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# OPTIMIZED MODEL FOR PREDICTING THE AVAILABILITY OF OBJECTS BASED ON DEEP LEARNING AND GEOSPATIAL FEATURES

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## ABSTRACT

**Context.** Today, predicting the availability of objects in spatially distributed systems remains one of the areas of computer science that constantly attracts the attention of researchers. There are many reasons for this. There is an increase in the amount of spatial information. New types of infrastructure networks are emerging, as well as the need for rapid decision-making in changing conditions. At the same time, traditional analysis methods do not always cope with the tasks of processing multidimensional data. This is especially true when it comes to complex or unstable environments. This opens up opportunities for applying deep learning methods that demonstrate high efficiency where classical approaches fail.

**Objective.** The study aims to optimize the model for predicting the availability of objects in spatially distributed systems by defining an efficient deep learning architecture that uses spatial and other infrastructure features to improve prediction accuracy and generalizability.

**Method.** To achieve this goal, deep learning architectures were used, including feed-forward models (FNN), convolutional neural networks (CNN), and recurrent neural networks (RNN, GRU, LSTM). During the modeling, methods of data normalization, training regularization, and a comprehensive system for evaluating the accuracy of forecasts using the mean square error, mean absolute error, and coefficient of determination were used.

**Results.** An optimized architecture of a recurrent neural network was built for the study, which includes a combination of two recurrent layers, Dropout regularization layers, and a fully connected layer. The analysis has shown that the proposed model provides high accuracy in predicting the availability of objects, demonstrating stability over a wide range of spatial data. Comparison of actual and predicted values confirmed the effectiveness of the proposed solution.

**Conclusions.** The proposed approach to building an optimized deep learning model for predicting the availability of objects provides a high level of generalization and accuracy, which creates prerequisites for its use in systems of intelligent decision support in spatially distributed environments.

**KEYWORDS:** deep learning, forecasting, object availability, geospatial data, RNN optimization, intelligent systems.

## ABBREVIATIONS

CNN is a convolutional neural network;

FNN is a feed-forward neural network;

GRU is a gate mechanism in recurrent neural networks;

LSTM is a long short-term memory as one of the artificial architectures of recurrent neural networks;

NetworkX is a Python library for graph and network research;

OpenStreetMap is an open project aimed at collecting, preserving, and distributing publicly available geospatial data;

OSMNX is a Python library that allows you to capture spatial geometries and model, design, visualize, and analyze real street networks from OpenStreetMap APIs;

RNN is a recurrent neural network.

## NOMENCLATURE

$\Delta_\theta$ is a gradient of a loss function calculated on the current batch;

$\eta$ is a learning rate;

$\theta$ is a set of network parameters (weights and offsets of all layers);

$\sigma$ is a sigmoidal function in the output layer used to obtain a probabilistic forecast of availability;

$A_i$ is an area of the community in square kilometers;

$b$ is a displacement vector;

$b_{ij}$ is a presence of the *j*-th obstacle on the territory of the *i*-th community;

$\vec{b}^{(l)}$ is a displacement vector;

$E$ is a set of edges representing road segments with specified attributes (length, type of pavement, number of lanes);

$F()$ is a model architecture;

$f(\cdot)$ is an activation function;

$f_i$ is an activation function of hidden layers (for example, ReLU);

$q_{kj}$ is a value of the *k*-th quality metric for the model, which includes indicators of accuracy, stability, and computational efficiency;

$\vec{h}^{(l-1)}$ is an output of the previous layer;

$h_t$ is a hidden state at a given time *t*;


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$\vec{h}_T$ is the last state of the LSTM after processing the entire sequence;

$\vec{k}$ is a convolution kernel;

$L_i$ is a total length of all roads within the community;

$N$ is a number of examples in the batch;

$n$ is a number of examples in the test sample;

$P_i$ is a population of the *i*-th community, which allows to estimate the potential load on rescue forces in case of emergencies;

$V$ is a set of vertices corresponding to the geographical coordinates of nodes (intersections, turns);

$w$ is a vector of weight parameters;

$W^{(l)}$ is a weight matrix of the *l*-th layer;

$w_j$ is a weighting factor of the corresponding obstacle on accessibility;

$w_i$ is a weighting factor of the importance of the i-th metric, determined in accordance with the research priorities;

$W_i$ are respectively weight matrices;

$x$ is an initial value of the feature;

$x_s$ is a feature vector;

$x_t$ is an input vector;

$x_{i+m,j+n}$ is a local feature matrix;

$x_{ji}$ is a separate *j*-th characteristic, which is a numerical or categorical description of the features of the *i*-th settlement;

$x_{\min}$ is a minimum value of the feature;

$x_{\max}$ is a maximum value of the feature;

$x_{\min}$, $x_{\max}$ are respectively minimum and maximum values of the feature;

$\langle x, y \rangle$ is an initial sample in the form of a set of cases;

$\langle x', y' \rangle$ is a subsample from the original set of cases;

$y_i$ is an actual value of the availability of voluntary rescue groups on the territory of communities for the i-th settlement;

$\bar{y}$ is an average of the actual values of $y_i$ ;

$\hat{y}_i$ is a predicted value of the availability of voluntary rescue groups on the territory of communities for the *i*-th settlement based on the model;

$y_s$ is a target value.

## INTRODUCTION

One of the important areas of modern informatics is the development of models for predicting the availability of objects in spatially distributed systems [1–3]. With the increasing complexity of infrastructure networks and the growing volume of geospatial data, there is a need to improve methods capable of providing accurate analysis of spatial dependencies and support for decision-making processes.

Traditional analytical approaches based on static maps or normative estimates are often not effective enough when dealing with high-dimensional data and variable spatial characteristics [4–6]. The complexity of the object environment, the heterogeneity of the distribution of features, and the dependence on numerous infrastructure and social factors pose new challenges to researchers regarding the accuracy and adaptability of forecasting models [7–10].

In this context, deep learning methods are of particular importance. The use of multi-layer neural networks, such as feed-forward networks (FNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs, GRUs, LSTMs), opens up opportunities for building models capable of processing large amounts of spatial data and identifying complex hidden dependencies. The development of optimized architectures of such networks for predicting the availability of objects is an important step in the development of intelligent decision support systems.

**Object of the study:** the process of predicting the level of availability of objects in spatially distributed systems based on the analysis of geospatial and other infrastructure characteristics.

**Subject of the study:** models and architectures of deep neural networks, their optimization, and application for predicting the availability of objects within intelligent decision support systems.

**The purpose of this work** is to develop an approach to the formation of an input spatial and infrastructural data set for predicting the availability of objects in spatially distributed systems and to substantiate an optimized model for predicting the level of availability of objects based on deep learning using spatial and infrastructural features.

**Tasks of the research:**

– To propose an approach to optimizing the model for predicting the availability of objects in spatially distributed systems by determining an effective deep learning architecture that uses spatial and infrastructural features to improve the prediction accuracy and generalization ability;

– To generate an input dataset based on geospatial information for training deep learning models focused on predicting the level of availability of objects in space-distributed systems;

– To justify the choice of deep neural network architecture, to optimize it according to the criteria of accuracy of predicting the availability of objects, and to evaluate the possibility of using the created model in decision support systems in spatial planning.

Deep learning methods used to analyze complex and high-dimensional data allow not only to identify hidden spatial patterns, but also to create effective predictive models for solving problems related to assessing the accessibility of objects. The combination of geoinformation resources with the capabilities of deep neural networks provides an increase in forecasting


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accuracy by taking into account the current state of the road network, spatial obstacles, route length, and other critical factors.

The study is aimed at substantiating the model for predicting the availability of objects based on geospatial features and deep learning, which involves the stages of building an input spatial set of characteristics, training a neural network on representative data, and further verifying the accuracy of the created model for practical use in strategic spatial analysis.

## 1 PROBLEM STATEMENT

Let the initial sample of geospatial and infrastructure data be given in the form of a set of precedents $\langle x, y\rangle$, where $x=\{x_s\}$, $y=\{y_s\}$, $x_s=\{x_{sj}\}$, $s=1,2,...,S$, $j=1,2,...,N$. In this case, each element of the data sample is a feature vector $x_s$ of dimensionality $N$, which corresponds to the target value $y_s$.

The task of synthesizing a neural network model is to find a pair of $\langle F(), w\rangle$, where $F()$ – is the model architecture, which is usually set by the user or system designer, and $w$ – is a vector of weight parameters that is configured based on the training set. Thus, the predicted value of the level of availability of objects is denoted as:

$$y_s^* = F(w, x_s),$$

and the criterion of training quality is the optimization of the error function:

$$f(F(), w, \langle x, y\rangle) \to \min.$$

An important aspect of building an effective model for predicting the level of availability of objects is also the task of forming a subsample from the original sample $\langle x, y\rangle$. This is formally reduced to finding a pair $\langle x', y'\rangle$ such that:

$$x' \subset \{x_s\}, \quad y' = \{y_s \mid x_s \in x'\}, \quad S' < S, \quad N' = N,$$

for which the value of the loss function when training on the subsample provides the best agreement with the full sample:

$$f(\langle x', y'\rangle, \langle x, y\rangle) \to \min.$$

Thus, a two-component problem arises: 1) building the architecture and parameters of the model; 2) selecting the most informative subsample for its training, which is especially important in cases with large or unevenly represented data.

## 2 LITERATURE REVIEW

Ensuring the availability of objects in spatially distributed systems remains one of the key issues of modern informatics and applied geographic information analytics. The uneven location of infrastructure facilities in many regions leads to a violation of the expected normative access time, which significantly affects the level of efficiency of territorial systems [11–14]. According to the researchers, the decrease in spatial accessibility is one of the factors of increasing vulnerability of territories, especially in conditions of limited resources and underdeveloped transport infrastructure.

Traditional approaches to assessing accessibility are usually based on normatively defined radii of action or administrative boundaries [15–18]. However, such methods do not take into account the actual topography of the place, the state of the road network, building density, and spatial barriers, which limit their applicability in complex and changing environments.

In recent years, the use of open geoinformation resources for building spatial analysis models has attracted considerable interest. In particular, OpenStreetMap (OSM) data are actively used to estimate the density of the road network, model routes, and identify infrastructure objects [19–21]. Thanks to the availability of automated data processing tools, such as the OSMNX and NetworkX libraries, it becomes possible to form structured feature sets that accurately reflect the real conditions of movement in space.

In parallel, there is an active development of methods for predicting the state of objects using deep learning algorithms [22–25]. Multilayer neural networks, convolutional architectures, and models based on graph structures demonstrate high efficiency in simple classification and regression tasks [26–28]. Such approaches allow for taking into account complex nonlinear relationships between spatial, infrastructural, and social characteristics.

At the same time, the integration of deep learning methods with open geospatial data to predict the level of accessibility of objects remains insufficiently developed. In particular, there is a scientific task of creating models that can comprehensively take into account both the topographic features of the territory and the parameters of transport accessibility, building density, the presence of physical obstacles, and other key features that determine the real accessibility of objects in space.

Thus, there is a scientific and applied task of creating a model capable of accurately predicting the level of accessibility of objects based on open geodata. Such a model will take into account not only the geographical distance but also the features of the road network, the presence of obstacles, building density, and other indicators necessary for making management decisions.

## 3 MATERIALS AND METHODS

Building a model for predicting the level of availability of objects in spatially distributed systems


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requires an integrated approach that combines the stages of geospatial data processing, formation of a set of features, selection and training of deep neural networks, as well as evaluation of the accuracy of the built models and analysis of the results. The proposed research methodology is based on the use of open geoinformation resources, spatial analysis tools, and deep learning algorithms to identify patterns in multidimensional spatial data (Fig. 1).

Step 1. Collecting and forming a database of spatial and infrastructural characteristics of the territories.

The first stage involves the creation of a holistic structured data set that includes key spatial and infrastructural features of the object environment [29–31]. The purpose of this stage is to obtain the input information necessary for the construction of features used in the process of training neural prediction networks. The main source of spatial information is open data containing information about the road network, building boundaries, infrastructure facilities, and natural features of the territory.

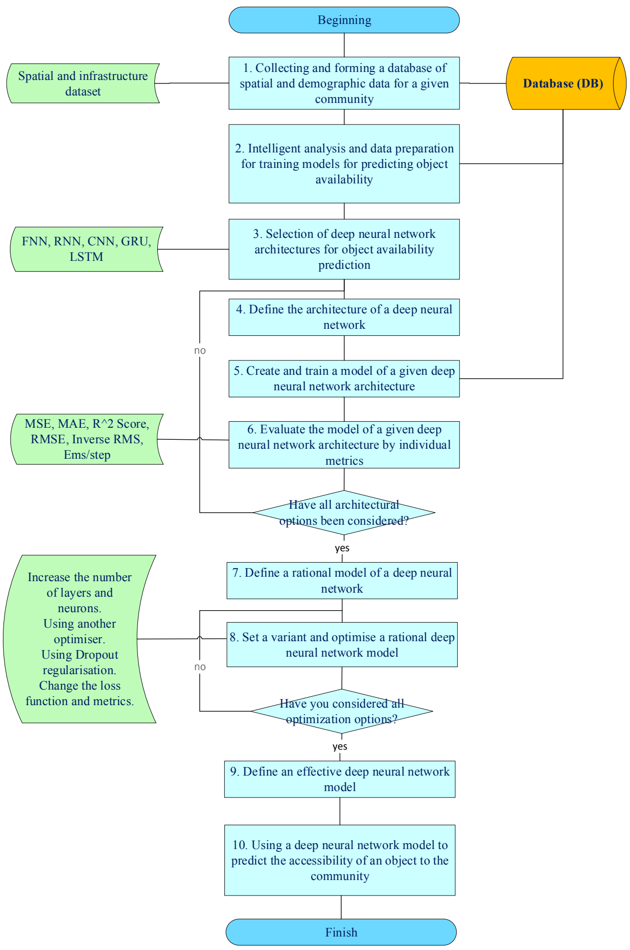


Figure 1 – An algorithm for researching to substantiate and optimize the architecture of a deep neural network model for predicting the availability of objects in spatially distributed systems

Building a model for predicting the level of accessibility of objects in spatially distributed systems involves an integrated approach that combines the stages of geospatial data processing, formation of an input set of features, building a deep learning model, and evaluating its accuracy.

At the first stage, we construct a directed graph of the road network that models the topological structure of the territory:

$$G = (V, E). \tag{1}$$

This graph is used to calculate the reachability metrics between points, which are used as features for modeling spatial accessibility.

At the same time, a set of spatial and infrastructural characteristics of the territory is formed by analyzing polygonal boundaries, road networks, the location of infrastructure facilities, and natural barriers. Spatial filtering allows you to select objects located within the analyzed area.

After that, important spatial indicators are calculated [32–34]. For example, the density of the road network for the *i*-th community is defined as:

$$\rho_i = \frac{L_i}{A_i}. \tag{2}$$

Indicator (2) allows us to assess the potential accessibility of settlements within the community.

To take into account natural obstacles, a barrier index is formed, which reflects the number of route intersections with natural obstacles (water bodies, forests) and is used as a factor in reducing operational accessibility:

$$B_i = \sum_{j=1}^{n} w_j \cdot b_{ij}. \tag{3}$$

The weighting factor $w_j$ for the impact of a particular obstacle on accessibility has different values (e.g., 0.7 for a river, 0.3 for a forest).

The population density $D_i$ is calculated based on official statistical data according to the formula:

$$D_i = \frac{P_i}{A_i}. \tag{4}$$

Step 2. Intelligent analysis and preparation of input data. At this stage, a preliminary analysis of spatial and infrastructural data is carried out to form a structured set of features for training deep learning models [35–38]. The main task is to identify the key characteristics that determine the level of spatial accessibility of objects within the analyzed area.

Within the constructed dataset, the target variable is determined – the accessibility index, which represents the


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presence or absence of conditions for ensuring access within a given spatial area. For each unit of analysis, a description is generated that contains a number of quantitative predictors that take into account the spatial, infrastructural, social, and transportation characteristics of the environment.

During the data cleaning, a number of procedures were carried out to improve the quality of input features for modeling. In particular, duplicates with the same geographical coordinates were eliminated to avoid the influence of duplicate records on the model training results. After the initial processing, the features were selected: attributes that did not carry an information load due to the lack of variability of values were excluded from the set. Such attributes included characteristics whose values were equal to zero in all records, which justified their removal from further analysis.

As a result of the preliminary analysis and data cleaning, eight informative features were formed, which are used to build models for predicting the spatial accessibility of objects. The selected features include characteristics of the road network, infrastructure provision and transport accessibility of the territory.

The formation of a compact set of features reduces the risk of model overtraining, avoids the influence of redundant or trivial parameters, and improves the quality and stability of the training process.

To minimize the impact of different scales of numerical characteristics, data are normalized [39]. In particular, indicators such as building density, number of infrastructure facilities, length of the road network, and area of territorial zones are brought to a unified scale [0;1] using minmax normalization:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \quad (5)$$

This approach ensures the same scale of input data for the model, which has a positive effect on the stability of weighting optimization and the speed of convergence during training.

The analysis of the scaling results showed that some spatial characteristics have a narrow range of variation, which indicates a significant uneven distribution of infrastructure elements within different territories. Normalization made it possible to adapt these features to a single scale without losing their impact on the modeling results.

As a result, a vector of input features is formed for each unit of analysis:

$$\vec{x}_i = [x_{1i}, x_{2i}, \ldots, x_{ni}]. \quad (6)$$

Preparing input data involves not only aggregating numerical indicators but also conceptually structuring spatial information in a form suitable for submission to deep learning models [40]. This approach provides comprehensive coverage of the factors that affect the accessibility of objects.

Step 3. Selecting the types of deep neural network architectures. After forming a structured set of spatial and infrastructural features for each territorial unit, the task is to choose the deep neural network architecture that best suits the data features and requirements for predicting the level of accessibility of objects.

The choice of architecture is determined by the nature of the input data, the type of forecasting task, and the requirements for accuracy and stability of the results. In this case, the input data is presented in the form of a tabular numeric array, where each row is a vector of features of the corresponding territorial unit formed according to (6).

The main goal is to build a model capable of predicting the value of the target variable in a binary classification task.

The basic option for working with tabular data is a Fully Connected Neural Network (FNN), which is a sequence of tightly connected layers, each of which performs a linear transformation of the input vector followed by a nonlinear activation:

$$\vec{h}^{(l)} = f\left(W^{(l)}\vec{h}^{(l-1)} + \vec{b}^{(l)}\right). \quad (7)$$

The FNN architecture is a universal function approximator and is well suited for processing structured numerical data. Depending on the complexity of the problem and the number of input features, the number of layers and the number of neurons in each layer are determined, which allows the model to be flexibly customized to specific forecasting conditions.

In cases where the input features have a pronounced spatial dependence, it is advisable to use convolutional neural networks (CNN). Such networks allow for effective detection of local spatial structures and patterns in the data by performing a convolutional operation:

$$s_{ij} = (\vec{x} * \vec{k})_{ij} = \sum_m \sum_n x_{i+m,j+n} \cdot k_{m,n}. \quad (8)$$

In this context, CNNs can be adapted to process spatial representations of data, for example, in the form of density distribution maps or environmental characteristic matrices.

If the study involves the processing of data sequences with time dynamics, it is advisable to use recurrent neural networks (RNNs), which allow modeling dependencies in time by preserving the internal state:

$$\vec{h}_t = f\left(W_x\vec{x}_t + W_h\vec{h}_{t-1} + \vec{b}\right). \quad (9)$$

Since classical RNN architectures are prone to the problem of gradient disappearance or explosion when working with long sequences, their modifications are often used in practice – Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). These architectures store information better over long time


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intervals and demonstrate high efficiency in time-dependent forecasting tasks.

In cases where the data have both spatial and temporal structure, it is advisable to use combined architectures, in particular, Recurrent Convolutional Neural Networks (RCNN). They allow for to simultaneously take into account of local spatial features and temporal dynamics of features, which makes them promising for modeling the evolution of the state of the spatial environment over time.

Step 4. Formalizing the basic architectures of deep neural networks. After determining the types of architectures suitable for solving the problems of predicting the availability of objects in spatially distributed systems, their structure is specified by formally setting the basic parameters. At this stage, the key characteristics of the network are determined, including the number of layers, the number of neurons in each layer, types of activation functions, loss function, optimization algorithm, and training parameters, such as the size of the data packet and the number of epochs.

For a Fully-connected Neural Network (FNN) model, the basic architecture usually includes one input layer, several hidden layers, and one output layer. The network structure is adapted to the dimensionality of the input feature vector. For example, when working with a feature vector of nnn features, the basic architecture may include an input layer with nnn neurons, two or three hidden layers with 128 and 64 neurons, respectively, and an output layer with one neuron to implement binary classification:

$$\begin{aligned} \vec{h}^{(1)} &= f_1(W^{(1)}\vec{x} + \vec{b}^{(1)}), \\ \vec{h}^{(2)} &= f_2(W^{(2)}\vec{h}^{(1)} + \vec{b}^{(2)}), \\ y &= \sigma(W^{(3)}\vec{h}^{(2)} + b^{(3)}). \end{aligned} \tag{10}$$

The choice of the number of layers and the number of neurons is made taking into account the dimensionality of the input data, the complexity of the problem, and the requirements for the generalization ability of the model.

In the case of Convolutional Neural Networks (CNNs), the basic architecture usually includes two or three convolutional layers with kernels of size $3\times3$ or $5\times5$ , each of which is accompanied by subsampling operations to reduce the dimensionality of the features. After the convolutional layers, a block of fully connected layers is formed, which ensures the integration of local features into global representations. This structure allows the model to efficiently detect spatial patterns in data represented as density matrices or images.

For recurrent architectures, such as LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit), the input data is represented in the form of sequences. The basic configuration of such models involves one or two memory layers with the number of neurons in the range of 64–128, after which the result is processed through the output dense layer:

$$\vec{h}_t = \mathrm{LSTM}(\vec{x}_t, \vec{h}_{t-1}), \quad y = \sigma(W\vec{h}_T + b)\,. \tag{11}$$

Regardless of the chosen architecture, binary cross-entropy is used to solve the problem of binary classification of the target variable as a function of losses:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[ y_i \cdot \log(\hat{y}_i) + (1-y_i)\cdot \log(1-\hat{y}_i) \right]. \tag{12}$$

A loss function of this type contributes to the correct training of the model in tasks with two possible classes of outcomes.

In the process of training deep neural networks for predicting the availability of objects, adaptive optimization algorithms are used, among which Adam and RMSProp are the basic ones. These methods provide efficient updating of weights based on the moments of gradients, which contributes to fast convergence even in multidimensional parameter spaces.

Regardless of the chosen architecture, binary cross-entropy is used to solve the problem of binary classification of the target variable as a function of loss:

Typical training parameter settings include:

– batch size – 32 or 64 examples per iteration;

– number of epochs – from 50 to 150, depending on the dynamics of the loss function during training;

– initial learning rate – usually set to 0.001 when using the Adam optimizer.

The initial setting of the basic architecture and optimization parameters forms the initial basis for the subsequent stage of fine-tuning the model to achieve the best forecasting results.

Step 5. Creating and training deep learning models. After defining the basic architecture of each model, its implementation is performed by initializing the network in accordance with the specified layer structure, activation functions, optimization algorithm, and loss function.

Let the input dataset be represented by a matrix $X \in \mathbb{R}^{n\times m}$, where $n$ – is the number of examples, and $m$ – is the number of features for each example. The target vector $\vec{y} \in \{0,1\}^n$ contains the corresponding values of the target variable.

The data set is divided into three parts – training, validation, and test samples in the ratio of 70:15:15. This division makes it possible to simultaneously train the model and evaluate its ability to generalize to unknown data.

The training process is aimed at minimizing the loss function $L(\theta)$ , which for the binary classification task has the form of cross-entropy:

$$L(\theta) = -\frac{1}{n}\sum_{i=1}^{n}\left[ y_i \cdot \log(\hat{y}_i) + (1-y_i)\cdot \log(1-\hat{y}_i) \right]. \tag{13}$$

Training is performed iteratively by epochs. During each epoch, the full set of training examples is divided


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into packages (battles) of fixed BBB size (e.g., 32 or 64 elements). The weights are updated after each battle is processed according to the stochastic gradient descent method or its adaptive variations:

$$\theta_{t+1} = \theta_t - \eta \cdot \Delta_\theta L_B . \quad (14)$$

At each step, the loss function and model accuracy are evaluated on the validation sample. If signs of overtraining are detected, when the validation error increases while the training error decreases, an early stopping mechanism is applied – fixing the best model state in accordance with the minimum value of the loss function on the validation data.

Thus, the process of creating and training models ensures the transition from a conceptual description of the architecture to the construction of a ready-made predictive model capable of effectively solving classification problems based on spatial and structural features.

Step 6. Evaluation of model performance by accuracy metrics. After completing the training stage, the effectiveness of the built models is evaluated on a test sample that was not used in the training and validation process. This approach allows us to determine the ability of the models to generalize and the accuracy of forecasting on new, previously unknown data.

To quantify the quality of forecasts, a set of metrics is used to comprehensively characterize the accuracy and stability of the models.

One of the basic metrics is the Mean Squared Error (MSE), which determines the average square of the difference between the predicted $\hat{y}_i$ and actual $y_i$ values:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 . \quad (15)$$

MSE is sensitive to large deviations, so it reflects the overall level of error.

To supplement the estimate, the Mean Absolute Error (MAE) is used:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| . \quad (16)$$

MAE is less sensitive to single large deviations and better demonstrates the average level of forecast error.

Another important metric is Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\text{MSE}} . \quad (17)$$

The RMSE has the same dimension as the predicted variable, which makes it easier to interpret the results.

The inverse of RMSE is used to estimate the inverse of the error:

$$\text{Inverse RMSE} = \frac{1}{\text{RMSE}} . \quad (18)$$

The value of (18) increases as the model accuracy improves.

The coefficient of determination ( $R^2$ ) is another key metric that shows how much of the variance in the dependent variable is explained by the model:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} . \quad (19)$$

A value $R^2$ close to 1 indicates that the model is a good fit to the actual data.

In addition to the classical metrics, the average error per step (EMS/step) is used to assess the stability of the models, which determines the average difference between the forecasts and the actual values at each step in the conditional scenario space. This metric allows us to assess the uniformity of forecasting quality across the entire dataset.

The analysis of the results allows us to identify the architecture that provides the best forecasting quality, the smallest errors, and the highest level of generalization. The selected model is further used for optimization and practical application in the tasks of predictive analysis of spatial characteristics.

Step 7. Selection of a rational deep neural network model. After building several architectural options and training the corresponding models, a comparative analysis of the results is carried out to select the most rational model. In this context, rationality is understood as the optimal ratio between forecasting accuracy and computational costs required for practical application.

The process of model selection is based on a multi-criteria approach, in which each model is evaluated by a vector of quality metrics:

$$Q(M_j) = (q_{1j}, q_{2j}, \ldots, q_{kj}) . \quad (20)$$

The computational complexity of the model may include such characteristics as the number of parameter parameters, training time, and the amount of RAM required for operation.

To make an objective choice, a trade-off is made between forecasting accuracy and computational efficiency. One approach is to build an aggregate quality function:

$$F(M_j) = \sum_{i=1}^{k} w_i \cdot q_{ij} . \quad (21)$$

The weights can be determined by experts depending on whether forecasting accuracy is preferred (higher weights for MSE, RMSE) or computational efficiency.


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Alternatively, the Pareto-dominance method can be applied, when a model is selected that is not inferior to any other model in all key metrics simultaneously.

In addition to quantitative characteristics, the stability of the learning process is also taken into account: smoothness of the loss function decline, absence of overfitting, and speed of gradient convergence. Models that demonstrate an excessive number of epochs before reaching the minimum or significant deviations of predictions on the test set are not considered rational, even with high accuracy rates on the training data.

Thus, the choice of a rational model is based on a comprehensive analysis of its quality, resource efficiency, and stability of the learning process.

Step 8. Optimization of the rational model architecture. After determining the rational architecture of the neural network, the stage of its targeted optimization is performed. The purpose of optimization is to reduce the forecasting error, increase the generalization ability of the model, and ensure computational efficiency without significantly complicating the structure.

Optimization begins with setting the quantitative characteristics of the architecture, in particular, determining the number of hidden layers $L$ and the number of neurons $n_l$ on each layer $l$. The next step is to choose the activation functions for each layer.

The standard activation function is the ReLU (Rectified Linear Unit), which is defined as:

$$f(x) = \max(0, x) . \quad (22)$$

To improve the handling of negative input values, modifications such as leaky ReLU or ELU can be applied, e.g:

$$f(x) = \begin{cases} x, & \text{if } x \ge 0, \\ \alpha x, & \text{if } x < 0, \end{cases} . \quad (23)$$

To prevent overtraining, regularization mechanisms are integrated into the architecture, in particular the Dropout method, which involves randomly “disconnecting” a certain part of neurons during each training iteration. If the probability of maintaining neuronal activation is denoted as $p$, then the output of the neuron during training looks like:

$$\vec{h}^{(l)} = \text{Dropout}(f(W^{(l)}\vec{h}^{(l-1)} + \vec{b}^{(l)}), p) , \quad (24)$$

where $z \sim \text{Bernoulli}(p)$.

Additionally, the Batch Normalization method is used to stabilize the learning process by normalizing the output values of each layer to zero mean and unit variance.

This stage results in the final version of the model that combines high forecasting accuracy, training stability, consistency with input data characteristics, and efficiency in terms of computational costs.

Step 9. Determination of an effective model. At the initial stage of optimization, an effective deep learning model is formally defined as one that has achieved the best results in terms of a set of criteria for prediction accuracy, stability of the learning process, and computational performance.

An effective model is defined as an architecture that minimizes the loss function $L$, demonstrates a stable value of the coefficient of determination $R^2$, and provides the lowest root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\text{MSE}} \to \min . \quad (25)$$

The final selected model is stored in the form of weighting parameters and a structural layout of layers. It is used as a basic solution for further forecasting tasks that require analysis of spatial or structural data.

Step 10. Use the model to predict the accessibility of objects. Once an effective model is determined, it is applied in the format of a predictive module that estimates the probability of a new object belonging to a certain accessibility class based on its spatial and infrastructural features.

Let the input vector of features of a new object be denoted as $x^*$. The model generates a prediction of the probability of belonging to a positive class according to the formula:

$$\hat{y} = f(x^*, \theta) . \quad (26)$$

The classification is based on the threshold principle: if $\hat{y} \ge \tau$, the object belongs to the availability class, if $\hat{y} < \tau$, the object is classified as inaccessible. The threshold value $\tau$ is usually set to 0.5, but can be adjusted depending on the requirements for sensitivity or specificity of the forecast.

The use of such a model allows for a quick assessment of the characteristics of new objects based on open spatial data, which expands the capabilities of analytical and forecasting systems in the field of spatial planning.

## 4 EXPERIMENTS

To perform experimental studies, the procedure for forming an input data set was implemented to solve the problem of creating a model for predicting the level of availability of objects in spatially distributed systems. Particular attention was paid to the use of open sources of geospatial information that provide the necessary level of detail of spatial, infrastructure, and logistics features. This approach allows to form a structured input dataset suitable for training deep learning models.

To demonstrate the practical application of the proposed approach, an example of forming an input feature database based on OpenStreetMap data was implemented. The choice of the source is due to the high availability, relevance, and structuredness of the data, which cover the key characteristics of road infrastructure,


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location of critical infrastructure facilities, types of buildings, street network density, and other relevant indicators.

The territory of Zolochiv territorial community in Lviv region (Ukraine) was chosen as an example of a spatial zone for building the input set. This region has a pronounced rural structure with significant internal differentiation by infrastructure features, which allows testing the model on data with a high level of variability. In the process of preparation, 16 features were identified for each of the community's settlements, including the density of the road network, the number of educational, healthcare, and critical infrastructure facilities, geographic accessibility indices, and building indicators.

All the obtained values were normalized using the Min-Max method to the interval , after which the training, validation, and test samples were formed. The created dataset was used as a basis for training deep learning models, the architecture of which was described in detail in the previous section. To determine a rational model, five basic architectures of deep neural networks were chosen (Fig. 2).

| Layer (type) | Output Shape | Param # |
|---|---|---|
| dense (Dense) | (None, 64) | 576 |
| dense_1 (Dense) | (None, 32) | 2,080 |
| dense_2 (Dense) | (None, 1) | 33 |

a

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv1d (Conv1D) | (None, 7, 32) | 96 |
| flatten (Flatten) | (None, 224) | 0 |
| dense_3 (Dense) | (None, 1) | 225 |

b

| Layer (type) | Output Shape | Param # |
|---|---|---|
| simple_rnn (SimpleRNN) | (None, 32) | 1,088 |
| dense_4 (Dense) | (None, 1) | 33 |

c

| Layer (type) | Output Shape | Param # |
|---|---|---|
| gru (GRU) | (None, 32) | 3,360 |
| dense_5 (Dense) | (None, 1) | 33 |

d

| Layer (type) | Output Shape | Param # |
|---|---|---|
| lstm (LSTM) | (None, 32) | 4,352 |
| dense_6 (Dense) | (None, 1) | 33 |

e

Figure 2 – Variants of deep neural network architectures for predicting the availability of volunteer rescue groups in rural communities: a – Fully-connected Neural Network (FNN); b – Convolutional Neural Network (CNN); c – Recurrent Neural Network (RNN); d – Gated Recurrent Unit (GRU); e – Long Short-Term Memory (LSTM)

They are applied to the task of binary classification of the availability of voluntary rescue services based on the given characteristics of rural communities. The first model is constructed as a classical feed-forward neural network (FNN) containing two hidden layers with 64 and 32 neurons, respectively, and uses the ReLU activation function, and the sigmoidal function is used as an output to obtain the probability of availability.

The second model is a convolutional neural network (CNN) that uses a Conv1D layer with 32 filters and a kernel size of 2. The input data is transformed into the form (8, 1), i.e. each of the eight normalized indicators is treated as a time step. After convolution, the data is flattened and processed in a dense layer with 16 neurons.

The third model implements the architecture of a simple recurrent network (RNN), which consists of a SimpleRNN layer with 32 units and has an output layer for classification. Similarly, a fourth model based on GRU elements was constructed, which replace the simple RNN with a more complex and resistant to gradient reduction structure. The number of GRU units in the layer is 32.

The fifth model is built using an LSTM layer that also uses 32 memory elements. This option is the most complex of the presented models due to the internal structure of the LSTM, which allows for more efficient modeling of dependencies in the sequence of input features. All models have an output layer with one neural unit and a sigmoid function to predict the probability of class 0 or 1. Visualizations of the architectures are created using the plot_model() function of the Keras library, which displays the shape of each layer and its parameters.

At the compilation stage, each of the models was configured with the same parameters: 1) the optimizer was Adam with a learning rate of 0.001; 2) the loss function was binary_crossentropy; 3) the evaluation metric was accuracy. This unified setting allows for a correct comparison between architectures, since they are all trained under the same conditions.

Training was performed for 50 epochs with a batch size of 8. For each model, after training was completed, an evaluation was performed on the test set using a special function evaluate_model, which returned the selected metrics (15–19). The obtained values were stored in the metrics_results dictionary, which allowed us to summarize the information for the subsequent visualization of the results and determination of the most efficient architecture.

## 5 RESULTS

As a result of the experimental study, the territory of the Zolochiv territorial community of the Lviv region (Ukraine) was chosen to build the input dataset. The information obtained is presented in the form of a DataFrame (df) (Table 1).


DOI 10.15588/1607-3274-2025-4-14

Table 1 – A fragment of the database for predicting the availability of volunteer rescue teams in the Zolochiv community of Lviv Oblast (Ukraine)

| | community | village | lat | lon | area_km2 | road_length_km | road_density | n_fire_stations | accessibility_index | n_schools | n_hospitals |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Золочівська громада | Підлисся | 49.933105 | 24.822783 | 0.0 | 128.522 | 0 | 0 | 0 | 3 | 0 |
| 1 | Золочівська громада | Гавареччина | 49.919228 | 24.884085 | 0.0 | 57.904 | 0 | 1 | 1 | 2 | 2 |
| 2 | Золочівська громада | Гутище | 49.918442 | 24.947210 | 0.0 | 88.026 | 0 | 1 | 1 | 3 | 1 |
| 3 | Золочівська громада | Розваж | 49.911228 | 24.797859 | 0.0 | 33.890 | 0 | 0 | 0 | 3 | 0 |
| 4 | Золочівська громада | Бужок | 49.895750 | 24.820013 | 0.0 | 129.492 | 0 | 0 | 0 | 3 | 0 |
| 5 | Золочівська громада | Білий Камінь | 49.896170 | 24.835809 | 0.0 | 113.608 | 0 | 0 | 0 | 3 | 0 |
| 6 | Золочівська громада | Ушня | 49.890568 | 24.919470 | 0.0 | 84.781 | 0 | 1 | 1 | 2 | 0 |
| 7 | Золочівська громада | Побіч | 49.890293 | 24.964476 | 0.0 | 86.296 | 0 | 1 | 1 | 1 | 0 |
| 8 | Золочівська громада | Черемошня | 49.893113 | 24.858039 | 0.0 | 95.729 | 0 | 0 | 0 | 3 | 0 |
| 9 | Золочівська громада | Бір | 49.880768 | 24.953941 | 0.0 | 85.989 | 0 | 1 | 1 | 2 | 0 |

In the resulting df, each record corresponds to one community settlement and contains numerical, spatial and categorical attributes that reflect the real conditions of the territory This completes the formation of the input dataset, which will be the basis for further analysis, construction of neural network models and forecasting the level of availability of volunteer rescue groups.

The description of the df attributes, which contains data for modeling the availability of volunteer rescue groups in rural communities, is presented in Table 2.

In the process of building a model for predicting the level of accessibility of objects in spatially distributed systems, the main target variable is the accessibility_index indicator, which reflects the presence or absence of spatial coverage of a given object, taking into account infrastructure and transport characteristics. To train the model, quantitative spatial and structural features describing individual territorial units are used (Table 2).

In particular, the set of input features includes the length of the road network, building density, the number of social and functional facilities (educational institutions, medical facilities, religious buildings, industrial zones), as well as the presence or absence of access to major transport arteries. Additionally, geographical coordinates (latitude and longitude) can be used, which are either entered into the model as predictors or used to visualise the results in the spatial environment.

The use of such features allows us to comprehensively describe the spatial and infrastructural profile of an object and improve the accuracy of the forecast of its availability. The scaled values of the input parameters used to train the models are shown in Table 3.

As can be seen from Table 3, the scaling of the features made it possible to bring all indicators to a single range [0;1], which is necessary for the stable functioning of deep learning models. Some features (e.g., n_fire_stations, n_hospitals) contain fragmented information that takes into account the partial presence of functional objects, reflected in the form of fractional values.

Table 2 – Characterization of the attributes of df, which contains data for modeling the availability of volunteer rescue groups in rural communities

| Attribute name | Type | Description |
|---|---|---|
| community | object (str) | Name of the territorial community |
| village | object (str) | Name of the village or settlement within the community |
| lat | float64 | Geographical latitude of the village centroid |
| lon | float64 | Geographical longitude of the village centroid |
| area_km2 | float64 | Area of the buffer zone around the settlement, km² |
| road_length_km | float64 | Total length of roads in the village buffer zone, km |
| road_density | float64 | Density of the road network (road_length_km/area_km2) |
| n_fire_stations | int64 | Number of fire stations (including voluntary formations) within the village buffer |
| accessibility_index | int64 | Binary sign (0 or 1) – whether the village has access to a voluntary rescue group (1 – has, 0 – does not) |
| n_schools | int64 | Number of schools within the village (indicator of critical social infrastructure) |
| n_hospitals | int64 | Number of medical facilities (hospitals, outpatient clinics, rural health posts) |
| n_churches | int64 | Number of places of worship (churches, chapels, etc.) – an indicator of places of mass gathering |
| n_industrial | int64 | Number of industrial facilities (industrial zones, factories, workshops) – potential sources of risk |
| n_buildings | int64 | Total number of buildings within the buffer |
| building_density | float64 | Building density: Number of buildings per unit area (buildings/km²) |
| major_road_access | int64 | Binary feature (0 or 1) – whether there is a main road nearby (primary or secondary according to OSM) |


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Table 3 – Fragment with the results of feature scaling

| | road_length_km | n_fire_stations | n_schools | n_hospitals | n_churches | n_industrial | n_buildings | major_road_access |
|---|---|---|---|---|---|---|---|---|
| **0** | 0.362206 | 0.0 | 0.272727 | 0.000000 | 0.285714 | 0.764706 | 0.271600 | 0.0 |
| **1** | 0.126874 | 0.5 | 0.181818 | 0.333333 | 0.523810 | 0.352941 | 0.323860 | 0.0 |
| **2** | 0.227254 | 0.5 | 0.272727 | 0.166667 | 0.619048 | 0.352941 | 0.170513 | 0.0 |
| **3** | 0.046848 | 0.0 | 0.272727 | 0.000000 | 0.238095 | 0.176471 | 0.100515 | 0.0 |
| **4** | 0.365438 | 0.0 | 0.272727 | 0.000000 | 0.333333 | 0.058824 | 0.014686 | 0.0 |

Particularly important is the major_road_access feature, which, despite its binary nature, allows the model to take into account the strategic accessibility of objects in terms of transport links, which has a significant impact on the formation of the forecast. The obtained set of features forms a vector of spatial representation of the object, which is the basis for the classification forecast of the level of accessibility in the deep learning model.

At the stage of analysing the relationships between spatial and infrastructural features and the target variable accessibility_index, a correlation matrix based on Pearson's coefficients was built. Such a matrix allows us to assess the strength and direction of the linear relationship between the variables included in the forecasting model (Fig. 3).

The analysis of the results showed that the highest level of positive correlation with the target variable is for n_fire_stations (r = 0.97), which indicates an almost linear relationship between the availability of facilities with the appropriate functionality and an increased level of accessibility.

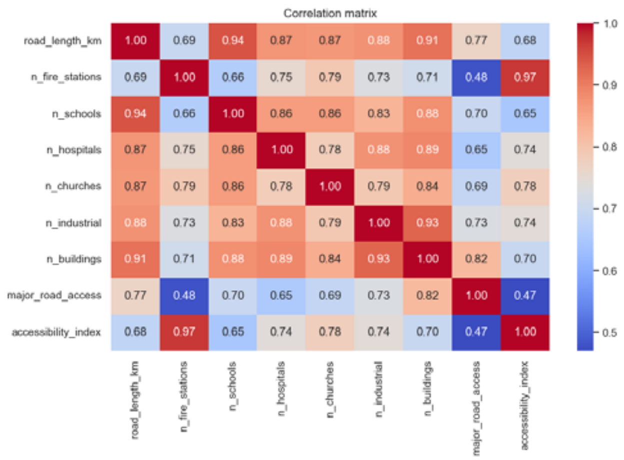


Figure 3 – Correlation matrix of relationships between input features and the target feature "accessibility_index"

Weaker, but statistically significant relationships are also observed for the variables n_hospitals (r = 0.47), n_industrial (r = 0.44), and n_buildings (r = 0.36). Their positive correlation may indicate the accompanying presence of infrastructure elements in areas with a higher level of general accessibility.

Moderate positive correlation is also demonstrated by road_length_km (r = 0.68) and n_churches (r = 0.30), while the relationship with n_schools is neutral-negative (r = –0.06), which may be due to indirect effects or the peculiarities of the distribution of educational institutions in the sample.

Major_road_access has the lowest correlation with the target indicator (r = 0.47), which indicates the presence of independent factors that do not provide a direct effect between transport accessibility and the predicted variable.

In general, the analysis allowed us to identify the most informative features that will have a decisive impact in the classification model. In particular, access to a voluntary rescue unit.

The study compared the effectiveness of five deep neural network architectures that implement different approaches to processing pro- tectively structured data. The corresponding results are presented in Fig. 4, which shows the numerical values of metrics characterizing the quality of the built models.

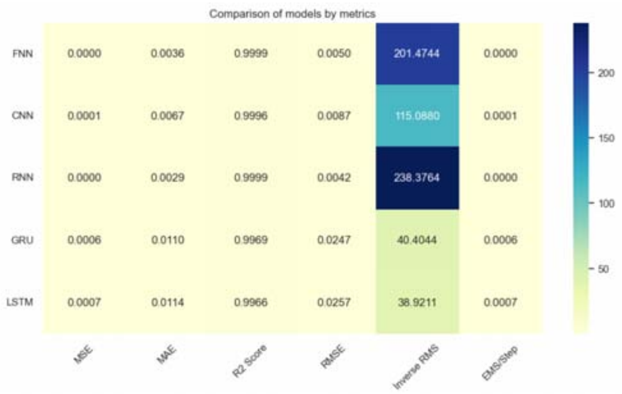


Figure 4 – Results of comparing the performance of deep neural network architectures

Among the evaluation indicators used are the mean square error (MSE), which allows us to determine the average square deviation of forecasts from actual values, and the mean absolute error (MAE), which reflects the average level of absolute deviation between the forecast and the target value. The coefficient of determination ($R^2$) is used to estimate the explained variance of the target variable, while the root mean square error (RMSE) provides a convenient interpretation of accuracy in the same units as the original variable. In addition, the Inverse RMSE allows for a unified presentation of the inverse effect of precision, providing an alternative interpretation. The generalized error per step (EMS/Step) allows you to evaluate the dynamics of error changes in the forecasting process over the entire data set.


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The application of these metrics made it possible not only to quantitatively compare the accuracy of different architectures, but also to identify models with the highest level of stability, adaptability, and generalizability for further practical use.

Based on the results shown in Fig. 4, it can be concluded that the recurrent neural network (RNN) model provided the best forecasting quality among all the considered architectures. In particular, it demonstrated the lowest mean square error (MSE0.000018) and mean absolute error (MAE=0.002879), which indicates a high accuracy of reproducing the dependencies between the features. The coefficient of determination for this model was $R^2$=0.999910, which indicates an almost complete ability to explain the variation of the target variable on the test sample. The RMSE was the smallest among all the models and amounted to only 0.004195, and the Inverse RMSE value reached 238.38, which further confirms the excellent consistency between the predicted and actual values.

Among the competitors, the closest results were shown by the FNN model, for which MSE=0.000025, MAE=0.003578, and $R^2$=0.999874. It is also characterized by a low RMSE value (0.004963), although it is inferior to RNN in all major accuracy criteria. The CNN model turned out to be slightly less accurate, with MSE=0.000075 and RMSE=0.008689, but at the same time retained a high value of the coefficient of determination ($R^2$=0.999614), which makes it competitive for predicting spatial dependencies.

Instead, the GRU and LSTM architectures showed significantly worse results. The RMSE value for GRU was 0.024750, and for LSTM – 0.025693, which is several times higher than the corresponding values of RNN and FNN models. In addition, the MAE in these cases exceeded 0.011, and the Inverse RMSE values were significantly lower – 40.40 and 38.92, respectively. This indicates less stability and worse generalization ability.

Thus, among the considered architectures, it is the RNN model that demonstrates the best balance between accuracy, stability, and the ability to reproduce complex spatial patterns. This model was chosen for further optimization and structural improvement, the results of which are presented in Fig. 5.

The optimized recurrent neural network model includes one layer of SimpleRNN with 32 neurons, which processes the input sequence of features and generates the corresponding representation of temporal dependencies. This layer provides a parameterized representation of spatially structured input data in the context of temporal dynamics. After the recurrent layer, a dense layer (Dense) with one output neuron and a sigmoidal activation function is applied, which implements the binary classification mechanism.

The total number of model parameters is 1,121, of which all are trained. Such a compact architecture allows to maintain high performance during training while providing sufficient flexibility to model dependencies between features. The model was compiled using the Adam optimizer and the binary_crossentropy loss function, which is the standard for two-class classification problems.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| simple_rnn_4 (SimpleRNN) | (None, 32) | 1,088 |
| dense_17 (Dense) | (None, 1) | 33 |

**Total params:** 1,121 (4.38 KB)
**Trainable params:** 1,121 (4.38 KB)
**Non-trainable params:** 0 (0.00 B)

Figure 5 – Architecture of an optimized recurrent neural network for modeling the level of availability of objects in spatially distributed systems based on deep learning

The model was trained for a specified number of epochs with controlled validation monitoring. Upon completion of the process, graphs were plotted showing the change in the loss function and accuracy in the training and validation samples. A visualization of the training dynamics is shown in Figure 6.

The analysis of the training dynamics of the optimized recurrent neural network presented in the graphs (Fig. 6) demonstrates an effective reduction in the loss function and a steady increase in model accuracy throughout the training process. The graph on the left shows that the values of the loss function for the training and validation sets decrease rapidly during the first 10 epochs, after which they stabilize at a low level. This behavior of the loss curves indicates the absence of overfitting and indicates the model's ability to generalize the input data.

The model accuracy graph (right) confirms the conclusions about the quality of training: the classification accuracy increases to over 98% at the initial stages and remains stable for both the training and validation sets. This indicates that the model is well matched to the training data and does not lose performance on new examples, which indicates the effectiveness of its architectural solution.

The achieved level of stability and accuracy is the result of the use of a deeper multilevel structure, Dropout type regularization, and the use of an optimized weight update algorithm (Adam). The visualized results confirm the feasibility of the chosen architecture for the classification task in spatially distributed systems.

Based on the above graph (Fig. 7), we can conclude that the optimized recurrent neural network model is highly accurate in reproducing the target values. The line of actual values, constructed on the basis of the real values of the accessibility variable, almost completely coincides with the graph of predicted values, which indicates the absence of significant errors in the classification of test examples.

The model correctly reproduces the binary structure of the target variable, clearly distinguishing objects with a high level of accessibility (designation 1) from objects with insufficient or no coverage (value 0). Particularly noteworthy is the complete coincidence of predicted and actual values in areas of sharp class change, which indicates the high sensitivity of the model to changes in the simple infrastructure characteristics of the input set.


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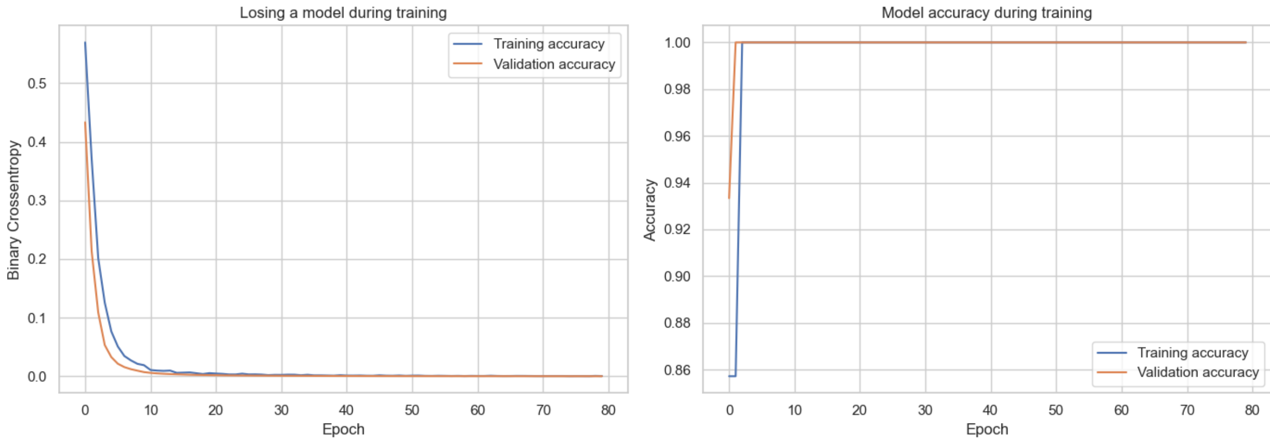


Figure 6 – Graphs of the loss function and accuracy of an optimized recurrent neural network during training for a model for predicting the availability of objects in spatially distributed systems

As a result of our research, a graph comparing the actual and predicted values of the target variable in the test sample using the optimized RNN model was constructed (Fig. 7).

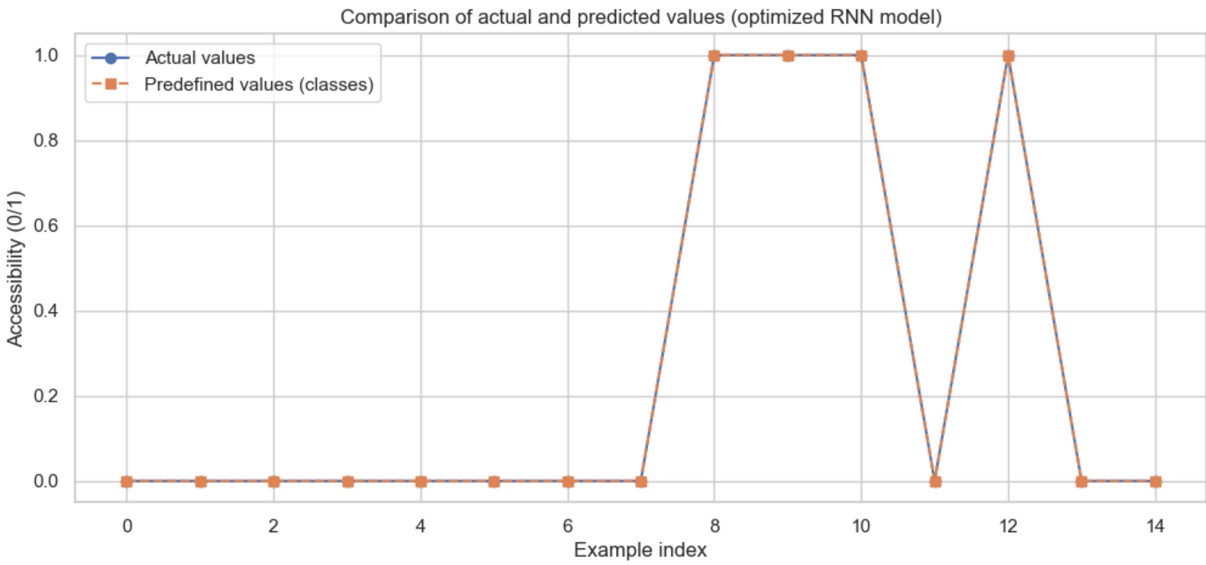


Figure 7 – Graph comparing the actual and predicted values of the target variable in the test sample using the optimized RNN model

The presence of only minor fluctuations or their complete absence confirms that the optimized model demonstrates not only the ability to highly accurate classification, but also the stability of prediction even under conditions of variability in the structure of test examples. This confirms the suitability of the constructed architecture for further use in predictive modeling tasks in spatial analysis systems.

The comparison between the baseline and optimized RNN model showed a significant improvement in the quality of forecasting after the implementation of the optimized architecture (Fig. 8).

Based on the results visualized in Figure 8, we can conclude that the quality of forecasting has significantly improved after optimizing the architecture of the recurrent neural network. All six presented metrics demonstrate a significant advantage of the optimized model compared to the baseline. In particular, the mean square error (MSE) decreased from 1.76×10–5 to 7.66×10–8, which indicates a significant decrease in the mean square deviation between predicted and actual values. The mean absolute error (MAE) demonstrates a similar trend, decreasing from 0.002879 to 0.000209, indicating an increase in accuracy at the level of individual examples.

The coefficient of determination ($R^2$) reached the ideal value of 1.000 in the case of the optimized model, as opposed to 0.99991 in the baseline, which confirms that the variation in the target variable on the test sample is fully explained. The root mean square error (RMSE) also decreased significantly, from 0.004195 to 0.000277, which strengthens the arguments in favor of high accuracy of predictions.


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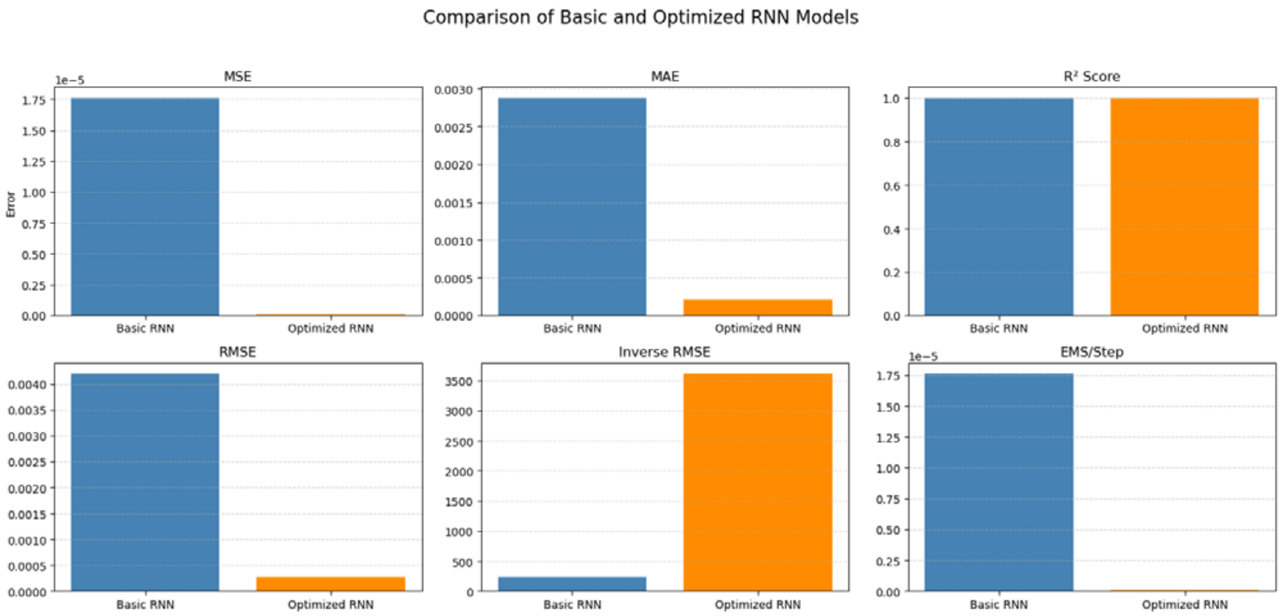


Figure 8 – Comparison of accuracy indicators between the baseline and optimized recurrent neural network model by the main metrics (MSE, MAE, $R^2$, RMSE, Inverse RMSE, EMS/Step)

The largest difference was recorded for the Inverse RMSE, which increased from 238.38 to 3612.75. This confirms that the optimized model provides significantly higher accuracy at the inverse transform scale. Similarly, EMS/Step, which characterizes the generalized error per observation unit, decreased by an order of magnitude: from 1.76×10–5 to 7.66×10–8, which indicates stable model behavior in a variable spatial environment.

Thus, the comparative analysis confirms the effectiveness of the optimization. The model based on the improved architecture demonstrates not only an increase in forecasting accuracy, but also increased stability, generalizability, and reliability when applied to new data.

## 6 DISCUSSION

The study was aimed at developing a model for predicting the level of accessibility of objects in spatially distributed systems using deep neural networks and geospatial data. A comprehensive analysis of the subject area was carried out, the peculiarities of forming an input dataset based on open sources of geoinformation, in particular OpenStreetMap, were outlined, and key areas for further improvement of the modeling process were identified.

The study identified several critical challenges related to forecasting the availability of facilities, including high heterogeneity of spatial characteristics and the need for models to be adaptive to changes in infrastructure conditions. To overcome these challenges, we propose an approach that combines the formation of a high-quality input set of features using open geodata and the optimization of the architecture of a deep neural network.

Based on the results of experimental training of the basic architectures, it was found that the recurrent neural network (RNN) provides the highest quality of forecasting, demonstrating the values of the main accuracy metrics, in particular the coefficient of determination and low levels of root mean square error (RMSE), which indicates a high correspondence of the model to real spatial dependencies.

Optimization of the RNN model by increasing the number of recurrent layers, applying Dropout regularization with a parameter of 0.2, and adjusting the number of neurons in the hidden layers significantly improved the results. After optimization, the model achieved even better accuracy, training stability, and generalization ability.

The results obtained showed that the proposed optimized architecture is able to effectively predict the level of accessibility of objects in complex spatial conditions. Prospects for further research are associated with scaling the approach to larger areas, as well as with the integration of the built model into geographic information systems for the operational analysis of spatial characteristics. An additional direction of development is the use of deep neural networks for automated processing of satellite images, which will optimize the formation of input features and increase the efficiency of planning spatial processes in various scenarios.

## CONCLUSIONS

As a result of the study, an approach was proposed that involves 10 steps to optimize the model for predicting the availability of objects in spatially distributed systems by building an effective deep learning architecture focused on the use of spatial and infrastructure features to improve the accuracy of forecasting and generalization of models.

The input dataset was formed on the basis of open geospatial information, which ensured the creation of a high-quality spatially structured dataset of 16 features for training deep learning models. Particular attention was paid to the selection of features that most significantly affect the prediction of accessibility of objects, including


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the characteristics of the road network, infrastructure facilities, and geographic accessibility indices.

Based on the analysis of 5 architectures of deep neural networks, the choice of a recurrent neural network (RNN) is substantiated as the most suitable for prediction tasks in spatially distributed environments. The architecture was optimized by adjusting the number of layers, neurons, regularization mechanisms, and activation functions, which allowed to achieve high prediction accuracy, training stability, and computational efficiency.

Evaluation of the results showed that the created model has a high potential for integration into decision support systems in the field of spatial planning, where operational assessment of the availability of objects in a dynamic environment is required.

The obtained results provide a basis for further research aimed at scaling the approach to larger regions, integration with satellite monitoring data, and extending the functionality of the models to work with multilayer spatial systems.

**Practical Significance:** The obtained results are of practical importance for the tasks of spatial analysis and prediction of the availability of objects in spatially distributed systems. The proposed approach to the formation of the input feature set using OpenStreetMap geographic information data, data normalization by the Min-Max method, and the construction of five architectures of deep neural networks (FNN, CNN, RNN, GRU, LSTM) ensured high quality of model training.

Among all the architectures, the basic recurrent neural network (RNN) model demonstrated the best results in terms of the main accuracy metrics. Further optimization of the RNN architecture by improving the network structure, applying regularization techniques, and tuning hyperparameters allowed us to further improve the results, achieving a high level of agreement between predictions and actual data.

The proposed solutions can be applied in a wide range of practical tasks related to spatial planning, optimization of facility availability, and predictive analysis in management decision-making systems.

**Recommendations for Further Research**: Based on the findings, it is advisable to conduct further research to expand the set of spatial and infrastructural features to improve the accuracy of models for predicting the accessibility of objects. Particular attention should be paid to improving the methods of accounting for the dynamics of changes in the transport network, the availability of communication routes, and the topological features of spatial structures. It is also promising to develop approaches to integrating deep learning models with geographic information systems to ensure automated updating of transport data in real time. In addition, it is advisable to study the possibilities of using ensemble modeling methods to increase the stability and reliability of forecasts in different spatial and temporal scenarios.

**Scientific Novelty**: The study proposes a new approach to predicting the availability of objects in spatially distributed systems based on the integration of deep learning and spatial data analysis methods. For the first time for this task, the optimization of the basic architecture of the recurrent neural network (RNN) is considered by introducing additional recurrent layers, applying Dropout regularization mechanisms, and increasing the number of neurons in the hidden layers. The proposed improvements allowed for significant improvement in the main accuracy indicators of the model without signs of overtraining, ensuring stability and high generalization ability in predicting complex spatial dependencies.

**Prospects for Further Research**: A promising direction for further research is to scale the proposed methodology to analyze large areas with various spatial and infrastructural characteristics. It is also advisable to study in depth the possibilities of using machine learning methods to automatically assess the importance of features that affect the prediction of object availability in spatially distributed systems. Particular attention should be paid to the development of new model performance metrics that will allow for a more comprehensive assessment of the quality of predictions in multidimensional spatial environments. The integration of neural network approaches with geographic information systems opens up prospects for creating adaptive analytical platforms that can quickly respond to changing spatial conditions and support real-time decision-making.

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## ОПТИМІЗОВАНА МОДЕЛЬ ПРОГНОЗУВАННЯ ДОСТУПНОСТІ ОБ'ЄКТІВ НА ОСНОВІ ГЛИБИННОГО НАВЧАННЯ І ГЕОПРОСТОРОВИХ ОЗНАК

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### АНОТАЦІЯ

**Актуальність.** На сьогодні прогнозування доступності об'єктів у просторово-розподілених системах залишається одним із тих напрямів інформатики, який постійно привертає увагу дослідників. Причин для цього чимало. Спостерігається збільшення обсягів просторової інформації. Появляються нові типи інфраструктурних мереж, а також потреба в оперативному прийнятті рішень у мінливих умовах. Водночас, традиційні методи аналізу не завжди справляються із завданнями обробки багатовимірних даних. Особливо це актуально, коли йдеться про складні або нестабільні середовища. Це відкриває можливості для застосування методів глибинного навчання, які демонструють високу ефективність там, де класичні підходи не працюють.

**Мета роботи.** Дослідження спрямоване на оптимізацію моделі прогнозування доступності об'єктів у просторово-розподілених системах шляхом визначення ефективної архітектури глибинного навчання, що використовує просторові та інфраструктурні ознаки для підвищення точності прогнозування та узагальнюючої здатності.


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**Методи.** Для досягнення поставленої мети було застосовано архітектури глибинного навчання, серед яких моделі прямого розповсюдження (FNN), згорткові нейронні мережі (CNN) та рекурентні нейронні мережі (RNN, GRU, LSTM). Під час моделювання використовувалися методи нормалізації даних, регуляризації навчання, а також комплексна система оцінювання точності прогнозів за допомогою середньої квадратичної помилки, середньої абсолютної помилки та коефіцієнта детермінації.

**Результати.** Під виконання дослідження було побудовано оптимізовану архітектуру рекурентної нейронної мережі, що включає комбінацію двох рекурентних шарів, шарів регуляризації Dropout та повнозв'язного шару. Проведений аналіз показав, що запропонована модель забезпечує високу точність прогнозування доступності об'єктів, демонструючи стабільність роботи на широкому спектрі просторових даних. Співставлення фактичних та прогнозованих значень підтвердило ефективність запропонованого рішення.

**Висновки.** Запропонований підхід до побудови оптимізованої моделі глибинного навчання для прогнозування доступності об'єктів забезпечує високий рівень узагальнення та точності, що створює передумови для її використання у системах інтелектуальної підтримки прийняття рішень у просторово-розподілених середовищах.

**КЛЮЧОВІ СЛОВА:** глибоке навчання, прогнозування, доступність об'єктів, геопросторові дані, оптимізація RNN, інтелектуальні системи.

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