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Primary care

How machine learning facilitates decision making in emergency departments: Modelling diagnostic test orders

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Abstract

Objectives: Since emergency departments (EDs) are responsible for providing initial care for patients who may need urgent medical care, they are highly sensitive to increased patient delays. A key factor that increases patient delays is ordering diagnostic tests. Therefore, understanding the factors increasing diagnostic test orders and proposing efficient models may facilitate decision making in EDs.

Methods: Month and week of the year, day of the week, and daily numbers of patients encoded based on 21 different ICD-10 codes were used as input variables. Daily test frequencies of patients requiring tests from laboratory and imaging services were modelled separately by linear regression models. Although significance of the input variables was identified based on these models, obtained forecasts and residuals were further processed by machine learning techniques to obtain hybrid models.

Results: Day of the week, and number of patients with ICD-10 codes of 'A00-B99', 'I00-I99', 'J00-J99', 'M00-M99' and 'R00-R99' were significant in both test types. In addition to these, although daily patient frequencies with 'H60-H95', 'N00-N99' and 'O00-O9A' were significant for laboratory services, 'L00-L99', 'S00-T88' and 'Z00-Z99' were significant for imaging services. Although prediction accuracies of regression models were, respectively, as 93.658% and 95.028% for laboratory and imaging services modelling, they increased to 99.997% and 99.995% with the machine learning-integrated hybrid model.

Conclusion: The significant factors identified here can predict increases in use of laboratory and imaging services. This could enable these services to be prepared in advance to reduce ED patient delays, thereby reducing ED overcrowding. The proposed model may also be efficiently used for decision making.

1 | INTRODUCTION

Emergency departments (EDs) provide care to patients experiencing a wide range of health issues, including life-threatening situations, and are often the gateway to health institutions. A main difference to many other health services is that EDs remain fully available for 24 hours and 7 days a week, both for walk-in patients and those arriving by an ambulance. The utilisation of emergency services has risen worldwide due to demographic changes, and increased health awareness and expectations.[1] This has become an issue in Turkey since there are now more applications to emergency services per year than the country's population. These rose from around 95 million in 2011 to more than 110 million in 2015, when Turkey's population was around 80 million.[2] In such an overcrowded setting, providing timely ED services has become a big challenge for ED staff although EDs are highly sensitive to increased delays and waiting times. Besides overcrowding and imbalances between demand and ED capacity, many other factors significantly influence patients' waiting times,[3] one of which is ordering diagnostic tests from laboratory and imaging services.

Diagnostic tests are widely used in EDs to make detailed investigation and treat patients correctly.[4] After doctors order any type of diagnostic tests, they must wait for the results to determine the final diagnosis, provide the right treatment and decide on patient status, such as discharge, admit to a hospital bed or transfer to a different department or hospital. The large volume of patient flow through laboratory and imaging services means that patients must often wait to have the ordered test, which creates bottlenecks in emergency services. Since diagnostic tests are essential for diagnosis and treatment, any improvement in operational planning can significantly reduce these delays and waiting times, thereby preventing system bottleneck in overcrowded ED environments. Besides, different patient characteristics may affect the type of diagnostic test ordered. Thus, for better planning, investigating laboratory and imaging type tests separately is crucial. However, to the best of our knowledge, there exists a lack in the literature in identifying factors affecting ordering these types of diagnostic tests separately and comparatively.

On the other hand, recent advances in technologies provide great opportunities for collecting, storing and analysing huge volumes of medical data. Machine learning, as one of the most noticeable among other technologies, enables decision makers through superior understanding of their organisations to make efficient decisions.[5] These technologies support decision making by turning raw data sets stored in databases into valuable information and developing efficient and performing prediction models. Having such excellences, although this technology has been widely used in various contexts, it has recently begun to receive attention in the emergency medicine literature.

Since modelling daily frequencies of diagnostic test orders from laboratory and imaging services and identifying significant factors increasing these orders have great importance in the emergency department literature and also in clinical practice, and implementation of machine learning technologies in this context is epochal to facilitate ED decision making, this paper contributes to the literature by proposing a hybrid model combining linear regression and machine learning technology for analysing and modelling the daily numbers of ED patients receiving diagnostic tests from laboratory and imaging services. As of the most superior machine learning technique, Multilayer perceptron (MLP) neural networks are used. The proposed hybrid model is therefore a two-stage model. The first stage uses multivariate linear regression and includes time-based variables such as month and week of the year, day of the week, and also the number of patients corresponding to each of the 21 different clinical diagnoses encoded by the 10th version of International Classification of Diseases (ICD-10) as model inputs. These models can identify ordering patterns for laboratory and imaging services, specifically time-based inputs and specific ICD-10 codes that increase diagnostic test orders. In the second stage, the predictions for daily numbers of test orders are further processed with MLP technique to increase the prediction performance and hence to obtain an improved model for daily numbers of test orders. Having high, nearly exact, modelling accuracies, the proposed hybrid model may efficiently be used to enable better planning of ED operations and facilitate decision making in EDs and therefore provides solutions to well-known problems of long waiting times, increased stay lengths and overcrowded ED environments.

In the emergency medicine literature, there are many studies of diagnostic tests. Although some demonstrate that diagnostic tests cause ED delays,[6,7] others evaluate the accuracy of diagnostic testing in disease management[8] or the performance of medical diagnostic laboratories in decision-making models.[9] Since unnecessary testing may be harmful, expensive and waste resources, many studies suggest interventions, such as targeting consensual behavioural changes,[10] education programs for medical staff,[11] analysing electronic medical records in detail to determine when tests are really needed[4,12] or reducing test requests. Hampers et al[13] and Silvestri et al[14] analysed the effects of displaying test costs on ordering patterns for laboratory and imaging services. Other studies have investigated the effects of specific factors on physicians' test ordering

What's known

Ordering diagnostic tests to treat patients efficiently increases waiting times and stay lengths of patients in emergency departments (EDs). This makes managing operations more challenging in overcrowded ED environments. Since overcrowding, long waiting times and increased stay lengths of patients are well-known problems of EDs, proposing models by taking the advantage of emerging technologies, such as machine learning, will provide efficient solutions in this context.

What's new

By implementing machine learning technologies, this article proposes a hybrid model for predicting daily frequencies of ordered diagnostic tests from laboratory and imaging services in EDs. Hybrid model is provided as a two-stage model where the pre-predictions on daily frequencies of test orders are generated based on the multivariate regression model in the first stage. The second stage follows as further processing these pre-predictions by machine learning techniques to obtain improved and nearly exact predictions. Thus, this study contributes to the literature in three folds: (a) significant factors (time-based factors and patient-specific factors) increasing daily frequencies of diagnostic test orders are presented, (b) an efficient prediction model is proposed which can facilitate decision making in EDs, and (c) as a solution of a well-known problem in ED context, a promising emerging technology, machine learning, is presented.

behaviours, such as workload,[15] language[16,17] and behavioural factors.[18] However, despite the large amount of research, this research contributes the literature by proposing a hybrid model which utilises an emerging technology for modelling daily number of diagnostic test orders in EDs in relation to time-based factors and frequencies of assigned ICD-10 codes.

2 | METHODS

2.1 | Study design

This is a retrospective study to investigate and model the effects of time-based factors and patient ICD-10 classifications on diagnostic test orders for laboratory and imaging services at a single ED located in a metropolitan region of Izmir City, Turkey. The local institutional review board approved this study.

2.2 | Study setting and participants

The data were obtained from a large urban training hospital with more than 1000 daily ED visits on average. One year's data from 2018 were used. All patients undergoing any laboratory or imaging diagnostic tests during the study period were included.

2.3 | Data sources and variables

The data were extracted and combined from three of the hospital's electronic warehouses to form a structured data set. The first warehouse records data on arriving patients and keeps protocol IDs, related time stamps, demographic information, such as gender, age, arrival mode, and triage category, and assigned ICD-10 codes by the specialised coders. The second warehouse keeps data on patients undergoing any laboratory investigation, whereas the third database stores data on patients undergoing any radiology (imaging) tests. These two warehouses both record patient protocol IDs, related time stamps (test ordering time, test initiating time, test result time, read time by staff, finalizing time, etc), hospital department or service ordering the test, and type of test ordered. Both databases list many different types of tests, although most laboratory tests were for haemogram, biochemistry, enzyme, hormone or blood type while imaging services were usually for roentgen, tomography, ultrasound and MRI. By interviewing clinicians, it was identified that, among such varieties and volumes of data, the ones which may have a significant effect on diagnostic test-order frequencies were the time-based data and ICD-10 codes.

The outcome variable was the daily number of patients requiring diagnostic tests, defined separately for laboratory and imaging services. Thus, two models were proposed based on these two variables, which were calculated by summing the number of patients recorded in the laboratory and imaging services databases for each day. The time-based input variables were month of year, numbered from 1 (January) to 12 (December), week of the year, numbered from 1 to 52, and day of the week, numbered from 1 (Monday) to 7 (Sunday). The final input variable was obtained from the database for arriving patients, which encodes patients' diagnoses based on the 21 main categories of the ICD-10 classification. For this study, each category was recoded, from the first, 'A00-B99', as d1 to the last, 'Z00-Z99', as d21. The daily number of patients arriving at ED from each of these diagnostic categories was summed to represent the last input variable. The first day of 2018 can be given as an example to illustrate the variable definitions for the complete structured database. On this day, 291 and 307 patients required a test from laboratory and imaging services, respectively (the outcome variables of the two models). The time-based input variables for this day were coded as 1 (month), 1 (week) and 1 (Monday). The number of patients arriving with each ICD-10 code was calculated as follows: 87 (d1), 1 (d2), 2 (d3), 1 (d4), 21 (d5), 22 (d6), 18 (d7), 17 (d8), 23 (d9), 462 (d10), 56 (d11), 8 (d12), 264 (d13), 42 (d14), 1 (d15), 5 (d16), 0 (d17), 196 (d18), 33 (d14), 52 (d20) and 214 (d21).

2.4 | Statistical analysis

Hybrid modelling which combines multivariate linear regression models and MLP neural networks was used in the statistical analysis. The model was proposed as a two-stage model. The first stage uses linear regression to identify the significant predictors of daily numbers of patients requiring diagnostic tests. Besides, the outputs of regression model were used as a basis or inputs of the MLP technique, which was the implemented machine learning technique in the second stage of the proposed model. Since, not only the predictions generated by the regression model but also the residuals (prediction errors) have valuable information in modelling, hybrid model integrating regression and machine learning were preferred to use instead of using machine learning techniques alone. Thus, in this study, predictions and residuals of the linear regression were further processed with MLP neural networks to obtain an improved model with increased prediction performances.

To present some background information on MLP neural network: MLP is one of the most widely used big data analytics techniques. It follows a supervised learning procedure which relies on learning by example, rather than learning by observation. In the data set, which is generally labelled as train data set, learning or training model is formed by using the backpropagation algorithm, which is the most computationally straightforward for training MLP.[19] MLP provides a multilayer-feedforward neural network for learning and computation of connected weights of the network. Set of weights in the layers are iteratively trained by MLP until finding the optimal scores of weights.[20] Layers are key components of the MLP model. Input layer, hidden layer and output layers are the main types of layers. Input layer consist of the variables of data set. For the given input variables $x1$, $x2$, $x3$,...,xn, and the target or output variable, y, MLP learns a non-linear function approximate for regression. The input layer does not have a computational role but serves to transmit input vector to the network. More than one hidden layer may exist between input and output layers. MLP is described as being fully connected, with each node connected to every node in the next and previous layers. A general structure of a MLP network with two hidden layers is illustrated in Figure 1.

In the statistical analysis, Python[21] was employed in this study. To build up a MLP network, *MLPRegressor* in neural network package of *sklearn* module in that performs regression with supervised neural network was used. Parameters of MLP network were tuned for the corresponding shape and nature of input data to find the best prediction results. Main parameters affecting the performance of MLPRegressor are learning rate, momentum and number of hidden layers. Learning rate represents the degree of the training speed of the network. In other words, as the learning rate increases, the network trains faster but at the cost of the possibility of generating an unstable network. The momentum parameter is used to balance the network and prevents the problems possibly caused by selecting a high learning rate which makes the network unstable.[22] These three parameters were optimised by trial-error method until the best model having the highest prediction accuracy was obtained. Accuracy was obtained based on the Mean Absolute Percentage Error (MAPE) values.

The flow chart of the proposed hybrid model was represented in Figure 2.

3 | RESULTS

3.1 | Descriptive statistics

During the study period, 483 182 patients arrived at the ED, of whom 112 058 (23.19%) required laboratory tests and 143 518 (29.70%) radiology tests. Figure 1 presents the daily and monthly distributions of average daily values for patient volume and patients receiving diagnostic tests.

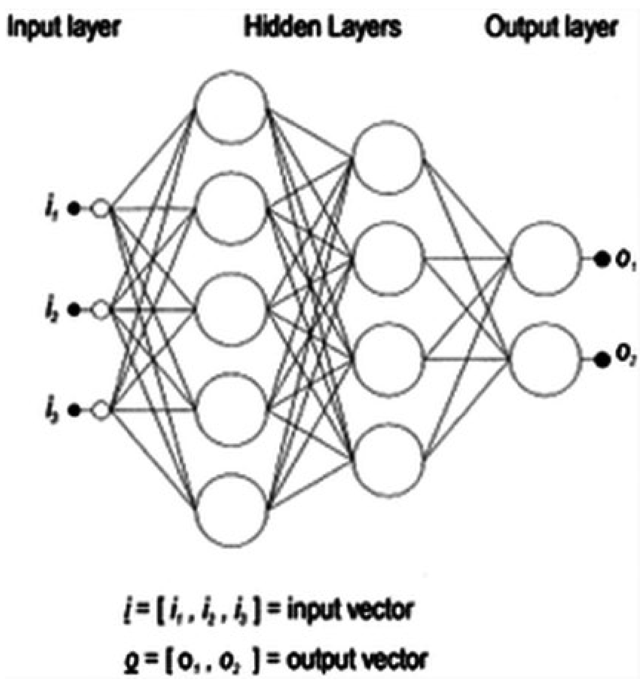

FIGURE 1 MLP neural network with two hidden layers

As Figure 3 shows, the average daily patient volume and the number of patients receiving diagnostic tests are distributed almost uniformly throughout the year. However, the daily distribution varies significantly, with the highest patient volumes on Saturdays, Sundays, and Mondays. Besides, significantly more patients receive diagnostic tests on Mondays than on other days.

3.2 | Model results

3.2.1 | Stage 1. Linear regression results

Linear regression models were developed to model the daily number of patients requiring diagnostic tests from laboratory and imaging services according to month and week of the year, day of the week, and daily number of patients with each ICD-10 diagnosis. Table 1 summarises the model results.

Table 1 shows that month and week of the year were not significant predictors. However, day was a significant predictor (at 90% confidence interval) of the daily number of patients receiving diagnostic tests from either service. It is also observed that daily number of admissions with clinical ICD-10 diagnoses of ‘A00-B99’, ‘I00-I99’, ‘J00-J99’, ‘M00-M99’ and ‘R00-R99’ was significant predictors for both of the models. The daily number of admissions with clinical ICD-10 diagnoses ‘H60-H95’, ‘N00-N99’ and ‘O00-O9A’ was also significant predictors of the daily number of patients requiring laboratory tests. In contrast, ‘L00-L99’, ‘S00-T88’ and ‘Z00-Z99’ also predict the daily number of patients receiving imaging tests. Probability plots of residuals which checks and supports the normality assumption of regression model are given in Appendix.

Based on the model coefficients presented in Table 1, regression lines of the daily numbers of patients receiving tests from these services were obtained. For each day (day i) of the study period, denoting each model predictors as x_1^i through x_{24}^i where x_1^i presents the corresponding month and x_{24}^i presents daily numbers of patients arriving at day i and clinically encoded with “Z00-Z99”, the predicted value of number of patients receiving tests from laboratory services on day i, $\widehat{y_1^i}$, was obtained based on Equation (1),

$$\begin{aligned}\widehat{y_1^i} = {} & 71.72+3.294x_1^i-0.509x_2^i-1.655x_3^i+0.356x_4^i-0.149x_5^i-0.049x_6^i-0.229x_7^i \\ & -0.016x_8^i-0.209x_9^i-0.309x_{10}^i-0.672x_{11}^i+0.565x_{12}^i+0.103x_{13}^i+0.155x_{14}^i+0.072x_{15}^i \\ & +0.094x_{16}^i+0.619x_{17}^i+1.230x_{18}^i+0.499x_{19}^i-4.155x_{20}^i+0.433x_{21}^i+0.124x_{22}^i+0.107x_{23}^i \\ & +0.033x_{24}^i \quad \text{for } i=1,\ldots,365.\end{aligned} \tag{1}$$

With the same input variables and representations, the predicted value of number of patients receiving tests from imaging services on day i, $\widehat{y_2^i}$, was obtained based on Equation (2),

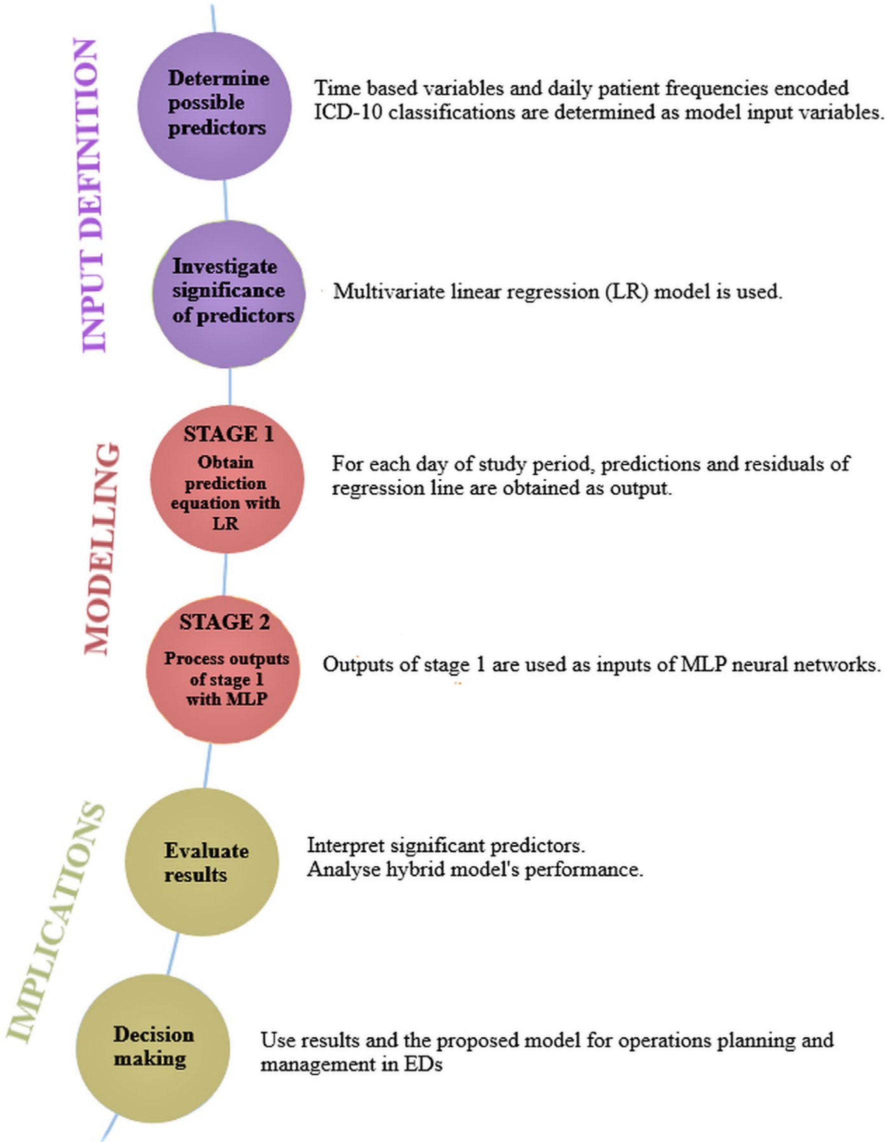

FIGURE 2 Flowchart of the proposed model

$$
\begin{aligned}
\widehat{y_2^i} =\; & 82.65-3.175x_1^i+1.754x_2^i-1.878x_3^i-0.106x_4^i+0.041x_5^i+0.811x_6^i-0.603x_7^i \\
& +0.095x_8^i-0.086x_9^i-0.501x_{10}^i-0.420x_{11}^i+0.860x_{12}^i+0.120x_{13}^i-0.117x_{14}^i+0.339x_{15}^i \\
& +0.441x_{16}^i+0.038x_{17}^i+0.690x_{18}^i-1.003x_{19}^i+3.834x_{20}^i+0.315x_{21}^i+0.598x_{22}^i+0.024x_{23}^i \\
& +0.093x_{24}^i \quad \text{for } i=1,\ldots,365.
\end{aligned} \tag{2}
$$

Denoting the actual numbers of patients arriving at day *i* and receiving diagnostic tests from laboratory and imaging services as y_1^i and y_2^i, respectively, the residuals of the obtained regression line for each day were obtained based on Equations (3) and (4),

$$e_1^i = y_1^i - \widehat{y_1^i} \quad \text{for } i = 1, \ldots, 365, \tag{3}$$

$$e_2^i = y_2^i - \widehat{y_2^i} \quad \text{for } i = 1, \ldots, 365. \tag{4}$$

Obtained predicted values and residuals were then processed with MLP neural networks to obtain an improved model.

3.2.2 | Stage 2. MLP implemented hybrid model results

The predicted values and residuals of the regression models were used as model input variables of the MLP neural networks and the actual values were the target or output variables of the algorithm. Three parameters of number of hidden layers, momentum and learning rate were properly optimised for modelling daily numbers of patients receiving tests from laboratory and imaging services properly. Then, the MLP algorithm generated updated predictions for the target variables which were, respectively, labelled as $\widehat{y_{1-\text{hybrid}}^i}$ and $\widehat{y_{2-\text{hybrid}}^i}$. The prediction accuracies of the obtained models were calculated based on the mean absolute percentage error (MAPE) statistics which were, respectively, calculated based on Equations (5) and (6) for modelling laboratory and imaging service orders,

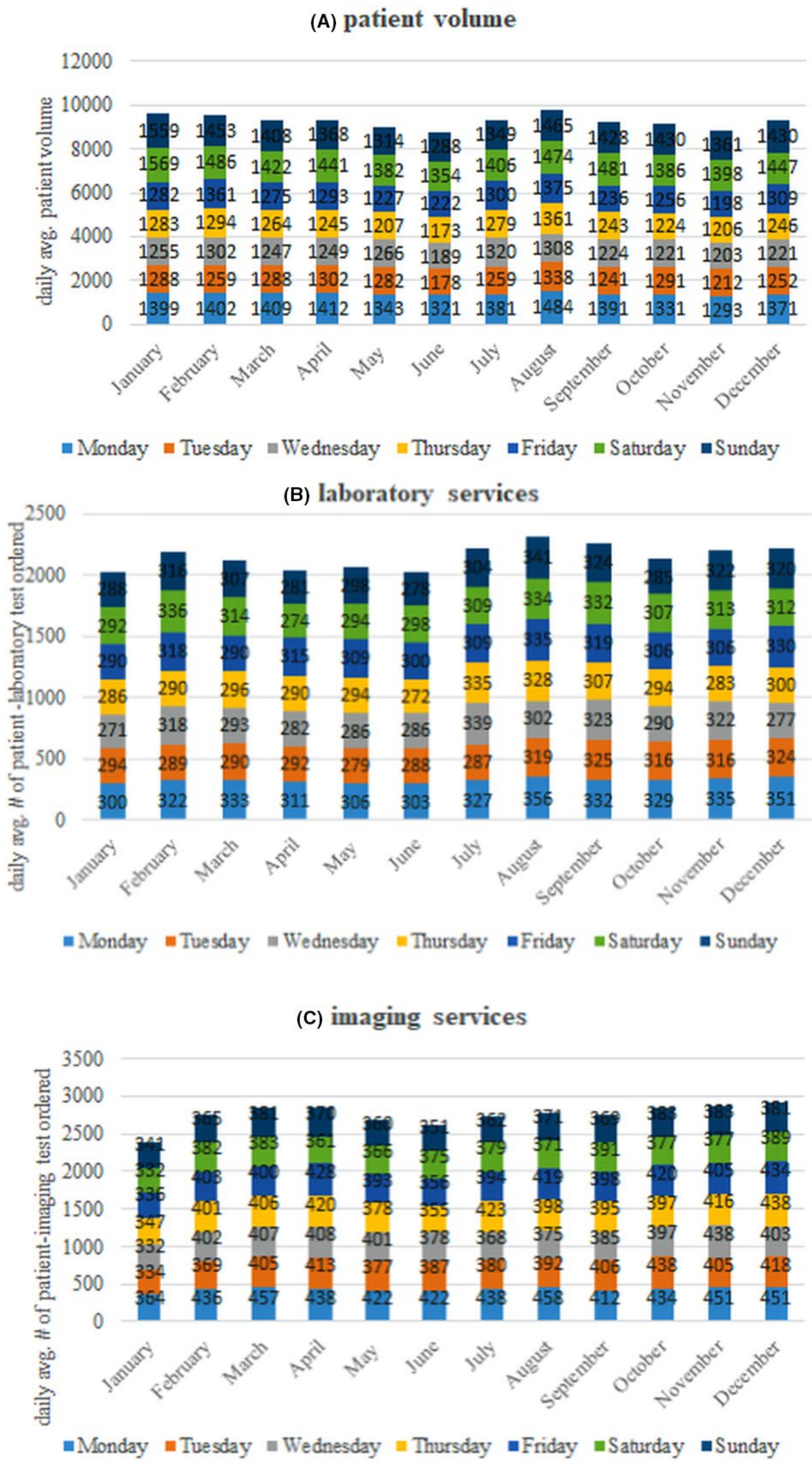

FIGURE 3 Daily and monthly distributions

TABLE 1 Summary of regression model results

Predictors	# of patients receiving laboratory tests				# of patients receiving imaging tests			
	Coef.	SE coef.	*T*	*P*	Coef.	SE coef.	*T*	*P*
Constant	71.72	22.92	3.13	.002	82.65	23.36	3.54	.000
Month	3.294	4.583	0.72	.473	−3.175	4.671	−0.68	.497
Week	−0.509	1.042	−0.49	.626	1.754	1.062	1.65	.100
Day	−1.655	0.92	−1.80	.073	−1.878	0.938	−2.00	.046
d1 (A00-B99)	0.356	0.053	6.73	.000	−0.106	0.054	−1.96	.050
d2 (C00-D49)	−0.149	1.227	−0.12	.904	0.041	1.250	0.03	.974
d3 (D50-D89)	−0.049	0.766	−0.06	.949	0.811	0.781	1.04	.300
d4 (E00-E89)	−0.229	0.525	−0.44	.662	−0.603	0.535	−1.13	.261
d5 (F01-F99)	−0.016	0.332	−0.05	.960	0.095	0.338	0.28	.778
d6 (G00-G99)	−0.209	0.216	−0.96	.335	−0.086	0.220	−0.39	.697
d7 (H00-H59)	−0.309	0.298	−1.04	.300	−0.501	0.304	−1.65	.100
d8 (H60-H95)	−0.672	0.295	−2.28	.023	−0.420	0.301	−1.40	.163
d9 (I00-I99)	0.565	0.186	3.05	.003	0.860	0.189	4.55	.000
d10 (J00-J99)	0.103	0.002	4.71	.000	0.120	0.022	5.41	.000
d11 (K00-K95)	0.155	0.081	1.91	.057	−0.117	0.083	−1.41	.158
d12 (L00-L99)	0.072	0.125	0.58	.564	0.339	0.128	2.66	.008
d13 (M00-M99)	0.094	0.035	2.70	.007	0.441	0.036	12.44	.000
d14 (N00-N99)	0.619	0.131	4.72	.000	0.038	0.134	0.28	.779
d15 (O00-O9A)	1.230	0.620	1.98	.048	0.690	0.632	1.09	.275
d16 (P00-P96)	0.499	0.742	−0.67	.502	−1.003	0.756	−1.33	.186
d17 (Q00-Q99)	−4.155	3.897	−1.07	.287	3.834	3.972	0.97	.335
d18 (R00-R99)	0.433	0.047	9.16	.000	0.315	0.048	6.53	.000
d19 (S00-T88)	0.124	0.115	1.08	.280	0.598	0.117	5.13	.000
d20 (V00-Y99)	0.107	0.116	0.92	.361	0.024	0.119	0.21	.838
d21 (Z00-Z99)	0.033	0.042	0.80	.424	0.093	0.042	2.21	.028
	R-squared: 62% *R*-squared adjusted: 59.4% *R*-squared pred: 56.6%				*R*-squared: 44.8% *R*-squared adjusted: 40.9% *R*-squared pred: 30.89%			

$$\mathrm{MAPE}^{\text{stage 1}}_{\text{laboratory}} = \frac{\sum_{i=1}^{365} y_1^i - \widehat{y_1^i}}{365},\quad \mathrm{MAPE}^{\text{stage 2}}_{\text{laboratory}} = \frac{\sum_{i=1}^{365} y_1^i - \widehat{y^i_{1-\text{hybrid}}}}{365} \quad \text{for } i = 1, \ldots, 365, \tag{5}$$

$$\mathrm{MAPE}^{\text{stage 1}}_{\text{imaging}} = \frac{\sum_{i=1}^{365} y_2^i - \widehat{y_2^i}}{365},\quad \mathrm{MAPE}^{\text{stage 2}}_{\text{imaging}} = \frac{\sum_{i=1}^{365} y_2^i - \widehat{y^i_{2-\text{hybrid}}}}{365} \quad \text{for } i = 1, \ldots, 365. \tag{6}$$

In Table 2, the summary results including inputs, output variable, optimised parameters of MLP technique and the model accuracies were presented.

The results of Table 2 mainly showed that, in the first stage, regression models performed well having around 95% accuracies. This is due to the fact that at least some of the identified variables were significant predictors of the daily numbers of patients receiving diagnostic tests. However, when regression model was combined with MLP algorithm in a proposed model, the prediction accuracies significantly improved in a way that the actual values were almost achieved in the predictions.

Daily actual and predicted values in two stages of the model were additionally shown in Figure 4.

As shown in Figure 4, the actual values and the predicted values of the hybrid model were almost the same for each day of the week for modelling both of the services. Although the predicted values of the regression models were also close to them, compared to the hybrid model they differ from the actual values for some.

4 | DISCUSSION

Because diagnostic testing has significantly improved the quality of healthcare and increased value, it will continue to be a key medical necessity in patient care. However, since these tasks are expensive and time-consuming, it is critical in an overcrowded ED environment to ensure that the right test is performed at the right time and in

TABLE 2 Summary results of hybrid model

Modelling for	Stage 1. Regression model			Stage 2. Regression and MLP-hybrid model			
	Input	output	Accuracy (1 − MAPE)	input	output	Optimized parameters of MLP	Accuracy (1 − MAPE)
Daily numbers of patients receiving tests from laboratory services	x_1^j through x_{24}^j	$\hat{y}_1^j$	93.658	$\hat{y}_1^j, e_1^j$	$\widehat{y_{1-\mathrm{hybrid}}^j}$	Hidden layer = 5, momentum = 0.5, learning rate = 0.5	99.997
Daily numbers of patients receiving tests from imaging services	x_1^j through x_{24}^j	$\hat{y}_2^j$	95.028	$\hat{y}_2^j, e_2^j$	$\widehat{y_{2-\mathrm{hybrid}}^j}$	Hidden layer = 3, momentum = 0.35, learning rate = 0.2	99.995

the right way for each patient. Predictability in determining medically appropriate tests has thus attracted attention[4,23,24] since this promotes compliance, decreases costs, and enables delivery of uniformly high-quality patient care. From an operations planning perspective, it is valuable to identify the factors affecting the daily number of diagnostic test orders and predict the daily number of patients requiring such tests. However, there is a gap in the literature regarding this issue. The present study is thus a pioneer in terms of improving ED operational planning because it identified significant factors affecting daily diagnostic test orders and separately modelled the daily numbers of patients receiving diagnostic tests from laboratory and imaging services.

The present study analysed and modelled time series data on diagnostic test orders in relation to month and week of the year and day of the week. Although the number of ED patients receiving diagnostic tests from either laboratory or imaging services does not significantly differ between months and weeks of the year, it differs across days of the week (Table 1). The insignificant effect of month and week of the year could be due to seasonal factors whereby different ICD-10 diagnoses vary during the year, thereby increasing the number of corresponding ED admissions. For instance, although ED admissions for certain infectious and parasitic diseases ("A00-B99") or circulatory system diseases ("I00-I99") increase significantly in winter,[25-27] admissions for skin and subcutaneous tissue ("L00-L99") and injury, poisoning and certain other consequences of external causes ("S00-T88") peak in summer.[28,29]

Regarding daily variation in number of patients receiving a diagnostic test, the peaks occur on Mondays (Figure 3B,C). This increase is resulted from an increase in patient volume (Figure 3A), which is most likely because patients who arrived just before weekend and required a diagnostic test that could not be ordered due to the weekend. This interpretation is supported by comparing the daily distributions of these time series by patient volume. Although EDs receive the most patients at weekends (Figure 3A), the largest number of patients receiving diagnostic test orders from both services occurs on Mondays, whereas the weekends have similar values to other weekdays.

The daily number of patients with specific ICD-10 clinical diagnoses also affected the daily number of patients receiving diagnostic tests and the total number of orders. As supported by previous studies of laboratory and imaging diagnostic test guidelines, admissions with specific ICD-10 codes are predictors for an increase in the number of patients required receiving these tests and thus the number of orders.[30-34] The regression models developed in this study show that when the daily number of 'I00-I99', 'J00-J99', 'M00-M99' and 'R00-R99' patients increases, the numbers of patients receiving laboratory and imaging tests also significantly increase (model coefficients are positive). However, an increase in the number of "A00-B99" patients predicts an increase in the number of patients requiring laboratory tests but a decrease in the number of patients requiring an imaging test (model coefficient is negative). Finally, although increases in the number of 'H60-H95', 'N00-N99' and 'O00-O9A' patients increase

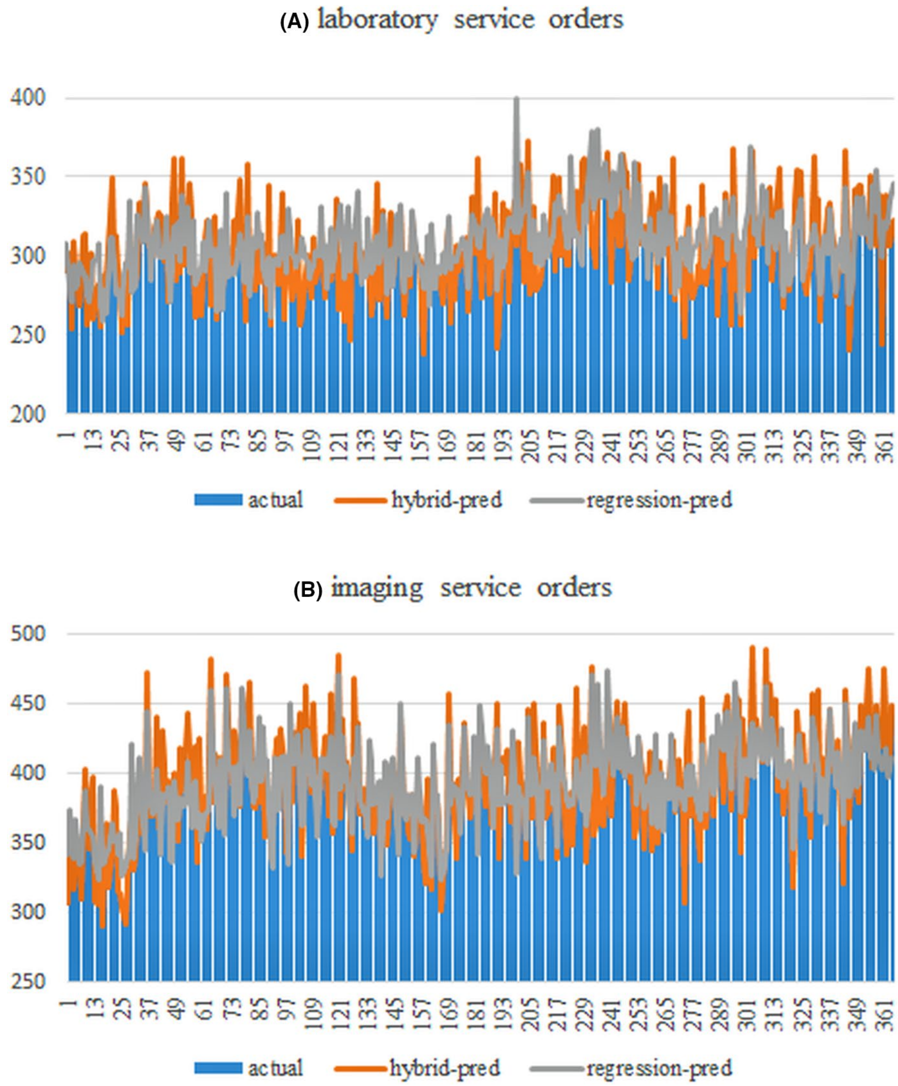

FIGURE 4 Daily actual and predicted values

the number of patients receiving laboratory tests, an increase in 'L00-L99', 'S00-T88' and 'Z00-Z99' patients leads to an increase in the number of patients receiving laboratory tests.

Another important finding was related to the obtained accuracies in the two-stage model. The results showed that stage 1 of the proposed model developed with the regression method performed relatively well having around 95% prediction accuracies. This result was related with the significance of at least some of the identified variables in modelling daily numbers of patients receiving diagnostic tests. Thus, the identified factors were very important in analysing and modelling ordering patterns of diagnostic test orders. However, the prediction performance was significantly improved when regression model results were combined with one of the most superior emerging machine learning technology, namely, MLP neural networks. The hybrid model performed almost exactly for predicting daily numbers of patients receiving tests from laboratory and imaging services. This highlighted the need of implementing this technology in health services[35-38] literature, specifically in the context of emergency medicine.[4,24]

This study has many implications from clinical practice perspective. The findings guide ED clinicians to facilitate decision making. For example, it is well known that the number of ED applications with respiratory system diseases ("J00-J99") increases significantly in winter. Since an increase in these ED admissions predicts an increase in the number of patients requiring both laboratory and imaging tests, these services should be prepared in advance. On the other hand, in summer, a significant growth is expected in the number of admissions for injury, poisoning and other consequences of external causes ("S00-T88"), which is likely to increase the number of patients requiring laboratory tests. Besides the effects of specific ICD-10 codes for diagnoses, ED clinicians can expect a day effect, with more laboratory and imaging tests requested on Mondays. Thus, ED operations could be improved by making the necessary preparations for these services beforehand. Especially when diagnostic services are likely to face over-demand, the number of clinicians can be increased, working hour schedules can be better prepared, clinicians can be trained and scheduled to increase their efficiency and information technology use can be improved both within hospital and for information sharing between hospital services. Such improvements in ED operations are critical from a practical viewpoint since they can significantly decrease patients' waiting times and loss times. This could then help solve the most well-known problem of EDs: overcrowding. On the other hand, although machine learning integrated model is proposed to a specific subject in ED context to facilitate ED operations, utilising the advantage of this promising technology for different clinical practices is highly recommended in this study. Thus, for specific context, by showing how implementation of this technology facilitate making decisions, this study also opens future research directions for clinical practices.

This study is mainly limited by its study design. Since it was a retrospective study using data from one institution only, the results may not be generalisable to other institutions. Additionally, the identified model predictors were widely used in the ED literature and many of them were found statistically significant; some of the other factors may also be included for daily numbers of diagnostic test modelling. Despite such limitations, this research opens precedence for other institutions aiming to analyse factors increasing daily numbers of diagnostic test orders and to propose efficient models for decision making.

5 | CONCLUSION

Implementing one of the most superior machine learning techniques, MLP neural networks, this study proposes a two-stage hybrid model for modelling daily numbers of patients requiring diagnostic tests from laboratory and imaging services. Although the first stage of the proposed model investigated the significance of the time-based variables (month and week of the year, and day of the week) and daily frequencies of patients encoded based on 21 ICD-10 categories based on linear regression model, it also formed the basis of the second stage of hybrid model. Daily predicted values and residuals (errors) of the prediction of regression model were further processed by MLP neural networks to obtain an improved model having higher prediction accuracies. Although obtained significant factors may predict increases in daily test orders from laboratory and imaging services, proposed hybrid model may efficiently be used for decision making in EDs.

DISCLOSURES

No conflict of interest was declared by authors.

AUTHOR CONTRIBUTIONS

MGA: Study concept and design, acquisition of the data and drafting of the manuscript. GS: Analysis and interpretation of the data, critical revision of the manuscript for important intellectual content and statistical expertise.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Çiğli Training and Research Hospital. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of Çiğli Training and Research Hospital.

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APPENDIX

Normality plots of residuals