

Article

Comparative Analysis of Artificial Intelligence Models in Forecasting Regional Economic Potential (The Case of Surkhandarya Region)

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Abstract: This article examines the problem of forecasting regional economic potential on the basis of statistical data for the districts of Surkhandarya region. Within the framework of the study, the forecasting performance of the MLP, Random Forest, XGBoost and LSTM models is assessed through a comparative benchmark analysis. The empirical analysis draws on a panel database of 184 observations covering the period 2011–2023. The models were evaluated using training and test samples separated chronologically. Based on the results, the model with the highest forecasting accuracy was identified, and scientifically grounded proposals and recommendations aimed at developing the economic potential of the region were formulated.

Keywords: benchmark analysis, entropy method, regional economic potential, LSTM, MLP, forecasting, Random Forest, XGBoost

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1. Introduction

Ensuring the sustainability of regional economic development, making efficient use of available resources and reducing inter-regional economic disparities are among the priority directions of contemporary economic policy. The “Uzbekistan – 2030” strategy sets out the tasks of aligning strategic planning documents for the development of sectors, industries and regions with clearly measurable performance indicators and of regularly monitoring their implementation [1]. The effective fulfilment of these tasks requires an objective assessment of the existing economic potential of regions, the identification of disparities in their level of development and an in-depth analysis of the factors generating such disparities across territorial units.

From this perspective, a comprehensive assessment of the economic structure of Surkhandarya region and of the development opportunities across its districts acquires particular scientific and practical importance. According to official statistics, in 2024 the gross regional product of the region amounted to 54,354.1 billion UZS, an increase of 5.9 per cent compared with 2023. Within gross value added, services accounted for 41.9 per cent, agriculture, forestry and fisheries for 39.1 per cent, industry for 9.6 per cent and construction for 9.4 per cent. Gross regional product per capita reached 18.67 million UZS, rising by 3.4 per cent [2]. Although these indicators characterise the general state and the sectoral structure of the regional economy, they do not fully reflect the internal

disparities between the districts and the city of Termez in terms of economic potential, the degree of resource utilisation and development opportunities. This gives rise to the need to assess regional economic potential not on the basis of individual indicators, but through an approach that comprehensively accounts for interrelated economic indicators [3].

Proceeding from the need for a comprehensive assessment of the inter-regional and intra-regional disparities outlined above, this study evaluates the economic potential of the districts of Surkhandarya region and the city of Termez using a multidimensional approach based on panel data for 2011–2023. Various economic indicators are combined into a single composite index, and their weights are determined objectively by means of the entropy method. The resulting index is adopted as the target variable to be forecast for the following year, and the capabilities of the MLP, Random Forest, XGBoost and LSTM models in forecasting it are compared on a single empirical basis. In addition, the relative importance of the indicators constituting the composite index is analysed across the models.

Early research on regional economic forecasting was dominated by traditional econometric approaches: applying panel ARDL and panel quantile regression models to Romanian regions, I. Georgescu et al. showed that research and development expenditure, IT infrastructure, and employment indicators play an important role in regional growth [4]. Such approaches, however, rely largely on linear relationships and cannot fully capture complex nonlinear processes, which has driven growing interest in machine learning models for forecasting regional indicators. Deep learning approaches have shown particular promise where temporal dynamics matter: S. Tuo et al. applied a deep convolutional neural network to forecast regional industrial-economy indicators [5]; Y. Li and Z. Wei found that an LSTM model produced smaller logistics-demand forecasting errors than grey models, linear regression, and BP neural networks [6]; and J. Seo et al., forecasting youth population across 229 South Korean municipalities with an LSTM model, showed that capturing temporal sequences offers a considerable advantage in regional demographic forecasting [7]. Decision-tree-based models have likewise proven effective at capturing regional and local differences: X. Zheng et al. combined machine learning with night-time light and geospatial data to estimate county-level poverty with high accuracy [8], while Z. Shangguan's XGBoost-SHAP analysis of the socioeconomic determinants of urbanisation in China demonstrated that explainable machine-learning models are powerful both for forecasting and for interpreting determinants [9] — indicating that, for multifactor indicators such as regional economic potential, interpretability matters as much as accuracy. From a methodological standpoint, comparing models on the same database under identical train–test conditions and evaluation metrics is essential: T. Hall and K. Rasheed's review of time-series prediction methods notes that model performance depends directly on data structure and task characteristics [10], and S. Xu et al.'s comparison of several models on identical time-series data showed that model selection requires a dedicated benchmark analysis [11] — together substantiating the need to compare the MLP, Random Forest, XGBoost, and LSTM models under identical conditions for the districts of Surkhandarya region.

The literature on Uzbekistan, by contrast, remains dominated by statistical, index-based, or classical econometric approaches to regional development: Y. Matyakubova analysed regional investment potential using panel data and highlighted the need to reduce investment imbalances among Uzbekistan's regions [12]; G. Musurmankulova examined the relationship between regional economic potential and sustainable growth and confirmed that development disparities between regions persist [13]; and N. Batirova examined the factors shaping industrial development in Tashkent region under an innovative economy [14]. A smaller body of domestic work has applied artificial intelligence and forecasting methods more directly: I. Ismailov demonstrated the practical value of an artificial neural network for forecasting urbanisation [15]; F.

Hojikulova applied an ARIMA model to forecast the volume of investment in Surkhandarya region's industrial enterprises [16]; and B. Turaev used the same approach to estimate the region's volume of construction work [17]. These domestic studies confirm that forecasting experience exists in Uzbekistan, but it remains largely confined to a single model or a single indicator; research that treats regional economic potential as a composite index and comparatively benchmarks the MLP, Random Forest, XGBoost, and LSTM models for forecasting it on a single experimental platform remains absent from the Uzbekistan context — the gap this article addresses.

2. Materials and Methods

This study is aimed at analysing, on a single empirical basis and according to common evaluation criteria, the comparative capabilities of the MLP, Random Forest, XGBoost and LSTM models in forecasting regional economic potential using data for the districts of Surkhandarya region. The methodological logic of the study was as follows: first, a composite index expressing regional economic potential was constructed; then this index was adopted as the target variable to be forecast for the following year; and finally, different model families were tested comparatively under identical experimental conditions. This approach made it possible to take into account the multifactor nature of regional development, to compare the models impartially and to assess forecasting accuracy according to uniform criteria.

The empirical base consists of panel data compiled for 2011–2023 across the district- and city-level territorial units of Surkhandarya region. The initial database included official statistical indicators relating to production, the services sector, investment activity, entrepreneurship and the labour market. An important principle observed in data preparation was that years with missing data were not filled with artificial values; on the contrary, only periods with official observations were retained. This prevented incorrect zero values or approximate figures from entering the models, particularly where observations for certain districts were incomplete. As a result, a final analytical sample consisting of complete observations suitable for forecasting was formed.

Since expressing regional economic potential through a single indicator is methodologically insufficient, the study assessed it in the form of a composite index. The entropy method was selected for constructing the composite index. This method makes it possible to determine objective weights for the indicators on the basis of their information content and reduces dependence on subjective expert judgement. The index comprises industrial output per capita, agricultural output per capita, services per capita, construction volume per capita, retail trade turnover per capita, investment per capita, the density of active enterprises, the density of active small businesses, the employment rate and the unemployment rate.

Table 1. Indicators constituting the regional economic potential index

Indicator	Construction / calculation method	Economic content
Industrial output per capita	<i>sanoat_hajmi/aholi_soni</i>	Reflects the industrial production capacity of the district
Agricultural output per capita	<i>qx_hajmi/aholi_soni</i>	Reflects the agricultural production potential of the district
Services per capita	<i>xizmatlar_hajmi/aholi_soni</i>	Reflects the capacity of the services sector

Construction volume per capita	<i>qurilish_hajmi/aholi_soni</i>	Indicates the intensity of construction activity and investment processes
Retail trade turnover per capita	<i>chakana_savdo_hajmi/aholi_soni</i>	Characterises the consumer market and trade activity
Investment per capita	<i>asosiy_kapital_investitsiya/aholi_soni</i>	Shows the relative volume of capital investment directed to the district
Density of active enterprises	<i>faol_korxona_soni/aholi_soni</i>	Reflects the activity of entrepreneurial and business entities in the district
Density of active small businesses	<i>kichik_biznes_faol_soni/aholi_soni</i>	Shows the real level of economic activity of small business
Employment rate	<i>bandlar_soni/aholi_soni</i>	Reflects the economic activity and employment of the population
Unemployment rate	<i>ishsizlar_soni/aholi_soni</i>	Reflects labour market tightness and underutilised labour resources

In the course of constructing the index, all indicators were first normalised using the min–max method. For positively oriented indicators the following formula was applied:

$$x_{ij}^* = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (1)$$

where: x_{ij}^* is the normalised value; x_{ij} is the value of indicator j for territorial unit i ; $\min(x_j)$ and $\max(x_j)$ are the minimum and maximum values of the corresponding indicator over the entire set of observations.

For negatively oriented indicators the inverse formula was applied:

$$x_{ij}^* = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (2)$$

the normalised values were then converted into shares:

$$p_{ij} = \frac{x_{ij}^*}{\sum_{i=1}^n x_{ij}^*} \quad (3)$$

where: p_{ij} is the share of observation i for indicator j , n is the number of observations.

The entropy value for each indicator was calculated using the following formula.

$$e_j = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}) \quad k = \frac{1}{\ln(n)} \quad (4)$$

At the next stage, the coefficient of diversification and the indicator weights were determined:

$$d_j = 1 - e_j \quad w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (5)$$

where: w_j is the entropy weight of indicator j , m is the number of indicators

The final regional economic potential index was constructed as the following weighted sum:

$$REPI_{it} = \sum_{j=1}^m w_j x_{ij}^* \quad (6)$$

where $REPI_{it}$ denotes the economic potential index of territorial unit i . Regional economic potential was thus formalised in the form of an index and was subsequently used as the target variable for the forecasting task.

The forecasting design was based on the principle of predicting the next-year regional economic potential index rather than reconstructing the index of the current year. Accordingly, the data were transformed to meet the requirements of a supervised learning model. For each district-year observation, the normalised economic indicators of the current year, the economic potential index of the previous year and the economic potential index of the following year were generated. Here the variable `lag_index` represents the previous-year economic potential index, while `target_next_year_index` denotes the index of the following year. The general functional form of the model was therefore specified as follows:

$$Y_{i,t+1} = f(X_{i,t}, REPI_{i,t-1}) \quad (7)$$

where $Y_{i,t+1}$ is the next-year regional economic potential index, $X_{i,t}$ denotes the normalised economic indicators of the current year, and $REPI_{i,t-1}$ is the index value of the previous year.

Table 2. Variables used in the benchmark models

Indicator	Construction / calculation method	Economic content
<i>norm_sanoat</i>	Min-max normalisation	Standardised expression of industrial potential
<i>norm_qx</i>	Min-max normalisation	Standardised expression of agricultural potential
<i>norm_xizmatlar</i>	Min-max normalisation	Standardised expression of the capacity of the services sector
<i>norm_qurilish</i>	Min-max normalisation	Standardised expression of construction activity
<i>norm_chakana</i>	Min-max normalisation	Standardised expression of retail trade turnover
<i>norm_invest</i>	Min-max normalisation	Standardised expression of investment activity
<i>norm_faol_korxona</i>	Min-max normalisation	Standardised expression of the density of active enterprises
<i>norm_kb_faol</i>	Min-max normalisation	Standardised expression of the density of active small businesses
<i>norm_bandlik</i>	Min-max normalisation	Standardised expression of the employment rate
<i>norm_ishsizlik</i>	Inverse min-max normalisation	Inverse standardised expression of the unemployment indicator
<i>lag_index</i>	$REPI_{i,t-1}$	Reflects the inertial effect of the previous-year economic potential index
<i>target_next_year_index</i>	$REPI_{i,t+1}$	The regional economic potential index to be forecast for the following year

The principal methodological feature of the study is the mutual comparison of the models on the same empirical base and within a single train–test design. To this end, the multilayer perceptron (MLP), Random Forest, XGBoost and Long Short-Term Memory (LSTM) models were included in the benchmark analysis. A structured dataset in a uniform format was used for the comparative evaluation of all models. The indicators listed in the first column of Table 2 were used as input factors in constructing these models.

The target variable was defined as *target_next_year_index*. For the LSTM model, the data were transformed into a sequence-based format. Specifically, observation blocks covering three consecutive years (sequence length, window = 3) were generated for each territorial unit. The model input thus acquired the structure *samples × timesteps × features*, making it possible to capture dynamic changes over time and sequential relationships between observations. The training and test samples were separated chronologically rather than randomly.

This decision is methodologically important for a forecasting task, as it prevented information about the future from leaking into the training process. The years 2011–2021 were taken as the training sample and 2022–2023 as the test sample. This split was expressed by means of the technical indicator *partition_mlp*, where a value of 1 denotes the training sample and 0 the test sample. The size of the analytical sample, the train–test distribution and the chronological splitting scheme are presented below.

Table 3. Analytical sample and chronological train–test splitting scheme

Indicator	Value
Initial time span	2011–2023
Final number of analytical observations	184
Training sample (train)	154
Test sample	30
Training period	2011–2021
Test period	2022–2023
Benchmark models	MLP, Random Forest, XGBoost, LSTM

In constructing the benchmark models, an appropriate set of parameters was defined for each model family. For the MLP model, several variants of the number of neurons in the hidden layer were first tested; at the next stage, the activation function, the regularisation parameters and the learning rate were tuned. For the Random Forest model, a search was performed over the number of trees, the maximum depth, the minimum number of observations required for a split, the minimum number of observations in a leaf node and the strategy for selecting the variables considered at each split. For the XGBoost model, a hyperparameter search was organised over the parameters *n_estimators*, *learning_rate*, *max_depth*, *subsample*, *colsample_bytree* and *min_child_weight*. For the LSTM model, the input data were converted into observation blocks covering three consecutive years for each territorial unit and shifted forward by one year at each step. The model was specified with a single hidden LSTM layer of 16 units, dropout regularisation of 0.1, the Adam optimiser and the mean squared error (MSE) loss function. In order to reduce the model's tendency towards overfitting, an early stopping mechanism was applied. Overall, the main parameters of the models included in the benchmark and the search space selected for tuning them are summarised in Table 4.

Table 4. Key parameters and tuning space of the benchmark models

Model	Key parameters / search space
MLP	Hidden layers: 1; number of neurons: 2, 3, 4; activation: relu, tanh; alpha: 0.0001, 0.001, 0.01; learning_rate_init: 0.001, 0.01
Random Forest	n_estimators: 200, 500; max_depth: 3, 5, None; min_samples_split: 2, 5; min_samples_leaf: 1, 2; max_features: sqrt, 0.8
XGBoost	n_estimators: 200, 500; learning_rate: 0.05, 0.1; max_depth: 2, 3, 4; subsample: 0.8, 1.0; colsample_bytree: 0.8, 1.0; min_child_weight: 1, 3
LSTM	sequence length (window) = 3; LSTM units = 16; dropout = 0.1; optimizer = Adam; learning_rate = 0.01; epochs ≤ 300; batch_size = 8; early stopping = 20 epochs

As Table 4 shows, the parametric tuning of the models included in the benchmark was organised taking into account the characteristics of the different model families. This system of parameters provided a methodological basis for the comparative evaluation of the models within a single experimental design.

A single system of evaluation metrics was applied for the comparative assessment of all models. The mean absolute error (MAE), the root mean squared error (RMSE) and the coefficient of determination (R^2) were selected as the main criteria. They were calculated as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (10)$$

where n is the number of observations, y_i is the actual value, $\hat{y}_i$ is the value predicted by the model, and $\bar{y}$ is the arithmetic mean of the actual values.

These evaluation metrics made it possible to compare the models on the training and test samples according to the same criteria. The main evaluation logic of the study was to give priority to the test-sample metrics, since it is precisely these that most fully express the generalisation ability of a model and its forecasting accuracy on previously unseen data. The computations were carried out in several software environments. Initial data preparation, normalisation and the calculation of the index by the entropy method were performed in Microsoft Excel. The initial architecture trials for the MLP model were conducted in IBM SPSS Statistics. The final benchmark computations were performed in Python using the pandas, scikit-learn, xgboost, tensorflow/keras and matplotlib libraries. This combined approach made it possible to prepare the data, build the models and compare them on a single methodological platform.

As a result of this methodological approach, a composite indicator of regional economic potential was formalised on the one hand, while on the other hand the

methodological basis required for an impartial comparison of the relative forecasting ability of different model families under identical empirical conditions was established.

3. Results and discussion

The results of the study were analysed in several successive stages. First, the optimal architecture for the MLP model was determined; then all models were comparatively evaluated using a single system of metrics; after that the importance of the independent variables was analysed; and finally an economic interpretation of the results obtained was provided.

In order to select the final architecture for the MLP model, several variants of the number of neurons in the hidden layer were evaluated on the basis of repeated runs. Variants with 2, 3 and 4 neurons were tested, and the error level on the test sample was adopted as the selection criterion. The repeated computations showed that the architecture with three neurons in the hidden layer stood out as the most appropriate variant in terms of the average test error. Accordingly, the 11-3-1 structure was adopted as the final architecture for the MLP model in the subsequent benchmark analysis.

Table 5. Results of repeated trials of the number of hidden-layer neurons for the MLP model

Number of neurons in the hidden layer	Number of repeated runs	Test error values	Average test error	Lowest test error	Conclusion
2	4	0.255; 0.260; 0.290; 0.307	0.278	0.255	Not optimal
3	5	0.196; 0.239; 0.183; 0.289; 0.259	0.233	0.183	Selected
4	4	0.294; 0.194; 0.290; 0.252	0.258	0.194	Not optimal

The results in Table 5 show that, among the variants tested for the number of neurons in the hidden layer, the architecture with three neurons recorded the best result in terms of the average test error. In this variant the average test error was lower than for the architectures with two and four neurons, and it therefore emerged as the relatively optimal configuration for the MLP model. For this reason, the 11-3-1 architecture was adopted as the final specification in the subsequent benchmark analysis.

Table 6. Comparative results of the benchmark models on the training and test samples

Model	Train MAE	Train RMSE	Train R ²	Test MAE	Test RMSE	Test R ²
MLP	0.0231	0.0354	0.8574	0.0605	0.0732	0.6503
Random Forest	0.0055	0.0103	0.9879	0.0407	0.0615	0.7528
XGBoost	0.0064	0.0102	0.9883	0.0397	0.0585	0.7768
LSTM	0.0212	0.028	0.9169	0.0332	0.0384	0.908

As Table 6 shows, the highest forecasting accuracy on the test sample was observed for the LSTM model. On the test sample this model recorded MAE = 0.0332, RMSE = 0.0384 and R² = 0.908. These figures indicate that it is the strongest model not only in

terms of the lowest error but also in terms of explanatory ability. Among the decision-tree-based models, XGBoost ranked second, showing $MAE = 0.0397$, $RMSE = 0.0585$ and $R^2 = 0.7768$ on the test sample. The Random Forest model was close to it, although it recorded a slightly lower overall accuracy ($MAE = 0.0407$, $RMSE = 0.0615$, $R^2 = 0.7528$). The MLP model showed relatively low test performance in the benchmark ($MAE = 0.0605$, $RMSE = 0.0732$, $R^2 = 0.6503$). These comparative results are also presented visually in the figure below.

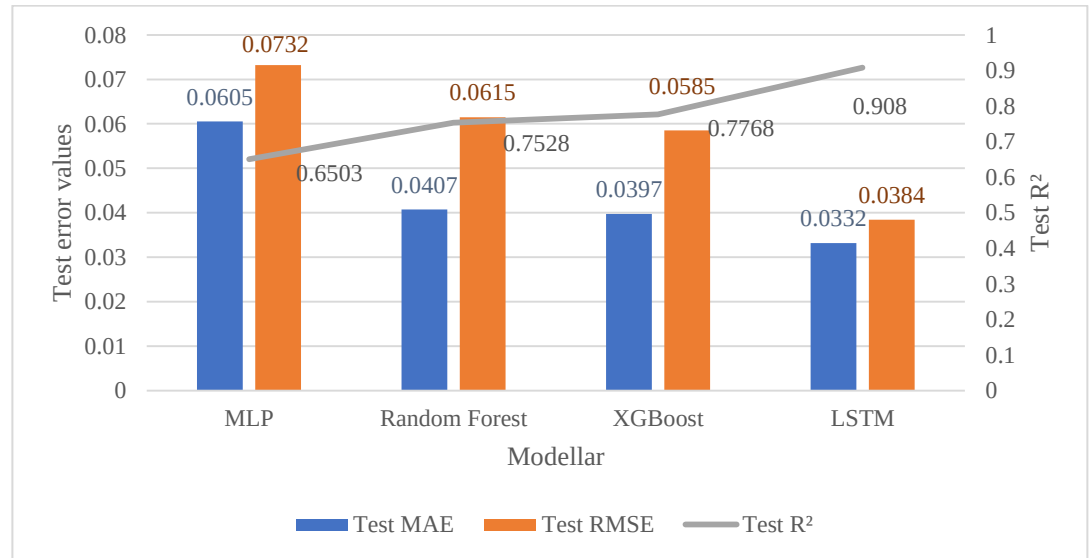
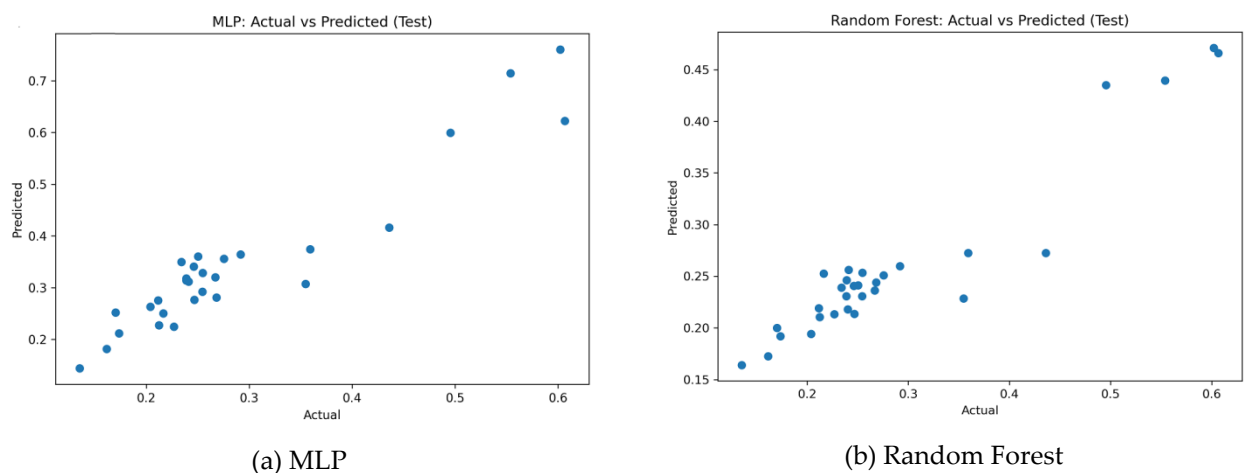


Figure 1. Comparison of the test MAE, RMSE and R^2 values of the benchmark models

A deeper interpretation of the results in Table 6 shows that the differences between the models are manifested not only in the final test metrics but also in their generalisation properties. In particular, the errors on the training sample were very low for the Random Forest and XGBoost models, which indicates that these models learned the training data with high accuracy. However, the gap between the training and test results also points to a certain tendency towards overfitting. For the LSTM model, by contrast, the difference between the training and test metrics was relatively balanced, which indicates a stronger generalisation ability. Scatter plots of the correspondence between actual and predicted values were used for a visual assessment of the predictive behaviour of the models.



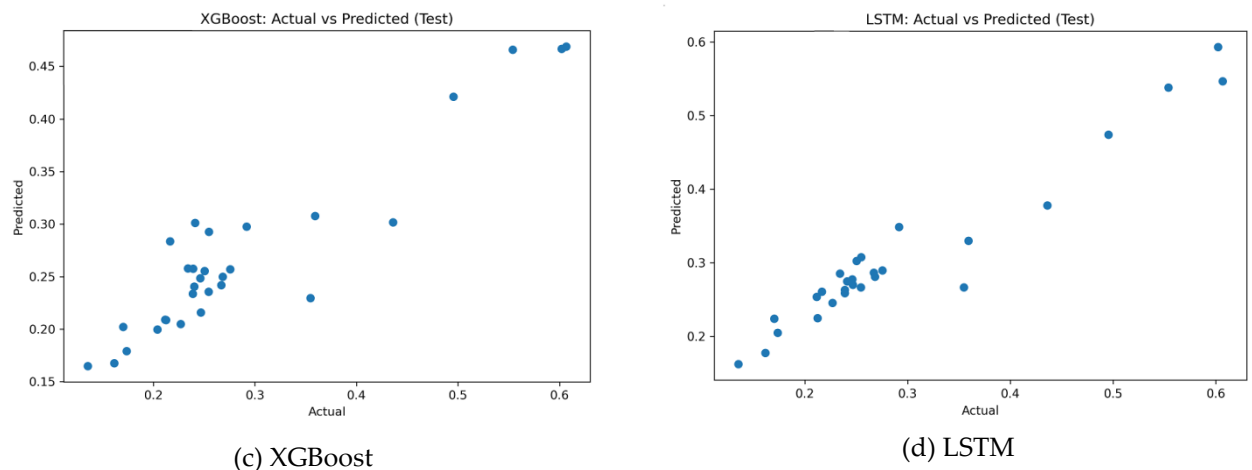


Figure 2. Comparison of actual and predicted values for the benchmark models: (a) MLP, (b) Random Forest, (c) XGBoost, (d) LSTM

As the panels of Figure 2 show, a positive correspondence between actual and predicted values is present for all models. However, the degree of this correspondence differs across the models. In particular, in the LSTM model the points are located relatively more densely and more regularly around the diagonal line, which also confirms visually its higher forecasting accuracy and generalisation ability. Although a general positive correspondence is likewise preserved in the XGBoost and Random Forest models, the dispersion of the points increases, especially in the zone of high values. In the MLP model the points are scattered relatively more widely around the diagonal, which is consistent with its relatively lower accuracy on the test sample.

The analysis of the importance of the input factors played an important role in revealing the economic content of the benchmark results. A comparative description of variable importance in the MLP, Random Forest and XGBoost models is presented in Table 7.

Table 7. Comparative description of variable importance in the MLP, Random Forest and XGBoost models

Variable	MLP, %	Random Forest, %	XGBoost, %
lag_index	100	100	100
norm_qurilish	39.9	59.2	67.7
norm_kb_faol	65.2	38.9	46.3
norm_xizmatlar	57.9	58.2	14.0
norm_invest	72.7	25.3	10.9
norm_faol_korxona	40.6	44.9	22.4
norm_sanoat	19.0	9.5	2.4
norm_bandlik	18.1	9.8	1.6
norm_chakana	21.1	5.1	2.3
norm_qx	10.7	10.7	5.6
norm_ishsizlik	13.3	10.2	1.3

The results in Table 7 show that, across all interpretable models, *lag_index* emerged as the factor with the highest importance. This indicates that regional economic potential possesses a strong inertial character, that is, the level of development in the previous year remains the dominant determinant in shaping the outcomes of the subsequent period. In the MLP model, *lag_index* is followed by *norm_invest*, *norm_kb_faol* va *norm_xizmatlar*; in

the Random Forest model, *norm_qurilish*, *norm_xizmatlar*, *norm_faol_korxona* hamda *norm_kb_faol* are relatively more important, while in the XGBoost model *norm_qurilish*, *norm_kb_faol*, *norm_faol_korxona* va *norm_xizmatlar* carry comparatively higher importance. These results show that, alongside temporal persistence, investment activity, construction, the business environment and the services sector play an important role in shaping regional economic potential.

The normalised variable importance for the MLP model is presented in a separate figure, because in this model the importance of the factors is estimated on the basis of neural network weights, whereas in decision-tree-based models (Random Forest, XGBoost) it is determined by the extent to which the error is reduced by the splits at the tree nodes. The importance measures produced by the two approaches therefore differ methodologically, and it would not be correct to present them together in a single figure.

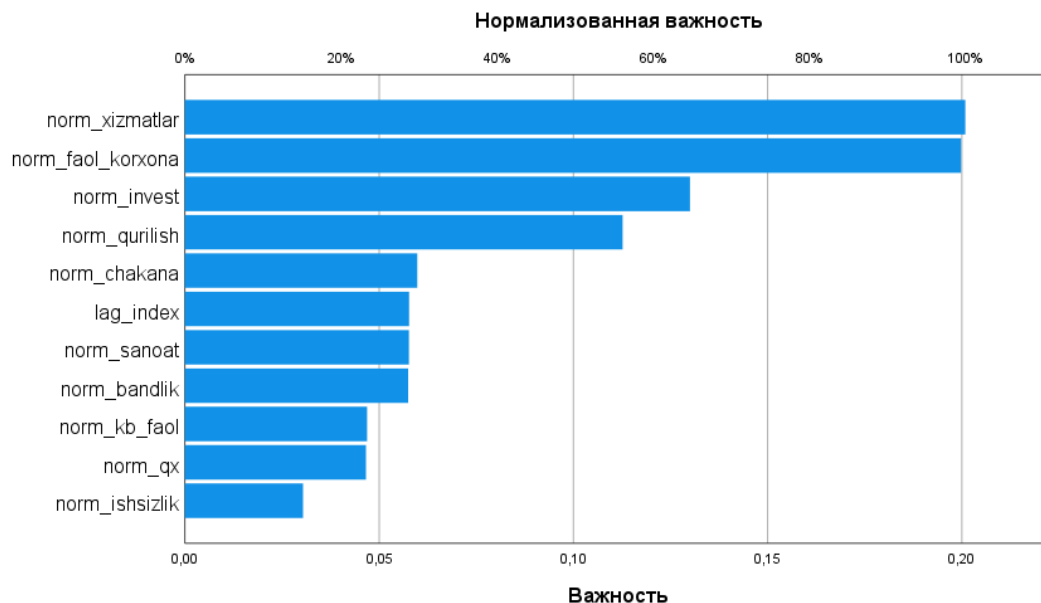


Figure 3. Normalised importance of the input factors in the MLP model

According to Figure 3, after *lag_index* the highest normalised importance in the MLP model is observed for *norm_invest* (72.7%) and *norm_kb_faol* (65.2%). In addition, *norm_xizmatlar* (57.9%), *norm_faol_korxona* (40.6%) and *norm_qurilish* (39.9%) also carry relatively high weight.

This shows that investment activity, small business, the services sector, enterprise activity and construction processes play a leading role in forecasting regional economic potential. The fact that *lag_index* has the highest importance indicates that the factor of continuity is preserved in regional development.

A comparative interpretation of variable importance for the decision-tree-based models is presented in a separate figure.

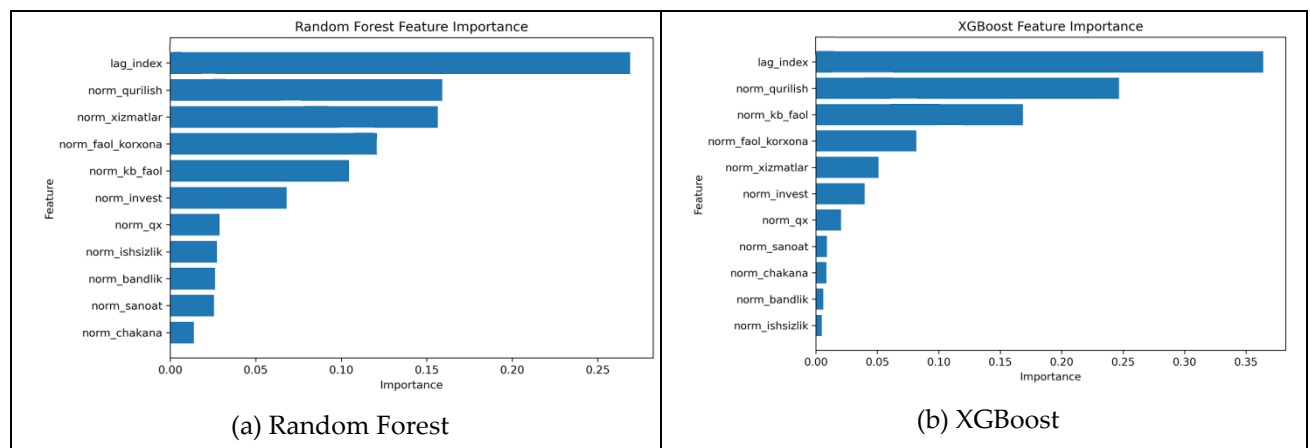


Figure 4. Comparative distribution of variable importance in the Random Forest and XGBoost models

According to Figure 4, in the Random Forest and XGBoost models the highest importance likewise belongs to *lag_index*. At the same time, indicators related to construction, active small business, active enterprises and services stand out as highly significant factors. While the weight of the temporal persistence component is more pronounced in the XGBoost model, the distribution of the factors appears relatively more balanced in the Random Forest model.

Overall, the benchmark results show that models accounting for temporal sequence have an advantage in forecasting regional economic potential across the districts of Surkhandarya region. In particular, the fact that the LSTM model demonstrated the highest test accuracy confirms the importance of taking temporal dependence and continuity into account in regional development processes. Among the decision-tree-based models, the superiority of XGBoost over Random Forest shows that the gradient boosting approach captures complex non-linear relationships relatively more effectively. The comparatively weaker results of the MLP model indicate that, under the selected empirical base and configuration, its performance on tabular regional data is more limited than that of decision-tree-based and sequence-based models.

4. Conclusions

This study was devoted to a comparative benchmark analysis of the MLP, Random Forest, XGBoost and LSTM models in forecasting regional economic potential using data for the districts of Surkhandarya region. Regional economic potential was expressed by means of a composite index constructed with the entropy method and was adopted as the target variable to be forecast for the following year. A single empirical base, a common train-test design and identical evaluation criteria made it possible to compare the models impartially.

The results obtained show that the highest forecasting accuracy on the test sample was observed for the LSTM model. This confirms that models accounting for temporal dependence and continuity have an advantage in assessing the dynamics of regional economic potential.

Among the decision-tree-based models, XGBoost performed better than Random Forest, while the MLP model recorded comparatively lower performance in the benchmark. Thus, within the selected empirical base, model performance followed the order LSTM → XGBoost → Random Forest → MLP.

The analysis of variable importance showed that the factor of temporal persistence is dominant in shaping regional economic potential. In particular, the identification of *lag_index* as the leading determinant across the interpretable models confirms that the

level of development in the previous year plays an important role in determining the outcomes of the subsequent period.

At the same time, the high importance of the indicators related to investment activity, construction, active enterprises, small business and the services sector shows that regional economic potential is structurally closely linked to capital investment, the business environment and the service economy.

Proceeding from the results of the study, it is advisable to strengthen several practical directions in regional economic policy. First, the development dynamics of the districts in previous years should be incorporated into planning and forecasting systems as a mandatory component. Second, measures aimed at increasing investment activity, developing the construction sector and raising the number of active small businesses and enterprises should be regarded as important instruments for strengthening regional economic potential.

Third, the high importance of the services sector calls for the development of targeted programmes to expand and diversify this sector across the districts. Fourth, introducing models such as LSTM and XGBoost into management practice at the regional and district levels may improve the quality of regional economic monitoring and short-term forecasting.

At the same time, the study has certain limitations. The analysis is confined to data for the districts of Surkhandarya region, and caution is required in generalising the results to other regions. In addition, although the LSTM model showed the highest forecasting accuracy, additional interpretive analysis techniques are required in order to explain in depth the relative influence of the input factors in this model. In future research it would be advisable to include additional institutional and infrastructural indicators and to apply interpretation methods for deep models.

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