UDC 004.032.26:658.15-044.3172
DOI: 10.15587/2706-5448.2024.306873

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

# DEVELOPMENT OF FUZZIFIED NEURAL NETWORK FOR ENTERPRISE BANKRUPTCY RISK ESTIMATION

*The object of this study is the assessment of the level of enterprise bankruptcy risk. It is a critical component in assessing the financial condition of an enterprise, and also serves as an indicator that allows the management team to reduce potential risks and develop their own strategies to strengthen the financial condition of the enterprise. One of the most challenging aspects of bankruptcy forecasting is the complex financial situations of bankrupt companies. By accurately predicting the risk of bankruptcy, businesses can take preventive measures to mitigate financial difficulties and ensure long-term sustainability. Previous methods, such as Altman's Z-score, are not accurate enough, as presented in the study. The paper investigates a modern approach to bankruptcy prediction based on a neural network with complex neural elements, namely neural arithmetic logic units (NALUs) and a custom phasing layer. This layer can process complex raw numerical values, such as financial indicators relevant to the analysis of a company's bankruptcy. Compared to Altman's Z-score, the developed method demonstrates a better F1 score in bankruptcy classification (48 %). On the raw data, the neural network demonstrates an improvement in the F1 score by about 40 % compared to the classical multilayer perceptron (MLP) with linear layers and nonlinear activation functions. A modern replacement for ReLU called Mish was used, which achieves better generalization. It was also assumed that the addition of new neural elements, which provide the neural network with arithmetic capabilities, contributes to the performance of processing non-normalized input data. This work highlights the importance of using advanced neural network architectures to improve the accuracy and reliability of forecasting in financial risk assessment. Using the parameters presented in the study, managers of enterprises will be able to more accurately assess the risk of bankruptcy.*

**Keywords:** *statistical model, bankruptcy risk assessment, neural arithmetic, machine learning.*

*Received date: 07.05.2024*
*Accepted date: 25.06.2024*
*Published date: 26.06.2024*



***How to cite***
*Sinkovskyi, A., Shulakov, V. (2024). Development of fuzzified neural network for enterprise bankruptcy risk estimation. Technology Audit and Production Reserves, 3 (2 (77)), 19–22. doi: https://doi.org/10.15587/2706-5448.2024.306873*

## 1. Introduction

In the modern economic landscape, the ability to accurately predict enterprise bankruptcy risk is of paramount importance. The financial health of an enterprise is not only critical for its stakeholders but also for the broader economy. The early identification of potential financial distress can enable management teams to take proactive measures to mitigate risks and implement strategies to safeguard the company's long-term sustainability [1]. In light of this, the advancement of predictive models for bankruptcy risk has garnered significant attention from both academia and industry practitioners.

Traditional methods of bankruptcy prediction, such as the Altman Z-score [2], have been widely utilized for decades. However, these methods often fall short in their predictive accuracy, particularly in the face of complex, modern financial landscapes. The evolving nature of financial data, characterized by increased volume and complexity, necessitates more sophisticated approaches to prediction. Recent advancements in machine learning have opened new avenues for improving the accuracy of bankruptcy risk assessment. Among these advancements, neural networks, and specifically neural arithmetic logic units (NALUs) [3], have shown great promise.

Despite the progress made with neural networks, there remains a gap in the literature regarding the integration of advanced neural cells and their impact on predictive performance.

While the Altman Z-score [2] and traditional multi-layer perceptrons (MLPs) provide a baseline for comparison, the potential of novel neural architectures, which can handle raw numeric data more effectively, has not been fully explored.

One of the most known approaches of analyzing enterprise bankruptcy risk is E. Altman's multiple discriminant analysis [2], along with similar methods developed by [4]. However, [5] has demonstrated that MDA has certain statistical limitations that impede its practical application. [6] partially addressed these limitations by introducing specific constraints, though these reduced the models' explanatory power. As a result, subsequent research has focused on developing new methods to overcome MDA's limitations, leading to the development of probabilistic models such as logistic regression (logit) [7].

The current body of research highlights several limitations in existing predictive models. Traditional statistical methods, while useful, often rely on linear assumptions that may not capture the complex, non-linear relationships present in financial data. Similarly, conventional neural network

ISSN 2664-9969

architectures, such as MLPs with linear layers and non-linear activation functions, may not fully leverage the arithmetic capabilities required for accurate financial analysis. Moreover, the choice of activation functions plays a crucial role in the generalization ability of neural networks. Recent developments, such as the Mish activation function [8], have shown superior performance compared to traditional functions like ReLU [9], yet their application in the context of bankruptcy prediction remains underexplored.

Following the work of [10], data mining methods were incorporated into bankruptcy prediction models, naturally addressing the shortcomings of traditional statistical methods. Additionally, [11] highlight both the advantages and the challenges of using neural networks, noting that numerous parameters must be established heuristically, requiring extensive model tuning.

Let's aim to address this gap by investigating a contemporary approach to bankruptcy risk estimation that incorporates NALUs and a custom fuzzification layer with a modern activation function Mish. These components are designed to process raw financial data directly, potentially leading to improved predictive accuracy.

The research proposes a novel approach to bankruptcy prediction by integrating NALUs and a fuzzification layer within a neural network architecture. The objective is to enhance the network's ability to process unnormalized, raw numeric values relevant to financial indicators. By leveraging the arithmetic capabilities of NALUs and the improved generalization provided by the Mish activation function, *this study aims* to develop a model that outperforms traditional methods in terms of predictive accuracy.

*The scientific aim* of this research is to develop a more accurate and reliable model for predicting enterprise bankruptcy risk. This involves identifying the mechanisms by which advanced neural cells, such as NALUs, improve the processing of raw financial data and contribute to enhanced predictive performance. Additionally, this study seeks to develop application techniques that effectively integrate these advanced neural cells into a neural network architecture tailored for financial risk assessment.

*From a practical standpoint*, the implementation of this advanced predictive model is expected to provide significant benefits for enterprise risk management. By achieving higher predictive accuracy, management teams can gain earlier and more reliable insights into potential financial distress. This, in turn, enables them to take timely and informed actions to mitigate risks, such as adjusting financial strategies, securing necessary resources, and implementing measures to strengthen the company's financial resilience.

## 2. Materials and Methods

The dataset used in this research is the «US Company Bankruptcy Prediction Dataset» sourced from Kaggle [12]. This dataset comprises 78682 records, each containing 21 financial indicators. The dataset is imbalanced, with 93 % of records representing financially stable (alive) companies and 7 % representing companies that have gone bankrupt (failed).

To address the imbalance in the dataset, it is possible to generate synthetic data to augment the minority class (bankruptcy outcomes). Synthetic data generation was performed using a variational autoencoder [13] with oversampling in the feature space to balance the class distribution, thus ensuring that the neural network is adequately trained on both alive and failed company records. The research was conducted using the following software and tools:

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

The experiments were carried out on an Apple M1 processor. This hardware setup provided the computational power necessary to train the neural network models efficiently.

In our architecture three key pieces are used, namely a NALU cell, a Fuzzifier (ours), and a Mish activation function (Fig. 1).

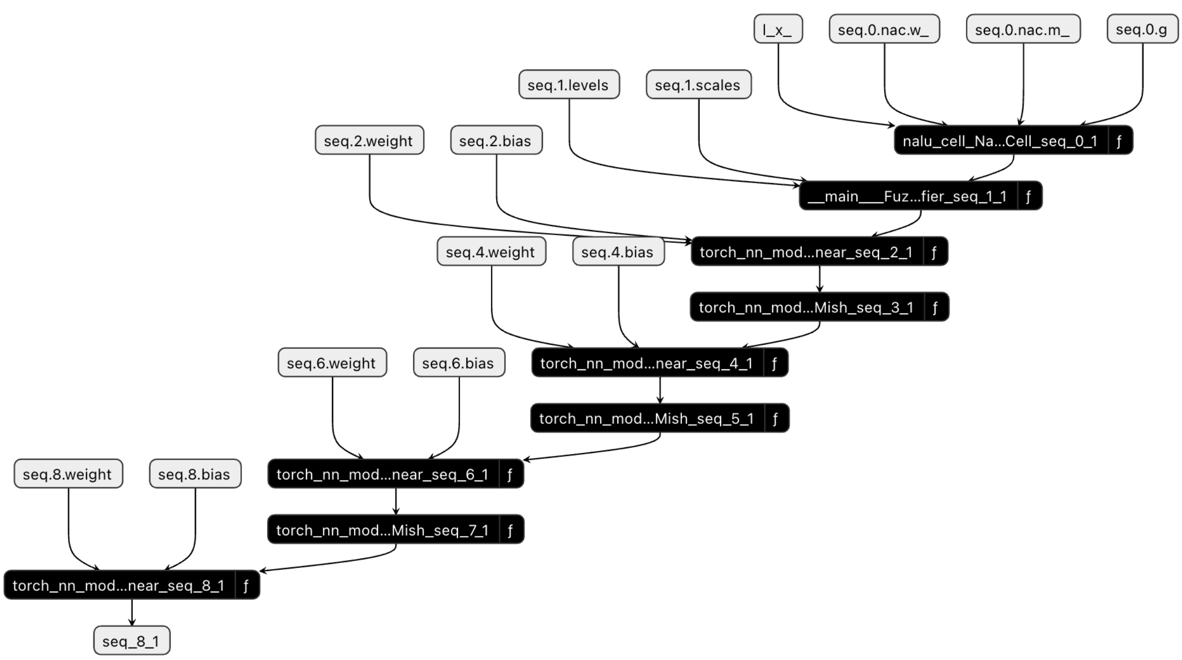


**Fig. 1.** Neural bankruptcy estimator network graph

Successful Altman Z-score involves calculating certain ratios, so it is possible to take inspiration from it and insert a NALU [3] as the first layer and feed its output to the fuzzifier. Neural Arithmetic Logic Units (NALUs) enhance network's ability to process raw numeric values and perform arithmetic operations directly. These units are designed to provide arithmetic capabilities such as addition, subtraction, multiplication, and division, which are essential for handling financial indicators in their raw form.

Due to the nature of neural networks, inputs should be normalized [14]. Thus, a custom fuzzification cell (Fig. 2) was developed to preprocess the raw numeric outputs of the NALU by converting them into a fuzzy representation as presented in [15], such as «Low», «Mid», «High» (Fig. 3), but the number of levels can be arbitrary. This transformation aims to handle the inherent uncertainty and variability in financial data more effectively, allowing the neural network to generalize better across different financial conditions. Each financial value is fuzzified and the results are concatenated.

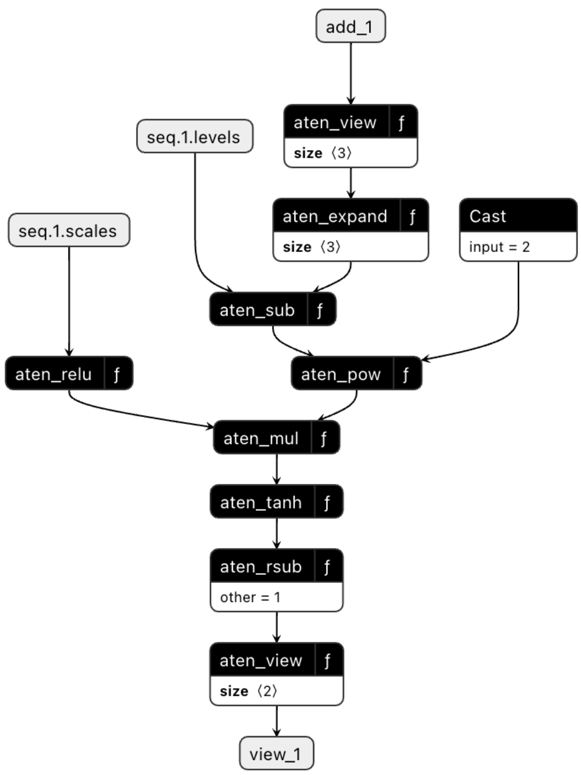


**Fig. 2.** Fuzzifier graph

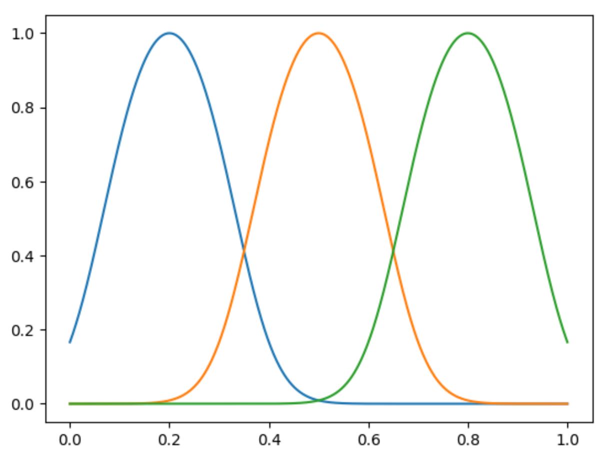


**Fig. 3.** A variable that is fuzzified into three different representations

The concatenated fuzzifier output is fed through a classical MLP with 3 layers of 128 neurons each, interlaced with Mish activations. The last layer maps 128 neurons to two output values, the binary distribution signifying the bankruptcy risk.

The modern activation function, Mish, was 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 [8]. This function helps in retaining more information during the forward and backward passes, contributing to the overall performance improvement of the network.

## 3. Results and Discussion

The model was trained for 100 epochs with hyperparameters from Table 1.

Table 2 presents prediction performance of 5-factor Altman model and our neural model. Although let's try different hyperparameters, the model mostly converged at F1-score of 65 %. It is possible to postulate that the dataset has noise in a form of hidden variables that can't be predicted. For example, an enterprise with some financial indicators could have improved its status the next year after the financial report, but another enterprise with the same parameters may not have adjusted its policies in a positive direction, so it is possible to left with a bankrupt and a successful business at the same financials making it a random choice.

**Table 1**

Training hyperparameters

| Optimizer | Adam |
|---|---|
| Learning rate | $1e^{-3}$ |
| Batch size | 128 |
| # of hidden neurons | 128 |
| # of hidden linear layers | 4 |

**Table 2**

Performance results

| Model | F1-score |
|---|---|
| Altman (5 factors) | 44 % |
| Nedosekin (5 experts, 18 factors) | 40 % |
| Ours (optimized with Adam) | 65 % |
| Ours (optimized with Nevergrad) | 50 % |

The results of our study demonstrate a significant improvement in the accuracy of predicting corporate bankruptcy compared to traditional methods. In particular, our model achieved an F1-indicator of 65 %, which is significantly higher than the results of Altman's model (44 %) and Nedosekin's model (40 %). This can be explained by the use of a more sophisticated neural network architecture that includes NALU and a fuzzifier, which allows for more efficient processing of raw financial data. In addition, the use of the Mish activation function contributed to better model generalization. These results differ from previous techniques in their greater accuracy and ability to process complex financial indicators without prior normalization.

The developed model can be used by financial analysts, investors, and business managers to more accurately assess

ISSN 2664-9969

the risk of bankruptcy. This allows the timely identification of potential financial problems and preventive measures. In addition, the model can be useful for credit institutions in assessing the creditworthiness of enterprises.

The main limitation is that the model was trained on historical data and may need to be updated regularly to take into account new economic realities. Also, the model may be less effective for enterprises with atypical financial indicators or in industries that are underrepresented in the training dataset. For practical implementation, it is necessary to develop a user-friendly interface and conduct additional testing on real data from Ukrainian enterprises.

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

In the future, it is planned to expand the research by making the model accept financial indicators conditionally when an enterprise doesn't have some of them. Another interesting area is the adaptation of the model to predict bankruptcy in various sectors of the economy and the development of an interpreted version of the model that can explain its forecasts. In addition, it is promising to study the possibility of using transfer learning to adapt the model to the specifics of the Ukrainian market in the context of limited local data.

## 4. Conclusions

In the course of the research, a novel approach to predicting bankruptcy risk using advanced neural network technique is developed. The proposed model, which integrates Neural Arithmetic Logic Units (NALUs) and a custom fuzzification layer, achieved a higher F1 score in bankruptcy prediction, outperforming the traditional Altman Z-score method.

The superior performance of our model can be attributed to our fuzzifier and the NALU's ability to handle raw numeric values directly and perform essential arithmetic operations. Additionally, the custom fuzzification layer effectively manages the inherent uncertainty and variability in financial data by converting numeric outputs into fuzzy representations. The use of the Mish activation function further enhances generalization performance compared to traditional ReLU.

These results are theoretically significant as they demonstrate the potential of advanced neural architectures in improving the accuracy of financial risk assessments. Practically, the enhanced predictive accuracy provides valuable tools for enterprise management teams, enabling them to take proactive measures to mitigate financial distress. The ability to predict bankruptcy risk with greater precision can help organizations ensure long-term sustainability and stability in a dynamic economic environment.

## 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. Long, Y. (2022). Early Warning Analysis of Company's Financial Risk based on Fuzzy Evaluation Method. *Proceedings of the International Conference on Big Data Economy and Digital Management*. doi: https://doi.org/10.5220/0011207900003440
2. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23 (4),* 589–609. doi: https://doi.org/10.1111/j.1540-6261.1968.tb00843.x
3. 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.*
4. Chibisova, I. (2012). Methods of estimation and prognostication of bankruptcy of enterprises. *Naukovi pratsi Kirovohradskoho natsionalnoho tekhnichnoho universytetu, 22 (2),* 389–394.
5. Eisenbeis, R. A. (1977). Pitfalls in the application of discriminant analysis in business, finance, and economics. *The Journal of Finance, 32 (3),* 875–900. doi: https://doi.org/10.1111/j.1540-6261.1977.tb01995.x
6. 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. doi: https://doi.org/10.1016/j.ejor.2007.11.036
7. Mihalovič, M. (2016). Performance Comparison of Multiple Discriminant Analysis and Logit Models in Bankruptcy Prediction. *Economics & Sociology, 9 (4),* 101–118. doi: https://doi.org/10.14254/2071-789x.2016/9-4/6
8. Misra, D. (2019). *Mish: A self regularized non-monotonic activation function*. arXiv:1908.08681. doi: https://doi.org/10.48550/arXiv.1908.08681
9. Brownlee, J. (2020). *A Gentle Introduction to the Rectified Linear Unit (ReLU)*. Machine Learning Mastery. Available at: https://machinelearningmastery.com/rectified-linear-activation-function-for-deep-learning-neural-networks
10. Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research, 18 (1),* 109–131. doi: https://doi.org/10.2307/2490395
11. Ahn, H., Kim, K. (2009). Bankruptcy prediction modeling with hybrid case-based reasoning and genetic algorithms approach. *Applied Soft Computing, 9 (2),* 599–607. doi: https://doi.org/10.1016/j.asoc.2008.08.002
12. *US Company Bankruptcy Prediction Dataset*. Utkarsh Singh. Available at: https://www.kaggle.com/datasets/utkarshx27/american-companies-bankruptcy-prediction-dataset
13. Shulakov, V., Sinkovskyi, A., Tryus, Y. (2023). Information technology for generating synthetic medical data based on neural networks. *Actual problems of medical, biological physics and computer science*. Vinnytsia: Edelweiss, 76–82.
14. 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. doi: https://doi.org/10.1109/23.589532
15. Nedosekin, A. O. (2008). Business risk assessment on the basis of fuzzy data. *Audit and Financial Analysis, 4,* 68–72.

✉***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*