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A MULTI-TASK NEURAL NETWORK FOR SIMULTANEOUS REGRESSION AND CLASSIFICATION OF REGIONAL SECURITY AND QUALITY OF LIFE INDICES IN UKRAINE

Abstract. In the face of contemporary geopolitical challenges and transformative processes, particularly the decentralization reform, the objective assessment and forecasting of regional stability have become critical tasks for ensuring Ukraine's sustainable development. This research addresses the lack of comprehensive, automated tools for analyzing the condition of territorial communities by developing and validating an innovative model based on artificial intelligence. The methodological foundation of this work is the development and testing of a multi-task deep learning neural network designed to simultaneously solve four related tasks. The model concurrently performs two regression tasks to predict the precise numerical values of the Regional Security Index (RSI) and the Quality of Life Index (LI), as well as two classification tasks to determine the categorical levels of these indices (low, medium, high). The theoretical basis for the formation of these target indices is the Quadruple Helix concept, which describes the synergistic interaction between government, business, the scientific community, and civil society. The model was trained on a unique dataset covering 1469 Ukrainian territorial communities and containing heterogeneous socio-economic and security indicators. The experimental results demonstrated the high efficiency of the developed approach. On the test set, the classification accuracy reached 93.9% for the Regional Security Index and 85.0% for the Quality of Life Index. In the regression tasks, the model showed low mean absolute error values, indicating high predictive accuracy for both categorical levels and specific index values. The study concludes that the created model is a powerful and effective tool for monitoring, analyzing, and forecasting the dynamics of regional development in Ukraine. The results can be used by state and local government bodies to develop targeted policies aimed at enhancing the resilience, cohesion, and attractiveness of Ukrainian regions.

Keywords: multi-task learning; deep learning; regional security; quality of life; predictive modelling; territorial communities; cybersecurity.

Introduction

In an era of global instability and transforming international relations, ensuring national security and sustainable development has become a primary objective for every state. Modern scientific paradigms view national security as a complex system, the effectiveness of which is determined not only by military potential but also by the resilience and cohesion of its society [1]. Social capital, economic stability, and the quality of life at the regional level form the foundation upon which national resilience to external and internal threats is built. Monitoring and forecasting regional development has become particularly acute for Ukraine, which is undergoing a difficult period of reform while confronting geopolitical challenges.

A key transformational process in this context is the reform of decentralisation that began in 2014. It has fundamentally altered the administrative-territorial structure, transferring significant powers and financial resources to newly established territorial communities [2]. As international experts have noted, this reform is one of the most successful in Ukraine; however, it has also exacerbated the problem of regional disparities and revealed the need for new governance tools [2]. Territorial communities have become the primary actors responsible for their residents' security, social infrastructure, and quality of life. To adequately analyse the processes occurring at this level, it is appropriate to apply the "Quadruple Helix" model as an analytical framework [3, 4]. This model describes the close digital and physical interaction between four key actors – government bodies, local businesses, educational institutions, and active civil society – which together form the complex socio-cyber-physical system of each community. In this system, cybersecurity is not merely one of the components but a cross-cutting condition for its stable functioning. Every digital link between the elements of the helix, whether electronic document exchange between the government and businesses or online platforms for civic initiatives, is a potential cyber vulnerability. Consequently, all participants in this system lack the tools for objective assessment and, most importantly, for forecasting situational development while considering these complex risks.

Traditional methods of regional analysis, which rely predominantly on annual statistical reports, are too inert to respond to dynamic changes promptly. They fail to account for the complex non-linear interdependencies among dozens of socio-economic factors. They are especially vulnerable in hybrid threats, where information operations and cyberattacks on local critical infrastructure can instantly destabilise the social situation [5, 6]. This gives rise to an urgent scientific and applied problem: an instrumental framework for the integrated, dynamic, and predictive analysis of the state of territorial communities.

A breakthrough in solving such problems is associated with the rapid development of artificial intelligence technologies, particularly deep learning architectures. Over the last decade, neural networks have proven effective in modelling complex, non-linear systems [7, 8]. They are successfully applied to evaluate the effectiveness of public policy [9], forecast macroeconomic indicators [10], and conduct micro-spatial analysis of economic growth [11]. These technologies have opened new horizons for preventive analysis, enabling a shift from observing facts to forecasting future events. The potential of deep learning is particularly significant in the security domain, where successful applications of machine learning for predicting armed conflicts [12, 13] and solving cybersecurity tasks [14] demonstrate the feasibility of adapting these methods to assess regional security. A modern understanding of regional security is impossible without its cyber dimension, as the resilience of communities directly depends on the security of their information systems and their ability to counter cyberattacks [14].

The complexity of the task lies in the fact that regional security and quality of life are deeply interconnected indicators. This relationship is not coincidental but is a direct consequence of the systemic effects within the described "Quadruple Helix" socio-cyber-physical system. A decline in the level of security leads to a deterioration in the quality of life, and conversely, socio-economic depression can become a catalyst for security threats. To simultaneously model such processes, the most effective and theoretically sound paradigm is Multi-Task Learning (MTL). Unlike training separate models, this architecture solves several tasks in parallel using a shared set of hidden features. This allows the model to capture the internal dependencies between the functions, leading to more accurate predictions and enhancing its generalisation ability [15, 16].

Given the identified scientific and practical gap, this research aims to develop and validate a multi-task neural network capable of performing simultaneous regression and classification of the integral indices of regional security and quality of life in the territorial communities of Ukraine. To achieve this aim, the research sequentially addresses several objectives. First, key theoretical approaches to modelling socio-economic and security systems are identified based on an analysis of scientific sources. Second, a comprehensive dataset is formed, aggregating statistical indicators at the level of territorial communities. The next step is the design of a unique multi-task neural network architecture. The key stage of the research is the process of training and comprehensively validating the developed model. Finally, an analysis of the obtained results is conducted to determine the practical significance of the model.

1. Literature review and problem statement

The scientific discourse surrounding regional development and security has undergone significant transformations in recent decades, shifting from traditional models of state governance to more complex, network-based approaches that account for the interaction of diverse actors. In parallel, the technological revolution driven by artificial intelligence has opened unprecedented opportunities for analysing and forecasting complex socio-economic systems. This section is dedicated to the systematisation and critical analysis of the scientific works that form this research's theoretical and methodological foundation. The study covers the evolution of innovation development models, the specifics of regional governance in the Ukrainian context, the potential of artificial intelligence for forecasting social and security processes, and the rationale for applying a multi-task learning architecture.

A fundamental concept explaining the mechanisms of innovation generation is the "Triple Helix" model, developed in detail by Henry Etzkowitz [17]. At its core lies the idea that innovative breakthroughs emerge at the intersection of three institutional spheres: universities, industry, and government. This model has found application in various contexts, including developing products for international security and defence, where close collaboration drives technological change [18]. However, the classic model proved insufficient to describe the realities of developing economies [19, 20]. This led to the evolution of the concept and the emergence of the "Quadruple Helix" model, which adds a fourth, equally important element: civil society [4]. Carayannis and Campbell define this element as a media- and culture-based public that shapes the demand for innovation and serves as a source of informal knowledge [4, 21].

The integration of these four components forms a complex socio-cyber-physical system, which is inextricably linked to cybersecurity challenges. The close digital interaction between universities (protecting intellectual property), businesses (securing production processes), the government (safeguarding state registries), and civil society (protecting personal data and countering disinformation) creates an extensive network of potential vulnerabilities. Thus, cybersecurity ceases to be a purely technical task and becomes a fundamental condition for the functioning and resilience of the entire regional innovation ecosystem. However, the practical implementation of these models in Ukraine faces serious obstacles, particularly the phenomenon of "means-ends decoupling" at the state level, where the formal introduction of innovative structures does not lead to real development due to the capture of institutions by vested interests [22].

Parallel to the evolution of governance concepts, there has been a rapid development in data analysis methods. Traditional approaches based on regression analysis are often ineffective for modelling the non-linear processes that characterise modern society [10]. Artificial intelligence technologies have actively filled this gap. Studies demonstrate the high potential of neural networks for evaluating public policy effectiveness [9], economic forecasting based on traditional [10] and non-traditional data, such as satellite imagery [11], as well as for conflict forecasting and ensuring security [12, 13]. Cybersecurity is a critically important application of artificial intelligence, where machine learning methods have become an integral part of systems for detecting intrusions, malware, and other threats [14]. However, as researchers note, the main obstacles to creating reliable predictive systems are poor data quality and the "black box" problem – the difficulty of interpreting the decisions made by neural networks [13].

When modelling such complex and interconnected phenomena as regional security and quality of life, the question of choosing the optimal neural network architecture arises. Predicting each of these indices separately fails to account for their internal dependence. The Multi-Task Learning (MTL) paradigm was developed precisely to address such challenges. The main idea of this approach is that the model learns to solve several related tasks simultaneously, which allows it to identify and utilise common patterns among them [15]. The advantage of this approach lies in its mechanism of shared knowledge. By training on multiple tasks, the model forms richer and more generalised feature representations of the input data in its hidden layers. Information from one task acts as an inductive bias for another, compelling the model to favour specific hypotheses and better distinguish meaningful patterns from random noise, which is especially important in limited data conditions [15, 16].

Thus, the literature analysis reveals a scientific problem: the lack of a toolkit that would allow for a comprehensive and predictive assessment of the state of territorial communities, considering the inseparable link between socio-economic indicators and security risks, particularly in cyberspace. Existing theoretical frameworks, such as the Quadruple Helix model, describe the system's complexity but do not offer quantitative tools for its analysis. At the same time, the powerful potential of modern deep learning methods remains underutilised for solving such integrated tasks.

Given this, the present research aims to bridge this gap. To achieve this goal, the work sequentially addresses several objectives. First, key theoretical approaches to modelling socio-economic and security systems are identified based on an analysis of scientific sources and the current state of the problem. Second, a comprehensive dataset is formed by aggregating statistical indicators at the level of territorial communities. The next step is designing and implementing a unique multi-task neural network architecture that combines regression tasks for obtaining precise numerical forecasts of the indices and classification tasks for their categorical assessment. The key stage of the research is the process of training and comprehensively validating the developed model. Finally, the results are analysed to determine the practical significance and potential applications of the model in the public administration system.

2. Theoretical foundations and research methodology

This comprehensive research combines methods of systems analysis, statistical data processing, and advanced artificial intelligence technologies to solve the stated problem. The methodological framework of the work is designed to ensure the transparency, reproducibility, and validity of the obtained results. It encompasses several sequential stages: from the formation of the theoretical basis and the operationalisation of target indicators to the design, training, and comprehensive evaluation of the deep learning predictive model.

The theoretical basis for the formation of the target indicators is the approach to assessing social impact and security in regional communities proposed in the work of Yevseiev et al. [5]. In our research, we adapt and expand this methodology, using the mathematical models developed therein to calculate the Regional Security Index (RSI) and the Quality of Life Index (LI) as target variables for subsequent predictive modelling. It is worth noting that although the original methodology [5] is based on the "Triple Helix" concept, for predictive analysis of modern Ukrainian communities, which are characterised by high civil society activity, we extend this framework to the "Quadruple Helix" model [4]. This approach allows for a more complete consideration of the interaction between government, business, educational institutions, and civil society, which is reflected in the data structure we have collected.

The mathematical model for assessing the Regional Security Index (RSI), according to the methodology [5], is a weighted sum of five key components that reflect the multidimensional nature of security:

$$RSI = 0.25 \cdot E + 0.20 \cdot S + \\ + 0.15 \cdot I + 0.25 \cdot C + 0.15 \cdot R,$$

where E is Economic Capacity, S is Social Stability, I is Infrastructure Accessibility, C is Civic Cohesion, and R is Security Risks.

Similarly, the Quality of Life Index (LI) is a weighted sum of five components that reflect both institutional and personal aspects of well-being:

$$LI = 0.30 \cdot T + 0.25 \cdot W + 0.15 \cdot P + \\ + 0.15 \cdot I + 0.15 \cdot A,$$

where T is the Level of Trust in Institutions, W is the Assessment of Personal Well-being, P is Participation in State/Social Programs, I is the Information Environment, and A is Political Activity/Interest.

The empirical basis of the research was a unique dataset covering 1469 territorial communities in Ukraine from 2018 to 2024. The data were collected from official sources like the State Statistics Service of Ukraine and the unified state open data web portal. Also, they included aggregated data on cyber incidents [14]. The dataset was structured to include indicators characterising all four components of the helix: government (trust_in_gov), business (gdp_per_capita), education (education_index), and civil society (volunteering_index, edem_petitions). Initially, over 80 different indicators were collected. After encoding categorical variables (names of oblasts, communities) using the "one-hot encoding" method, the final feature vector for each community grew to 1377 values (Table 1). Such high dimensionality and data sparsity make using neural networks, which can effectively handle such data, more appropriate than classical statistical models.

Table 1 – **Descriptive statistics of key variables**

Variables	Count	Mean	Std	Min	25%	50%	75%	Max
population_total	1469.0	26014.32	75569.42	1793.0	6526.0	11690.0	21494.0	1421125.0
urban_population_pct	1469.0	0.32	0.33	0.0	0.0	0.29	0.53	1.0
gdp_per_capita	1469.0	4.36	1.65	2.32	3.56	4.001	4.59	27.88
budget_per_capita	1469.0	4.36	1.65	2.32	3.56	4.01	4.59	27.88
education_index	1469.0	0.89	0.3	0.0	1.0	1.0	1.0	1.0
healthcare_index	1469.0	0.84	0.17	0.5	0.74	0.84	0.92	2.6
trust_in_gov	1469.0	0.42	0.08	0.19	0.36	0.42	0.47	0.85
political_activity_index	1469.0	0.82	0.88	0.0	0.39	0.46	0.59	4.49
crime_rate	1469.0	0.21	0.39	0.0	0.0	0.0	0.0	1.0
protest_activity	1469.0	0.21	0.39	0.0	0.0	0.0	0.0	1.0
volunteering_index	1469.0	0.29	0.84	0.0	0.0	0.0	0.0	11.0
edem_petitions	1469.0	0.14	0.35	0.0	0.0	0.0	0.0	1.0
edem_consultations	1469.0	0.08	0.28	0.0	0.0	0.0	0.0	1.0
edem_participatory_budget	1469.0	0.13	0.33	0.0	0.0	0.0	0.0	1.0
edem_open_hromada	1469.0	0.06	0.24	0.0	0.0	0.0	0.0	1.0
sum_osbb_2020	1469.0	21.12	92.84	0.0	0.0	1.0	8.0	1502.0
Youth_councils	1469.0	0.08	0.29	0.0	0.0	0.0	0.0	2.0
Youth_centers	1469.0	0.22	0.71	0.0	0.0	0.0	0.0	10.0
Business_support_centers	1469.0	0.66	6.93	0.0	0.0	0.0	0.0	254.0
travel_time	1469.0	92.12	55.15	0.0	49.4	85.2	126.3	300.7
Area	1469.0	383.13	295.99	2.4	181.3	296.65	494.9	2497.1
distance_to_russia_belarus	1469.0	178.57	103.04	0.33	96.09	169.83	255.1	418.97
distance_to_eu	1469.0	306.94	227.29	0.41	106.58	263.08	491.45	897.29
mountain_hromada	1469.0	0.06	0.23	0.0	0.0	0.0	0.0	1.0
near_seas	1469.0	0.05	0.21	0.0	0.0	0.0	0.0	1.0
turnout_2020	1469.0	0.42	0.08	0.19	0.37	0.42	0.47	0.85
war_zone_27_04_2022	1469.0	0.18	0.38	0.0	0.0	0.0	0.0	1.0
war_zone_20_06_2022	1469.0	0.21	0.4	0.0	0.0	0.0	0.0	1.0
war_zone_23_08_2022	1469.0	0.22	0.42	0.0	0.0	0.0	0.0	1.0
war_zone_10_10_2022	1469.0	0.22	0.41	0.0	0.0	0.0	0.0	1.0
youth_pct	1469.0	0.32	0.05	0.09	0.29	0.32	0.34	0.59
working_age_pct	1469.0	0.72	0.02	0.54	0.71	0.72	0.73	0.84
old_age_pct	1469.0	0.006	0.02	0.0	0.0	0.0	0.01	0.16
RSI	1469.0	55.19	22.13	1.4	55.34	63.41	68.99	92.33
LI	1469.0	39.28	11.81	1.73	34.82	39.7	45.09	75.89
RSI_label	1469.0	1.01	0.82	0.0	0.0	1.0	2.0	2.0
LI_label	1469.0	1.01	0.82	0.0	0.0	1.0	2.0	2.0

A detailed analysis of Table 1 confirms the significant heterogeneity of the data, reflecting deep regional disparities in Ukraine. For example, the population_total indicator ranges from 1,793 to 1,421,125 people, with the standard deviation (75,569) being almost three times the mean value (26,014), indicating the presence of large urban agglomerations and a significant number of small rural communities. Similar extreme variance is observed in economic indicators such as sum_osbb_2020 (number of co-owner associations) and Business_support_centers, where the maximum values are orders of magnitude higher than the median. Such non-uniformity creates complex non-linear dependencies that traditional linear models cannot effectively capture, which further justifies the choice of a neural network as the primary modelling tool.

Numerical features were standardised to prepare the data for input into the neural network. To convert the continuous values of RSI and LI into discrete categories ("low," "medium," "high"), the quantile method was used (Fig. 1). This approach, unlike division into equal intervals, guarantees the balance of classes in the training sample.

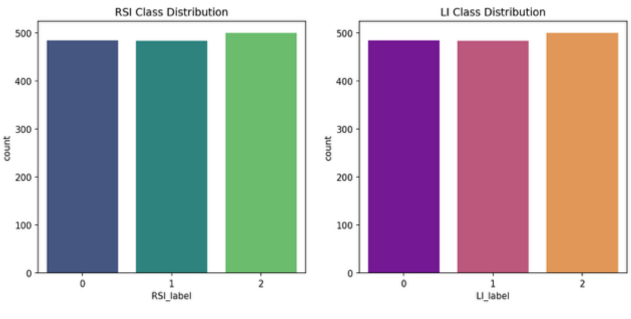

Fig. 1. Distribution of communities by RSI and LI index classes

As seen in Fig. 1, using the quantile method allowed the creation of almost perfectly balanced classes. For both indices, each of the three categories (0 - low, 1 - medium, 2 - high) includes approximately 490 communities. This is a key advantage of this approach as it prevents model bias towards more numerous classes, which often occurs when splitting by fixed thresholds. Thanks to this balance, the neural network receives an equal number of examples for each category, creating favourable conditions for training an effective and unbiased classifier.

To solve the stated problem, a multi-task deep learning neural network (MTL, Table 2) architecture was chosen. This choice is justified because the tasks of predicting RSI and LI are closely related. The use of MTL allows the model to learn shared data representations, which leads to improved generalisation ability and acts as an effective regularisation mechanism [15, 16].

Table 2 – **Detailed architecture of the developed neural network**

Layer	Type	Number of neurons	Activation function	Regularization	Purpose
Shared unit					
Input	Input	1377	-	-	Receiving input data
Dense 1	Fully Connected	512	ReLU	Batch Norm, Dropout (0.3)	First-level feature extraction
Dense 2	Fully Connected	256	ReLU	Batch Norm, Dropout (0.3)	Second-level feature extraction
Branching block					
RSI Branch	Fully Connected	64	ReLU	-	Specific features for RSI
LI Branch	Fully Connected	64	ReLU	-	Specific features for LI
RSI Label Branch	Fully Connected	64	ReLU	-	Specific features for RSI class
LI Label Branch	Fully Connected	64	ReLU	-	Specific features for LI class
Вихідний блок	Fully Connected				
RSI Output	Fully Connected	1	Linear	-	RSI numerical value forecast
LI Output	Fully Connected	1	Linear	-	LI numerical value forecast
RSI Label Output	Fully Connected	3	Softmax	-	RSI class forecast
LI Label Output	Fully Connected	3	Softmax	-	LI class forecast

The presented architecture shows that the model's shared block consists of two powerful fully-connected layers with 512 and 256 neurons. This capacity was chosen empirically to provide the model with sufficient flexibility to capture complex patterns in the high-dimensional feature space, without being overly cumbersome, which could lead to overfitting. Using the ReLU activation function allows the model to learn nonlinear dependencies. After each layer, batch normalisation is applied to stabilise training, and the Dropout method with a rate of 0.3 is used to prevent overfitting. After the shared block, the architecture branches out. This complex parameter-sharing architecture is a classic approach in multi-task learning, which forces the model to learn universal, generalised data representations in the shared body and then specialise this knowledge for each specific task in separate branches.

For training and objective evaluation of the model, the dataset was divided into training (68%), validation (12%), and testing (20%) sets. The training process was based on the backpropagation method using a combined loss function. This function is a weighted sum of the loss functions for each task, allowing for simultaneous model optimisation for regression and classification. The total loss function had the following form:

$$Loss_{total} = w_1 \cdot MSE(RSI) + w_2 \cdot CCE(RSI_{cat}) + \\ + w_3 \cdot MSE(LI) + w_4 \cdot CCE(LI_{cat}),$$

where MSE is the Mean Squared Error, used for regression tasks; CCE is the Categorical Cross-Entropy, applied for classification tasks; and w_i are the weight coefficients. The weights for the classification tasks (w2, w4) were set to 1.5 to give them higher priority during training, while the weights for the regression tasks (w1, w3) were equal to 1.0. The Adam algorithm was chosen as the optimiser. It has proven itself well for working with large datasets and complex architectures due to its ability to change the learning rate adaptively. To control the process and prevent overfitting, mechanisms of early stopping halt training if the model's quality on the validation set ceases to improve, and dynamic learning rate reduction were used.

Standard metrics comprehensively assessed the model's quality on the test set. For regression tasks: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination R^2. For classification tasks: accuracy, precision, recall, and F1-score. Using such a comprehensive set of metrics allows for a complete understanding of the effectiveness of the developed model.

3. Evaluation of the predictive model's effectiveness

The effectiveness of the developed multi-task deep learning model was comprehensively evaluated on a test set, which comprised 20% of the total dataset and was not used during the training process. This approach objectively assesses the model's ability to generalise its learned knowledge to new, previously unseen data. The analysis included calculating quantitative metrics, examining the training process dynamics, and conducting a detailed review of classification errors.

Standard metrics for classification and regression tasks were employed to assess the model's quality. For the evaluation of classification tasks, accuracy was used, calculated as the ratio of the number of correct predictions to the total number of predictions:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}.$$

For the evaluation of regression tasks, the Mean Absolute Error (MAE) was used, which shows the average absolute deviation of the predicted values from the actual values and is robust to outliers in the data:

$$AE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \,,$$

where n is the number of samples in the set, y_i is the actual value, and $\hat{y}_i$ is the predicted value.

To provide a general overview of the model's predictive capability, the key metrics of its performance on the test set are summarised in

Table 3 – **Key performance metrics of the model on the test set**

Task	Metric	Value
RSI Classification	Accuracy	93.9%
RSI Regression	MAE	2.49
LI Classification	Accuracy	85.0%
LI Regression	MAE	2.10

The data presented in Table 3 indicate the high predictive power of the developed model. The classification accuracy for the regional security level, which reached 93.9%, is an excellent result, signifying the model's high reliability in identifying risk categories. The accuracy for the quality of life index (85.0%) is also high, considering this social construct's complexity and multifaceted nature. The low MAE values are particularly indicative. A mean absolute error of 2.49 points for RSI and 2.10 points for LI, on a theoretical index range of 0 to 100, means that the average deviation of the forecast from the actual value is only 2-2.5%. This demonstrates the high precision of the quantitative predictions, making the model suitable for practical application in detailed monitoring and analysis of regional development. Such levels of accuracy are comparable to results obtained in advanced studies where machine learning has been applied to forecast socio-economic indicators [11]. To visualise the training process's dynamics and check the model for overfitting, graphs of the loss functions and accuracy changes at each epoch were plotted. Fig. 2 shows the dynamics of the loss function for the regression tasks.

As can be seen from the graphs in Fig. 2, the loss function values for both regression tasks decrease rapidly during the first 15-20 epochs, after which the curves plateau, indicating the stabilisation and convergence of the training process. It is critically important that the curves for the training (blue line) and validation (orange line) sets remain very close to each other throughout the entire process. This is a key indicator that the model generalises well and does not simply memorise the training data. Such behaviour is direct evidence of the successful application of regularisation methods, particularly the Dropout and Batch Normalisation layers in the neural network architecture. This effectively prevented it from overfitting on the complex, high-dimensional data.

Similar conclusions can be drawn from analysing the accuracy dynamics for the classification tasks, presented in Fig. 3.

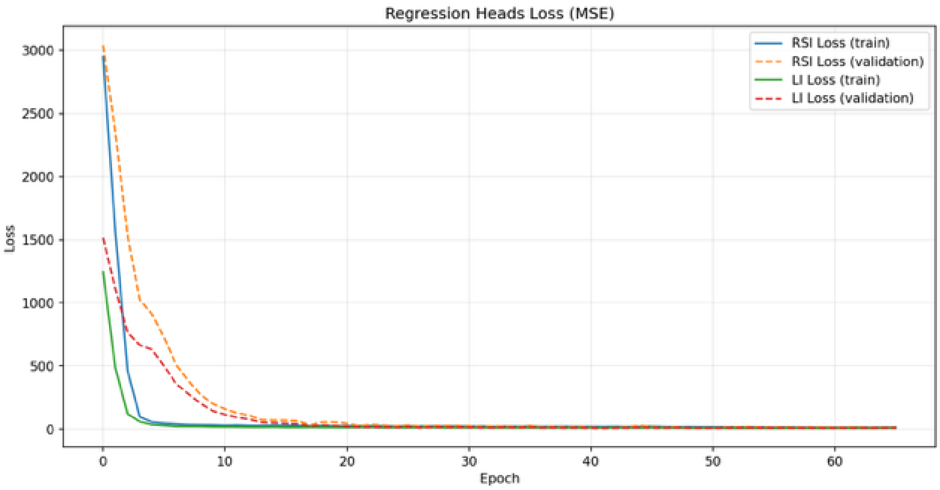

Fig. 2. Dynamics of the loss function (MSE) for the RSI and LI regression tasks

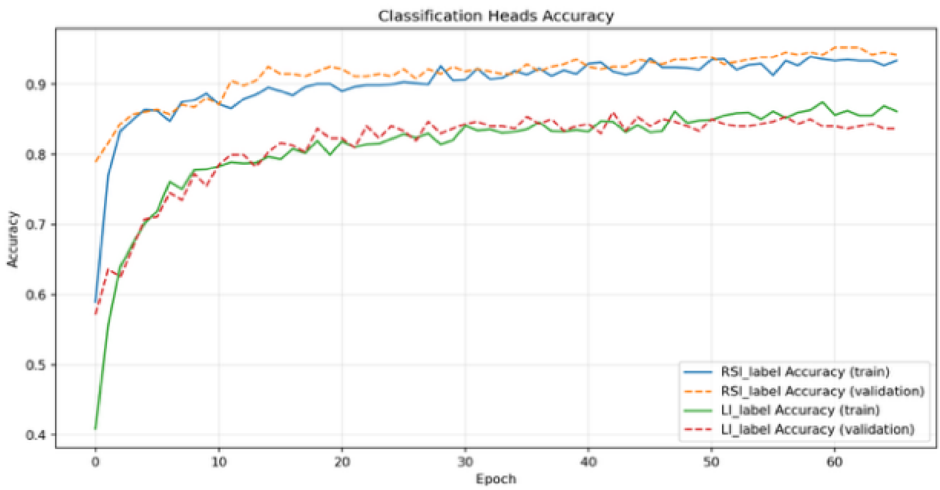

Fig. 3. Dynamics of accuracy for the RSI and LI classification tasks

The graphs in Fig. 3 confirm the conclusions drawn from the analysis of the loss functions. The accuracy on the training (blue line) and validation (orange line) sets increases rapidly in the initial epochs and stabilises at a high level. The absence of a significant gap between the two curves confirms that the model did not overfit and demonstrates a high generalisation ability.

Confusion matrices were constructed to visualise the relationship between the actual and predicted classes on the test set for a more in-depth analysis of the nature of the errors made by the model.

A detailed analysis of the confusion matrix for the Regional Security Index (RSI), presented in the left part of Fig. 4, demonstrates exceptional classification quality. Out of 98 communities with a low security level (class 0), the model correctly identified 96, and only two were mistakenly assigned to the medium class. Similarly, out of 98 communities with a high security level (class 2), 95 were correctly classified. Most errors (13 out of 18) occur at the boundary between adjacent classes. Critically, there were no instances where a community with a low security level (class 0) was classified as having a high level (class 2), and vice versa. This underscores the model's reliability in identifying risk zones and its ability to capture the target variables' ordinal nature correctly. A similar, though less pronounced, trend is observed for the Quality of Life Index (LI) classification, shown in the right part of Figure 4. The most significant number of errors occurs when classifying the medium level (class 1), which is expected, as this class borders the other two. However, even in this case, gross errors (confusion between classes 0 and 2) are practically absent, which attests to the high quality and adequacy of the developed model.

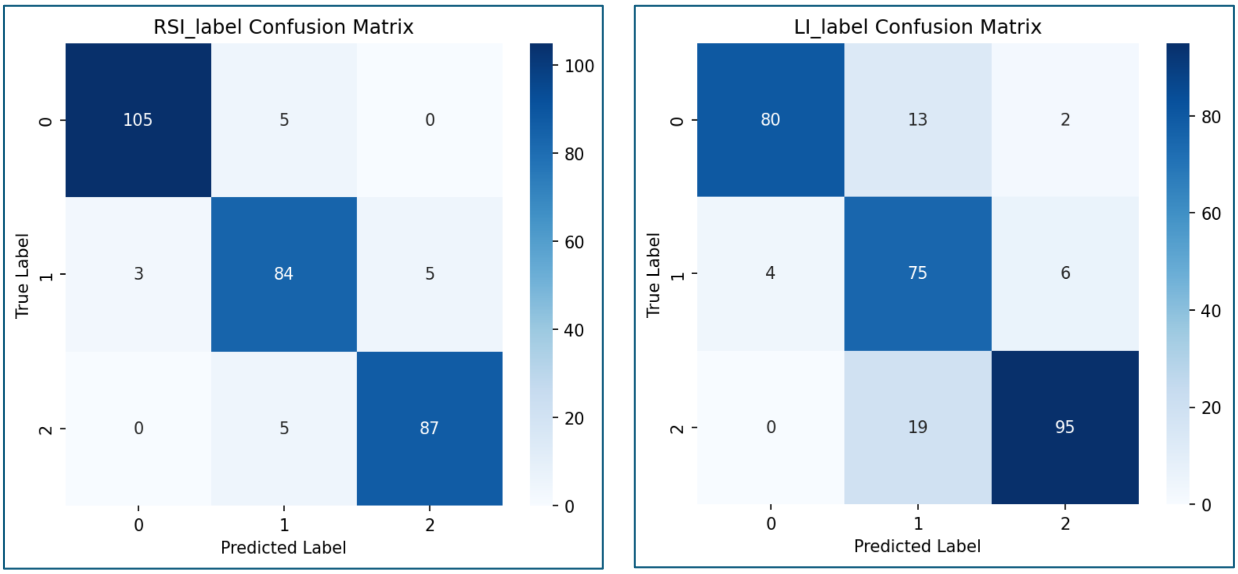

Fig. 4. Confusion matrices for RSI and LI classification on the test set

4. Discussion of results

The results obtained from evaluating the developed multi-task neural network are multifaceted and require a thorough interpretation from both technical and socio-political perspectives. This section is dedicated to discussing the key findings, analysing the identified patterns, considering the practical significance of the model, and outlining the limitations of the research.

The high accuracy achieved by the developed model indicates that modern deep learning methods are a potent tool for modelling and forecasting complex, non-linear socio-economic systems at the regional level. The model's success can be attributed to several factors. First, applying a multi-task learning architecture allowed the model to effectively leverage shared information between the closely related tasks of predicting security and quality of life, which enhanced its generalisation ability. Second, the deep architecture with multiple fully-connected layers and non-linear activation functions enabled the approximation of the complex function that links a community's input characteristics to its level of resilience.

To understand which specific factors have the most significant impact on the formation of the indices, a correlation analysis was conducted between all numerical features and the target variables RSI and LI. Its results allow for identifying the most critical drivers of development and vulnerabilities at the community level.

The analysis of correlations for the Regional Security Index (RSI), presented in the left part of Fig. 5, leads to several key conclusions. The most substantial negative impact on security is the factor of a community's presence in a war zone, which is an expected and tragic consequence of the full-scale invasion. The distance to the border with the aggressor also shows a significant negative correlation. This confirms that geographical proximity to the source of the threat is a critical risk factor. On the other hand, the strongest positive factors that increase the level of security are economic indicators: GDP per capita and budget per capita. This suggests that economically capable communities are more resilient and secure.

The analysis of correlations for the Quality of Life Index (LI), shown in the right part of Fig. 5, reveals a slightly different but logical picture.

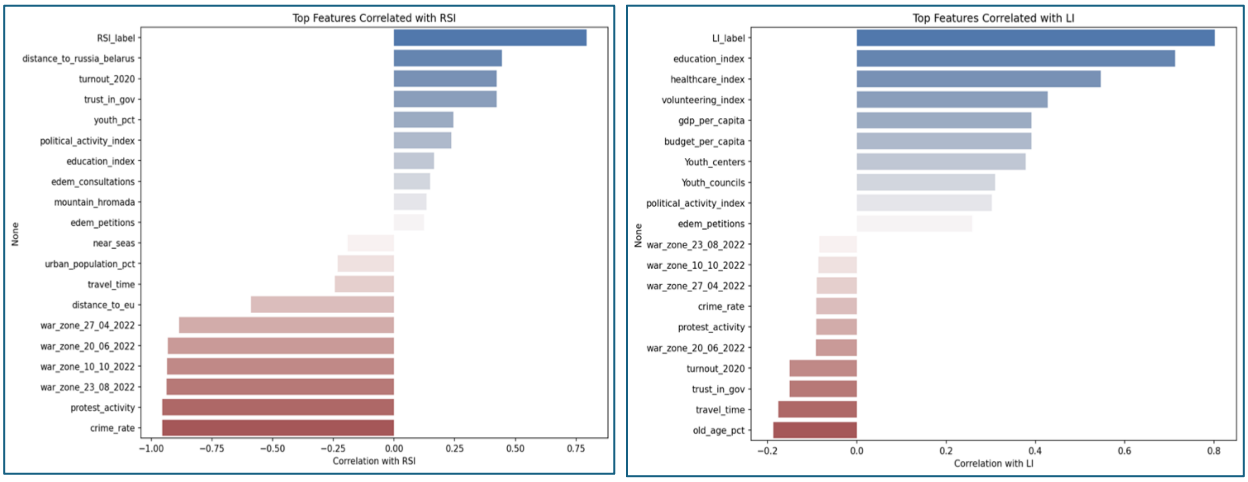

Fig. 5. Confusion matrices for RSI and LI classification on the test set

The most important positive factor is trust in government, which underscores the key role of legitimacy and the effectiveness of local self-government in citizens' perception of well-being. Economic indicators and the level of urbanisation also demonstrate high correlations. The factors that most negatively affect the quality of life are the same as those involving security: being in a war zone and proximity to the border with the aggressor. This indicates that the war is a dominant factor that overrides all other aspects of life in the affected regions.

An aggregation of the indices at the level of Ukrainian oblasts (regions) was performed to identify geospatial patterns in the distribution of security and quality of life.

The data in Table 4 clearly illustrate a geographical gradient of security and quality of life in Ukraine, which has significantly deepened the war.

Table 4 – **Mean values and standard deviations of RSI and LI indices by region of Ukraine**

Region_name	RSI_mean	RSI_median	RSI_std	RSI_count	LI_mean	LI_median	LI_std	LI_count
Lvivska	71.41	70.46	5.48	73	41.78	41.25	9.96	73
Ternopilska	70.82	70.69	6.74	55	37.1	38.67	12.58	55
Ivano-Frankivska	68.57	68.71	7.52	62	39.16	40.64	10.88	62
Khmelnytska	68.53	68.68	5.213	60	34.56	36.95	12.19	60
Volynska	68.51	68.35	5.38	54	41.79	39.98	11.19	54
Vinnytska	67.73	66.71	6	63	37.61	38.07	10.13	63
Poltavska	67.69	66.71	6.63	60	42.83	43.1	10.48	60
Rivnenska	67.23	67.29	5.87	64	41.01	41.38	9.19	64
Kyivska	66.38	66.26	6.78	69	48.7	46.54	11.18	69
Zhytomyrska	66.08	65.63	5.28	66	40.97	40.53	7.01	66
Zakarpatska	65.6	64.58	7.96	64	38.19	39.38	11.99	64
Chernihivska	65.2	65.55	9.85	57	39.63	39.65	10.5	57
Cherkaska	63.83	63.56	5.71	66	38.14	37.73	11.85	66
Odeska	63.53	62.77	6.19	91	39.06	39.86	10.8	91
Kirovohradska	62.55	62.21	5.25	49	36.71	39.92	13.22	49
Chernivetska	61.25	61.27	6.12	52	35.78	36.41	10.06	52
Dnipropetrovska	60.42	62.37	13.42	86	41.67	39.59	10.77	86
Sumska	51.15	60.31	17.41	51	37.8	38.15	10.83	51
Mykolaivska	40.97	46.15	21	52	39.16	39.38	9.86	52
Zaporizka	22.73	14.27	18.26	67	40.72	40.27	9.67	67
Luhanska	15.41	12.04	7.08	37	30.31	28.84	15.97	37
Donetska	13.99	10.75	6.21	66	34.61	35.11	19.39	66
Kharkivska	12.5	10.9	9.42	56	41.9	40.65	10.17	56
Khersonska	10.52	9.73	5.32	49	35.96	38.27	10.07	49

The highest mean RSI values are concentrated in the western and central oblasts, which are relatively distant from the combat zone. Conversely, the lowest indicators are observed in the oblasts most affected by military actions and occupation. High standard deviation values in oblasts such as Dnipropetrovsk and Sumy indicate significant internal heterogeneity: these regions contain both relatively stable communities and those located in direct combat zones. This inequality poses a long-term threat to national unity and requires a differentiated approach to recovery policies.

From a cybersecurity perspective, the obtained results allow for considering the RSI and LI indices as comprehensive indicators of the "social attack surface." Regions with low indicators are more vulnerable to hybrid threats, which combine cyberattacks with information-psychological operations. Low trust in government, economic difficulties, and social tension create a favourable environment for mass social engineering, where it is much easier to spread disinformation and panic. In turn, a low RSI increases the risks to critical infrastructure.

Therefore, the developed model is an academic achievement and a powerful decision-support tool that enables a shift from reactive to proactive governance. Its practical significance lies in its potential use as an early warning system for socio-technical threats. Government bodies can integrate the model's forecasts to identify communities showing a downward trend in resilience indicators and to detect "at-risk groups" in advance. Furthermore, the model can function as a "digital proving ground" for scenario modelling, where analysts can assess the potential impact of policy decisions on a community's resilience to hybrid threats. This facilitates an evidence-based allocation of resources, allowing for the prioritised direction of funds towards strengthening cyber defence or launching media literacy campaigns in the communities predicted to be the most vulnerable.

Despite its high accuracy, this research has limitations that open avenues for future scientific research. First, the model is based primarily on annual statistical data, which does not allow for tracking short-term dynamic changes. Second, the current architecture is a "black box" model, which complicates the detailed interpretation of how each factor influences the final prediction. Given this, promising directions for future research include the implementation of temporal dynamics using recurrent neural network architectures, the integration of Explainable AI (XAI) methods to increase the model's transparency, and the expansion of the dataset by incorporating more dynamic data sources, such as sentiment analysis of news feeds or social media data.

5. Scenario modelling and vulnerability analysis

One of the key advantages of the developed toolkit is its ability to analyse historical data and serve as a predictive analytics system for scenario modelling. By varying input parameters that reflect potential policy decisions or changes in external conditions, the model allows for an assessment of the likely impact of these changes on the integral indices of security and quality of life. This transforms the model into a unique "digital proving ground" that can be used to support decision-making and formulate differentiated strategies for enhancing the resilience of communities.

To demonstrate this capability, a series of experiments was conducted by applying the trained model to hypothetical yet realistic scenarios of community development, generated based on real data. We will consider three characteristic archetypes of communities that illustrate the range of the model's capabilities.

The first scenario models a "border community with high risks." It is characterised by low economic indicators, geographical proximity to the aggressor's border, and presence in a combat zone. For such a profile, the model confidently predicted an expectedly low level of the Regional Security Index (predicted RSI value – 27.63, category – "low") and a low level of the Quality of Life Index. From a cybersecurity perspective, such a community is a highly vulnerable target. Economic hardship, low trust in institutions, and physical danger create ideal conditions for hostile information-psychological operations.

The population of such a community is more susceptible to the influence of disinformation, the spread of panic, and phishing attacks disguised as promises of social benefits.

The second scenario represents an "economically resilient community in the rear." High GDP and budget per capita indicators, a high level of trust in government, developed infrastructure, and a significant distance from the combat zone characterise this archetype. For such a community, the model predicted high levels for both the Regional Security Index (predicted RSI value – 64.43, category – "high") and the Quality of Life Index (predicted LI value – 48.53, category – "high"). In the cybersecurity dimension, such a community is a High-Value Target.

Its stability and economic potential make it an attractive target for complex, sophisticated cyberattacks (Advanced Persistent Threats, APTs), the purpose of which could be industrial espionage, the theft of sensitive data from local authorities, or destabilisation aimed Undermining trust in successful regions.

The third scenario describes a "community with hidden social risks." It may have average economic indicators and not be in an immediate combat zone, but an elevated crime rate and a low level of civic cohesion characterise it. The model's forecast for this case showed a low level of the Regional Security Index (predicted RSI value – 37.79) with a medium level of the Quality of Life Index. Such communities can be described as "soft targets."

They are an ideal ground for massive, indiscriminate malicious campaigns, such as the spread of ransomware targeting local authorities or utility companies or using residents' devices to create botnets for further attacks.

In addition to analysing static profiles, the model allows for "what-if" analysis, assessing the potential impact of policy interventions. For example, for the first "border community" scenario, one could model the effect of a successful investment project by artificially increasing the GDP and budget per capita indicators in the input data.

Applying the model to this updated data can provide a new, improved forecast for the RSI and LI indices. This enables government bodies to identify problem regions and quantitatively assess which type of assistance (financial investment, enhanced security measures, information campaigns) will significantly increase a specific community's resilience. Thus, the developed model is transformed from an analytical tool into an interactive decision-support system.

Conclusions

This research successfully developed and validated an innovative tool based on a deep multi-task learning architecture for the comprehensive forecasting of the Regional Security Index (RSI) and the Quality of Life Index (LI) at the level of territorial communities in Ukraine. The developed model demonstrated high predictive capability, achieving an accuracy of 93.9% for RSI classification and 85.0% for LI classification, as well as low mean absolute error values, which confirms its reliability and effectiveness as a predictive analytics tool for complex socio-economic systems.

The key scientific contribution of this work is multifaceted. First, it introduces the first comprehensive predictive tool in Ukraine that integrates a theoretical framework of regional development, based on the "Quadruple Helix" concept, with advanced artificial intelligence methods. Second, the research proves the methodological effectiveness of the multi-task learning paradigm for modelling interconnected socio-economic and security indices, which is a significant contribution to the field of computational social sciences. The analysis of key factors empirically confirmed that economic capacity, civic cohesion, and geographical proximity to the combat zone are decisive for regional security. In contrast, the quality of life correlates most strongly with the level of trust in government.

The practical significance of the research lies in creating a powerful decision-support tool for government bodies, local self-government, and structures responsible for national security. The proposed model can be used for proactive monitoring of regional vulnerabilities, early detection of crisis phenomena, scenario modelling of policy impacts, and more effective allocation of resources, particularly in cyber defence. Thus, this work makes a substantial contribution to the development of tools for analysing and forecasting regional development, which is especially important for ensuring the resilience and security of Ukraine in the current conditions.

Despite the results obtained, it is essential to acknowledge certain limitations of this research, which open avenues for future work. First, the model is based on a static data snapshot, which does not allow for the analysis of the dynamics of the indices over time. Second, deep neural networks are inherently "black boxes," which complicates the detailed interpretation of their decisions.

In light of this, promising directions for future research include the development of dynamic models based on recurrent neural networks for time-series analysis and the integration of Explainable AI (XAI) methods to enhance the transparency and interpretability of the forecasts.

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Багатозадачна нейронна мережа для одночасної регресії та класифікації індексів регіональної безпеки та якості життя в Україні

О. С. Кушнерьов, С. С. Погасій, Є. О. Меленті, Є. О. Севрюкова, Д. М. Риков

Анотація. Актуальність. В умовах сучасних геополітичних викликів та реформи децентралізації, об'єктивна оцінка та прогнозування стабільності регіонів стає ключовим завданням для сталого розвитку України. Дане дослідження вирішує **проблему** відсутності комплексних автоматизованих інструментів для аналізу стану територіальних громад шляхом розробки та валідації інноваційної моделі на основі штучного інтелекту. **Методологічною основою** роботи є розробка та апробація багатозадачної нейронної мережі глибокого навчання, спроєктованої для одночасного вирішення чотирьох пов'язаних завдань: двох задач регресії для прогнозування точних числових значень Індексу Регіональної Безпеки (RSI) та Індексу Якості Життя (LI), а також двох задач класифікації для визначення категоріального рівня цих індексів (низький, середній, високий). **Теоретичним підґрунтям** для формування цільових індексів виступає концепція «Чотирикратної спіралі», що описує синергетичну взаємодію між владою, бізнесом, науковою спільнотою та громадянським суспільством. Модель навчалася на унікальному наборі даних, що охоплює 1469 українських територіальних громад та містить гетерогенні соціально-економічні та безпекові показники. **Результати експериментів** продемонстрували високу ефективність розробленого підходу. На тестовій вибірці точність класифікації для Індексу Регіональної Безпеки досягла 93.9%, а для Індексу Якості Життя – 85.0%. У задачах регресії модель показала низькі значення середньої абсолютної помилки, що свідчить про високу точність прогнозування. **Висновки дослідження** підтверджують, що створена модель є потужним інструментом для моніторингу, аналізу та прогнозування динаміки регіонального розвитку в Україні. Результати роботи можуть бути використані органами державної влади та місцевого самоврядування для розробки цільових політик, спрямованих на підвищення стійкості, згуртованості та привабливості українських регіонів.

Ключові слова: багатозадачне навчання; глибоке навчання; регіональна безпека; якість життя; предиктивне моделювання; територіальні громади; кібербезпека.