Predicting the Number of Emergency Department Patients with Forecasting Models Based on Machine Learning

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Abstract

An emergency department (ED) is a specialized area where patients usually arrive in critical condition and require immediate care. Medical staff know that in these cases reacting quickly is crucial for saving patients' life. Since supplies, personnel and infrastructure are limited resources, the efficiency in their use is fundamental to operate adequately. Therefore, planning well in advance is fundamental to optimize the use of the existing resources. This research presents an interesting approach to forecast the number of patients received at the ED of a public hospital by means of implementing and comparing model bases in machine learning algorithms. This investigation was carried out following a 4-phase methodology: analysis, design, development, and validation. During the phase of analysis, the ED database with recorded collected during 2020 was reviewed and preprocessed. Data were prepared and organized to show number of patients visiting ED every day. During the phase of design, machine learning algorithms for forecasting were analyzed and compared. Among others: linear regression, artificial neural network, machine support vectors, and Gaussian methods. The development and the validation phases were carried out entirely using the data processing software WEKA 3.9.6 with the forecasting package version 1.1.27. In total, over seventy thousand records corresponding to ED visits occurred during 2020 were used in the investigation. Data were divides in two datasets: one for building forecasting models and another one for comparing predicted and actual values. Six forecasting horizons were study: 60, 45, 30, 15, 10, and 6 days. For each horizon four machine learning algorithms were used to predict the number of ED visits. To evaluate and compare predictions, the usual error metrics were considered: MAE, MSE, RMSE, and MAPE. Forecasting results revealed notorious differences in the accuracy of the predicted values. Although no big differences are noticeable when forecasting short periods, the prediction error is considerable when forecasting a long period of 60 days. In this case, MAPE fluctuated between 39% and 16% depending on the algorithm. When forecasting short periods, for instance 5 days, MAPE varied between 17% and 14%. In conclusion, experimental results showed that ML-based forecasting algorithms can be used to predict the number of ED visits with accuracy even when with long forecasting horizons. The application of such approach might be of great help to estimate resource requirements and to support decision making.

Keywords
Demand Forecasting, Machine Learning Algorithms, Emergency Department, Linear Regression, and Artificial Neural Network.

1. Introduction
In many countries, including Chile, the government is the most important funding source for healthcare. Since it is money collected from tax-payers, there is a real necessity for being efficient in the use of these resources (Budarin and Elbek, 2022).

The overcrowding in emergency departments is a serious and globalized problem. It so commonly associated with ineffective or incomplete treatments that difficult discharging unrecovered patients. Counting with accurate forecasts of future demand for medical care would help planning and allocating resources more efficiently, improving both the efficiency and the overall quality perceived by patients (Tuominen et al., 2022).

Different statistical tools and forecasting models have been used for decades in the health care sector. Recently, in Kenya a SEIR model (Susceptible, Exposed or latent, Infectious or Removed) to forecast the COVID-19 pandemic was developed using ARIMA (autoregressive integrated moving averages). The results and findings were crucial to develop strategies to stop the propagation of the pandemic (Kiarie et al., 2022).

Another example, is the development of a reliable short-term prediction model to predict the number of respiratory tract infections (RTI) in northeast China using seasonal autoregressive integrated moving average (SARIMA) models, memory long-term (LSTM), and Facebook's Prophet (Prophet) for predicting the number of hospitalized RTI patients (Feng et al., 2022).

In Philippines, a multilayer perceptron neural network was implemented to forecast the progress of the COVID-19 crisis using data obtained from the Philippines HIV/AIDS and ART Registry (Aribe et al., 2022).

In China an investigation proposed a hybrid ensemble forecasting technique including the accumulated generating operation (AGO), least squares support vector regression (LSSVR), and time trend element to forecast a seasonal time series characterized by nonlinearity and uncertainty (Zhou et al., 2023).

Nowadays, new forecasting techniques based on machine learning are being used with good result in the health care sector. To name few examples:

i. Starting from the premise that readmissions have a negative impact in the health system, a study carried out in the Komotini General Hospital to predict the number of readmissions was implemented with the following four machine learning algorithms: support vector machines with a linear kernel, support vector machines with a radial basis function (RBF) kernel, balanced random forests, and weighted random forests (Michailidis et al., 2022).
ii. Inspired by the problems faced by a palliative care center that provides various medical, nursing, psychological and social services, two deep learning models based on long-shot term memory (LSTM) were proposed to predict demand at individual and at collective level. The first one predicts the type and time of the demanded service for patient with a given demographic and health profile. The collective model predicts demand for a set of services in the following week and for patients with an specific profile (Soltani et al., 2022).
iii. In England, at a Hospital for Children, electronic record data from non-identifiable patients were analyzed to understand the effect of mitigation measures on seasonal respiratory infection rates. The results were compared to predictions obtained forecasting models based on machine learning (Bowyer et al., 2022).

This investigation compared the predictions of various forecasting models based on machine learning algorithms (linear regression, support vector machines for regression, back propagated multilayer perceptron neural network, and Gaussian processes) to estimate the numbers of patients who visit the emergency room of a large public hospital located in the south of Chile. All modes were entirely developed using WEKA 3.9.6 with the forecasting package version 1.1.27 (Witten et al, 2017). Predicted values are compared to actual values by means of the classical error measures: MAE, MSE, RMSE, and MAPE (Khan and Osińska, 2023).

1.1 Objective
To estimate the number of patients visiting an emergency department by means of comparing the predicted values generated by forecasting algorithms based on machine learning.

2. Literature Review
2.1 Machine learning
Machine learning is usually referred as the branch of artificial intelligence (AI) that uses algorithms to find patterns and to learn from datasets through experience. There several types of machine learning algorithms: supervised, unsupervised, and reinforcement algorithms. In supervised learning, the training is carried out using labelled datasets. This means that the class or the value to be predicted is included in the dataset so it can be used for training. In the case of unsupervised learning, instead, the desired class is not known.

2.2 Time series
A time series consist of a collection of data points in time order, usually taken at successive equally spaced points in time. For instance, daily, weekly, or month number of patients who visit an ED.

2.3 Forecasting
When working with time series, forecasting can be understood as the prediction of future values based on the analysis of historical data by means of applying statistics and modeling techniques. Time series are can be characterized by five components: level, trend, seasonality, cyclicity, and noise (Figure 2). Not necessarily all of need to be present always.

- Level: it can be understood as a base line where other components are superposed.
- Trend: it represents the increase or decrease of the time series over time.
- Seasonality: it is pattern periodically repeated over time.
- Cyclicity: is as pattern not periodically repeated over time.
- Noise: It is the random component of data.

2.4 Linear regression
Algorithms based on a linear regression learns to make a weighted sum of the considered features in such a way that they all approach the actual value. During the model construction, w_i and bias are adjusted to fit the actual value.
Actual value = w_1 * feature_1 + … + w_n * feature_n + bias
A common practice is the inclusion of lags to shift actual values to move them to a different point of time.

2.5 Gaussian processes
A Gaussian process is a collection of random variables, any finite number of which have a joint Gaussian distribution (Rasmussen and Williams, 2006). It is a Bayesian non-parametric method (Roberts et al, 2013) whose theoretical background and its used in forecasting has been deeply studied (Tolba et al., 2019).

3. Methods
This investigation is carried out following a classic 4-phase methodology: analysis, design, construction, and validation (Figure 1).

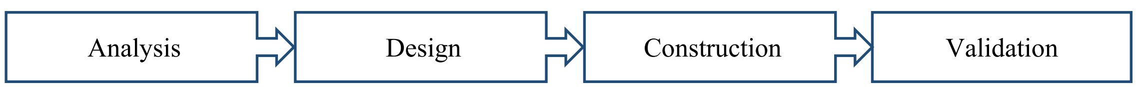

Figure 1. Four-phase methodology

3.1 Analysis
During the phase of analysis, ED database was preprocesses and prepared for the following phases. For the purposes of this investigation, data only data collected 2020 were considered.

ED database contained approximately seventy thousand records of visit. Every time a patient visited ED a new record was added. Every record consists of over 50 fields with data about patients, from arrival time to insurance type. For forecasting purposes though, not all fields were necessary. In fact, the number of daily patients was enough. Monthly and daily ED visits are shown in Table 1 and Figure 2) respectively.

Table 1. Monthly ED patient arrivals

Month	**Visits**
January	9,025
February	8,042
March	6,518
April	3,674
May	4,213
June	4,374
July	5,226
August	5,734

September	6,317
October	6,388
November	6,142
December	6,094

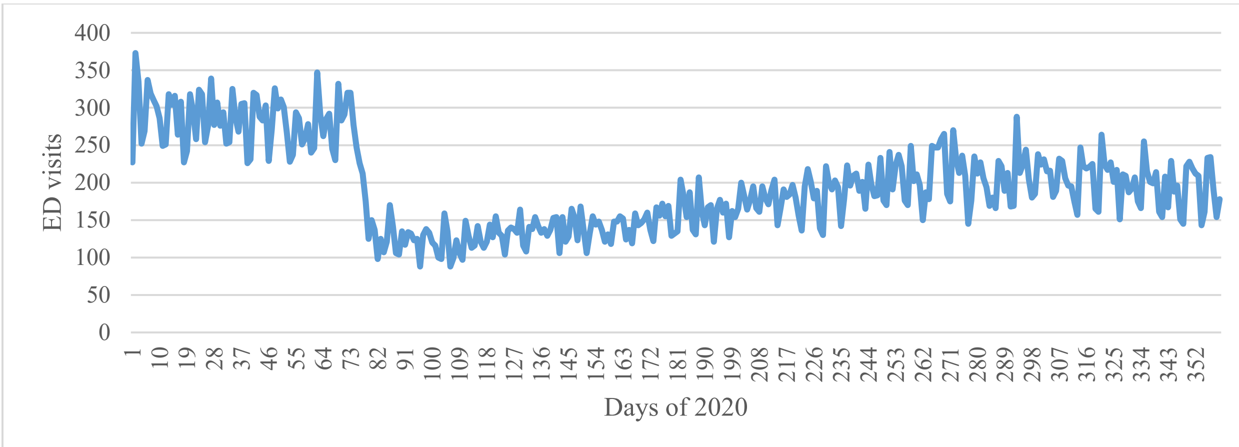

Figure 2. Daily ED patient arrivals

3.2 Design

ED database can be seen as a matrix whose rows represents the arrival or visit of a patient and whose columns are fields with data related to the visit.

During the design phase, six datasets were prepared. Each representing a different horizon of time. The first one containing the number of visits between January and October, leaving November and December to make comparison with the predications (Table 2).

Given that February of 2020 had 29 days, there are 366 days with data. Figure 3 shows graphical the data, or days, considered to build each forecasting model.

Table 2. Dataset creation

Dataset	**Construction data (days)**	**Prediction horizon (days)**
DS-305	305	61
DS-320	320	46
DS-335	335	31
DS-350	350	16
DS-355	355	11
DS-360	360	6

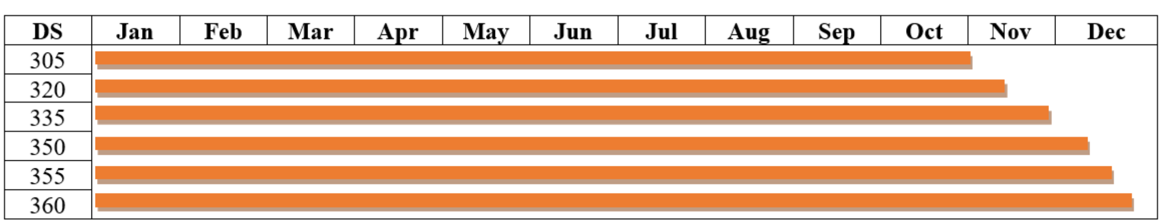

Figure 3. Days included in the construction of forecasting models

The idea is to use a fraction of the actual ED visits to build forecasting models based on machine learning which be used to predict the number of future ED visits. Predicted values were then compared to actual values.

The scheme used to compare the accuracy of predicted values is presented in Table 3. For each dataset, forecasting models based on four different machine learning algorithm were constructed. Predicted values for the number of ED visits were compared to actual values using MAE, MSE, RMSE, and MAPE.

Table 3. Dataset creation

Algorithm	**MAE**	**MSE**	**RMSE**	**MAPE**
Linear regression	√	√	√	√
Artificial neural network	√	√	√	√
Gaussian methods	√	√	√	√
Support vector machine	√	√	√	√

3.3 Construction

The construction of the forecasting models commenced with the smallest dataset. It contained 305 days of data corresponding to the lapse between January and October of 2020. The remaining 61 days of 2020 were held out to be compared to the predicted values later on.

A graphic comparison of the predicted values and the actual values is given in Figure 4, where ANN stands for artificial neural network, and SVM stands for support vector machine. The correlation coefficient between the corresponding set of values is presented in Table 4.

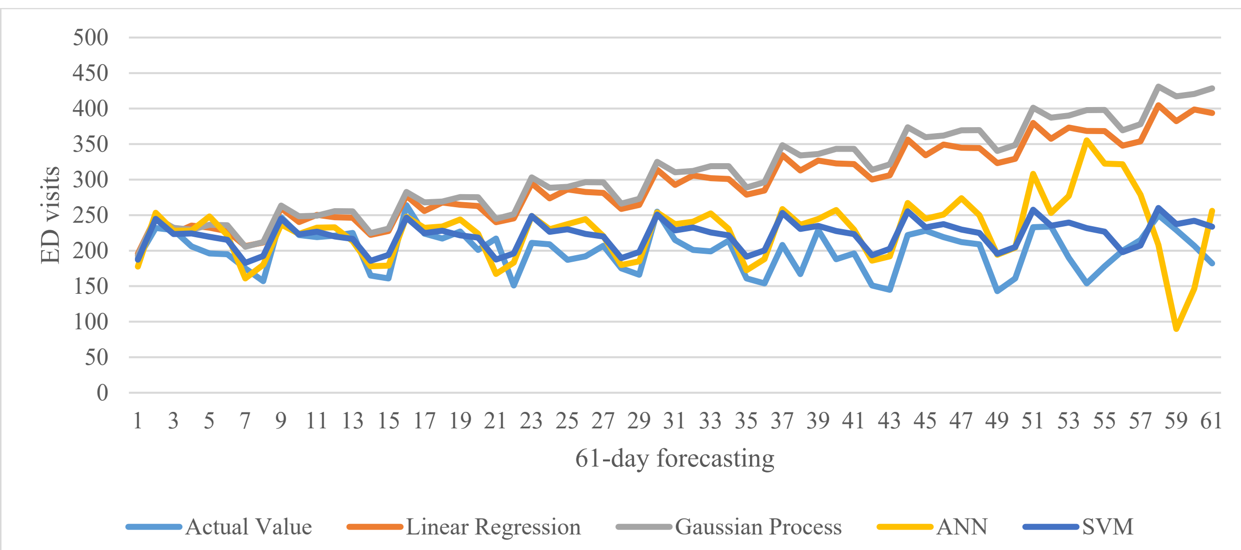

Figure 4. Actual and predicted values for 61-day forecasting

Table 4. Correlation matrix 61-day forecasting

	Actual values	Lin. Regression	Gaussian processes	ANN	SVM
Actual values	1				
Lin. Regression	0.14	1			
Gaussian processes	0.12	0.99	1		
ANN	0.25	0.38	0.37	1	
SVM	0.68	0.55	0.52	0.49	1

The forecasting models behind the predicted values are not trivial. For instance, in the case of lineal regression, multiple lags and additional variables were included as it is shown below:

```
Predicted value =   15.5351 * DayOfWeek=wed,thu,tue,fri,mon +
                    -9.131  * DayOfWeek=thu,tue,fri,mon +
                    12.3468 * DayOfWeek=tue,fri,mon +
                    27.5242 * DayOfWeek=mon +
                   -15.5353 * Weekend +
                    -0.1223 * Date-remapped +
                     0.7106 * Lag_Patients-1 +
                    -0.1244 * Lag_Patients-2 +
                     0.2732 * Lag_Patients-3 +
                     0.0852 * Lag_Patients-4 +
                    -0.1513 * Lag_Patients-5 +
                     0.2708 * Lag_Patients-6 +
                    -0.1652 * Lag_Patients-7 +
                     0      * Date-remapped^3 +
                    -0.0017 * Date-remapped*Lag_Patients-1 +
                     0.0013 * Date-remapped*Lag_Patients-2 +
                    -0.0006 * Date-remapped*Lag_Patients-4 +
                     0.0007 * Date-remapped*Lag_Patients-5 +
                     0.0004 * Date-remapped*Lag_Patients-7 + 166,735
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Figure 5 and Table 5 presents the graphical comparison and the correlation coefficients between the actual values and the predicted values in the case of the 46-day forecasting. Both ANN and SVM-based models' prediction are more accurate when forecasting 46 days ahead.

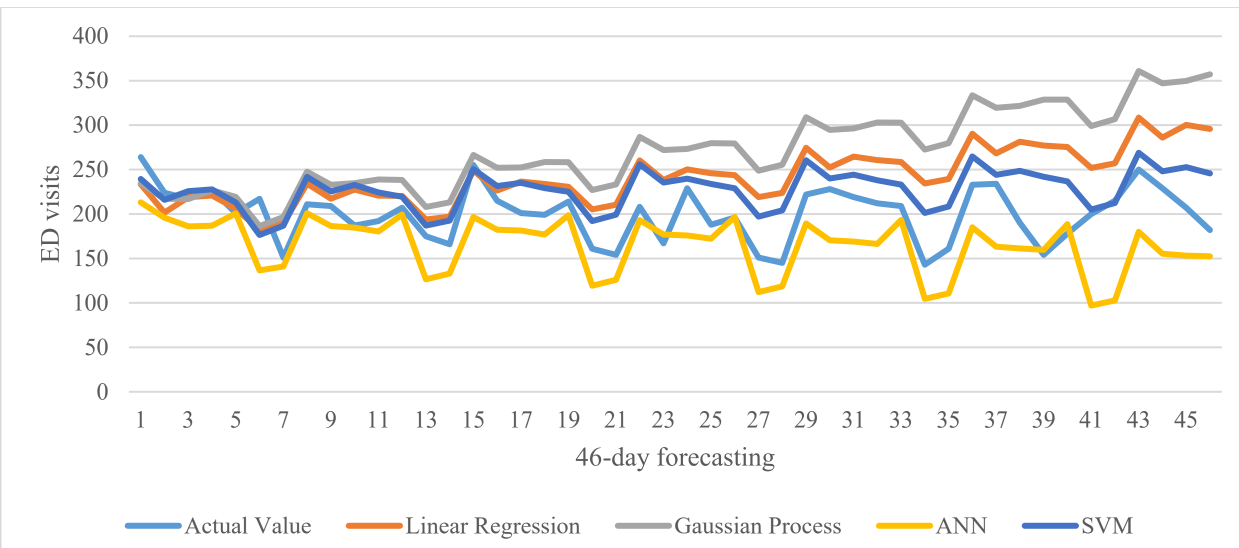

Figure 5. Actual and predicted values for 46-day forecasting

Table 5. Correlation matrix 46-day forecasting

	Actual values	Lin. Regression	Gaussian processes	ANN	SVM
Actual values	1				
Lin. Regression	0.32	1			
Gaussian processes	0.19	0.98	1		
ANN	0.60	0.14	0	1	
SVM	0.59	0.83	0.71	0.62	1

Figure 6 and Table 6 presents the graphical comparison and the correlation coefficients between the actual values and the predicted values in the case of the 31-day forecasting. In this case, only the model based on Gaussian processes is notoriously inaccurate.

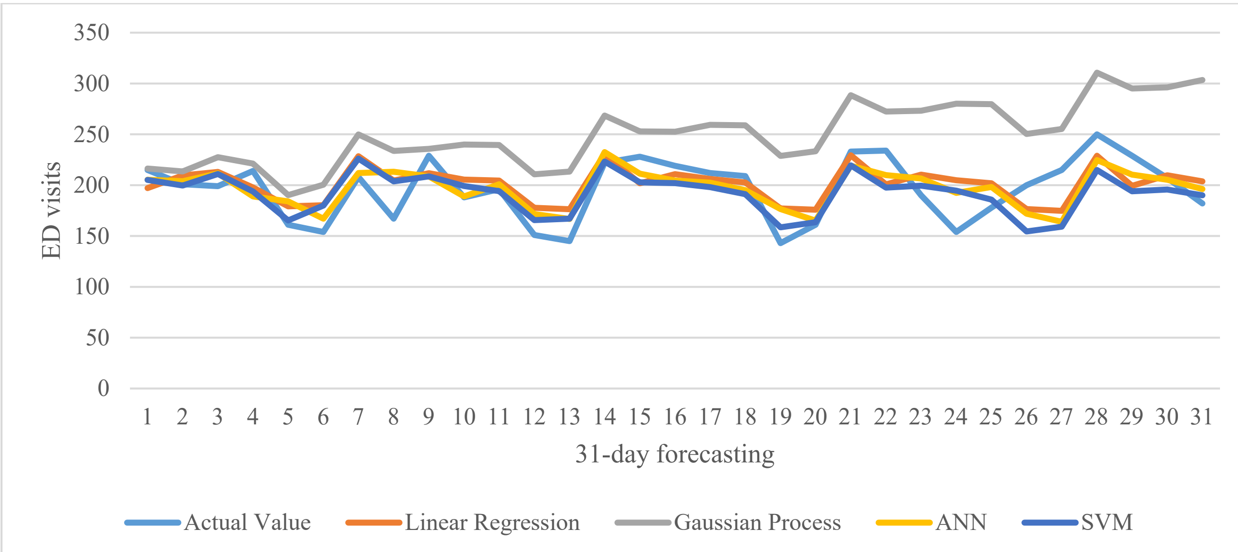

Figure 6. Actual and predicted values for 31-day forecasting

Table 6. Correlation matrix 31-day forecasting

	Actual values	Lin. Regression	Gaussian processes	ANN	SVM
Actual values	1				
Lin. Regression	0.63	1			
Gaussian processes	0.49	0.54	1		
ANN	0.68	0.91	0.50	1	
SVM	0.62	0.95	0.37	0.91	1

Figure 7 and Table 7 presents the graphical comparison and the correlation coefficients between the actual values and the predicted values in the case of the 16-day forecasting. Here all models predict values close to actual values.

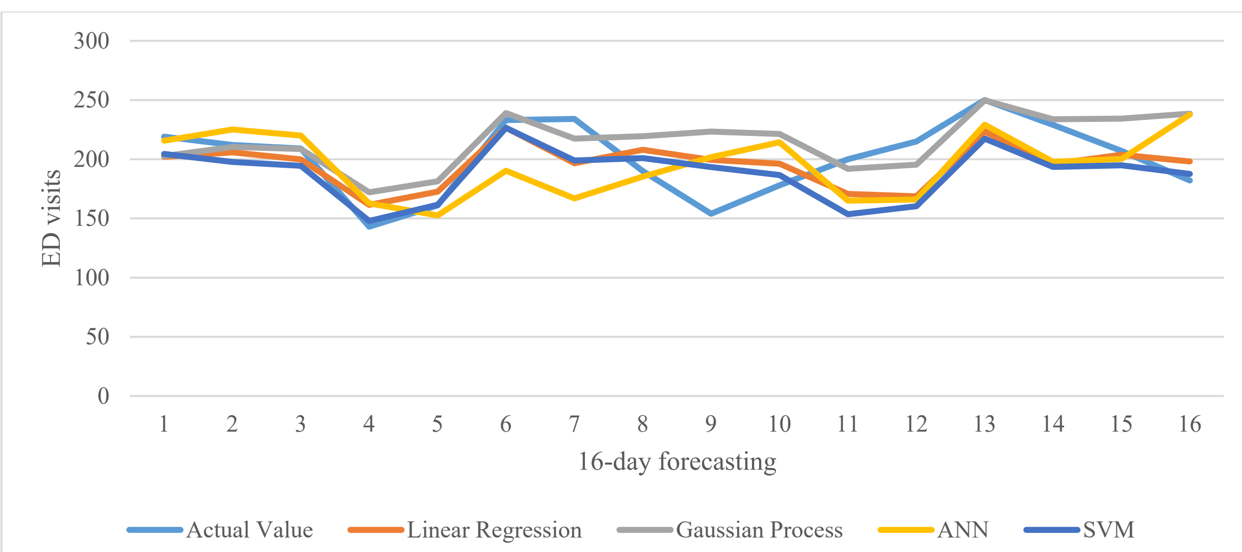

Figure 7. Actual and predicted values for 16-day forecasting

Table 7. Correlation matrix 16-day forecasting

	Actual values	Lin. Regression	Gaussian processes	ANN	SVM
Actual values	1				
Lin. Regression	0.57	1			
Gaussian processes	0.53	0.85	1		
ANN	0.27	0.66	0.65	1	
SVM	0.62	0.98	0.81	0.61	1

Figure 8 and Table 8 presents the graphical comparison and the correlation coefficients between the actual values and the predicted values in the case of the 11-day forecasting. As the forecasting horizon decreases all models seem to predict more accurate values.

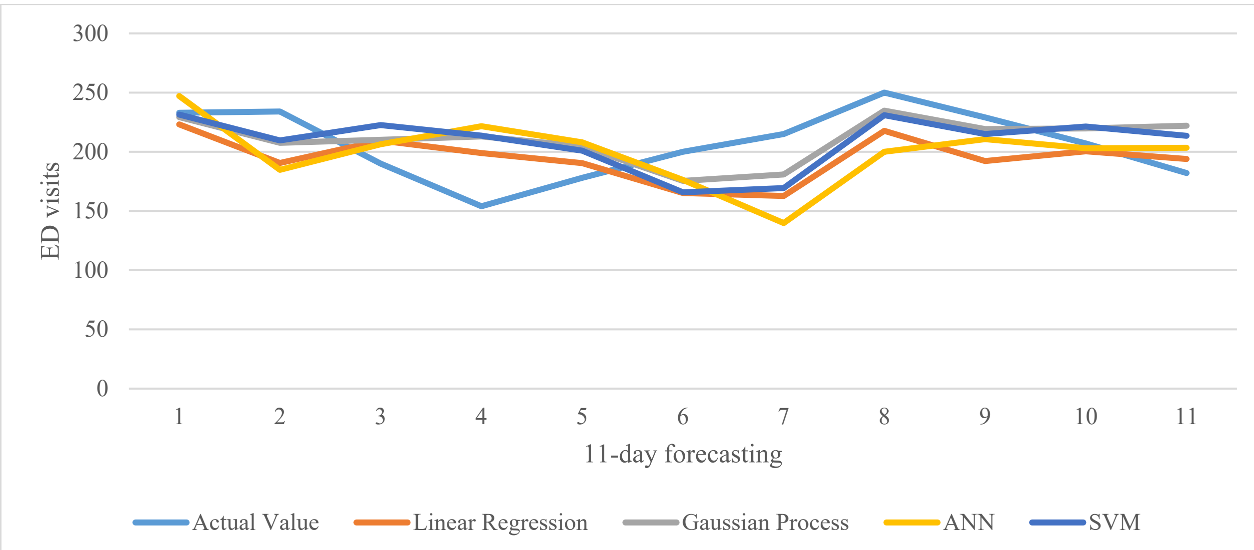

Figure 8. Actual and predicted values for 11-day forecasting

Table 8. Correlation matrix 11-day forecasting

	Actual values	Lin. Regression	Gaussian processes	ANN	SVM
Actual values	1				
Lin. Regression	0.22	1			
Gaussian processes	0.26	0.91	1		
ANN	-0.11	0.82	0.74	1	
SVM	0.20	0.96	0.96	0.78	1

Figure 9 and Table 9 presents the graphical comparison and the correlation coefficients between the actual values and the predicted values in the case of the 6-day forecasting.

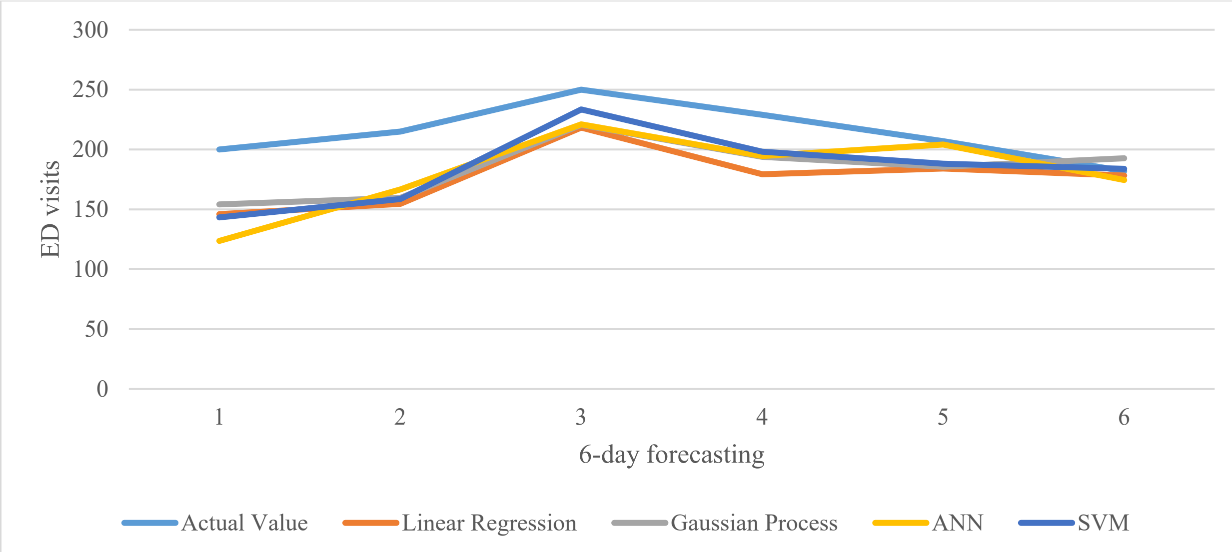

Figure 9. Actual and predicted values for 11-day forecasting

Table 9. Correlation matrix 6-day forecasting

	Actual values	Lin. Regression	Gaussian processes	ANN	SVM
Actual values	1				
Lin. Regression	0.61	1			
Gaussian processes	0.54	0.97	1		
ANN	0.61	0.91	0.87	1	
SVM	0.68	0.98	0.98	0.92	1

3.4 Validation
Part of the available data of 2020 was held out with the only intension of comparing predicting values to actual values that were not used during the construction of the forecasting models. Eliminating in this way, any possible bias caused by a validation made with preciously know data. In other words, the validation data were completely unknown to the forecasting models.

4. Data Collection
The accuracy of the predictions, expressed in terms of error measures, depends on the forecasting horizon. Even though noticeable differences in the values of the error measures exist, the fluctuation depends greatly on the algorithm in use and not only on the horizon. This fact is shown in Table 10, Table 11 Table 12, and Table 13, where the accuracy obtained with the based on support vector machines when the horizon varies from 61 to 6 days is better.

Table 10. Forecasting with linear regression

	61-day	**46-day**	**31-day**	**16-day**	**11-day**	**6-day**
MAE	95.35	46.00	20.49	21.40	27.70	37.02
MSE	12,331.41	2,968.45	549.12	632.23	1,005.20	1,758.98
RMSE	111.05	54.48	23.43	25.14	31.70	41.94
MAPE	50.39	24.80	11.11	10.92	13.60	17.07

Table 11. Forecasting with Gaussian processes

	61-day	**46-day**	**31-day**	**16-day**	**11-day**	**6-day**
MAE	108.46	73.97	53.47	21.80	24.76	32.97

MSE	15,971.89	7,412.56	3,773.93	861.83	833.78	1,307.02
RMSE	126.38	86.09	61.43	29.35	28.88	36.15
MAPE	57.07	39.30	29.05	12.21	13.04	15.33

Table 12. Forecasting with ANN

	61-day	46-day	31-day	16-day	11-day	6-day
MAE	39.85	35.86	18.06	28.29	33.62	33.04
MSE	2,948.19	1,939.65	471.67	1,180.69	1,625.65	1,707.41
RMSE	54.29	44.04	21.72	34.36	40.32	41.32
MAPE	20.98	17.66	9.40	14.31	16.81	15.45

Table 13. Forecasting with SVM

	61-day	46-day	31-day	16-day	11-day	6-day
MAE	23.94	30.95	19.05	21.01	27.28	30.17
MSE	903.41	1,355.37	551.16	708.19	978.89	1,327.71
RMSE	30.06	36.82	23.48	26.61	31.29	36.44
MAPE	13.25	16.92	10.17	10.26	14.21	14.12

5. Results and Discussion

A set of complete side by side comparisons of the proposed models for different forecasting models is presented in Table 14, Table 15, Table 16, Table 17, Table 18, and Table 19. Differences in terms of error measures are evident. Being predictions made with SVB-based models the most consistent of all.

It must be cleat that, although the same algorithm is used, models are different for each horizon because they were constructed with different number of days. Thus, a SVM-base model for 61-day forecasting is different from a SVM-based model for 45-day forecasting.

Table 14. Error measures for 61-day forecasting

Error Measure	Lin. Regression	Gaussian processes	ANN	SVM
MAE	95.35	108.46	39.85	23.94
MSE	12,331.41	15,971.89	2,948.19	903.41
RMSE	111.05	126.38	54.29	30.06
MAPE	50.39	57.07	20.98	13.25

Table 15. Error measures for 46-day forecasting

Error Measure	Lin. Regression	Gaussian processes	ANN	SVM
MAE	46.00	73.97	35.86	30.95
MSE	2,968.45	7,412.56	1,939.65	1,355.37
RMSE	54.48	86.09	44.04	36.82
MAPE	24.80	39.30	17.66	16.92

Table 16. Error measures for 31-day forecasting

Error Measure	Lin. Regression	Gaussian processes	ANN	SVM
MAE	20.49	53.47	18.06	19.05
MSE	549.12	3,773.93	471.67	551.16
RMSE	23.43	61.43	21.72	23.48
MAPE	11.11	29.05	9.40	10.17

Table 17. Error measures for 16-day forecasting

Error Measure	Lin. Regression	Gaussian processes	ANN	SVM
MAE	21.40	21.80	28.29	21.01
MSE	632.23	861.83	1,180.69	708.19
RMSE	25.14	29.35	34.36	26.61
MAPE	10.92	12.21	14.31	10.26

Table 18. Error measures for 11-day forecasting

Error Measure	Lin. Regression	Gaussian processes	ANN	SVM
MAE	27.70	24.76	33.62	27.28
MSE	1,005.20	833.78	1,625.65	978.89
RMSE	31.70	28.88	40.32	31.29
MAPE	13.60	13.04	16.81	14.21

Table 19. Error measures for 6-day forecasting

Error Measure	Lin. Regression	Gaussian processes	ANN	SVM
MAE	37.02	32.97	33.04	30.17
MSE	1,758.98	1,307.02	1,707.41	1,327.71
RMSE	41.94	36.15	41.32	36.44
MAPE	17.07	15.33	15.45	14.12

6. Conclusion

ED database is an extensive collection of data from which valuable information about daily operations can be extracted. Since the efficiency in the use of limited resources is crucial for the public health system, it is worthwhile exploring new approaches, methodologies and tools to help support planning and managing tasks.
Monthly number of ED patients revealed the presence of trends, seasonality, and randomness. All of which is an obstacle for any prediction attempts.

Contrary to classical and well-studied approaches, this works was focused in the use of machine learning instead. The idea was simple, splitting up the data leaving a fraction for building forecasting models and the part for comparing predicted and actual values. Four algorithms were used to forecast and four error measures were used to compare results. In all cases, six forecasting horizons were compared.

Experimental work showed that for short forecasting periods all algorithms were able to forecast accurately and MAPE fluctuating between 14% and 17%. In the case of long forecasting periods, for instance 61 days, predicted values were usually far from actual values. However, values predicted with ANN and SVM were clearly closer to actual values than those ones predicted with models based either on linear regression or Gaussian processes. Here MAPE fluctuated between 13% and 57%.

Another interesting fact is the consistency in the accuracy of the prediction with the SVM-based model regardless the magnitude of the forecasting horizon. Other models’ performances seemed to be affected by the extension of the forecasting period .

Finally, this word showed that some forecasting models based on machine learning algorithms delivers good results even when the dealing with long forecasting horizons. The consistency in the accuracy of the predictions obtained with a SVM-based model indicates that the proposed approach can be useful to predict the number of ED patients and therefore, it could be used to support planning and managing tasks.

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Biographies

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Paola Leal is an industrial engineer and university professor. She earned Licentiate Degree in Engineering from Universidad de La Frontera, and Master of Sciences from Universidad Mayor, Temuco, Chile. She has taught lectures in Operations Research, Logistics, and Supply Chain Management for engineering students. During her academic tenure she has been appointed in different management positions and has mentored over a sixty students. Her research interests include logistics, optimization, and supply chain management.