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Developing a Neural Network to Assess Staff Competence and Minimize Operational Risks in Credit Organizations

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Abstract

The paper is devoted to the issues of controlling the operational risks of credit organizations associated with employees. One of the leading sources of operational risks associated with the actions of staff is insufficient employee qualification. This can cause a reduction in the accessibility and quality of the services offered by credit organizations, as well as potential financial and reputational losses. The goal of the study is to create an artificial neural network using a high-level Keras library in Python that would automatically monitor the level of critical personnel competence given its impact on the occurrence of operational risk events. The research objectives encompass analyzing employee competence indicators' influence on operational risk occurrence, identifying key indicators for an artificial neural network, determining its architecture, creating datasets, and conducting comparative analysis of trained neural networks. The article outlines the primary set of indicators producing the greatest impact on the possibility of the emergence of operational risk associated with the actions of the credit organization's employees. The paper also presents the results of testing the generated sets of training and test data using application software packages that implement mathematical methods to assess the consistency of the generated data sets. Graphs showing the results of training and testing of the constructed neural network are provided. The research findings are novel and can enable credit organizations to majorly automate the monitoring of personnel-related operational risk.

Keywords: Artificial Neural Network, Forward Propagation, Keras High-Level Library, Machine Learning, Neural Network.

Introduction

Monitoring of operational risks is an important aspect of the work of a credit organization. Even though the Basel Committee on Banking Supervision (BCBS) in its regulatory documents (1) describes in detail a set of actions that banks should perform to monitor operational risks, in practice credit organizations face great difficulties in dealing with the operational risk associated with the actions of personnel. This can be explained, first and foremost, by the difficulty of identifying and formalizing said risk.

The concept of operational risk is defined by the BCBS in the International Convergence of Capital Measurement and Capital Standards as a risk of losses resulting from inadequate or ineffective internal processes, the actions of people or technical systems, or external events (1).In previous studies (2, 3), methods utilizing neural networks to monitor the operational risks faced by a credit organization due to IT usage were proposed. This paper addresses operational risks related to the actions of the credit organization's personnel, including unintentional errors, deliberate actions, or omissions. Minimizing such risks is one of the most pressing challenges for credit organizations.

Literature review

In human resources management, it has long been common practice to use competency models (maps) describing the required knowledge, skills, and behavioral indicators needed to perform specific duties to find employees of the right professional level. Such maps are developed both for specific

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positions or functions and for departments or even organizations as a whole (4).

However, once they become a business process performer, an employee who perfectly complies with all the requirements may demonstrate a level of competence lower than expected due to various circumstances. The presence of this factor will detrimentally affect the results of the business process and cause operational risk events, which can entail financial and reputational losses (5). In the process of this research, factors affecting the occurrence of operational risks associated with personnel actions have been analyzed. Previous studies have considered as such factor's employees' level of education and professional skills, commitment and responsibility, team communication, experience, age, workload, etc. (6). There are about two dozen factors identified, which have different levels of impact on business processes from the point of view of the possibility of operational risk events. Due to the large number of indicators, the bulk of them were categorized into two groups by the nature of their impact: a group of professional criteria (competence) and a group of supra-professional skills (soft skills).

The competence of personnel involved in a business process is an aggregate value of each worker's competence. In the course of the study, the most significant indicators of professional competencies that produce the most impact on the possibility of operational risk events were identified. In this, it was assumed that an employee cannot occupy their position without a certain (basic) set and level of competencies.

The level of impact of personnel competence on operational risks in a business process was defined using the red (critical) – amber (medium) – green (low) (RAG) method of assigning criticality status (7).

To timely identify inconsistencies in the demonstrated level of competence by an employee or team of employees, it is convenient to have a common universal assessment tool. As a rule, organizations resort to scoring systems (8), which, regrettably, are not always successful in detecting problem areas due to imperfections in assessment scales. It is also common for competency assessment to be substituted for disciplinary control (9), which is certainly important, but still does not constitute a comprehensive assessment that identifies operational risks associated with personnel actions.

In recent years, the use of neural networks to assess the competence of employees, in particular, based on evaluations given by department heads, has been gaining popularity (10). This approach has a significant disadvantage of biased evaluations due to the influence of interpersonal relations. Another group of approaches is based on the use of test systems and systems of compliance with the required competencies (11, 12). Yet these systems are usually used either in the preliminary selection of applicants or in estimating the need to improve or update employees' knowledge and skills. There is no single approach to developing scales to assess employee competence.

Each employee is an executor of a business process and has an impact on its functioning. This influence can be evaluated by a rather large set of indicators, characterizing, in particular, employees' professional competence and non-specialized sura-professional skills (soft skills).

The purpose of this work is to determine the level of competence demonstrated by an employee when performing business tasks in terms of assessing its impact on the occurrence of operational risk events using a neural network.

The research objectives set to achieve the goal of the study are:

1. to analyze employee competence indicators from the point of their influence on the possibility of occurrence of operational risk in the execution of business processes.
2. to determine the key indicators characterizing the level of employee competence, which will serve as input parameters for an artificial neural network (ANN).
3. to determine the architecture (topology) of the developed ANN.
4. to create training and test datasets for the ANN.
5. to train neural networks of different architectures and perform their comparative analysis.

Methodology

Study Design

In the framework of the study, we formed a database of 2688 records with employee competence indicators and the resultant assessment of their competence (green, amber, and red zones) performed by three experts from the Plekhanov Russian University of Economics (Russia) in 2023. The assessment was chosen to be made based on the following categorical indicators: total experience in the field of the position held, current experience in the organization, level of education, completion of additional training courses, violations of technological discipline and their consequences, promotions and rewards, and the frequency of changing the company of employment. The assessment also takes into account one continuously changing parameter – the grade point average in the academic certificate.

The obtained training sample was analyzed for the presence of dependencies between the identified indicators and the presence of the impact of independent input variable parameters on the dependent output parameter. Qualitative characterization of the closeness of links between factors in the dataset was performed through Spearman's rank correlation coefficient (13) evaluated with the Chaddock scale (14). Spearman's correlation coefficient was calculated using statistical analysis tools of the Loginom analytical low-code platform. Furthermore, the set of input parameters was assessed in terms of impact on the membership of objects in one or another class. To identify redundant independent parameters, for each input characteristic, we plotted either bar charts or probability density plots, which show a smoother distribution by flattening the parameter variations. Graph visualization was performed using the Plotly and Seaborn libraries in the Python language (15).

Regarding ANN models, the study of the efficiency of training focused on the possibility of using a multilayer perceptron with two and three hidden layers, or Deep Neural Network (DNN). In this, we analyzed network architectures that demonstrated the best results in solving similar tasks, in particular, those examined by Chumakova *et al.* (3). The existence of ANNs with similar typologies will enable the application of the proposed ANN as a unified module in an intelligent system for identifying operational risks associated with personnel actions. The modeling and testing of neural networks were performed using the Keras high-level library in Python.

Research Stages

The beginning stage of the study consisted in analyzing the traditional indicators used in personnel evaluation (16). The investigation focused on their effect on business processes in terms of the possibility of operational risk events, as well as on the application of various units of measurement in assessing these indicators. Among the considered indicators of professional skill assessment, we highlighted: experience working in the current position, total work experience in the sphere, level of education (meeting/exceeding requirements), completion of additional advanced training courses, grade point average in the academic certificate, the level of labor and technological discipline, and the history of mistakes that led (or could lead) to financial and/or reputational losses. Additional competence assessment factors include the presence of debt obligations and conscientiousness in repayment (percentage of monthly payments relative to salary), the presence of dependents, and the employee's age and health group. Another group of criteria considered includes those to evaluate supra-professional skills (soft skills), such as communication skills, loyalty to the company, management skills, stress tolerance, efficiency of thinking, creativity, and responsibility (17).

In this paper, we investigated the possibility of using an ANN to assess the level of personnel competence as a factor in the occurrence of operational risk events. The construction of the ANN to assess the impact of soft skills was proposed to be carried out as a separate study and described in a separate paper.

In determining the list of ANN input parameters for assessing the level of staff competence, it was assumed that the organization hires employees who fully meet all the requirements for the applicant's skills and competencies. In addition, the organization strictly monitors the level of competence of its employees by organizing regular refresher courses with tracking the level of knowledge and skills acquired (18). In this case, all employees should have a sufficient level of knowledge to perform their job duties, and the employee's competence level is proposed to be considered as the level of influence on the possibility of occurrence of operational risk events in a business process: "red (critical, intervention is required) – amber (medium) – green (low)". In this way, we identified 10 input parameters (input layer neurons), namely: current work experience in the organization and the sphere of activity, exceedance of the required level of education, grade point average in the academic certificate, the presence of advanced training certificates provided that they are optional, the frequency of violation of technological and labor discipline, the presence of acknowledgments/commendations, the presence of penalties, promotions in the last 5 years, and the frequency of job change. All the parameters, except for the grade point average, were taken as categorical values.

At the next stage, data sets were generated, and based on the values of the specified competence indicators, an expert assessment of the competence level was performed in terms of its impact on the possibility of operational risk events. Further, the obtained sample was statistically analyzed for the presence of interrelations of independent characteristics among themselves, as well as their influence on the dependent output indicator. The detection of dependence between the input parameters indicates data redundancy. The correlation between the features in the data set was assessed using the Spearman rank correlation coefficient, which belongs to the indicators assessing the closeness of the relationship. Spearman's coefficient was calculated in pairs for each of the parameters using the Loginom low-code platform. Quantitative evaluation of the closeness of the relationship was performed via the Cheddock scale, according to which a coefficient value in the range of 0.1 to 0.3 indicates a weak relationship, and in the range of 0.3 to 0.5 – a moderate relationship.

Further analysis of the obtained training sample came down to assessing the influence of each of the input parameters on the aggregated employee competence index (ANN output parameter with "red"/"amber"/"green" values). For categorical parameters, bar charts were constructed with each class column divided into different color sections in proportion to the number of dependent values. To evaluate the continuous parameter, a probability density plot was constructed to show a smoother distribution by flattening the changes in the parameter. The visualization of charts and graphs was performed using Plotly (Canada) and Seaborn (USA) libraries in the Python language (19-21).

Proceeding from the results of previous stages of research, it was proposed to train several neural network models with 2-3 hidden layers of the type 10-m-3. Following general heuristic recommendations, m (the number of neurons in the hidden layer) was taken as m = 15, 20, and 25. The training was conducted for 200 epochs. Based on the results of a previous study (3), the Adam optimizer, implemented in the Keras software library, was used to determine employee competence as a component of operational risk occurrence assessment. The functions sigmod and tanh (hyperbolic tangent) were compared as the activation function of the hidden layer, and softmax was compared as the activation function of the output layer. The MSE (mean squared error)/ loss function was used together with the optimizer. Training was performed on the general sample, divided into the training sample, which constituted 80% of the total number of training sets (2150 sets), and the validation and testing samples, which made up 10% each.

ANN Model

Through the conducted analysis, we selected the indicators having the greatest influence on the possibility of occurrence of operational risk events, which were then used as input parameters for the ANN:

1. Work experience in organizations in the area of business (performance of functions within the business process).
2. Total work experience in the sphere (performance of functions within the business process).

3. Education (complies with requirements, exceeds requirements).
4. Grade point average in the Academic Certificate.
5. Additional certificates that are not mandatory.
6. Violations of technological discipline.
7. Penalties.
8. Acknowledgments/ Commendations.
9. Promotions in the last 5 years.
10. Frequent Change of Jobs (More Than Once Per Year).

In quantitative terms, the grade point average in the academic certificate is set as a continuously changing value, while the other parameters are taken as elements of a finite set. Specifically, the parameters of the presence of certificates, penalties, acknowledgments/commendations, promotions in the last 5 years, and the frequency of job change take the values "yes" (present) and "no" (absence). The level of education is considered as either corresponding to or exceeding the requirements of the business process. Work experience is set as ranges of values (years) under the condition that it cannot be less than required by the occupied position and can only exceed it (e.g., "by over 2 years" or "by over 5 years"). Quantitative assessment of the indicator of violation of technological discipline employed the gradations "rarely", "occasionally", and "often".

Thus, the generalized ANN model for determining the impact of competence of business process participants on the possibility of operational risk events can be described by an input layer of 10 neurons and 3 neurons in the output layer (risk level) with the values "low (green)", "medium (amber)", and "high (red)". The total size of the general sample generated by experts was 2688 sets.

Analysis of the created datasets for their usability in ANN training and testing was performed by quantification of Spearman's correlation coefficient for pairwise comparison.

Results

One of the factors generating operational risk is the actions (or inaction) of staff in performing business tasks. These actions are largely defined by the professional skills of business process participants. Organizations have long been monitoring employees' level of knowledge and competencies, holding interviews and various knowledge tests when hiring workers, and organizing a variety of advanced training courses during employment.

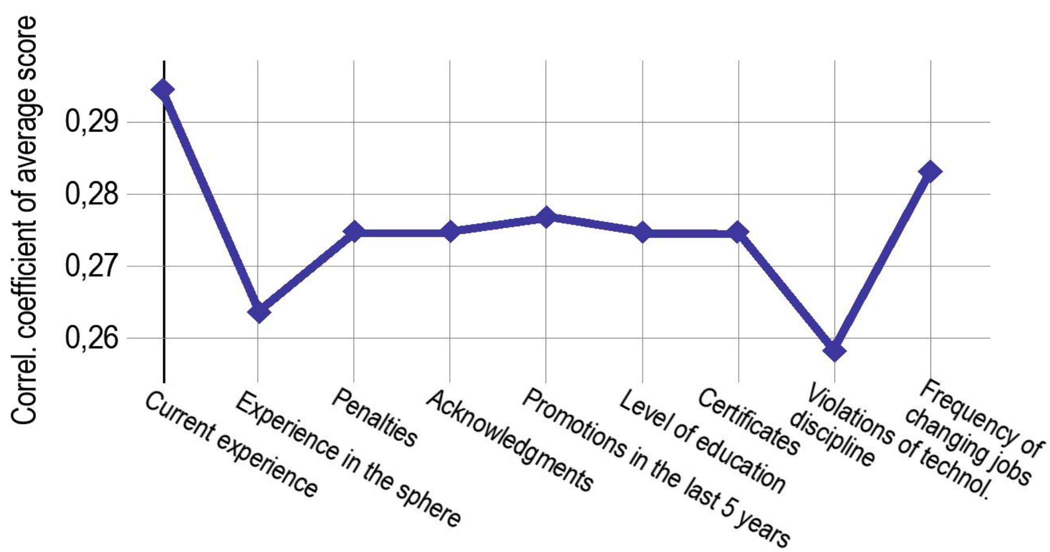

Figure 1(a): Change in Spearman's correlation coefficient. Grade point average in the academic certificate.

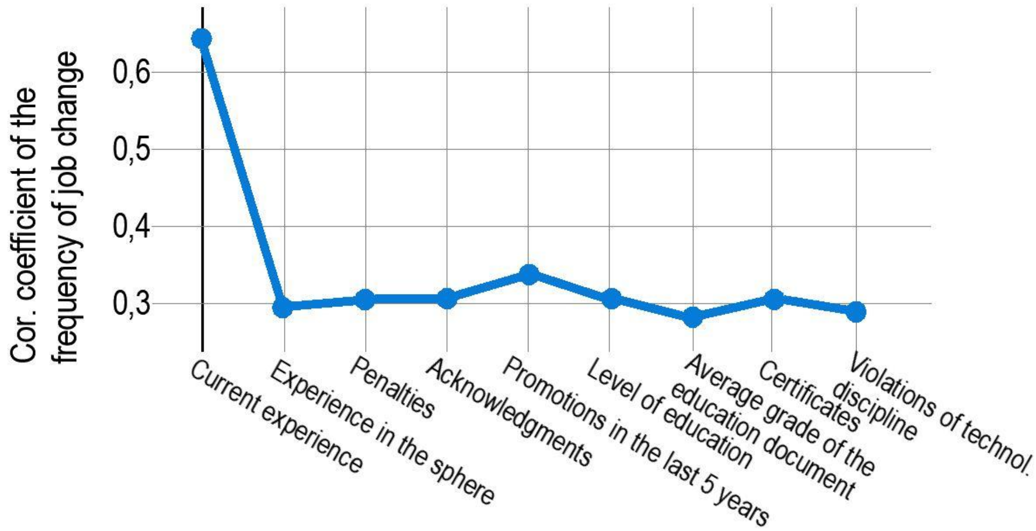

Figure 1(b)**:** Change in Spearman's correlation coefficient. Frequency of job change**.**

However, a sufficient level of knowledge demonstrated by an employee does not entirely exclude the possibility of operational risk associated with their actions as a participant in a business process. The onset of operational risk events is commonly conditioned not only by employees' low level of professional knowledge but also by certain parameters closely associated with it and affecting the efficiency of the application of this knowledge. The parameters considered as such factors include the level of education, general health, financial independence, marital status, personal qualities, etc. Some of the parameters examined are found to produce very little or even no impact on the emergence of operational risk events (16).

Spearman's correlation coefficient was found to vary in the range of 0.26 to 0.34.

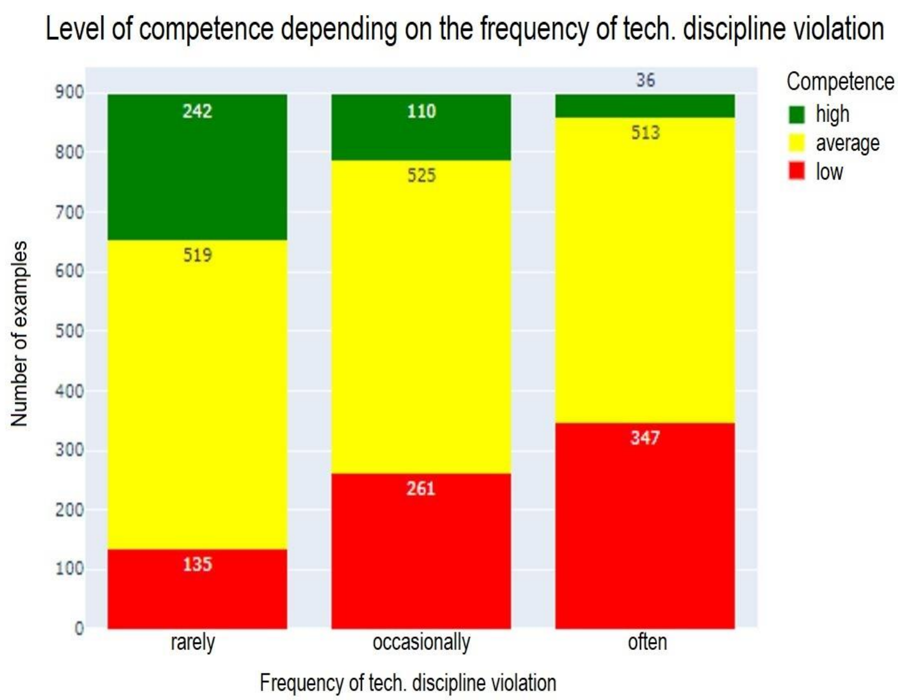

Figure 2: Diagrams of the level of competence against the frequency of violation of technological discipline

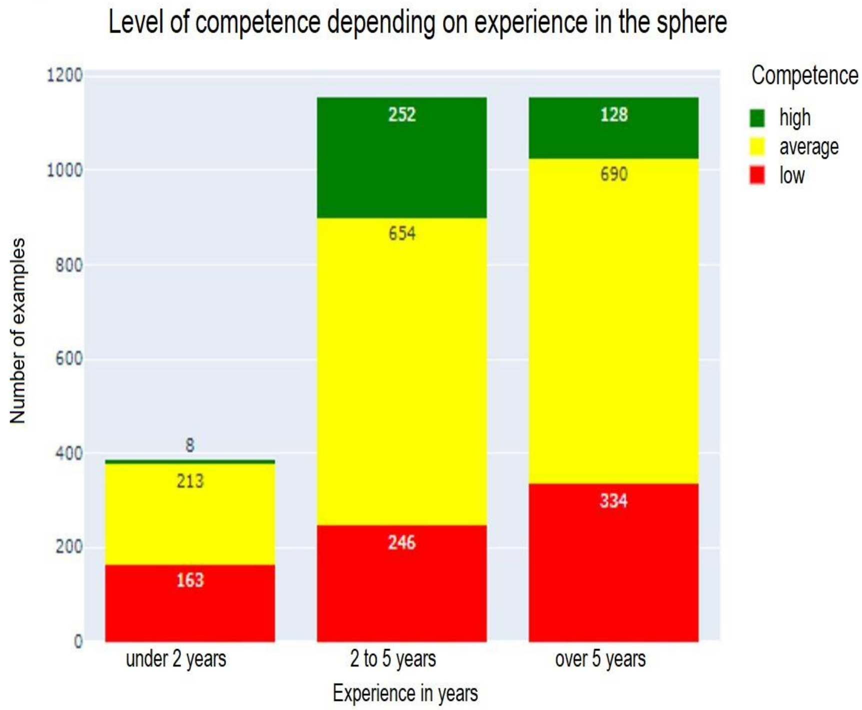

Figure 3: Diagrams of the level of competence against total experience in the current sphere

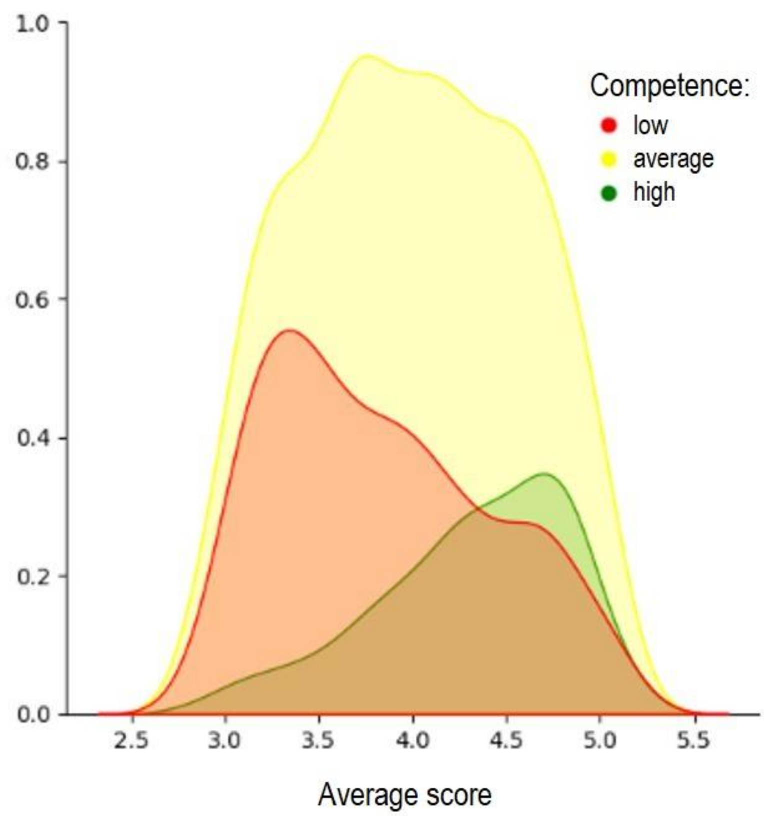

Figure 4: Probability density graph for average score

Table 1: Network precision on the training sample

		Activation function							
		sigmoid				tanh			
DNN model		Acc.	Valid.	Test	mse	Acc.	Valid.	Test	mse
	10-15-15-3	96.65	92.22	92.54	0.04	98.14	93.0	94.03	0.03
2 hidden layers	10-20-20-3	98.33	93.74	92.54	0.04	99.4	93.48	94.4	0.03
	10-25-25-3	99.35	94.37	93.66	0.03	99.86	94.33	95.9	0.023
	10-15-15-15-3	95.86	91.78	92.91	0.04	98.7	94.07	96.64	0.022
3 hidden layers	10-20-20-20-3	98.23	93.48	92.16	0.036	98.74	95.7	94.4	0.032
	10-20-20-20-3	98.88	94.59	94.03	0.033	99.21	95.7	94.5	0.038

According to the Chaddock scale for qualitative assessment of the closeness of connection of the rank correlation coefficient, these values indicate a weak connection. Figure 1a shows the dependence of the rank correlation coefficient on all the other indicators. The trend demonstrated in this figure is characteristic of virtually all of the parameters. One exception is the frequency of job change (Figure. 1b), which shows a moderate dependence on the experience of working in the current position (correlation coefficient equal to 0.65).

Furthermore, we analyzed the effect of each particular independent input parameter on the dependent output. Bar charts were constructed for the categorical parameters with the distribution of the number for each parameter, categorized by trait classes. Figure 2 shows a diagram of the frequency of violations of technological discipline in the workplace.

Figure 2 indicates that the distribution of input values across output clusters is uniform, meaning that there is no direct dependence on only one of the parameter values.

Figure 3 presents a diagram for total work experience in the line of business, which demonstrates the presence of a bias towards more experienced staff, which is consistent with the desire to hire more experienced workers. Nevertheless, there is no unambiguous correlation.

For the only continuously varying parameter, estimation of the average grade point average in the academic certificate, a probability density graph of a random continuous variable was plotted (Figure 4).

Figure 4 shows that employees with higher scores are more prevalent in the high-competence group and vice versa. However, the two graphs do not match completely, indicating that the grade point average in the academic certificate does affect the estimated level of competence and can be used as an input parameter for the designed neural network.

Training of the ANN for determining employee competence

To determine the optimal network structure, we conducted training experiments for forward propagation networks with different numbers of hidden layers and neurons per hidden layer, as well as with different training parameters: activation functions and weight updating algorithms (optimizers). The results are summarized in Table 1. For the Adam optimizer, the MSE loss function was applied, the value of which is given in brackets.

The provided results are obtained as a result of 200-epoch training, and a higher number of epochs does not improve network precision. The learning precision indicators given in the table are obtained at batch_size=32, while larger or smaller weight update batches resulted in lower precision. The retraining effect is not observed.

The results of the conducted training cycles (Table 1) show that the best precision is offered by the 10-25-25-3 architecture network using a hyperbolic tangent activation function. The respective learning curve is presented in Figure 5.

Table 1 demonstrates that the precision of the network model is higher than its evaluation on the test sample. The trend persists even after repeatedly mixing the data between and within samples.

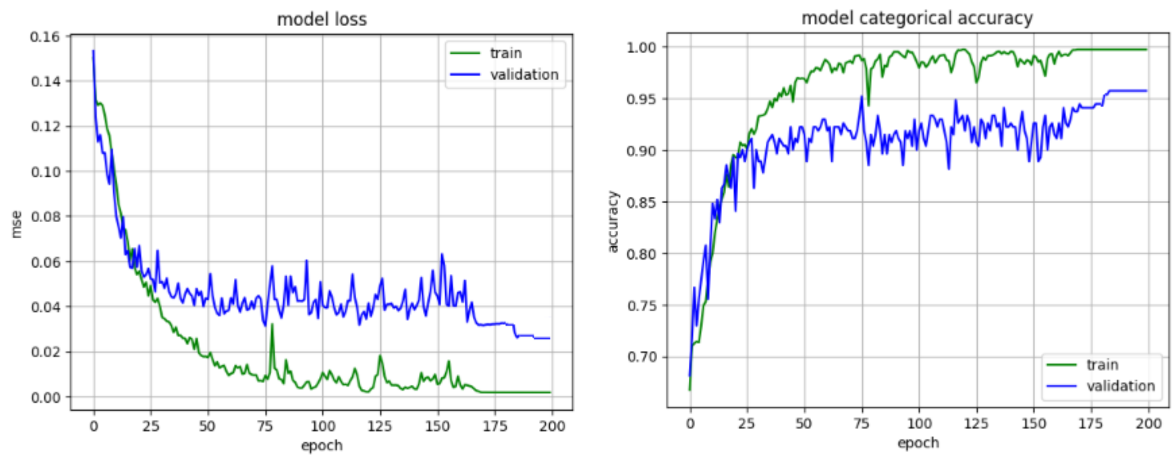

Figure 5: Learning curves of a forward propagation ANN with the 10-20-20-3 architecture

Discussion

The conducted research suggests that the ANN can be used in the system of indication of the occurrence of operational risk events related to personnel competence. The obtained test accuracy of the constructed ANN has a high enough value equal to 95%.

The network model that gives the best results is rather similar to the model for preventive indication of the emergence of operational risk events related to the use of Information Technology (IT) that was obtained by. Chumakova *et al.* (3). The difference consists in the employed activation function, although the two models are very close in terms of precision, differing by no more than 2%. The homogeneity of the obtained models suggests the possibility of implementing a unified modular (homogeneous in module architecture) system of interconnected neural networks for preventive indication of all types of events and sources of operational risks.

The research addresses the complexities and potential challenges associated with using neural networks to monitor operational risks in credit institutions, such as the difficulty in gathering comprehensive and accurate data, concerns over data privacy, the risk of model overfitting, potential biases within the data or model design, and the reliance on historical data which may not accurately predict future behaviors. These factors underscore the need for robust model validation, careful consideration of data inputs, and ongoing model adjustments to ensure fairness, accuracy, and relevancy in predicting operational risks associated with personnel actions.

As a direction of further research, we intend to examine the possibilities of constructing an ANN to assess employees' supra-professional skills (soft skills) and propose an ANN architecture for a comprehensive assessment of credit organization staff from the standpoint of the possibility of operational risk events related to the actions of employees involved in the business process.

Based on the application of an ANN, the study proposes a method of assessing the competence of personnel given its impact on the possibility of occurrence of operational risk events associated with the action of a credit organization's staff (unintentional mistakes, intentional action, or inaction). The ANN models found to be the most effective in assessing personnel competence are similar to those described by E.V. Chumakova et al. (3), designed to estimate operational risks in the process of using IT. This suggests the possibility of using a system of unified network modules for a comprehensive assessment of the operational risks of a credit organization, taking into account all possible sources of operational risk: imperfect or erroneous internal processes of a credit organization; actions of personnel and other persons; failures and deficiencies of information, technological, and other systems, as well as external events.

The described research findings are novel and can provide a basis for creating intelligent systems to monitor operational risks associated with the actions of credit organizations' personnel. With due regard to adaptation, the proposed solutions can also be utilized by companies in various industries outside the financial sector.

Conclusion

This study significantly advances the application of artificial intelligence in organizational risk management by demonstrating the effectiveness of Artificial Neural Networks (ANN) in assessing personnel competence and predicting operational risks. By integrating a variety of personal and professional parameters, the ANN enhances predictive capabilities, which can be adapted across different modules within a unified system, potentially applicable across various industries beyond finance. This modular approach not only improves targeted training and personnel management but also serves as a foundation for developing intelligent systems that autonomously monitor and mitigate risks, thus fostering more resilient organizational practices.

Abbreviation

Basel Committee on Banking Supervision (BCBS); Artificial Neural Network (ANN); Red– Amber – Green (RAG method of assigning criticality status); Deep Neural Network (DNN); Mean Squared Error (MSE); Information Technology (IT)

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Nil

Author Contributions

Ekaterina Vitalevna Chumakova: Conceptualization, Methodology, Writing - Original Draft Preparation, Visualization. Dmitry Gennadievich Korneev: Methodology, Software, Data Curation, Writing - Reviewing and Editing. Mikhail Samuilovich Gasparian: Validation, Formal Analysis, Investigation. Valery Alexandrovich Titov: Resources, Supervision, Project Administration. Ilia Sergeevich Makhov: Conceptualization, Writing - Reviewing and Editing, Funding Acquisition.

Conflict of Interest

Authors have no conflict of interest to declare.

Ethics Approval

Nil

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