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Modelling of an Intelligent Geographic Information System for Population Migration Forecasting

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Abstract: A generalized model of population migration is proposed. On its basis, models of the set of directions of population flows, the duration of migration, which is determined by its nature in time, type and form of migration, are developed. The model of indicators of actual migration (resettlement) is developed and their groups are divided. The results of population migration are described, characterized by a number of absolute and relative indicators for the purpose of regression analysis of data. To obtain the results of migration, the author takes into account the power of migration flows, which depend on the population of the territories between which the exchange takes place and on their location on the basis of the coefficients of the effectiveness of migration ties and the intensity of migration ties. The types of migration intensity coefficients depending on the properties are formed. The *lightgbm* algorithm for predicting population migration is implemented in the intelligent geographic information system. The migration forecasting system is also capable of predicting international migration or migration between different countries. The significance of conducting this survey lies in the increasing need for accurate and reliable migration forecasts. With globalization and the connectivity of nations, understanding and predicting migration patterns have become crucial for various domains, including social planning, resource allocation, and economic development. Through extensive experimentation and evaluation, developed migration forecasting system has demonstrated results of human migration based on machine learning algorithms. Performance metrics of migration flow forecasting models are investigated, which made it possible to present the results obtained from the evaluation of these models using various performance indicators, including the mean square error (MSE), root mean square error (RMSE) and R-squared (R2). The MSE and RMSE measure the root mean square difference between predicted and actual values, while the R2 represents the proportion of variance explained by the model.

Index Terms: Population Migration, Migration Data Analysis, Geocoding, Regression Analysis, Intelligent System, Decision-making.

1. Introduction

Recently, there has been an increase in the range of practical tasks related to decision-making based on obtaining, analyzing, modeling and forecasting the development of population migration with a change of residence, as a mechanical movement of people across the administrative boundaries of territories for different time periods. The primary research objective is to develop a comprehensive understanding of the factors influencing population migration. By uncovering the complex dynamics behind migration, we strive to enhance the accuracy and reliability of migration forecasting. The core problem we aim to solve is the lack of accurate and reliable migration forecasts, which prevents effective decision-making in various fields. The consequences of inaccurate or outdated predictions can lead to inefficient resource allocation and missed opportunities for economic development.

The objectives of the paper are:

1. Build models to describe migration, its characteristics, types and forms.
2. Model and characterise indicators of actual migration (resettlement).
3. Conduct modelling studies of the dependence of inter-regional relations and the intensity of migration exchange on their components.
4. To build decision trees and regression analysis of population migration trends.
5. Develop a migration forecasting system based on machine learning methods.
6. Evaluate the effectiveness of the proposed migration models.

Population migration by its very nature is a complex social process that affects the socio-economic development of human life to varying degrees. Statistical data on migration processes, their analysis and decision-making are widely used in a number of social, sectoral and applied areas. The interrelationships between migration and social change have become more profound than at any previous stage. The study of population migration is of great theoretical and practical importance. Identifying patterns and features of migration allows us to supplement the system of theoretical knowledge in this area, models, concepts, etc. From a practical point of view, the study of migration processes is essential for improving the scientific level of plans and projects for the development of individual regions, in particular in forecasting various industries and their services.

2. Related Works

Population migration forecasting is a challenging task characterized by a high level of error [1] and is the most important component of demographic changes along with birth and death rates. Modern methods of forecasting migration activity require improvement to be more relevant to current challenges in the socio-demographic sphere.

In [2], the tasks related to the sustainable development of regional systems are investigated and solved by means of a work that applies new mathematical methods of analysis and forecasting the development of these systems. This approach is based on system modelling of sustainable development indicators of the region and includes mechanisms for analyzing and preventing changes in the dynamic characteristics of the system. This work contributes to the improvement of economic, social and environmental indicators of the region in terms of sustainable development. A predictive socio-ecological-economic model of the region's development is proposed, which is based on the methods of statistical analysis and optimal management tasks. This model takes into account various aspects of the concept of sustainable development at the regional level. Real, optimization and recreational scenarios of the region's development have been developed. Using the theory of fuzzy sets, a sustainable development scenario was created based on these scenarios.

In [3], broad issues related to external labour migration of Ukrainian citizens are discussed. The study examines theoretical and applied aspects of labour emigration. It analyses the course of external labour migration in the context of the overall socio-economic situation, using data from state statistics and special sample surveys. Particular attention is paid to the analysis of the results of the first nationwide survey on labour migration conducted in mid-2008. The socio-economic characteristics of external labour migrants, directions of labour emigration, working conditions and stay of Ukrainian citizens abroad are studied. The article estimates the earnings of labour migrants and remittances, and assesses the impact of labour emigration on the development of the labour market in Ukraine. Proposals for the development of migration policy and improvement of labour migration statistics are developed [4].

The paper [5] discusses issues related to the potential use of big data in official (state) statistics. The authors consider the advantages of this approach, such as timeliness, wide coverage of certain parts of the target population and reduction of the cost of collecting such data. They also identify the problems that arise when using big data and need to be addressed. Arguments are presented to support the existence of prototype tools in applied and official statistics that, with appropriate development and adaptation, could address the main of these problems.

Experts from the Ptukha Institute of Demography and Social Research of the National Academy of Sciences of Ukraine [3-5], the National Institute for Strategic Studies [6, 7], and the Institute of Regional Research named after M.I. Dolishniy of the National Academy of Sciences of Ukraine [8, 9] conduct scientific research on regional and border migration. Some researchers are working on improving the methodology for forecasting regional migration in the short term and issues of re-emigration [10, 11]. However, there is currently a lack of specialized publications related to methods of forecasting population migration that take into account performance and intensity coefficients of migration links to obtain an overall migration coefficient.

3. Material and Methods

The main source of information on population migration is official statistics, which includes current migration records and data from population censuses. In addition, selective surveys are conducted, the purpose of which is usually to determine the reasons for movement [12-15]. Population migration is studied using a system of indicators, each of which reveals a particular aspect of the phenomenon. Moreover, in today's world, various criteria influence population migration, such as climate change in a continental region or on the planet, military conflicts or wars, diseases or pandemics, nomadism, tourism, work or shift trips, and so on.

We can present a generalized model of population migration as a tuple:

$$MN = < NP, TM, TypM, FM >, \tag{1}$$

where NP – set of population flow directions, TM – duration of migration, $TypM$ – migration type, FM – migration form.

The set of directions of population flows is defined by the model:

$$NP = < p_v, p_z >, \tag{2}$$

where p_v – internal flows within a country that occur between different units of a particular administrative division, $p_z = \{em, im, reem, rep\}$ – external flows of a country that take place between states, regions of the planet, and continents. Accordingly, the elements of the set em – emigration, which characterizes the movement of citizens of a specific state abroad; im – immigration, as the entry of foreign citizens into the country; $reem$ – reemigration, which characterizes the return of former or valid citizens of the country to their homeland; rep – repatriation, which means the return of a population that was forcibly removed.

The duration of migration TM can be determined by its nature in terms of time and is proposed to be set in the form of a set:

$$TM = < TM_p, TM_t, TM_s, TM_m >, \tag{3}$$

TM_p – permanent or irreversible durations of migration, characterizing the movement of the population to a permanent or long-term place of residence; TM_t – moving for a relatively short time; TM_s – annual movements of people related to work, recreation at resorts, nomadic migration; TM_m – pendulum duration of migration, which determines regular daily or weekly trips to work or study outside the place of residence.

Type of migration $TypM$ may include:

$$TypM = < M_{st}, M_{ssh}, M_{sm}, M_{ms}, M_{kp}, M_{td}, M_m, M_{pt} >, \tag{4}$$

M_{st} – migration of seasonal tourism; M_{ssh} – migration of seasonal agricultural production; M_{sm} – migration from rural areas to cities, which occurs in developing countries in the process of urbanization; M_{ms} – migration from cities to rural areas, characteristic of developed countries (ruralization); M_{kp} – nomadic and pilgrimage migration; M_{td} – temporary and long-term migration, M_m – pendulum migration; M_{pt} – border and transit migration.

Form of migration FM is given by the set:

$$FM =< FM_K, FM_n, FM_d, FM_p, FM_l >, \tag{5}$$

where FM_K – managed or socially organized form of organization; FM_n – unorganized form of organization; FM_d - voluntary form of organization; FM_p – compulsory form of organization; FM_l – legal or illegal form of organization.

Migration indicators can characterize the overall level of population mobility of territories, the scale, structure, directions, and effectiveness of migration flows for a certain period [12, 16-19]. The most accurate indicator of the level of migration mobility is the number of relocations during the entire lifetime of individuals of a certain age or the population as a whole [5, 8, 20-22]. Indicators of actual migration (relocations) can be divided into three groups:

$$P_{FM} =< P_Z, P_S, P_{MO}, P_{pow}, P_{intens}, P_{effectivm} >, \tag{6}$$

where common P_Z, which characterize the migration processes common to the territory; special (structural) P_S, which characterize the migration of specific socio-demographic groups, as well as indicators of interdistrict (interterritorial) exchange P_{MO}, that characterize migration links between specific territories of migration exchange. They include power indicators P_{pow}, intensity P_{intens} and effectiveness of migration in Fig.1.

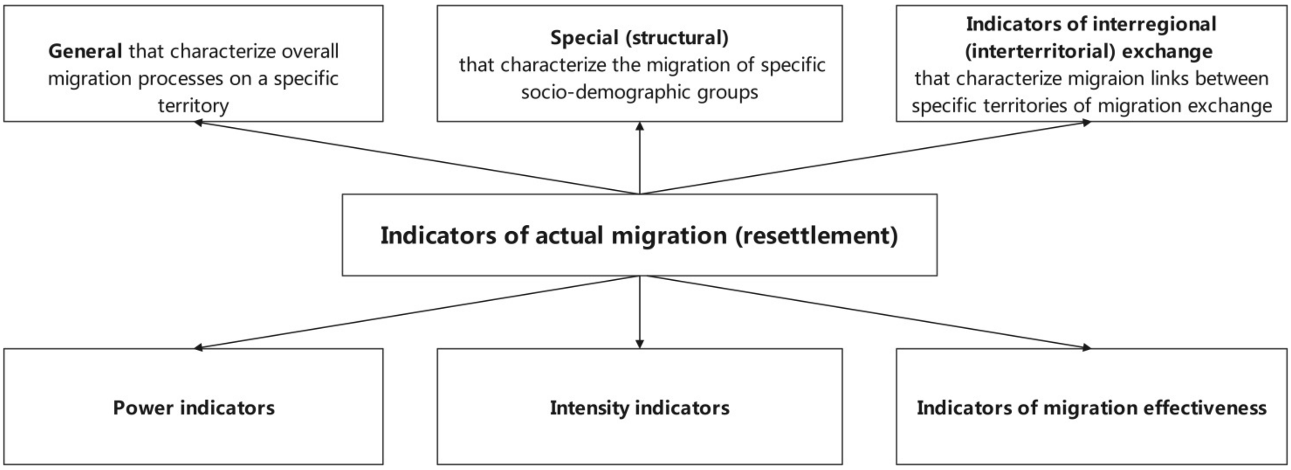

Fig. 1. Indicators of actual migration (resettlement)

The results of population migration are characterized by a number of absolute and relative indicators: a) the number of people arriving for permanent residence from other settlements (P_m); b) the number of those who left for permanent residence in other settlements (V_m); c) net migration or mechanical growth $S_m = P_m - V_m$.

Interregional connections are primarily characterized by the strength of migration flows, which depend on the population size of the areas involved in the exchange and their location. The result of this exchange is expressed in the migration balance or through the use of migration connection performance coefficients (MCPC). The intensity of migration exchange, which is independent of the population size of the regions of origin and destination, is determined using coefficients of migration connection intensity (CMCI). They allow the influence of the population size of the regions of origin and destination on the intensity of interregional migration to be excluded and are calculated as the ratio of the share of arrivals in a given region in the total inflow (CMCI by arrival) or departures in the total outflow (CMCI by departure) to the proportion of the population of the region of origin in the total population of the area maintaining migration connections with it [1, 2, 23]:

The formula for calculating the CMCI by arrival is:

$$K_{ij} = \frac{P_{ij}}{P_{ji}} : \frac{S_j}{S_i} \times 1000 \cdot \tag{7}$$

The formula for calculating the CMCI by departure is:

$$K_{ij} = \frac{V_{ij}}{V_{ji}} : \frac{S_j}{S_i} \times 1000, \tag{8}$$

where P_{ij} – the number of arrivals in the region j from region i; V_{ji} – the number of dropouts from the region j in region i; S_i – average population of the region i over period; S_j – the total number of output regions with which the region i supports migration links.

Migration intensity is a statistical characteristic of population mobility, which reflects its frequency in certain territorial and demographic groups and is expressed by the migration intensity coefficient (MIC). [16-18, 24].
MIC can be calculated for the entire population of a given territory (total territorial MIC) as well as for its different structural elements such as gender, age, nationality, and others. Let's categorize the types of intensity coefficients of migration based on their properties:

1. The coefficient of intensity of arrival (immigration) is a quantitative characteristic of individuals who have arrived or reside in a given region but have a different region of origin, divided by the average population in this region. In other words, the population that has been at risk of receiving (them) immigrants.

$$I_j = \frac{P_{ij}}{S_i} \times 1000; \tag{9}$$

2. The emigration intensity coefficient is a quantitative characteristic of individuals who have left a particular region (country), divided by the average (over the period) population of the region, i.e. the population that is at "risk" of emigration.

$$I_j = \frac{B_{ij}}{S_i} \times 1000; \tag{10}$$

3. Return migration intensity coefficient: the sum of arrivals and departures, divided by the average population of the destination region.

$$I_j = \frac{P_{ij} + B_{ij}}{S_j} \times 1000; \tag{11}$$

4. The net migration intensity coefficient: the difference between the numbers of arrivals and departures divided by the average population of the receiving region.

$$I_j = \frac{P_{ij} - B_{ij}}{S_j} \times 1000; \tag{12}$$

where P_{ij} – the total number of arrivals in the region j from all regions; B_{ij} – the total number of dropouts from the region j; S_j – average population of the region j for the period under study.

Special coefficients are calculated for individual groups that make up migration flows, as migration indicators directly depend on the composition of migrants. For example, age-specific migration intensity coefficients are calculated as the ratio of the number of migrants of a given age to the average population of that age in the region of origin or settlement. Similarly, other coefficients can be calculated, such as the ratio of the number of male and female populations to the total population, the percentage of working-age population, non-working population, etc.

Migration intensity coefficients allow us to assess the level of population mobility in a particular area, as well as compare the levels of population mobility of regions of different ranks and sizes, identify the dynamics of migration movements regardless of changes in population size, and predict changes in these trends in the future. However, the use of this indicator is limited by the fact that its value depends not only on the intensity of migration links of one region with others, but also on the migration capacity of the region of settlement and the migration potential of the region of origin, therefore the obtained data cannot be used with 100% probability and additional data must be used in the analysis.

One of the main characteristics of migration is its effectiveness. The effectiveness of migration is equal to the ratio of the number of emigrants to immigrants. There is a numerical characteristic called the migration effectiveness coefficient. Usually, this indicator is calculated per 1000 immigrants and can be calculated both overall and interregional.

The total migration coefficient is calculated using the formula [2, 5, 11]:

$$m = \frac{M}{P \cdot k}, \tag{13}$$

where M – the number of migrants; P – average population size; k – a constant that is equal to a value from 1 to 100 (the result is expressed as a percentage) or to 1000 (the result is expressed in ppm).

Special coefficients are calculated for individual groups that make up migration flows because migration indicators depend directly on the composition of migrants. For example, age-specific migration intensity coefficients are calculated as the ratio of the number of migrants of a certain age to the average population of that age in the region of origin or settlement. Similarly, other coefficients can be calculated, such as the ratio of the number of male and female populations to the total population, the percentage of working-age population, non-working population, and so on.

By calculating special coefficients for individual groups within migration flows, allows us to gain a deeper understanding of the factors influencing migration patterns. This analysis facilitates the identification of key drivers, such as socio-economic indicators and geopolitical factors, which contribute to more accurate predictions and a better understanding of migration dynamics.

4. Implementation of an Intelligent Geographic Information System

The system is developed using elements of a geographic information system (GIS) [6, 10, 15] - a web system that utilizes geocoding, regression analysis, and neural networks to analyze migration data and provide insights into migration patterns and drivers.

To support working with geographic data, the GeoDjango [7, 19] web framework is used. This framework also provides access to spatial queries that allow filtering and analyzing data based on location, as well as the ability to store spatial data in spatial databases for efficient storage and processing of geospatial data.

The *lightgbm* algorithm [8, 21-26] used is a type of machine learning model called a decision tree (Fig. 2) with gradient boosting.

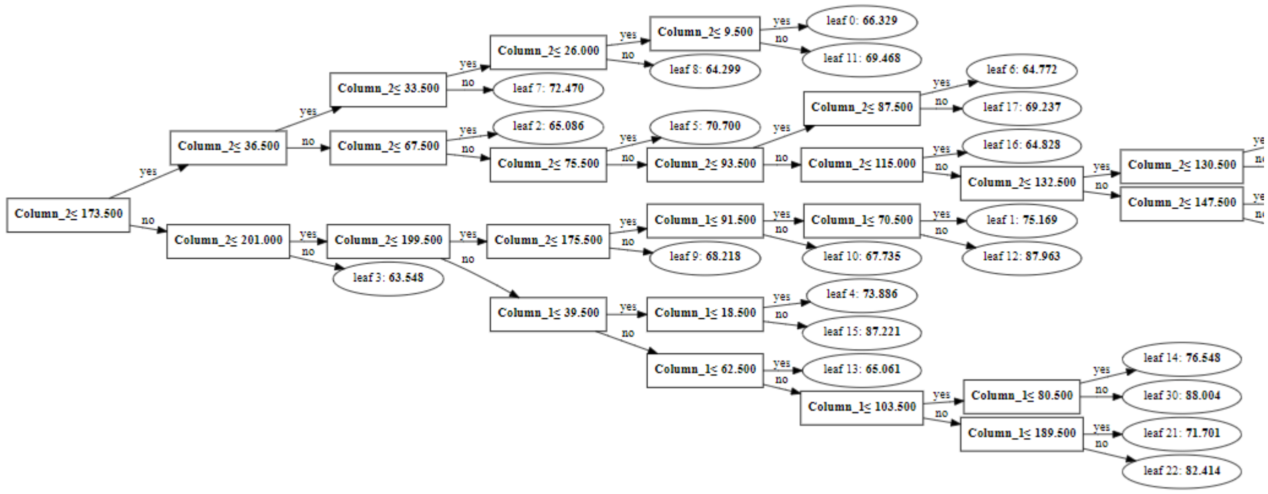

Fig. 2. Partial *lightgbm* decision tree

The *lightgbm* algorithm is used for predicting immigration and emigration based on country and age population data. The model works by analyzing a large dataset of immigration and emigration data and population age data for each country. The algorithm uses this data to train a model that can accurately predict future immigration and emigration patterns based on the provided input data.

The first step in using *lightgbm* is preparing the input data [9, 21, 27-28]. This involves selecting the relevant features and variables that will be used for prediction. In this case, the features are the country and age of the population. The data is then split into training and validation sets. Once the input data is prepared, the *lightgbm* algorithm is used to train a decision tree model. The model is trained using the gradient boosting algorithm, meaning it creates a series of decision trees, each optimized to minimize the errors of the previous tree. This process continues until the model reaches an optimal level of accuracy.

For analyzing migration data, the system includes regression analysis (Fig. 3) and neural networks. Regression analysis is used to model the relationship between migration and various factors such as demographic, economic, and environmental variables, to identify key migration factors and predict future migration patterns. Neural networks, on the other hand, are used to model complex relationships between variables and increase the accuracy of predictions over time. Once the model is trained, it can be used for prediction. The model receives new data, such as country and age of the population, and generates a prediction of immigration or emigration for that country based on the previously provided training data.

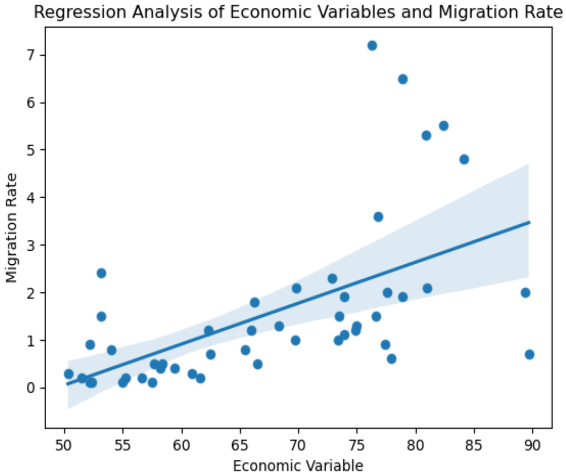

Fig. 3. Graph of regression analysis

The *lightgbm* algorithm is particularly effective for predicting immigration and emigration, as it is designed to handle large and complex datasets. It can handle missing data and automatically select the most important features for prediction.

Despite the significant potential of the migration forecasting system to provide valuable information on migration patterns and factors, there are also limitations and potential issues to consider. One such problem is the accuracy of the predictions. Although the *lightgbm* algorithm is capable of processing large and complex datasets, the accuracy of the predictions still depends on the quality and reliability of the data sources. Inaccurate or incomplete data can lead to inaccurate predictions, which can ultimately limit the usefulness of the system. The evaluation metrics for *lightgbm* are the root mean squared error (RMSE) of 70.30 and R-squared, a statistical measure that represents the proportion of variance in the dependent variable that is explained by the independent variables, of 0.595.

Continuous updating and monitoring of the model are also necessary to ensure that the system remains up-to-date and effective over time. Migration patterns and models can change quickly, and the model must be able to adapt to these changes to provide accurate predictions.

Fig. 4. Interactive map of internal population migration

To display migration data, the system uses the JavaScript library Leaflet [10, 23, 29], which allows for customization of the map's appearance and functionality. This library enables the aggregation of data by regions and countries, and then displaying it on the map with latitude and longitude coordinates.

The migration forecasting system is capable of predicting internal migration within a country, including migration between regions (Fig. 4), as well as international migration or migration between different countries (Fig. 5).

One way to analyze internal migration is to study age indicators of migration between regions. This can help identify trends in population movements based on different age groups, such as young people moving to cities for education or employment. For example, the system can analyze data on the number of people in different age groups who have moved between regions over a certain period of time, and use this information to forecast future migration patterns.

The migration forecasting system is also capable of predicting international migration or migration between different countries (Fig. 5).

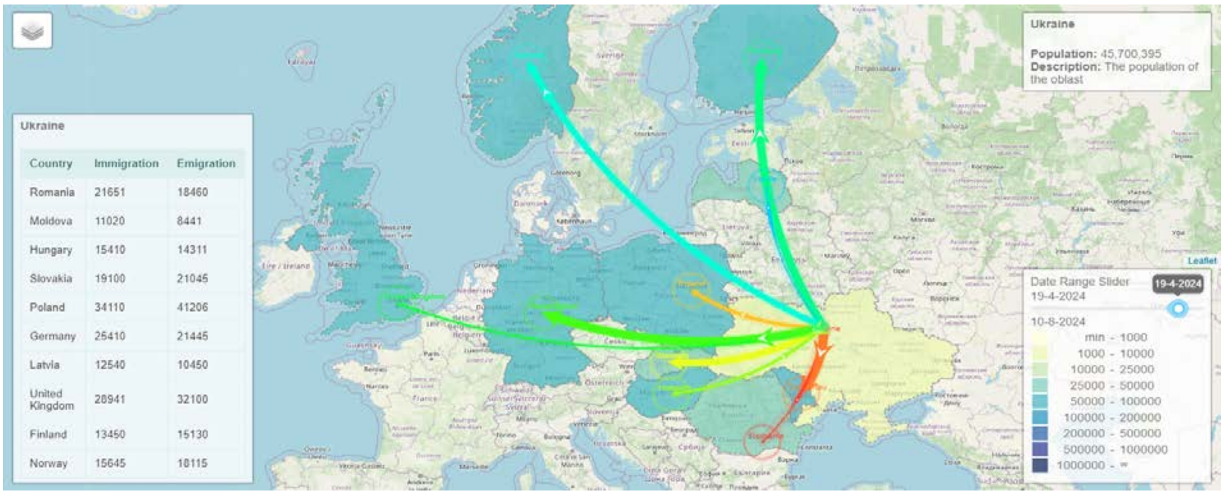

Fig. 5. Interactive map of international population migration

5. Results and Discussion

In this study, we evaluated several models for the prediction of migration flows using different machine learning algorithms. The models tested included Ridge Regression, Lasso Regression, Random Forest, Gradient Boosting, Support Vector Regression, Multi-Layer Perceptron, and LightGBM. To ensure optimal performance, we employed GridSearchCV to search for the best set of hyperparameters for each model.

Table 1 presents the results obtained from the evaluation of these models using various performance metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2). The MSE and RMSE measure the average squared difference between the predicted and actual values, while R2 represents the proportion of variance explained by the model.

Table 1. Performance Metrics of Migration Flow Prediction Models

Model	MSE	RMSE	R2
Ridge Regression	5954	77.168	0.18
Lasso Regression	6212	78.818	0.15
Random Forest	897	29.954	0.87
Gradient Boosting	2867	53.544	0.60
Support Vector Regression	7043	83.922	0.04
Multi-Layer Perceptron	6660	81.609	0.09
LightGBM	714	26.727	0.90

Among the tested models, Random Forest and LightGBM achieved the lowest MSE and RMSE values, indicating their superior performance in accurately predicting migration flows. Random Forest obtained an MSE of 897 and an RMSE of 29.954, while LightGBM achieved an MSE of 714 and an RMSE of 26.727. These results suggest that both ensemble-based models can effectively capture the complex patterns and relationships within the migration data.

Overall, the evaluation of these models provides valuable insights into their predictive capabilities for migration forecasting. The results highlight the superior performance of Random Forest and LightGBM in accurately predicting migration flows. These models can be considered as strong candidates for integration into a robust migration forecasting system.

6. Conclusions

An integrated model of population migration has been proposed. The models of the set of population flow directions, migration duration, which can be determined by its nature over time, and models of migration type and form have been described. For further analysis of migration data in an intelligent system, indicators of actual migration (relocation) were grouped with subsequent calculation of population migration results characterized by a number of absolute and relative indicators. In this regard, performance coefficients of migration links and intensity coefficients of migration links were determined and taken into account to obtain the overall migration coefficient. To implement the population migration model, the *lightgbm* algorithm was used. The evaluation metrics for the *lightgbm* are Root Mean

Squared Error (RMSE) of 26.727 and R-squared, statistical measure that represents the proportion of the variance in the dependent variable that is explained by the independent variables, (R2) of 0.90.

The migration prediction system based on GIS, regression analysis, neural networks, and the *lightgbm* algorithm is a powerful tool for predicting migration patterns within and between countries. This creates potential to provide valuable information about migration patterns and drivers, as well as help governments and organizations plan and prepare for future demographic changes.

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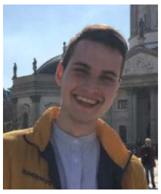

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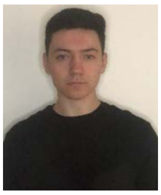

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