OPTIMIZATION OF HEALTH SERVICE SCHEDULE

Anđelija Đorđević*, Aleksandar Milenković*, Dragan Janković*, Lazar Stamenković**
* Faculty of Electronic Engineering, University of Niš, 18000 Niš, Serbia
** Zucchabar, Inc., Millbrae, California, USA, 18000 Niš, Serbia
andjelija.djordjevic@elfak.ni.ac.rs, aleksandar.milenkovic@elfak.ni.ac.rs, dragan.jankovic@elfak.ni.ac.rs, lazar2@zucchabar.com

***Abstract*— It is a frequent case of cancellation or absence of patients on scheduled medical care. This behavior results in additional costs and unnecessarily long waiting times for patients arriving on scheduled appointments. This paper attempts to minimize the consequences of the problem by predicting patients' cancellations and absences by applying logistic regression, enabling employees at healthcare institutions to optimize their existing schedules and reduce the number of empty appointments. Prediction is made using a model that is trained on actual data collected in several health institutions in Serbia from 2010 to 2019.**

I. Introduction

The waiting time for scheduled medical examinations can be long and while some patients wait for their examinations (sometimes for months), some scheduled appointments remain empty due to patients not turning up for their appointments. The absence or dismissal of a patient is a common event. This behavior not only causes long waiting times even though there are vacancies, but also causes numerous staff and material costs to work. In the United Kingdom, such costs are estimated at one billion pounds per year [1]. Table I presents data from the Niš Health Center of the percentage of patients who cancelled or failed to appear for a scheduled appointment out of the total number of appointments throughout the years. For these reasons and because of the data presented in the table, there was a need to create models to optimize appointment scheduling.

TABLE I.
REVIEW OF THE PROPORTION OF PATIENTS WHO HAVE CANCELLED OR FAILED TO APPEAR THROUGHOUT THE YEARS

Year	The proportion of patients who canceled or failed to appear
2018	21%
2017	25%
2016	32%
2015	34%
2014	33%
2013	35%
2012	57%

The problem of cancellation and absence of patients from the scheduled appointments in this paper is reduced by predicting whether or not the patient will show up for a scheduled appointment. Non-attendance and cancellation in this paper represent the same event – non-attendance. The created model is based on real data collected using the MEDIS.NET Medical Information System from 2010 to 2019 (personal data of patients, doctors and operators are not known due to confidentiality, but each personal data is represented by a numeric identifier) [2]. By processing the existing patient attendance and non-attendance data and creating a logistic regression model, the probability of a patient not being available for a scheduled appointment is obtained. Depending on the likelihood obtained, users may also offer a given appointment to another patient, if a prediction of non-attendance is obtained.

The solution to this problem is based on real data from healthcare institutions in Serbia. The circumstances of the moment when the appointment is scheduled and when the examination is being held, as well as the history of non-attendance and cancellations depending on the patient, doctor and operator who made the appointment are reviewed. The applied solution is closely related to the problems of scheduling medical examinations and the collected real data, therefore this is a specificity that differentiates it from the existing solutions of similar problems.

The application of artificial intelligence in medicine is of special importance in situations such as the COVID-19 pandemic. Coronavirus disease 2019 (COVID-19) is a disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), first detected in China in December, 2019 [3]. By the end of May 2020, 6 057 853 cases of COVID-19 and 371 166 deaths had been confirmed in 216 countries, areas or territories [4]. In Israel, artificial intelligence has been used to detect high-risk COVID-19 patients, based on their existing health data, including a person’s age, BMI, health conditions such as heart disease or diabetes, and previous history of hospital admissions. This approach was also used to help determine the level of treatment the people it flags might require if they fall sick –whether they should be cared for at home, put up in a quarantine hotel, or admitted to hospital [5]. Due to the high number of infected medical workers and infected patients, and thus insufficient accommodation in hospitals for the infected, a solution in the form of EQuarantine was presented, the system for monitoring coronavirus patients for remote quarantine. It is based on fused multiple data from various sensors to detect the degree of development of the disease and the seriousness of the health condition. The data extracted from multiple sensors are gathered sequentially based on multi-variable measurements [6].

The problem of cancellations and absences of patients from scheduled examinations is much more pronounced in situations such as the COVID-19 pandemic when the number of examinations was reduced due to decreased resources because many health workers were transferred to repair the consequences of the pandemic. During the COVID-19 pandemic, a lot of appointments remained unrealized because patients did not show up for medical appointment due to emergency measures in the country. In order to schedule appointments better and spend available resources more efficiently, so as to increase the percentage of occupancy and utilization of available appointments, it is desirable, with the artificial intelligence, to predict patient cancellations and absences and use the scheduling of more examinations in the same time.

II. Related Work

The considered problem of cancellation and non-attendance is not unique and exists in all areas of life where reservations are possible. In a related way, the costs and problems caused by non-attendance or cancellations in reserved rooms at hotels, tables at restaurants or seats at airplanes can be minimized.

Non-arrival or cancellation may occur when booking a hotel room. In [7], it was proved that it is possible to construct a model that will predict failure with an accuracy greater than 90%. The model was created using data from four different hotels in Portugal. The hotel management, in the situation that may lead to the absence of the client, offers special benefits. It is often about free hotel services or discounts when visiting the sights in the area. Such actions cause additional costs, but these costs are still lower than the costs of the client's absence in the reserved period.

Apart from health facilities and hotels, restaurants and airlines have a similar problem. The data used to form the machine learning model are most often existing cancellation / non-arrival data, but the International Air Transport Association (International Civil Aviation Organization, 2010) has developed a standard called PNR (Personal Name Record) and these data are also in use, most often by airlines. The reason for the special interest of airlines in predicting cancellations is the high rate of non-arrival and cancellation of booked flights, which ranges from 30% to 50% of all bookings [7].

III. Results and Discussion

The prediction of patients' cancellation was made using supervised learning by creating a logistic regression model with L1 regularization [8]. The solution to this problem was implemented in the *PyCharm*, integrated development environment, in the Python programming language. *NumPy* [9] and *pandas* [10] libraries were used to process input and create features. The *scikit-learn* library was used to create, test and evaluate the model, as well as to further process the features to give the model better results [11]. The *matplotlib.pyplot* library was used for graphical representations [12]. K-fold cross-validation with 5 folds was used. The presented results represent the mean value of the obtained results from 5 different divisions into test and training sets.

A central part of problem-solving is data processing. In the data collected initially there were 2 171 029 records and 12 attributes of which the final 261 were created. The attributes are the date and time of the moment when the appointment is scheduled and when the examination is being held, an identifier of the insured, operator and doctor, specialization, age, gender, the basis of insurance and chronic diagnosis of the patient. To solve this problem, the attributes of a day of the month, month, Serbian feast, Christmas and New Year, the national holiday, day of the week, time of day and the number of days from the time when the appointment was scheduled to the time the examination is being held were derived from the input attributes. Based on the operator's, patient's and doctor's identifiers and the history of non-attendance and cancellations of their existing data, attributes of *probability of patient cancellation*, *probability of doctor cancellation* and *probability of operator cancellation* were made. These three attributes contributed to the largest increase in model accuracy. A detailed analysis of the contributions of each input feature to model training yielded the final attributes. Some final features are obtained by combining multiple input attributes. In some cases, more final features have been created from one input attribute, while the rest of the finite attributes are the result of modifying the corresponding input in the form of scaling or categorization. The relation of initial and final features is given in Table II.

The model created with this solution has an accuracy of 80%. The result obtained is good enough for the model to have a practical application, however, there is room for

TABLE II.
THE RELATION OF INITIAL AND FINAL FEATURES

Initial features	Final features
identifier of the insured	probability of patient cancellation
start date time	day of the month
	Month
	Serbian feast
	Christmas and New Year
	The national holiday
	day of the week
	time of the day
end date time	-
identifier of the doctor	probability of doctor cancellation
identifier of the operator	probability of operator cancellation
identifier of the operator who canceled the term	-
date and time when the appointment is scheduled	day of the month
	month
	Serbian feast
	Christmas and New Year
	The national holiday
	day of the week
	time of the day
	number of waiting days
age	age
gender	gender
status	label
specialization	specialization
chronic diagnosis	chronic diagnosis

error so the predictions must be taken with reserve. It is very important that the model does not produce an additional problem in the form of the frequent prediction that the patient will not come, and the opposite happens (a large number for the false-positive value), as this leads to the potential appointment of another patient in the same term. The arrival of both patients leads to problems in service delivery, patient dissatisfaction, and may delay the next appointment. It is necessary to minimize this number. Changing the logistic regression threshold results in different values of model metrics.

When the threshold is 0.5, 62.25% of non-arrivals will be predicted, but 10.31% of the times patients will come, the model will potentially make a double appointment. For the 0.6 and 0.7 thresholds, respectively, 57.1% and 50.48% of non-arrivals are expected to occur, and only 6.07% and 2.76% of the total patients' appointments where patients will come, will be predicted as potentially empty terms. Which threshold value will be taken depends on whether in a particular situation a larger problem is caused by empty or duplicate appointments. The relationship between these values is represented by the ROC curve given in Fig. 1. Changes in the values of model metrics with the change in threshold height are shown in Table III.

The obtained results prove that there is a connection between patient's data and non-attendance at the examination. Although the current model can be used in health care institutions with certain restrictions, this result represents the beginning of solving the problem. The accuracy of the model was significantly increased by adding three attributes, the probability of non-attendance of a specific patient, the probability of empty examination for a specific doctor, and the probability of non-attendance on an examination scheduled by a specific operator. All three attributes are related to the ID of the patient, doctor, or operator, respectively, and calculate the probability of absence for examinations that occurred in the past. The attribute gets the value of the ratio of the number of absences for a given ID to the total number of scheduled examinations that are corresponding to the identifier of the patient, doctor, or operator. Before adding these attributes, the accuracy of the model was 71%, while with their addition it increased to 80%. Based on this significant increase and the specificity of the most important attributes for the absence of patients, the conclusion is that the human factor is very important for the absence of patients. Therefore, it is recommended that for the further progress of this project, new collected data should be more personal, such as the length of the journey that the patient must travel from the place of residence to the health institution, the type of vehicle he uses, family status and similar.

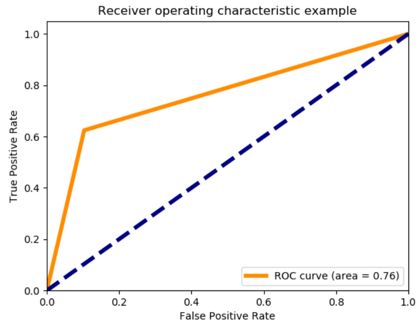

Figure 1. ROC curve for 50% threshold

A. *Important Features*

Discovering the most important features for a patient's absence can have an impact on this problem. Influencing these attributes can lead to a reduction in blank terms. As L1 regularization, also known as Lasso feature selection, was used to regularize the created model, in this way the most significant attributes, *National holidays* and specializations of doctors – *Oral surgery*, *Occupational medicine*, *Speech therapist*, *Dental prosthetics*, *Epidemiology* and *Radiology* were discovered. Also, Recursive Feature Elimination was used, which highlighted the same attributes as Lasso feature selection, except for *Epidemiology*, but added an *Ultrasound diagnostics* and the basis of Employee Insurance to this set: *Citizens of the Republic of Serbia who are employed on the territory of the Republic by foreign or international organizations and institutions*, and *An employed parent who is absent from work until the child reaches the age of three*. The conclusion is that the national holiday and the specialization of doctors have a great influence on the absence of patients. It is necessary to pay special attention to medical examinations where these attributes have positive values.

Similarly, the attributes that have the greatest impact on the arrival of patients at the scheduled examination were found. These are the attributes *Day of the week – Sunday* and specializations –*General medicine*, *Gynecology and obstetrics*, *Otorhinolaryngology*, *Pediatrics* and *Doctor of medicine.*Specific basics of insurance are also part of important attributes for coming to the scheduled appointment –*Health insurance during the procedure of exercising the right to financial compensation;Religious official; Off-premises employers;Cash compensation upon*

TABLE III.
IMPACT OF THRESHOLD CHANGE ON MODEL METRICS

Threshold	Accuracy (%)	*F*-measure (%)	precision (%)	recall (%)	sensitivity (%)	specificity (%)	AUC
0.1	50.66	57.31	41.22	93.96	93.96	27.09	0.61
0.2	67.43	64.17	52.4	82.75	82.75	59.09	0.71
0.3	74.84	67.44	61.98	73.95	73.95	75.32	0.75
0.4	78.25	68.59	69.84	67.39	67.39	84.17	0.76
0.5	80.02	68.71	76.67	62.25	62.25	89.69	0.76
0.6	80.95	67.87	83.65	57.1	57.1	93.93	0.76
0.7	80.76	64.9	90.87	50.48	50.48	97.24	0.74
0.8	77.32	53.39	96.76	36.87	36.87	99.33	0.68
0.9	67.99	16.92	99.25	9.25	9.25	99.96	0.55

cessation of self-employment; Inclusion in compulsory health insurance; International Agreement – Conventions, family member of pensioners, insured persons of countries with which an international agreement on social insurance has been concluded, whose residence is in the Republic of Serbia; Military and civilian invalids; Pension beneficiary according to domestic regulations; Independent dental activity; Persons who are included in targeted preventive examinations, i.e. screening according to appropriate national programs.

The types of doctor's specializations and the basis of patient's insurance take the largest share in the significance of the attributes for arrival and non-arrival at scheduled examinations. One of the possible reasons for that is that both of these types of attributes are initially categorical and one-hot-encoding [13] was performed on them during preprocessing. Both the doctor's specialization and the basis of patient's insurance have a wide variety of possible values, which after separation into categories leads to many new features, where all records are divided into disjoint sets, some of which may not have a sufficient number of samples. If an arrival (non-arrival) occurs for each of the specimens of one category of specialization or insurance basis, this may contribute to the great importance of the given attribute for a specific event, and it is possible that due to the lack of samples of that category, the event happened by accident. Fig. 2 shows the total number of absences by specialization categories. In Table IV specialization codes are associated with names. The picture shows that none of the specializations that were singled out as significant for non-attendance has a lot of recorded absences. The most absences are *33 – General medicine* and *18 – Gynecology and obstetrics*, but these are also the two specializations with the largest number of records in the data. As Fig. 2 does not express the specialization important for the absence of patients for scheduled examinations, Fig. 3 gives a logarithmic presentation of the total number of absences by categories of specializations. Important specializations are those for which a significantly higher number of absences was recorded than the number of arrivals. Fig. 4 shows the percentage of absences for each specialization in relation to the total number of recorded examinations for a given specialization.

IV. Practical Implementation

The practical implementation of the model is possible with the currently obtained results. When scheduling an examination, if the model predicts that the patient will not

TABLE IV.
THE RELATION OF INITIAL AND FINAL FEATURES

Code	Specialization
2	Internal medicine
4	Pediatrics
6	Neurology
18	Gynecology and obstetrics
19	Otorhinolaryngology
20	Ophthalmology
21	Dermatovenerology
22	Physical medicine and rehabilitation
23	Radiology
28	Hygiene
29	Epidemiology
32	Occupational medicine
33	General medicine
35	Sports medicine
42	Neuropsychiatry
43	Pediatric and preventive dentistry
44	Dental diseases and endodontics
46	Jaw orthopedics
47	Dental prosthetics
48	Oral surgery
49	General dentistry
50	Dentist
51	Other
53	Medical doctor
100	Health Associate
1003	X-ray diagnostics
1004	Ultrasound diagnostics
1125	Speech therapist

come, it is possible to schedule another examination at the same time. However, care must be taken when scheduling double appointments for not creating additional problems. In the case of the arrival of a patient for whom the model predicted an absence, there would potentially be two patients at the same time. This situation could prevent quality service. There are crowds and delays with scheduled appointments, which can sometimes be a bigger problem than not coming to the scheduled check-up. Therefore, there must be restrictions when scheduling on the model non-arrival predictions, because the oversight is not always accurate. First of all, no more than two examinations can be scheduled at the same time, even when the model predicts that both will remain empty. The second restriction refers to the number of scheduled appointments in one day. During the day, a small number of examinations that would take place outside the planned can be held without any problems. It is necessary to prevent a lot of additional examinations during one day

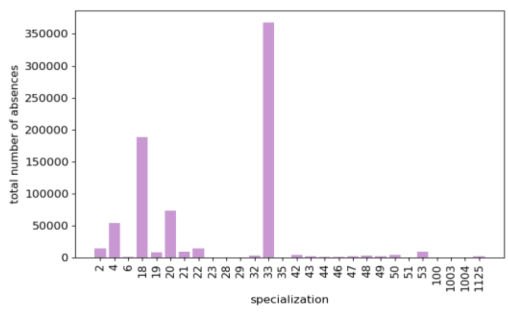

Figure 2. The total number of absences by specialization categories

Figure 3. Logarithm of the total number of absences by specialization categories

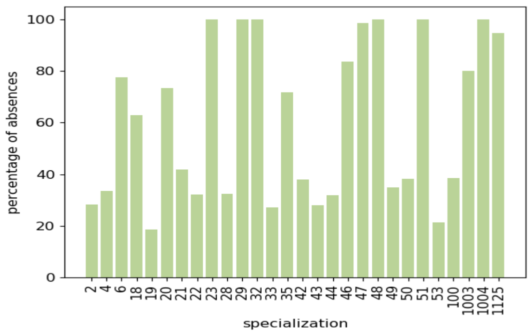

Figure 4. Percentage of absence for specialization

for a specific examination in the same office. The measure of precision can be used to select which medical appointments will be duplicated because precision represents the ratio of TP values to the total number of predicted absences (TP + FP). If a threshold of 50% is used, then 76.67% of the total number of predicted absences should be doubled, and the rest should be left because there is a possibility that the forecast is wrong. The error should not be taken into account when it is predicted that the patient will come (FN values). However, it is recommended that for the first use of the created model, this percentage should be reduced to 30-50% of duplication of terms for which non-attendance is foreseen and that over time this percentage increases unless significant failures occur, but no more than a measure of precision.

Another possibility of using the model, which cannot produce additional problems, is in the form of reminders or checking patients with an appointment that is not expected to come. This is a frequent case of a reduction of cancellations in the hotel industry because, in the season of all reserved rooms, the arrival of two different clients in the same room must not happen. Clients who are predicted not to come are contacted, checked to see if they are coming, or offered special benefits. Similarly, patients who are presumed not to show up can be checked or reminded by phone or an e-mail. The reminder date must be far enough away from the scheduled examination to allow enough time for a new appointment in case of cancellation, but also close enough for the patient's response to be valid.

V. CONCLUSION

For the purpose of optimizing the schedule of health services, this paper proposes the prediction of patients' absences from scheduled appointments. The prediction was performed by creating a model of supervised learning with logistic regression and L1 regularization over real data collected using the medical information system MEDIS.NET. The created model predicts absences with an accuracy of 80%. The most significant increase in the accuracy of the model occurred by adding attributes that are related to the patient's, doctor's, and operator's ID, while most of the significant attributes for the patient's absence are the specialization of the doctor, more precisely the type of examination. Due to these results, the suggestion for further work is to collect more personal data. Working with other algorithms may lead to a new improvement. The obtained model can be used in the presented form to optimize the schedule of health services where another examination in the same period would be scheduled for the anticipated absence, but in one day there should be no more duplicate terms with the predicted absence than the model precision. Another possibility is a reminder of the scheduled examination for a patient who is expected not to come. This paper represents the beginning of optimizing the appointment scheduling in healthcare institutions. Further work is desirable and can contribute to better model results. The considered problem in medicine is a special case of absence and cancellation in general. The results presented in this paper can be useful for research problems in a wide variety of disciplines.

ACKNOWLEDGMENT

This work has been supported by the Ministry of Education, Science and Technological Development of the Republic of Serbia.

REFERENCES

[1] Npj Digital Medicine. Nelson A, Herron D, Rees G, Nachev P, “Predicting scheduled hospital attendance with artificial intelligence “. Available from: https://www.nature.com/articles/s41746-019-0103-3 (accessed May 2020).

[2] Rajković P, Janković D, Milenković A, “Developing and Deploying Medical Information Systems for Serbian Public Healthcare – Challenges, Lessons Learned and Guidelines”, ComSIS, Vol. 10, No. 3, June 2013, p. 1429-1454, DOI: 10.2298/CSIS120523056R, ISSN: 1820-0214.

[3] Ghinai I, McPherson T, Hunter J, Kirking H, Christiansen D, Joshi K, et al. “First known person-to-person transmission of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in the USA”. Available from: https://www.thelancet.com/pdfs/journals/lancet/PIIS0140-6736(20)30607-3.pdf (accessed May 2020).

[4] WHO. Coronavirus disease (COVID-19) outbreak. World Health Organization, 2020. Available from: https://www.who.int/emergencies/diseases/novel-coronavirus-2019?gclid=CjwKCAjwq832BRA5EiwACvCWsdUIFwCUhs72sMkbAn_rWQKL3uv7bdEgMIlD1OiVxK5kFnBNuvQYzxoCugIQAvD_BwE (accessed May 2020).

[5] MIT Technology Review. Heaven W, “Israel is using AI to flag high-risk covid-19 patients” Available from: https://www.technologyreview.com/2020/04/24/1000543/israel-ai-prediction-medical-testing-data-high-risk-covid-19-patients/ (accessed May 2020).

[6] El-Din D, Hassanein A, Hassanein E, Hussein W, “E-Quarantine: A Smart Health System for Monitoring Coronavirus Patients for Remotely Quarantine” Available from: https://arxiv.org/ftp/arxiv/papers/2005/2005.04187.pdf (accessed May 2020).

[7] Antonio N, Almeida A, Nunes L, “Predicting hotel booking cancellations to decrease uncertainty and increase revenue“, 2017.

[8] Towards data science: “Intuitions on L1 and L2 Regularisation” Available from: https://towardsdatascience.com/intuitions-on-l1-and-l2-regularisation-235f2db4c261 (accessed May 2020).

[9] NumPy: „NumPy. The fundamental package for scientific computing with Python“. Available from: https://numpy.org/ (accessed May 2020).

[10] Pandas: „Pandas“. Available from: https://pandas.pydata.org/ (accessed May 2020).

[11] Scikit-learn: „Machine Learning in Python“. Available from: https://scikit-learn.org/stable/ (accessed May 2020).

[12] Matplotlib: „Visualization with Python“. Available from: https://matplotlib.org/ (accessed May 2020).

[13] Kaggle: “One-Hot Encoding: The Standard Approach for Categorical Data”. Available from: https://www.kaggle.com/dansbecker/using-categorical-data-with-one-hot-encoding (accessed May 2020).