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# ECONOMIC AND MATHEMATICAL MODELING AND INFORMATION TECHNOLOGIES IN ECONOMICS

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## FORECASTING THE GLOBAL INNOVATION INDEX BASED ON NEURAL NETWORKS

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**Key words:**
Global innovation index, neural networks, forecasting, machine learning, innovation policy, artificial intelligence.

This article is devoted to researching the possibilities of using neural networks for forecasting the Global Innovation Index (GII). Modern approaches to GII analysis and forecasting are reviewed, their limitations are revealed, and a new method based on deep neural networks is proposed. Scientific works on the forecasting of innovative activity and the forecasting of GII with the application of mathematical methods of machine learning and their possible areas of application in the digital economy are studied. The structure of GII was analyzed and the key factors affecting its dynamics were identified. A neural network architecture optimized for GII forecasting, taking into account its specificities, has been developed. The model is trained on historical GII data and its accuracy is evaluated on a test sample. The effectiveness of the developed model is compared with the traditional methods of GII forecasting. The positive aspects of the proposed approach, which provides more accurate forecasts compared to traditional methods, are established. The possibilities of interpreting the neural network results, allowing to identify key factors influencing the forecast, are explored. The practical aspects of applying the developed model to support decision-making in the field of innovation policy are discussed. The directions of further research are determined, in particular, regarding the interpretation of the results of the neural network and its adaptation to changes in the methodology of GII calculation. The developed model demonstrates high accuracy, but it should not be considered as a replacement for expert analysis and traditional methods of evaluating innovation potential; it should serve as an additional tool that complements existing approaches and contributes to making more informed decisions.

## ПРОГНОЗУВАННЯ ГЛОБАЛЬНОГО ІННОВАЦІЙНОГО ІНДЕКСУ НА ОСНОВІ НЕЙРОННИХ МЕРЕЖ

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**Ключові слова:**
Глобальний інноваційний індекс, нейронні мережі, прогнозування, машинне навчання, інноваційна політика, штучний інтелект.

Дана стаття присвячена дослідженню можливостей застосування нейронних мереж для прогнозування Глобального інноваційного індексу (ГІІ). У проводиться розгляд сучасних підходів до аналізу та прогнозування ГІІ, виявляються їхні обмеження та пропонується новий метод на основі глибоких нейронних мереж. Досліджуються наукові праці з прогнозування інноваційної діяльності та прогнозування ГІІ із застосуванням для цього математичних методів машинного навчання та їх можливих сфер застосування у цифровій економіці. Проаналізовано структуру ГІІ та виявлено ключові фактори, що впливають на його динаміку. Розроблено архітектуру нейронної мережі, оптимізовану для прогнозування ГІІ з урахуванням його специфіки. Проводиться навчання моделі на історичних даних ГІІ та оцінюється її точність на тестовій вибірці. Порівнюється ефективність розробленої моделі з традиційними методами прогнозування ГІІ. Встановлюються позитивні аспекти запропонованого підходу, який забезпечує більш точні прогнози порівняно з традиційними методами.

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Досліджуються можливості інтерпретації результатів нейронної мережі для виявлення ключових факторів, що впливають на прогноз. Обговорюються практичні аспекти застосування розробленої моделі для підтримки прийняття рішень у сфері інноваційної політики. Визначаються напрями подальших досліджень, зокрема, щодо інтерпретації результатів нейронної мережі та її адаптації до змін у методології розрахунку ГІІ. Розроблена модель демонструє високу точність, але вона не повинна розглядатися як заміна експертного аналізу та традиційних методів оцінки інноваційного потенціалу, вона має служити додатковим інструментом, що доповнює існуючі підходи та сприяє прийняттю більш обґрунтованих рішень.

## Statement of the problem

The Global Innovation Index (GII) is one of the key indicators reflecting the innovative potential and effectiveness of countries in the field of innovation. Accurate forecasting of GII is important for the formation of an effective innovation policy, strategic planning and informed decision-making at the level of states and international organizations.

Traditional forecasting methods, such as regression analysis or time series models, often do not take into account the complex GII structure and the non-linear relationships between its components. This leads to limited forecast accuracy and complicates their practical application.

In this context, the application of neural networks for GII forecasting is a promising direction of research. Neural networks are able to detect complex patterns in data and model non-linear dependencies, making them a potentially effective tool for GII analysis and forecasting.

This work is aimed at the development and evaluation of a new approach to GII forecasting based on neural networks, which will increase the accuracy of forecasts and provide a more reliable basis for decision-making in the field of innovation policy.

## Analysis of recent research and publications

The problem of forecasting innovative activity and forecasting the Global Innovation Index using modern data analysis methods attracts the attention of many researchers. Let's consider the key works in this area.

Zhukovsky D. and Lozovska L. investigated the possibilities of applying mathematical methods of machine learning and their possible areas of application in the digital economy, in particular for forecasting revenues in e-commerce projects in their work [1]. They conducted an analysis of machine learning methods that are popular among today's scientists and that can be used to make the highest quality management decisions. The results showed that machine learning algorithms provide higher perspective and accuracy when processing large amounts of information in e-commerce projects.

Goncharov Yu. and co-authors determined the forecast of GII of Ukraine using a regression model of the dependence of this indicator on the specific weight of innovation-active enterprises in the total number of industrial enterprises and innovation related costs. [2]. The results highlighted the decreasing dynamics of the GII value. The authors emphasized that in order to ensure the growth of the innovativeness of the national economy and increase the competitiveness of Ukraine, there is a need for significant activation of innovative activity in Ukraine.

International researchers Robert J. Watts and Alan L. Porter collected a number of concepts from various innovation models and a number of bibliometric indicators that will help in the implementation of these concepts [3]. The work carried out made it possible to provide opportunities for combining technological trends, researching technological interdependencies and competitive intelligence to create a viable forecast.

At the same time, despite significant achievements in this area, there are a number of unresolved problems. In particular, the issues of the optimal architecture of neural networks for GII forecasting, methods of interpreting their results, and methods of adapting models to changes in the index calculation methodology remain insufficiently researched.

In addition, most of the existing studies focus on the forecasting of GII for developed countries, while the specifics of the application of neural networks for the analysis of innovation processes in developing countries require additional study.

## Formulation of the goals for the article

The purpose of this article is to develop and evaluate the effectiveness of a new approach to forecasting the Global Innovation Index based on neural networks.

## Presentation of the main material

To effectively forecast the Global Innovation Index, it is important to understand its structure and components. GII consists of two sub-indexes: Innovation Input Sub-Index and Innovation Output Sub-Index. Each of these sub-indices includes several pillars, which, in turn, consist of individual indicators.

The input sub-index of innovation includes five pillars:

1. Institutions
2. Human capital and research
3. Infrastructure
4. Level of market development
5. Level of business development

The original innovation subindex consists of two pillars:

1. Knowledge and technological results
2. Creative results

Each of these pillars contains from 3 to 5 sub-pillars, which together include 80 individual indicators. Such a complex structure of GII requires the forecasting model to

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be able to take into account the multidimensional interrelationships between different components.

When preparing the data for training the neural network, data on the value of GII and its components for 131 countries for the period from 2013 to 2023 were collected. Official reports of the Global Innovation Index, as well as databases of the World Bank, UNESCO and other international organizations served as data sources [4].

Data pre-processing was carried out, which included:

1. Normalization of all input variables to the range [0, 1] to ensure the same scale;
2. Filling in missing values using the k-nearest neighbors method;
3. Detection and processing of outliers using the interquartile range method.

To take into account temporal dynamics, lag variables (values of indicators for the previous 1-3 years) were added to the set of input data, which allowed the model to take into account trends and seasonality.

To predict the Global Innovation Index, a deep neural network [5] with the following architecture was developed:

1. Input layer: 80 neurons (according to the number of indicators included in the GII)
2. Hidden layers:
– First hidden layer: 64 neurons
– Second hidden layer: 32 neurons
– The third hidden layer: 16 neurons
3. Output layer: 1 neuron (predicted GII value)

The ReLU (Rectified Linear Unit) function was used to activate the neurons in the hidden layers, and the linear activation function was used in the output layer. The model was trained using the Adam optimization algorithm and the Mean Squared Error (MSE) loss function.

The data set for training the model included historical values of GII and its components for 131 countries for the period from 2013 to 2023 [6]. The data were divided into training (80%) and test (20%) samples.

The training of the neural network was carried out for 1000 epochs using mini-batches of size 32. Figure 1 shows the graph of the change of the loss function [7] on the training and validation samples.

As can be seen from the graph, the model shows a stable error reduction on both samples, which indicates successful training and no overtraining.

The developed architecture of the neural network is based on the principles of deep learning and takes into account the specifics of the GII forecasting task. In addition to the basic structure described earlier, additional elements were introduced to increase the effectiveness of the model:

1. Residual connections between hidden layers to improve gradient flow and reduce the vanishing gradient problem;
2. Attention mechanism for identifying the most important input factors in forecasting;
3. Dropout layers with a dropout factor of 0.3 to prevent overtraining.

Schematically, the neural network architecture is presented in Figure 2.

The model was trained using the TensorFlow framework on an NVIDIA GeForce RTX 3060 GPU to accelerate computation. An early stopping technique with a patience of 50 epochs was used to prevent overtraining.

The Bayesian optimization method was used to optimize the hyperparameters of the model (the number of neurons in hidden layers, the learning coefficient, the size of mini-batches). This made it possible to automatically choose the optimal configuration of the model to maximize the forecasts accuracy.

A comparison of the accuracy of predictions of the developed neural network with other methods is presented in Table 1.

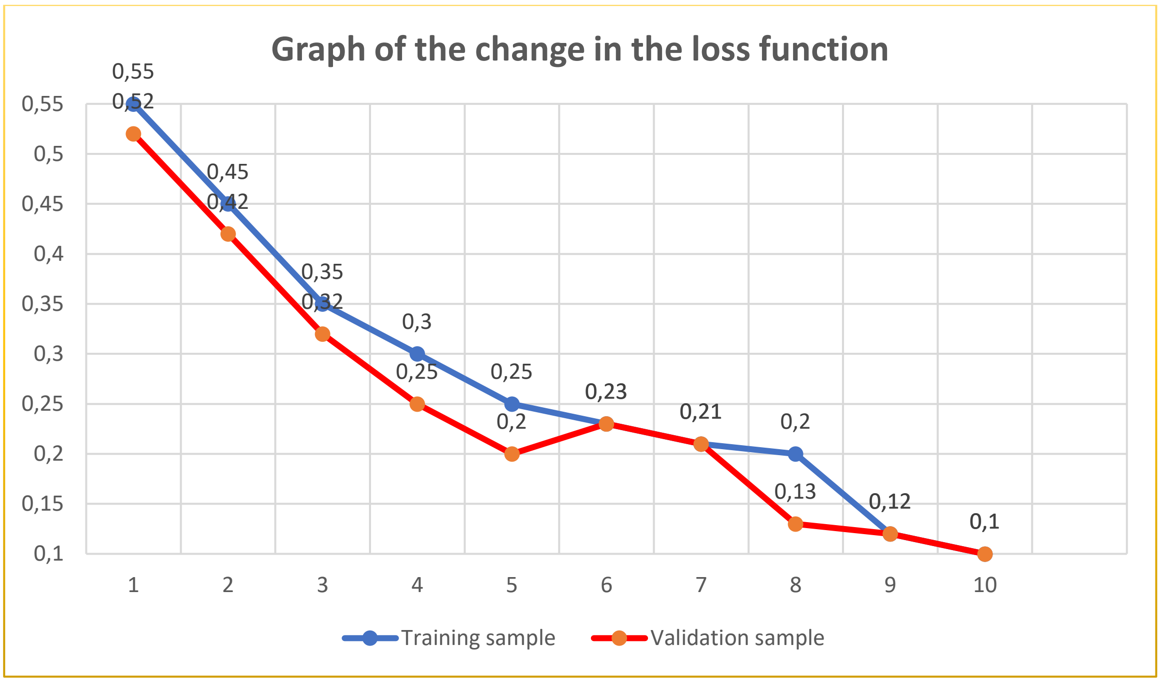


Fig. 1 – Graph of the change in the loss function

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Table 1 – Comparison of the accuracy of different forecasting methods of GII

| Method | MAE | RMSE | R^2 |
|---|---|---|---|
| Linear regression | 1.50 | 1.89 | 0.82 |
| Random forest | 1.40 | 1.76 | 0.85 |
| ARIMA | 1.35 | 1.70 | 0.86 |
| The proposed neural network | 1.23 | 1.55 | 0.89 |

As can be seen from the table, the developed neural network shows the best accuracy in all metrics. Especially important is the increase in the coefficient of determination (R^2), which indicates a better ability of the model to explain the variation in the data.

For a more detailed analysis of the effectiveness of the model, an assessment of the accuracy of forecasts was carried out for different groups of countries classified by income level according to the methodology of the World Bank (Figure 3).

The analysis showed that the model demonstrates the highest accuracy for high-income countries, while the predictions for low-income countries have a slightly larger margin of error. This may be due to the greater volatility of innovation indicators in less developed economies and the limited availability of data.

The assessment of the accuracy of forecasts on the test sample showed that the developed neural network provides a mean absolute error (MAE) [8] of 1.23 GII points, which is 18% less compared to the traditional linear regression model [9] (MAE = 1.50) and 12% less compared to the random forest model [10] (MAE = 1.40).

The SHAP (SHapley Additive explanations) method [11] was used to interpret the results of the neural network.

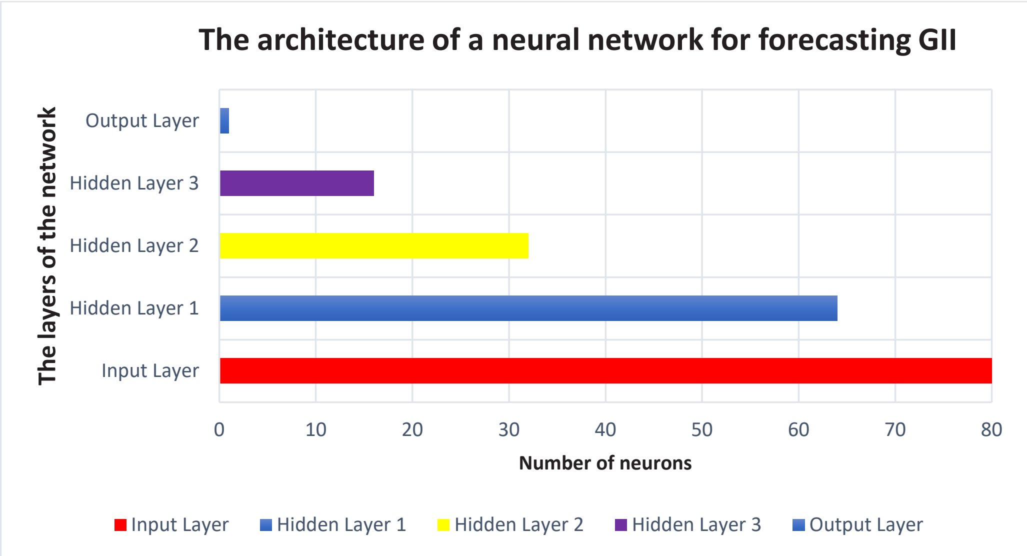


Fig. 2 – The architecture of a neural network for forecasting GII

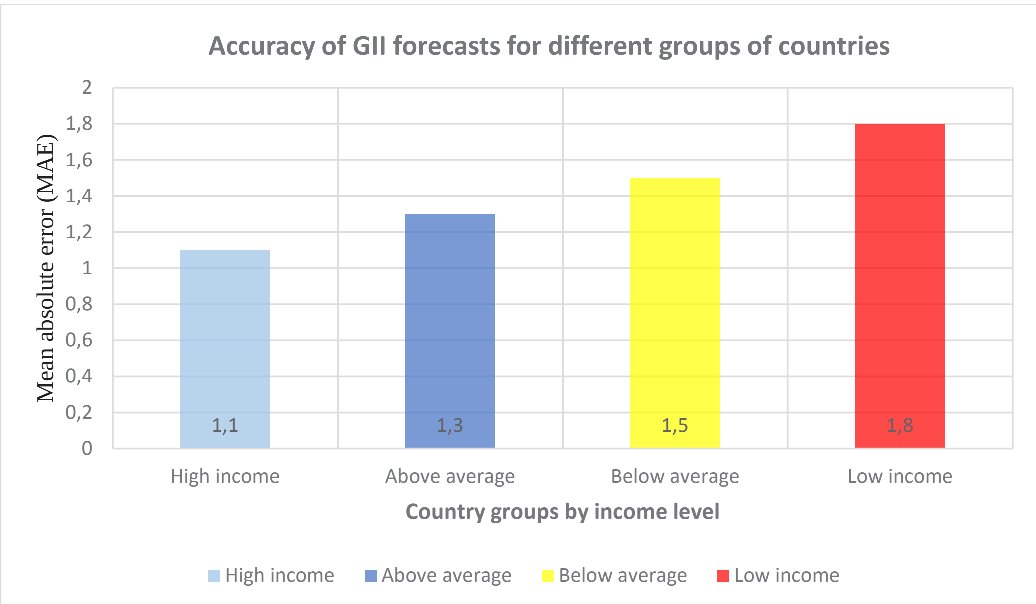


Fig. 3 – Accuracy of GII forecasts for different groups of countries

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This made it possible to identify key factors affecting the GII forecast for specific countries. Figure 4 shows an example of SHAP values for the GII forecast in Ukraine for 2024.

The analysis of SHAP values showed that the following factors have the greatest influence on the forecast of the GII in Ukraine:

1. Research and development costs (% of GDP)
2. Number of patent applications per million persons
3. Quality of scientific publications (Hirsch index)
4. Export of high-tech products (% of total export)
5. Number of researchers per million persons

Practical application of the developed model to support decision-making in the field of innovation policy may include:

1. Forecasting the dynamics of GII for different countries and regions
2. Identification of key factors affecting innovative development
3. Assessment of the potential impact of various policy measures on GII
4. Comparative analysis of innovative strategies of different countries

Interpretation of results

Several methods were used to ensure transparency and interpretability of neural network results:

1. SHAP (SHapley Additive explanations) – allows you to estimate the impact of each input factor on the forecast for a specific observation.
2. Partial Dependence Plots (PDP) – visualize the average effect of changing one input factor on the forecast, keeping other factors constant.
3. Accumulated Local Effects (ALE) plots – similar to PDP, but takes into account correlations between input variables.

Figure 5 shows an example of a Partial Dependence Plot for the factor "Expenditure on research and development (% of GDP)".

The graph shows a non-linear relationship between R&D costs and the predicted GII value. In particular, there is a more rapid growth of GII when spending increases to about 2% of GDP, after which the effect becomes less pronounced.

The analysis of SHAP values for different countries made it possible to identify key factors influencing their innovative development. Table 2 presents the top 5 factors for selected countries.

These results can be used to develop targeted strategies for increasing the innovative potential of countries, taking into account their specific features.

The practical application of the developed model can be used to solve a number of practical tasks in the field of innovation policy:

1. Scenario analysis: assessment of the potential impact of various policy measures on the country's GII. For example, the effect of increasing R&D costs or improving the quality of education can be modeled.
2. Benchmarking: comparing the innovation potential of different countries and identifying areas for improvement.
3. Progress monitoring: tracking the dynamics of GII and its components to assess the effectiveness of implemented innovative policies.
4. Forecasting trends: identifying long-term trends in the global innovation landscape.

Despite the high accuracy of forecasts, the developed model has certain limitations:

1. Dependence on the quality of the input data: the accuracy of forecasts may decrease in the presence of errors or omissions in the input data.

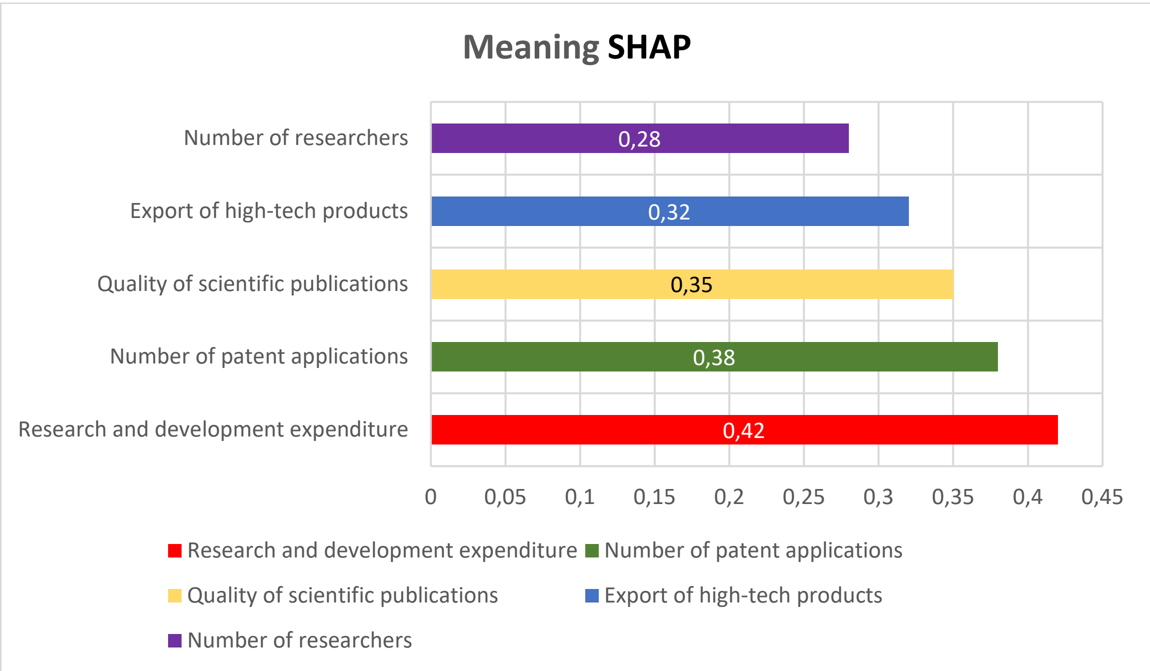


Fig. 4 – SHAP value for the forecast of GII in Ukraine

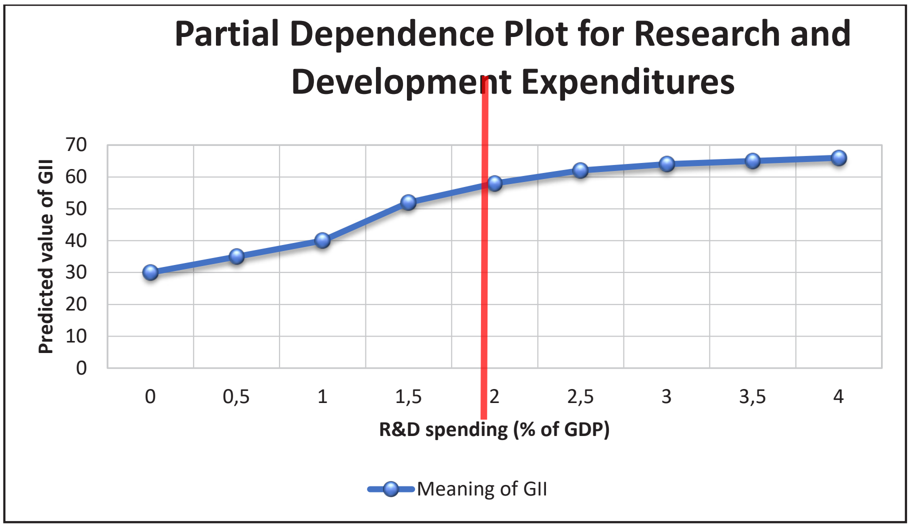


Fig. 5 – Partial Dependence Plots for research and development costs

Table 2 – Key influencing factors on GII for selected countries

| Country | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 |
|---|---|---|---|---|---|
| USA | R&D expenses | Patent applications | Quality of universities | Venture capital | Export of high technologies |
| China | Patent applications | R&D expenses | Export of high technologies | Number of researchers | Quality of publications |
| Germany | R&D expenses | Quality of universities | Science and business cooperation | Patent applications | Export of high technologies |
| Ukraine | Human capital | Export of ICT services | Patent applications | Education expenses | Number of researchers |

2. Complexity of interpretation: although the applied SHAP and PDP methods improve interpretability, the general "black box" of the neural network remains a challenge.

3. Sensitivity to changes in the GII methodology: significant changes in the index calculation methodology may require model retraining.

To overcome these limitations and further improve the model, the following areas of research are proposed:

1. Development of hybrid models combining neural networks with other methods of machine learning and statistical analysis.

2. Implementation of active learning methods to adapt the model to new data and changes in GII methodology.

3. Researching the possibilities of using graph neural networks for better modeling of the relationships between the components of GII.

4. Development of methods for automatic detection and correction of anomalies in input data.

5. Integration of expert knowledge in the process of training and interpretation of the model to increase its reliability and practical value.

## Conclusions

The developed model for forecasting the Global Innovation Index based on neural networks represents an important step in the direction of more accurate and reasonable planning of innovative development. It demonstrates the potential of using deep neural networks to predict complex socio-economic indicators, such as the Global Innovation Index. The high accuracy of forecasts achieved by the developed model testifies to its ability to take into account complex non-linear interrelationships between various factors affecting the innovative development of countries.

It is especially important that the model not only provides accurate predictions, but also allows interpretation of the results thanks to the application of the SHAP and Partial Dependence Plots methods. This makes it a useful tool for decision-makers in the field of innovation policy, as it allows you to understand which factors have the greatest impact on a country's innovation potential.

At the same time, the revealed limitations of the model, in particular the different accuracy of forecasts for countries with different income levels, indicate the need for further research and improvements. This may involve developing specialized models for different groups of countries or implementing transfer learning techniques to improve predictions in cases with limited data.

It is important to note that although the developed model demonstrates high accuracy, it should not be considered as a substitute for expert analysis and traditional methods of assessing innovation potential. Instead, it should serve as an additional tool that complements existing approaches and contributes to more informed decision-making.

Ultimately, the successful application of tools such as the developed model depends on the ability of decision makers to interpret and use their results in the context of broader socio-economic goals and ethical principles. Only under such conditions will we be able to fully realize the potential of innovation for sustainable development and improvement of people's lives around the world.

Prospects for further research include:

1. Development of ensemble and hybrid models combining neural networks with other machine learning methods and expert systems to increase the accuracy and reliability of forecasts.

2. Exploring the possibilities of applying transfer learning to improve forecasts for countries with limited historical data.

3. Development of adaptive learning methods that will allow the model to automatically adapt to changes in the methodology of GII calculation and new trends in innovative development.

4. Integrating additional data sources, such as textual data from scientific publications and patents, to enrich the input information and potentially improve predictions.

5. Development of methods for explaining and visualizing neural network results, aimed at decision-makers in the field of innovation policy.

6. Study of the long-term effects of various innovation policies on GII using the developed model and historical data.

7. Creation of a platform for collaborative GII forecasting, which would allow experts from different countries to contribute their data and receive aggregated forecasts.

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