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Deep Learning Models for Airport Demand Forecasting With Google Trends:

A Case Study of Madrid International Airports

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ABSTRACT

Managers gain new insights into how operational benefits can be achieved. Forecasting problems for passenger flow in airports are gaining interest among marketing researchers, but comparison of stochastic optimisation methods via deep learning forecasts with search query data is not yet available in the aviation field. To fill this gap, the current study predicts the demand of Madrid airport demand with Google search query data using H2O deep learning method. The findings indicate that there is a long-term relationship between search queries and actual passenger demand. Besides, search queries "fly to madrid," and "flights to madrid spain" were found to be the cause of the actual domestic air passenger demand in Madrid. Also, to determine the best forecasting accuracy, stochastic gradient descent (SGD) optimisers were used. Specifically, findings indicate that Adam is a better optimiser increasing forecasting accuracy for Madrid airports.

KEYWORDS

Airport Demand Forecasting, Big Data Analytics, Consumer Search Behaviour, H2O Deep Learning, Stochastic Gradient Descent

1. INTRODUCTION

The global popularity of the Internet and the reach of digital information to the masses have enabled consumers to benefit from this technology and changed the way they seek information about the products desired to buy. Search engines such as Google, Bing and Yahoo have enabled people to get the information they need from the internet (Lai et al., 2017).

Theoretically, it can be thought that the Internet provides a large amount of information to its users with less time, effort, and cost. These conveniences can also be said to change the traditional information-seeking behavior of consumers, such as watching mass media or asking sales staff about their product or service (Peterson and Merino, 2003). In this context, to buy a new camera, to see the newest movies in theaters showtimes around, to search for air tickets or hotels, consumers can easily use internet search engines. Therefore, it can be said that it is possible to predict the collective search behavior by looking at the frequencies and time series of online search of activities such as retail, cinema, or travel (Goel et al., 2010). For example, as an important customer group of airline transport, tourists can use search engines to get air and traffic information and plan their routes as they wish

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(Fesenmaier et al., 2011; Li et al., 2017). In this respect, Google, one of the biggest search engines of today, has provided useful data about the search trends of the communities to the researchers with the "Google Trend" service (Dreher et al., 2018). Google Trends offers the daily or real-time search trends for a given region, as well as the frequency of searches for a given term from 2004. It can also display the search frequency of the search term by indexing it between 0-100 on the chart by filtering according to region, search category or search type (web, image, news, etc.)[1].

In the literature, most of the studies using Google Trends data have been performed for prediction. The first and most popular research among these studies was conducted by Ginsberg et al. (2009) to estimate the influenza virus activity in the US. Looking at the popular and the most cited studies related to demand forecasting with search query data, Pan et al. (2012) estimated the hotel room demand with search query data for a special tourist destination by applying autoregressive moving area (ARMA) models. Hand and Judge (2012) predicted cinema participation using the ARIMA method with Google Trends search information. Bangwayo-Skeete and Skeete (2015) estimated the demand for tourism with Google trend search data by comparing the Autoregressive Mixed-Data Sampling (MIDAS) method with other autoregressive models. In the prediction models, they showed that MIDAS method gives better results when Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) criteria are considered. Dimpfl and Jank (2016), using autoregressive models, determined investors' attention with daily search query data and estimated the stock market volatility with the help of these data. Rivera (2016) proposed a dynamic linear model (DLM) and predicted hotel registrations with search query volume. He compared the model with Seasonal Autoregressive Integrated Moving Average (SARIMA), Holt-Winters (HW) and seasonal naïve (SNAIVE) and found that DLM works better in long-term prediction. Önder and Gunter (2016) concluded that using autoregressive model, Google web and image search results in local language increased the predictive power of tourism demand. Li et al. (2017) predicted the tourism volume with web search queries related to various tourism words by applying Generalized Dynamic Factor Model (GDFM). In another study, Google web or image search volumes on country and city basis were estimated by comparing different models such as HW and Naïve (Önder, 2017). Park, Lee, and Song (2017) forecasted short-term tourists' entry on the basis of country with Google Trends data using ARIMA and SARIMA methods. Sun et al. (2019) predicted the number of tourists arrivals using machine learning methods and comparing the success of different search engines.

In the aviation indusrty, airport and airline planners need to predict demand and to improve forecast accuracy to escape uncertain economic climates and misinformed infrastructure investments (Suh and Reyerson, 2019). Also, handling airport capacity problems in Europe is one of the major objectives of extensive investment projects (Sismanidou and Tarradellas, 2017). In this sense, it is understood that the studies about forecasting aviation demand with web search queries are very limited. Accordingly, Kim and Shin (2016) have developed a model to predict short-term airline demand based on monthly passenger arrivals and weekly internet search queries. Shin et al. (2017) tested the relationship between international airport arrivals and search term volume data by Granger causality analysis, suggesting that search activities occur before the flights takes place and can be used for forecasting.

Lastly, demand forecasting studies for sectors such as tourism, entertainment and transportation have shown that web search query data increases predictive success. Furthermore, time series regression models, neural network methods and artificial intelligence algorithms are the main methods applied in these studies. However, no study, to my knowledge, predicted demand for the airports of a specific city with Google search queries using H20 deep learning method.

In this study, Madrid airport market demand was predicted with Google Trends search data of consumers using H2O deep learning method. Thus, the current work makes 2 contributions to the field:

1. To reflect demand for Madrid airports, the selection of search queries of passengers was made by using Google Ads Keyword Planner. The findings indicate that the planner recommends useful

keywords for Google Trends analysis. Most of keywords show better causality between actual airport demand and passenger searches for Madrid.
2. H20 model based on artificial neural network (ANN) is presented for forecasting passenger flow to Madrid. To improve forecasting accuracy, various stochastic optimization methods are compared.

In summary, to make the prediction, the strength and direction of the relationship between the search queries and the actual number of international arrival airline passengers in Madrid airports were determined. For this purpose, cointegration and Granger causality tests are performed, then accuracies of SGD optimizers are compared with RMSE and MAPE evaluation techniques to determine the best predictive success. The rest of this study is organized as follows: Section 2 provides information about H2O deep learning with SGD optimizations. Section 3 describes the methodology, data set statistics, and the findings of the study. In the last part of the study, findings will be discussed, and suggestions will be made for future studies.

2. DEEP LEARNING

In solving major problems related to increasing data, deep learning comes to the fore as a successful method that can be applied in the field of business (LeCun et al., 2015). Deep learning used to understand and analyze complex structures of any amount of data, is also adopted by today's giant technology companies, especially Google (Ahmed et al., 2018). Previous work shows that deep learning is a common technique to forecast consumer demand with web search data. In this respect, ANN (Artificial Neural Network) is a widely used deep network architecture that predicts consumer demand in various industries, such as tourism (eg., Law et al., 2019; Sun et al., 2019; Hu and Song, 2020), oil (Yu et al., 2019), and health (Xu et al., 2019).

2.1 Artificial Neural Network (ANN)

ANN, inspired by biological nervous systems such as the human brain, is a mathematical model designed with the use of interconnected nerves as processing elements (Zhang et al., 1998). In the main use of ANN, the process is based on determining the inputs to be taught to the system and obtaining the desired outputs with mathematical operations in hidden layers.

In causal forecasting problem, independent or predictor variables are defined as the inputs for ANN. The functional relationship can be written as follows:

$$y = f\left(x_1, x_2, x_3, \ldots x_p\right)$$

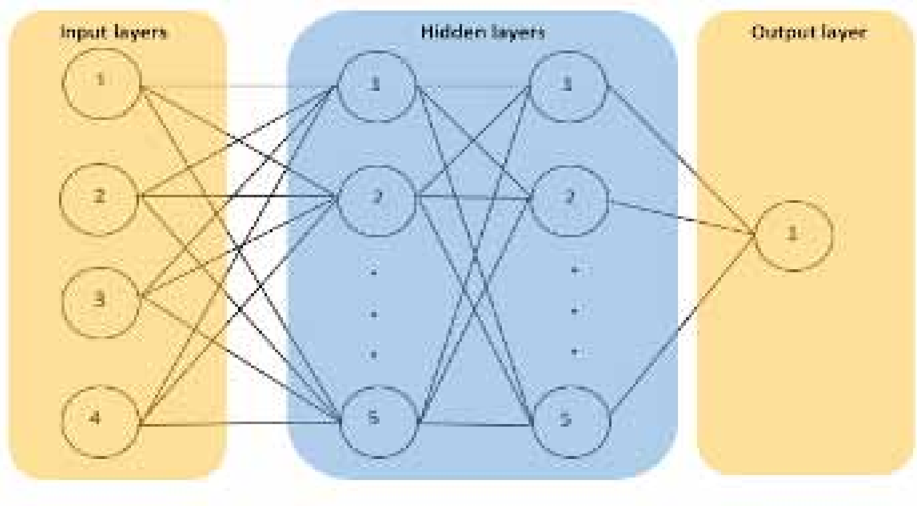
where $x_1, x_2, x_3, \ldots, x_p$ are independent variables as well as y is a dependent variable. For time-dependent forecasting problem, the inputs are past time series, and the output is obtained as future values. The equation can be calculated as follows:

$$y_{t+1} = f\left(y_t, y_{t-1}, \ldots, y_{t-p}\right)$$

where yt is the observation of t time (Zhang et al., 1998).

As a deep neural network technique, multi-layer feed forward neural networks (MLF) are the most popular neural networks trained with a back propagation learning algorithm and consist of neurons, that are ordered into layers (see Fig. 1) (Svozil et al., 1997).

Figure 1. A FFNNs process



In neural network applications, learning rate and momentum should be determined to get the optumum values after the data set is split as training and test set. As the learning rate, which can take values between 0 and 1, decreases, the processing time of the algorithm increases at unacceptable levels and vice versa. In addition, the fact that this ratio is too large leads to overshoot the optimal solution (Larose, 2005).

2.2 H2O

H2O is a fast and memory-efficient deep learning architecture that follows the model of mult-layer, feedforward neural networks including supervised training protocol for predictive regression (Candel and LeDell, 2020). Previous research Recently an increasing number of studies are concentrating on forecasting problems by using H20 package in RapidMiner to conduct their analysis in deep learning (Tung and Yaseen, 2021). In this study, H2O is trained with stochastic gradient descent using back-propagation that leads each compute node trains the data and contributes to the model.[2]

2.3 Optimization Alghoritms in Deep Learning

In deep learning applications, stochastic optimization (SO) plays an important role to minimize or maximize objective functions when facing randomness problem. As one of essential method for business (Hannah, 2015), SO has several tools such as Stochastic Gradient Descent (SGD), (Adaptive Gradient Algotihm) Adagrad, Adadelta, (Root Mean Square Propagation) RMSProp, and (Adaptive Moment Estimation) Adam, and (Nesterov-accelerated Adaptive Moment Estimation) Nadam to improve efficiency in terms of accuracy, convergence rate and training time (Okewu et al., 2019).

RMSProp developed by Tieleman and Hinton (2012) uses variable learning rate to improve training network according to individual parameters (Soydaner, 2020; Singla et al., 2022). As suited for recurrent networks, it uses a moving average of squared gradients to divide the gradient by (Mierswa et al., 2006).

AdaGrad is a modified SGD stochastic optimization paradigm that employs proximity to control the gradient steps of the algorithm and improves on the convergence performance of the standardized SGD (Duchi et al., 2011; Sezer et al., 2020). "It uses set learning rate as a baselind and decreases it during training. The rate is adjusted for each weight and reduced when more updates are performed." (Mierswa et al., 2006).

Adadelta is found by Zeiler (2012) to overcome the continual decay of the learning rate problem that is also faced by AdaGrad. This technique is like AdaGrad but adjusts learning rate based on moving window averages instead of all collected gradients (Mierswa et al., 2006).

Adam is a stochastic algorithm for first-order gradient-basd optimization of objective functions proposed by (Kingma and Ba, 2014). As a popular algorithm for deep learning techniques, Adam uses and combines AdaGrad to handle sparse gradients and the functionality of RMSProp to solve non-stationaty objective problems. This method can easily be used with large datasets and/or high-dimensional parameter spaces (Kingma and Ba, 2014). In practice, Adam can be used for forecasting models (Lu et al., 2021).

As an extension of Adam, Adamax algorithm is based on infinity norm and calculates gradients with stochastic objective (Soydaner, 2020).

3. METHODOLOGY

To predict the airline market demand with Google searches related to air transport in Madrid airports the stationary of the variables was determined with Augmented Dickey-Fuller (ADF) test in this section. Next, the cointegration between the variables was determined and the strength and direction of the relationship between them was tested by Granger Causality analysis. Deep learning was implemented for forecasting. The data and experimental findings used in this stage of the study are included.

3.1 Data

This study uses monthly data of GT and air passenger by main airports in Madrid, Spain from January 2005 to October 2021. As third biggest capital city in Europe, Madrid was chosen for the analysis. To select the right keywords, Google Ads Keyword Planner was used. In this tool, all countries and territories were selected, language was chosen as English and all searches were filtered considering average monthly searches. According to the results of Keyword Planner, “flights to madrid”, and “flights to madrid spain” had great number of related monthly searches. The current study only considers three most popular keywords because Vozlyublennaia (2014) advised not to use too many search terms that might create to much unrelated noise. To predict airline passenger demand for all airports of Madird, each of these keywords was entered into the GT as a search query. Countries were filtered as worldwide; all categories and web search queries were chosen on GT tool. To forecast demand for Madrid airline market, the actual number of arrival passengers between 2005-2021 were retrieved from the official statistics page of eurostat database.[3] Fig 2 summerizes comparison of monthly number of passengers (arrival) for Madrid’s airports and GT data for a given search terms respectively.

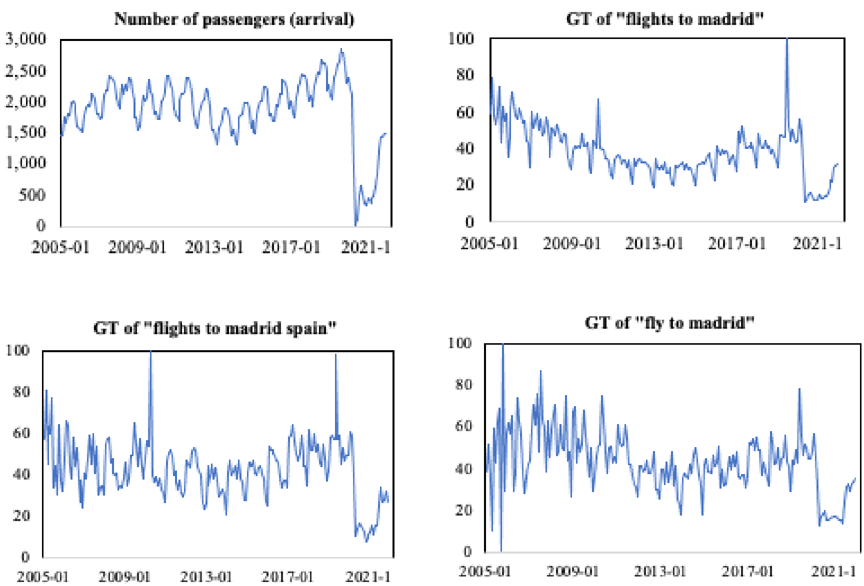
Looking at graphs, Google searches and the number of passengers arrived at Madrid airports appear to decline rapidly at the onset of COVID-19 pandemic period. Similarly, it can be clearly observed from the graphics that the Google searches increased, and the number of arrival passengers tried to respond to these calls during the New Year’s Eve and the period when the restrictions were lifted.

Queries about flights are a result of consumers’ search for information on the airline market based on time (Koçak, 2020), thus reflecting demand. In this respect, estimating the number of flights depends on determining causality between flight-related search searches and actual number of flights.

3.2 Cointegration and Granger Causality Tests

Stationary, co-integration and Granger causality tests had been performed using EViews12 package program to determine the relationship between variables at this stage of the study. ADF unit root tests were implemented for stationary (Dickey and Fuller, 1979). The last situation of the model parameters was determined to minimize Akaike Information Criteria (AIC) (Akaike, 1973).

Figure 2. Monthly data of passengers and GT



According to the test results, number of passengers (arrival) in Madrid and the search terms "flights to madrid", "flights to madrid spain", and "fly to madrid" are stationary at the original level (see Table 1).

The long-run relationship between time series was determined according to Engle and Granger (1987) method by last squares. The time series derived from the regression analysis were tested for the cointegration at the original level (see Table 2).

Looking at the results, there is a long-term relationship between actual number of passengers and Google Trends data with a critical value of %5. Based on the results of this report, the Granger causality analysis can be performed to determine whether the GT data can lead to forecast the number of passengers for Madrid airports in the next step.

To determine the strength and the direction of long-term relationship between variables, Granger Causality test was implemented. Accordingly, the causality of the time series was carried out by taking 2 lag-length criteria and vector autoregressive (VAR) model was developed for the research (see Table 3). The equations implemented for the model is shown as follows:

Table 1. Stationary test results

Datasets	Estimator	Max. Legs	Original level	
			t-value**	p-value***
Number of passengers (arrival) in Madrid airports	SIC*	14	-4.3805	0.0030
GT of "flights to madrid"	SIC	14	-4.7577	0.0007
GT of "flights to madrid spain"	SIC	14	-5.2446	0.0001
GT of "fly to madrid"	SIC	14	-10.5666	0.0000

* Schwarz info criterion
** Null hypothesis was rejected at the 0.01 level
*** MacKinnon (1996) one-sided p-values

Table 2. Co-integration between datasets

Co-integration	Original level	
	ADF t-value*	**p-value****
Number of passengers (arrival) vs GT of "flights to madrid"	-3.6320	0.0297
Number of passengers (arrival) vs GT of "flights to madrid spain"	-5.8508	0.0000
Number of passengers (arrival) vs GT of "fly to madrid"	-6.0652	0.0000

* Null hypothesis was rejected at the 0.05 level
** MacKinnon (1996) one-sided p-values

Table 3. Granger Causality between Google Trends search queries and actual airline market demand data

Hypothesis	Prob	Result
H0: GT of "flights to madrid" does not cause the number of air passengers of Madrid	0.3903	Accepted
H0: GT of "flights to madrid spain" does not cause the number of air passengers of Madrid	0.0064	Rejected
H0: GT of "fly to madrid" does not cause the number of air passengers of Madrid	0.0464	Rejected

$$\left(passengers\right)_t = \sum_{i=1}^{n} a_i \left(searchquery\right)_{t-i} + \sum_{j=1}^{n} b_j \left(passengers\right)_{t-j} + u_{1t}$$

$$\left(searchquery\right)_t = \sum_{i=1}^{n} c_i \left(passengers\right)_{t-i} + \sum_{j=1}^{n} d_j \left(searchquery\right)_{t-j} + u_{2t}$$

where a, b, c and d are the parameters, n is the lag-length, t is the time, u_{1t} and u_{2t} are the regression residuals.

Looking at Table 3 that shows Granger Causality tests of the variables, Google Trends searches related to consumer demand for "flights to madrid spain" and "fly to madrid" cause the actual air passenger demand for Madrid ($p<0,05$). However, the analysis represents no causality between GT of "flights to madrid" and the number of air passengers arrived at Madrid. This shows that forecasting air passenger demand with GT of "flights to madrid" is not feasible. Thus, forecasting model will be built by remaining variables.

3.3 Evaluation of Forecasting Accuracy

In this section, H2O was applied via RapidMiner 9.6 package program (Mierswa et al., 2006) to forecast Madrid airline market demand with Google Trends data. The data were divided into training and testing subsets. The model was trained with data from January 2005 to April 2019, whereas the testing data includes the date between May 2019 and November 2021.

Thus, "flights to madrid", "flights to madrid spain" and "fly to madrid" search queries and arrival passenger demand data sets were selected as input neurons. The forecasted number of domestic passengers constituted the output layer. 203 monthly data between 2005-2021 was selected for the test and the rest 10-year data was devoted to training data in the forecasting model.

To evaluate the forecasting performance, root mean square error (RMSE) (Tang et al., 2012) and mean absolute percentage error (MAPE) (Sun et al., 2019) were used for the research. The equations for these calculations are represented as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} \left(\hat{x}_t - x_t\right)^2}{S}}$$

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{x_t - \hat{x}_t}{x_t} \right|}{S} \times 100$$

where S is the size of observations in test data, x_t is the actual number of airline passengers, $\hat{x}_t$ express forecasted number of passengers.

H2O deep learning model set 50 hidden layers at L1 and L2 respectively. Learning cycle (Epoch) was implemented as 150, mean squared error was set for loss function, standard backpropagation was used, and Xavier (Glorot and Bengio, 2010) was selected for weight initialization in the model. Lastly, RMSProp, AdaGrad, Adadelta, Adam, Nadam, and Adamax were implemented to find the best optimization solution for the forecasting model.

In the experiment, forecasting performance of Madrid passenger demand with GT search queries is evaluated using 6 optimizers in deep learning algorithm and compared by RMSE and MAPE. Accordingly, Table 4 shows the findings of the comparisons.

As seen in Table 6, the proposed H2O model with Adam optimizer presents lowest RMSE and MAPE. According to forecasting performance results, Adam is followed by Adamax, RMSProp, Adadelta, and AdaGrad, respectively.

4. CONCLUSION AND FUTURE WORK

In today's world where traditional information-seeking behavior has changed dramatically, many airline passengers now search on the internet before decision making and purchase accordingly. In this sense, many studies in the literature have revealed that search queries on a certain topic affect the actual data and proved that econometric models and statistics can predict future demand with web search indexes.

Looking at the forecasting applications, it is seen that neural networks are used in addition to autoregressive models. However, neural networks used for the prediction model, it is of great importance that SGD optimizers are adjusted to achieve optimal success. Thus, this study predicted monthly airline market demand with Madrid search queries on Google Trends. For this purpose,

Table 4. Comparisons of the forecasting models

Algorithm	Optimizer	RMSE	MAPE
H2O	RMSProp	33009	2.070
	AdaGrad	410838	25.748
	Adadelta	118374	7.421
	Adam	79*	0.006*
	Adamax	130	0.009

* Indicating the lowest error rate (RMSE and MAPE)

monthly data was retrieved for the period of 2005-2021 and optimization techniques of H2O deep learning method were implemented.

According to the results of Granger causality tests done before the prediction, there is a long-term relationship between the actual number of arrival international flights and related Google Trends search queries data. Considering the studies in the literature which investigated the relationship between internet search index and consumer demand in various business sector (e.g., Pan et al., 2012; Hand and Judge, 2012; Önder and Gunter, 2016; Önder, 2017; Sun et al., 2019), the findings obtained from this research are in line with these studies. Furthermore, search queries on Google related to flights for Madrid arports cause the actual data when looking at the direction of this relationship.

Experiments of this study indicates that Adam optimizer for H2O deep learning method can significantly increase forecasting accuracy compared to other optimization techniques. Also, it should be noted that previous studies suggest that Adam works best for deep learning models (Fatima, 2020) forecasting problems (e.g., Karyotis et al., 2019; Ahmad et al., 2021).

In a nutshell, considering the Google search queries by airline companies in determining the future demand will contribute to the use of resources more optimally as well as the formation of the right pricing strategies. Also, forecasting airport demand and improving accuracy provides protection against uncertain economic fluctuations and misinformed infrastructure investments (Suh and Reyerson, 2019). Another positive aspect of the study is that it helps marketing experts and scholars working in this field to identify trends for passenger demand. In addition, accurate forecasting of airline demand will ensure that resources in other industries such as high-speed train and busses are used properly, and that the government makes future sustainable plans for the sector at an optimum level. Accordingly, this study develops a model to forecast Madrid airport demand and tries to improve accuracy by comparing SGD optimizers. In this respect, an airport manager in Europe can predict saturation levels and know when the airport exceeds capacity most hours of the day which brings scarce airport capacity, as a problem defined by Madas and Zografos (2010).

Looking at future studies, the internet has changed the traditional search behaviors of today and enables customers to access information with less time, effort, and cost (Peterson and Merino, 2003). This indicates that airline passengers can use the web search engines before buying tickets. In terms of the findings from this study, the following limitations should be taken into consideration. First, Google is the only search engine selected. Although Google search queries produce reasonable results within the framework of the literature examined, it is necessary to use the query results produced by other internet search indexes in the determination of airline passenger demand in future studies. Second, for this study, only 3 search terms were used. Increasing the amount of query terms in future studies can also contribute to obtaining better results. Third, the number of international arrival passengers has been forecasted with H2O deep learning method. Using and compare other techniques such as ARIMA, CNN or LSTM may contribute to future studies.

REFERENCES

Ahmad, R., & Kumar, R. (2021). Very Short-Term Photovoltaic (PV) Power Forecasting Using Deep Learning (LSTMs). In *2021 International Conference on Intelligent Technologies (CONIT)* (pp. 1-6). IEEE. doi:10.1109/CONIT51480.2021.9498536

Ahmed, M., & Pathan, A. S. K. (2018). Investigating deep learning for collective anomaly detection-an experimental study. In *International Symposium on Security in Computing and Communication* (pp. 211-219). Springer, Singapore.

Akaike, H. (1973). Maximum likelihood identification of Gaussian autoregressive moving average models. *Biometrika*, *60*(2), 255–265. doi:10.1093/biomet/60.2.255

Aydore, S., Zhu, T., & Foster, D. P. (2019). Dynamic local regret for non-convex online forecasting. *Advances in Neural Information Processing Systems*, *32*, 7982–7991.

Bangwayo-Skeete, P. F., & Skeete, R. W. (2015). Can Google data improve the forecasting performance of tourist arrivals? Mixed-data sampling approach. *Tourism Management*, *46*, 454–464. doi:10.1016/j.tourman.2014.07.014

Candel, A., & LeDell, E. (2020). Deep Learning with H2O. (6th ed.), H2O.ai, Inc, Mountain View, CA, pp.1-55.

Çelik, U., & Başarır, Ç. (2017). The prediction of precious metal prices via artificial neural network by using RapidMiner. *Alphanumeric Journal*, *5*(1), 45–54. doi:10.17093/alphanumeric.290381

Cen, Z., & Wang, J. (2018). Forecasting neural network model with novel CID learning rate and EEMD algorithms on energy market. *Neurocomputing*, *317*, 168–178. doi:10.1016/j.neucom.2018.08.021

Chang, G. W., Lu, H. J., Chang, Y. R., & Lee, Y. D. (2017). An improved neural network-based approach for short-term wind speed and power forecast. *Renewable Energy*, *105*, 301–311. doi:10.1016/j.renene.2016.12.071

Corani, G. (2005). Air quality prediction in Milan: Feed-forward neural networks, pruned neural networks and lazy learning. *Ecological Modelling*, *185*(2-4), 513–529. doi:10.1016/j.ecolmodel.2005.01.008

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427–431.

Dimpfl, T., & Jank, S. (2016). Can internet search queries help to predict stock market volatility? *European Financial Management*, *22*(2), 171–192. doi:10.1111/eufm.12058

Dozat, T. (2016). Incorporating nesterov momentum into adam. *ICLR workshop paper*. https://openreview.net/pdf?id=OM0jvwB8jIp57ZJjtNEZ

Dreher, P. C., Tong, C., Ghiraldi, E., & Friedlander, J. I. (2018). Use of Google Trends to Track Online Behavior and Interest in Kidney Stone Surgery. *Urology*, *121*, 74–78. doi:10.1016/j.urology.2018.05.040 PMID:30076945

Duchi, J., Hazan, E., & Singer, Y. (2011). Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research*, *12*(7), 2121–2159.

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, *55*(2), 251–276. doi:10.2307/1913236

Fatima, N. (2020). Enhancing performance of a deep neural network: A comparative analysis of optimization algorithms. *Advances in Distributed Computing and Artificial Intelligence Journal*, *9*(2), 79–90. doi:10.14201/ADCAIJ2020927990

Fesenmaier, D. R., Xiang, Z., Pan, B., & Law, R. (2011). A framework of search engine use for travel planning. *Journal of Travel Research*, *50*(6), 587–601. doi:10.1177/0047287510385466

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., & Brilliant, L. (2009). Detecting influenza epidemics using search engine query data. *Nature*, *457*(7232), 1012–1014. doi:10.1038/nature07634 PMID:19020500

Glorot, X., & Bengio, Y. (2010). Understanding the difficulty of training deep feedforward neural networks. In: *Proceedings of International Conference on Artificial Intelligence and Statistics*, (pp. 249–256). IEEE.

Goel, S., Hofman, J. M., Lahaie, S., Pennock, D. M., & Watts, D. J. (2010). Predicting consumer behavior with Web search. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(41), 17486–17490. doi:10.1073/pnas.1005962107 PMID:20876140

Granger, C. W. (1981). Some properties of time series data and their use in econometric model specification. *Journal of Econometrics*, *16*(1), 121–130. doi:10.1016/0304-4076(81)90079-8

Hand, C., & Judge, G. (2012). Searching for the picture: Forecasting UK cinema admissions using Google Trends data. *Applied Economics Letters*, *19*(11), 1051–1055. doi:10.1080/13504851.2011.613744

Hannah, L. A. (2015). Stochastic optimization. International Encyclopedia of the Social & Behavioral Sciences, 2, 473-481.

Hu, M., & Song, H. (2020). Data source combination for tourism demand forecasting. *Tourism Economics*, *26*(7), 1248–1265. doi:10.1177/1354816619872592

Karyotis, C., Maniak, T., Doctor, F., Iqbal, R., Palade, V., & Tang, R. (2019). Deep Learning for Flood Forecasting and Monitoring in Urban Environments. *18th IEEE International Conference On Machine Learning And Applications (ICMLA)*, (pp. 1392-1397). IEEE. doi:10.1109/ICMLA.2019.00227

Khatabi, A., & Cherif, W. A. (2019). Combination of Global and Local Features for Brain White Matter Lesion Classification. *Pattern Recognition and Image Analysis*, *29*(3), 486–492. doi:10.1134/S1054661819030118

Kim, S., & Shin, D. H. (2016). Forecasting short-term air passenger demand using big data from search engine queries. *Automation in Construction*, *70*, 98–108. doi:10.1016/j.autcon.2016.06.009

Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Koçak, B. B. (2020). Exploring and identification of passengers'web search goals using "ticket" related queries in the airline market: A google trends study. *Pazarlama ve Pazarlama Araştırmaları Dergisi*, *3*, 443–460.

Lai, K., Lee, Y. X., Chen, H., & Yu, R. (2017). Research on web search behavior: How online query data inform social psychology. *Cyberpsychology, Behavior, and Social Networking*, *20*(10), 596–602. doi:10.1089/cyber.2017.0261 PMID:29039705

Larose, D. F. (2005). *Discovering knowledge in data: an introduction to data mining*. Wiley-Interscience.

Law, R., Li, G., Fong, D. K. C., & Han, X. (2019). Tourism demand forecasting: A deep learning approach. *Annals of Tourism Research*, *75*, 410–423. doi:10.1016/j.annals.2019.01.014

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature, 521*(7553), 436-444.

Li, X., Pan, B., Law, R., & Huang, X. (2017). Forecasting tourism demand with composite search index. *Tourism Management*, *59*, 57–66. doi:10.1016/j.tourman.2016.07.005

Lu, Y., Park, Y., Chen, L., Wang, Y., De Sa, C., & Foster, D. (2021, July). Variance Reduced Training with Stratified Sampling for Forecasting Models. In *International Conference on Machine Learning* (pp. 7145-7155). PMLR.

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, *11*(6), 601–618. doi:10.1002/(SICI)1099-1255(199611)11:6<601::AID-JAE417>3.0.CO;2-T

Madas, M. A., & Zografos, K. G. (2010). Airport slot allocation: A time for change? *Transport Policy*, *17*(4), 274–285. doi:10.1016/j.tranpol.2010.02.002

Mierswa, I., Wurst, M., Klinkenberg, R., Scholz, M., & Euler, T. (2006) YALE: Rapid prototyping for complex data mining tasks. In *Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM. doi:10.1145/1150402.1150531

Noorollahi, Y., Jokar, M. A., & Kalhor, A. (2016). Using artificial neural networks for temporal and spatial wind speed forecasting in Iran. *Energy Conversion and Management*, *115*, 17–25. doi:10.1016/j.enconman.2016.02.041

Norgaard, M., (2000). Neural network based system identification tool-box. *Tech. Re 00-E-891*. Department of Automation, TechnicalUniversity of Denmark.

Okewu, E., Adewole, P., & Sennaike, O. (2019). Experimental comparison of stochastic optimizers in deep learning. In *International Conference on Computational Science and Its Applications* (pp. 704-715). Springer, Cham. doi:10.1007/978-3-030-24308-1_55

Önder, I. (2017). Forecasting tourism demand with Google trends: Accuracy comparison of countries versus cities. *International Journal of Tourism Research*, *19*(6), 648–660. doi:10.1002/jtr.2137

Önder, I., & Gunter, U. (2016). Forecasting tourism demand with Google trends for a major European city destination. *Tourism Analysis*, *21*(2-3), 203–220. doi:10.3727/108354216X14559233984773

Pan, B., Chenguang Wu, D., & Song, H. (2012). Forecasting hotel room demand using search engine data. *Journal of Hospitality and Tourism Technology*, *3*(3), 196–210. doi:10.1108/17579881211264486

Park, S., Lee, J., & Song, W. (2017). Short-term forecasting of Japanese tourist inflow to South Korea using Google trends data. *Journal of Travel & Tourism Marketing*, *34*(3), 357–368. doi:10.1080/10548408.2016.1170651

Peterson, R. A., & Merino, M. C. (2003). Consumer information search behavior and the Internet. *Psychology and Marketing*, *20*(2), 99–121. doi:10.1002/mar.10062

Rivera, R. (2016). A dynamic linear model to forecast hotel registrations in Puerto Rico using Google Trends data. *Tourism Management*, *57*, 12–20. doi:10.1016/j.tourman.2016.04.008

Salehi, H. S., Barchini, M., & Mahdian, M. (2020, February). Optimization methods for deep neural networks classifying OCT images to detect dental caries. In *Lasers in Dentistry XXVI* (Vol. 11217, p. 112170G). International Society for Optics and Photonics. doi:10.1117/12.2545421

Sari, N. R., Mahmudy, W. F., Wibawa, A. P., & Sonalitha, E. (2017). Enabling external factors for inflation rate forecasting using fuzzy neural system. *Iranian Journal of Electrical and Computer Engineering*, *7*(5), 2746–2756. doi:10.11591/ijece.v7i5.pp2746-2756

Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing*, *90*, 106181. doi:10.1016/j.asoc.2020.106181

Shin, E., Yang, D. H., Sohn, S. C., Huh, M., & Baek, S. (2017). Search Trend's Effects On Forecasting the Number of Outbound Passengers of the Incheon Airport. *Journal of IKEEE*, *21*(1), 13–23. doi:10.7471/ikeee.2017.21.1.13

Shinde, A., Kale, S., Samant, R., Naik, A., & Ghorpade, S. (2017). Heart Disease Prediction System using Multilayered Feed Forward Neural Network and Back Propagation Neural Network. *International Journal of Computer Applications*, *166*(7), 32–36. doi:10.5120/ijca2017914080

Singla, P., Duhan, M., & Saroha, S. (2022). Solar Irradiation Forecasting by Long-Short Term Memory Using Different Training Algorithms. In *Renewable Energy Optimization, Planning and Control* (pp. 81–89). Springer. doi:10.1007/978-981-16-4663-8_7

Sismanidou, A., & Tarradellas, J. (2017). Traffic demand forecasting and flexible planning in airport capacity expansions: Lessons from the madrid-barajas new terminal area master plan. *Case Studies on Transport Policy*, *5*(2), 188–199. doi:10.1016/j.cstp.2016.08.003

Soydaner, D. (2020). A comparison of optimization algorithms for deep learning. *International Journal of Pattern Recognition and Artificial Intelligence*, *34*(13), 2052013. doi:10.1142/S0218001420520138

Suh, D. Y., & Ryerson, M. S. (2019). Forecast to grow: Aviation demand forecasting in an era of demand uncertainty and optimism bias. *Transportation Research Part E, Logistics and Transportation Review*, *128*, 400–416. doi:10.1016/j.tre.2019.06.016

Sun, S., Wei, Y., Tsui, K. L., & Wang, S. (2019). Forecasting tourist arrivals with machine learning and internet search index. *Tourism Management*, *70*, 1–10. doi:10.1016/j.tourman.2018.07.010

Svozil, D., Kvasnicka, V., & Pospichal, J. (1997). Introduction to multi-layer feed-forward neural networks. *Chemometrics and Intelligent Laboratory Systems*, *39*(1), 43–62. doi:10.1016/S0169-7439(97)00061-0

Tang, L., Yu, L., Wang, S., Li, J., & Wang, S. (2012). A novel hybrid ensemble learning paradigm for nuclear energy consumption forecasting. *Applied Energy*, *93*, 432–443. doi:10.1016/j.apenergy.2011.12.030

Tieleman, T., & Hinton, G. (2012). Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude. *COURSERA: Neural networks for machine learning, 4*(2), 26-31.

Tung, T. M., & Yaseen, Z. M. (2021). Deep learning for prediction of water quality index classification: Tropical catchment environmental assessment. *Natural Resources Research*, *30*(6), 4235–4254. doi:10.1007/s11053-021-09922-5

Vozlyublennaia, N. (2014). Investor attention, index performance, and return predictability. *Journal of Banking & Finance*, *41*, 17–35. doi:10.1016/j.jbankfin.2013.12.010

Xu, S., & Chan, H. K. (2019). Forecasting medical device demand with online search queries: A big data and machine learning approach. *Procedia Manufacturing*, *39*, 32–39. doi:10.1016/j.promfg.2020.01.225

Yu, L., Zhao, Y., Tang, L., & Yang, Z. (2019). Online big data-driven oil consumption forecasting with Google trends. *International Journal of Forecasting*, *35*(1), 213–223. doi:10.1016/j.ijforecast.2017.11.005

Zeiler, M. D. (2012). Adadelta: an adaptive learning rate method. *arXiv preprint arXiv:1212.5701*.

Zhang, G., Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, *14*(1), 35–62. doi:10.1016/S0169-2070(97)00044-7

ENDNOTES

1 https://support.google.com/trends/answer/4365533?hl=tr&ref_topic=6248052 (Erişim Tarihi: 09.06.2019)

2 https://docs.rapidminer.com/latest/studio/operators/modeling/predictive/neural_nets/deep_learning.html (Accessed: 11.03.2022).

3 https://ec.europa.eu/eurostat/en/web/main/data/database (Accessed: 27.02.2022)