ISSN 2664-9969

UDC 004.032.26:658.15-044.3172
DOI: 10.15587/2706-5448.2024.309963

**Artem Sinkovskyi,**
**Volodymyr Shulakov**

# DEVELOPING A NEURO-FLEXIBLE MECHANISM OF BANKRUPTCY RISK ESTIMATION BASED ON CONDITIONAL PARAMETERS

*The object of the study is the estimation of the risk of enterprise bankruptcy. The work is aimed at developing a new model for estimating the risk of enterprise bankruptcy. Estimating the risk of bankruptcy is critical to assessing a company's financial health. It serves as a key indicator that enables management teams to proactively mitigate potential risks and develop strategies to strengthen the company's financial position over time. It is possible to enhance our prior bankruptcy prediction model by eliminating the Neural Arithmetic Logic Unit (NALU) block and refining the fuzzifier block to assess if the new architecture can effectively simulate approximate arithmetic for discovering complex financial ratios and relationships. The new model uses our bespoke «neuro-flexible» mechanism that incorporates a fuzzifier block as its initial layer, transforming each financial parameter into a fuzzy representation without any NALU blocks down the line. This approach allows the model to process undefined or missing inputs, enhancing its robustness in varied financial scenarios. The fuzzified values are then processed through linear layers with Mish activation, known for superior generalization performance. Key improvements include optimal categorization of raw numbers through embedding vectors and significant acceleration in learning speed. Experiments conducted using PyTorch on an Apple M1 processor demonstrated a substantial average prediction performance of 72 %, indicating the efficacy of the proposed enhancements in bankruptcy estimation. Bankruptcy risk is important for assessing a company's financial health. It helps management teams reduce risks and strengthen the company's finances. By predicting bankruptcy risk, companies can take steps to avoid financial problems and stay in business.*

**Keywords:** *statistical model, bankruptcy risk estimation, Neural Arithmetic Logic Unit, fuzzifier block, machine learning.*

*Received date: 08.06.2024*
*Accepted date: 12.08.2024*
*Published date: 14.08.2024*



***How to cite***
*Sinkovskyi, A., Shulakov, V. (2024). Developing a neuro-flexible mechanism of bankruptcy risk estimation based on conditional parameters. Technology Audit and Production Reserves, 4 (2 (78)), 20–23. https://doi.org/10.15587/2706-5448.2024.309963*

## 1. Introduction

Bankruptcy risk estimation is a critical area of financial analysis with significant implications for both enterprises and their stakeholders. Accurate prediction of bankruptcy can prevent financial losses, guide strategic decisions, and enhance overall economic stability. Given the complexities of modern financial systems and the dynamic nature of markets, robust models for bankruptcy prediction are invaluable tools for risk management. This study seeks to advance the field by introducing a novel, improved approach that improves the accuracy and reliability of bankruptcy risk estimation.

Traditional methods of predicting bankruptcy, like the Altman Z-score [1], have been used for decades. But they do not always work well, especially in modern financial situations. Financial data is becoming more complex. Hence, it is necessary to find the better ways to predict bankruptcy. New machine learning techniques should help us do this.

Despite progress with neural networks, there is still a gap in the literature about how to use them to improve prediction. While the Altman Z-score and traditional multilayer perceptrons provide a baseline for comparison, the upper bar of performance of new neural architectures is not known.

One of the most well-known ways to analyze enterprise bankruptcy risk is E. Altman's multiple discriminant analysis [1], along with similar methods developed in [2]. However, work [3] has shown that MDA has certain statistical limitations that make it difficult to use in practice. [4] tried to address these limitations by introducing specific constraints, but this reduced the models' explanatory power. Subsequent research has focused on developing new methods to overcome MDA's limitations. This has led to the development of probabilistic models such as logistic regression (logit) [5].

Despite the progress made, existing models still exhibit limitations in terms of flexibility, computational efficiency, and the ability to manage incomplete datasets. Despite the success of our previous approach [6], it is possible to believe that there is more to squeeze out of bankruptcy prediction using neural algorithms. There is a clear need for a more adaptable and efficient architecture that can handle a wide range of financial scenarios, including situations with missing data. Besides that, most, if not all, previous solutions require the user to input all the parameters the model uses.

This study aims to address these challenges by enhancing our previous model for bankruptcy risk estimation that eliminates the NALU block and refines the fuzzifier block. *The scientific goal* is to create a model that can effectively simulate approximate arithmetic for discovering complex financial ratios and relationships without the computational overhead associated with NALU blocks and specifically without the need to input all the financials used by the model. *The practical goal* is to enhance the robustness of bankruptcy predictions, allowing enterprises to better manage financial risks and take proactive measures to avoid insolvency.

By achieving these aims, it is possible to contribute a more flexible, efficient, and accurate tool for bankruptcy risk estimation. This will enable companies to make more informed financial decisions, thereby reducing the possibility of bankruptcy and promoting long-term financial stability.

## 2. Materials and Methods

It is possible to improve on our previous research [6] by completely removing the NALU block and enhancing the fuzzifier block to check whether the new architecture can simulate approximate arithmetic when discovering complex financial ratios and relationships.

A brief overflow of our previous model. Firstly, financial indicators are unnormalized, meaning they may have an arbitrary numerical value. Due to the nature of neural networks, inputs should be normalized [7] to achieve maximal performance. Because it is not possible to feed raw numbers into the bankruptcy estimation neural network, it is possible to transform raw numbers into fuzzy embeddings through our custom fuzzifier blocks. An intuition about fuzzy representation can be derived, meaning continuous quantities of discrete categories such as notions of «Low», «Mid», «High». Of course, the discretization can be arbitrary.

The model should be able to at least utilize basic arithmetic. The widely-known Altman Z-score operates with ratios of financial indicators, because ratios being dimensionless quantities provide generalization to arbitrary currencies. Previously, Neural Arithmetic Logic Units (NALU) [8] block was used to empower the network with arithmetic abilities. Addition, subtraction, multiplication, and division are essential for handling financials in their raw form. In this study, it is possible to explore the power of embedding vectors to optimally categorize raw numbers so that the network learns easily. Embedding vectors were first proposed by [9] to learn word representations for language models.

Our new model employs a special mechanism (Fig. 1), which it is possible to refer to as «neuro-flexible» mechanism. The first layer in our improved model is the fuzzifier block. Fuzzy representations of the inputs processed by the fuzzifier allow input parameters to be undefined. This is useful in scenarios where an enterprise does not have all the financials prepared or calculated. Thus, it is possible to attribute the property of flexibility to our model.

Firstly, each financial parameter ($x \in \mathcal{R}$) is transformed into a fuzzy representation ($N$-dimensional vector $\mu$, Fig. 2):

$$\vec{s} = relu(\vec{L}) \cdot \sigma(\vec{W}) + 10^{-5},$$

$$\vec{\mu} = 1 - \tanh\left[\left(\frac{-\vec{L} + x}{\vec{s}}\right)^2\right],$$

where $relu(\vec{x}) = \max(0, \vec{x})$; $\sigma = 1/(1+e^{-x})$; parameter $\vec{W} \in R^N$ is learned.

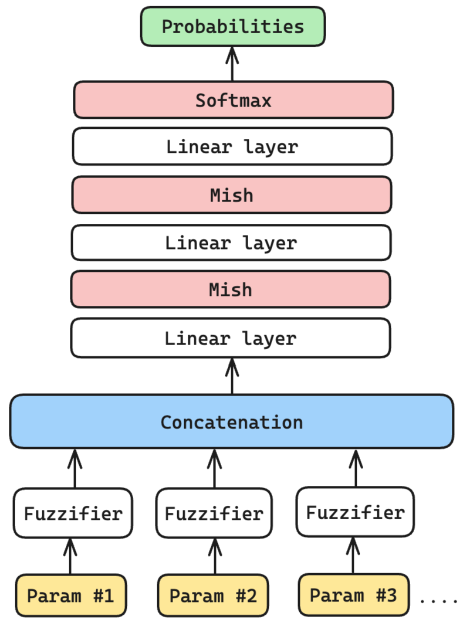


**Fig. 1.** The new neuro-flexible architecture for estimating bankruptcy

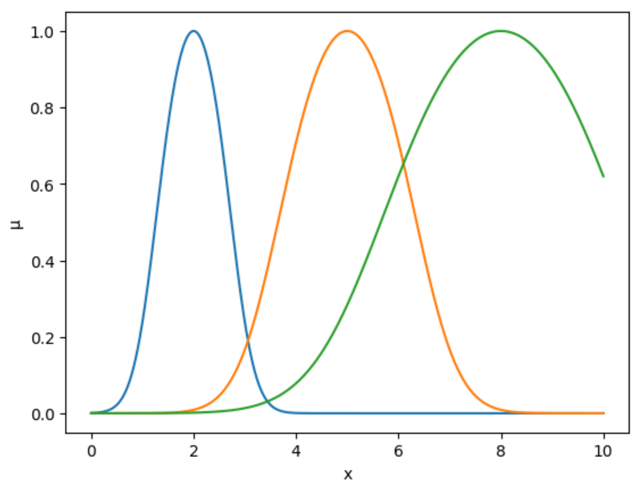


**Fig. 2.** Example conversion of a single number ($x \in [0;10]$) into a three-dimensional fuzzy vector (three $\mu$-values at a single point of the corresponding curves correspond to the components of $\mu$-vector), i. e. $\mu(5) = (0; 1; 0.25)$. Fuzzifier block learns the widths of the curves

To calculate $\vec{L}$ for a parameter $P$, dataset column $P$ is sorted in ascending order and a uniformly-spaced $N$ values are taken from the column $P$ as follows:

$$P = sortAscending(P),$$

$$step = \frac{P}{N},$$

$$L_i = P_{i^*step}.$$

This algorithm chooses the best center points for the fuzzy relationship function, taking into account the underlying distribution of the financial values of $P$. For example, if the dataset contains many small values and only few big values of $P$, this algorithm ensures that the fuzzy relationship function will contain detailed centers for small values of $P$.

Only scaling adjustments are learned (through parameter $\vec{W}$). $\bar{s}$ is multiplied by center points because, firstly, this is logical to spread the relationship of large quantities and shrink small quantities. It is possible to notice a triple learning speed improvement with these scaling adjustments.

The fuzzified values are then concatenated and fed through a sequence of linear layers with Mish activation. Each linear layer contains 128 neurons. Mish is employed in place of the traditional ReLU function. Mish is a smooth, non-monotonic activation function that has been shown to achieve better generalization performance in deep learning models [10].

The output of the model is two neurons with the first specifying the probability of bankruptcy absence and the second is bankruptcy probability.

It is possible to theorize that if a parameter is irrelevant to bankruptcy estimation, the fuzzifier will learn to output zero $\bar{\mu}$. This implies that if a user does not have a particular value for a parameter, it can be zeroed out as a notion of an undefined value. Hence, the network bases its predictions only on available parameters.

The research was carried out with the following software, libraries, and tools:

– *VS Code*: the primary IDE for writing and managing the codebase.
– *Jupyter notebooks*: employed for the fast development of the experiments.
– *Python*: the programming language used for all aspects of the research.
– *PyTorch*: a deep learning framework to build and train the neural models.

The experiments were carried out on an Apple M1 processor. The aforementioned hardware setup furnished the requisite computational power to facilitate the training of neural network models in an efficient manner.

## 3. Results and Discussion

The dataset used is «US Company Bankruptcy Prediction Dataset» from Kaggle [11] with 78682 records consisting of 18 parameter columns. Only 7 % of companies in the dataset filed for Chapter 7 or Chapter 11 of U.S. bankruptcy codes. The remaining 93 % of records describe stable situations. It is possible to split the dataset into 80 % and 20 % portions for training and validation, respectively.

To see how important the parameters are to predicting bankruptcy, it is possible to calculate mutual information of the target variable and financial parameters (Fig. 3) using the methods from [12].

To measure the dual estimation performance of absence and presence of bankruptcy simultaneously, let's devise a special «superscore» defined as follows. *S*-score provides the minimum value of either negative or positive rates so that it is possible to be really sure of the least the model can achieve with the validation data set:

$$SS = TNR \cdot TPR,$$

where *TNR* is the true negative rate and *TPR* is the true positive rate:

$$TPR = \frac{TP}{TP + FN};\ TNR = \frac{TN}{TN + FP}.$$

The model was trained for 40 epochs with the hyperparameters from Table 1.

**Table 1**

Training hyperparameters

| Optimizer | Adam |
|---|---|
| Learning rate | 1e-3 |
| Batch size | 256 |
| # of hidden neurons | 128 |
| # of hidden linear layers | 3 |

Table 2 presents prediction performance of the 5-factor Altman model and our fuzzy-flexible neural model. The experiments show that our new neuro-flexible model beats our previous model and achieves better scores overall, attributing 16 % of *S*-score to dataset noise. This shows that fuzzification really has an impact when converting raw numbers into embeddings, resulting in astonishing generalization and arithmetic abilities.

**Table 2**

Performance results

| Model | Avg accuracy | *S*-score |
|---|---|---|
| Altman (5 factors) | 60 % | 36 % |
| Fuzzy with NALU | 69 % | 48 % |
| Neuro-flexible | 72 % | 53 % |

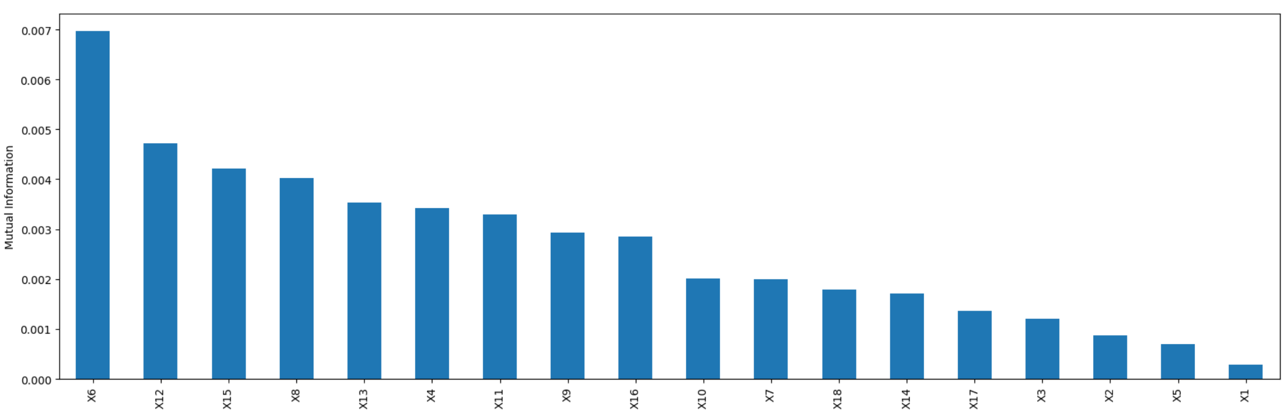


**Fig. 3.** Measures of dependencies between financials and discrete bankruptcy prediction

It is possible to achieve what was planned in our previous paper [6], namely making the model accept financial indicators conditionally. The new results show an average forecasting efficiency of 72 %, which indicates a high performance of the proposed model improvements for bankruptcy risk assessment. This figure exceeds some results reported in the literature, where financial risk modeling efficiency often ranges from 60 % to 70 %. Our improvements, including the elimination of the NALU block and the use of the fuzzifier with Mish activation function, provided improved data summarization and faster learning, allowing for more efficient modeling of complex financial relationships.

The results obtained can be used to predict the bankruptcy of enterprises using different sets of parameters conditionally, which will allow managers to take measures to avoid or minimize financial problems better even if they don't have all the financials that we trained our model on. This will help to increase the financial stability of enterprises and improve strategic planning and risk management.

The main limitations of our study are the dependence on the quality of the training dataset. The model may have limited efficiency in cases where the data is incomplete or has a significant amount of noise. In addition, the results of the model may vary depending on the selected financial indicators and market conditions.

The conditions of martial law in Ukraine did not affect the conduct of the study.

To further improve the model, let's necessitate expanding the dataset and involving data preprocessing methods. Another promising area is the development of integrated systems for assessing financial risks in real time, which will allow business managers to respond more quickly to changes in market conditions and potential risks.

## 4. Conclusions

An improved approach to estimating enterprise bankruptcy is presented compared to our previous model and alternatives such as Altman [1]. With a superior average score of 72 %, our neuro-flexible architecture also provides a way to input undefined financial parameters when users have less indicators than the dataset the model was trained on.

This work suggests that embedding continuous inputs into fuzzy representations is a natural way to feed the neural networks. With the help of the modern activation function Mish and custom initialization of fuzzy blocks, it is possible to believe we achieved state-of-the-art model generalization and performance in the area of bankruptcy estimation given the used dataset.

The results show that advanced neural architectures can improve financial risk assessments. They can help enterprise management teams take action to avoid financial problems. Being able to predict bankruptcy risk more accurately can help organizations stay stable in a changing economy.

## Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.


## Financing

The study was performed without financial support.


## Data availability

Manuscript has no associated data.

## Use of artificial intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, which is described in the research methodology section.

### References


1. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23 (4),* 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x
2. Chibisova, I. (2012). Methods of estimation and prognostication of bankruptcy of enterprises. *Naukovi pratsi Kirovohradskoho natsionalnoho tekhnichnoho universytetu, 22 (2),* 389–394.
3. Eisenbeis, R. A. (1977). Pitfalls in the application of discriminant analysis in business, finance, and economics. *The Journal of Finance, 32 (3),* 875–900. https://doi.org/10.1111/j.1540-6261.1977.tb01995.x
4. Premachandra, I. M., Bhabra, G. S., Sueyoshi, T. (2009). DEA as a tool for bankruptcy assessment: A comparative study with logistic regression technique. *European Journal of Operational Research, 193 (2),* 412–424. https://doi.org/10.1016/j.ejor.2007.11.036
5. Mihalovič, M. (2016). Performance Comparison of Multiple Discriminant Analysis and Logit Models in Bankruptcy Prediction. *Economics & Sociology, 9 (4),* 101–118. https://doi.org/10.14254/2071-789x.2016/9-4/6
6. Sinkovskyi, A., Shulakov, V. (2024). Development of fuzzified neural network for enterprise bankruptcy risk estimation. *Information and Control Systems, 3 (2 (77)),* 19–22. https://doi.org/10.15587/2706-5448.2024.306873
7. Sola, J., Sevilla, J. (1997). Importance of input data normalization for the application of neural networks to complex industrial problems. *IEEE Transactions on Nuclear Science, 44 (3),* 1464–1468. https://doi.org/10.1109/23.589532
8. Trask, A., Hill, F., Reed, S. E., Rae, J., Dyer, C., Blunsom, P. (2018). Neural arithmetic logic units. *Advances in neural information processing systems, 31.*
9. Bengio, Y., Ducharme, R., Vincent, P., Janvin, C. (2003). A neural probabilistic language model. *Journal of Machine Learning Research, 3,* 1137–1155.
10. Misra, D. (2019). *Mish: A self regularized non-monotonic activation function.* https://doi.org/10.48550/arXiv.1908.08681
11. Utkarsh Singh. *US Company Bankruptcy Prediction Dataset.* Available at: https://www.kaggle.com/datasets/utkarshx27/american-companies-bankruptcy-prediction-dataset
12. Kraskov, A., Stögbauer, H., Grassberger, P. (2004). Estimating mutual information. *Physical Review E, 69 (6).* https://doi.org/10.1103/physreve.69.066138



✉***Artem Sinkovskyi,*** *Assistant, Department of Computer Science and System Analysis, Cherkasy State Technological University, Cherkasy, Ukraine, e-mail: a.sinkovskyi@chdtu.edu.ua, ORCID: https://orcid.org/0009-0009-8877-7351*

***Volodymyr Shulakov,*** *Department of Computer Science and System Analysis, Cherkasy State Technological University, Cherkasy, Ukraine, ORCID: https://orcid.org/0009-0000-2697-8486*

✉*Corresponding author*