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A Machine Learning Approach to Forecast International Trade: The Case of Croatia

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Abstract

Background: This paper presents a machine learning approach to forecast Croatia's international bilateral trade. **Objectives:** The goal of this paper is to evaluate the performance of machine learning algorithms in predicting international bilateral trade flows related to imports and exports in the case of Croatia. **Methods/Approach:** The dataset on Croatian bilateral trade with over 180 countries worldwide from 2001 to 2019 is assembled using main variables from the gravity trade model. To forecast values of Croatian bilateral exports and imports for a horizon of one year (the year 2020), machine learning algorithms (Gaussian processes, Linear regression, and Multilayer perceptron) have been used. Each forecasting algorithm is evaluated by calculating mean absolute percentage errors (MAPE). **Results:** It was found that machine learning algorithms have a very good predicting ability in forecasting Croatian bilateral trade, with neural network Multilayer perceptron having the best performance among the other machine learning algorithms. **Conclusions** Main findings from this paper can be important for economic policymakers and other subjects in this field of research. Timely information about the changes in trends and projections of future trade flows can significantly affect decision-making related to international bilateral trade flows.

Keywords: machine learning; WEKA; international trade; MAPE; Multilayer perceptron; Croatia.

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Introduction

Artificial intelligence originated in the 1950s and has become a multidisciplinary field with applications in nearly every aspect of human life. Machine learning is an application of artificial intelligence for finding patterns and regularities in data (Kulkarni & More, 2016). Therefore, machine learning has many applications in the field of economics. One is forecasting macroeconomic variables, an important toolkit for many countries. It is important to recognise that artificial intelligence and machine learning have important implications for international macroeconomics and trade, Goldfarb and Trefler (2018). Previous investigations were oriented to a compare of machine learning methods with traditional ones, Mitrea et al. (2009), Zekić-Sušac et al. (2014), forecasting realized variance using high-frequency data, Arnerić et al. (2018), stock price prediction using neural networks, Medić et al. (2020), comparison of multivariate statistical analysis and machine learning methods in retailing, Ćorić (2016).

This paper presents the application of machine learning algorithms in forecasting bilateral international trade flows in the case of Croatia. Because trade influences production, prices, employment, and wages, it is important to correctly predict future trade patterns and flows. Batarseh et al. (2020) are almost a high priority for timely decision-making. The seminal paper in this field of research can be attributed to Nuroglu (2012), who analysed the bilateral trade flows of Turkey with its major trading partners. He used panel data models and neural networks on annual data from 1985 to 2010. In Turkey's bilateral trade flows analysis, neural networks were superior to the traditional panel data models.

This paper follows the research method introduced by Wohl and Kennedy (2018) and Quimba and Barral (2018), who forecasted international trade flows using neural networks. Wohl and Kennedy (2018) assembled a dataset using variables from the international trade gravity model. Input variables were the distance between countries, the importer's and exporter's GDP, and dummy variables (language, border, colonial relationship, and trade agreements). On the other side output variable was the value of bilateral trade flows. Quimba and Barral (2018) compare the gravity models (estimated with the OLS, PPML, and GPML estimators) with the neural networks using panel data to analyse the bilateral trade flows between APEC economies. The study's results pointed to neural networks' strong capacity to make the most accurate estimations and predictions of bilateral trade flows.

This paper aims to evaluate the performance of machine learning algorithms in predicting international bilateral trade flows related to imports and exports in the case of Croatia. The input variables in the analysis are GDP exporter, GDP importer variables, distance, and dummy variables (Language, Border, Landlocked, and WTO). In contrast, the output variables are the values of bilateral trade imports and exports. The data were collected for the period from 2001 to 2019. The software WEKA forecasts Croatian bilateral trade flows for a one-year-ahead horizon (the year 2020). It is an open-source machine learning software comprising its algorithms (Gaussian processes, Linear regression, and neural network Multilayer perceptron). According to Abirami and Chitra (2020), a Multilayer perceptron is an add-on to a forward neural network. In contrast, neural networks are the most used machine learning algorithms. All machine learning algorithms can be classified into two basic groups: supervised and unsupervised.

The precision of forecasting algorithms is inspected by calculating the mean absolute percentage errors (MAPE). The expected result is the good predictive capability of machine learning algorithms in forecasting Croatian bilateral trade flows. Therefore, the paper's hypothesis states that machine learning algorithms will have a good predictive capability in forecasting Croatian bilateral trade (the value of MAPE is lower than 10). The paper contributes to the state-of-the-art by employing three machine learning algorithms in predicting bilateral trade flows in the case of one small country, Croatia.

The structure of paper consists of five sections. After the introduction, the literature review elaborates on bilateral international trade forecasting using neural networks. In the methodology and data section, the explanation of data, data sources, and research methods is presented. The paper's most important findings are displayed and discussed in the results and discussion section. The final chapter presents concluding remarks.

Bilateral international trade forecasting using neural networks

Table 1 is the chronological overview of studies on bilateral international trade forecasting using neural networks.

Table 1
Overview of studies related to bilateral international trade forecasting using neural networks

Authors (Year)	The goal of the paper	Data forecasted	Method/algorithm used	The best method
Nuroglu (2012)	Forecasting E15 bilateral trade flows	EU15, 1964 -2003	Panel data, neural networks	Feed-forward two layers network
Circlaeys et al. (2017)	Bilateral trade flows prediction	1.9 million data points, 1800s to 2014, 200+ countries	Six machine learning models	Feed-forward neural network
Baxter and Srisaeng (2018)	Prediction of Australia's export air cargo demand	Australia, from 1993 to 2016	Multilayer perceptron	Multilayer perceptron
Quimba and Barral (2018)	Prediction of bilateral trade flows of APEC countries	21 APEC countries, 8,329 observations, from 1996 to 2001	OLS, PPML, GPML, Neural networks	Neural network
Wohl and Kennedy (2018)	Forecasting bilateral trade flows	91,094 obs. for 68 partner countries from 1986 to 2006	OLS, PPML, Neural networks	Multilayer perceptron regressor
Almog et al. (2019)	Forecasting bilateral trade flows	200 countries, from 1950-2000	Gravity models, Enhanced Gravity Model (EGM)	EGM
Dumor and Yao (2019)	Estimating China's Trade within the Belt and Road Initiative	China's bilateral trade exports from 1990 to 2017	OLS, PPML, Neural network	Fully connected neural network
Nyoni (2019)	Forecast Zimbabwe's exports and imports	Zimbabwe, from 1975 to 2017	Neural networks	Neural network with Hyperbolic Tangent Function
Vidya and Prabheesh (2020)	Forecasting future trade after the COVID-19 pandemic	15 global trading countries, 2016Q4-2020Q1	Neural Networks	Recurrent neural network
Batarseh et al. (2021)	Forecasting global beef trade flows	Australia, Germany, Netherlands, France, US, from 1989 to 2018	ARIMA, GBoosting, XGBoosting, Light Gradient Boosting Machine (LightGBM)	LightGBM
Chan (2021)	Estimation of United States-Asia clothing trade	United States, China, and 15 South and Southeast Asian countries, 2012-2018	Multiple regression, Neural Network	Neural Network using a k-fold cross-validation procedure
Gopinath et al. (2021)	International agricultural trade forecasting	Seven major agricultural commodities, 1962-2016	LightGBM, XGBoost, Random forest, Extra trees regression, Neural network	scikit-neural network

Source: Authors' work

Nuroglu (2012) investigated bilateral trade flows among EU15 countries from 1964 to 2003 using a panel data analysis and neural network modeling. When comparing out-of-sample forecasting performances, neural networks produced much lower MSE, making them superior to the panel models. According to Circlaeys et al. (2017), neural networks are a promising approach to predicting bilateral trade flows. The results of the comprehensive study on 1.9 million data points from the 1800s to 2014 for 200+ countries and territories showed that feed-forward neural networks improved the gravity model's prediction performance by the test R^2 score of 0.15 using the same set of features.

Baxter and Srisaeng (2018) employed an artificial neural network to predict Australia's export air cargo demand. The observed period was from the year 1993 to the year 2016. The artificial neural network was based on multilayer perceptron architecture. It fed a multilayer feed-forward network with data randomly divided into three sets. Those are training, testing set, and model validation. Four goodness-of-fit measures were selected to find the best-fit model. Those metrics are mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE). The results suggested that the artificial neural network correctly predicted Australia's annual export air cargo demand. Quimba and Barral (2018) explore neural network models in understanding bilateral trade in APEC. They compare different gravity model estimators, such as OLS, PPML, and GPML, with the neural network. The neural network estimation was found to be far superior to other estimations.

Wohl and Kennedy (2018) analyse bilateral international trade using neural networks (NN), constructing a dataset assembled from the variables belonging to the gravity trade model. The authors used test data to measure how different methods, such as an OLS estimator, a Poisson pseudo-maximum likelihood estimator (PPML), and a neural network generalise to the data. It was found that a neural network with country-fixed effects yields the most accurate out-of-sample predictions, as seen in a comparison of root mean squared errors. Almog et al. (2019) introduced the Enhanced Gravity Model (EGM) of trade, which combines the gravity trade model with the network approach within a maximum-entropy framework. China's trade with its trade partner countries within the Belt and Road Initiative was estimated using neural network analysis, Dumor and Yao (2019). It was found that neural networks performed better than the gravity model estimators of international trade flows.

Nyoni (2019) forecasted Zimbabwe's exports and imports by employing the neural network approach on annual time series of data over the period from 1975 to 2017. Neural networks were evaluated using the forecast evaluation statistics or error metrics; mean squared error (MSE) and mean absolute error (MAE). The results showed that neural networks yielded reliable forecasts of Zimbabwe's exports and imports over the observed period. The COVID-19 outbreak led to a drastic reduction in trade interconnectedness and density among countries changing the structure of trade-network, Vidya and Prabheesh (2020). The forecasted exports and imports declined in all observed countries until December 2020 due to the adverse impact of the COVID-19 pandemic. Batarseh et al. (2021) employed machine learning models (ARIMA, GBoosting, XGBoosting, and LightGBM) to predict future trade patterns. The accuracy of models presented in this paper was in the range of 69% to 88%. Chan (2021) estimated the United States-Asia clothing trade using multiple regression analysis and artificial neural networks. The analysis was conducted for clothing exports from 2012 to 2018, while the trade pattern prediction was estimated for 2019. The paper's main findings conclude that artificial neural networks had much more accurate predictions of bilateral trade flows than the standard basic gravity trade models. Gopinath et al. (2021)

forecasted the international agricultural trade of seven major agricultural commodities using machine learning tools. Results of the analysis pointed to the high relevance of the machine learning models in forecasting trade patterns relative to traditional approaches, with neural network approaches providing a better fit over the long term.

Methodology

Data

This paper observes Croatian bilateral trade (exports and imports) with other countries from 2001 to 2019, with forecasts for 2020. The input variables in the model are the GDPs of exporting and importing countries, the distance between countries, and dummy variables (language, border, landlocked, and WTO). The input, as mentioned above, variables are the main explanatory variables in the gravity model of international trade. So they are often used in the estimation of gravity models of trade. Therefore, we have used those variables as input variables for machine learning algorithms. The output variables are exports from Croatia and imports to Croatia. The full list of variables and their brief description and data sources is presented in Table 2.

Table 2
List of observed variables

Variable	Description	Source
Exports	Exported value, in US$ thousand	Trade Map (2021)
Imports	Imported value, in US$ thousand	Trade Map (2021)
GDP Exporter	Gross domestic product of the exporting country, current US$	World Bank (2021)
GDP Importer	Gross domestic product of importing country, current US$	World Bank (2021)
Language	Importer and exporter have the same language (0 = No, 1 = Yes)	CEPII
Border	Importer and exporter have the same border (0 = No, 1 = Yes)	CEPII
Distance	Importer and exporter distance, in km	CEPII
Landlocked	Importer/exporter is landlocked (0 = No, 1 = Yes)	CEPII
WTO	Importer and exporter are both members of the World Trade Organization in the same year (0 = No, 1 = Yes)	World Trade Organization (2021)

Source: Authors'

The data for the analysis are provided from various sources: Trade Map, World Bank, CEPII, and WTO. CEPII is the Centre d'Études Prospectives et d'Informations Internationales, main French institute for research into international economics. Both variables, Exports and Imports are expressed in thousands of US$. The Exports variable observes the value of exports from Croatia to other countries, whereas the Imports variable shows the value of imports to Croatia from a certain country worldwide. Variables GDP Exporter and GDP Importer give information about the gross domestic product value of a country that exports goods and services and the gross domestic product value of a country that imports them. Variable language is a binary variable that takes the value of one if both exporting and importing countries share the same language as an official in their country. An irregular border is also a binary variable. If exporting and importing countries are neighboring countries, an irregular border takes the value of one. Variable distance measures the distance between capital cities of trade partner countries in kilometers. If a country does not have direct access to the open sea, the variable Landlocked is equal to one. When the importer and the exporter countries are both members of the World Trade Organization, the value of the variable WTO is equal to one.

Trend analysis and forecasting

The analysis will also use descriptive statistics to describe trends in Croatian exports and imports from 2001 to 2019. The analysis used 2,881 data values from Croatian export value records and 2,895 from Croatian import value records. However, in the analysis, yearly export and import averages were used.

Although Croatia has traded with more than 180 countries worldwide, only the most important trading partners in the paper will be emphasised. Croatia was analysed as a single country, although the analysis could be made for many more countries. The idea is to present a framework for analysis that could be implemented to forecast bilateral international trade flows comprehensively.

Different forecasting techniques and algorithms are applied to forecast the future values of Croatian bilateral exports and imports for 2020. For that purpose, a WEKA, which is an open-source machine learning software (University of Waikato (2021), and selected machine learning algorithms (Gaussian processes, Linear regression, and Multilayer perceptron), with default settings, will be applied.

The multilayer perceptron is a feed-forward artificial neural network that is mostly known and frequently used. The neurons in the Multilayer perceptron are trained with the backpropagation learning algorithm. Learning consists of adjusting perceptrons' weights, providing lower errors on the training data. The expression describing the predictive capacity of the Multilayer perceptron is:

$$f(x) = \left(\sum_{i=1}^{m} w_i * x_i\right) + b \tag{1}$$

where m is the number of neurons in the previous layer, w is a random weight, x is the input value, and b is a random bias, Data Science (2020). The strong predictive capability of neural network Multilayer perceptron comes from its networks' hierarchical (multi-layered) structure.

Gaussian processes have been developed by Rasmussen and William (2006) and have often been used for forecasting time-series phenomena, as well as Linear regression. A Gaussian process is a random process where any point $x \in \mathbb{R}^d$ is assigned a random variable $f(x)$ and where the joint distribution of a finite number of these variables $p(f(x_1), \dots, f(x_N))$ is itself Gaussian:

$$p(f|X) = \mathrm{N}(\mathrm{f}|\mu, \mathrm{K}) \tag{2}$$

Given a training dataset with noise-free function values f at inputs X, a Gaussian process prior can be converted into a Gaussian process $p(f_*|\mathrm{X}_*, X, f)$, which can then be used to make predictions f_* at new inputs X_*, Kraser (2018). Linear regression supports regression-type problems and works most naturally with numeric attributes. It is fast to train and can have great performance if the output variable for your data is a linear combination of your inputs, Brownlee (2019).

$$x = w_0 + w_1 a_1 + w_2 a_2 + \dots + w_k a_k \tag{3}$$

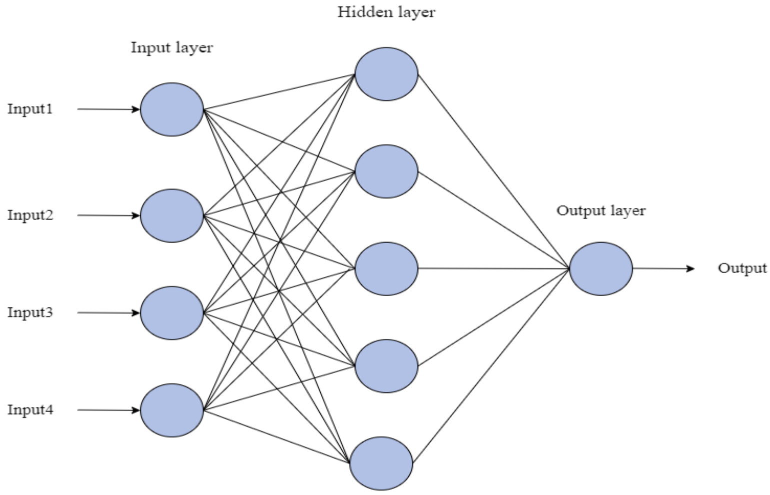
Then we calculate weights from training data and predict a value for the first training instance (a):

$$w_0 a_0^{(1)} + w_1 a_1^{(1)} + w_2 a_2^{(1)} + \dots + w_k a_k^{(1)} = \sum_{j=0}^{k} w_j a_j^{(1)} \tag{4}$$

Finally, choose weights to minimize square error on training data, Hall et al. (2011).

$$\sum_{i=1}^{n}\left(x^{(i)}-\sum_{j=0}^{k}w_j a_j^{(1)}\right)^2 \tag{5}$$

Figure 1
The structure of Multilayer perceptron



Source: Authors' illustration

In Figure 1, the structure of the Multilayer perceptron is illustrated. It contains the input, visible, hidden, and output layers with fully connected weights between layers. The input layer receives the input signal to be processed. An arbitrary number of hidden layers is placed between the input and output layers, representing the computational engine of the Multilayer perceptron. For the hidden layer neurons, sigmoid functions are frequently used, leading to smooth transitions instead of hardline decision boundaries as when using step functions, Menzies et al. (2014). Prediction and classification tasks by the output layer, Abirami (2020). The preparation of Croatian export data for the *.arff file inputted into the WEKA interface is displayed in the following form (Figure 2).

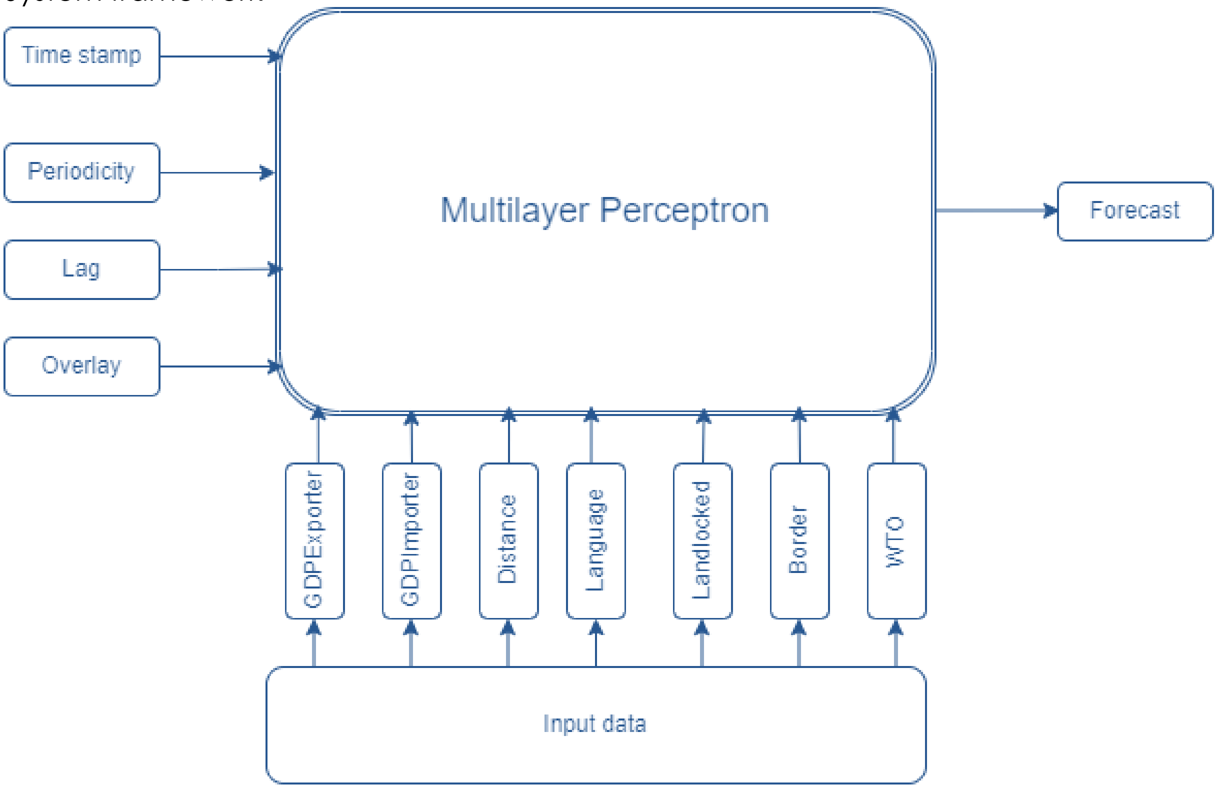
Figure 2
Structure of the Weka file for the Croatian exports

```
@relation 'Exports'
@attribute Year date "yyyy"
@attribute Exports numeric
@attribute GDPExporter numeric
@attribute GDPImporter numeric
@attribute distance numeric
@attribute language numeric
@attribute border numeric
@attribute Landlocked numeric
@attribute WTO numeric
@data
2001,1106529, 23054778851.2787, 1167012796420.58, 517.05, 0,0,0,1
2002,1114986, 26813968850.5192, 1270712309429.7,   517.05, 0,0,0,1
2003,1651020, 34682900712.6654, 1574145823927.77, 517.05, 0,0,0,1
2004,1834388, 41587470546.7946, 1803226967966.23, 517.05, 0,0,0,1
…
2016, 1864324, 51601147665.8089, 1875797463583.87, 517.05, 0,0,0,1
2017, 2140708, 55481644098.0495, 1961796197354.36, 517.05, 0,0,0,1
2018, 2511138, 61375222347.0256, 2091544955092.31, 517.05, 0,0,0,1
2019, 2382927, 60752588976.3175, 2003576145498.04, 517.05, 0,0,0,1
```

Source: Authors' work

In this example, the data for bilateral trade with Italy are presented. Figure 3 is the system framework for conducting the analysis (forecasting Croatian international bilateral trade). The system framework is constructed from input data related to gravity variables, WEKA's settings related to the time stamp, periodicity, lags, overlay, and a performing algorithm (in this case, Multilayer perceptron).

Figure 3
System framework



Source: Authors' illustration

Model validation

The evaluation of each forecasting algorithm will be made by applying and calculating the mean absolute percentage error (MAPE). Mean absolute percentage error is defined as follows:

$$MAPE = \frac{\sum_{t=1}^{T}\left|\frac{y_t - F_t}{y_t}\right| \cdot 100}{T}, y_t \neq 0 \qquad (6)$$

where y_t is the value of time series at time t, F_t is forecast at time t, T is the number of pairs of actual values and forecasts. The lower the value of MAPE a certain forecasting algorithm will have, it will be more successful in forecasting the Croatian bilateral exports and imports. MAPE values will be interpreted according to the range of observed errors. "The value of MAPE lower than ten can be interpreted as highly accurate forecasting, the value of MAPE in the range of 10-20 can be interpreted as good forecasting, the value in the range of 20-50 is reasonable forecasting while the value of MAPE higher than 50 can be interpreted as inaccurate forecasting" Žmuk and Jošić (2020:477). Each forecasting algorithm will be observed and compared in general, as well. Finally, the recommendation about which forecasting algorithm should be optimally used in forecasting exports and imports could be brought.

Results

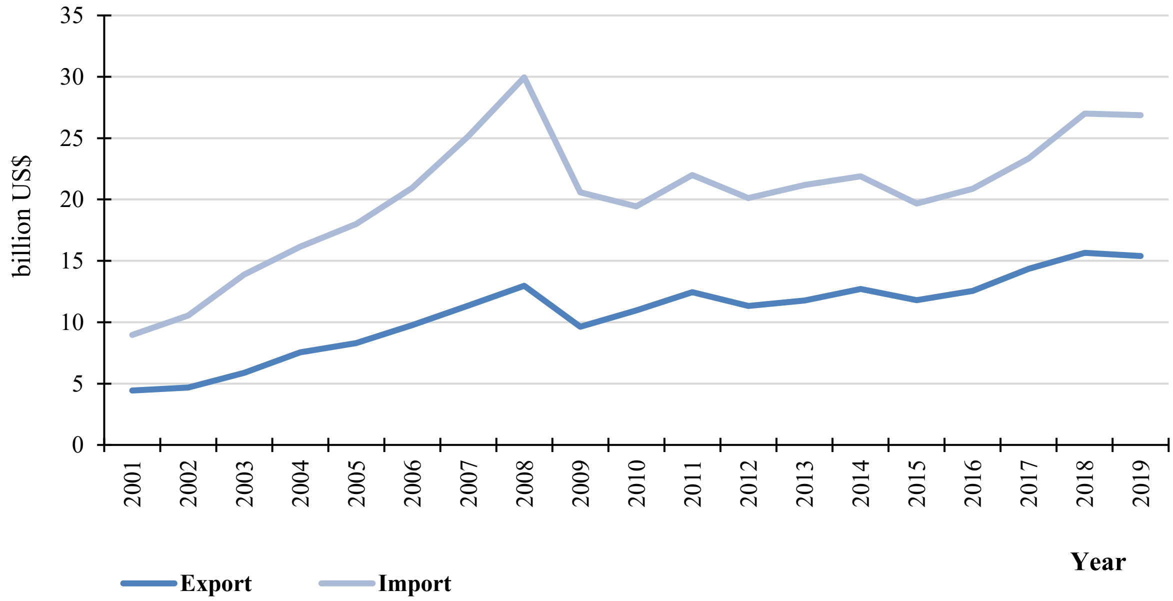
Trend analysis

Croatia maintains bilateral foreign trade in goods and services with more than 180 countries worldwide. The annual values of exports and imports in Croatia from 2001 to 2019 are presented in Figure 4. It can be seen that the volume of trade is rising throughout the observed period despite the sharp drop in 2008 and 2009.

The exports were constantly lower than the imports in the observed period, with imports increasing from 2001 to 2008. Due to the financial crisis in 2008, exports and imports decreased in 2009, but the drop in imports was larger than the drop in exports. After 2009 it seems that the absolute difference between exports and imports remained the same. Croatia has the largest share of trade in a few countries, so that they can be observed as its main trading partners.

Figure 4

Values of Croatian exports and imports, 2001 to 2019, in billions of US$



Source: Authors', Trade Map (2021).

In Table 3, the top 10 countries according to the share in average export value of Croatia in the period from 2001 to 2019 are displayed. Croatia mostly exports to Italy, Bosnia and Herzegovina, Germany, and Slovenia. Croatia had an average export value above 10% of total exports for each country individually, after which comes Austria with an average share of 7% in the total export value. All other countries had significantly lower exports share with 3% or lower. Croatian has a land and sea border with Italy, Slovenia, Hungary, and Bosnia and Herzegovina, and a common language with Bosnia and Herzegovina. All countries from the list are also members of the World Trade Organization.

In Table 4, the countries with the highest share in average imports value in the period from 2001 to 2019 are shown. Similar to the value of exports, the most important Croatian import trading partner countries are Italy and Germany. More than 30% of these two countries' imports to Croatia are combined.

Table 3
Top 10 countries according to the share in average exports value of Croatia, data from 2001 to 2019

Importer	Share in average export value (%)	Language	Border	Distance from Croatia (km)	Landlocked	WTO
Italy	18%	0	1	517	0	1
Bosnia and Herzegovina	13%	1	1	290	0	1
Germany	12%	0	0	912	0	1
Slovenia	10%	0	1	117	0	1
Austria	7%	0	0	271	1	1
United States of America	3%	0	0	6,909	0	1
Hungary	3%	0	1	302	1	1
France	3%	0	0	1,082	0	1
Russian Federation	2%	0	0	1,875	0	1
United Kingdom	2%	0	0	1,341	0	1

Note: Language (0-not common language, 1-common language); Border (0-no common border, 1-common border); Landlocked (0-No, 1-Yes); WTO (1-WTO member, 0-no member)
Source: Authors', Trade Map (2021), CEPII

Table 4
Top 10 countries according to share in the average imports value to Croatia, data from 2001 to 2019

Exporters	Share in average export value (%)	Language	Border	Distance from Croatia (km)	Landlocked	WTO
Italy	16%	0	1	517	0	1
Germany	15%	0	0	912	0	1
Slovenia	9%	0	1	117	0	1
Austria	7%	0	0	271	1	1
Russian Federation	6%	0	0	1,875	0	1
Hungary	5%	0	1	302	1	1
China	5%	0	0	7,649	0	1
France	3%	0	0	1,082	0	1
Bosnia and Herzegovina	3%	1	1	290	0	1
Netherlands	3%	0	0	1,085	0	1

Note: Language (0-not common language, 1-common language); Border (0-no common border, 1-common border); Landlocked (0-No, 1-Yes); WTO (1-WTO member, 0-no member)
Source: Authors', Trade Map (2021), CEPII

Forecasting
Croatian exports and imports are forecasted by applying Gaussian processes, Linear regression, and Multilayer perceptron algorithms. All three forecasting algorithms were applied to forecast bilateral trade flows to each country with whom Croatia exported or imported some goods and services from 2001 to 2019 separately. Consequently, over 500 forecasting procedures were conducted (separately for each partner country times three machine learning forecasters). The export forecasting process considered the following input variables: Exports, GDP Exporter, GDP Importer, Language, Border, Distance, Landlocked, and WTO. Also, each forecasting algorithm was evaluated by observing MAPE. For example, the results of the CRO-ITA bilateral exports forecast for the year 2020 were presented in Table 5, while the graphical

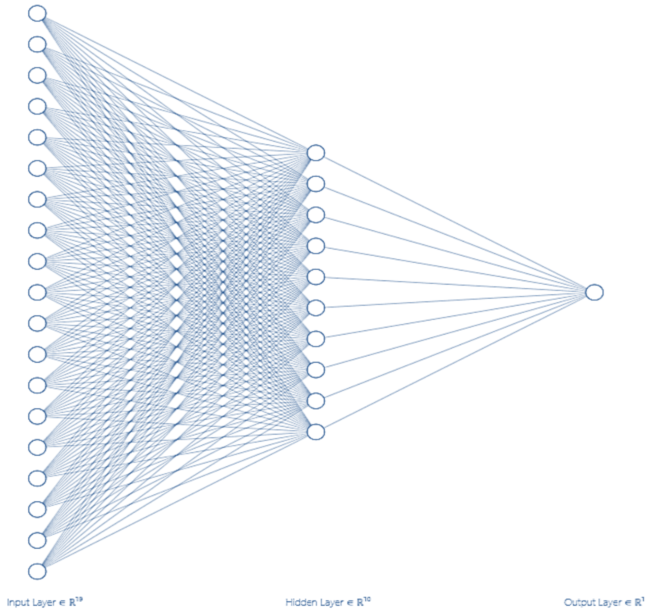
presentation of the Multilayer perceptron was displayed in Figure 5. The projection was made for 2020; in this case, the MAPE value was 14.69.

Table 5
The results of the CRO-ITA bilateral exports forecast for the year 2020, Multilayer perceptron, GDP in 000

Year	Exports	GDP_Exp	GDP_Imp	Language	Border	Distance	Landlocked	WTO
2001	1,106,529	23,054,778	1,170,000,000	0	0	517	0	1
2002	1,114,986	26,813,968	1,270,000,000	0	0	517	0	1
2003	1,651,020	34,682,900	1,570,000,000	0	0	517	0	1
2004	1,834,388	41,587,470	1,800,000,000	0	0	517	0	1
2005	1,860,237	45,376,744	1,860,000,000	0	0	517	0	1
2006	2,397,480	50,423,077	1,950,000,000	0	0	517	0	1
2007	2,360,141	60,073,426	2,210,000,000	0	0	517	0	1
2008	2,694,857	70,234,425	2,400,000,000	0	0	517	0	1
2009	1,993,759	62,600,093	2,190,000,000	0	0	517	0	1
2010	2,209,989	59,918,313	2,130,000,000	0	0	517	0	1
2011	2,111,687	62,537,851	2,290,000,000	0	0	517	0	1
2012	1,892,256	56,580,819	2,190,000,000	0	0	517	0	1
2013	1,851,904	58,194,069	2,140,000,000	0	0	517	0	1
2014	1,921,306	57,639,588	2,160,000,000	0	0	517	0	1
2015	1,717,513	49,525,747	1,840,000,000	0	0	517	0	1
2016	1,864,324	51,601,147	1,880,000,000	0	0	517	0	1
2017	2,140,708	55,481,644	1,960,000,000	0	0	517	0	1
2018	2,511,138	61,375,222	2,090,000,000	0	0	517	0	1
2019	2,382,927	60,752,588	2,000,000,000	0	0	517	0	1
2020*	2,629,761	59,497,585	1,870,000,000	0	0	517	0	1

*Note: Language (0-not common language, 1-common language); Border (0-no common border, 1-common border); Landlocked (0-No, 1-Yes); WTO (1-WTO member, 0-no member); *projections*
Source: Authors'

Figure 5
Graphical presentation of the Multilayer perceptron



Source: Authors using LeNail (2019).

Table 6 presents the aggregate results classified by the number of countries, and the sum of shares in average exports value from 2001 to 2019, according to the range of MAPE value for each applied forecasting algorithm. The more detailed analysis results for Croatian exports on an individual country level are available on request from the authors.

Table 6
The MAPE, according to the forecasting approach, is the sum of shares in average exports value, data from 2001 to 2019, forecasts for the year 2020

Mean absolute percentage error - range	Number of countries			Sum of shares in average exports value from 2001 to 2019		
	Gaussian processes	Linear regression	Multilayer perceptron	Gaussian processes	Linear regression	Multilayer perceptron
0-10	6	92	77	50.36%	47.11%	69.80%
10-20	16	4	25	29.73%	43.85%	26.24%
20-30	18	3	13	10.07%	3.04%	0.81%
30-40	13	3	4	2.87%	1.16%	0.17%
40-50	9	1	5	0.99%	0.06%	0.02%
50 and more	122	81	51	5.98%	4.78%	1.65%
Total	184	184	175	100.00%	100.00%	98.69%

Source: Authors' calculations

According to the research results, the most inappropriate forecasting algorithm is the Gaussian process. It has the lowest number of countries for which the MAPE value was lower than 50%. However, it excellently forecasts trade with main trading partner countries, as seen from the sum of shares in average export value. On the other hand, Linear regression has the highest number of countries for which the MAPE value was below 10%. In contrast, the Multilayer perceptron has the lowest number of countries with larger forecasting errors (50 and more). There are many countries in all three forecasting algorithms for which the MAPE is higher than 50%. It turns out that countries with MAPE higher than 50% generally have lower export shares than those with a MAPE lower than 50%. There are so many countries with large MAPE values because Croatia does not have equally large and continuous exports to all countries in the world. The total sum of shares in average exports value is not equal to 100% for Linear regression and Multilayer perceptron algorithms because the research procedure for some countries could not be applied due to technical limitations.

Using the same approach for the exports, Croatian imports are forecasted by applying the Gaussian process, Linear regression, and Multilayer perceptron algorithms. All three forecasting algorithms were applied for each country separately, from which Croatia imported some goods and services from 2001 to 2019. Again, over 500 forecasting procedures were conducted. In the forecasting process following variables were considered: Imports, GDP Exporters, GDP Importer, Language, Border, Distance, Landlocked, and WTO.

Table 7 shows the sum of shares in average imports value from 2001 to 2019, according to the MAPE of the certain forecasting approach. According to Table 7, the most inefficient forecasting algorithm again turned out to be the Gaussian process due to the lowest number of countries with MAPE lower than 50%. On the other hand, Multilayer perceptron achieved the highest accuracy among the three algorithms, resulting in the highest number of countries with MAPE lower than 50%. Multilayer perceptron achieved the highest accuracy (MAPE lower than 10%) for 89.86% of countries in the sample. The more detailed analysis results for Croatian imports on an individual country level are available on request from the authors.

Table 7
The MAPE, according to the forecasting approach, is the sum of shares in average imports value, data from 2001 to 2019, forecasts for the year 2020

Mean absolute percentage error - range	Number of countries			Sum of shares in average import value from 2001 to 2019		
	Gaussian processes	Linear regression	Multilayer perceptron	Gaussian processes	Linear regression	Multilayer perceptron
0-10	6	53	99	37.11%	17.63%	89.86%
10-20	29	5	11	53.58%	37.06%	0.56%
20-30	17	3	12	2.84%	0.88%	0.07%
30-40	15	5	5	2.70%	0.24%	0.13%
40-50	13	4	11	0.45%	0.02%	0.03%
50 and more	108	117	49	3.32%	44.13%	9.33%
Total	188	187	187	100.00%	99.97%	99.98%

Source: Authors' calculations

It can be concluded that machine learning algorithms have a very good predictive ability in forecasting Croatian bilateral international trade, with neural network Multilayer perceptron having the best performance. It has been noticed that the estimation techniques are more precise when forecasting trade for countries having a higher share in overall Croatian bilateral trade. The results obtained from this paper are comparable with other studies in this field of research, claiming that neural networks yield reliable forecasts of countries' exports and imports over the observed period. According to Wohl and Kennedy (2018), neural networks can generate fairly accurate predictions about international trade. They use a small number of economic, geographic, and historical variables in the prediction process. In certain cases, the neural network's estimations can be close to actual trade values, even ten years beyond the training period. Out-of-sample root means squared errors were the lowest for the neural network estimator using country-year fixed effects with a deviation of U$0.6 million, which explains 79 percent of export variability around its mean, Quimba and Barral (2018). The superiority of neural networks in predicting international trade can aid in better understanding the interregional freight distribution, commodities, specific trade sectors, and the impact of trade agreements on global trade.

In this paper, the value of MAPE metrics lower than 10 in a very high percentage of cases for exports and imports showed that the best or the most precise predicting algorithm is the neural network Multilayer perceptron. This is in line with previous research findings that neural networks outperform standard statistic and econometric algorithms and machine learning algorithms in projecting bilateral trade flows. Baxter and Srisaeng (2018) obtained a MAPE value of 2.44% for the artificial neural network in predicting Australia's export air cargo demand which was extremely good precision. Furthermore, Nyoni (2019) obtained a value of errors of 2.24% for Zimbabwe's bilateral exports and 1.56% for Zimbabwe's bilateral imports. It can be concluded that machine learning algorithms are a suitable tool for analysing and predicting bilateral international trade flows in Croatian settings, indicating that they could also be useful for other similar, open economies.

Conclusion

The paper aimed to forecast bilateral international exports and imports in Croatia for 2020 using machine learning algorithms (Gaussian processes, Linear regression, and

Multilayer perceptron). It was found that machine learning algorithms can precisely forecast Croatian international bilateral trade flows for a one-year horizon. The MAPE metrics showed that a Multilayer perceptron is the best or the most precise predicting algorithm. Therefore, the paper's hypothesis that machine learning algorithms have a good predictive capability in forecasting Croatian bilateral trade can be accepted as valid.

The limitation of the paper is related to the impossibility of machine learning algorithms to predict bilateral trade in a few cases, which can be observed as a technical limitation of the analysis. Generally, the limitation of neural network models is that it fails to describe causal relationships between the variables.

Further research could be made to compare the efficiency of machine learning algorithms with the trade gravity models, Pseudo Poisson Maximum Likelihood (PPML), and other estimators. Additionally, the analysis could be extended by forecasting the horizon larger than one year; however, in that case, the precision of machine learning algorithms in predicting bilateral trade flows is expected to be lower. Another approach to which special attention should be paid is the ensemble approach, Salama et al. (2022). The accuracy of machine learning algorithms and neural networks in predicting bilateral trade flows can be very beneficial for policymakers, researchers, and firms in making decisions related to international bilateral trade.

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