10.63550/ICEIP.2026.24.64.078

A System for Analyzing Staff Performance Using Neural Network Technologies

Matytsina Irina Aleksandrovna [1][a], Barkalov Vadim Vyacheslavovich [2][b], Korobova Lyudmila Anatolyevna [2][c] and Chernyaeva Svetlana Nikolaevna [1][d]

[1]Voronezh branch Admiral Makarov State University of Maritime and Inland Shipping, Voronezh, Russia,
[2]Voronezh State University of Engineering Technologies, Voronezh, Russia
irina210390@mail.ru

Keywords: efficiency analysis, neural networks, food industry, MCNN, personnel monitoring, production processes, cost optimization.

Abstract: This article examines the problem of improving the operational efficiency of food industry enterprises, particularly vegetable oil processing plants, in the context of the digitalization of the economy. The authors emphasize the importance of implementing innovative solutions based on data processing and machine learning technologies to reduce costs and increase productivity. A new labor efficiency analysis system using neural network models is proposed. A methodology for developing and implementing this system, aimed at identifying factors affecting employee productivity and generating recommendations for enterprise managers, is described. The advantages of using neural networks, in particular Multi-Channel Neural Networks (MCNN), are detailed, allowing for the efficient processing of large volumes of data and the generation of accurate forecasts. The study demonstrated high results: recognition accuracy reached 96%. This indicator demonstrates the model's ability to reliably interpret employee behavior and quickly respond to changes in the production process. The system demonstrates good potential for practical implementation in large industrial companies, facilitating informed management decision-making and improving product quality control. The authors conclude that further development of intelligent big data analytics tools is essential to enhance the competitiveness of domestic manufacturers in the context of market globalization and increasingly stringent consumer demands. The conclusion emphasizes the importance of integrating new technologies and the need for continuous monitoring and analysis of the effectiveness of technological innovations.

[a] https://orcid.org/0000-0001-9236-9654
[b] https://orcid.org/0009-0000-7904-7626
[c] https://orcid.org/0000-0003-1349-732X
[d] https://orcid.org/0000-0002-5564-9806

10.63550/ICEIP.2026.24.64.078

1 INTRODUCTION

The relevance of this topic is determined by the growing role of decision-making systems in HR management in domestic business and manufacturing. During software development, time managers must monitor employee productivity, analyze their activity during work hours, and make informed personnel decisions. In a context where companies need to quickly respond to issues related to productivity or employee satisfaction, automated information systems (IS) are becoming a key tool for process management.

A personnel performance analysis system using neural network technologies is aimed at increasing productivity and reducing costs in the food industry, particularly at vegetable oil processing plants. The development is based on the use of neural networks to identify key performance factors, uncover hidden potential, and prevent errors. A Wear OS-based app collects accelerometer data, recording employee movements, allowing for activity analysis. The MCNN (multi-channel neural network) architecture ensures high accuracy in recognizing time series patterns, making the system useful for monitoring and optimizing production processes.

Amidst rapid technological advances and digital transformation, finding solutions to improve efficiency and reduce costs is becoming a critical task for companies. This is especially important in the food industry, especially at vegetable oil processing plants. Data processing and machine learning technologies, including neural network models, open new horizons for analyzing production processes, allowing for insights into areas for improvement.

The developed labor efficiency analysis system is aimed at supporting such enterprises. Using neural networks, it helps identify key factors influencing productivity and base management decisions on them. This isn't just performance monitoring; the analysis allows us to discover even hidden potential for improving operational efficiency.

The labor efficiency analysis system using neural networks truly solves several important problems for the oil and fat industry.

2 MATERIALS AND METHODS

For an industry where precision and efficiency are so crucial, the system enables the identification of bottlenecks in the production process and the analysis of employee performance. This helps not only monitor productivity but also proactively identify potential failures and deviations from required standards. As a result, work can be adjusted promptly and resources can be allocated to maintain high productivity.

One of the system's notable advantages is the ability to accurately track areas where production costs can be reduced. The neural network analyzes the performance of each employee. This helps optimize costs and increase profitability, which is especially important in a highly competitive market.

The system also helps prevent errors and potential emergencies. It helps identify behavioral patterns that can lead to abnormal situations and offers tools to mitigate these risks. Notably, the analysis can even identify employees who need additional training or those experiencing stress or fatigue, which also impacts work quality.

In a large-scale production environment with a multi-level structure and complex processes, the system becomes a valuable assistant for managers. Based on the provided data and forecasts, decisions about personnel changes and the development of incentive and training programs can be made more confidently. This not only facilitates personnel management but also helps make it more transparent and understandable.

To monitor production activity at the oil refinery, a Wear OS-based app was developed. It automatically collects accelerometer data, with data transmission configured on the server side, minimizing the need for personnel intervention and ensuring regular data delivery.

Before developing the personnel performance analysis system, all existing processes and subprocesses were structured to better understand the oil refinery's operations. The quality of the finished product depends entirely on certain intermediate, monotonous operations. The precision, consistent frequency, and accuracy of these operations demonstrate compliance with process regulations. Therefore, the task of assessing personnel performance is relevant at all stages of production. A context diagram of the personnel performance analysis process is shown in Figure 1. The input stream is accelerometer data. A neural network serves as the mechanism. The process of analyzing (assessing) personnel performance must comply with the technical specifications of the process and sampling standards. The final output is the employee's performance.

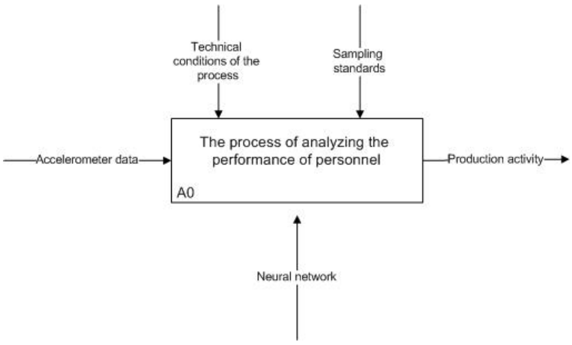

Figure 1: Business process of analysing personnel performance.

The context diagram decomposition is shown in Figure 2. Three stages are identified in the analysis process: accelerometer initialization, employee activity tracking using accelerometer readings, and work time activity analysis. The analysis stages are represented in the decomposition diagram as functional blocks. As a result of the decomposition, intermediate flows are identified. The output of block 1 is the input of block 2 (intermediate flow)—information about accelerometer start; the output of block 2 is the input of block 3 (intermediate flow)—employee activity time.

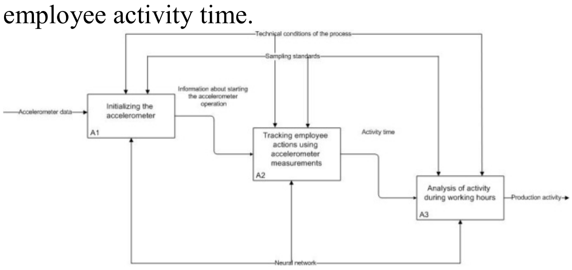

Figure 2: Decomposition of the analysis process.

The app collects data at the specified time, activates the watch's accelerometer, and begins recording acceleration along three axes—X, Y, and Z—at a specified frequency. This allows for precise tracking of employee movements in the work area, recording everything with timestamps. This allows for determining not only the nature of activity but also its duration, intensity, and periods of rest (Figure 3).

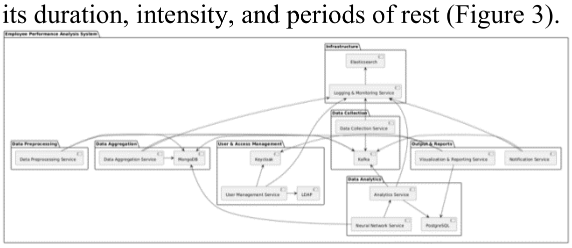

Figure 3: Interaction of system micro services.

Additionally, to prevent data loss when a stable connection is lost, the application features a local caching feature. In such cases, data is temporarily stored on the device and sent to the server upon the first stable connection. This is particularly useful for production facilities, where connectivity can be unstable, and helps maintain a continuous flow of information. Every evening, at the end of the workday, or upon a signal from the server, the watch begins transmitting collected data to the central system via a secure connection. The data is sent to a Kafka message queue, which forwards it to microservices for further aggregation and preprocessing. This ensures that data enters the system in near real time—critical for accurate analysis and timely management decisions regarding employee production activity.

The MCNN (Multi-Channel Neural Network) architecture is a structure consisting of three sequential stages, each aimed at stepwise "peering" into the time series to identify significant features (Figure 4). This step-by-step strategy allows the network to more effectively analyze and classify features that traditional methods typically miss.

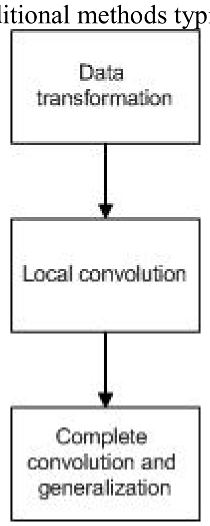

Figure 4: MCNN architecture.

The first stage is data transformation.

The initial stage involves a series of transformations designed to represent the data with varying levels of detail. Interestingly, this can involve both simple techniques (such as the original representation of the series) and more advanced methods, such as the Fourier transform or wavelet transform. Each processing method uniquely reveals the temporal and frequency characteristics of the data, providing a richness of information for analysis. This lays the foundation for precise feature extraction in subsequent stages.

The second stage is local convolution.

Next, each transformed version of the series is passed to its own convolutional branch, which uses filters capable of highlighting small but significant details, from peak activity to short-term fluctuations. Such patterns can be particularly important for classification, as their appearance often characterizes specific features of the data. A key advantage of MCNN at this stage is its ability to focus on key features in short time intervals that might otherwise be overlooked with traditional processing.

The third stage is full convolution and generalization.

After each convolutional branch has extracted its features, the neural network combines the results to create a generalized representation of the time series. The final softmax layer transforms this multi-layer processing into a probability prediction, which is used for the final classification.

The advantage of this architecture lies in the neural network's adaptability to various data types, effectively identifying more complex and multi-scale patterns than traditional methods. This makes it particularly useful for analyzing complex time series, where both temporal and frequency features of the data are important.

After training, the network is run on validation data to understand how well it has learned the patterns hidden in the original examples. The results were truly impressive: recognition accuracy was 96%, demonstrating the high quality of the model (Figure 5).

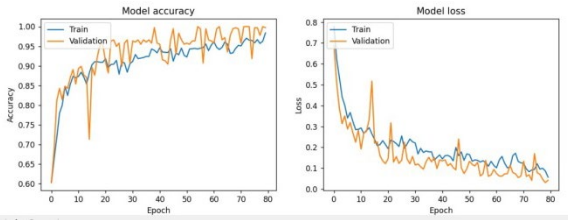

Figure 5: Training a neural network.

A high level of accuracy indicates that our model was able to correctly extract the key features required for classification and successfully handled a wide range of data variations. In practice, this means that the neural network not only "remembered" the training data but was also able to transfer its knowledge to new cases. It is not susceptible to overfitting, allowing it to confidently handle data that differs slightly or significantly from the training data.

The testing phase showed that the neural network recognizes not only obvious patterns but also more complex, less obvious features. For example, the network successfully handled tasks where the time series patterns had similar characteristics or when it was necessary to consider implicit relationships.

High accuracy provides confidence that the model is robust and reliable in real-world conditions. The model demonstrated the ability to extract key features with minimal distortion, making it highly promising for use in mission-critical tasks where errors can be costly. During testing, attention was paid to how the model handles edge cases—situations where the correct answer may not be so obvious. Remarkably, the network demonstrated stability even under such challenging conditions, further confirming its generalization capabilities and excellent adaptability.

3 CONCLUSIONS

The development of digital technologies is having a significant impact on improving the efficiency of industrial production, especially in the vegetable oil processing industry. The use of modern data analysis tools and neural networks offers significant opportunities for optimizing work processes and reducing costs. The developed labor efficiency analysis system using neural network models allowed companies to identify key factors determining productivity and take timely measures to eliminate problem areas.

The following results were achieved during the project. First of all, the activity monitoring app for Wear OS was implemented exactly as intended: it automatically collects data at the right time and requires minimal user intervention. This is not only convenient – in a production environment where every second counts, this approach actually saves resources, eliminating the need for employees to be distracted by technical details.

Reliable data transmission is ensured, even during internet outages. Local data caching allows all necessary information to be saved and then automatically sent at the earliest possible opportunity. The implementation of this technology was one of the key discoveries in the project: it ensures the continuity of data, which can be used to build improvements in production processes.

Particular attention is paid to monitoring employee actions, enabling the prompt detection and elimination of potential violations of production regulations. The system demonstrates high accuracy in recognizing employee work actions, reaching 96% when tested on real data. This high-quality modeling was made possible by a well-designed Multi-Channel Neural Network (MCNN) architecture capable of identifying subtle patterns and complex employee behavior.

Using the system improves operational efficiency and reduces production risks, making work processes more manageable and controllable. Thus, implementing this approach significantly reduces operating costs and enhances the competitiveness of domestic manufacturers in the global market. The results of the studies confirm the high effectiveness of the proposed solution and point to prospects for further development of labor efficiency analysis technology at large food processing enterprises.

REFERENCES

Khaikin, S., 2006. Neural Networks: A Complete Course.

Evstratova, E., 2018. Application of neural network analysis in personnel management processes, *Young scientist*

Lisovsky, A., 2020. Application of neural network technologies for the development of control systems, *Strategic decisions and risk management*

Azarnova, T.V., Stepin, V.V., Shchepina, I.N., 2014. Improving the Efficiency of Personnel Development Management Methods Based on Neural Network Models and Fuzzy Expert Technologies, *Vestnik of VSU*

Korobova, L. A., Tolstova I. S., Kharitonov, I. M., 2022. Software and hardware tool for APCS diagnostics: data monitoring and automation system state management, *Information technologies in construction, social and economic systems*

Korobova, L. A., Tolstova, I. S., Matytsina, I. A., Mironova, M. S., 2021. *J. of Physics: Conference Series : Current Problems*

Maika, A. N., Korobova, L.A., 2024. *Engineering technologies*