financial condition of a company.

3. Accounting data, such as balance sheets, income statements, and cash flow statements, can also be used as inputs to bankruptcy prediction models. These data can provide a more detailed view of a company's financial condition than financial ratios alone.

4. Non-financial data such as news, industry reports, and social media sentiment can also be used as inputs to bankruptcy prediction models. These data can provide insight into factors that may affect a company's financial condition but are not directly related to its financial statements [11].

5. Industry data, such as production volumes, orders, or inventory levels, can be used to understand the factors that affect the financial condition of companies operating in certain industries.

The choice of inputs depends on the specific requirements of the bankruptcy prediction model and the availability of relevant data. In practice, a combination of these inputs is often used to build a comprehensive bankruptcy prediction model, which allows to accurately identify companies at risk of financial instability.

The author suggests building a model based on financial ratios and types of economic activity, which are two common types of input data used in bankruptcy prediction models. There are several reasons why these data can be valuable for bankruptcy forecasting:

1. Financial ratios provide a quantitative view of a company's financial condition: they are calculated based on the company's financial statements, which allows comparing the company's financial performance with other companies or with industry benchmarks. By using financial ratios as input data to bankruptcy prediction models, it is possible to obtain a more quantitative view of the company's financial condition, which is often a key factor in determining the risk of bankruptcy [13]; [15].

2. Financial ratios provide a standardized way of comparing companies: they are standardized across companies, making them useful for comparing the financial position of companies in different industries or of different sizes. Such standardization may be useful in developing a comprehensive bankruptcy prediction model that can identify companies at risk of financial instability in different industries [14].

3. The type of economic activity can provide insight into industry-specific factors: this is a categorical input parameter that provides information about the type of industry or sector of the economy in which the company operates. Different industries have different factors that can affect a company's financial position, such as changes in consumer demand or supply chain disruptions. By including the type of economic activity as an input to the bankruptcy prediction model, it is possible to gain insight into these industry factors and adjust the forecasts accordingly [20]; [38].

4. The type of economic activity can help identify macroeconomic trends: it can provide insight into macroeconomic trends that may affect the company's financial condition. For example, companies in industries that are highly dependent on changes in interest rates may be more likely to experience financial difficulties if interest rates rise. Taking into account the type of economic activity as an input factor, it is possible to adjust forecasts based on broader economic trends [13]; [14].

In general, financial ratios and type of economic activity can be valuable inputs to bankruptcy prediction models, allowing us to get a more quantitative view of a company's financial condition and adjust our forecasts based on industry and macroeconomic factors. Therefore, in the process of building neural networks, we selected financial ratios and the Classification of types of economic activity (CTEA) indicator, which characterizes the type of economic activity.

Table 1 describes the financial ratios used in the construction of the neural network for determining the financial stability of economic systems.

Table 1

Financial performance indicators of companies that will be used in the process of building a neural network model are selected

Line code	Description	Line code	Description
1095	Non-current assets	1695	Current liabilities and provisions
1101	Production inventories	1700	Liabilities related to non-current assets held for sale and disposal groups
1160	Current financial investments	1900	Equity and liabilities
1165	Cash and cash equivalents	2000	Net income from sales of products (goods, works, services)
1195	Current assets	2250	Financial expenses
1300	Assets	2290	Financial result before taxation (profit)
1420	Retained earnings (uncovered loss)	2295	Financial result before taxation (loss)

1495	Shareholders' equity	2350	Net financial result (profit)
1595	Long-term liabilities and provisions	2355	Net financial result (loss)

Based on open data [https://data.gov.ua/dataset/24069422-5825-41f6-81f7-89567e5e2ac9] for 2019 and 2020.

The pool of ratios listed is useful for bankruptcy prediction because they provide a comprehensive view of a company's financial health and solvency. The ratios cover a range of financial metrics, including profitability, liquidity, efficiency, and debt management, which are all important indicators of a company's ability to meet its financial obligations. By comparing a company's financial ratios to industry benchmarks and historical trends, investors and analysts can identify warning signs of financial distress and potential bankruptcy risk. Overall, the pool of ratios provides a robust set of financial metrics that can be used as valuable tool for predicting bankruptcy risk (Table 2).

Table 2
Selected financial ratios of companies that will be used in the process of building a neural network model

Ratio	Characteristic	Settlement
The share of assets generated from retained earnings	This ratio indicates the extent to which a company is relying on internally generated funds to finance its growth rather than external borrowing. A higher share of assets generated from retained earnings can indicate a more financially stable company	1420 / 1300
Return on assets calculated on the basis of earnings before interest and taxes	This ratio measures the profitability of a company's assets, regardless of how they are financed. A high return on assets indicates that a company is generating strong profits from its investments	(2290 - 2250) / 1300
The ratio of shareholder capital and liabilities ratio	This ratio indicates the extent to which a company's operations are financed by equity or debt. A higher ratio of shareholder capital to liabilities can indicate a more stable company with a lower risk of bankruptcy	1495 / (1595 + 1695 + 1700)
Asset turnover ratio	This ratio measures how efficiently a company is using its assets to generate revenue. A higher asset turnover ratio can indicate a more profitable and efficient company	2000 / 1300
Ratio of net working capital to total assets	This ratio measures the company's short-term liquidity by comparing its current assets to its current liabilities. A higher ratio can indicate a more liquid and financially stable company.	1195 / 1300
Net profit to assets ratio	This ratio measures the profitability of a company relative to its total assets. A higher ratio can indicate a more profitable and efficient company	(2350 - 2355) / 1300

Ratio of taxable profit to short-term debt	This ratio measures a company's ability to generate profits relative to its short-term debt obligations. A higher ratio can indicate a company that is better able to meet its short-term debt obligations	2290 / 1695
Ratio of highly liquid assets to sales revenue	This ratio measures a company's ability to meet its short-term obligations with highly liquid assets such as cash and marketable securities. A higher ratio can indicate a more liquid and financially stable company	(1160 + 1165) / 2000
Ratio of assets to borrowed funds	This ratio measures the extent to which a company's assets are financed by debt. A higher ratio can indicate a higher level of financial risk and a greater risk of bankruptcy	1300 / (1595 + 1695)
Ratio of inventories to sales revenue	This ratio measures the efficiency of a company's inventory management. A lower ratio can indicate a more efficient and profitable company	(2350 - 2355) / 1300
Return on total capital	This ratio measures the profitability of a company's investments, taking into account both equity and debt financing. A higher return on total capital can indicate a more profitable and efficient company	(2350 - 2355) / 2000
Coverage ratio	This ratio measures a company's ability to meet its interest and debt payments with its earnings. A higher coverage ratio can indicate a lower risk of default and bankruptcy	1101 / 2000
Financial independence ratio	This ratio measures the extent to which a company is reliant on external financing. A higher financial independence ratio can indicate a more financially stable and independent company	2290 / 1900
Ratio of current assets to non-current assets	This ratio measures the proportion of a company's assets that are short-term versus long-term. A higher ratio can indicate a more liquid and financially stable company	1195 / 1695
Ratio of net sales revenue to current liabilities	This ratio measures a company's ability to meet its short-term obligations with its revenue. A higher ratio can indicate a more financially stable and solvent company	1495 / 1900
Balance sheet to net sales revenue ratio	This ratio measures the efficiency of a company's asset management by comparing its balance sheet assets to its net sales revenue. A higher ratio can indicate a more efficient and profitable company	1195 / 1095

Ratio of the difference between current assets and current liabilities to current assets	This ratio measures the liquidity of a company by comparing its current assets to its current liabilities	2000 / 1695
The share of assets generated from retained earnings	This ratio indicates the extent to which a company is relying on internally generated funds to finance its growth rather than external borrowing. A higher share of assets generated from retained earnings can indicate a more financially stable company	1300 / 2000
Return on assets calculated on the basis of earnings before interest and taxes	This ratio measures the profitability of a company's assets, regardless of how they are financed. A high return on assets indicates that a company is generating strong profits from its investments	(1195 + 1695) / 1195

Compiled according to open data [https://data.gov.ua/dataset/24069422-5825-41f6-81f7-89567e5e2ac9] for 2019 and 2020.

Table 3 shows the total number of companies by type of business and their financial statements, which are publicly available and presented on official websites. However, the financial information presented is not uniform, which makes it impossible to make calculations, so the analysis is supplemented with companies from the "other enterprises" section, which contributes to the universalization of calculations.

Table 3

Composition of the sample of business entities of Ukraine

Type of business entity	Number of positions in open data for 2019 and 2020	
	Balance sheet	Statement of financial results
State institutions	26 654	27 167
Banks	84	66
Small enterprises	267 397	267 397
Micro enterprises	197 137	197 137
Other enterprises	18 667	18 315
Total	509 939	510 082

Compiled based on data from [https://data.gov.ua/dataset/24069422-5825-41f6-81f7-89567e5e2ac9]

The financial statements presented in Table 2 are used to analyze the availability and correctness of data and select only a part of the companies that will be used as the basis for building a neural network model. Separately, the following financial statement lines were used as output indicators: 2000 "Net income" and 2190 "Financial result" and the distribution of the selected companies by CTEA, as shown in Table 4.

Our research excludes banking institutions; consequently, subsequent analyses utilized standard reporting codes derived from Forms 1 and 2.

Table 4
Sectoral distribution of the selected enterprises with general aggregated financial indicators of their activity

Sector	Number of companies	Total income (billion UAH)	Total financial result (billion UAH)
Processing industry	3240	1557,45	-10,82
Financial and insurance activities	3081	85,83	35,79
Wholesale and retail trade, repair of motor vehicles	2898	2636,6	31,72
Transportation, warehousing, postal and courier activities	880	422,71	33,49
Professional, scientific and technical activities	849	265,62	-12,42
Agriculture, forestry and fisheries	842	217,39	3,43
Construction	783	163,53	0,59
Total	12573	5349,13	81,78

Based on data from [https://data.gov.ua/dataset/24069422-5825-41f6-81f7-89567e5e2ac9]

As bankruptcy prediction models continue to evolve, the role of neural networks in developing more accurate and reliable models will remain critical. Most previous studies on bankruptcy prediction, including those using machine learning, have used a relatively small datasets and a small number of financial indicators. Therefore, to build a feed-forward neural network (FNN), the input parameters are formed as follows:

1. A total of 12573 companies were selected (Table 4).
2. The financial ratios of companies for 2019 and 2020 were formed (Table 2).
3. The indicator of the CTEA group was added, which was displayed in the form of 20 columns for each CTEA group in a binary format (0 or 1).

In building a recurrent neural network (RNN), the input parameters have the following difference: similar financial ratios for 2019 and 2020 were used, but they were divided into separate groups and presented in the form of a two-dimensional matrix. All coefficients are normalized using the log(x) function, and abnormally large and small values are found using the Z-score and replaced with the maximum permissible values. The confusion matrix and precision are used for the test, which are useful tools for evaluating the performance of machine learning models.

5. Discussions

A confusion matrix is a table that summarizes the performance of a binary classification model by showing the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This is an effective way to evaluate model performance because it provides a clear breakdown of the types of errors made by the model. This can be especially useful in cases where the cost of different types of errors is different, such as in medical diagnosis or fraud detection [39].

Precision is a common evaluation metric that measures the proportion of correctly classified cases out of the total number of cases. It is a simple and intuitive measure of model performance that can be used to compare different models or to evaluate the performance of a single model over time. Precision is often used in cases where the cost of different types of errors is the same, such as in spam filtering or sentiment analysis [40]. Fig. 1 shows the confusion and accuracy matrices for the constructed models of neural networks FNN, RNN with closed recurrent elements, and RNN with long short-term memory.

Together, these two tools provide a comprehensive view of the model's performance, as shown in Fig. 1. The confusion matrix provides detailed information about the types of errors the model makes, while accuracy provides a simple assessment of overall performance. By combining these tools, one can better understand how well a model is performing and identify areas for improvement. However, it is important to note that precision may give false results in cases where the distribution of classes is unbalanced, and in such cases, it is advisable to use other evaluation metrics such as accuracy, recall, and score.

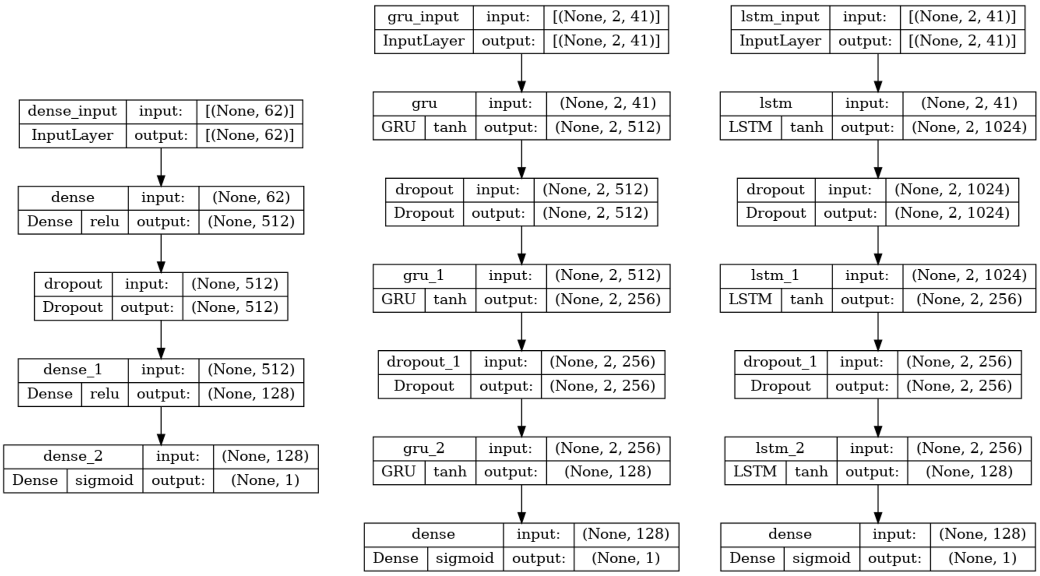

Figure 1: Layers of developed FNN, Gated Recurrent Unit RNN and Long Short-Term Memory RNN

The analysis of the effectiveness of the created models of neural networks FNN, RNN with closed recurrent elements, and RNN with long short-term memory (Fig. 1) was conducted on the basis of a separate test sample representing 20% of all data.

The constructed models are characterized by a medium-term scope, forecasting bankruptcy occurrences within a 2–3-year time horizon.

In machine learning, a dataset is usually split into two parts: a training set and a test set. The training set is used to train the machine learning model. It is a subset of the original dataset that the model uses to learn the underlying patterns in the data. The training set typically contains the input features (e.g., independent variables) and the corresponding output labels (e.g., dependent variable) for each data point. The goal is to train the model to learn the relationship between the input features and the output labels so that it can make accurate predictions on new data.

The test set, on the other hand, is used to evaluate the performance of the trained machine learning model. It is a subset of the original dataset that the model has not seen before. The test set typically contains the input features, but the output labels are withheld. The model then uses the input features to make predictions on the output labels, and the predicted values are compared to the true output labels to measure the model's performance. By using separate training and test sets, we can estimate how well the model generalizes to new, unseen data. This is important because the ultimate goal of the model is to make accurate predictions on new, real-world data that it has not seen during training. By evaluating the model's performance on a test set, we can estimate its ability to generalize and make accurate predictions on new data. The test result is shown in Table 5.

Table 5
Evaluation of the obtained models (%) of FNN, RNN with closed recurrent elements and RNN with long short-term memory

Model	Current	The company's projected state of affairs		Accuracy	Precision	Recall	f1-scores
		stable	bankruptcy				
FNN	stable	82,1%	17,9%	92,55%	97,78%	82,14%	88,49%
	bankruptcy	14,5%	85,5%				
GRU RNN	stable	82,84%	17,16%	88,39%	97,65%	82,79%	88,89%
	bankruptcy	19,74%	80,26%				
LSTM RNN	stable	85,92%	14,08%	85,83%	97,63%	85,75%	90,68%
	bankruptcy	22,37%	77,63%				

The built neural network models of FNN, RNN with closed recurrent elements and RNN with long short-term memory have relatively high-performance evaluation indicators, which indicates that they predict bankruptcy with high probability. This is an important factor for a bankruptcy prediction model, as false positive predictions can have significant consequences.

The FNN model has the highest accuracy, precision, and f1-scores, indicating that it is the best model overall in terms of its ability to make accurate predictions and balance between accuracy and precision.

The GRU RNN and LSTM RNN models have lower precision and f1-scores than the FNN model, but they have higher recall scores. This indicates that these models can better identify actual bankruptcies, but at the expense of a higher number of false positive predictions.

The relatively high false negative (FN) rates for all three models indicate that there is room for improvement in bankruptcy prediction. False negatives indicate that the models fail to identify companies that will go bankrupt, which can have significant consequences for investors and creditors.

In general, the FNN neural network model is the most efficient according to the obtained performance indicators (Table 5). However, it may be useful to further investigate false negative predictions in order to identify areas for improving this model.

6. Conclusions

Bankruptcy prediction models have been significantly improved in recent years by the development of new deep learning techniques, such as neural networks, which has led to significant improvements in their accuracy and reliability. Neural networks are particularly well suited for predicting the financial stability of economic systems due to their ability to process large amounts of data and identify complex patterns and relationships in the data. There is a need for more sophisticated models for predicting the financial stability of economic systems that can handle increasingly complex and diverse data sources, such as social media, web analytics, and alternative data. This will require the development of new deep learning methods and the integration of different data sources. In addition, the growing adoption of blockchain technology and the emergence of decentralized finance (DeFi) platforms are expected to further complicate models for predicting the financial stability of economic systems.

Therefore, in the process of building neural networks to determine the financial stability of economic systems, financial ratios and the CTEA indicator, which characterizes the type of economic activity, were selected. The ratios cover a number of financial indicators, including profitability, liquidity, efficiency, and debt management, which are important indicators of a company's ability to meet its financial obligations. In general, the pool of ratios provides a reliable set of financial indicators that can be used as a valuable tool for predicting bankruptcy risk.

The information on more than 500 thousand companies by type of business and their financial statements, which are publicly available and presented on official websites, is summarized. However, the available financial information is not uniform, which makes it impossible to make calculations, so the sample was checked for availability and correctness of data and only a part of the companies was selected, which is then used as the basis for building a neural network model. Thus, a total of 12573 companies were selected, which were subsequently used to build a neural network model for determining the financial stability of economic systems, financial ratios of companies for 2019 and 2020 were formed, and the indicator of the CTEA group was added.

The advantages of using feedforward neural networks (FNN) and recurrent neural networks (RNN) are substantiated. The constructed models of FNN, RNN with closed recurrent elements and RNN with long short-term memory have relatively high-performance evaluation indicators, which indicates that they predict bankruptcy with high probability. Tools such as the confusion matrix and precision are used to confirm the performance of the built model. The combination of these tools gives an idea of how well the neural network model for determining the financial stability of economic systems works and allows us to identify areas for improvement.

7. References

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