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Evaluating the Effectiveness of Deep Learning Models in Financial Time Series Analysis

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Abstract

In recent years, critical global events such as the enduring impact of the COVID-19 pandemic and the Ukraine war have raised questions among specialists about countries' capability to navigate economic challenges properly. The resulting volatility observed in financial markets has directed researchers to explore new predictive models, with a particular emphasis on Deep Learning models known for their capacity in handling uncertainty and outliers. In this research, three distinct Deep Learning models were applied to study the indices of Central and Eastern European Union (EU) countries: Bulgaria (SOFIX), Croatia (CROBEX), Czech Republic (PX), Estonia (Tallinn), Hungary (BUX), Latvia (Riga), Lithuania (Vilnius), Poland (WIG), Romania (BET), Slovakia (SAX) and Slovenia (SBITOP). The analysis is based on daily data collected from November 23, 2017 to November 23, 2022. The findings indicate that all three models successfully captured the data patterns within a relatively low number of epochs. Furthermore, the chosen evaluation metrics, including Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error, yielded comparable results across all the models. This study underscores the significance of advanced predictive modeling, particularly Deep Learning, in the context of capital market analysis, especially during times of economic uncertainty.

Keywords: stock markets, deep learning models, COVID-19 pandemic, Ukraine war, CEEC economies.
Jel codes: C55, E17, E44

1. Introduction

The development of a country's capital market and its importance for the sustainability of its economic growth represents a major area of interest in the economic literature. The health crisis set off in 2020 by the COVID-19 virus and the events generated by the Ukraine war have led to increased concerns regarding the world countries to overcome the current economic crisis and to ensure a sustainable economic growth. The present economic global context accentuated the economic uncertainty while the application of modern data analysis techniques to develop more effective prediction models is an important topic not only for academics but also for the business environment and policymakers.

The transition process to the market economy started in the '90s by the Central and East European countries has generated major structural changes, because of the privatization measures of state companies, of the liberalization of prices, of financial sectors and capital markets. Considering their adherence to the European Union, these countries had to reduce the economic gaps compared to the developed countries while in the 2000s, the CEE countries registered high rates of economic growth, they attracted significant international investments and offered highly attractive stock market returns (Syriopoulos, 2014).

The 2008 economic crisis highlighted the economic vulnerability of the CEE countries and more recently, the COVID-19 sanitary crisis and the energetic crisis triggered in 2022 have emphasized the uncertainty regarding the capacity of these countries to face the new global challenges. Thus, the analysis of stock markets for the Central and East European countries and identification of high-performance prediction models during such a great economic uncertainty represents a focal topic in the current economic and social context. For these countries, an important objective of the economic policy is the insurance of the real convergence with the developed countries and their financial integration.

In this paper, we study the indices for the stock markets from eleven countries, members of European Union, namely Bulgaria (SOFIX), Croatia (CROBEX), Czech Republic (PX), Estonia (Tallinn), Hungary (BUX), Latvia (Riga), Lithuania (Vilnius), Poland (WIG), Romania (BET), Slovakia (SAX) and Slovenia (SBITOP) using daily data from 23.11.2017 to 23.11.2022. In this respect, we developed three different deep learning models. The first model consists of Dense layers (Tishby and Zaslavsky, 2015; Tishby et al., 1999; Larochelle et al., 2009), the second model is formed of Long Short-Term Memory layers (Hochreiter and Schmidhuber, 1997) and Dense layers and the third one contains Bidirectional Long Short-Term Memory, Long Short-Term Memory and Dense layers. To assess the performance of these models we used the Mean Absolute Error, the Mean Squared Error and the Root Mean Squared Error. The empirical research on the financial series was predominantly ruled by the estimation of GARCH models (*Generalized Autoregressive Conditional Heteroskedasticity*) (Engle, 1982; Bollerslev, 1986). The application of deep learning methods for the financial series analysis is relatively recent and their use is justified by their high prediction performance.

At the time of this study, we have not found any other investigations in the literature on the stock markets for the CEE countries using deep learning models which should describe the unprecedented current period generated by the COVID-19 sanitary crisis, the energy crisis and the Ukraine war.

The paper is structured as follows: in Section 2, we present a survey of the literature on the importance of stock markets for the economic development and on the methods applied for the prediction. Section 3 describes the data and the methodology that was used for the estimation of the models for stock markets indices. In Section 4, we present the empirical analysis for the 11 CEE countries members of European Union, while the last section presents the main conclusions.

2. Literature review

The importance of stock markets for the economic growth and development of a country represents a matter of interest for both academics and policymakers. The development of stock markets can stimulate the information about firms (Levine, 2004) and a larger and more liquid market has a positive implication for capital allocation (Merton, 1987; Grossman and Stiglitz, 1980; Kyle, 984; Holmstrom and Tirole, 1993). The imperfections of the capital markets can also influence growth by impeding investment in human capital, which implies a suboptimal allocation of resources (Galor and Zeira, 1993).

The importance of the development of stock markets was highlighted in other studies due to its influence on fostering corporate governance (Jensen and Meckling, 1976) which has a positive impact on the firm performance with effect on the national growth rate (Stiglitz and Weiss, 1983; Fama and Jensen, 1983 a, b).

The influence of the financial development on growth effects was underlined by Greenwood-Jovanovic (1990) who proved that the rate of return on investment will be higher in a financially developed economy. The financial system offers the investors an "idiosyncratic risk insurance", convincing them in this way to engage in higher return but also riskier portfolios. Additionally, this system is more transparent about the different investment projects, helping the investors to better manage their funds. In the same direction, Mankiw, Romer and Weil (1992) studied the influence of the financial development for level effects, while Atje and Jovanovic (1993) found that the stock market development affects both, the level and the growth rate of economic activity.

The Central and Eastern European countries underwent in the 90s major structural reforms for the transition to the market economy, by adopting market liberalization measures and privatization of state companies. The development of stock markets was a major objective of the economic policy in light of their adherence to the European Union and their economic and financial integration was seen as an important factor to ensure their economic growth.

The first stock exchange from the CEE countries was open in Budapest (Budapest Stock Exchange) in 1990, followed by Warsaw Stock Exchange, open in 1991. The CEE stock markets developed continuously, both from the point of view of market capitalization and of the daily trade volume.

The financial crisis set off in 2008 highlighted the instability of the financial system in the CEE countries which affects the financial integration, deepening the economic gaps between more and less developed EU countries. The degree of financial integration of CEE countries affects the economic efficiency (Albulescu, 2011) even if its benefits resulting from international risk sharing have a positive potential welfare gain for all these countries (Demyanyk and Volosovych, 2008).

Cappiello et al. (2006a) assess the degree of financial integration of a selected number of new EU member states (Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Poland and Slovenia), among themselves and with the euro area. They found that these countries experienced different degrees of integration and different speeds of convergence with the euro zone; the largest new member states from CEE countries (the Czech Republic, Hungary and Poland) registered strong comovements both between themselves and with the euro area while the smaller countries experienced a very low degree of integration between themselves. Syllignakis and Kouretas (2006) analyze the short- and long-term relationships between seven Central Eastern European (CEE) stock markets and two developed stock markets (German market and the US market). They found that five stock markets in central Europe (Czech Republic, Hungary, Poland, Slovenia and Slovakia) have a significant common permanent component with the German and the US stock markets, while the Estonian and Romanian markets are segmented.

Using multivariate GARCH models, Horvath and Petrovski (2013) showed that the degree of stock market integration of Central Europe (the Czech Republic, Hungary and Poland) with the Western Europe is much higher than integration of South Eastern Europe (Croatia, Macedonia and Serbia).

Peša et al. (2017) in their study made for two groups of emerging countries from CEE (Central and Eastern Europe) and SEE (South East Europe) countries proved that there is a positive impact of capital inflows and industrial production in these countries. By applying an ARDL panel estimates they confirm the hypothesis of procyclicality of stock exchanges regarding the economic activity of CEE and SEE countries.

The empirical research on the CEE stock markets was focused in studying its dynamics, volatilities, and linkages and comovements with other mature markets. These studies mainly use the vector autoregression or the vector error correction modeling to examine linkages and comovements between different emerging and developed stock markets and GARCH (*Generalized Autoregressive Conditional Heteroskedasticity*) models to assess dynamic stock market risk-return properties, time-varying correlations and volatility transmissions (Syriopoulos, 2014). The CCC model (Engle, 1982; Bollerslev, 1986), the DCC model (Engle, 2002), and the ADCC model (Cappiello et al., 2006b) were the most popular multivariate GARCH models (Bauwens et al., 2006).

The recent development of deep learning models which describe a machine learning technique determined their use in the study of financial series to build an effective prediction model.

Zhan et al. (2018) combine the time convolution with Long Short-Term Memory (LSTM) and propose a novel deep learning model named Time Convolution Long Short-Term Memory (TC-LSTM) networks. Using two real market datasets they proved that the proposed model outperforms other three baseline models in the mean square error.

The deep learning models which are convolutional neural networks, recurrent neural networks, and deep belief networks (Zhang et al., 2021) stood out compared to the linear or machine learning models, presenting a better ability of modelling nonlinear relationships between the inputs and target variable in the context of big data (Jiang, 2021).

3. Data & Methodology

Section „Data & Methodology” consists of 2 main subsections. In the first subsection, we briefly introduce the dataset. Also, herein, we discuss about the preprocessing steps we have applied upon the initial dataset. Regarding the second section, it summarizes the methodology based on which the paper grounds up.

3.1. Data

The data in this paper consists of the daily closing prices of eleven indices from the following countries: Bulgaria (SOFIX), Croatia (CROBEX), Czech Republic (PX), Estonia (Tallinn), Hungary (BUX), Latvia (Riga), Lithuania (Vilnius), Poland (WIG), Romania (BET), Slovakia (SAX) and Slovenia (SBITOP). Our data set was downloaded from https://www.investing.com/ and covers a period of 5 years from 23.11.2017 to 23.11.2022.

To avoid over-fitting during training process, the last 20% of the data set is separated as a validation set. Thus, the training set consists of the first 80% of the entire sample which contains approximately 985 observations[1], while the remaining 20% with approximately 239 observations is used as the validation set. More details are provided in the table below.

Table 1. Sub-datasets description

country	**index**	**training set size (number of observations)**	**validation set size (number of observations)**	**training set (period covered)**	**validation set (period covered)**
Bulgaria	SOFIX	975	237	23.11.2017 – 19.11.2021	22.11.2021 – 23.11.2022
Croatia	CROBEX	983	239	23.11.2017 – 23.11.2021	24.11.2021 – 23.11.2022
Czech	PX	990	241	23.11.2017 – 24.11.2021	25.11.2021 – 23.11.2022
Estonia	Tallinn	993	241	23.11.2017 – 25.11.2021	26.11.2021 – 23.11.2022
Hungary	BUX	984	239	23.11.2017 – 25.11.2021	26.11.2021 – 23.11.2022
Latvia	Riga	985	239	23.11.2017 – 26.11.2021	29.11.2021 – 23.11.2022
Lithuania	Vilnius	983	239	23.11.2017 – 23.11.2021	24.11.2021 – 23.11.2022
Poland	WIG	988	240	23.11.2017 – 24.11.2021	25.11.2021 – 23.11.2022
Romania	BET	988	240	23.11.2017 – 23.11.2021	24.11.2021 – 23.11.2022
Slovakia	SAX	984	239	23.11.2017 – 23.11.2021	24.11.2021 – 23.11.2022
Slovenia	SBITOP	986	239	23.11.2017 – 25.11.2021	26.11.2021 – 23.11.2022

Source: own contribution

[1] Each observation contains past 10 days closing prices and next day closing price

Both training and validation set are normalized. Transforming raw data before fitting the machine learning models often enhances the performance. Therefore, we decided to normalize the data. In this paper, we have chosen min-max normalization. Min-max scaling shrinks the data within the given range, usually of 0 to 1. It is important to mention that the shape of the original time series does not change.

3.2. Methodology

This section aim to present the methods that reside behind the 3 models developed. In the first part of the section, we present the method based on which we developed the first model, namely neural network. Going further, we describe recurrent neural network, the special type of neural network behind the second model. Finally, we detail the bidirectional recurrent neural network, the ground of the third model.

Neural network, also known as artificial neural network (ANN) or simulated neural network (SNN), represent a method used often in Deep Learning. The name and structure are inspired from human anatomy, mimicking the way biological neurons transmit signals to each other. The fundamental unit of a neural network is the "neuron". Analogous to a biological neuron, an artificial neuron is a computational unit that can receive input, process it, and propagate it further in the network.

The first model is composed of 4 Dense layers[2] (dense, dense_1, dense_2 and dense_3). First and third layer contains 8 neurons each. Regarding the second layer, it contains 16 neurons. Finally, the last layer is formed of 1 neuron. As activation function[3], we used Rectified Linear Unit Function (RELU) for the first 3 Dense layers. As to the optimizer[4] and loss function, we have chosen Adam[5] and Mean Absolute Error. It is worth mentioning that optimizer and loss function was the same for all the 3 models.

A Recurrent Neural Network (RNN) is a special type of neural network adapted to work with data involving sequences (for example, time series). In contrast, feed-forward neural networks can be used for time series, but they are intended for datasets containing records that are independent of each other. However, if the data is sequential so that record i depends on record i-1, it is preffered to consider the dependencies between these records. RNNs include the concept of "memory" which helps them to store states/information from previous inputs (t_{i-n}, …, t_{i-2}, t_{i-1}) to generate the next output of the sequence (t_i).

The second model is formed of two Long Short-Term Memory (LSTM) layers (lstm, lstm_1) and 2 Dense layers (dense, dense_1). LSTM layer is a type of RNN layer. Compared to traditional RNN layers, LSTM can control memory over time and the flow of information into and out of the layer through the use of three "gates", the input, output, and forget gates (Hochreiter and Schmidhuber, 1997).

For sequential data, so far we have assumed that the main objective is to model the next output (t_i) given the previous context (t_{i-n}, …, t_{i-2}, t_{i-1}) traversed in one direction (from left to right). Although this is a typical scenario, it is not the only one we may encounter. It is important to note that a model that is not able to take advantage of the previous context (t_{i-n}, …, t_{i-2}, t_{i-1}) traversed in two directions (from left to right and from right to left) will perform poorly.

Bidirectional Recurrent Neural Networks (BiRNNs/BRNNs) were created in 1997 by Schuster and Paliwal to increase the amount of input information available for the network: "To overcome the limitations of a regular RNN […] we propose a bidirectional recurrent neural network (BRNN) that can be trained using all available input information in the past and future of a specific time frame. […] The idea is to split the state neurons of a regular RNN in a part that is responsible for the positive time direction (forward states) and a part for the negative time direction (backward states)" (Schuster and Paliwal, 1997). Shortly, bidirectional recurrent neural networks connect two hidden layers of opposite directions at the same output layer. Thus, the output layer obtains information from past and future states simultaneously.

The third model is composed of 1 Bidirectional LSTM layer (bidirectional), 1 LSTM layer (lstm_1) and 2 Dense layers (dense, dense_1). Similar to the other 2 models, the last layer is formed of 1 neuron. From complexity point of view, this model is the most complex.

[2] A dense layer is a layer that is deeply connected with its preceding layer which means the neurons of the layer are connected to every neuron of its preceding layer

[3] In neural networks, the activation function is a function that is used for the transformation of the input values of neurons. Basically, it introduces the non-linearity into the networks of neural networks so that the networks can learn the relationship between the input and output values

[4] Optimizers are algorithms or methods used to change the attributes of the neural network such as weights and learning rate to reduce the losses

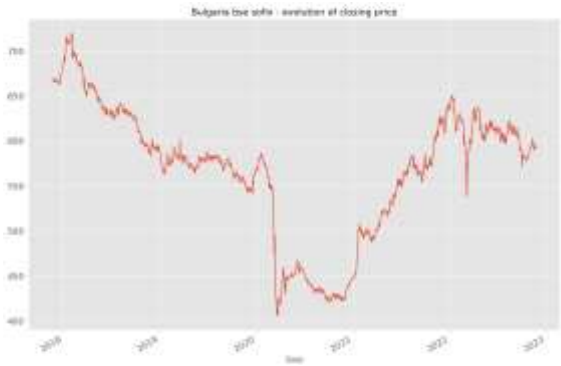
[5] The Adam optimization algorithm is an extension to stochastic gradient descent that has recently seen broader adoption for deep learning applications in computer vision and natural language processing

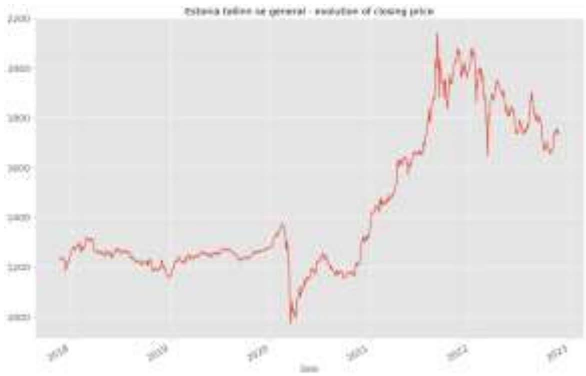
4. Empirical results

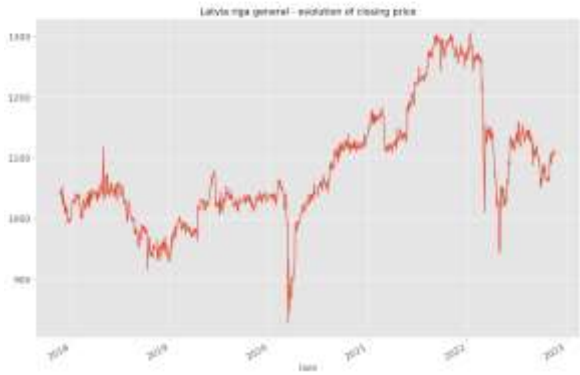
Section „Empirical results” consists of 4 subsections. In the first subsection, we describe the dataset. In subsection 2, we attempt to present the structure of three different Deep Learning models. Further, in subsection 3, a validation analysis is conducted to highlight the performance of developed models. Finally, we report the results obtained in the inference process.

4.1. Dataset description

The data used in this paper is composed of a main dataset which, at his turn, contains eleven sub-datasets, one for each index. Below you can find the evolution of closing prices for all the eleven indices (from 23.11.2017 to 23.11.2022). Thus, these graphs cover both training and validation sets. It is important to mention that the closing prices are expressed in different currencies depending on the country.







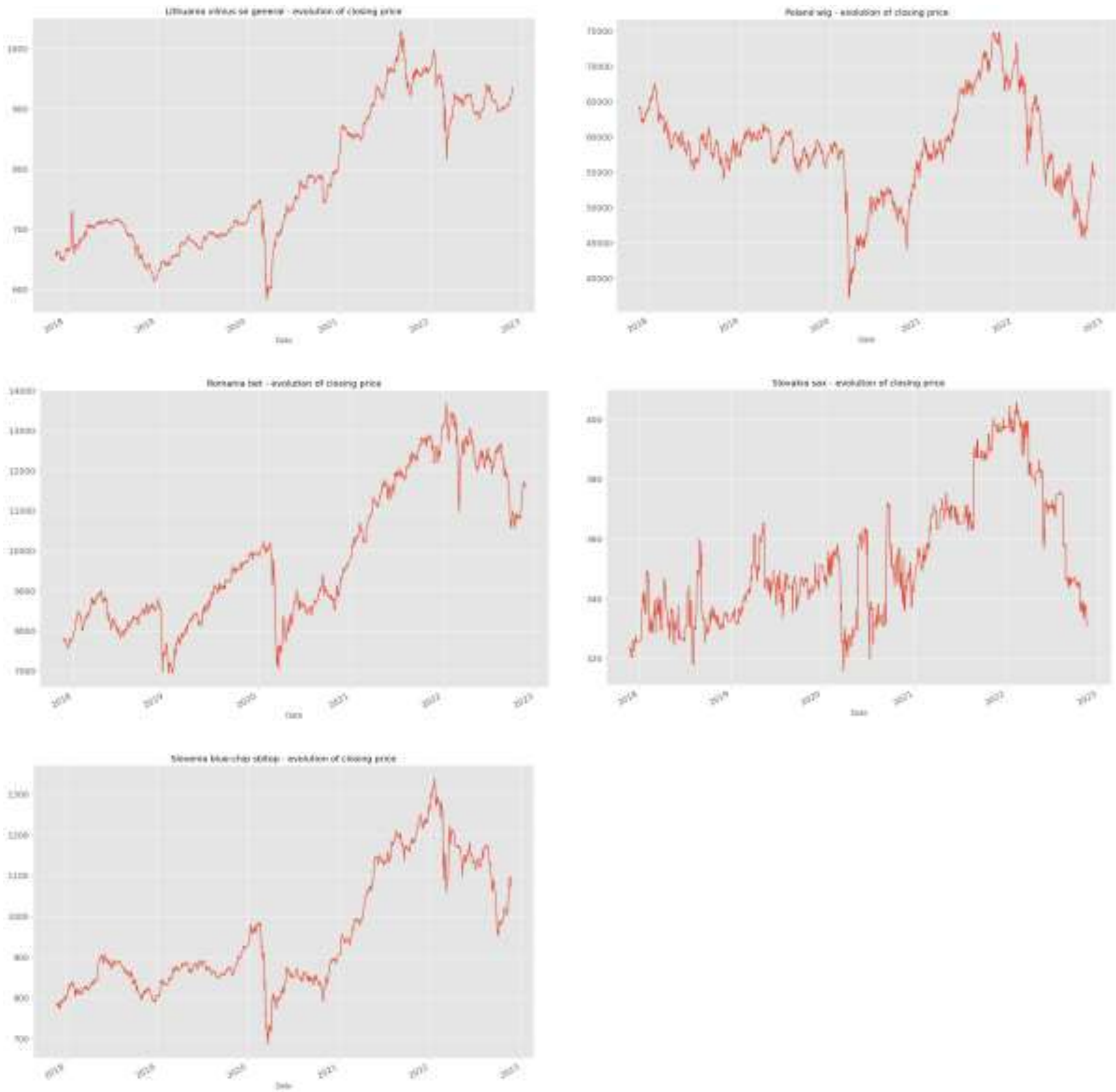


Figure 1. Evolution of closing prices (SOFIX, CROBEX, PX, Tallinn, BUX, Riga, Vilnius, WIG, BET, SAX, SBITOP)

Source: own contribution

Based on the graphs presented above we can conclude that the majority of the indices have a clear upward trend in the long term. This suggests that the time series are not stationary. In addition, we can clearly notice that all the indices suffered at the beginning of 2020. In 2020, COVID-19 swept the world and changed various aspects of human society, such as economy and finance, life and health, migration and population. According to the government statistics and reliable data, during COVID-19 pandemic, thousands of stores and companies were closed or went bankrupt, causing numerous people to lose their jobs. Another interesting fact is related to the 2022 – 2023 period. In this time frame, all the indices have a clear downward trend. This descending trend is caused by different factors such as energy crisis and Ukraine war.

4.2. Models presentation

The empirical analysis undertaken in this study has the scope of highlighting the capability of advanced predictive models to perform during unstable periods from economical point of view. In that respect, we developed three different Deep Learning models. The first model consists of Dense layers. Regarding the second model, it is formed of Long Short-Term Memory layers, but also of Dense layers. Finally, last model contains Bidirectional Long Short-Term Memory, Long Short-Term Memory and Dense layers. Detailed structures are presented further in Table 2.

Table 2. Models description

Model name	Layer name	Layer type	Output shape	Number of parameters
model 1	dense	Dense	(None, 8)	88
model 1	dense_1	Dense	(None, 16)	144
model 1	dense_2	Dense	(None, 8)	136
model 1	dense_3	Dense	(None, 1)	9
model 2	lstm	LSTM	(None, 10, 25)	2700
model 2	lstm_1	LSTM	(None, 25)	5100
model 2	dense	Dense	(None, 25)	650
model 2	dense_1	Dense	(None, 1)	26
model 3	bidirectional	Bidirectional LSTM	(None, 10, 50)	5400
model 3	lstm_1	LSTM	(None, 25)	7600
model 3	dense	Dense	(None, 25)	650
model 3	dense_1	Dense	(None, 1)	26

Source: own contribution

As can be seen, the first model has the fewest parameters – 377 parameters (88 + 144 + 136 + 9), and the last model has the most – 13676 parameters (5400 + 7600 + 650 + 26). The number of parameters had a direct influence on the training process. The higher number of parameters led to longer training times. Finally, compared to the second and third model, first model is the least complex.

4.3. Models validation

Given the fact that the main dataset contains 11 sub-datasets, one for each index, we applied the three models for all the 11 sub-datasets. Thus, in the end, we ended with a total number of 33 models. Table nr. 3 summarizes the results obtained on the validation set.

Table 3. Metrics results on validation

	MAE (model 1)	MAE (model 2)	MAE (model 3)	MSE (model 1)	MSE (model 2)	MSE (model 3)	RMSE (model 1)	RMSE (model 2)	RMSE (model 3)
Bulgaria (SOFIX)	0.0241	0.027	0.026	0.0011	0.0014	0.0012	0.0336	0.0375	0.0341
Croatia (CROBEX)	0.0229	0.0299	0.0249	0.001	0.0018	0.0012	0.0312	0.0421	0.0348
Czech (PX)	0.0201	0.0309	0.0261	0.0008	0.0016	0.0011	0.0274	0.0404	0.0336
Estonia (Tallinn)	0.0237	0.028	0.0233	0.001	0.0014	0.001	0.0322	0.0372	0.0314
Hungary (BUX)	0.034	0.0437	0.0332	0.0021	0.0038	0.0021	0.0455	0.062	0.0463
Latvia (Riga)	0.0295	0.0414	0.038	0.002	0.0042	0.0033	0.0443	0.0647	0.0572
Lithuania (Vilnius)	0.0126	0.024	0.022	0.0004	0.0012	0.001	0.019	0.0353	0.0312
Poland (WIG)	0.0395	0.0411	0.0344	0.0027	0.0029	0.0021	0.0518	0.054	0.0454
Romania (BET)	0.0323	0.0359	0.0317	0.0018	0.0024	0.0019	0.043	0.0494	0.0435
Slovakia (SAX)	0.0238	0.0325	0.028	0.0014	0.0023	0.0019	0.0376	0.0475	0.0439
Slovenia (SBITOP)	0.0263	0.0341	0.0263	0.0013	0.0024	0.0015	0.0363	0.0489	0.0386

Source: own contribution

For the comparison purposes, we used three different metrics. MAE, which stands for mean absolute error. MSE, which stands for mean squared error and RMSE, which stands for root mean squared error. It is worth mentioning that the normalized values were used for computing the metrics.

Based on the results, all the 33 models are accurate since validation metrics are all low. By comparing MAE (model 1), MAE (model 2) and MAE (model 3), we can affirm that most of the indices are best forecasted with model 1 (6 out of 11 indices). Indices: Tallinn, BUX, WIG, BET are best forecasted with model 3. Regarding SBITOP, the corresponding MAE is the same for both model 1 and model 3.

4.4. Predictions analysis

This section aims to highlight the results obtained by applying the models on the validation sets. As such, below we attach a series of comparative graphs (real prices vs. predicted prices).


Bulgaria bse sofix - real prices vs predicted prices (2021-12-08 00:00:00 - 2022-11-23 00:00:00)
y_real
y_pred_model_1
y_pred_model_2
y_pred_model_3
Price
Date


Croatia crobex - real prices vs predicted prices (2021-12-08 00:00:00 - 2022-11-23 00:00:00)
y_real
y_pred_model_1
y_pred_model_2
y_pred_model_3
Price
Date


Czech republic px - real prices vs predicted prices (2021-12-09 00:00:00 - 2022-11-23 00:00:00)
y_real
y_pred_model_1
y_pred_model_2
y_pred_model_3
Price
Date


Estonia tallinn se general - real prices vs predicted prices (2021-12-10 00:00:00 - 2022-11-23 00:00:00)
y_real
y_pred_model_1
y_pred_model_2
y_pred_model_3
Price
Date


Hungary budapest se - real prices vs predicted prices (2021-12-10 00:00:00 - 2022-11-23 00:00:00)
y_real
y_pred_model_1
y_pred_model_2
y_pred_model_3
Price
Date


Latvia riga general - real prices vs predicted prices (2021-12-13 00:00:00 - 2022-11-23 00:00:00)
y_real
y_pred_model_1
y_pred_model_2
y_pred_model_3
Price
Date


Lithuania vilnius se general - real prices vs predicted prices (2021-12-08 00:00:00 - 2022-11-23 00:00:00)
y_real
y_pred_model_1
y_pred_model_2
y_pred_model_3
Price
Date


Poland wig - real prices vs predicted prices (2021-12-09 00:00:00 - 2022-11-23 00:00:00)
y_real
y_pred_model_1
y_pred_model_2
y_pred_model_3
Price
Date

Figure 2. Real prices vs. predicted prices (validation sub-datasets)

Source: own contribution

As we can observe, all the models were capable to predict the closing prices with a high precision. These graphs confirm that, even if spikes are present (the periods right after March 2022 and the ones after September 2022), the Deep Learning models can handle the uncertainty and generate accurate predictions.

5. Conclusions

In this paper, we developed three different Deep Learning models and applied them on 11 sub-datasets containing the indices: SOFIX, CROBEX, PX, Tallinn, BUX, Riga, Vilnius, WIG, BET, SAX and SBITOP. The first model consists of Dense layers. Regarding the second model, it is formed of Long Short-Term Memory layers, but also of Dense layers. Finally, last model contains Bidirectional Long Short-Term Memory, Long Short-Term Memory and Dense layers. The results proved that Deep Learning models can handle the uncertainty and generate accurate predictions, even if crises are present. The evaluation metrics showed the approaches to be promising, mean absolute errors, mean squared errors and root mean squared errors being very low on validation sub-datasets.

For further research, we plan to improve models from performance point of view and extend the dataset size. Firstly, we can increase the number of epochs. At this moment, we train all the models for 10 epochs. Besides number of epochs, we can tune multiple hyperparameters, such as: number of units, batch size, activation function. Secondly, we should try to develop a model that include 2 Bidirectional LSTM layers. Lastly, we would like to extend the dataset size in order to be able to split it up into 3 parts: train, validation and test.

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