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METHODS OF FORECASTING AND DATA CLASSIFICATION BASED ON NEURAL NETWORKS

Abstract. *The article is devoted to a comprehensive review of neural network models in forecasting and classification tasks. Finding the strengths and weaknesses of different forecasting methods using neural networks. Exploring the possibilities of improving the use of neural networks in forecasting and classification tasks.*

The purpose of the work. *The purpose of this work is to study methods of forecasting and data classification based on neural networks. Which means a review of existing approaches and finding new ways to improve the solution of the above problems. Finding ways to improve existing models. The task of this study is to compare existing methods of using neural networks in forecasting problems and to obtain new approaches to improve existing methods.*

Methodology. *It is based on the analysis of scientific publications on neural network models, as well as prediction and classification methods. For this purpose, the characteristics and methods of comparative analysis of the strengths and weaknesses of neural networks are provided. As well as recommendations for improving prediction methods, where possible.*

Scientific novelty. *The solution to the problems set and the scientific novelty of this research lies in identifying ways to improve methods and in a criterion-based comparison of existing methods for using neural networks in data classification and prediction tasks, improving new approaches based on existing ones to improve the processing processes of the above-mentioned tasks.*

Conclusions. *Analysis of neural network models in forecasting tasks revealed their strengths and weaknesses. Criterion analysis established the advantages of forecasting methods using neural networks. Recommendations for improving forecasting methods are proposed.*

Key words: *methods of forecasting, classification methods, neural network models, machine learning.*

Ярослав ПАВЛЕНКО, Наталя ВАЛЕНДА. МЕТОДИ ПРОГНОЗУВАННЯ ТА КЛАСИФІКАЦІЇ ДАНИХ НА ОСНОВІ НЕЙРОННИХ МЕРЕЖ

Анотація. *Стаття присвячена комплексному огляду моделей нейронних мереж у задачах прогнозування та класифікації. Знаходження сильних та слабких сторін різних способів прогнозування із застосуванням нейронних мереж. Дослідження можливостей поліпшення використання нейронних мереж у задачах прогнозування та класифікації.*

Мета роботи. *Метою цієї роботи є дослідження методів прогнозування та класифікації даних на основі нейронних мереж. Що означає огляд вже наявних підходів та знаходження нових способів для вдосконалення вирішення вищевказаних задач. Знаходження способів поліпшення існуючих моделей. Завданням даного дослідження є порівняння існуючих методів використання нейронних мереж у задачах прогнозування і в здобутку нових підходів для покращення існуючих методів.*

Методологія. *Базується на аналізі наукових публікацій моделей нейронних мереж, а також методів прогнозування та класифікації. Для цього використано надання характеристики та методи порівняльного аналізу сильних та слабких сторін нейронних мереж. А також надання рекомендацій щодо поліпшення методів прогнозування, де це можливо.*

Наукова новизна. *Вирішення поставлених задач та наукова новизна даного дослідження полягає у виявленні способів поліпшення методів та у критеріальному порівнянні існуючих методів використання нейронних мереж, у задачах класифікації та прогнозування даних, вдосконалення нових підходів на основі вже існуючих, для покращення процесів обробки вищезазначених задач.*

Висновки. *Аналіз моделей нейронних мереж у задачах прогнозування виявив їх сильні та слабкі сторони. Критеріальний аналіз встановив переваги методів прогнозування із використанням нейронних мереж. Запропоновано рекомендації щодо вдосконалення методів прогнозування.*

Ключові слова: *методи прогнозування, методи класифікації, моделі нейронних мереж, машинне навчання.*

Problem statement. The relevance of this topic is largely justified by the interest of scientists in the field of information technology. Since there are different approaches to forecasting and classification problems at the moment, it is important to study them to identify the likelihood of their improvement.

Also, such studies are relevant due to the practical need to study methods and various models in the commercial sector. The available methods are diverse and rely on different approaches to the use of neural networks, but are still not perfect in solving certain problems. That is why there is a demand for the prospect of their improvement and optimization. Therefore, the analysis and criterion-based comparison of existing methods and tools is a popular task.

Modern progress in the field of information technology intensively develops existing approaches in various data analysis tasks. And sometimes modern scientific progress introduces new technologies intensively, even ahead of the development of the existing ones and the introduction of innovations. Therefore, there is a growing need for a comprehensive analysis of existing approaches in order to find their advantages in individual tasks and the possibility of their improvement.

Training neural networks begins with a variety of data that are collected and used to train models. Large amounts are required for deep learning [8]. The size of the data has a significant impact, since the more data there is, the more efficiently the program works.

Since different neural network models may be suitable for different tasks, it is important to evaluate their advantages and disadvantages specifically in prediction and classification tasks.

Another important task is to find new useful approaches to improve and use them in data forecasting and classification tasks.

Even some varieties of the same neural network may have a significant advantage over others, for example, in forecasting tasks, since they are better suited to detecting dependencies, both short-term and long-term. When analyzing the research problem, one should also pay attention to the analysis of forecasting methods in tasks with incomplete or heterogeneous data.

As the world rapidly grows in. terms of the amount of data that needs analysis and the need to make informed decisions based on available data (possibly incomplete and heterogeneous) in various industries, it is important to explore new approaches and analyze existing methods of forecasting and classifying data.

Neural networks, in some cases, demonstrate high efficiency in machine learning tasks, but sometimes their application in real-world conditions can often face a number of challenges [9].

For example, such challenges often include the need to adapt models to the specifics of the data, increasing their robustness to noise, and the ability to generalize their application across different types of data. The importance of this research is due to both the increasing complexity of modern forecasting tasks and the need for highly accurate and reliable algorithms for data classification in various industries, such as finance, medicine, energy, and others.

The need to improve existing prediction and classification methods is especially relevant in conditions where there is insufficient information in the data models to analyze the behavior of the system or to provide an assessment of it. Since many tasks involve performing a certain analysis on data of different formats and sources, this requires research and comparison of models for compliance with these features and their effectiveness in analyzing different data. Therefore, sometimes the integration of heterogeneous data sources is important for research.

It is important to critically compare the key capabilities, advantages and disadvantages of information technologies for data forecasting using neural networks, using metrics for assessing efficiency and accuracy.

Modern neural networks can often require significant computational resources and large data sets for training, which can limit their application in some practical tasks [10]. Therefore, research and benchmarking of prediction and data classification approaches that take these limitations into account are of utmost importance.

Analysis of recent research and publications. Recently, intensive development of research in the field of application of neural networks has been ongoing. New practices of application are being developed and already accepted methods are being modernized [5].

Due to the growth of computing power and the availability of large amounts of data, the rapid development of the application of neural networks in forecasting and classification tasks has taken place. For example, the development of recurrent architectures has proven its effectiveness in time series forecasting tasks. This has made it possible to significantly increase the accuracy of forecasting compared to classical methods such as ARIMA or regression analysis [11]. Various scientific publications demonstrate the integration of neural networks into various fields of use. For example, on stock exchanges, they can be used to predict rates and global trends. Neural network models used for forecasting can also be used in other fields, for example, in DSS [14]. In medicine, they can be used to classify images to detect the development of diseases. Rapid progress creates new challenges for research. Analysis of recent research and publications.

The purpose of this article is to analyze and generalize the criteria-based comparison of the main neural network models in data forecasting and classification tasks, as well as to determine their effectiveness in performing individual tasks.

To implement this goal, the following tasks have been formulated: 1) to analyze existing neural network architectures; 2) to describe their features in forecasting and classification tasks; 3) to conduct a criteria-based comparison of methods and identify their advantages and disadvantages; 4) to consider examples of the use of neural networks for data forecasting and recovery of lost data; 5) to provide recommendations on existing neural network models; 6) to identify promising areas of research in the future.

To achieve this goal, it is necessary to generalize and systematize the existing material on neural network models, forecasting and classification methods, problems and challenges of the existing research processes, and also to conduct a comprehensive criteria-based comparison of the advantages and disadvantages of existing architectures.

Presentation of the main material. The tasks of forecasting and data classification are key components of the analysis and processing of digital data in the modern field of information technology.

Classification is aimed at assigning objects to a certain category according to their input parameters and certain patterns. Forecasting, in turn, means predicting future values of the system taking into account the existing patterns in past data. Classical forecasting tasks include such methods of time series analysis as ARIMA and SARIMA, as well as linear and polynomial regression [3]. They are mainly used to find the result for data with simple trends and seasonality, but can reveal weaknesses in the presence of a significant amount of noise or a large amount of lost data.

Key features of classical forecasting methods:

– ARIMA. A statistical method of modeling time series. Sometimes it can be weak for nonlinear processes, but its advantage is the clarity of the parameters.

– SARIMA. An extension method of ARIMA, but its use is more directed specifically to seasonal fluctuations. Therefore, this method is effective in problems where it is important to take seasonality into account seasonality.

– Linear regression. A mathematical model that describes the relationship between variables as a straight line on a graph.

– Polynomial regression. Improves linear regression because it takes into account curvilinear dependencies.

Classical classification problems include methods such as logistic regression, discriminant analysis, and the kNN method. Such classical approaches are effective for small amounts of data, but can be vague in the absence of defined parameters.

Key features of classical classification methods:

– Logistic regression. A binary classification model that works well for simple tasks, but has difficulties in scaling to multi-class data.

– LDA method. The method searches for linear boundaries between classes.

– kNN method. The method is effective in object classification tasks based on similarity to the closest examples.

Unlike classical approaches to data prediction and classification, neural networks can demonstrate much greater efficiency and flexibility [15]. Because neural networks can detect complex dependencies in large amounts of data and provide high accuracy of prediction and classification.

Neural networks are increasingly becoming a standard in many areas of prediction and classification. For example, in security and medical image processing tasks and in forecasting fluctuations and trends in the financial sector. The active development of artificial intelligence has ensured the introduction of improved neural network architectures, such as convolutional (CNN), recurrent (RNN, LSTM) and transformer models [2]. Also, a significant impetus for their development was the fact that modern data is characterized by a large volume and various nonlinear connections.

Neural networks consist of layers – combinations of neurons. Neural networks can have a single-layer or multilayer structure. Layers can be: output, hidden, input.

In a multilayer neural network (in addition to the main layers), there are also intermediate layers. In different architectures of neural networks, the number of intermediate layers can be different. The number depends on the complexity of the neural network.

During the calculation, neurons receive data from a layer and transmit it to the next neurons [7]. Such actions create connections that have their own weight and are called synapses.

CNN architecture is characterized by the use of convolutional layers to find local features. The advantages of the architecture include: high efficiency in working with graphic information. The architecture does not require manual creation of features and can perfectly detect object patterns. CNNs are typically used for image processing, but CNNs can also be used for prediction tasks. For example, to predict the next value of a financial chart by treating the chart data as a sequence of local patterns.

RNNs use recurrent connections that help take into account previous states of the sequence. RNNs use connections that can form directed loops (Fig. 1). This approach allows them to store hidden state and information about the inputs to the sequence. Effective use in time series forecasting tasks is a feature of RNNs.

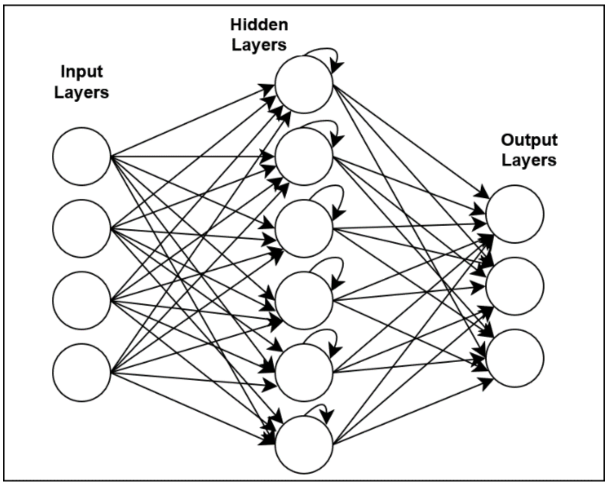

Fig. 1. RNN scheme

The architecture of RNN consists of the following components: input layer, recurrent connection, hidden layer. The main feature is the recurrent connection [4]. This approach allows you to store information at each time step.

The LSTM architecture is an improved RNN, but with memory caches to store long-term dependencies [6]. The feature of LSTM is that this model can store information for a long time. It is convenient to use in prediction and classification tasks. Transformers is a modern neural network architecture characterized by the use of the attention mechanism. This mechanism helps to process all elements of a sequence simultaneously. Unlike other neural network models, transformers analyze the entire context at once, rather than step by step. This approach allows for the effective detection of global dependencies. Transformers are commonly used in text analysis, but they can also be used in other areas. For example, they can be used to predict time series. Using the attention mechanism allows the model to analyze dependencies between elements regardless of their distance. In forecasting, the model can take into account not only the latest values, but also past ones.

During the study, it is important to apply criterion-based comparison of neural network models in data prediction and classification tasks. During the search and preparation of information from open sources, the advantages of the models were analyzed [13]. Also, it is advisable to use linear adaptive convolution with weighting coefficients. Based on the analyzed information from literary sources, we will evaluate the models [1]. We will evaluate the models according to the criteria (Tab. 1). The criteria are indicated by an ordinal scale from 1 to 10.

Table 1

Vector description of models according to selected criteria

Models	Criteria				
	Ability to model long-term dependencies	Speed	Model size, complexity	Accuracy in forecasting tasks	Accuracy in classification tasks
CNN	3	7	7	5	9
RNN	6	6	7	7	7
LSTM	9	7	6	9	8
Transformers	10	7	6	9	9

Since CNN has worse parameters, according to the Pareto principle, this model can be excluded [12]. Therefore, we will exclude this model from the calculations and continue the calculation of utility.

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To perform a qualitative comparative analysis, we will perform normalization and create a normalized description of alternatives. As a result, all values will be in the range from 0 to 1, where 1 corresponds to the best value, and 0 corresponds to the worst value.

The next step is to proceed to the normalization calculations and enter the data (Tab 2).

Table 2

Normalized vector description of alternatives

Models	Criteria				
	Ability to model long-term dependencies	Speed	Model size, complexity	Accuracy in forecasting tasks	Accuracy in classification tasks
RNN	0	0	1	0	0
LSTM	0	1	0	1	0.5
Transformers	1	1	0	1	1

Since certain criteria have different priorities in model evaluation, they are different in importance. We use linear adaptive convolution with weighting coefficients to calculate the utilities.

As a result, the utility (k) of the models in forecasting and classification tasks will be as follows: RNN (k = 0.16), LSTM (k = 0.52), Transformers (k = 0.65).

So, as a result of the criterion comparison with weight coefficients, we can conclude that transformers have greater utility. It was also found that the given neural network models can improve the results when adding additional layers.

Conclusions. As a result of the criterion comparison based on the selected indicators, the relative utility of the models in forecasting and classification tasks was determined. The results indicate that transformer architectures have greater utility and demonstrate the best balance between accuracy in forecasting and classification tasks. Transformers have some of the highest indicators. The results also showed that LSTM remains very effective in forecasting time series.

The study analyzed classical methods of forecasting and classification of data: ARIMA, SARIMA, regression models, logistic regression, kNN. Also, an analysis of modern approaches based on neural networks was carried out: CNN, RNN, LSTM, transformers. It was found that classical algorithms remain useful in conditions of limited data volumes and pronounced dependencies. Neural networks have high performance in most modern tasks. They have the ability to take into account long-term dependencies and work in forecasting and classification tasks. The comparison results indicate the prospects of using transformer architectures in both forecasting and classification tasks.

It has been found that the prediction results of neural network models can be improved by adding additional layers. Further research in this direction can focus on increasing the number of layers and making changes to the architecture of neural networks, developing hybrid approaches. Therefore, neural networks are an effective tool for modern data analytics.

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