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DEEP LEARNING ALGORITHM FORECASTING THE UNEMPLOYMENT RATES IN THE CENTRAL EUROPEAN COUNTRIES

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Abstract. The aim of this paper is to forecast the monthly unemployment rate's time series using deep learning algorithms. Based on data from five Central European countries, we tested the forecasting performance of the 'conventional' Box–Jenkins methodology in comparison with three deep learning models: the CNN (Convolutional Neural Network), the MLP (Multilayer Perceptron) and the random forest algorithm. The MAPE, MAE, RRMSE, and MSE error tests were used for testing the forecasting results. In our results, the ARIMA model was outperformed by one of the deep learning algorithms in all cases. The medium-term predictions suggest that in the Central European area, unemployment will remain relatively high in the future.

Keywords*: unemployment, forecasting, machine learning, random forest, multilayer perceptron.*

JEL Classification: E24, E27, C53

INTRODUCTION

An important topic in economic research is the unemployment rate forecasting. The purpose of this article is to compare the forecasting performance of the 'conventional' ARIMA models with the machine learning algorithms and then, to estimate time-series predictions. In this paper the following machine learning techniques are used: the CNN (Convolutional Neural Network), the Multilayer Perceptron (MLP) and the random forest algorithms. The evaluation of the used models' performance precedes the forecasting of the five Central European countries unemployment rate.

The research question of this paper is whether the machine learning algorithms show more accurate forecasting capabilities than the Box–Jenkins methodology for the examined data and represent a realistic alternative to the unemployment rate forecasting methodologies.

All calculations of this paper were performed in a Python environment (using the Pandas, Numpy, Matplotlib, Math, Statsmodels, Arch and Keras libraries).

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1. LITERATURE REVIEW

The unemployment rate forecasting time series models in economic literature, has initially appeared in Montgomery et al. (1998) and Proietti (2003) nonlinear vs. linear approach, while autoregressive models in Floros (2005) and Kurita (2010). In the forecasting literature, the Box–Jenkins methodology occupies a significant place, often compared with other models in Mahipan et al. (2013), Dritsak (2016), Dritsakis and Klazoglou (2018), and Davidescu and Paul (2021).

The European unemployment rate forecasting uses different methodological approaches, including ARIMA, ANN, and deep learning techniques, in Katris (2020), Celbiş (2023), and Gogas et al. (2022).

The Artificial Neural Network (ANN) methodologies represent a preferable approach to time series forecasting for the panel regression or Box–Jenkins methodology, as Longhi et al. (2005), Fernandes et al. (2008), Flores et al. (2012), Katris (2020), Davidescu and Paul (2021), and Yamacli and Yamacli (2023) suggest. Similarly, the results of the NAR model forecasting proved to be more similar to real values compared to the results of the ARIMA model in Madaras (2018). There exist combined models, for example, ANN–ARIMA hybrid model for unemployment rate forecasting in Chakraborty et al. (2021), although the MLP–ARIMA hybrid model outperforms the ANN–ARIMA models in Khashei and Hajirahimi (2019).

Deep learning algorithms were used in different fields of unemployment predictions. In Tilo et al. (2023), the forecast refers to South Africa's unemployment rate prediction, using feature selection techniques on a large-scale database; Kütük and Güloglu (2019) predicted the job entrance probabilities for unemployed persons using deep learning algorithms for classification; and Kunaschk and Lang (2022) predicted the probability of becoming long-term unemployed under the COVID-19 circumstances; while Gogas et al. (2022) predicted the monthly European unemployment based on three deep learning algorithms, and Yamacli and Yamacli (2023) the Turkish unemployment rate under the COVID-19 uncertainties.

Sezer et al. (2020) provided a literature review of machine learning techniques used in financial time series forecasting, while Mirete-Ferrer et al. (2022) offered a comprehensive review of this topic for asset management.

The CNN (Convolutional Neural Network) algorithm is generally used for classification and deep learning image processing (Zhang et al., 2018). The core of this neuron network is represented by the convolutional layers, which contain a set of filters, used as tensors for the output (Lecun et al., 1998). The CNN algorithm was used for unemployment rate forecasting, with moderate results in Nhose et al. (2023). Although the improved versions of the CNN algorithm have also been proven to be effective for forecasting, in this article the basic model is used. An updated version of the CNN algorithm, the CNN–LSTM model, where the convolutional layers are followed by the LSTM network, provided a good forecasting performance for car sales prediction in Ou-Yang et al. (2022). Similarly, the CNN and LSTM combined model was used for house price forecasting (Ge, 2019).

In the case of the feedforward Multilayer Perceptron (MLP) algorithm, between the input of time series' observations and output of forecasts, the network contains an arbitrary number of neurons in the hidden layers (Brownlee, 2018, pp. 4, 54, 257) As other machine learning algorithms, the MLP model, also was used for time series forecasting in different areas. 15-input layer including robust MLP network forecasting for the monthly electricity demand proved to be more appropriate than other ANN time series models in Comert and Yildiz, (2021). In Ncibi and Gasm (2022), the American stock market index, and in Borghi et al. (2021), the COVID-19 cases time series, were predicted using the MLP algorithm, while a hybrid MLP model was used in Khashei and Hajirahimi (2019) for stock forecasting and in Li et al. (2022), for credit risk assessment estimation.

The core of the random forest algorithm constitutes a multiple decision tree, which is independently trained (Athey and Imbens, 2019; Yoon, 2021; Breiman, 2001). Cervelló-Royo and Guijarro (2020) have performed a NASDAQ index-based forecasting performance comparison for deep learning techniques. Their results suggest that the random forest algorithm outperforms the GBM (Gradient Boosting Machines) algorithm and the GLM (Generalized Linear Model) for this particular case. The random forest algorithm was used by Haq et al. (2021) for stock market variables feature selection in a deep generative model and the stock market price index forecasting compared with other models by Patel et al. (2015). There exist combined models; for example, Moon et al. (2018) developed MLP – a random forest hybrid model.

The random forest algorithm was used for stock market predictions by Nabipour et al. (2020), for the euro area unemployment rate forecasting by Gogas et al. (2022), for the U.S. unemployment rate during the COVID-19 circumstances by Zhao and Hou (2022), for rural European unemployment forecasting by Celbiş (2023) and Gogas et al. (2022), for the oil price forecasting, based on a long period time series by Gupta et al. (2022). In Yoon (2021), the random forest algorithm predicted correctly the GDP growth, and in Weinblat (2018), based on European firms' organizational and financial variables, their probabilities of becoming highly growing firms were also appropriately predicted.

Summarizing the machine learning algorithms used in time series forecasting, there is a debate regarding the performance of these models, in some cases compared to the Box–Jenkins methodology, as in Katris (2020), Davidescu and Paul (2021), and Yamacli and Yamacli (2023). Including different economic and financial time series, the machine learning techniques represent useful alternatives. Kunaschk and Lang (2022) indicate that the random forest performance is higher than those of logistic regression, as well as Cervelló-Royo and Guijarro (2020) proved to be better, and in Gogas et al. (2022), this algorithm performs better than the decision trees and supports vector machines and deep learning algorithms. While Choudhary et al. (2022) suggest that the conventional ARIMA models have better performance than the MLP, CNN and LSTM deep learning algorithms. Therefore, in this regard, there is no consensus in the literature, and the prediction possibilities differ depending on the examined cases.

2. UNEMPLOYMENT IN CENTRAL EUROPEAN COUNTRIES

The actuality of unemployment rate forecasting and analysis is given by the new economic situation, starting from 2020, with the COVID-19 lockdowns and measures, followed by those consequences on the labour market. Being in the same geographic area, the five Central European countries have faced similar economic challenges (pandemic restrictions, growing unemployment, etc.), but they also have different economies and labour markets. Therefore, the unemployment rate evolved differently in the 2020–2022 period. The database used for estimations contains the monthly unemployment rate in Czechia, Hungary, Poland, Romania, and Slovakia between January 2010 and August 2022. One could notice that a growing tendency has started in all countries from 2020, after a long decreasing period (Fig. 1).

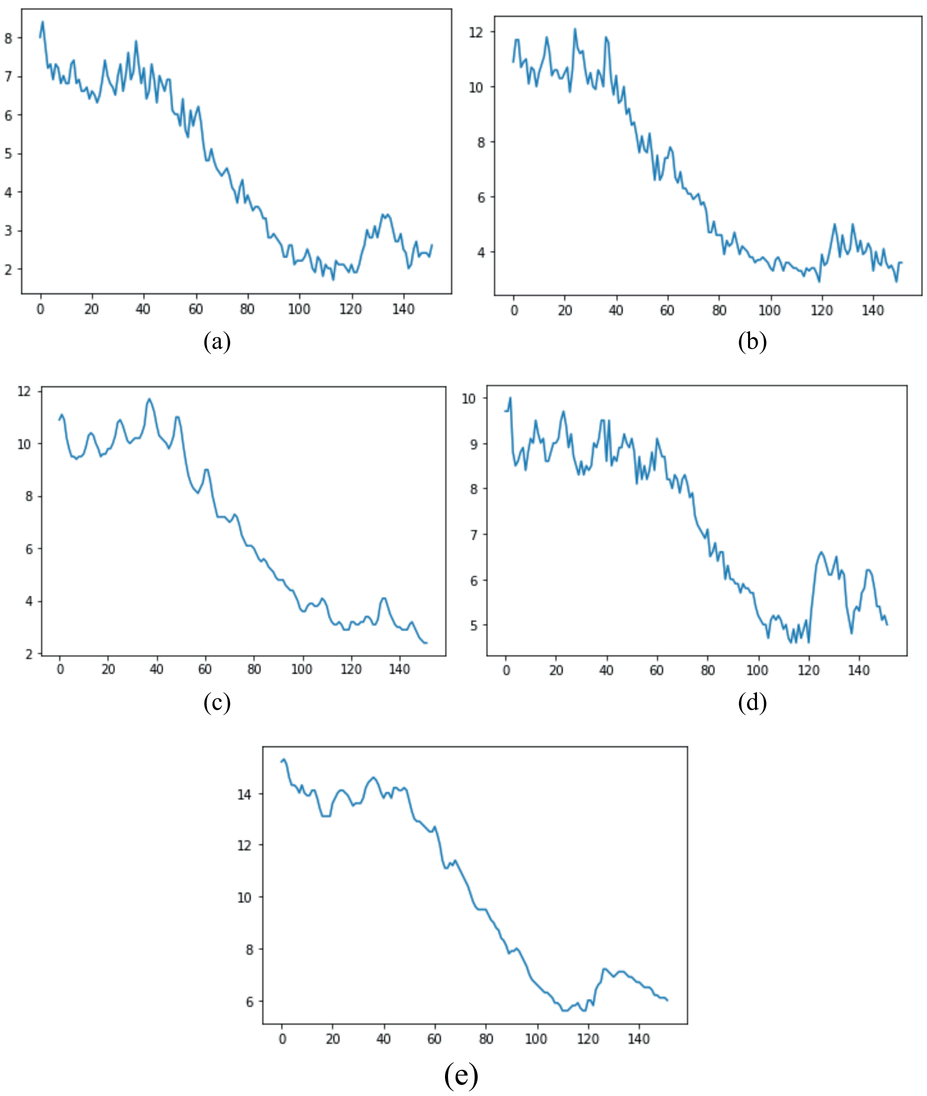


Fig. 1. The unemployment rate in Czechia (a), Hungary (b), Poland (c), Romania (d), and Slovakia (e) between January 2010 and August 2022 (EUROSTAT).

In the examined period, the maximum values of the unemployment rate were registered in February 2010 in Czechia, January 2012 in Hungary, February 2013 in Poland, March 2010 in Romania, and February 2010 in Slovakia (Fig. 1, Table 2).

Table 2. The Summary Statistics of Unemployment Rates (the author's calculation; EUROSTAT)

Countries	Mean	Median	Max.	Min.	Std. Dev.	Obs.
Czechia	4.52	4.10	8.40	1.70	2.06	152
Hungary	6.52	5.30	12.10	2.90	3.01	152
Poland	6.69	6.40	11.70	2.40	3.05	152
Romania	7.23	7.30	10.00	4.60	1.63	152
Slovakia	10.12	9.70	15.30	5.60	3.38	152

3. THE ARIMA METHODOLOGY ESTIMATION

As discussed above, the monthly unemployment rate and time series are frequently forecasted using the Box–Jenkins methodology, which is presented in detail in Tsay (2005).

The results of the ADF statistics fail to reject the null non-stationarity for all of the original unemployment rates. The PP and KPSS test results indicate the same. The first differenced series stationarity is confirmed by the ADF test in Czechia, Hungary, and Romania, as well as by the PP and KPSS tests in all five cases (Table 3).

Table 3. Univariate Unit Root Tests (the author's calculation; EUROSTAT)

Countries	Original time series			First Differences		
	ADF	PP	KPSS	ADF	PP	KPSS
Czechia	–1.027	–1.219	1.557***	–12.120***	–14.476***	0.108
Hungary	–1.137	–1.086	1.558***	–13.875***	–17.210***	0.133
Poland	–0.669	–0.515	1.593***	–2.631*	–5.424***	0.206
Romania	–0.706	–1.258	1.490***	–3.782***	–15.276***	0.072
Slovakia	–1.298	–0.909	1.574***	–2.216	–9.241***	0.187

*** significance level 0.01; ** significance level 0.05; * significance level 0.1.

The following ACF and PACF tests were used for the AR's p and MA's q values specification (Fig. 2).

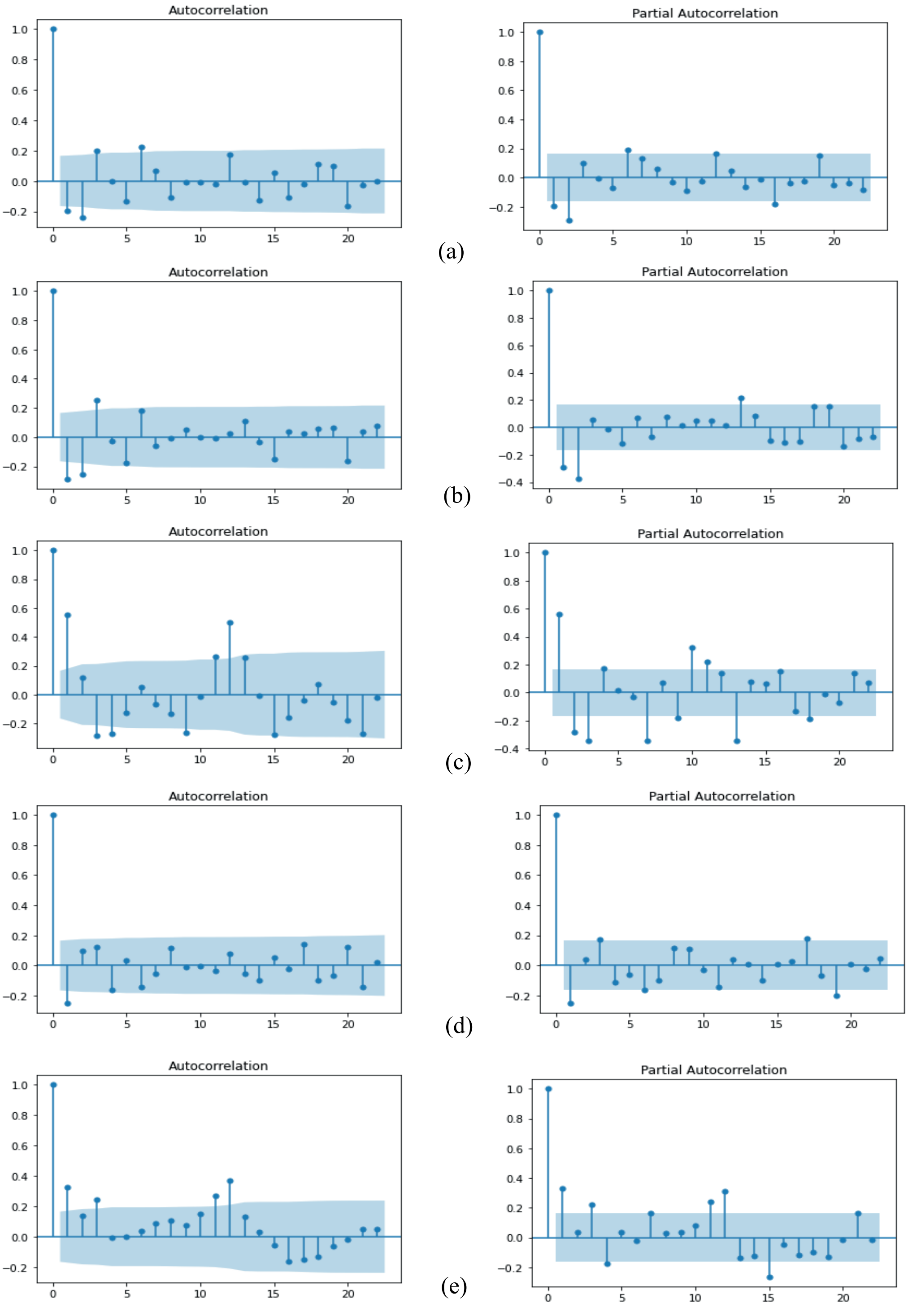


Fig. 2. The autocorrelation and partial-autocorrelation tests results for the first differenced unemployment rate time series in Czechia (a), Hungary (b), Poland (c), Romania (d), and Slovakia (e) (the author's calculation; EUROSTAT).

The autocorrelation and partial-autocorrelation tests results indicate the *p* and *q* coefficient values for the unemployment rate ARIMA(*p,d,q*) models. The results suggest ARIMA (1,1,1) processes for Czech Republic, Hungary, Romania, and Slovakia, respectively ARIMA (2,1,2) model for Poland (Fig. 2). But the best-fitting models were identified using the AIC (Akaike Information Criteria). Based on the AIC test results, these are ARIMA (2,1,2) model in Czech Republic, Hungary and Romania, ARIMA (3,1,2) in Poland, respectively ARIMA (2,2,3) in Slovakia (Table 3).

Table 3. AIC (Akaike Information Criteria) Tests for the ARIMA Models (the author's calculation; EUROSTAT)

Country	Model	AIC
Czechia	ARIMA(1,1,1)	84.651
	ARIMA(2,1,1)	62.330
	ARIMA(2,1,2)	61.748
	ARIMA(3,1,2)	66.329
	ARIMA(2,1,3)	63.357
Hungary	ARIMA(2,1,2)	180.187
	ARIMA(3,1,2)	183.984
	ARIMA(2,1,3)	181.936
Poland	ARIMA(2,1,2)	–86.754
	ARIMA(3,1,2)	–75.970
	ARIMA(2,1,3)	–88.539
Romania	ARIMA(1,1,1)	88.821
	ARIMA(2,1,1)	90.105
	ARIMA(2,1,2)	76.657
	ARIMA(3,1,2)	85.687
Slovakia	ARIMA(1,2,1)	–75.300
	ARIMA(2,2,2)	–71.281
	ARIMA(2,2,1)	–73.307
	ARIMA(3,2,2)	–71.710
	ARIMA(2,2,3)	–71.083

4. DATA PREPARATION FOR THE DEEP LEARNING ALGORITHMS, THE NEURON NETWORK SPECIFICATION AND THE TRAINING PROCESS

A six-step flowchart was set up for deep learning algorithms' forecasting, with selected models according to Breiman (2001) and Brownlee (2018). In the first two steps, the time series database was loaded in the Python environment and divided into training and test parts (Fig. 3).

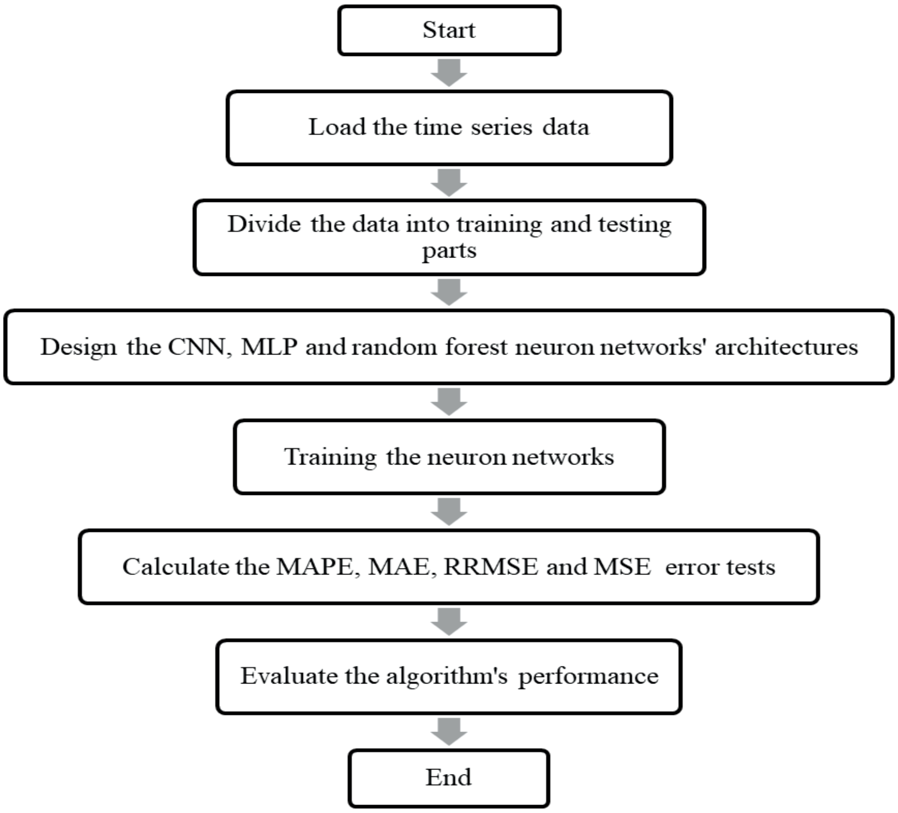


Fig. 3. The flowchart for the deep learning algorithms' forecasting (developed by the author).

The unemployment rates of each country used for the deep learning forecasting were prepared for the MLP and CNN neuron networks' training. The time series was shaped into three-dimensional samples for training and one-dimensional output for testing, as Brownlee (2018, p. 54) suggests, which means a $t = 3$ delay. As a demonstrative example, the first five values of the Czech unemployment rate are presented, where input values of January, February and March were used to predict the value of April, and so on (Table 4).

Table 4. Univariate Unit Root Tests (the author's calculation; EUROSTAT)

Original time series		**Training data sample**			
Date	Unemployment rate	Input time steps			Output time steps
2010-01	8.0	8.0	8.4	7.8	7.2
2010-02	8.4	8.4	7.8	7.2	7.3
2010-03	7.8	7.8	7.2	7.3	6.9
2010-04	7.2	7.2	7.3	6.9	7.3
2010-05	7.3	7.3	6.9	7.3	7.2
…	…	…	…	…	…

The input of the random forest algorithm is a one-dimensional vector.

The third step includes customizing the architecture for the CNN, MLP, and random forest networks. The CNN algorithm's neuron network contained in order the input sequence, the one-dimensional convolution layer with 64 filters, followed by the hidden layer with 50 neurons and a second hidden layer with one neuron (Brownlee, 2018) (Fig. 4).

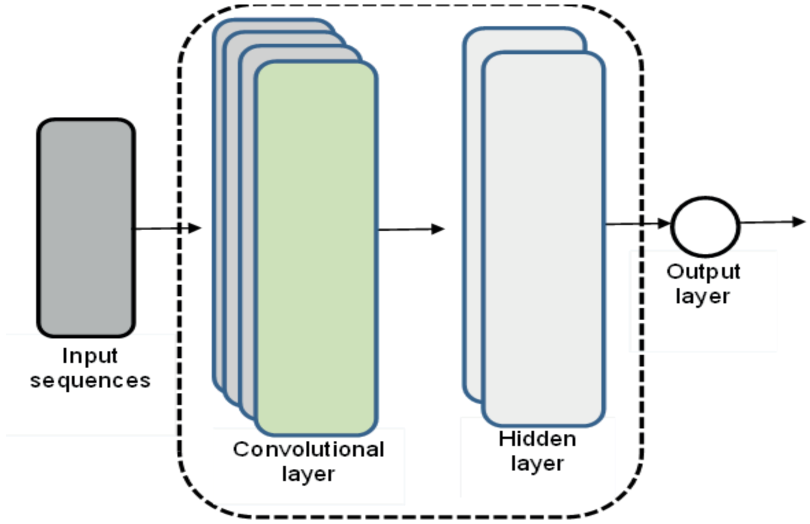


Fig. 4. The network structure of the CNN (Convolutional Neural Network) algorithm (created by the author).

The MLP algorithm's network structure was specified according to Brownlee (2018), using three input nodes, one hidden layer with 100 neurons and one output in free-forward mode (Fig. 5).

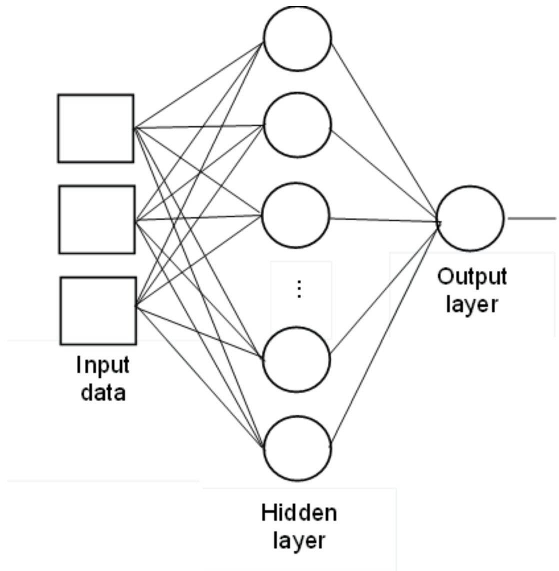


Fig. 5. The network structure of the MLP (Multilayer Perceptron) algorithm (created by the author).

The above-constructed models were trained using the training data sample for a 2000 epoch set, using the ReLu activation function.

The third deep learning model of the estimations was the original version of the random forest algorithm specified according to Breiman (2001) and set up for time series forecasting as Tyralis & Papacharalampous (2017) suggest. The regression three of the random forest algorithm are growing with the selection and estimation of one from a set of variables, which are randomly independent among each other. Therefore, the algorithm made one-step forecasting for the time series (Tyralis & Papacharalampous, 2017).

There are different approaches regarding the number of trees in the random forest. Probst & Boulesteix (2017) set it to 100 trees and Tyralis & Papacharalampous (2017) to 500 trees, but for our calculations, in this paper, the authors have set up 1000 trees, as proposed by Kuhn and Johnson (2013, p. 200).

5. FORECASTING'S PERFORMANCE ANALYSIS

The ARIMA models specified in the first part, respectively the CNN, MLP and random forest algorithms were used for a performance analysis. The forecast errors were tested using the real unemployment rate values for a t = 10 period (monthly data from November 2021 to August 2022). The following error tests were used: the mean absolute percentage error (MAPE), mean absolute error (MAE), relative root mean square error (RRMSE), and mean squared error (MSE) tests, as suggested by Matloff (2017), Moon et al. (2018), Nabipour et al. (2020), and Mirete-Ferrer et al. (2022) (Table 5).

Each error test contains, in a different manner of calculation, the following main components: n represents the number of observations; x_t is the actual value; and f_t is the forecasting value. The equation of the mean absolute percentage error (MAPE) refers to the accuracy of predictions.

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{x_t - f_t}{x_t}\right| \qquad (1)$$

The mean absolute error (MAE) estimates the closeness of forecasts related to actual values using the following equation.

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|f_t - x_t\right| \qquad (2)$$

The relative root mean square error (RRMSE) is the standard deviation of the forecasting errors, and the equation contains the normalized sum of squared errors.

$$\text{RRMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\frac{x_t - f_t}{x_t}\right)^2} \qquad (3)$$

The mean squared error (MSE) measures the predictors' quality, and the equation contains the squares of the x_t actual value and f_t forecasting values.

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n}\left(x_t - f_t\right)^2 \tag{4}$$

Table 5. Error Tests of the Models (the Author's Calculation; EUROSTAT)

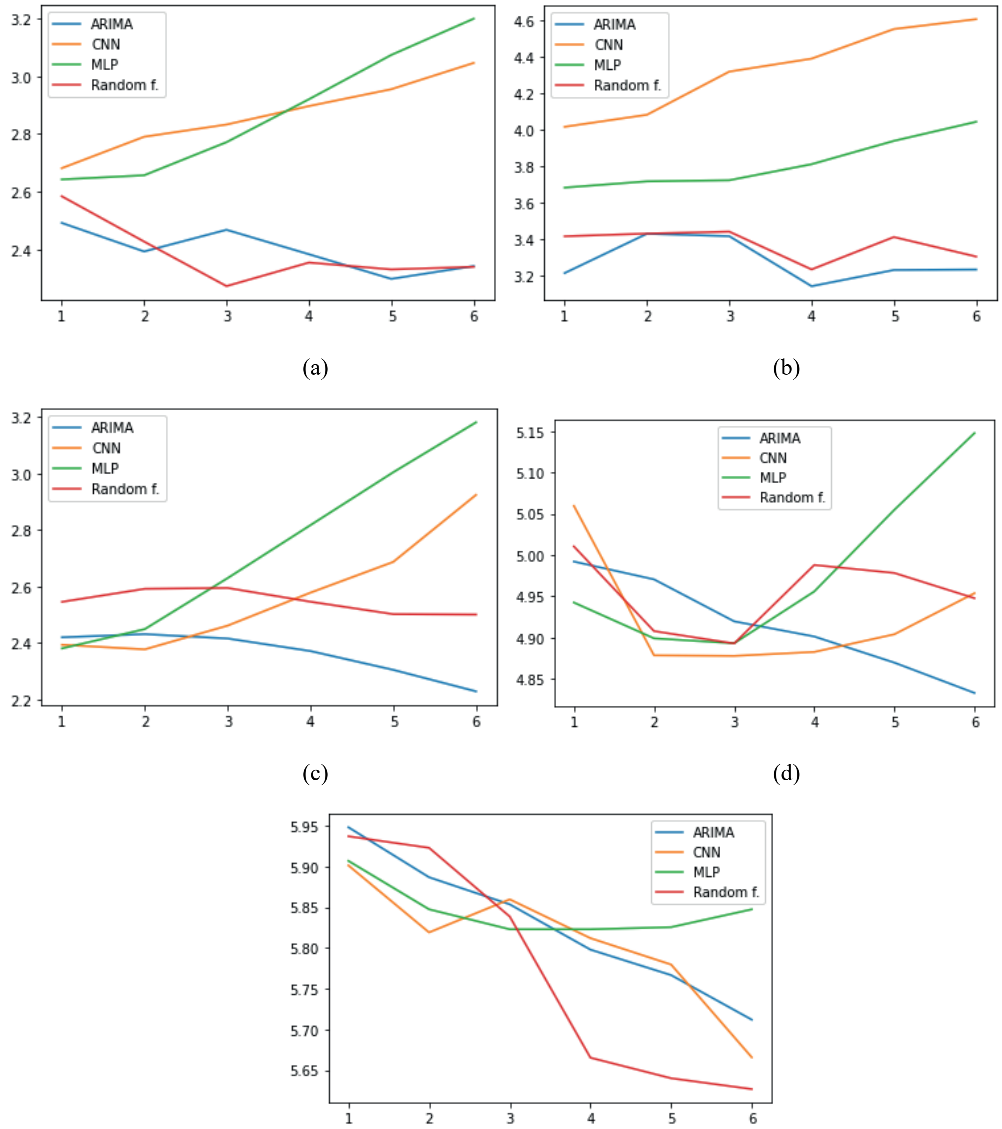
Countries	Model	MAPE	MAE	RRMSE	MSE
Czechia	ARIMA	64.06057	4.008795	0.640726	16.07949
Hungary	ARIMA	43.44141	2.718144	0.434894	7.404768
Poland	ARIMA	57.60256	3.604665	0.576123	13.00027
Romania	ARIMA	13.68732	0.859235	0.138369	0.759968
Slovakia	ARIMA	1.514135	0.093226	0.017968	0.01211
Czechia	CNN	63.05194	3.946193	0.630568	15.58178
Hungary	CNN	41.89122	2.624737	0.419173	6.91665
Poland	CNN	48.6967	3.058365	0.490001	9.539481
Romania	CNN	14.15618	0.886593	0.141773	0.789846
Slovakia	CNN	1.832342	0.113167	0.021199	0.01689
Czechia	MLP	13.25636	0.3136	0.1447	0.117836
Hungary	MLP	6.198546	0.206958	0.088701	0.078185
Poland	MLP	17.98344	0.467733	0.225401	0.320812
Romania	MLP	4.758145	0.281397	0.059521	0.130627
Slovakia	MLP	2.988284	0.183527	0.036229	0.048674
Czechia	Random forest	62.71354	3.92794	0.627538	15.47898
Hungary	Random forest	41.37844	2.58861	0.414181	6.711232
Poland	Random forest	52.88435	3.31114	0.529599	11.00827
Romania	Random forest	9.484416	0.59031	0.110733	0.470381
Slovakia	Random forest	1.458075	0.09112	0.01674	0.01083

As the MAPE, MAE, RRMSE, and MSE test results indicate, for the five countries there are different results in the order of forecasting methodologies' performance. In the case of the Czech, Hungarian, Polish and Romanian unemployment rates forecasting, the MLP algorithm's error indicators were the lowest. In the case of the Czech, Hungarian and Romanian unemployment rates, the second fitting model, namely the random forest algorithm outperforms the CNN and ARIMA. For the Polish unemployment rate, the CNN algorithm's performance occupies the second place, followed by the random forest algorithm and the ARIMA model (Table 5).

The random forest algorithm's forecasting fits best in the case of the Slovakian unemployment rate, where the ARIMA model outperforms the other two machine learning methods (the CNN and MLP algorithms). Similarly, the ARIMA outperforms the CNN algorithm in the case of Romania (Table 5).

6. A MEDIUM-TERM FORECASTING OF THE CENTRAL EUROPEAN COUNTRIES' UNEMPLOYMENT RATE WITH ARIMA AND MACHINE LEARNING ALGORITHMS

The prior research was concerned with selecting the most suitable Box–Jenkins model for the five Central European countries' unemployment rates, also creating the architecture of the deep learning models and training them for this database. The selected models are as follows: in Czechia, Hungary and Romania ARIMA(2,1,2), in Poland ARIMA(3,1,2), and in Slovakia ARIMA(2,2,3). Afterwards the CNN network was designed for a 64-filters' one-dimensional convolution layer and one hidden layer containing 50 neurons, the MLP network with three input nodes – one output and a 100-neuron containing hidden layer and the forest algorithm network with 1000 trees. The monthly unemployment rate, for a medium-term (six-month period) was forecasted based on these models. The best fitting MLP forecasting results indicate a growing unemployment rate in the first four countries, while the random forest forecasting has a relatively slow decreasing tendency for Slovakia, where this model had the smallest error in the testing period. The ARIMA models and the CNN algorithm forecasting results indicate a moderate increasing tendency in all cases except Slovakia (Fig. 6).



(a) (b)

(c) (d)

(e)

Fig. 6. The unemployment rate forecasting results in Czechia (a), Hungary (b), Poland (c), Romania (d), and Slovakia (e) (the author's calculation; EUROSTAT).

CONCLUSIONS

Based on the database of monthly unemployment rate series from the five Central European countries, in the univariate unit root tests, the null of non-stationarity fails to be rejected in all cases. While in Czechia, Hungary, and Romania, the first differenced series stationarity was confirmed.

The autocorrelation and partial autocorrelation tests results were used for ARIMA models specification, of which, based on the AIC criteria values were selected the best fitted ones: in Czechia, Hungary, and Romania an ARIMA(2,1,2) model, in Poland, ARIMA(3,1,2), and in Slovakia ARIMA(2,2,3).

In the second part, the data was shaped into training and testing parts and prepared for deep learning algorithms usage, according to Brownlee (2018). For the CNN, MLP and random forest algorithms, the neuron network's architecture was specified based on literature, for unemployment rate forecasting in the Python environment. A 10-months period from the original time series was used for the MAPE, MAE, RRMSE, and MSE error tests' estimations to analyse the model's performance. Our results indicate that in the case of the Czech, Hungarian, Polish and Romanian unemployment rate forecasting, the MLP algorithm's errors were the lowest. The random forest algorithm in the case of Slovakia outperforms the ARIMA model and the other two deep learning techniques. Our results are in line with Kunaschk and Lang (2022), Cervelló-Royo and Guijarro (2020), and Gogas et al. (2022) regarding the better performance of random forest algorithm than the conventional methodologies or deep learning techniques, and with the results of Nhose et al. (2023), where the CNN algorithm used for unemployment rate forecasting had the lowest performance compared to other machine learning techniques.

Although in the case of Czechia, Hungary, and Poland, the ARIMA model has the highest error test results, one could not conclude that the machine learning algorithms' forecasts proved to be better than the conventional methodology in all cases. In Slovakia and Romania, the ARIMA model outperforms the CNN algorithm and, in the first country, outperforms the MLP algorithm as well. These results are in line with the findings of Choudhary et al. (2022), who made forecasting on time series of currencies.

The final part of the paper contains a medium-term forecasting for unemployment rates, based on all models. The results suggest increasing trends in all Central European countries, except for Slovakia. The results of this study indicate that unemployment remains a real economic problem in the future.

Summarizing the scientific value of this study: in the case of examined data, the MLP and random forest algorithms perform better than the 'conventional' Box–Jenkins methodologies in unemployment rate forecasting.

The limitation of the present study comes from designing deep learning models' network architecture, where it could be possible to experiment with other types of models, for example, growing the number of hidden layers or neurons. Future research is recommended to include hybrid deep learning techniques in unemployment rate forecasting.

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