A novel hybrid deep learning approach for tourism demand forecasting

Houria Laaroussi, Fatima Guerouate, Mohamed Sbihi
LASTIMI, Superior School of Technology of Sale, Mohammed V University in Rabat, Rabat, Morocco

Article Info	ABSTRACT
	This paper proposes a new hybrid deep learning framework that combines search query data, autoencoders (AE) and stacked long-short term memory (staked LSTM) to enhance the accuracy of tourism demand prediction. We use data from Google Trends as an additional variable with the monthly tourist arrivals to Marrakech, Morocco. The AE is applied as a feature extraction procedure to dimension reduction, to extract valuable information and to mine the nonlinear information incorporated in data. The extracted features are fed into stacked LSTM to predict tourist arrivals. Experiments carried out to analyze performance in forecast results of proposed method compared to individual models, and different principal component analysis (PCA) based and AE based hybrid models. The experimental results show that the proposed framework outperforms other models. *This is an open access article under the [CC BY-SA](#) license.*

Corresponding Author:

Houria Laaroussi
LASTIMI, Superior School of Technology of Sale, Mohammed V University in Rabat
Rabat, Morocco
Email: hourialaaroussi@research.emi.ac.ma

1. INTRODUCTION

The tourism sector is at the heart of the economic development, there has been increasing interest, among academics as well as practitioners, in the forecasting of tourism demand [1]. Considering the perishable nature of tourism industry, the necessity of accurate forecasts remains crucial [2]. The accurate forecasting of tourism demand help to decision making on tourism and policy planning [3], [4].

Nowadays, The internet contains a huge quantity of information that can be used to predict tourist volume [5], and this motivates tourism researchers to investigate new kind of data like search engine data to increase the accuracy prediction. Search engine data are a real-time daily, weekly and monthly index of the volume of queries that users submit into search engines [6]. Several studies showed that search engine can predict tourist volumes and examine travelers' intention. For instance, [7] brings a new indicator for tourism demand forecasting created from Google Trends' search query and discovered that Google Trends data can increase the prediction performance [8]. Used two different search engines, Google and Baidu to predict the tourist volumes to Hainan Province [9]. Forecast tourist arrivals in Hainan province from August 2008 to October 2015.

Search Engine Queries have distinct strengths over traditional data, including distinct time horizons (especially daily, weekly, and monthly) and not only ability to indicate the tendencies of the searchers' plans for travel products but also offer predictability about their future travel behaviors [10]. As a result, researchers have employed internet data to reinforce traditional data and integrated them into prediction models.

However, when introducing the internet query data into forecasting models, extraction of the most relevant information from dataset is an important challenge for researchers. Among the most prevalent

methods to feature extraction is the dimensionality reduction method which attempts to eliminate the excess and inaptness resulting from the high-dimensional data. Since high dimensionality causes data noise, redundancy, increase the computational cost and tend to provoke overfitting and poor generalization [11]. Dimensionality reduction approaches are classified into linear and nonlinear techniques [12]. Principal component analysis (PCA) is a linear technique which has been frequently adopted in tourism demand forecasting [13]. PCA reduces the dimensions by transforming data to principal components. The concept of PCA is a data transformation method that is used to reduce the dimensionality of a dataset with various variables to a smaller number of independent variables which seize the information of the dataset by condensing the common patterns and therefore the variation of the whole dataset. Nevertheless, those approaches focus on removing linear relationship and give reduced computation time for the learning process. Nonlinear methods involve different techniques, such as kernel PCA [14], and auto-encoder [15], where learning can be performed with maintaining the nonlinear properties. Auto-encoder can provide more information from the original data set. In this paper, autoencoders (AE), a neural network technique, is trained to reconstruct its input, is applied as a non-linear mapping and to choose relevant features. Limited researches have applied autoencoder to predict tourism demand. For example, [15] used stacked autoencoder with echo-state regression (SAEN) to predict tourist flow. Empirical evidence demonstrates that SAEN performs better than the other techniques.

Apart from data, the method can hugely impact the prediction accuracy. accurate tourism demands prediction has been still an important problem for the researchers for many decades, considering its stochastic and non-linear nature. Tourism demand prediction methods is classified into the following: time series econometric and artificial intelligence (AI) models [16]. Time series techniques most frequently used as benchmarks in tourism forecasting studies. They are primarily because of the ability to predict future time series by identifying historical patterns. Econometric models try to analyze the relations between tourism demand and explanatory variables such as income and price. The principal drawback of Time series techniques and econometric models is that they cannot depict the nonlinear and stochastic nature of tourism flow [17]. They perform poorly with nonlinearity of tourism demand. Computational intelligence techniques aim to solve the complex engineering and optimization problems. The traditional machine learning forecasting methods can be adopted to find the non-linear relationship. Lately, they require manual feature extraction and selection which are complex. On top of that, they cannot handle massive quantity of data. Then, deep learning was suggested to surmount these difficulties.

Deep learning techniques have been employed as novel alternatives for tourism demand prediction. Far from artificial neural network (ANN), recurrent neural network (RNNs) contains cyclic connections. The activations pattern of the network are retained at each time step to supply a short-term memory [18]. The drawback of RNNs is the vanishing and exploding gradient problem [19]. Long short-term memory (LSTM) was designed to tackle the vanishing and exploding gradient problems of conventional RNNs. However, LSTM has evolved to be one of the most favored prediction techniques in numerous areas, particularly in resolving intricate nonlinear prediction problems. Many research has been used LSTM in tourism demand. For example, [20] used LSTM method to forecast tourism demand and found that LSTM has better prediction results [21]. Employed a deep learning approach to forecast monthly Macau tourist arrival volumes. Experimental findings showed that the deep learning approach remarkably exceeds support vector regression and artificial neural network models.

In this study, we put forward a new framework combining Internet search index, Dimensionality reduction and deep learning to forecast tourist volume. The anticipation capacity of the framework is by reason of three aspects: first, pertinent search query data immensely provide the best fit; second, autoencoder reduce the dimension of the data using the hidden layer representation and learn high-level predictive indicators from search query data (SQD); moreover, stacked LSTM can reduce time complexity and have hidden layers which able to learn the characteristic information and the relevance initiating complex dataset. Still, Limited researches have used Stacked LSTM and autoencoder to forecast tourism demand. The suggested framework is employed to forecasting Marrakech tourist arrivals. The remainder of this study is arranged as follows: in section 2, the suggested research method is introduced, while in section 3 the results and discussion are reported. In section 4 the conclusion of the study is presented.

2. RESEARCH METHOD
2.1. Methodology
This section discusses the structure of the proposed framework. Our model, that combines autoencoder and stacked LSTM for predicting the tourism demand, is highlighted in Figure 1. It consists of five steps data collection, preprocessing data, feature extraction, forecasting model and evaluation model.
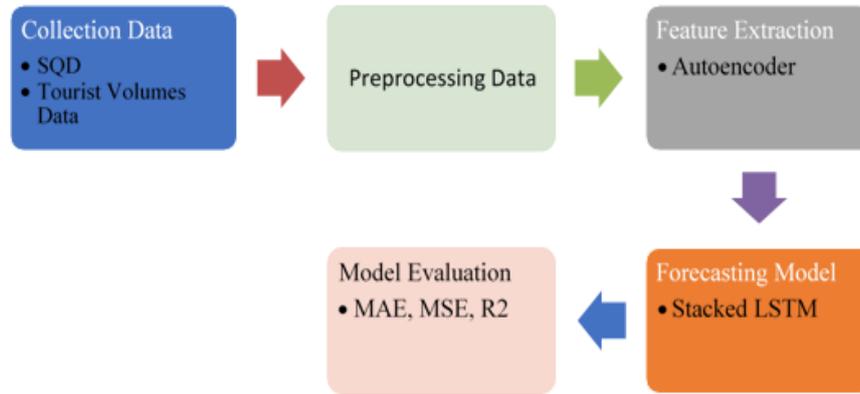
Figure 1. The framework of the proposed model

2.2. Data collection
2.2.1. Historical tourism demand data
We have chosen Marrakech city, Morocco to train and test our model, and its tourism has grown at full speed. We collected the monthly tourist arrivals data for the January 2012 to August 2019 period from the official website of Tourism Observatory in Morocco. We limited the sample to 92 months.

2.2.2. Search volume data
The search queries data is generated from search engine google Trend. In this step, we identified six categories related to the destination. Categories and keywords are in the same discussed in [22]. For each category we determine the seed search keywords and subsequently convert these keywords into Arabic and French, as they are the main languages in Marrakech, Morocco using Google Translate. For each designated keyword inquired extended keywords by means of Google Trends related queries. In the end, we utilized PyTrends library to extract the keyword search volumes. We discovered 763 keywords linked to the first collection search keywords provided via Google related queries.

2.3. Preprocessing data
The collected data hold hundreds of features having the problem of noisy and missing values, which will impact the prediction of the model. So, it is required to clean and arrange data before treating it. After removing duplications and missing data extremely low volume, we normalized the data using min-max normalization algorithm. It helped to better train the proposed model. This utilized in mapping the features in the [0, 1] range.

2.4. Feature extraction
Autoencoder is a type of neural network designed for unsupervised learning method which All data is unlabeled [23]. It attempts to get its output the same as its input [24] and it is designed to reduce data dimensions by learning how to ignore the noise in the data. Figure 2 illustrates an auto encoder network.

It consists of an input, a hidden and an output layer. The input X and output layer Y are same number of nodes. The second layer is the hidden layer H with K nodes is for feature extraction. An AE consists of an encoder part and a decoder part. The encoder is usually used to reduce multidimensional data to low-dimensional data, it maps the input to a hidden layer. The process is formulated as (1):

$$H = S_1(WX + b) \tag{1}$$

where S_1 is an activation function (sigmoid function, rectified linear unit (ReLU), and hyperbolic tangent), W represents weight matrix, and b is a bias of encoder.

The decoder reconstructs the input from the encoded representation by minimizing by the reconstruction error. The process is presented as (2):

$$Y = S_2(W'X + b') \tag{2}$$

S_2 is an activation function, W' is weight matrix, and b' isa bias of decoder. Training an autoencoder aims to reduce the reconstruction loss function, which is measured using mean squared errors or cross-entropy losses.
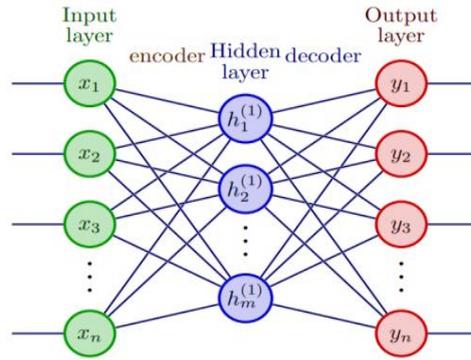
Figure 2. The architecture of an autoencoder

2.5. Forecasting model

A stacked LSTM architecture defined as an LSTM model that includes multiple LSTM layers where each layer holds multiple memory cells. We stack layers to create a hierarchical feature representation of the input data. Figure 3 illustrates the architecture of three-layered stacked LSTM. The stacked LSTM was initially devised by [25]. Equally known as deep LSTM, the stacked LSTM model applies multiple LSTM layers that are stacked before the forwarding to output layer at the final output. Stacked LSTM model with one to seven hidden layers is constructed for training the tourism demand prediction model. In this paper, an RNN, ANN, and support vector regression (SVR) was adopted, as a benchmark model.
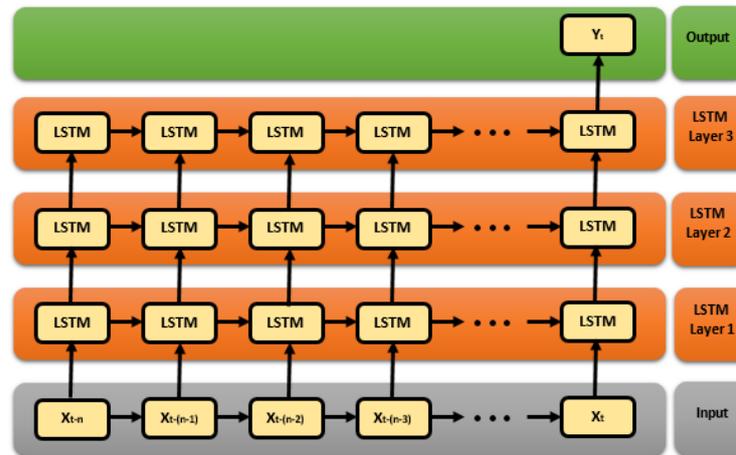
Figure 3. The architecture of a Stacked LSTM

2.6. Evaluation model

To verify the forecasting accuracy of different models, we adopted three main evaluation criteria mean absolute error (MAE), root mean square error (RMSE), and R2. The most appropriate forecasting model is the one that records the lowest MAE and highest R2 values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-)^2} \tag{4}$$

$$R2 = 1 - \frac{\sum_{i=1}^{n}|y_i-\hat{y}_i|}{\sum_{i=1}^{n}|y_i-\bar{y}_i|} \tag{5}$$

where y_i and $\hat{y}_i$, denote the actual and the predicted value, n is the number of samples.

3.   RESULTS AND DISCUSSION

We employed a simple autoencoder, to implement this autoencoder model, our network was composed of three layers, where the input layer had 701 neurons and the hidden layer contained 150 neurons. The number of cycles epoch was selected as 5000, we opted for Adam optimization, we chose ReLU as activation function. The batch size was determined to 12. We used the cross-entropy as the loss function. The learning rate was 0.001. The loss of the autoencoder model's training is illustrated in Figure 4.
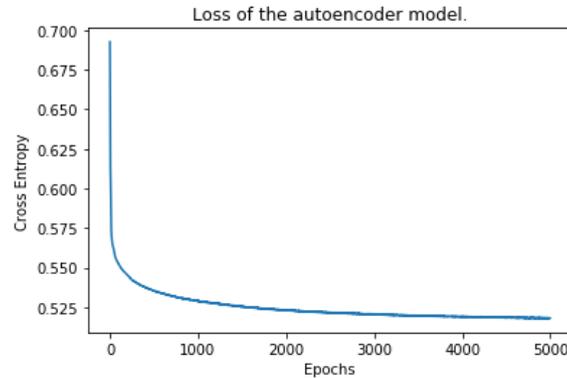
Figure 4. The loss of the autoencoder model during training

In this study 80% of the data was set to train the models and the rest is used to test the performance of the models. The implementations are carried out employing deep learning libraries, namely, KERAS and TensorFlow using Python. We fed the extracted features into stacked LSTM for predicting the tourist arrivals in Marrakech. we constructed one to seven hidden layers stacked LSTM models. Table 1 represents R2, MSE and MAE training and testing errors of our proposed stacked LSTM architectures with the different hidden LSTM layers. it is quite clear that The LSTM network with three hidden layers has smaller MAE and RMSE; in addition, it achieves the highest R2. Therefore, the three layers is selected as the most favorable model. The different stacked LSTM models are illustrated in Figure 5 with one layer stacked LSTM in Figure 5(a), two layers in Figure 5(b), three layers in Figure 5(c), four layers in Figure 5(d), five layers in Figure 5(e), six layers in Figure 5(f) and seven layers in Figure 5(g). We plot the predicted values against actual values.

Table 1. Training and testing errors of different stacked LSTM architectures

Hidden LSTM layers	Training set			Test set		
	R2	MAE	RMSE	R2	MAE	RMSE
1	92.18	0.041755	0.003044	91.40	0.044350	0.004315
2	90.86	0.042829	0.003560	89.37	0.04867	0.004063
3	**97.45**	**0.021153**	**0.000992**	**96.52**	**0.024431**	**0.001169**
4	89.98	0.047321	0.003902	88.29	0.053940	0.004170
5	84.91	0.059891	0.005878	83.32	0.060775	0.006191
6	64.46	0.088984	0.013844	63.75	0.095810	0.019137
7	63.98	0.089470	0.014033	62.83	0.09892	0.021213

MAE, RMSE and R2are used to verify the effectiveness of the proposed model. Our model is compared with other machine learning algorithms (SVR and ANN), deep learning models (RNN), different PCA based and AE based hybrid models. The findings are provided in Table 2. The results indicate that the proposed AE-3 LSTM method has shown good performance. Based on the R2, MAE and RMSE criteria, it is evident from Table 2 that the AE-3 LSTM shows improved accuracy of 97.45% than other models considered for comparison, namely RNN, LSTM, PCA–RNN, PCA–LSTM, SVR, ANN, PCA–SVR, PCA–ANN, AE–RNN and AE-3 LSTM. Then, our deep architecture. Achieves the smallest errors on MAE and RMSE criteria compared with the benchmark models. Compared to PCA, the results of the AE seem to exhibit better performance.

Figure 6 displays the forecasting curves to show the difference between the developed models. It can be noticed that prediction given by AE–3layer LSTM model is closer to the real value. There is a great deal of deviation between true and predicted values for other models. Once more, this validates the dependability of the proposed AE–3layer LSTM model.
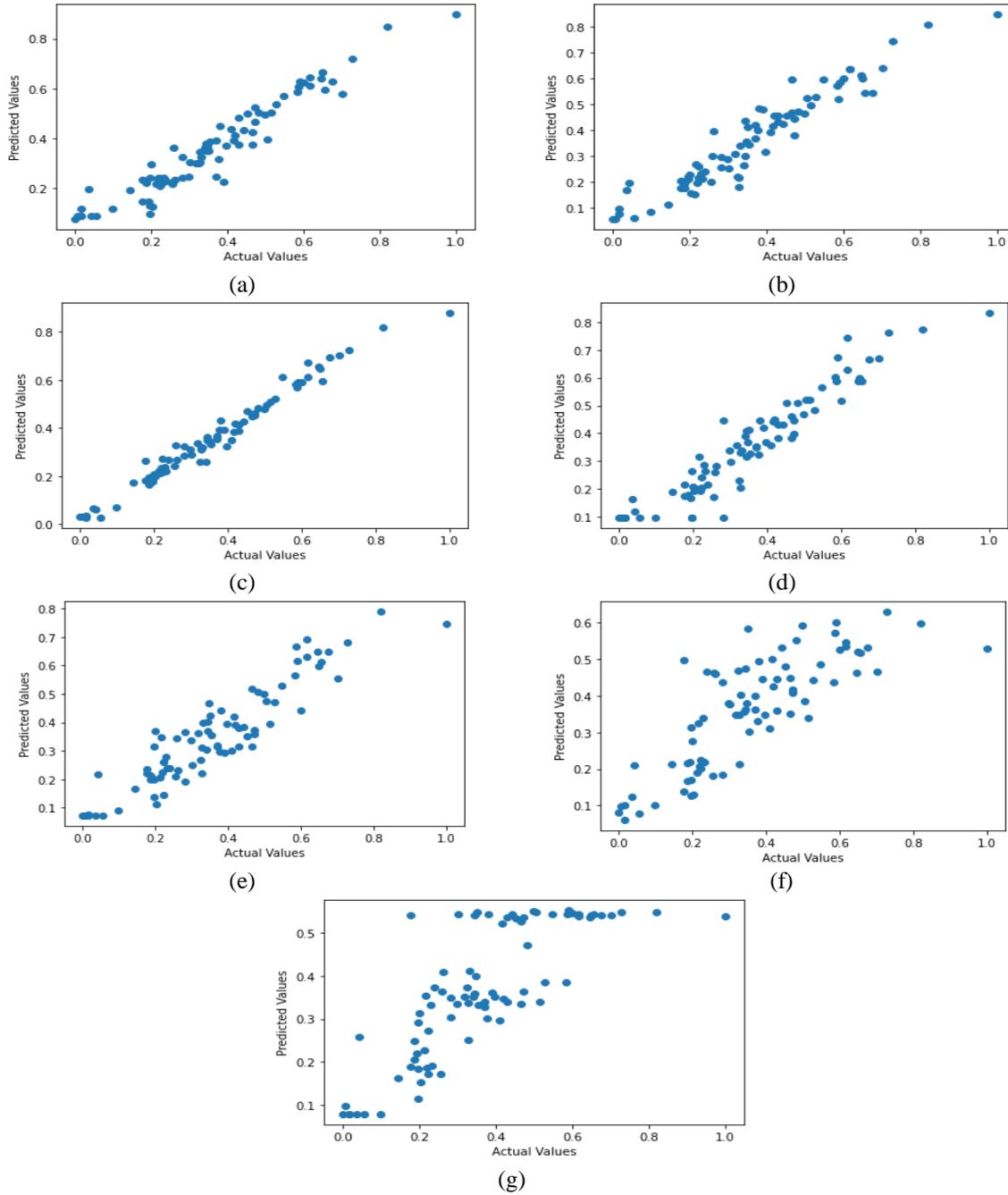
Figure 5. Tourism demand with: (a) 1 layer stacked LSTM in, (b) 2 layers in, (c) 3 layers in, (d) 4 layers in, (e) 5 layers in, (f) 6 layers in, and (g) 7 layers in

Table 2. Performance comparison between our model and other models

Prediction	Train set			Test set		
Model	R2	MAE	RMSE	R2	MAE	RMSE
RNN	95.16	0.031904	0.001749	94.36	0.036290	0.003107
LSTM	96.74	0.025742	0.001035	95.63	0.027096	0.001379
PCA–RNN	89.80	0.047989	0.003989	88.70	0.051927	0.004183
PCA–LSTM	90.24	0.042965	0.003972	89.45	0.048309	0.004057
SVR	95.54	0.028326	0.001489	94.73	0.033936	0.002159
ANN	95.29	0.030582	0.001687	94.47	0.034905	0.002974
PCA–SVR	95.01	0.032948	0.001827	94.12	0.037853	0.003205
PCA–ANN	94.43	0.034948	0.002982	93.68	0.039423	0.003493
AE–RNN	95.37	0.029853	0.001549	94.58	0.034483	0.002537
AE-3 layer LSTM	**97.45**	**0.021153**	**0.000992**	**96.52**	**0.024431**	**0.001169**
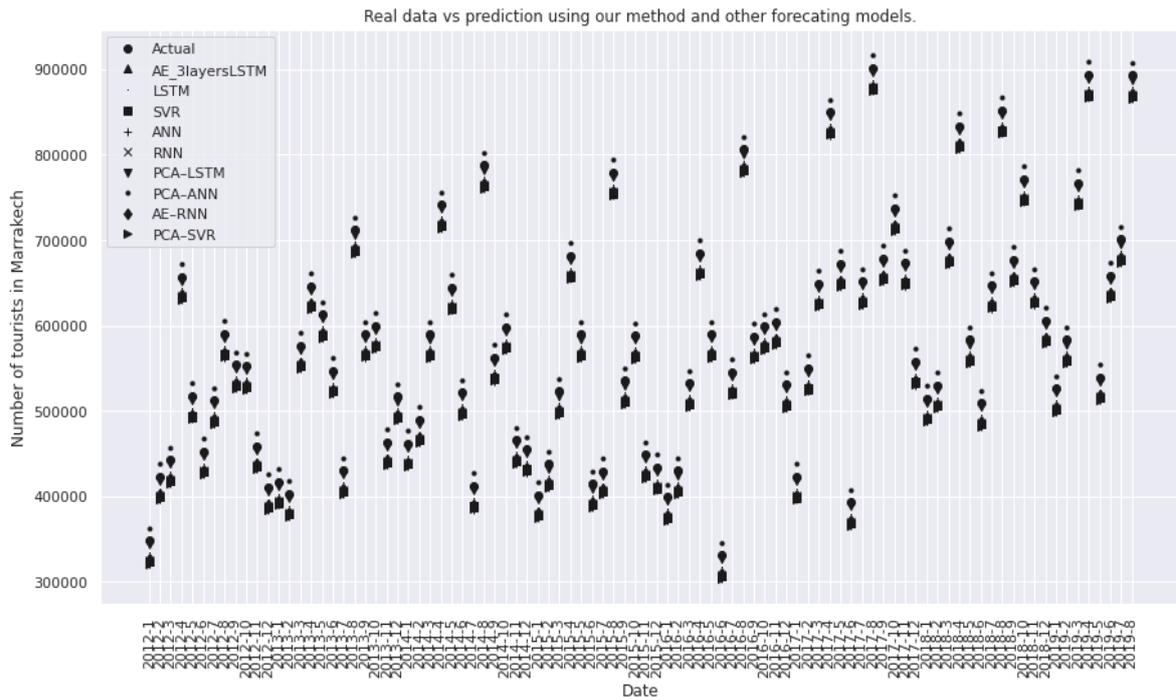
Figure 6. Comparison of actual and predicted tourism demand using different model

4. CONCLUSION

Accurate tourism demand forecasting is vital to tourism industry. A new framework, consisting of Google search data, autoencoder and stacked LSTM is conducted to forecast tourism demand. In the combined framework, a nonlinear feature extraction-based approach is developed in order to reduce the high dimensionality, autoencoder network is first applied to generate a high quality, meaningful features from nonlinear data extracted from search engine data. AE employed in learning features and reducing dimensions as an alternative to PCA in obtaining significant generalization. Then, appropriate stacked LSTM architecture is applied. The proposed AE-stacked LSTM exhibits better performance in the case of 3hidden LSTM layers, compared with individual deep learning methods, shallow ML methods, classical shallow feature extraction procedures PCA and AE based hybrid models. the proposed auto encoder-stacked LSTM model appears to be the good fit model.

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BIOGRAPHIES OF AUTHORS

Houria Laaroussi is from Rabat, Morocco, and she attended National High School of Mines of Rabat where he graduated in 2015 with an Engineering degree in Computer Science. She is presently doing research on the various applications of the machine learning and deep learning on Tourism demand. She can be contacted at email: hourialaaroussi@research.emi.ac.ma.
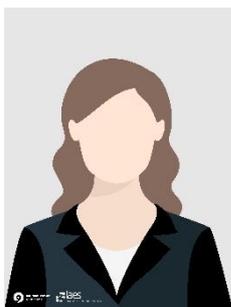
Fatima Guerouate is from Rabat, Morocco. She is now a professor of computer science and researcher at the Mohammed V University in Rabat, EST Sale. Her research is focused on Deep Learning, Big Data, MDA and eLearning in Higher Education. She has 19 years' experience in teaching. She can be contacted at: fatima.guerouate@est.um5.ac.ma.

Mohamed Sbihi is from Rabat, Morocco. Since 1996, he is professor of automatic and information processing at Superior School of Technology of Sale (EST), Mohammed V University in Rabat. His research is focused on Automation and industrial computing, Embedded systems, Maintenance of automated systems, Robotics, Image processing and Data analysis. He can be contacted at email: mohammed.sbihi@um5.ac.ma.