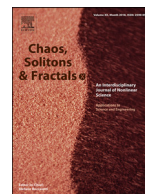




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Forecasting emergency department overcrowding: A deep learning framework



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ABSTRACT

As the demand for medical cares has considerably expanded, the issue of managing patient flow in hospitals and especially in emergency departments (EDs) is certainly a key issue to be carefully mitigated. This can lead to overcrowding and the degradation of the quality of the provided medical services. Thus, the accurate modeling and forecasting of ED visits are critical for efficiently managing the overcrowding problems and enable appropriate optimization of the available resources. This paper proposed an effective method to forecast daily and hourly visits at an ED using Variational AutoEncoder (VAE) algorithm. Indeed, the VAE model as a deep learning-based model has gained special attention in features extraction and modeling due to its distribution-free assumptions and superior nonlinear approximation. Two types of forecasting were conducted: one- and multi-step-ahead forecasting. To the best of our knowledge, this is the first time that the VAE is investigated to improve forecasting of patient arrivals time-series data. Data sets from the pediatric emergency department at Lille regional hospital center, France, are employed to evaluate the forecasting performance of the introduced method. The VAE model was evaluated and compared with seven methods namely Recurrent Neural Network (RNN), Long short-term memory (LSTM), Bidirectional LSTM (BiLSTM), Convolutional LSTM Network (ConvLSTM), restricted Boltzmann machine (RBM), Gated recurrent units (GRUs), and convolutional neural network (CNN). The results clearly show the promising performance of these deep learning models in forecasting ED visits and emphasize the better performance of the VAE in comparison to the other models.

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1. Introduction

The hospital emergency departments (EDs) are often the first access point delivering urgent care to patients with sudden illness and injury without prior appointment [1]. This makes the operating of EDs more challenging and with resource constraints due to the diverse needs of the patients, various treatment levels, and unexpected times of patients' arrival, different than the other hospital departments [2]. All over the years, the demand for EDs services has been steadily increasing. Accordingly, EDs are confronted with high pressure engendered by the high patient flow, which makes them among the most crowded entities of hospitals. Numerous studies on EDs have revealed that these establishments have more and more difficulties in fulfilling their missions. Inap-

propriate management of crowding would result in inadequate ED functioning [3], which could lead to negative patient outcomes [4]. Of course, improving healthcare in EDs is constrained by adequate control of health expenditure and care process, and proactively manage the patient flow.

Over the last decades, the demand for medical care has rapidly expanded worldwide, which makes crowding in EDs a global challenge. For instance, the 719 French emergency structures handled 21 million passages in 2016, 3.5% more than in 2015. This increase continues the trend observed for twenty years. In 1996, the number of ED visits stood at 10.1 million in France. It then increased, steadily, by 3.5% per year on average (DREES, 2018). There is a continuous increase in demands for ED services (medical and surgical treatments) and EDs are usually confronting an influx of patients around the world [5–8]. The EDs overcrowding is manifested by a prolonged waiting time and increasing patient length of stays in these healthcare establishments [9,10]. In addition, inadequate management of overcrowding affects the

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job satisfaction of medical staff and the quality of treatment of patients [11,12]. Conventional practices of the EDs management of patient flux proved to be very beneficial and should be maintained. However, it is worthwhile to notice that they seem inefficient for handling situations with major perturbations (e.g., irregular influx, seasonal, epidemic, heat waves, and cold waves). A potential solution for improving EDs pro-activity is to predict the patient flux in advance in order to give ED managers enough time to prepare for these demands (planning, mobilize the necessary resources).

With the presence of EDs overcrowding problem and limited resources (human and material), forecasting (hourly or daily) of patient demand for ED care is certainly a key solution to mitigating this problem [13]. Faced with the growing demand for emergency medical care [14,15], EDs must integrate into their mode of operation a sufficient level of resilience (proactive capacity) that allows them to anticipate care requests (forecasting ED demands) and quickly mobilize the necessary resources (adapt medical resources to the demand for care) [16–18]. The traditional medical resources organization can be ineffective in absorbing a high influx of patients, which frequently results in strain conditions that increase medical errors and medical staff stress and reduce the satisfaction of patients [8,19,20]. Thus, the accurate forecasting of ED visits is critical for mitigating ED overcrowding problem and enable controlling patient flow in an efficient way. Given a reliable ED demands forecasting, the hospital managers can choose the best strategy to handle the expected large number of ED demands and ensure optimal use of available resources. Also, such information can be used by hospital administrations to develop a proactive patient flow strategy that makes better use of the available resources and avoid overcrowding that may lead to strain situations [3,13,21–23].

All over the years, several methods have been developed to improve the quality of modeling and forecasting of ED demands. Among the existing models applied to forecast ED demands, time-series models are the most widely used ones [13,24]. These methods include autoregressive integrated moving average (ARIMA) and its variants, and Holt-Winters methods [13,18]. For instance, in Araz et al. [25], different univariate forecasting methods including Holt-Winters, exponential smoothing, and ARIMA have applied to forecast ED visits related to influenza in Omaha, Nebraska. Results showed that linear regression models provide improved forecasting when incorporating Google Flu Trends data as a predictor. In [26], a seasonal ARIMA model has been applied to forecast ED visits at the Braga Hospital in Portugal. In [18], a method based on a multivariate ARIMA model has been introduced for forecasting ED visits in Lille hospital France. Time-series models, such as ARIMA and its extensions could reach a satisfactory performance when or patients' arrival time-series data exhibits regular variations, but the forecast quality is obvious when the ED visits time-series shows irregular variations. To bypass this shortcoming, non-parametric models and shallow machine learning methods, which are more flexible, are used in improving patients flow forecasting [19,27,28]. For instance, in Xu et al. [27], the artificial neural network is used to forecast daily ED visits. Also, in Handy et al. [28], a neural network methodology is applied for hospital admission forecasting. In [29], decision trees, Naive Bayesian classifiers have been applied to predict inpatient length of stay using a geriatric hospital dataset. Results indicate the naive Bayesian models outperform the C4.5 algorithm of the decision tree in predicting length of stay. In [30], artificial neural networks, and decision trees have been applied to analyze and classify healthcare coverage. In addition, due to their flexibility, machine learning methods have been employed in many healthcare domains such as heart disease, healthcare coverage, burn and injured patients, hospital length of stay, care demands, and COVID-19 modeling and forecasting [19,31–35].

The objective of this paper is to anticipate the occurrence of strain situation within EDs by forecasting the daily and hourly patient arrivals. Accurately forecasting of ED visits is important to efficiently managing hospital resources, such as beds and staff resources (e.g., doctors and nurses), and optimally reducing delays in discharging patients, delays in tiding rooms, and waiting time. The aforementioned shallow methods are generally not suited to uncover implicit and relevant information. Recently, deep learning has developed as an important field of research in modeling and forecasting time series data, both in academia and industry [36–41]. Deep Learning is the result of the concatenation of more layers into the neural network framework [42,43]. Deep learning models are powerful tools to model implicit relationships between of process variable, enable complicated pattern recognition, and they are especially useful in describing time dependents in time series data. Deep learning methods automatically extract informative features from large data [43]. The main goal of this paper is to provide an effective approach to forecast hourly and daily ED visits based on deep learning framework. The contributions of this work are three folds. At first, a variational autoencoder (VAE) model is adopted to forecast ED visits. To the best of our knowledge, this is the first time that the VAE is investigated to improve forecasting of ED visits time-series data. In addition, this study conducts a performance comparison of eight deep learning methods including Recurrent Neural Network (RNN), Long short-term memory (LSTM), Bidirectional LSTM (BiLSTM), Convolutional LSTM Network (ConvLSTM), restricted Boltzmann machine (RBM), Gated recurrent units (GRUs), and convolutional neural network (CNN) are selected as data-driven models for ED visits forecasting. Furthermore, to guide short- and long-term ED management, both one- and multi-step-ahead forecast are considered in this study. Data sets collected from the pediatric emergency department of Lille (France) are used to evaluate the performance of the eight deep learning models in forecasting daily and hourly patient arrivals. The remaining of this article is organized as follows. Section 2 provides a brief presentation of the VAE model and how it can be applied for forecasting. Section 3 presents the used data and discusses the ED visits forecasting results (hourly, daily, one-step, and multistep forecasting) and comparisons. Finally, conclusions are outlined in Section 4.

2. Methodology

2.1. Variational autoencoders

Variational Autoencoders (VAEs) come out as one of the most effective deep models to learn relevant from complex data in an unsupervised way [42,44]. They are an important class of generative-based models that have gained attention in the machine learning community [42]. A particularly attractive feature of VAEs is their dimensionality reduction capability, which allows for compressing high dimensional data into a lower-dimensional representation enabling flexible generation of new data and quantitative comparisons. The VAEs are powerful tools to approximate complex data distributions and could be constructed efficiently with stochastic gradient descent [44]. In addition, VAE can better solve the overfitting problem in the traditional autoencoders and improve data sampling via a regulation process during the training. Moreover, the superior performance of VAEs for generating different types of complex data has been demonstrated in many applications, such as handwritten digits, faces, forecasting based on static images, and modeling urban networks [45]. In this paper, VAE is introduced to forecast ED visits time series data. Fig. 1 depicts a schematic illustration of the structure of a VAE.

Essentially, a VAE is composed of an encoder and a decoder similar to conventional autoencoders. Basically, the encoder and decoder are neural networks. The role of the encoder is encoding

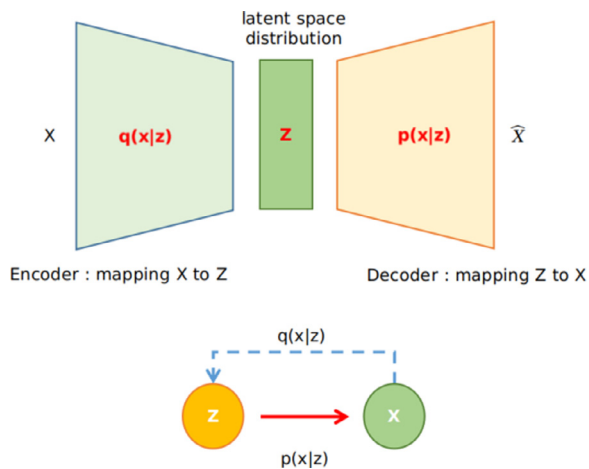


Fig. 1. Variational autoencoders (VAEs).

the input data, \mathbf{X} into a latent space as distribution, $q(\mathbf{z}|\mathbf{x})$. The latent (called hidden) space possesses much fewer dimensions compared to the input data. It is worth pointing out that the encoder should be constructed to learn an effective compression of the input data into this lower-dimensional space. After that, a sample, $z \sim q(\mathbf{z}|\mathbf{x})$, can be obtained from the code distribution. The role of the decoder $p(\mathbf{x}|\mathbf{z})$, which is a neural network, is to generate the data point x from the input z . Finally, the error of reconstruction is computed and backpropagated via the network. Basically, the decoder enables obtaining the datapoint x from low-dimensional latent representation z . However, it is worthwhile to notice that this projection based on the decoder results in some loss of information. The loss of information is reduced during the training of a VAE model by minimizing the difference between original input and the encoded-decoded data.

Towards this end, the loss function, $\mathcal{L}(q)$, is minimized by the VAE based on training data. The loss function of the VAE consists of the reconstruction loss (on the output layer), and a regularizer (on the latent layer). The reconstruction loss aims to make an effective encoding-decoding process, while a regularizer enables regularizing the latent space structure to get the distributions from the encoder as similar as possible to a predefined distribution (Gaussian distribution is the most commonly used in the literature).

$$\mathcal{L}(q) = \underbrace{\mathbb{E}_{z \sim q(\mathbf{z}|\mathbf{x})} (\log p(\mathbf{x}|\mathbf{z}))}_{\text{Reconstruction term}} - \underbrace{KL(q(\mathbf{z}|\mathbf{x})||p(\mathbf{z}))}_{\text{Regularization term}}, \quad (1)$$

The key role of the first term of (1) is to reinforce the decoder to efficiently learn data reconstruction. Indeed, the larger value in this term is an indicator of unsuited reconstruction of the data x from its corresponding latent z and vice versa. The regularizer is defined by the Kulback-Leibler (KL) divergence between two probability distributions of the encoder ($q(\mathbf{z}|\mathbf{x})$) and of the prior of the latent variable (\mathbf{z} , $p(\mathbf{z})$). Here the KL is used to quantify the closeness between the two distributions. The minimization of the loss function with respect to the parameters of the encoder and decoder is performed using the gradient descent method over the training phase. Of course, minimizing the loss function is performed for guaranteeing the obtention of regular latent space, z , and appropriate sampling of new observation based on $z \sim p(x|z)$. More details about the VAE model can be found in Doersch [46].

2.2. The proposed VAE-based forecasting strategy

In our work, the ED visits time-series data is smoothed to remove outliers and enhance data quality. To this end, an exponen-

tially weighted moving average (EWMA) filter is applied to the collected data to smooth the data and remove outliers. The smoothed data points based on EWMA filter are computed as

$$\begin{cases} S_t = \nu y_t + (1 - \nu)S_{t-1} \\ S_0 = \mu_0 \end{cases} \quad (2)$$

where y_t is the number of ED visits at time t , S_t , is the filter output at time t , and $\nu \in [0, 1]$ is the smoothing parameter that defines the depth of the memory of EWMA. Here, the data is slightly smoothed to keep the most variability in the original data.

After that, the smoothed data is normalized within the interval 0 and 1. The normalization of the smoothed data, \tilde{s} is given by:

$$\tilde{s} = \frac{(s - s_{\min})}{(s_{\max} - s_{\min})} \quad (3)$$

where s_{\min} and s_{\max} denotes respectively the minimum and maximum of the smoothed ED visits time series data. After the forecasting process, this normalization is reversed so that the forecasted data correspond to the original ED visits time series. This is done as follows:

$$s = \tilde{s} * (s_{\max} - s_{\min}) + s_{\min}. \quad (4)$$

Dataset is then split into training and testing sub-datasets. The training dataset is formed using the sliding window of fixed length called *time-steps* or *lag* (Fig. 2) algorithm. This result in mapping of sequence of values S_x to its next value S_y , which is required for supervised learning (e.g., RNN models), however unsupervised learning approach needs only S_x (e.g., VAE).

As discussed above, the VAE is naturally an autoencoder trained based on unsupervised learning. The main objective of a VAE model is to extract and discover features from the underlining training dataset and map them to a new feature space (encoding) using the statistical variational inferences. In this paper, we pre-train the VAE via unsupervised learning to initialize a deep neural network (DNN) for forecasting ED visits time-series data. To this end, we introduce the output layer of the VAE model a predictor layer. The predictor layer has 1 unit, i.e., the output of the predictor (Fig. 3). The goal of the predictor layer is to map the output of the VAE model into a scalar data point that can be compared with the original time-series data.

At first, the parameters of the VAE model are computed in the training, where the target DNN is initialized. We add a new layer with a single output to the VAE model for forecasting (see the flowchart). This first step is usually called pre-training, which is accomplished through unsupervised learning to obtain a better local optimum or even the global optimal region. Next, the fine-tuning step is performed to optimize the model parameters via supervised training. The coupled VAE and forecaster layer is ready to forecast the next value of a given data sequence. Indeed, after the pretraining, the whole structure of the VAE is fine-tuned in order to optimize its parameters and improve its performance. Specifically, this phase is done via supervised learning using the backpropagation (BP) algorithm which adjusts the weight matrices and bias of the network to achieve the optimal states of the parameters that minimize the loss function of the actual data and predicted data. Actually, fine-tuning the model parameters aim to derive the network to reach the global optima using the mapping of historical data arranged into a sequence with the next value for each sequence in the training dataset. The flowchart of VAE-based forecasting is displayed in Fig. 4.

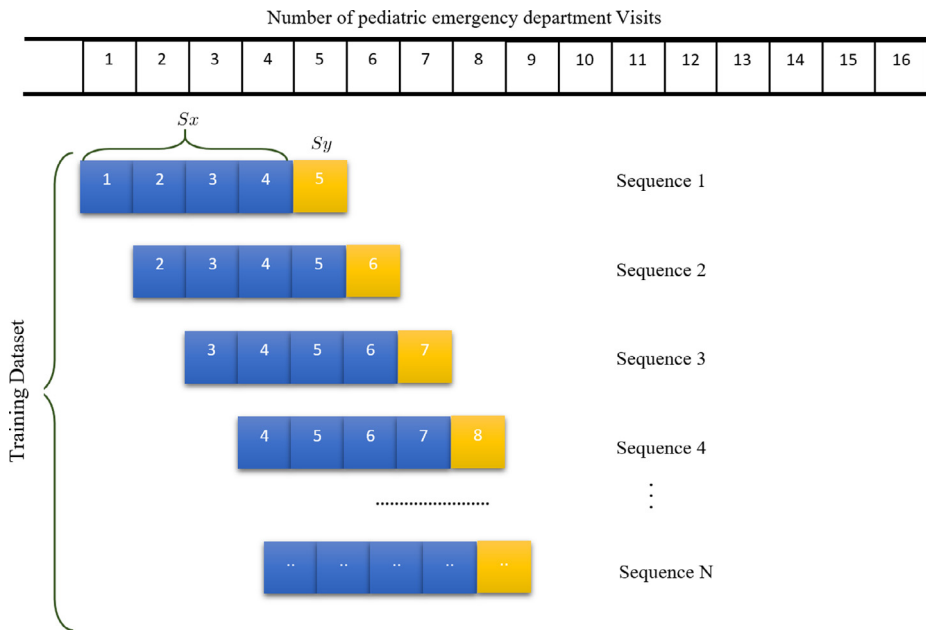


Fig. 2. Training dataset preparation using sliding window.

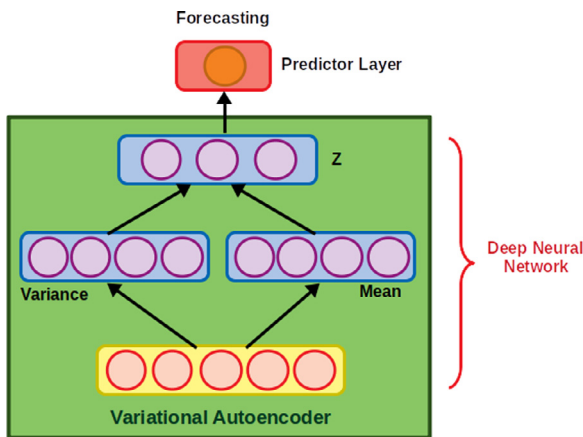


Fig. 3. Proposed VAE-based forecasting framework.

2.3. Evaluation metrics

For performance comparisons, the following indexes have been adopted to quantify the forecasting of PED visits: Coefficient of determination (R^2), Root Mean Square Error (RMSE), mean absolute error (MAE), and explained variance (EV).

$$R^2 = \frac{\sum_{i=1}^n (y_i - \bar{y}) \cdot (\hat{y}_i - \bar{y})^2}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2} \cdot \sqrt{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}}, \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2}, \quad (6)$$

$$MAE = \frac{\sum_{t=1}^n |y_t - \hat{y}_t|}{n}, \quad (7)$$

$$EV = 1 - \frac{\text{Var}(\hat{\mathbf{y}} - \mathbf{y})}{\text{Var}(\mathbf{y})}, \quad (8)$$

where y_t is the number of PED visits, \hat{y}_t is its corresponding forecasted values, and n is the number of data points. Lower RMSE and MAE values are more precise forecasting quality is.

3. Results and discussion

Deep learning models, which could automatically learn relevant information from time-series data, are investigated in this paper to make a reliable forecast of PED visits. Here, the VAE-based forecasting model will be investigated for hourly, daily, one-step and multistep forecasting of PED visits time series data. Also, comparison with seven competitors is presented to show the effectiveness of the VAE model. Specifically, we compared the performance of VAE model to seven deep learning models namely RNN [47], LSTM [47], BiLSTM [48], ConvLSTM [49], GRUs [50], RBM [51] and CNN [52].

3.1. Case study: PED at CHRU-Lille

This study is conducted based on data for arrivals to the PED in CHRU-Lille. The CHRU-Lille hospital assists around four million inhabitants in Nord-Pas-de-Calais in France, and its PED admits on average 23,900 patients per year. Also, the PED shares with other hospital departments the access of its resources (e.g., clinical laboratory, scanner, and X-rays).

The five main stages characterizing the patient treatment process in the PED are (Figs. 2 and 5):

1. Administrative registration,
2. Handling by hostesses
3. Nurse consultation,
4. Patient admission for medical consultation,
5. Patient admission for additional examination if needed.

The treatment process in PED starts upon the arrival of the patient to the PED and concludes when a patient is either sent home or transferred to another department of the hospital. At arrival, the patient information, such as the reason for coming, age, phone number, and health history, is recorded by the administrative agent. After that, the patient is guided towards the PED (Fig. 5). Next, the patient is examined by the medical staff, and he is headed according to his situation for a medical specialist, waiting room, consultation box, vital emergency room, or to the short-term hospitalization unit. It is worth to point out that patients

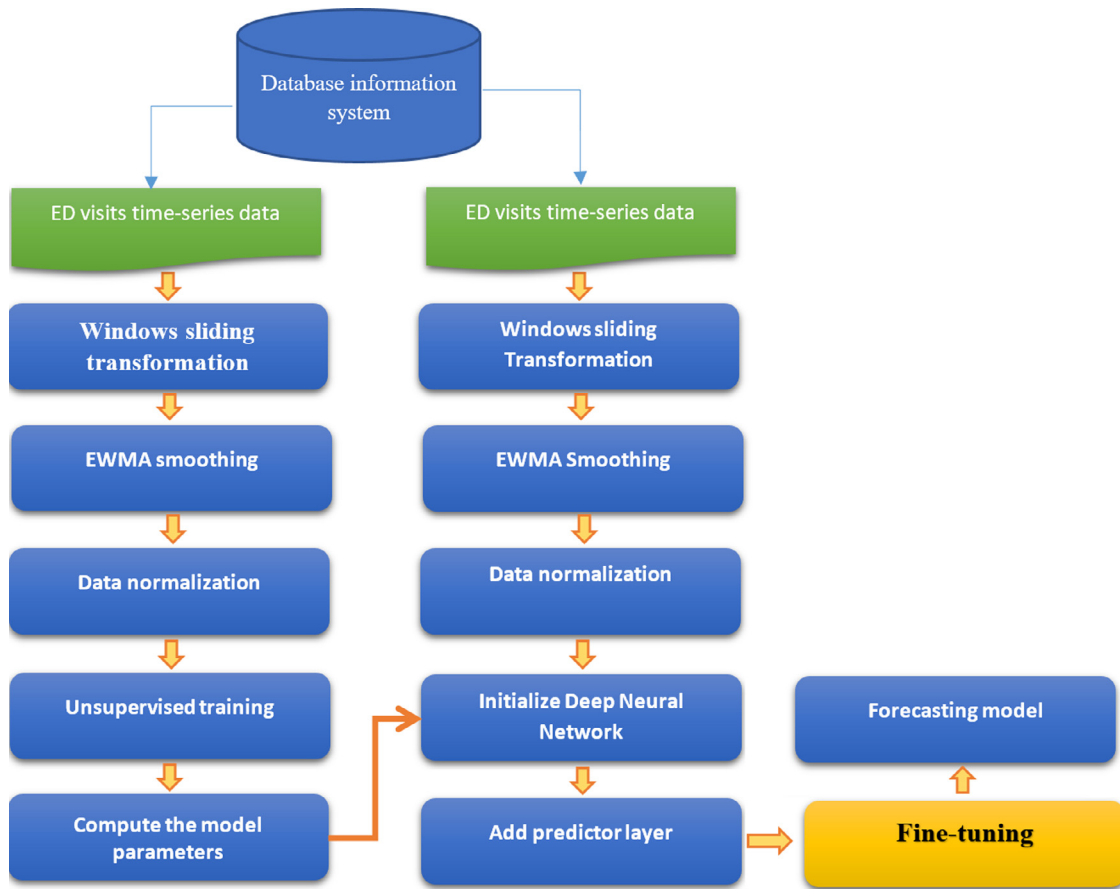


Fig. 4. VAE-based ED visits forecasting strategy.

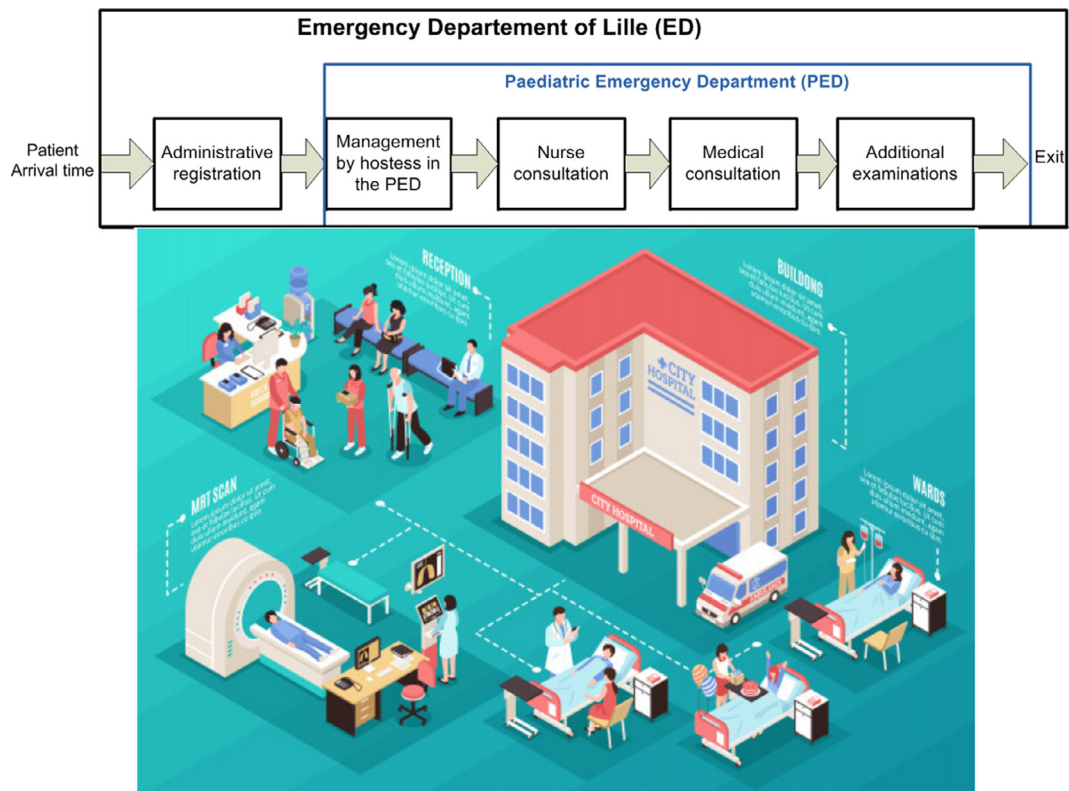


Fig. 5. General PED care process.

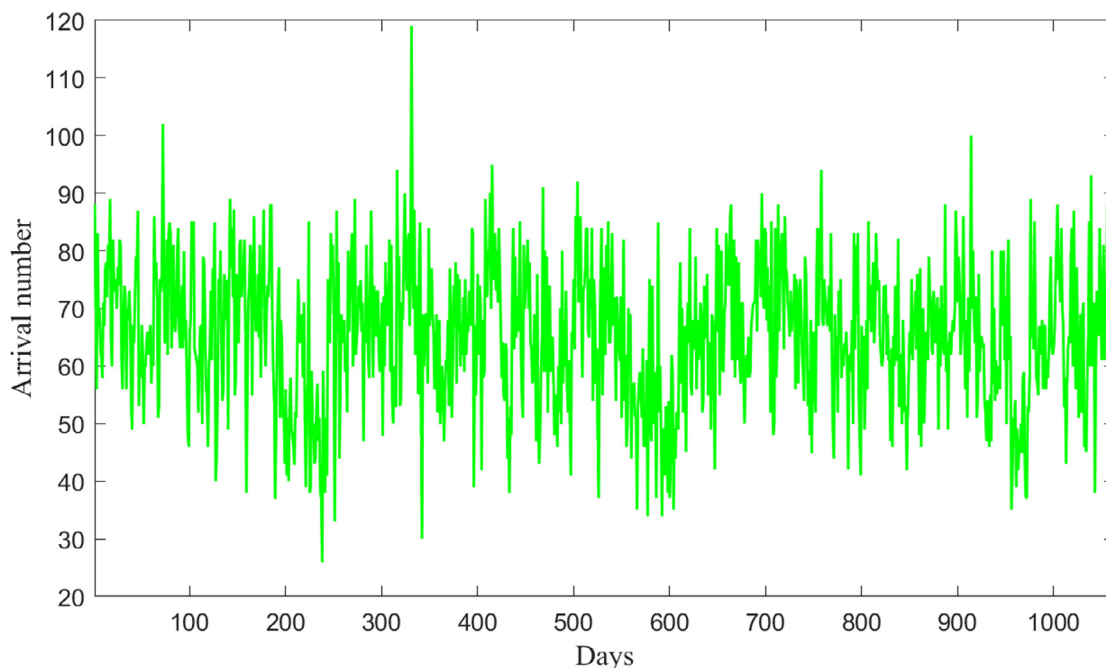


Fig. 6. Daily PED visits recorded from January 2011 to November 2013.

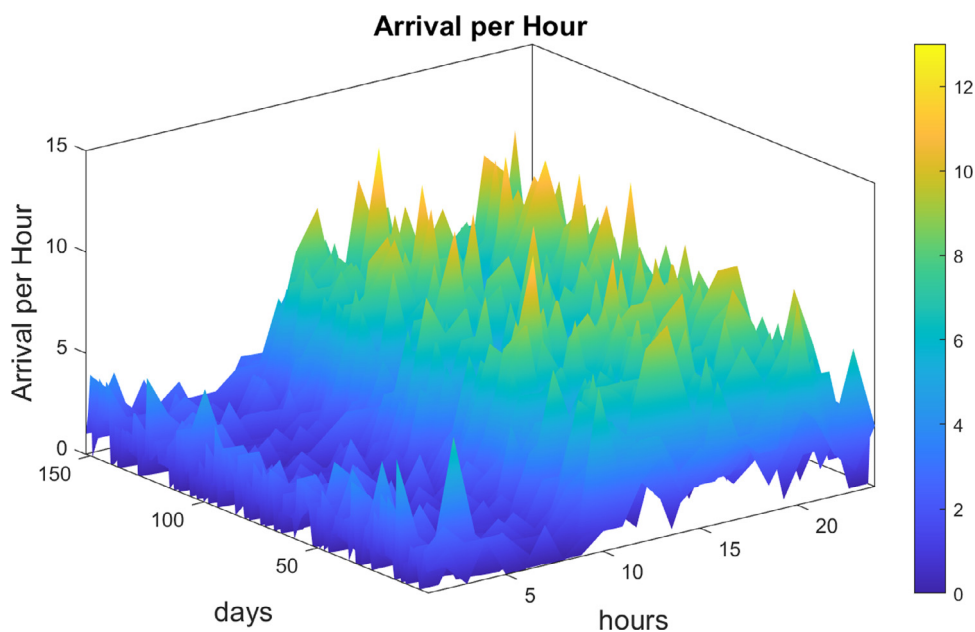


Fig. 7. Distribution of hourly PED visits.

are immediately accepted by the PED without a preliminary registration if they arrive via the mobile emergency and resuscitation service (SMUR) or firemen. In this situation, the administrative process can be done after the treatment.

3.2. Data analysis

The data used in this study consist of a number of visits at PED of Lille collected from January 2011 to November 2013 every hour (Fig. 6). To give an idea of the evolution of this time series data, Fig. 7 depicts the shows the hourly distribution of the number of visits at the PED from November 2011 to March 2012. Fig. 7 indi-

cates that the number of visits fluctuated significantly within the day. The visit rate is more than one patient each 5 min.

The actual total number of visits at the PED per month in 2011 and 2012 are illustrated in Fig. 8. Three periods can be distinguished: the winter/epidemic period (November–March) and the period between April and October with the lowest visits between July to September. As expected, the patient flow is relatively high in the epidemic period, while fewer visits are observed from July to September maybe because most of the people are on vacation during this period.

Fig. 9 illustrates the box plots of the patient visits at the PED by day of week. The number of visits to the PED fluctuates along with

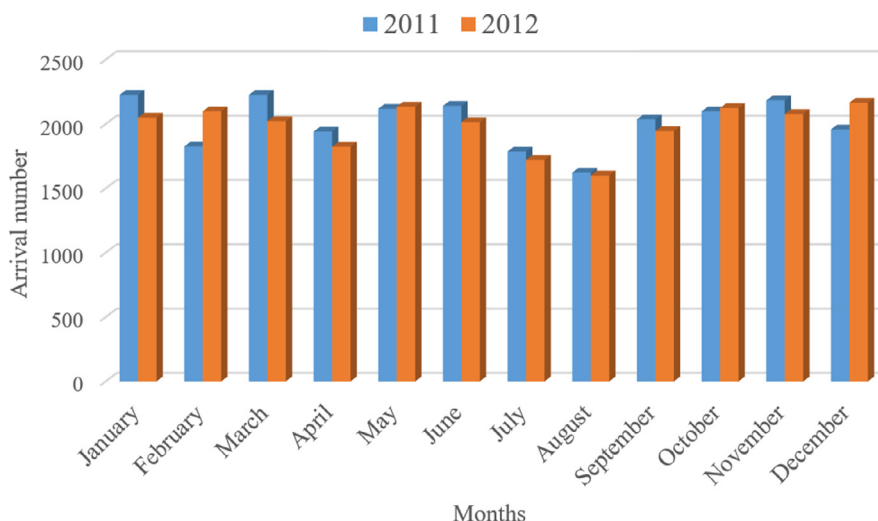


Fig. 8. The number of monthly visits in 2011 and 2012.

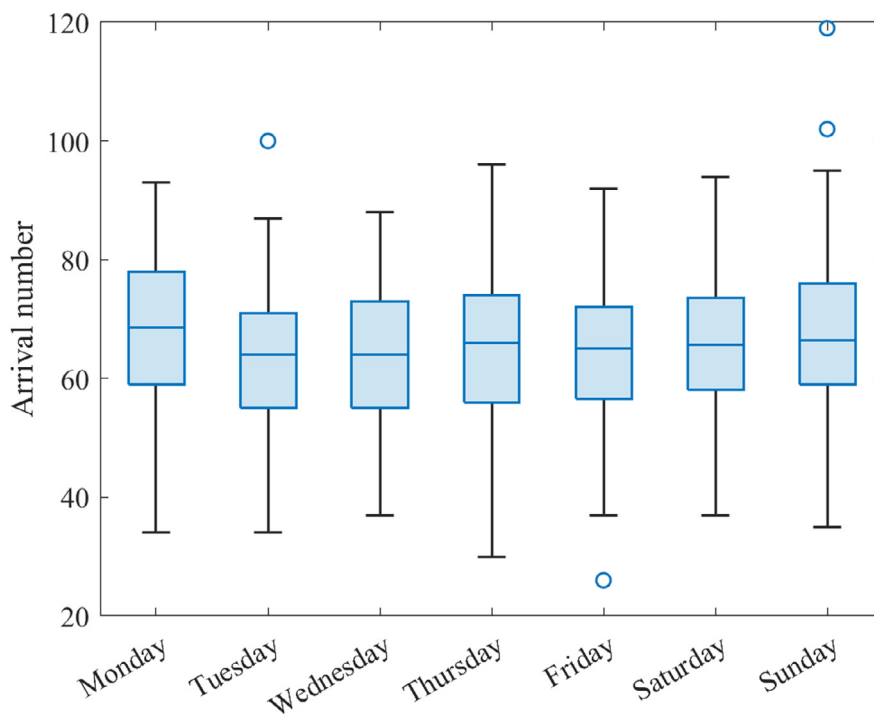


Fig. 9. Box plots of visits by day of the week from January 2011 to November 2013.

the day of the week. We also observed that Sunday and Monday and Thursday are the most overloaded. A larger number of visits are recorded on Sundays and Mondays. This can be due to the closure of family clinics and some events including holidays, sporting occasions, and festivals in the region.

Fig. 10 shows the sample autocorrelation function (ACF) of the hourly patient visits at the PED. ACF quantifies the correlation of a given time series data with itself at differing time lags, which could anticipate the time period length between two successive maxima. Fig. 10 shows the presence of a daily cycle (seasonality) in patient visits time series data.

3.3. Forecasting hourly ED visits

As time-series data of the patient visits at the PED is related to many factors including meteorological conditions and epidemic

events, it is relatively challenging to model and track its trend in the future. Accurate short-term forecasting of the patient visits at the PED is essential to optimize the planning of nursing rosters, the management of available staff within the emergency department, and assist in bed occupancy estimation. In this study, data-driven models to forecast patient visits to the emergency department using advanced structures of deep learning methods are presented. This study aims to build and compare data-driven models to forecast patients' attendance at PED of Lille hospital. Specifically, the performances of LSTM, GRU, RNN, BiLSTM, ConvLSTM, RBM, CNN, and VAE models are compared in forecasting the number of visits at the Lille PED. Towards this ends, the trained models are used to forecast the number of PED visits based on testing datasets. The training set consists of 70% of data collected from January 2011 to November 2013. Parameters of the constructed deep learning models using training data are listed in Table 1. These parameters are

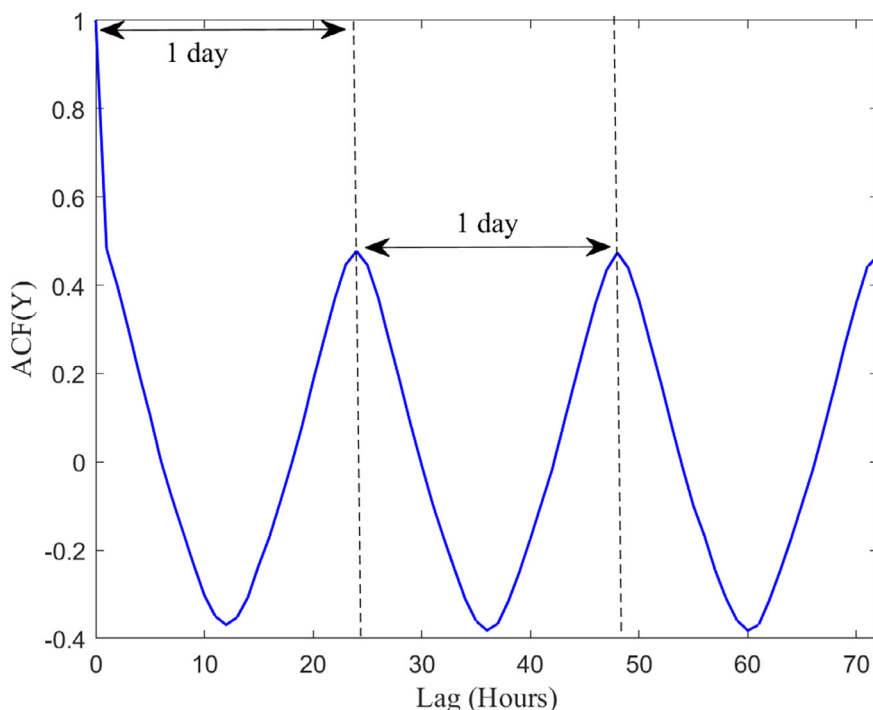


Fig. 10. Sample ACF of hourly visits at PED.

Table 1
Model parameters.

Model	Hidden Units	Batch size	Epochs	Learning rate	Optimizer	Gibbs	Layers	Filter	Kernel
GRU	32	50	200	0.0001	Rmsprop				
ConvLSTM	32	50	200	0.0001	Rmsprop				
BiLSTM	32	50	200	0.0001	Rmsprop				
LSTM	32	50	200	0.0001	Rmsprop				
RNN	32	50	200	0.0001	Rmsprop				
VAE	32	50	200	0.0001	Rmsprop		5		
CNN		50	200	0.0001	Rmsprop		3	64	3
RBM	16	50	200	0.0001	Rmsprop	5	2		

obtained by minimizing the cross-entropy of the reconstructed error during the training.

Forecasting future evolution of patient flow in EDs is one of the main pillars in establishing successful management plans which improve resource allocation and strategic planning, and hence greatly help hospital managers in enhancing decision-making. Forecasting results from the considered deep learning methods based on testing data are shown in Fig. 11. It can be seen that deep learning models are able to reasonably capture the future evolution of the patient flow time series.

Fig. 12 displays the scatter plots of the recorded and the forecasted patient visits at the PED for the eight investigated deep learning models. There is a clear correlation between the measured and forecasted patient visits at the PED.

The forecasting accuracy of the investigated deep learning models in terms of R2, RMSE, MAE, and EV, when applied to hourly patient visits at PED are summarized in Table 2. Table 2 indicates that the overall forecasting quality of the eight deep learning models is satisfying. This forecasting result is promising. It confirms

Table 2
Evaluation of each forecasting approach based on hourly testing data.

Models	R2	RMSE	MAE	EV
LSTM	0.942	0.430	0.300	0.943
GRU	0.945	0.419	0.296	0.945
RNN	0.941	0.432	0.317	0.942
BiLSTM	0.941	0.434	0.309	0.943
ConvLSTM	0.941	0.433	0.337	0.943
RBM	0.946	0.416	0.292	0.946
VAE	0.949	0.402	0.295	0.950
CNN	0.936	0.452	0.313	0.938

that the forecasted patient visits data closely follow the recorded patients' visit trend. Also, Table 2 shows that the VAE model exhibited slightly superior performance in comparison to the other methods by achieving an R2 of R2 = 0.949 and explaining most

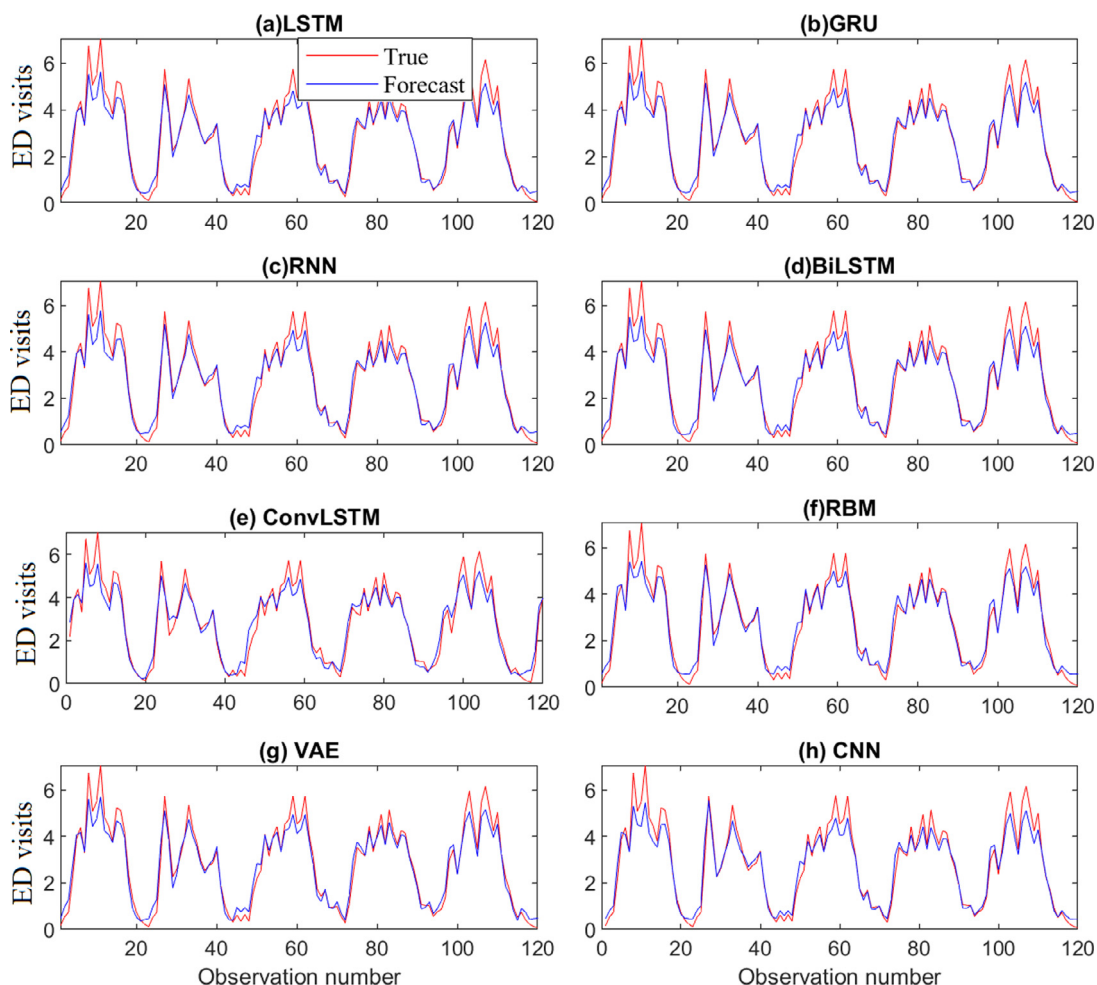


Fig. 11. Records vs. forecast of ED visits of each forecasting approach.

of the variance in data (i.e., $EV = 0.95$). For RBM, the forecasting quality is relatively comparable to the VAE model by reaching and R^2 of 0.946 and it can capture 94.6% of the total variance in the testing patient visits time series data. Then, RNN-based models, RNN, LSTM, BiLSTM, and GRU are providing acceptable forecasting with R^2 of 0.941, 0.941, 0.942, 0.945, respectively. Generally, RNN-based models are useful to model time dependencies and memorize sequential events. They show great success in different practical applications in the literature. However, it is worthwhile to notice that a simple RNN is usually confronted with learning issues due to the vanishing gradient and exploding gradient. GRU as an improved version of LSTM exhibits high performance in comparison to the other RNN-based methods (i.e., $R^2 = 0.945$). Table 2 indicates that CNN showed the lowest forecasting accuracy with an R^2 of 0.936. Indeed, the CNN model is more appropriate for 2D data such as images and is not designed for time series data.

3.4. Forecasting daily ED visits

To further investigate the performance the eight deep learning models, in this section we consider daily patient visits time series data. Accurate daily forecasting of ED visits provides relevant information for assisting medium-term planning, such as the assignment of rotas. Such information is very useful for tactical planning to decide staff should be contacted on call and to get a prior

knowledge about situational awareness. Of course, a precise forecast is needed to giving support for decisions. In this experiment, the eight models are first trained using daily PED visits and then will be evaluated using testing data. It is known that deep learning models would offer good performance when applied to a large amount of data and enough training data is available. In this section, we investigate the performance when applied to a relatively small-sized dataset (daily PED visits data).

Forecasting results of daily ED visits from the eight deep learning models based on testing data are shown in the left panel of Fig. 13. Also, scatter plots of the measured power against forecasted power obtained from the considered models are displayed in the right panel of Fig. 13. Similar conclusions hold true also for daily ED visits forecasting. Fig. 13 indicates that the forecasting result from the eight models are satisfying.

To more clearly compare the forecasting performance of deep learning methods, box plots of the forecasting errors in the testing daily PED data for each of the eight methods are displayed in Fig. 14. RNN has the largest errors as it can be seen in the width of the central box and whiskers corresponding to the forecasting errors of the RNN approach. The LSTM, GRU, BiLSTM, and VAE have compact box plots with relatively shorter interquartile ranges and whiskers, and errors are tightly packed around zero. That is, these four models provide lower forecasting errors than the other models. Also, it emphasizes the superior performance of the VAE model over the other models.

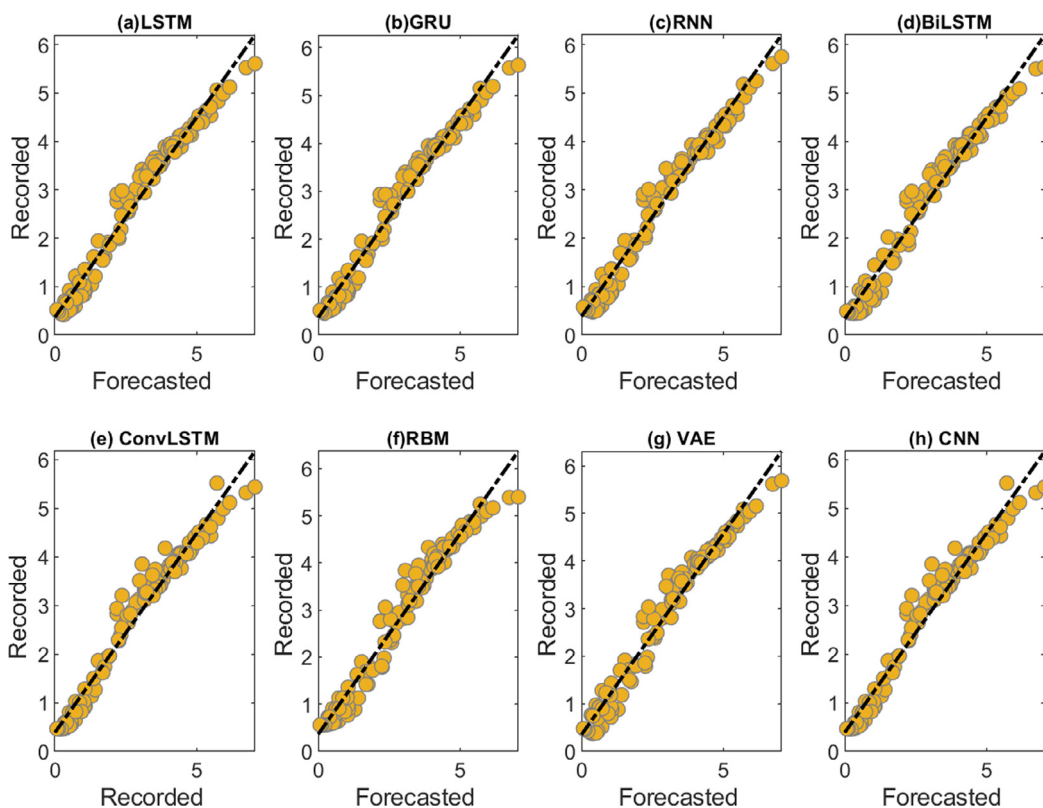


Fig. 12. The scatter plots of recorded versus forecasted patient visits at the PED for each forecasting approach.

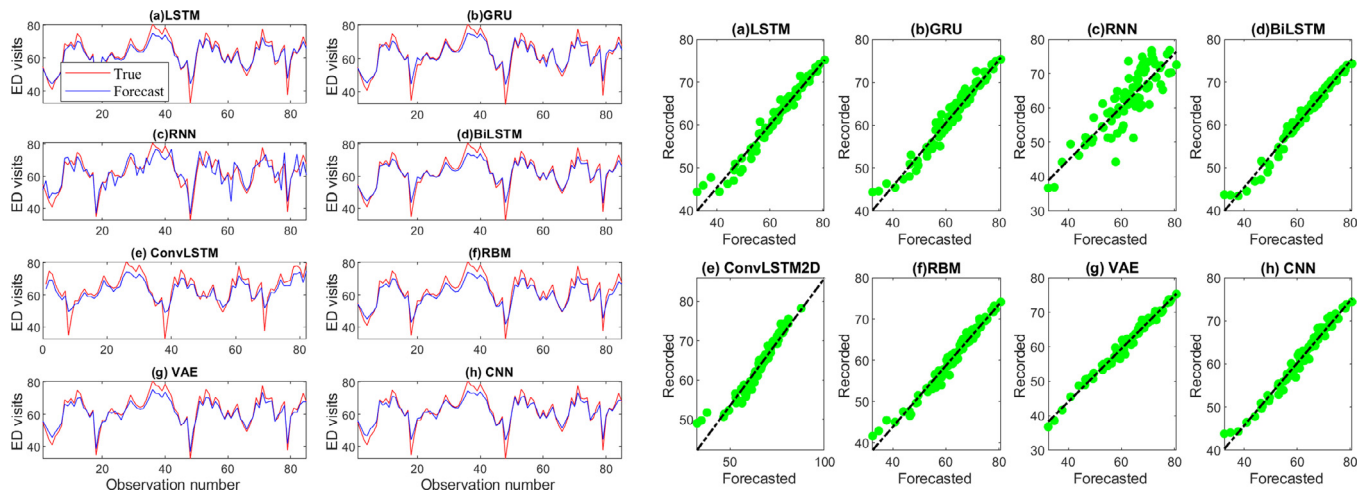


Fig. 13. Left panel: Records vs. forecast of ED visits of each forecasting approach. Right panel: The scatter plots of recorded versus forecasted patient visits at the PED for each forecasting approach.

A comparison of forecasting results of considered models when applied to daily patient visits at PED data, are listed in Table 3. It can be seen that the VAE model offers superior forecasting performance in terms of R2, RMSE, MAE, and EV, compared to the other models. It achieves the highest forecasting accuracy with an R2 of 0.925.

3.5. The forecasting results for multi-step ahead

Accurate multi-step forecasting models are helpful in efficiently managing patients flow at PED. In this experiment, the effectiveness of the eight deep learning models are evaluated for the

Table 3
Evaluation of daily forecast of ED visits.

Models	R2	RMSE	MAE	EV	RMSLE
LSTM	0.905	3.082	2.197	0.909	0.004
GRU	0.907	3.046	2.249	0.908	0.004
RNN	0.757	4.937	3.985	0.757	0.006
BiLSTM	0.916	2.897	2.124	0.919	0.003
ConvLSTM	0.812	4.348	3.344	0.841	0.007
RBM	0.883	3.430	2.810	0.918	0.004
VAE	0.925	2.738	2.318	0.938	0.002
CNN	0.909	3.014	2.292	0.911	0.004

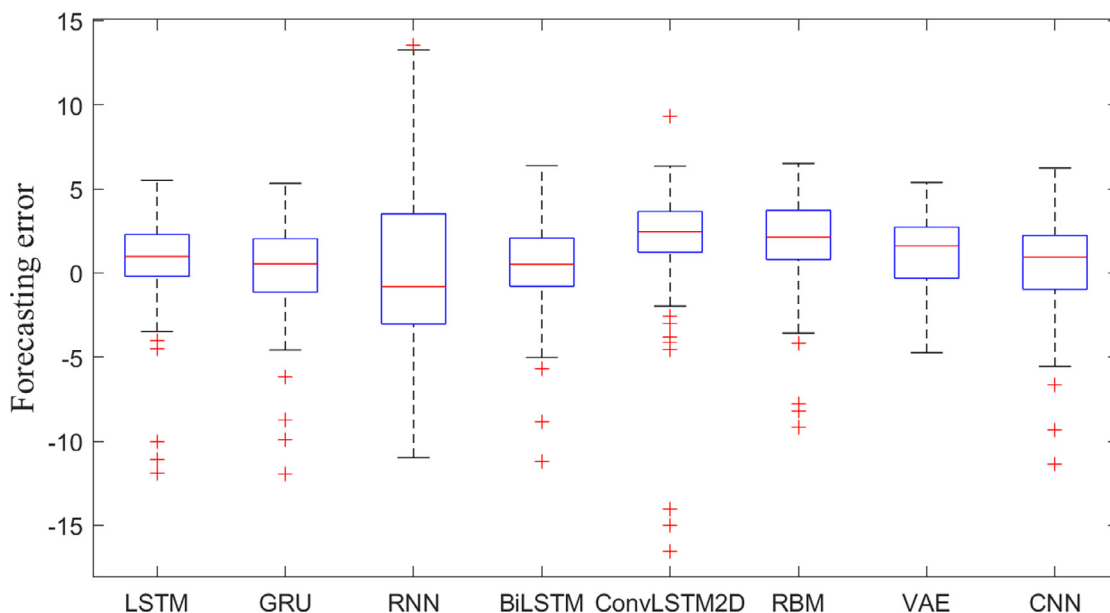


Fig. 14. Boxplots of forecasting error of each approach based on testing.

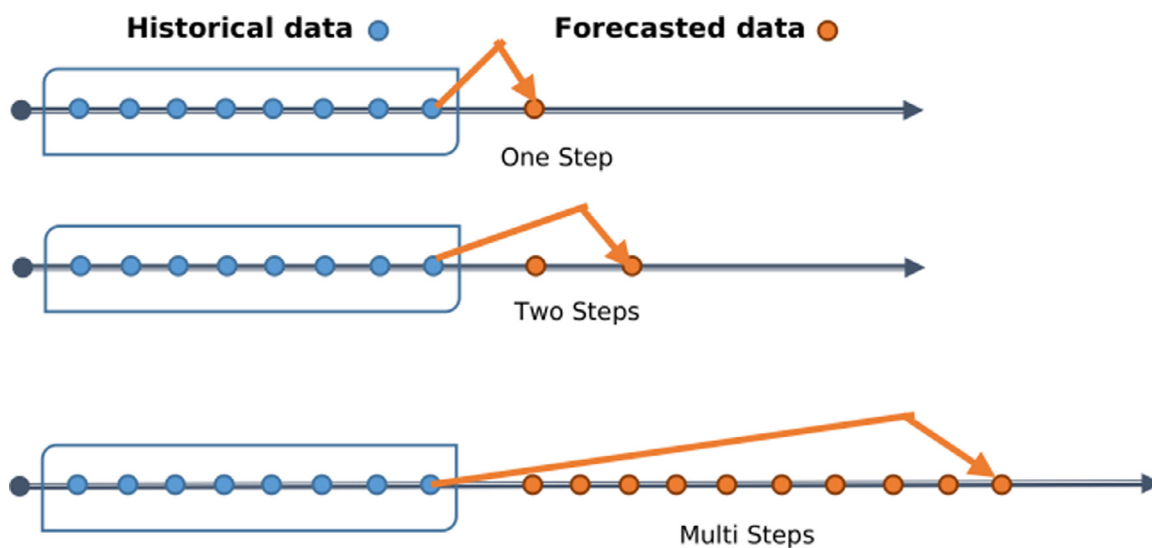


Fig. 15. Basic illustration of multi-steps forecasting procedure.

multistep ahead forecasting of hourly PED visits. Fig. 15 shows the difference between one-, two-, and multistep-ahead forecasting. By using the historical data $x = [x_1, x_2, \dots, x_l]$, the values to be forecasted by one-, two-, and multistep-ahead forecasting are x_{l+1} , x_{l+2} , and x_{l+n} , respectively.

Here, the results of 2, 3, 4 steps-ahead forecasting of PED visits based on the hourly data are listed in Table 4. Results indicate that it is not easy to obtain an accurate forecasting result in compari-

son with one-step-ahead forecasting. However, it can be observed that the VAE method achieves superior forecasting performance for 2, 3, and 4-steps forecasting by reaching an R^2 of 0.753, 0.652, and 0.579, respectively. In summary, the VAE-based forecasting approach offers a promising way to forecast (hourly, daily, one-step, and multistep) PED visits compared to the other competitors. However, these multi-step forecasting results can be improved by using large training datasets.

Table 4
Multistep-step-ahead forecasting of ED visits for each method.

Multi-steps	Model	R2	RMSE	MAE	EV
2	LSTM	0.74	0.941	0.728	0.553
2	GRU	0.726	0.963	0.74	0.557
2	RNN	0.75	0.921	0.702	0.532
2	BiLSTM	0.749	0.923	0.711	0.546
2	ConvLSTM	0.731	0.958	0.722	0.534
2	RBM	0.684	0.999	0.767	0.686
2	VAE	0.753	0.915	0.701	0.517
2	CNN	0.703	0.995	0.733	0.514
3	LSTM	0.642	1,104	0.855	0.68
3	GRU	0.627	1,124	0.866	0.654
3	RNN	0.655	1,082	0.831	0.641
3	BiLSTM	0.654	1,085	0.838	0.635
3	ConvLSTM	0.665	1.07	0.811	0.637
3	RBM	0.487	1.274	0.986	0.49
3	VAE	0.652	1.092	0.853	0.661
3	CNN	0.585	1,206	0.903	0.668
4	LSTM	0.594	1,181	0.926	0.745
4	GRU	0.59	1,182	0.919	0.73
4	RNN	0.599	1,167	0.906	0.695
4	BiLSTM	0.606	1,156	0.902	0.696
4	ConvLSTM	0.627	1,128	0.858	0.66
4	RBM	0.352	1.431	1.109	0.355
4	VAE	0.579	1.204	0.948	0.756
4	CNN	0.5	1,328	1,006	0.767

4. Conclusion

Accurate forecast of patient arrivals at an ED is essential to ED managers for efficient management of the available human and material resources and to reduce the patient waiting time and length of stay. This paper introduces a Variational AutoEncoder (VAE) approach to patient arrivals modeling and forecasting. A VAE model is used to learn the variation of the number of ED’s patient arrivals and forecast the future trend of ED visits. The forecasting accuracy of this approach has been tested using data collected from PED in Lille regional hospital center, France. Seven other promising forecasting models, RNN, LSTM, BiLSTM, ConvLSTM, GRUs, RBM, and CNN, were also applied with the same data sets. We compared their forecasting results with those obtained by the VAE approach. Two types of forecasting were conducted: one-step and multiple-step-ahead forecasting. It is worth pointing out that this is the first time that the VAE, RBM, CNN, ConvLSTM, BiLSTM models are introduced for improving the forecasting of ED’s visits time-series data. The results indicated the superior performance of VAE in comparison to the other models in all considered cases.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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