MATHEMATICAL MODELING AND COMPUTING, Vol. 12, No. 1, pp. 299–309 (2025)

The role of functional activation in neural networks in the context of financial time series analysis

Senyk A. P.[1], Manziy O. S.[1], Pelekh V. R.[1], Futryk Y. V.[1], Senyk Y. A.[2]

[1]*Lviv Polytechnic National University,*
12 S. Bandera Str., 79013, Lviv, Ukraine
[2]*National Forestry University of Ukraine,*
103 Gen. Chuprynky Str., 79057, Lviv, Ukraine

(Received 18 April 2024; Revised 1 March 2025; Accepted 6 March 2025)

Nowadays, neural networks are among the most popular analysis tools. They are effective in solving classification, pattern recognition, and clustering problems. This paper provides a detailed description and analysis of the operational principles of two neural networks, namely a Siamese network and a multilayer perceptron. A model for using these neural networks in time series forecasting is proposed. As an example, a web application was created in which the described neural networks were used to analyze the correlation between pairs of financial assets and assess the risk level of an investment portfolio. Modern information technologies, visualization methods, and advanced analysis tools used in the developed software product provide users with a comprehensive understanding of their investments, allowing them to assess risks and opportunities, as well as determine strategies for maximizing income and diversifying their selected set of financial assets. The research results demonstrate the effectiveness of the Siamese network and multilayer perceptron in forecasting the prices of financial assets on the stock market and applying the obtained results in investment management tasks.

Keywords: *neural networks; data analysis; time series; modeling; visualization; forecasting; perceptron; web application.*

2010 MSC: 91B30 **DOI:** 10.23939/mmc2025.01.299

1. Introduction

Neural networks are one of the most popular pattern recognition tools with high speed and guarantee of correctness of the result. At the same time, more and more studies confirm their effectiveness in forecasting and classification, as neural networks have the ability to detect patterns in time series and as a result, they can be used to predict the future trend and create accurate forecasts.

Analysis of economic processes is a difficult task, as economic processes are modeled using factors that have weakly expressed trends. Such factors are difficult to mathematically model. And precisely because of this, the task of finding effective alternative methods of forecasting and researching problems of an economic nature is urgent.

Another no less important stage of research is the correct interpretation of the obtained results and the creation of effective recommendations based on the conclusions drawn. Although predicting the future situation is an extremely difficult task, certain conclusions can be drawn based on the analysis of historical statistical data. Analysis and visualization are among the most common modern techniques used in various types of research. That is why creating web applications that are easy to use and understandable for the lay user is an important task of forecasting and management.

The work is devoted to the description of the web application developed by the authors, which demonstrates the use of the capabilities of neural networks and modern methods of forecasting time series for solving investment management problems. The main attention is paid not only to the functional aspects of the development, but also to the analysis of modern trends in the field of information technologies, as well as to the comparison of existing analogues on the market.

2. Analysis of recent research and publications

A general description of the architecture of the Siamese neural network, as well as an outline of the main computing areas recommended for its use, is presented in [1, 2]. The work [3] describes the use of a Siamese-type neural network in pattern recognition for financial market analysis and forecasting. The practical application for technological purposes of a complex neural network consisting of five Siamese networks and a Bayesian network is described in [4].

A number of works by Oleksandra Manzii [5–7] and Yulia Senyk [8, 9] are devoted to the development of information systems to support decision-making in the organization of an effective set of investment portfolios by comparing the growth dynamics of the financial market. In the proposed information systems, a visualization process is applied, which presents available tabulated information in a structured form of schemes, graphs, charts, and also forecasting investment risks and profitability, which was carried out using modern mathematical methods and artificial intelligence tools.

Construction of time series forecasts based on deep learning was carried out in [10]. The work summarizes the means of researching financial time series, and also presents an artificial neural network and deep learning methods. The stock index forecasting model is also considered, and the influence of historical factors on the model is analyzed. The application of time series analysis in business research, which provides a rationale for the distinctions between correlation, association, and causation in sustainability issues, is reviewed in [11]. It is noted that in widely used correlation analysis (Pearson and Spearman correlation coefficients), the main focus is on changes in two variables regardless of the influence of other variables. The book [12] reviews the main competing approaches to modeling multiple time series: simultaneous equations, ARIMA, error correction models, and vector autoregression. Studies presenting the role of artificial neural networks and machine learning in the use of spatial information are provided in the article [13]. Mathematical aspects, in particular neural network learning problems, are related to infinite-dimensional optimization over Banach spaces of functions, the solutions of which are known to be fractional and polynomial splines. The specific Banach space depends on the choice of activation function [14].

An overview of existing software products allows us to conclude that specialized software solutions for analyzing and visualizing data and business analytics are widely available on the Internet. The following services are the most popular among them: Personal Capital, Quicken Premiere, StockMarketEye, Bloomberg Terminal, Morningstar Portfolio Manager, Portfolio Visualizer and others. The considered services are used to manage investments and risks by conducting in-depth analysis, generating reports, and modeling investment scenarios, which allow for the development of optimal risk avoidance strategies. Price action charts and influence charts are intuitive tools that allow you to make effective decisions.

At the same time, the analysis of modern trends in software development shows the high potential of using machine learning and artificial intelligence systems. Modern systems offer powerful functionality for data manipulation and analysis, supervised and unsupervised learning algorithms used for neural networks, simplifying the process of building models.

The purpose of the research is to apply neural networks for analysis, visualization, and forecasting, using the example of building a system of financial instruments with a given level of risk.

Task statement. The conducted analysis confirms the effectiveness of using neural networks for forecasting time series and expanding their application in areas where such methods are becoming increasingly popular.

The main stages when using neural networks for forecasting time series are:

- Choosing a network architecture — determining the optimal neural network architecture, such as the number of layers, the number of neurons in each layer, and the types of layers.
- Data preparation — preparing data for model training and testing. This can include normalizing the data, removing outliers, splitting the data into training and test sets, etc.
- Model training — using a training data set to train a neural network. During training, the model tries to establish relationships between input data (historical prices of financial instruments) and output data (forecasted prices).

- Model validation — verifying the trained model on a test dataset to evaluate its accuracy and efficiency.
- Parameter optimization — applying optimization methods to improve model accuracy.

With the help of neural networks, it is possible to detect complex implicit connections, and therefore it is relevant to study the possibility and effectiveness of neural networks in forecasting the prices of financial assets on the stock market and the use of the obtained results in investment management tasks. Based on the analysis and comparison of existing services, modern technologies, libraries and taking into account the needs of the modern investment market, it was decided to develop our own neural networks and a web application that will allow users to select and analyze assets when creating a portfolio with a given level of risk. When receiving input data, a simple and easy free service for current and historical currency exchange rates and cryptocurrency rates — FMPAPI — was used. The research uses web technology and deep machine learning for investment management.

3. Siamese neural network and its application to analyze the correlation of a pair of financial assets

Siamese neural networks (SNNs) were first introduced in the 1990s. The main idea was to create two identical neural networks capable of comparing feature vectors of two input data. This was a revolutionary step in solving problems related to image recognition, such as identity verification and object matching.

SNNs consist of two identical networks that are trained together using the so-called 'contrastive loss function'. This allows the network to learn to extract and compare features between two different inputs. Typical applications include comparing images to determine whether they are of the same subject and identity verification, where the system determines whether a face or fingerprint belongs to a specific person.

The SNN learning algorithm is based on the principle of reducing the distance between similar input data and increasing the distance between different data. A loss function is used to penalize the network if similar data is treated as different, or different data is treated as similar. Learning is done through optimization techniques such as gradient descent.

The basis for SNN is the theory of optimization and gradient descent. Optimization in SNN consists in finding the optimal weights of the network to minimize the loss function. Gradient descent allows this optimization to be performed efficiently by iteratively adjusting the weights in the direction of the fastest decreasing loss function.

In SNN, as in many other types of neural networks, different activation functions are used. The most popular of these are ReLU (Rectified Linear Unit) and its variations (e.g., Leaky ReLU, Parametric ReLU), the sigmoid function, and the hyperbolic tangent. ReLU is often considered the optimal choice due to its ability to efficiently solve the vanishing gradient problem and speed up learning.

The choice of the activation function can significantly affect the effectiveness of SNN learning. Activation functions determine how the neurons in the network are activated, affecting the network's ability to learn and adapt. For example, ReLU and its variants help keep gradients large and non-zero, which facilitates faster learning.

Distance calculation in SNN is used to measure the similarity between data pairs. Metrics such as Euclidean distance, Manhattan distance, or cosine similarity are commonly used. The choice of distance calculation method depends on the specific task. For example, Euclidean distance works well when similarity can be measured as the direct distance between points in space. Cosine similarity is effective when the direction of the vectors is more important than their magnitude.

Training a Siamese neural network involves tuning hyperparameters such as learning rate, number of epochs, and loss function. Performance evaluation includes the analysis of metrics such as accuracy and loss on training and validation datasets.

The architecture of the Siamese neural network is based on convolutional layers. The network consists of three main convolutional layers (Conv1D), each of which uses the ReLU (Rectified Linear

Unit) activation function. After each convolutional layer, a BatchNormalization layer is applied to normalize the output data and improve the stability and efficiency of training.

The convolutional layers are followed by the MaxPooling1D layers, which reduce the size of the original data by selectively summarizing the features in certain areas. This helps reduce the dimensionality of the data and prevent overtraining.

After a sequence of convolutional and pooling layers, the raw data is flattened using the Flatten layer, turning it into a one-dimensional vector. Next are two fully connected layers (Dense) with 256 and 128 neurons, respectively, both with ReLU activation. A Dropout layer with a percentage of 0.3 is applied between these fully connected layers to reduce the risk of overtraining by accidentally turning off some neurons during training.

The final step in the architecture of the Siamese neural network is to combine the output data from both parallel subnetworks using the Subtract (variation of Euclidean distance) layer, which subtracts the feature vectors from each other. The result is then passed through a single-neuron fully connected layer with sigmoidal activation to produce a final binary prediction that shows how similar the two input data sets are.

Unlike standard convolutional or fully connected neural networks, Siamese neural networks focus on measuring relativity between data pairs. This makes them ideal for tasks where the degree of similarity or difference needs to be assessed, such as in financial time series modeling.

The architecture proposed in the study differs from classical Siamese networks in that it uses convolutional layers for time series analysis. Traditional Siamese networks often use fully connected layers or image-oriented architectures. This approach clearly shows the adaptation of the Siamese network to the specific needs of processing financial time series. Data processing includes calculation of percentage changes and normalization using the z-score method. These are approaches that help standardize financial time series, making the data more amenable to neural network analysis.

Dividing the dataset into training and validation samples is key to testing model performance. Effective data management, including proper allocation and diversity of positive and negative pairs, is critical to achieving high model accuracy and generalizability.

In the created implementation, when training the Siamese neural network, the Adam optimizer is used with a learning speed of 0.005, "binary_crossentropy" as a loss function, and various callback methods are used to control the learning process. Using callbacks to save the best model and stop early helps avoid overtraining and ensure optimal performance. After training, the evaluate method is used to determine the performance of the model on validation data. The obtained results indicate that the training of the model is successful and effective. The high accuracy and low loss on both the training and validation data sets indicate that the model has good generalization ability and can perform the prediction task well on new data.

At the end of the program execution, we save the trained Siamese neural network model for further use in other programs of the project.

4. Multilayer Perceptron and its use for analyzing the risk level of an investment portfolio

A Multilayer Perceptron (MLP) is a basic form of artificial neural network used for a variety of machine learning tasks, including classification, regression, and time series prediction. MLP consists of three main types of layers: an input layer, one or more hidden layers, and an output layer. Each layer consists of neurons that use activation functions to transform input data. MLP is distinguished by its ability to learn to represent non-linear relationships between input and output data.

MLP traces its origins to early work in neural networks, particularly Frank Rosenblatt's perceptron in the 1950s. However, the limitations of the perceptron, particularly its inability to solve problems that are not linearly separable, led to the development of the MLP. An important step in the development of MLP was the introduction of the error backpropagation algorithm in the 1980s, which made it possible to effectively train multilayer networks. Since then, MLPs have undergone significant development and improvement, making them indispensable in modern machine learning. Compared to other types of neural networks, such as convolutional (CNN) or recurrent (RNN) neural networks, MLPs are more basic and less specialized, but still effective for a wide range of tasks.

In our research, the task is to develop an MLP for the classification of investment portfolios according to the level of risk. The model should distinguish between high and low risk portfolios based on their composition.

MLPs can have different numbers of hidden layers and neurons in each layer, which affects their complexity and ability to generalize data. This model includes three hidden layers (with 64, 32 and 32 neurons) and an output layer with a sigmoid activation function for binary classification. This allows the model to learn complex non-linear dependencies in the data, which is important for accurately classifying portfolios by risk level.

Data for the model is generated artificially according to a proven algorithm. Each investment portfolio must contain assets, each of which is characterized by a ticker, weight (portfolio share) and asset risk level. In the project, they are used to create a set of features, which are then standardized before training the MLP. The result is a list of portfolios, where each portfolio contains information about assets and an overall risk label. The visualization of the obtained result is a pie chart of the portfolio.

Initialization. The function initializes two empty lists, X and y, which will be used to store the input features (X) and target labels (y).

Processing of Each Portfolio. For each portfolio in the portfolios list function:

- Extracts characteristics of each asset, such as the weight of the asset in the portfolio and its risk. These features are combined into one large list of features for each portfolio.
- Adds this feature list to the X list.
- Adds the portfolio risk label (0 or 1) to the y list.

Creating Numpy Arrays. X and y lists are converted to Numpy arrays for compatibility with TensorFlow and other deep learning libraries.

Data scaling and normalization are key aspects of data preparation for MLP training. These methods equalize the value ranges of different features, which contributes to more efficient and stable network learning. The paper uses StandardScaler for data standardization, which helps to rank the training data with a standard mean of 0 and a standard deviation of 1.

Dividing the data into training and test sets allows you to assess the overall ability of the model to generalize knowledge to new data. Using the train_test_split function, the data is split into 80% for training and 20% for testing, ensuring that both sets are representative.

The MLP learning process involves forward propagation (data is passed through the network generating predictions) and error backpropagation (updating network weights to minimize error). This process is repeated over several training epochs. Optimizers manage the process of updating weights in the network. The model uses the Adam optimizer, which is efficient and widely used due to its adaptive learning rate properties.

Hyper-parameters such as batch size, number of epochs, training rate and network architecture affect the efficiency and quality of training. In

```
Epoch 1/10
2/2 [==============================] - 0s 6ms/step - loss: 0.6511 - accuracy: 0.6167
Epoch 2/10
2/2 [==============================] - 0s 1000us/step - loss: 0.6107 - accuracy: 0.6833
Epoch 3/10
2/2 [==============================] - 0s 2ms/step - loss: 0.5716 - accuracy: 0.7500
Epoch 4/10
2/2 [==============================] - 0s 2ms/step - loss: 0.5352 - accuracy: 0.8500
Epoch 5/10
2/2 [==============================] - 0s 2ms/step - loss: 0.4993 - accuracy: 0.8750
Epoch 6/10
2/2 [==============================] - 0s 983us/step - loss: 0.4646 - accuracy: 0.9250
Epoch 7/10
2/2 [==============================] - 0s 2ms/step - loss: 0.4294 - accuracy: 0.9500
Epoch 8/10
2/2 [==============================] - 0s 999us/step - loss: 0.3954 - accuracy: 0.9583
Epoch 9/10
2/2 [==============================] - 0s 2ms/step - loss: 0.3622 - accuracy: 0.9583
Epoch 10/10
2/2 [==============================] - 0s 2ms/step - loss: 0.3296 - accuracy: 0.9667

Validation:
1/1 [==============================] - 0s 88ms/step - loss: 0.3796 - accuracy: 0.9667
Validation accuracy: 0.9666666388511658
Validation loss: 0.37956202030181885
```

Fig. 1. Console output of the model training process.

our case, we chose 10 training epochs
and a batch size of 64, which is a standard choice for many tasks.

Analysis of the model training process is presented in Figure 1.

- At the first epoch, the accuracy of the model started at about 61.67%, indicating a better result than random guessing.
- With each subsequent epoch, both accuracy and loss improved. The accuracy increased to 96.67% at the 10th epoch, which is a significant improvement and indicates effective learning.
- The loss has decreased from the original 0.6511 to 0.3296, indicating that the model is getting better at predicting the correct labels for the training data set.

Model validation analysis:

- The accuracy on the validation data set was also 96.67%, which indicates the high generalization ability of the model.
- Validation losses were relatively low (0.3795), which further confirms the effectiveness of the model.

Fig. 2. Training process visualization.

The training plot in Figure 2 shows that with each epoch the training accuracy increased (represented by the orange line), while the loss decreased (represented by the blue line). This trend is an indicator that the model has not overtrained and that the training process was efficient. The results of the training show the successful and effective training of the model. The high accuracy and low loss on both the training and validation datasets indicate that the model has good generalization ability and can potentially perform well in classification on new data.

5. Web application for formation and analysis of an investment portfolio with a given level of risk

The result of the research is the created web application — an innovative tool designed to help investors in the formation and analysis of their investment portfolios with a given level of risk.

In addition to creating an investment portfolio, the developed application offers comprehensive portfolio analysis using advanced algorithms and machine learning models.

The web application is designed for a wide range of users — from newbies in the field of investments to experienced investors who seek to optimize their investment strategies with the help of advanced technologies.

The main functions of the created application are the following.

Asset selection mechanism (Figure 3):

- Users can choose assets from various categories such as bonds, gold, ETFs, stocks, etc.
- Each asset is classified by risk level (low, medium, high), which helps investors understand potential risks.
- The application provides detailed information about each asset, including historical data and a description.
- Assets are presented as tiles that display asset categories and their tickers.
- Users can copy an asset's ticker with one mouse click to fill their investment portfolio.

Investment allocation (Figure 4):

- Users specify the amount of the initial investment and the percentage of the financial cushion.

- They can allocate the investment among the selected assets in a percentage ratio.
- Algorithms automatically calculate actual investment amounts for each asset based on a given allocation.

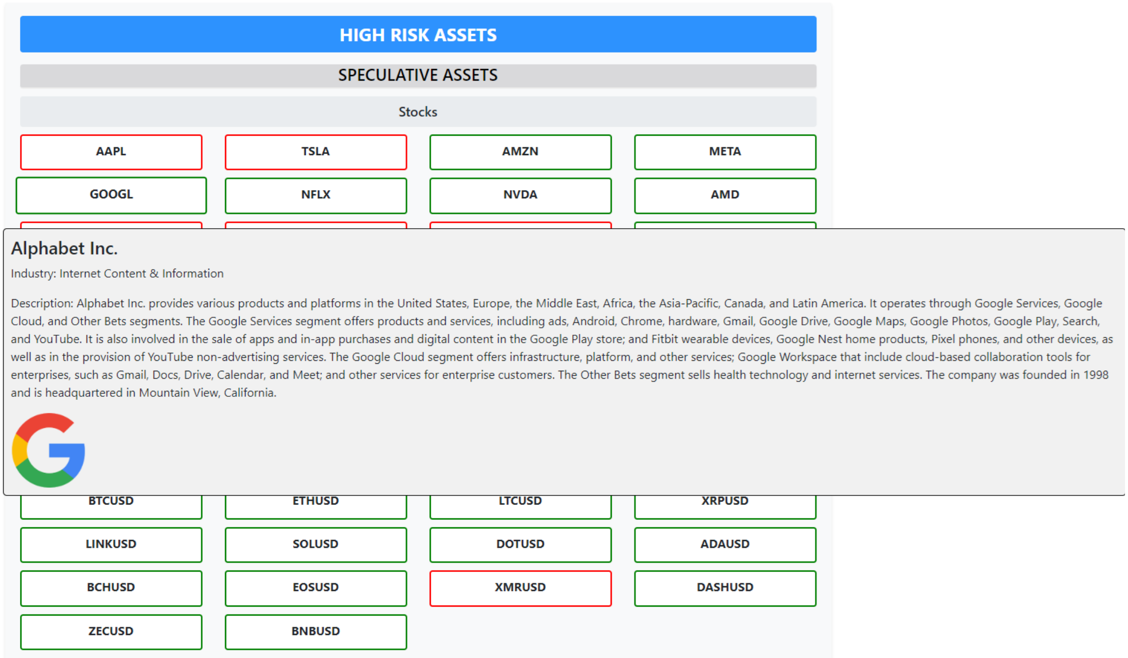

Fig. 3. GOOGLE asset info view (Alphabet Inc. company).

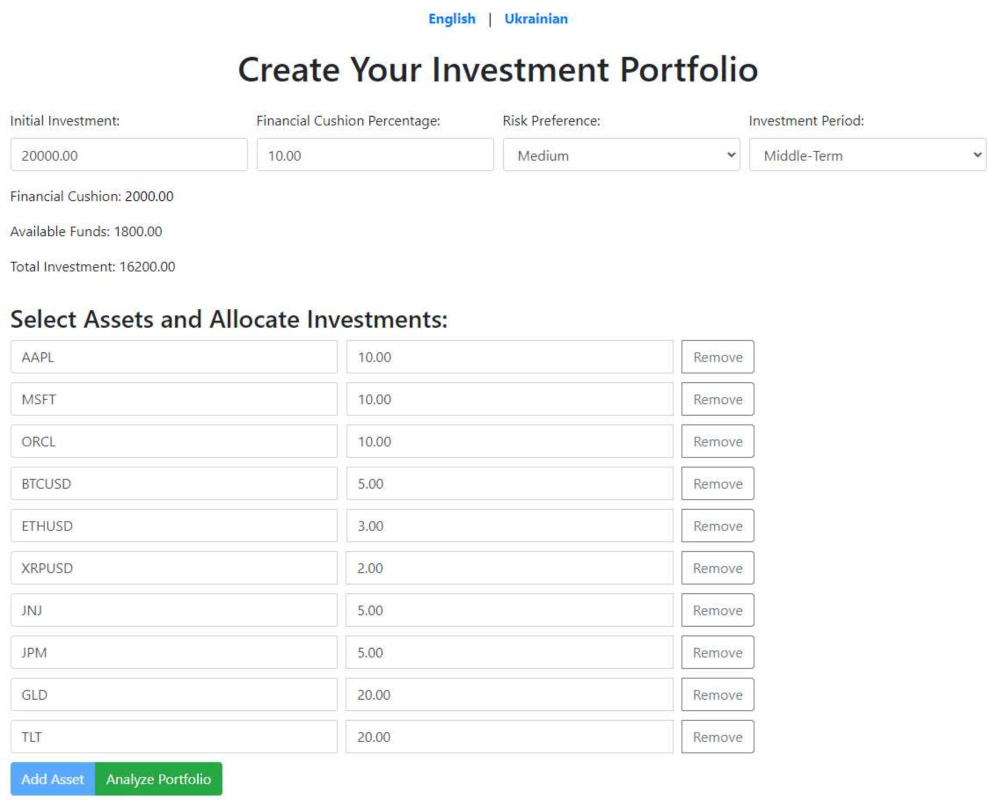

Fig. 4. An example of filling an investment portfolio with 10 (maximum) assets.

Portfolio risk assessment (Figure 5):

- Using neural networks, the application analyzes the overall risk of the portfolio based on the selected assets and their weights.
- The portfolio is compared to the user's risk profile, providing recommendations for its optimization.

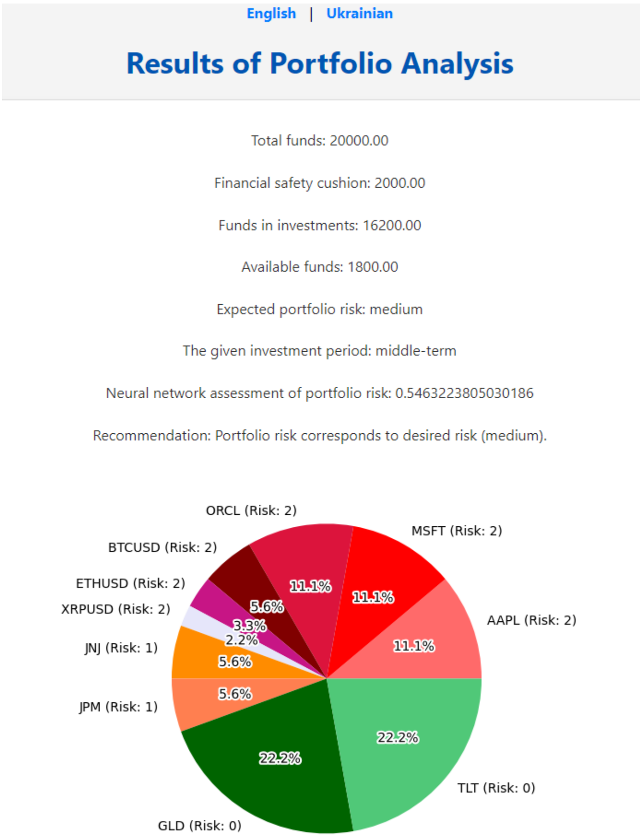

Fig. 5. Results of the analysis of the portfolio of 10 assets part 1.

Analysis of correlations (Figure 6) is carried out with the help of heat maps, which are used to visualize the relationships between assets in the portfolio. The model uses two approaches: classical — Pearson's correlation and analysis from the Siamese neural network. The latter is a more complex analysis that takes into account not only linear relationships, as in the case of Pearson's correlation, but also more complex patterns and dependencies in the behavior of assets. This approach allows for a deeper analysis of the portfolio's risk structure.

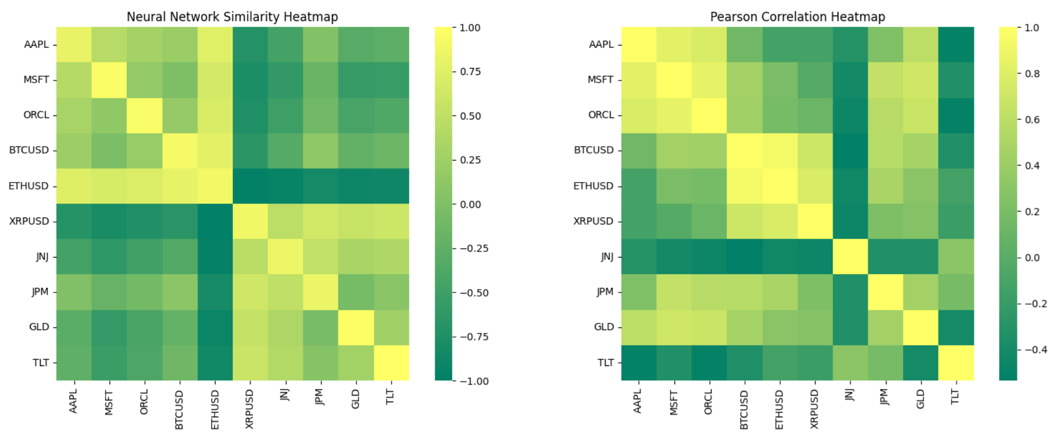

Fig. 6. Results of the analysis of the portfolio of 10 assets part 2.

Analysis of the volatility of assets in the portfolio (Figure 7):

- The volatility of each asset is calculated based on their historical data.
- The total volatility of the portfolio is determined by the graph, which helps users to understand the potential fluctuations in the value of the portfolio.

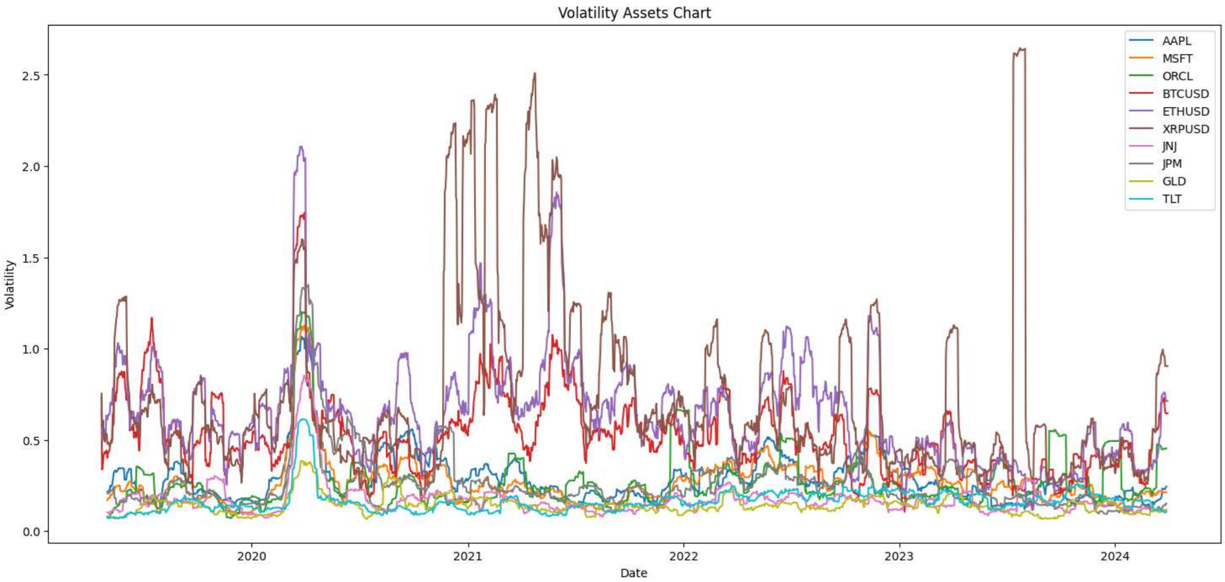

Fig. 7. Results of the analysis of the portfolio of 10 assets part 3.

Forecasting of potential income is based on an analysis of the daily percentage return of each asset, which is calculated based on their historical data. With the daily return graph, the user can estimate the potential income of each individual asset in the portfolio.

Forecasting and analysis of asset trends is carried out on the basis of historical data for different periods of time, which makes it possible to determine short-term and long-term trends of assets included in the investment portfolio. The obtained forecasts of growth or decline in the value of assets are used to provide recommendations for efficient replacement of assets in the portfolio:

- If the asset shows a long negative trend, the application suggests alternative assets from the common sector, but with a positive trend.
- this approach helps to balance the portfolio, reducing risks and increasing the potential return of the portfolio.

Implemented portfolio analysis tools provide users with a comprehensive understanding of their investments, allow them to assess risks and opportunities, and identify strategies to maximize income and diversify portfolios.

The web application uses the Flask–Babel library, an extension to Flask that provides multilingual support. This makes it easy to translate text content into different languages, making the interface comprehensible to an international audience.

6. Conclusions

Analysis of modern trends in software development shows the high potential of using machine learning and artificial intelligence systems. Modern systems offer powerful functionality for data manipulation and analysis, supervised and unsupervised learning algorithms used for neural networks, simplifying the process of building models. With the help of neural networks, it is possible to detect complex implicit connections. Therefore, it is relevant to study the possibility and effectiveness of using neural networks in forecasting the prices of financial assets on the stock market and using the obtained results in investment management tasks.

The paper provides a detailed description and analysis of the Siamese neural network and multilayer perceptron. Algorithmic trading using neural networks has become common in stock markets. As confirmation of this, the paper illustrates the role of neural networks as an effective tool for predicting the prices of financial instruments. The creation of a Siamese neural network and a Multilayer Perceptron for analyzing the correlation of assets and risks of investment portfolios is described, which serves as evidence of an understanding of modern machine learning methods and their application in financial analysis. At the same time, it is pointed out that it is important to consider their limitations and risks, such as overtraining and sensitivity to noise in the data.

Neural networks can analyze amounts of data, including historical asset prices, economic indicators, and news. Using deep learning, neural networks can detect complex correlations and predict trends, and this has made it possible to build an effective model that helps investors make informed decisions for effective planning and investment management. The work shows an example of using a neural network to optimize investment portfolios taking into account individual goals and risks of investors, as well as recommending the optimal allocation of assets.

The web application proposed in the paper is proposed to be used as an advisory tool for individual non-professional or inexperienced investors with low financial stability. It provides users with a detailed analysis of the risk, potential volatility, and returns of various assets, allowing them to effectively plan and manage their investments.

In addition, it should be noted that the conducted research makes it possible to recommend the use of neural networks for solving other problems of investment management. An example can be the task of detecting anomalies and fraud in the markets. Neural networks can analyze transactions and patterns to identify potential violations and unusual activity. In addition, neural networks can analyze current market conditions and automatically execute trades based on predefined strategies. This allows you to dynamically respond to rapidly changing market conditions and execute trades in real-time. Neural networks can help investors assess and manage risk, perform probability-of-loss analysis, and calculate optimal position sizes to adhere to predetermined risk levels.

However, it is important to remember that investments are always associated with risks and neural networks are not a universal solution. Proper understanding and use of these technologies, combined with financial analysis and expertise, remain key to successful investments.

[1] Chicco D. Siamese Neural Networks: An Overview. Artificial Neural Networks. Methods in Molecular Biology. **2190**, 73–94 (2021).

[2] Serrano N., Bellogín A. Siamese neural networks in recommendation. Neural Computing and Applications. **35**, 13941–13953 (2023).

[3] Basu T., Menzer O., Ward J., SenGupta I. A Novel Implementation of Siamese Type Neural Networks in Predicting Rare Fluctuations in Financial Time Series. Risks. **10**, 39 (2022).

[4] Malykhina G., Guseva A. Application of Siamese Neural Networks for the Type of Emergency Determination. CSIS'2019: Proceedings of the XI International Scientific Conference Communicative Strategies of the Information Society. 9, 1–5 (2020).

[5] Sverstiuk A., Dubynyak T., Manziy O., Senyk A., Ohloblin P. Bayesian click model and methods of estimating its parameters. CEUR Workshop Proceedings. **3628**, 389–403 (2024).

[6] Dubyniak T. S., Manziy O., Gancarczyk T., Senyk A., Futryk Y. Specialized information system for support of the process of recruiting securities. CEUR Workshop Proceedings. **3468**, 117–125 (2023).

[7] Senyk A., Manziy O., Futryk Y., Stepanyuk O., Senyk Y. Information system supporting decision–making processes for forming of securities portfolio. Journal of Lviv polytechnic national university "Information systems and networks". **11**, 39–55 (2022).

[8] Senyk A. P., Manziy O. S., Ohloblin P. E., Senyk Y. A., Krasiuk O. P. Application of the Bayesian approach to modeling credit risks. Mathematical Modeling and Computing. **11** (4), 1025–1034 (2024).

[9] Stepanyuk O., Senyk A., Manziy O., Pavlyuk N., Senyk Y. Information system of analysis for segmentation of the securities portfolio of the product market. Scientific Messenger of LNU of Veterinary Medicine and Biote1chnologies. Series Economical Sciences. **25** (101), 11–21 (2023).

[10] Xu Z., Zhang J., Wang J., Xu Z. RETRACTED ARTICLE: Prediction research of financial time series based on deep learning. Soft Computing. **24**, 8295–8312 (2020).

[11] Rezaee Z., Aliabadi S., Dorestani A., Rezaee N. J. Application of Time Series Models in Business Research: Correlation, Association, Causation. Sustainability. **12** (12), 4833 (2020).

[12] Brandt P. T., Williams J. T. Multipletime series models. SAGE Publications, Inc. (2007).

[13] Goel A., Goel A. K., Kumar A. The role of artificial neural network and machine learning in utilizing spatial information. Spatial Information Research. **31** (3), 275–285 (2023).

[14] Parhi R., Nowak R. D. The Role of Neural Network Activation Functions. IEEE Signal Processing Letters. **27**, 1779–1783 (2020).

Роль функціональної активації нейронної мережі на прикладі аналізу фінансових часових рядів

Сеник А. П.[1], Манзій О. С.[1], Пелех В. Р.[1], Футрик Ю. В.[1], Сеник Ю. А.[2]

[1] *Національний університет "Львівська політехніка", вул. С. Бандери, 12, 79013, Львів, Україна*
[2] *Національний лісотехнічний університет України, вул. Ген. Чупринки, 103 79057, Львів, Україна*

В наш час нейронні мережі є одним з найпопулярніших інструментів аналізу. Вони є ефективними при розв'язанні задач класифікації та аналізу, розпізнаванні образів та кластеризації. У цій роботі проведено детальний опис та аналіз принципів роботи двох нейронних мереж, а саме, сіамської мережі та багатошарового перцептрона. Запропоновано модель використання цих нейронних мереж для прогнозування часових рядів. Як приклад, створено веб-додаток, в якому використано описані нейронні мережі для аналізу кореляції пар фінансових активів та при аналізі рівня ризику інвестиційного портфеля. Використані в створеному програмному продукті сучасні інформаційні технології, методи візуалізації та сучасні інструменти аналізу забезпечують користувачам комплексне розуміння їхніх інвестицій, дозволяють оцінити ризики та можливості, а також визначити стратегії для максимізації доходу та диверсифікації обраного набору фінансових активів. Результати проведеного дослідження свідчать про ефективність застосування сіамської мережі та багатошарового перцептрона при прогнозуванні цін фінансових активів фондового ринку та використання отриманих результатів у задачах інвестиційного менеджменту.

Ключові слова: *нейронні мережі; аналіз даних; часовий ряд; моделювання; візуалізація; прогнозування; персептрон; веб-додаток.*