The value of shares prediction in an unstable economy using neural networks

Valentina Moskalenko[a], Anastasija Santalova[a], Nataliia Fonta[b] and Elena Nikulina[a]

[a] *National Technical University "Kharkiv Polytechnic Institute", Kyrpychova str. 2, Kharkiv, 61002, Ukraine*
[b] *DataArt, square Zakhysnykiv Ukrayiny 7/8, Kharkiv, 61000, Ukraine*

Abstract

The relevance of this research topic is due to the need to develop algorithmic provision of the market value forecasting for shares in Ukraine and the introduction of the concept for increasing information transparency of the domestic stock market. All this will help improve the investment market, provide investment and development of Ukrainian companies and the economy as a whole. An analysis of research on the use of methods for computational intelligence, including neural networks to model the behavior of stock market participants and solve the problem of forecasting. A study was conducted based on using neural networks of different architecture to predict the market value of shares in the stock markets of Ukraine, which are in the process of formation and development. The following models of neural networks were chosen for experimental research: Long short-term memory; Convolutional neural network; a hybrid model that combines two neural network architectures CNN and LSTM; a hybrid model consisting of a variational mode decomposition algorithm and a long-term memory neural network (VMD-LSTM). Four shares of the Ukrainian Stock Exchange were selected for forecasting: Tsentrenergo (CEEN); Ukrtelecom (UTLM); Kriukivs'kyi Vahonobudivnyi Zavod PAT (KVBZ); Raiff Bank Aval (BAVL). Estimates of forecast quality are calculated. It was concluded that it is advisable to use the LSTM network to forecast stocks that are on the stock exchanges of countries with unstable economies.

Keywords 1

Forecasting, Investment, Neural network, Long-term memory, Convolutional neural network, Variational decomposition

1. Introduction

An important condition for the stable development of any national economy is the stock market. The presence of a developed stock market provides corporations with great opportunities to raise share capital and creates conditions for their further development. However, in order for the domestic stock market to be able to accumulate investors, it has:

1) comply with the principle of information transparency;
2) create conditions for compliance with corporate governance standards;
3) be predictable.

The ability to predict stock market movements is one of the factors that makes stocks an attractive financial instrument for investors. Investors then begin to use stocks not only as a means of gaining control of the company, but also to manage risk, save savings and generate investment income.

The study of prospects and features of the use for methods developed in world practice for forecasting the market value of shares in countries where stock markets are in the process of formation and development, for example, in Ukraine, becomes particularly relevant.

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EMAIL: valentinamosk17@gmail.com (V. Moskalenko); nastia.santalova@gmail.com (A. Santalova); natalia.fonta@dataart.com (N. Fonta); elniknik02@gmail.com (E. Nikulina)
ORCID: 0000-0002-9994-5404 (V. Moskalenko); 0000-0002-9949-4500 (A. Santalova); 0000-0001-5593-1409 (N. Fonta); 0000-0003-2938-4215 (E. Nikulina)

Problems to be solved when investing financially:

1. The problem of accuracy for price forecasting is relevant for all speculators in the stock market. Its essence is that at present there is a risk of lacking accuracy on the one hand to predict using classical mathematical methods, but on the other hand the lack of new methods that allowed the rules of all factors, parameters, to create separate forecasts of financial indicators.
2. The choice of methods for forecasting the market value of shares in an unstable economy. Using forecasting research methods based on time series analysis, there is what is happening in assessing the effectiveness of complex atomic models compared to basic models, such as ARIMA or LSTM, or with very similar architectures. Extensive research has also been done in countries with stable economies.

This article deals with study of the neural network using with different architecture to predict the market value of shares in the stock markets of countries that are in the process of formation and development.

2. Background and Related Work

2.1. Solving investment problems using the methods of computational intelligence

Optimization methods are traditionally used to optimize the structure of the securities investment portfolio. But in the context of the large-scale task of forming an investment portfolio, such methods may not be effective, so there are many scientific publications that suggest the use computational intelligence methods, such as genetic algorithms.

The article [1] conducted a study on the application of genetic algorithm to optimize the investment portfolio. Four Lithuanian companies included in the official list of the OMX Baltics stock exchange were selected to create an investment portfolio in accordance with the selected criteria. The optimal investment portfolio was built in MATLAB using a genetic algorithm. The results of the study showed that the portfolio based on genetic algorithms in 2013 achieved a better risk-return ratio than the portfolio optimized by deterministic and stochastic programming.

The modeling using the classical mathematical approach to pattern building is no longer effective, because the stock market is a complex system in which the strategies of its participants are constantly changing. Therefore, in recent years, there has been a lot of research on the use of agent modeling to study the behavior of market participants and solve other problems. Consider some publications.

In the article [2], using modeling based on agents and simple rules, a model was created that can simulate the behavior of indices in the stock market. The model took into account the impact of both investment and peripheral parties, mimicking the diversity and complex network of influences that stimulate market change. It has been found that adding appropriate agent classes to integrate other expected effects, along with improving the mechanisms that control agent behavior, can improve the model.

The article [3] presents an agency model for simulating prices in financial markets both in stationary conditions and in stressful situations. The model supports different scenarios in the market.

In [4] it is proposed to consider the market as the interaction of three types of agents with different investments and risk preferences. Genetic network programming is combined with the state-of-action-reward-state-of-action (SARSA) algorithm for market design based on the adaptation of technical agents. The pricing mechanism based on the auction mechanism of the Chinese securities market is taken into account. The characteristics of time series are analyzed to determine whether there is excessive volatility in four different markets.

In the article [5], a multi-agent model of the spot futures market is developed to analyze the micro-mechanism of shock transmission in the spot and futures markets. It is considered that there are two stocks and one futures contract for a stock index in the spot futures market. Agents are heterogeneous. The spot market and the futures market are linked by arbitrageurs. The simulation results showed that the spot futures market model can reproduce various important stylized facts, including the joint price movement between stock index prices and index futures prices.

2.2. Stock forecasting models using artificial neural networks

Since the stock market depends on many factors, for the effective operation of market participants need to use different methods to predict the market value of securities. Statistical forecasting methods make it possible to obtain forecasts for more or less stable markets. But in conditions of instability or uneven growth and decline of the market, new approaches to forecasting must be used. In recent decades, prediction methods using neural networks, genetic algorithms, etc. have begun to develop very actively.

The paper [6] reviews 148 researches utilizing neural and hybrid-neuro techniques to predict stock markets, categorized based on 43 auto-coded themes obtained using NVivo 12 software. Findings highlight that AI techniques can be used successfully to study and analyze stock market activity.

Consider some more of these methods.

The article [7] uses an encoder-decoder attention mechanism model that adds an attention mechanism from two aspects of function and time. The encoder and decoder use an LSTM neural network. Simulation and experiment results show that the introduction of the attention mechanism can lead to smaller forecast errors.

This paper [8] proposes a pattern-based stock trading system. The significance of this study is the development of a stock price prediction model that exceeds the market index using ANN-based deep learning and utilizing the results to analyze and forecast highly volatile stock price patterns.

A comprehensive big data analysis routine using hybrid machine learning algorithms was developed to predict the direction of daily returns for the SPDR S&P 500 ETF (ticker: SPY). Researchers aim to apply the simplest set of algorithms to the smallest amount of data, while both the most accurate prediction results and the highest risk-adjusted returns are desirable. This problem is addressed in the study [9].

In the study [10], artificial neural network and random forest methods were used to predict the next day's closing price for five companies belonging to different sectors of activity. Financial data: The opening, high, low, and closing prices of a stock are used to create new variables that are used as input to the model.

The study [11] proposes a new prediction method based on deep learning technology, which integrates traditional stock financial index variables and social media text features as inputs of the prediction model. This study uses Doc2Vec to build long text feature vectors from social media and then reduce the dimensions of the text feature vectors by stacked auto-encoder to balance the dimensions between text feature variables and stock financial index variables. Based on wavelet transform, the time series data of stock price is decomposed to eliminate the random noise caused by stock market fluctuation. this study uses long short-term memory model to predict the stock price.

Article [12] uses a semi-parametric method known as accelerated regression (BRT) trees to predict stock returns and monthly volatility. The results show that the expansion of the set of conditional information leads to greater accuracy of out-of-sample forecasting compared to standard models.

Article [13] predicts Microsoft stock prices using geometric Brownian motion and multilayer perceptron techniques. The prediction of stock prices using geometric Brownian motion was started by calculating the inverse of the data. Then the validity of the returned value is checked. The value of the profit should be normally distributed. Then the calculation is done to get the values of drift and volatility.

The article [14] proposes a method of deep learning, based on a convolutional neural network, to predict the movement of stock prices in the Chinese stock market. The opening price, the maximum price, the minimum price, the closing price and the volume of shares received from the Internet are set as input data for building the network architecture. The result showed that using a deep learning method based on a convolutional neural network to predict stock price movements in China is quite reliable.

The method of creating market forecasting models using multi-agent and fuzzy systems is presented in [15]. Agents in the system represent traders fulfilling buy and sell orders in the market, and fuzzy systems are used to model the rules followed by traders making trades in the real market, and intuitionist fuzzy logic to model the uncertainty of their decisions. Experiments have shown that the identification of specialized agents gives better results.

2.3. Review of services for forecasting the value of shares

IKnowFirst. It uses an algorithm to predict the value of shares based on artificial neural networks and genetic algorithms. Constantly retrained on data for the last 15 years, issues a set of predictions for 3, 7 and 14 days, 1 and 3 months and 1 year. The service displays the forecast trend as a number, positive or negative, along with a wave chart that predicts how the waves will overlap the trend. This helps the investor to decide in which direction to trade, at what point to enter into the transaction and when to leave. Some promotions are included in several separate modules. Thus, you can get multiple predictions based on different data sets. Each module consists of several submodules that give an independent forecast. If submodules give conflicting predictions, this should be a warning sign. Six different filters are used to refine forecasts. Focused on professionals, the site is not user-friendly, the interface and experience are not obvious, many professional terms. Also, quite inconvenient interface of the service itself, it is necessary to import into Excel, the result in the form of a table without explanation, then it is suggested to configure the parameters (risk, signal and predictability). It is not possible to select specific companies; the selected ones are displayed outside the forecasts. There is no Ukrainianization of the site and service interface. The service works on the principle of subscription for individual blocks of shares, there are no shares of Ukrainian companies.

FinBrain. The algorithm is based on ensembles of decision trees used to analyze numerical and textual data that affect the dynamics of stock prices. FinBrain offers stock price forecasts for 10 days and 12 months ahead for more than 10,000 assets that are updated daily. The list includes assets listed in S & P500, NASDAQ, NYSE, Crypto Currencies, Foreign Currencies, DOW30, ETFs, Commodities, UK FTSE 100, Germany DAX, Canada TSX, HK Hang Seng, Australia ASX, Tadawul TA. This service also works on a subscription system for forecasting individual set of shares. The site does not have a Ukrainian-language interface, there are no shares of Ukrainian companies available for forecasting. The user interface and experience are better than in the previous case. The site has a personal account where it is possible to track forecasts and analyze charts, there is a separate tab for selected assets.

Danel Capital. Danel Capital offers a forecast based on artificial intelligence and data that reflects the likelihood that stocks will outperform the market in the medium term (90 market days). Gives own rating from 1 to 10 for assets, general, fundamental, technical and semantic. Quote from the site: “The range of Smart Score ratings is from 1 to 10”. Shares with Smart Score 1 have the least opportunity to bypass the market. On the contrary, stocks with a Smart Score rating of 10 have the greatest opportunity to bypass the market. The benchmark for US listed stocks is the S&P 500 and for European stocks the STOXX 600.Sstocks with 9 or 10 Smart Score should be considered as attractive stocks to add to portfolio, and stocks with a rating of 1 or 2 Smart Score - stocks to be avoided in the medium term. Smart Score is calculated using artificial intelligence algorithms (crucial tree ensembles) that analyze more than 10,000 fundamental, technical and mood indicators daily. There is no Ukrainian-language interface or shares Ukrainian companies. So far, only a professional tariff plan is available on the site, which includes all available for forecasting promotions. In the near future, the creators of the service plan to introduce several more tariff options.

StocksNeural. Here the user can receive signals to buy / sell based on forecasts of stock prices and current prices. It is possible to receive notifications when you should start trading on the stock exchange. The service algorithm uses recurrent neural networks (RNN) and convolutional neural networks (CNN). Models are regularly replenished. The daily pipeline for models includes the steps required to download and pre-process new market data, calculate model accuracy and performance indicators, and make trading recommendations according to the forecast and strategy parameters. On the site there is an opportunity to make a paid subscription and get access to the service.

Based on the analysis of existing services for forecasting stock prices, it can be concluded that the proposals differ in the final type of forecasts and interface, but all options have a similar set of disadvantages:

- no Ukrainianization of the interface;
- limited set of stocks available for forecasting;
- high entry threshold (lack of clear user manual);
- all services are available only with a paid subscription (high cost);

- there is no possibility of forecasts aggregation, which complicates the integration into the daily work of the investor-user of the service.

Telegram bots and channels would be more user-friendly, but at the moment they provide either investment ideas and subjective opinions, or track current performance.

3. Designing the architecture of the neural network to predict the market value of shares

The following neural networks were selected for experimental studies:

1. A network having a fully connected network structure with four layers; the architecture combines two layers of the Long short-term memory (LSTM) class with two layers of the Dense class. This architecture is relatively simple and is a good start for solving time series problems. The Dense class and the LSTM class from the Keras Deep Learning Library are used to define this structure. As a rule, the number of neurons in the first layers should cover the size of the input data. Input contains values for 50 dates. Thus, the input form must have at least 50 neurons - one for each value. In the last layer we will have only one neuron, which means that the forecast will contain one price point for one time step as the basic, most common neural network.
2. Convolutional neural network (CNN), the architecture of which is described in the article by Chen and He [14], which justifies the maximum efficiency of such a configuration as an example of a fundamentally different neural network architecture. However, in a study [14], the neural network is used to solve classification problems. The proposed architecture was adapted to perform regression by replacing the Softmax layer with a fully connected layer consisting of a single neuron. All convolutions are two-dimensional, the size of the cores is 3x3, the number of filters for the first three convolution layers is 32, 64 and 128, respectively, the rest are 256. The size of the core of the pulp is 2x2.
3. CNN-LSTM is a hybrid model that combines two different neural network architectures. The architecture proposed by Wu and others [16] was chosen because it has proven effectiveness. The number of neurons in the LSTM and the fully connected layer is not specified, so it is implemented based on the values for previous models - 256.
4. VMD-LSTM is a hybrid model consisting of a classical machine learning algorithm and a neural network. The combination of variational mode decomposition (VMD) and LSTM is implemented on the basis of the article [17]. The parameters for the LSTM module are not specified in the article, so the implementation proposed in this paper coincides with the simple LSTM.

To compare the forecast quality of different models, four shares of the Ukrainian stock market were selected:

- Tsentrenergo (CEEN);
- Ukrtelecom (UTLM);
- Kriukivs'kyi Vahonobudivnyi Zavod PAT (KVBZ);
- Raiff Bank Aval (BAVL).

The development was carried out in the Python programming language version 3.8 using the libraries InvestPy, Pandas, NumPy, Scikit-learn, Keras, Matplotlib and VmdPy.

InvestPy is a Python package for extracting financial historical data. It is designed to download historical data from Investing so that it can be retrieved through Python for future reference. Pandas is a Python software library for data processing and analysis. Pandas data manipulation is built on top of the NumPy library, which is a lower-level tool. Provides special data structures and operations for manipulating numerical tables and time series. Scikit-learn is one of the most widely used Python packages for Data Science and Machine Learning. It contains functions and algorithms for machine learning: classification, prediction, and grouping of data. Keras is an open-source library written in Python that provides interaction with artificial neural networks. It is an add-on for the TensorFlow framework. This library contains numerous implementations of commonly used building blocks of neural networks such as layers, objective and transfer functions, optimizers, and many tools to simplify working with images and text. Matplotlib is a Python programming language library for visualizing

data with two-dimensional (2D) graphics (3D graphics are also supported). Vmdpy Is a function for decomposing a signal according to the Variational Mode Decomposition method.

The training of all models took place over 100 epochs (the same number for all models is necessary for the possibility of adequate comparative analysis of their quality), because the error of each model has time to reach the plateau. To improve the quality of forecasting, many articles on this topic propose preliminary normalization of data in the range [0,1], which is also implemented in this study. When choosing an architecture, metrics are designed for normalized data, in other cases for output.

Choosing the right number of layers from the beginning is difficult or even impossible. The usual approach is to try different architectures and find out which one works best by trial and error. Then the architecture and performance of the model are tested and improved in a few iterations.

The market price of a stock can changes very rapidly. That is why "fresh" data are needed for more accurate forecasting. In this study, this was achieved by importing and downloading prices from the API. The invest library was used for this purpose. Due to this library, prices for the period from 01.01.2010 to the current date (12.02.2022) were obtained. **Figure 1** shows the results obtained for the CEEN share.

Date	Open	High	Low	Close	Volume	Currency
2012-01-05	8.55	8.57	8.40	8.44	216400	UAH
2012-01-06	8.47	8.47	8.30	8.34	119100	UAH
2012-01-10	8.37	8.59	8.37	8.50	159200	UAH
2012-01-11	8.50	8.51	8.33	8.33	176900	UAH
2012-01-12	8.40	8.47	8.24	8.32	254300	UAH
...	...	...	...	...	...	...
2016-01-26	4.36	4.42	4.30	4.39	39300	UAH
2016-01-27	4.30	4.37	4.30	4.37	36500	UAH
2016-01-28	4.40	4.44	4.24	4.29	84800	UAH
2016-01-29	4.35	4.37	4.34	4.37	28700	UAH
2016-02-01	4.37	4.37	4.34	4.37	5200	UAH

[1000 rows x 6 columns]

Figure 1: Historical data on the CEEN market price

This data can also be presented in the form of a graph (**Figure 2**).

Figure 2: Historical data on the market price of CEEN

In order to be able to test the models, the data set must be divided into two parts: 80% - data for training, and 20% - test data. To improve the work with the data, it was normalized with MinMaxScaler in the range from 0 to 1. Next, training data has been created, based on which the neural network should be trained. To do this, several slices of training data (x_train), the so-called mini-packages, were formed. In the learning process, the neural network sequentially processes the mini-packets and creates a separate forecast for each mini-package.

Neural networks learn in several iterations. The prediction error is reduced by regulating the strength of the connection between neurons (weight) according to a certain algorithm. The model needs a second list (y_train) to assess the quality of the forecast, which contains the actual price values. During training, the model compares forecasts with real data and calculates learning error to minimize it over time.

In order to comprehensively assess the forecast quality of each model, the following metrics will be calculated:

- MAE (Median Absolute Error) is a measure of errors between paired observations that express the same phenomenon;
- MAPE (Mean Absolute Percentage Error);
- MDAPE (Median Absolute Percentage Error).

MDAPE and MAPE are error rates used to evaluate machine learning regression models. The difference is that MDAPE returns the median value of all errors, while MAPE returns the average. MAPE is more sensitive to emissions than MDAPE.

4. Results of experiments and analysis

At the first stage of the research, the LSTM network was trained and forecasts for the months of 2022 for the market value of shares available on the Ukrainian Stock Exchange were obtained: CEEN - **Figure 3**; UTLM - **Figure 4**; KVBZ - **Figure 5**; BAVL - **Figure 6**.

Also, in these figures, the results of calculations of estimates for errors of forecasts of MAE, MAPE, MDAPE are given. In Figures 3 - 18, the predicted value of the shares is marked in orange, and the difference between the predicted value and the real value is highlighted in gray.

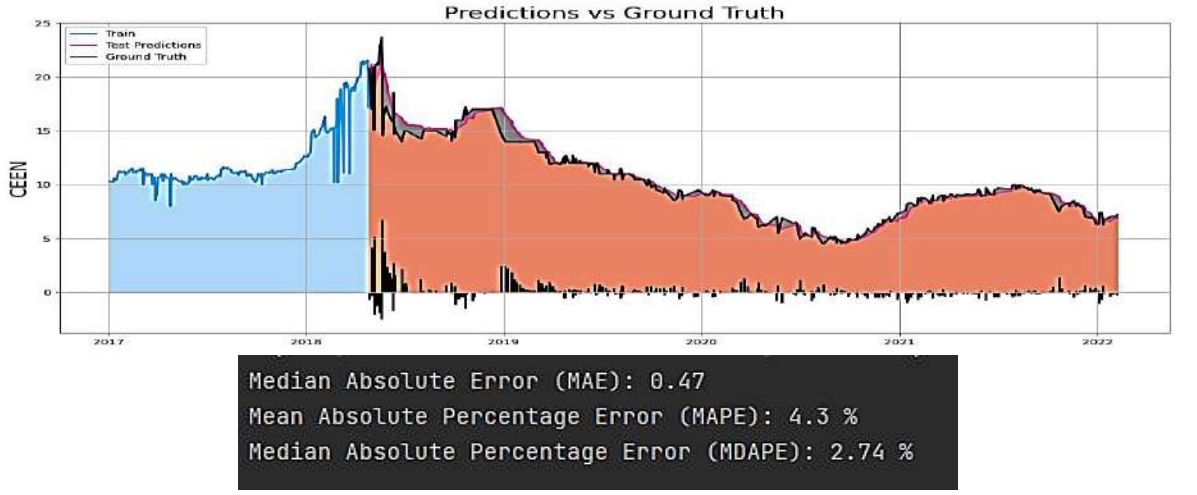


Figure 3: Forecasts of the market value of CEEN shares and assessments of the quality of the forecast on the LSTM network

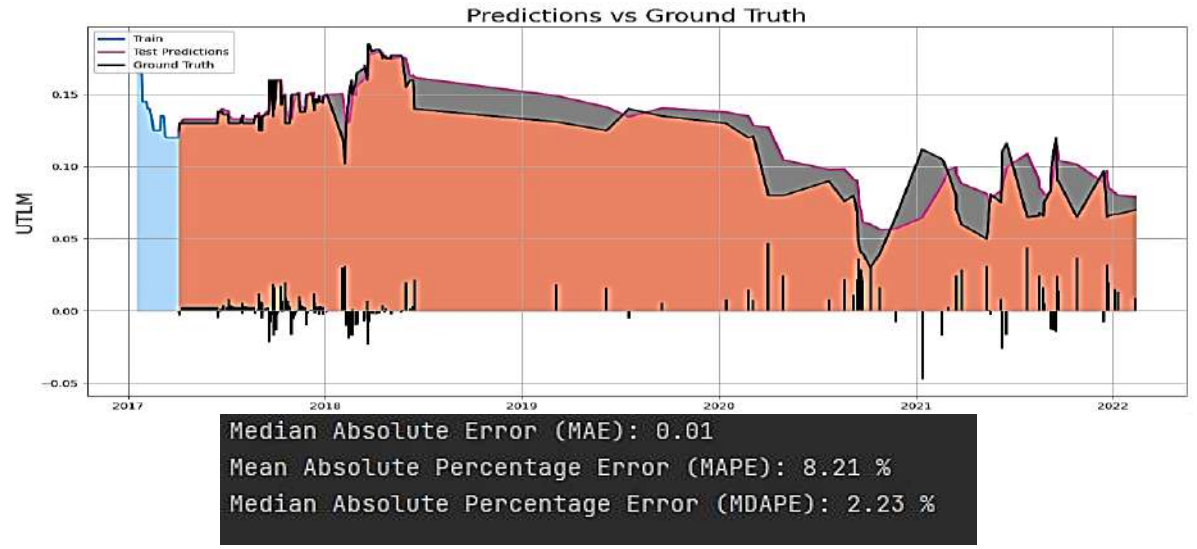


Figure 4: UTLM stock market value forecasts and LSTM forecast quality assessments

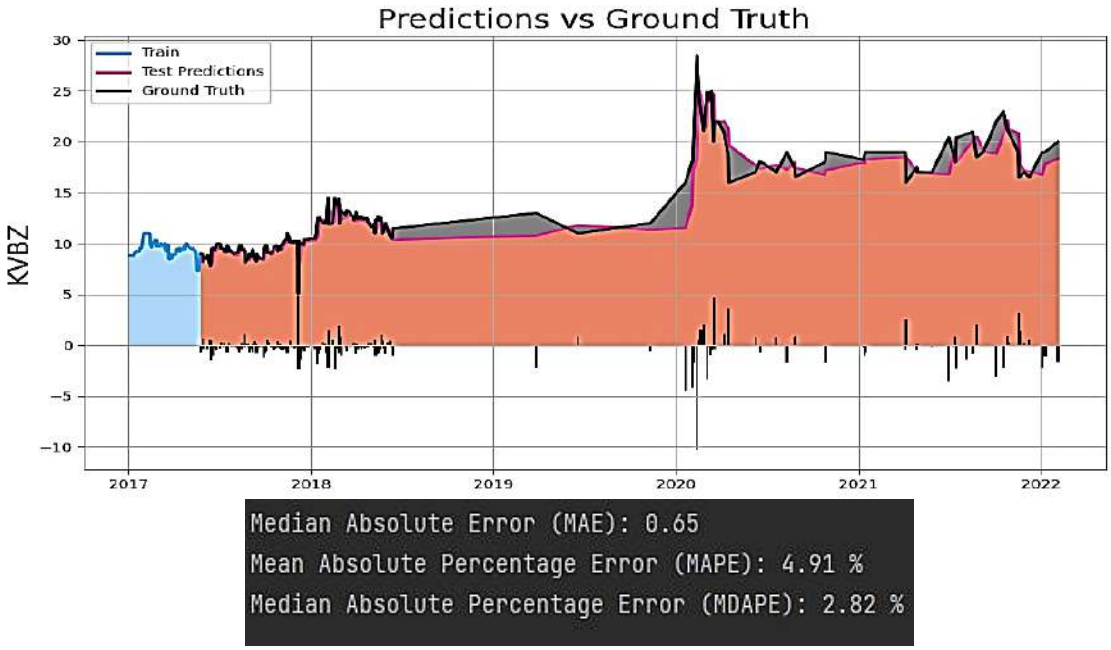


Figure 5: KVBZ stock market value forecasts and LSTM forecast quality assessments

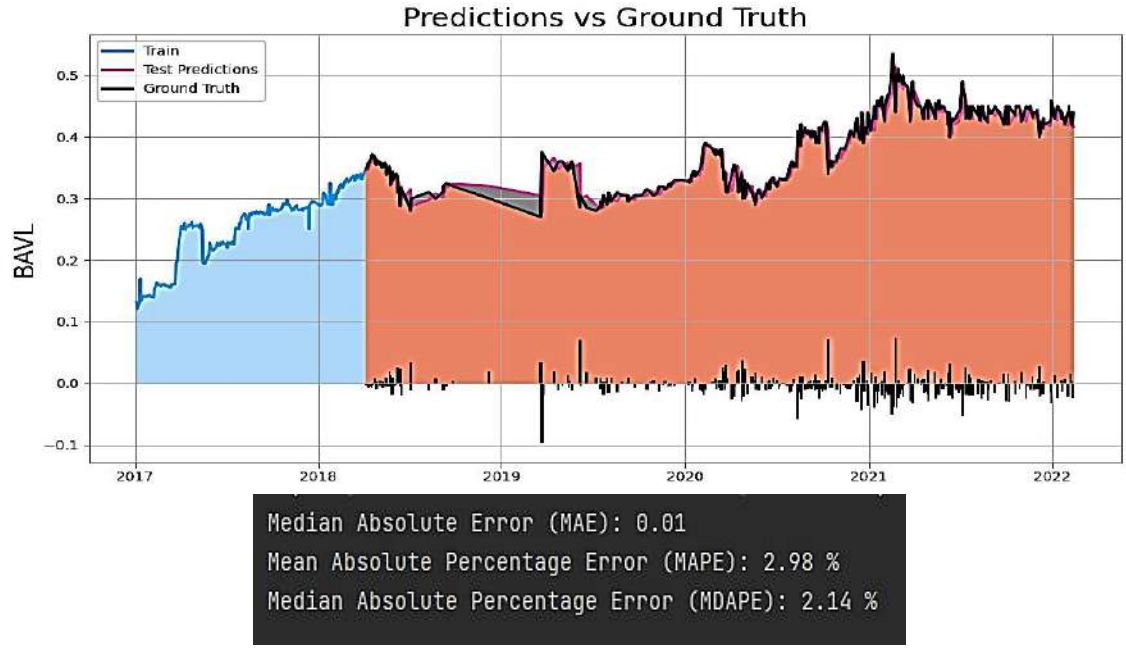


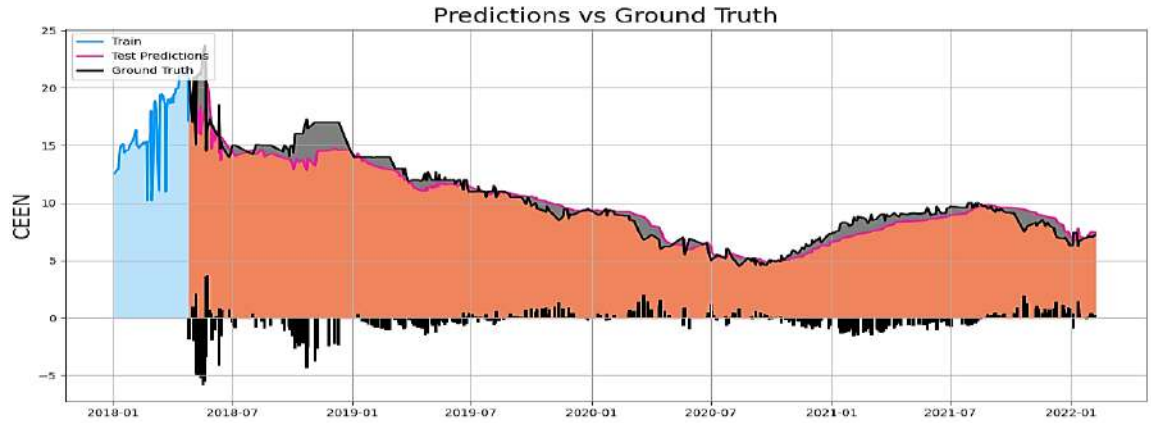
Figure 6: BAVL stock market value forecasts and LSTM forecast quality assessments

Figures 3-6 show that the LSTM network does not always accurately predict the price of shares, this is especially noticeable in the UTLM stock (Figure 4). Forecast data for UTLM and KVBZ indicates that it is impossible to apply this method in case of sharp and significant market fluctuations.

Therefore, this neural network is not advisable to be used for the Ukrainian stock market.

In the second stage of the study, the CNN network was trained and forecasts for the months of 2022 for the market value of shares were obtained:

CEEN - **Figure 7**;
UTLM – **Figure 8**;
KVBZ - **Figure 9**;
BAVL - **Figure 10**.




```
Median Absolute Error (MAE): 0.78
Mean Absolute Percentage Error (MAPE): 7.27 %
Median Absolute Percentage Error (MDAPE): 5.77 %
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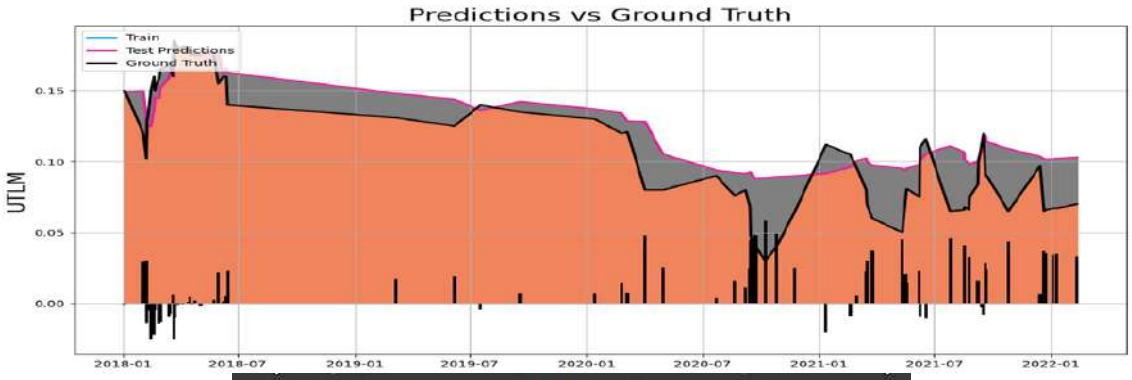
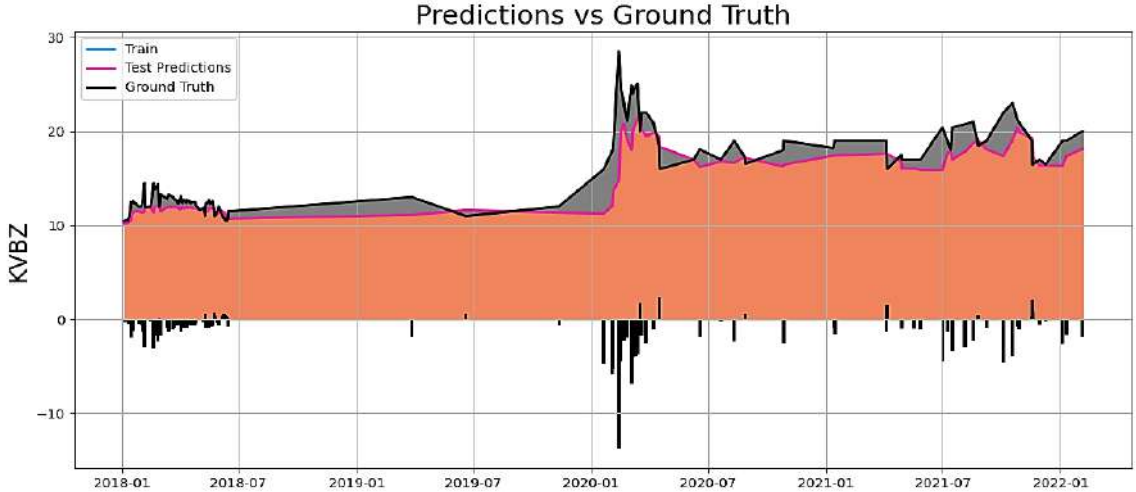
Figure 7: Forecasts of the market value for CEEN shares and estimates the quality of the forecast on the CNN network




```
Median Absolute Error (MAE): 0.01
Mean Absolute Percentage Error (MAPE): 11.52 %
Median Absolute Percentage Error (MDAPE): 3.29 %
```

Figure 8: UTLM stock market value forecasts and CNN forecast quality assessments

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Median Absolute Error (MAE): 0.83
Mean Absolute Percentage Error (MAPE): 5.74 %
Median Absolute Percentage Error (MDAPE): 3.47 %
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Figure 9: KVBZ stock market value forecasts and CNN forecast quality assessments

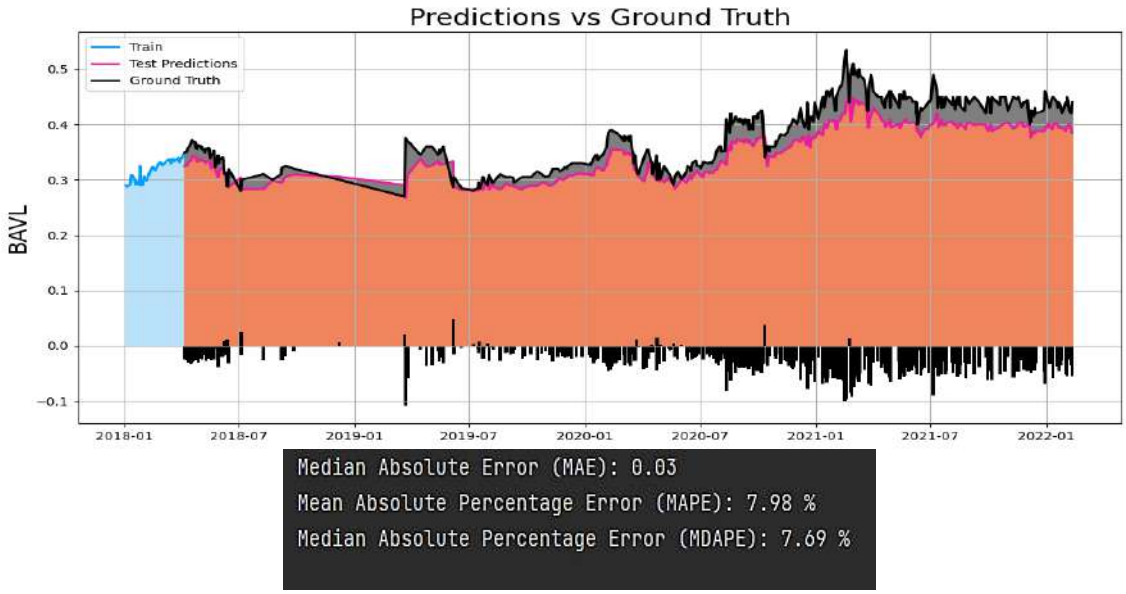


Figure 10: BAVL stock market value forecasts and CNN forecast quality assessments

As it can be observed the CNN network also showed not very good results, in Figure 8 it can be seen a big difference between the gray and orange zone (real and predicted data). CNN network has the same as LSTM weak side: in the case of sharp jumps both down and up, the forecast error increases greatly.

In the third stage of the study, the CNN-LSTM hybrid model network was trained and forecasts for the months of 2022 for the market value of shares were obtained:

CEEN - **Figure 11**;

UTLM - **Figure 12**;

KVBZ - **Figure 13**;

BAVL - **Figure 14**.

The hybrid network CNN-LSTM proved to be worse than CNN and LSTM separately. Significant forecast error exists even in the absence of sharp changes in the share price. MARE from 9.7 to 17.4 indicates the impossibility of using in real life and the high probability of financial losses due to a false forecast.

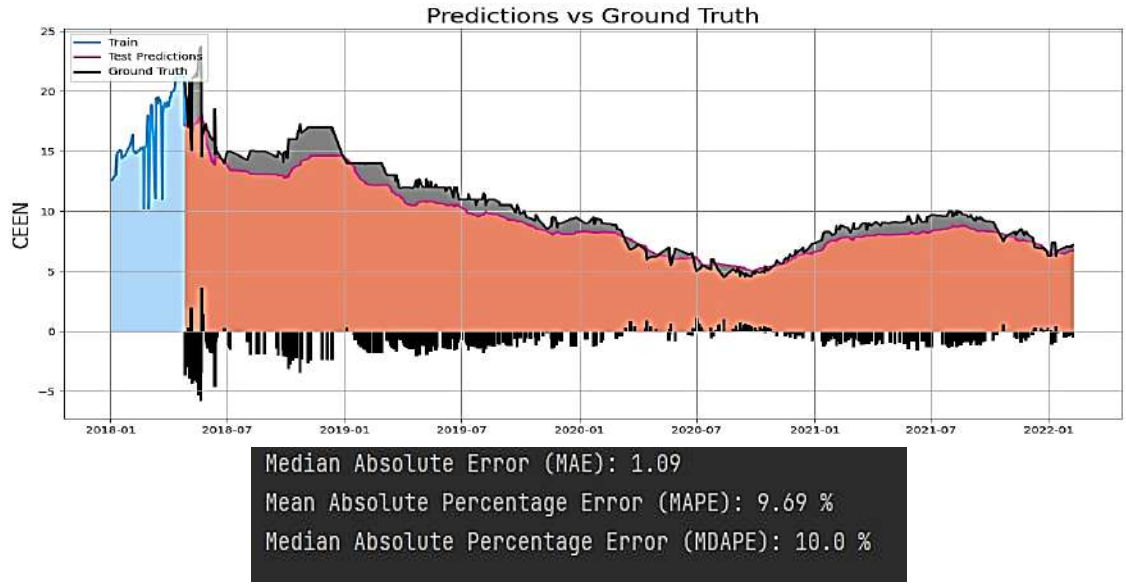
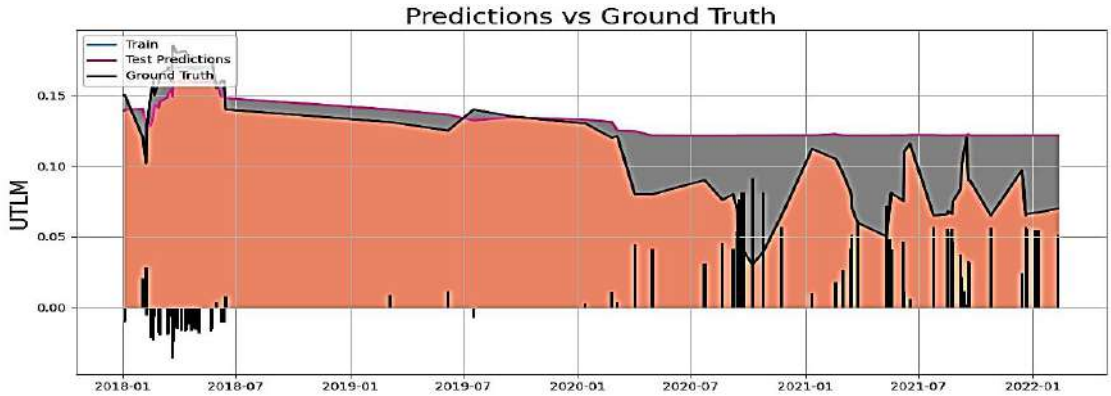


Figure 11: CEEN stock market value forecasts and CNN-LSTM hybrid forecast network quality assessments




```
Median Absolute Error (MAE): 0.01
Mean Absolute Percentage Error (MAPE): 17.41 %
Median Absolute Percentage Error (MDAPE): 3.96 %
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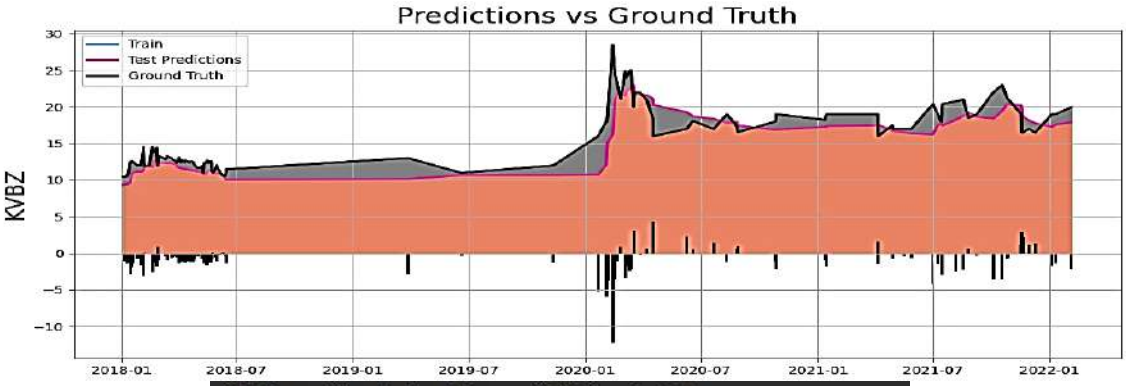
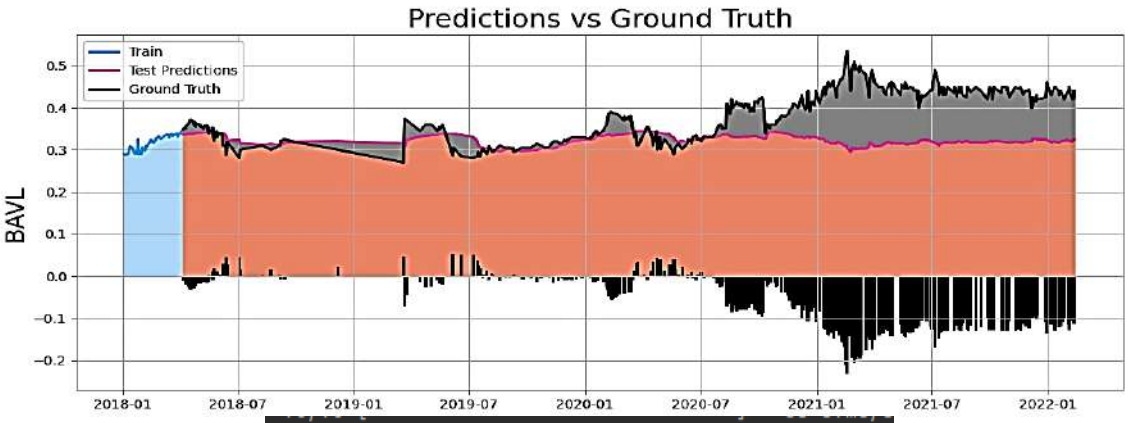
Figure 12: UTLM stock market value forecasts and CNN-LSTM hybrid forecast network quality estimates




```
Median Absolute Error (MAE): 1.25
Mean Absolute Percentage Error (MAPE): 10.37 %
Median Absolute Percentage Error (MDAPE): 9.8 %
```

Figure 13: KVBZ stock market value forecasts and CNN-LSTM hybrid forecast network quality assessments




```
Median Absolute Error (MAE): 0.07
Mean Absolute Percentage Error (MAPE): 15.51 %
Median Absolute Percentage Error (MDAPE): 14.44 %
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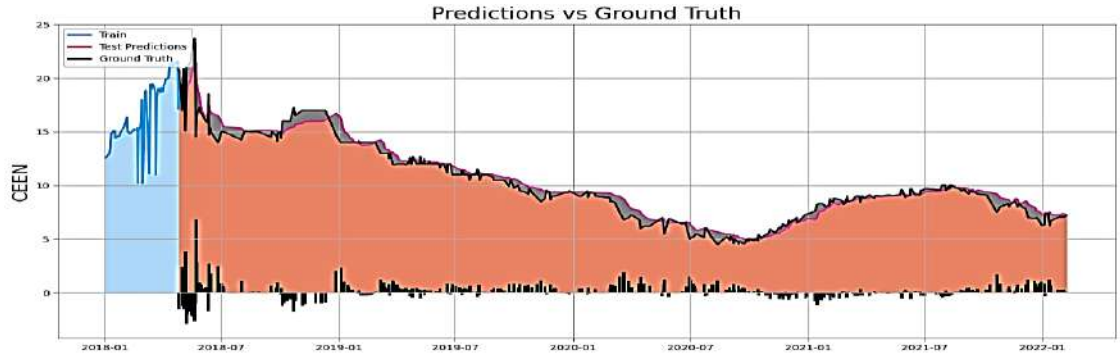
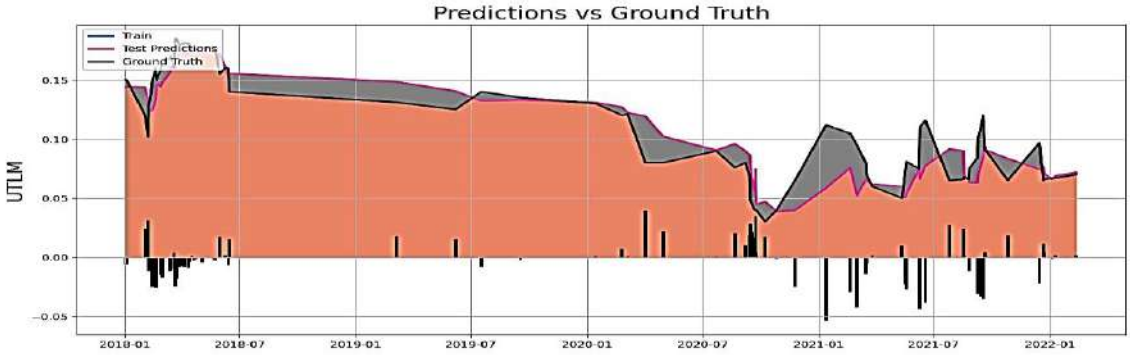
Figure 14: BAVL stock market value forecasts and CNN-LSTM hybrid forecast network quality assessments

At the fourth stage of the study, the network of the hybrid model VMD-LSTM was trained and forecasts for the months of 2022 for market value of shares were obtained: CEEN - **Figure 15**; UTLM - **Figure 16**; KVBZ - **Figure 17**; BAVL - **Figure 18**.



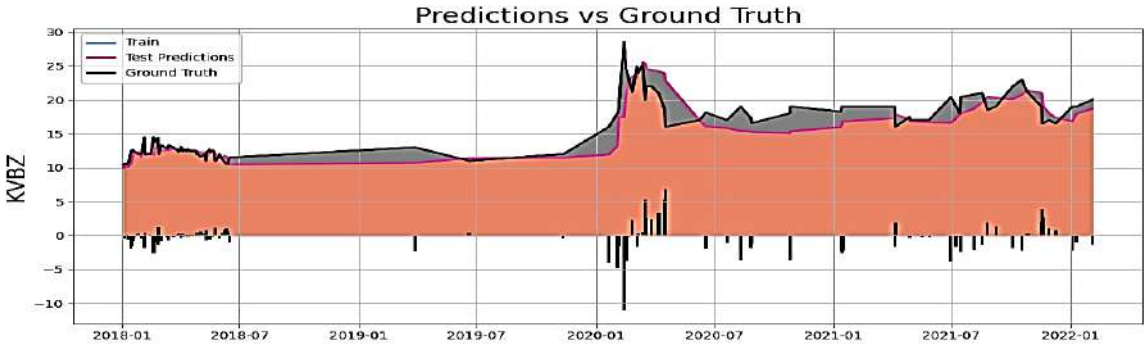

```
Median Absolute Error (MAE): 0.53
Mean Absolute Percentage Error (MAPE): 5.3 %
Median Absolute Percentage Error (MDAPE): 3.59 %
```

Figure 15: Forecast of market value of CEEN shares and assessment of forecast quality on the VMD-LSTM hybrid model network




```
Median Absolute Error (MAE): 0.01
Mean Absolute Percentage Error (MAPE): 8.87 %
Median Absolute Percentage Error (MDAPE): 4.65 %
```

Figure 16: UTLM stock market value forecasts and forecast quality assessments over the VMD-LSTM hybrid model network




```
Median Absolute Error (MAE): 0.8
Mean Absolute Percentage Error (MAPE): 5.86 %
Median Absolute Percentage Error (MDAPE): 3.94 %
```

Figure 17: KVBZ stock market value forecasts and forecast quality assessments over the VMD-LSTM hybrid model network

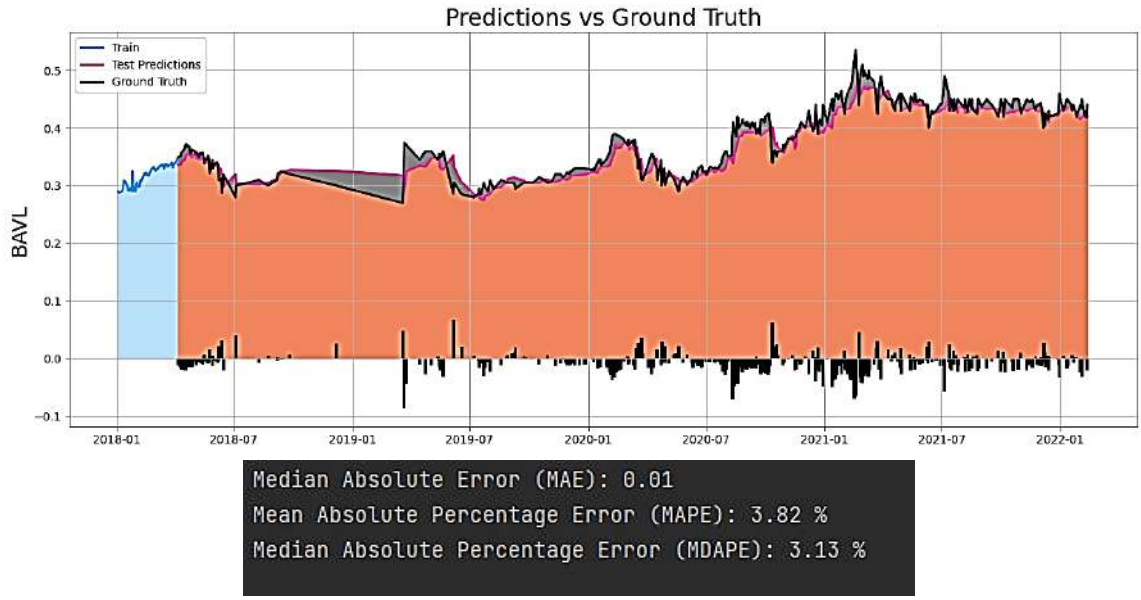


Figure 18: BAVL stock market value forecasts and forecast quality assessments over the VMD-LSTM hybrid network

Figures 15 and 18 show that the predicted cost is as close as possible to the real data. The low level of errors indicates the possibility of using this model in real conditions

Analyzing Figures 3 - 18, we can conclude that the most preferred network for the Ukrainian market is VMD-LSTM. It shows the smallest deviation of the predicted data from the real ones.

5. Conclusion and Future Work

Research of prospects and peculiarities of using the methods of forecasting the market value of shares developed in world practice in Ukraine, where stock markets are in the process of formation and development.

The analysis of scientific sources based on the results of research on modeling the behavior of stock market participants and solving the problem of forecasting using artificial neural networks are carried out.

The research was conducted on the use of neural networks of different architectures to forecast the market value of shares on the stock exchange of Ukraine. The following models of neural networks were chosen for experimental research: LSTM; CNN; a hybrid model that combines two neural network architectures CNN and LSTM; a hybrid model consisting of a classical machine learning algorithm and a neural network (VMD-LSTM). It was concluded that it is advisable to use an artificial neural network LSTM to predict selected stocks.

The task of predicting the market value of shares on the stock exchange of Ukraine is solved for planning the investment activity of a company in the strategic period [18]. Investment activity is considered from the point of view of the direction for company development [19].

The future research will focus on:

1. To continue research on the choice of neural network architecture for forecasting the market value of shares on the Ukrainian stock market.

2. Develop a software system for forecasting the market value of shares, which allowed the investor to forecast the value of shares and form investment portfolios.

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