THE ANALYSIS OF COVID-19'S EFFECTS ON EMERGENCY DEPARTMENT-LOS USING LSS APPROACH AND MACHINE LEARNING

Teresa ANGELA, TAT, Trunfio
Department of Advanced Biomedical Sciences, University of Naples "Federico II", Naples, Italy

ARIANNA, AS, SCALA*
Department of Public Health, University of Naples "Federico II", Naples, Italy

GIOVANNI, GI, Improta
Department of Public Health, University of Naples "Federico II", Naples, ItalyInterdepartmental Center for Research in Healthcare Management and Innovation in Healthcare (CIRMIS), University of Naples "Federico II", Naples, Italy

ABSTRACT

Using the Lean Six Sigma methodology, specifically the DMAIC cycle, the impact of COVID 19 on patients' duration of stay in the Emergency Department (ED-LOS) of Santa Maria della Pietà, located in Nola, Italy, was investigated. Despite having originated in the manufacturing sector, LSS is now widely used in a variety of areas, such as healthcare, finance, and services. According to the findings, ED-LOS increased significantly in 2020 (the COVID19 year) as opposed to 2019 (the year before COVID19). In both datasets, Machine Learning algorithms show that age is the main predictor. It is considered that the new protocols implemented by the hospital management are the main cause of the trend.

CCS CONCEPTS

• **General conference proceedings, Health informatics, Health care information systems**;

KEYWORDS

Lean six Sigma, Machine Learning, DMAIC, LOS, Emergency department

ACM Reference Format:
Teresa ANGELA, TAT, Trunfio, ARIANNA, AS, SCALA, and GIOVANNI, GI, Improta. 2024. THE ANALYSIS OF COVID-19'S EFFECTS ON EMERGENCY DEPARTMENT-LOS USING LSS APPROACH AND MACHINE LEARNING. In *2024 8th International Conference on Medical and Health Informatics (ICMHI 2024), May 17–19, 2024, Yokohama, Japan.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3673971.3674007

1 INTRODUCTION

Lean Six Sigma is a methodology that combines the concepts of Lean Manufacturing and Six Sigma to improve the efficiency of organizational processes. Despite having its roots in the manufacturing industry, it has now expanded to numerous other industries, including the healthcare industry.

The Lean methodology places a strong emphasis on identifying and eliminating waste from processes in order to boost output and save costs. On the other hand, the data-driven Six Sigma technique seeks to minimize operational variability and errors in order to attain near-perfect quality. It aims to lessen process variance and defects by employing statistical techniques and tools, mainly DMAIC (Define, Measure, Analyze, Improve, Control) or DMADV (Define, Measure, Analyze, Design, Verify) processes [1-6].

Lean Six Sigma projects improve processes and yield measurable results by applying the DMAIC problem-solving methodology. DMAIC stands for Define, Measure, Analyze, Improve, and Control. Each stage represents a milestone in the process of identifying and solving problems [7-9].

Defining the issue or area in need of improvement, outlining the project's objectives, and determining its scope are all done at this phase of the project. One of the most important products of this phase is a project charter that describes the goals, timetable, and scope of the work.

Measure: Gathering data on the process under study is the aim of the Measure phase. Measurement systems and data gathering methods are assessed to ensure the accuracy and reliability of the data.

Analyze: By analyzing the information acquired during the measure phase, the analyze phase seeks to identify areas for improvement or the root causes of the issue. The goals are to prioritize areas for improvement and learn more about the factors influencing process performance.

Improve: The goal of the Improve phase is to implement the solutions to the main problems identified in the Analyze phase. Depending on how well they address the issues that have been recognized, several solutions are taken into consideration, evaluated, and selected [10, 11].

Control: The control phase's objective is to ensure that the process modifications are long-lasting. A technique to look at how COVID-19 has impacted ED length of stay is Lean Six Sigma (LSS). In order to screen patients for COVID-19, isolate suspected cases,

*Corresponding author: ariannascala7@gmail.com.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).
ICMHI 2024, May 17–19, 2024, Yokohama, Japan
© 2024 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-1687-4/24/05
https://doi.org/10.1145/3673971.3674007

and stop the virus from spreading within the hospital setting, emergency departments (EDs) must put new policies and procedures into place.

The length of stay (LOS) is one metric used to evaluate the efficacy of medical procedures [12].

Due to its significance, many studies have used sophisticated mathematical techniques, such as regression models [13, 14] or classification algorithms [15, 16], to produce accurate predictions from a predetermined sample of independent variables. The two main ED indicators, abandonment rate [17, 18] and ED-LOS [19], have been studied in several South Italian hospitals. An LSS technique is used by Cesarelli et al. [20], Raiola et al. [21], and Trunfio et al. [22] to reduce treatment-related infections and postoperative hospital stays in patients following laparoscopic cholecystectomy. Owing to its importance, a large number of research have employed complex mathematical methods, like classification algorithms [15, 16] or regression models [13, 14], to provide precise predictions from a preselected sample of independent variables. Numerous hospitals in South Italy have conducted studies on the two primary ED indicators, namely abandonment rate [17, 18] and ED-LOS [19]. Cesarelli et al. [20], Raiola et al. [21], and Trunfio et al. [22] all employ an LSS approach to lower treatment-related infections and lengthen hospital stays for patients who have had laparoscopic cholecystectomy surgery.

The research aims to assess the impact of COVID-19 on ED-LOS through the application of an LSS approach, with a particular focus on the DMAIC cycle. Specifically, a statistical comparison will be performed between the data collected in 2020 (during the epidemic) and 2019 (before to the COVID-19 pandemic).

2 METHODS

2.1 Lean Six Sigma Method

The impact of COVID-19 on ED-LOS was assessed. The DMAIC cycle was employed for this analysis, and the data was gathered utilizing the ”Santa Maria della Pietà” database, which is located in Nola, Italy. The five primary steps of the DMAIC were defined as follows: define, measure, analyze, improve, and control.

An multidisciplinary working team is put together during the first phase, which also establishes the project's goals and deadlines. In 2019, patient data from the ED was examined. For the 44918 patients, the following variables were gathered:

- Age,
- Gender (Male/Female),
- Triage code (White/Green/Yellow/Red),
- Arrival mode (Autonomous/Via ambulance),
- Discharge mode (Discharge to home/Hospitalization/Transfer to another hospital/ Deceased in ED/Refuses hospitalization/LWBS / Abandonment before ED record closure/Discharge to territorial facilities/Dead on arrival),
- Time of admission (0:00–06:00 / 06:00–12:00 / 12:00–18:00 / 18:00–24:00)
- ED-LOS (minutes)

The results for every subgroup are shown in the table below.
The data reported in the measure phase was assessed in the analyze phase. The findings show that patients who are transferred to another hospital, who arrive at the hospital via ambulance, and who are older all have lengthier stays. The acquired data enable us to assess the impact of COVID-19 on ED-LOS for the purpose of examining and assessing the day-to-day operations of the emergency department. The Improve phase takes into account all hospital policies and initiatives put in place to halt the COVID-19 pandemic's spread. It was noted that fewer people visited the emergency room during the pandemic year, particularly for less critical or urgent cases.

2.2 Machine Learning Models

In order to predict the length of stay in the emergency department (ED_LOS), machine learning models such as Random Forest (RF), Decision Trees (DT), and K-Nearest Neighbors (KNN) have been implemented. Two ED_LOS categories were chosen, taking into account both extended (> 120 min) and short (<= 120 min) LOS.

The methodological strategy that was used was 10-fold cross-validation. First, preprocessing is done on the dataset to manage missing values and normalize characteristics. This dataset contains pertinent features such patient demographics, organizational data, and clinical procedure data. To ensure an equitable distribution of classes representing varying lengths of stay, the dataset is then divided into ten subgroups.

Nine subsets are utilized to train the model in each cross-validation iteration, with the remaining subset being used for validation. Performance measures, including F1-score, accuracy, precision, sensitivity, and specificity, were assessed for every model on the validation set. To ensure thorough evaluation, this process is continued until all subsets have been used for validation. Ultimately, the model that exhibits the best average performance over all folds is chosen as the ultimate classifier to forecast the duration of hospital stay.

3 RESULTS

3.1 Lean Six Sigma Method

The results presented in this study are achieved by applying the control phase, which is the final stage of the DMAIC cycle. Specifically, a comparison was made between the COVID year (2020) and the pre-COVID19 (2019) year data. The purpose of the paper is to assess how the pandemic affected the emergency department's regular operations. The dataset distribution for the two years under research in terms of the identified variables is displayed in the following table.
As expected, the data demonstrated that, for every triage code in the COVID-19 year, there was a notable decrease in the number of accesses, and that the length of stay was shortened over that same year.

The table below presents a comparison of ED-LOS for the two years under consideration. Specifically, to assess the statistical significance of the two distributions, the t-test was run at a 95% significance level.
The average length of stay in the COVID-19 year was substantially longer ($p<0.05$) according to the ED-LOS comparison. This outcome is noted independent of the patient's entrance time and mode of transportation to the hospital. Additionally, with the exception of the most serious cases, the difference is large for all triage codes. In the latter instance, the difference in LOS between the two years

Table 1: Result of initial observation.

		N	ED_LOS year 1 (mean ± standard deviation)
N		44918	
Gender			
	M	23705	162,9 ± 306
	F	21213	159,6 ± 322,6
Triage code			
	White	2889	155,3 ± 504,2
	Green	36022	135,2 ± 246,4
	Yellow	5739	323,3 ± 469,6
	Red	268	277,8 ± 478,4
Arrival mode			
	Autonomous	41057	142,9 ± 268,4
	Via ambulance	3786	361,5 ± 585
Time of admission			
	0:00 - 6:00	4185	159,6 ± 363,2
	6:00 - 12:00	13484	168,4 ± 308,9
	12:00 - 18:00	13348	165,1 ± 327,2
	18:00 - 0:00	13901	151,5 ± 288,7
Age			
	Under 18	7033	89,9 ± 398
	18 < Age<40	11925	126,4 ± 223,6
	40 < Age < 65	14933	155,8 ± 235,6
	Over 65	11027	252,2 ± 398
Discharge mode			
	Discharge to home	26908	141,2 ± 248,1
	Hospitalization	8153	237 ± 380
	Transfer to another hospital	379	328 ± 335,2
	Deceased in ED	34	359,9 ± 400,5
	Refuses hospitalization	0	-
	LWBS	2265	198,4 ± 705,8
	Abandon before ED record closure	1794	160,2 ± 308
	Discharge to territorial facilities	5383	119,2 ± 175,5
	Dead on arrival	2	18,5 ± 6,4
Length of stay (LOS)			
	ED_LOS	44918	161,3 ± 313,9

is negligible. Additionally, the statistical test demonstrated that the following increases are noticeably greater for patients who are released from the emergency department:

- Discharge to home
- Hospitalization
- Transfer to another hospital
- Deceased in ED
- Abandon before ED record closure
- Discharge to local facilities

3.2 LOS binary classification models for year 2019

The average performance metrics obtained for each classification model are reported in the following table.
The table shows how the best performance are achieved by the RF algorithm. However, while high sensitivity is reported for both DT and RF models, a very limited specificity is obtained across all the adopted classifiers.
The following table shows the confusion matrix of the best classification model, namely the RF, having proved highest accuracy and F1-score, taken as a balance metrics between precision and recall of the model.
By analyzing the impact of the predictors on the best classification model, the following figure, displaying the feature importance bar chart, allows a preliminar investigation of the model decision-making process based on each the predictors' weigth.
As from the above figure, the most influencing variables in the models are the age and discharge mode, followed by triage code and arrival mode. Lower impact on predicatability is given to LWBS rate, time of admission and gender.

Table 2: Comparison between the two distributions.

	Year 2019	Year 2020
N	44918	30985
Gender		
M	23705	16538
F	21213	14447
Triage code		
White	2889	1828
Green	36022	25007
Yellow	5739	3969
Red	268	181
Arrival mode		
Autonomous	41057	27057
Via ambulance	3786	3876
Time of admission		
0:00 - 6:00	4185	2745
6:00 - 12:00	13484	10146
12:00 - 18:00	13348	9270
18:00 - 0:00	13901	8824
Age		
Under 18	7033	3618
18 < Age<40	11925	8533
40 < Age < 65	14933	10873
Over 65	11027	7961
Discharge mode		
Discharge to home	26908	16204
Hospitalization	8153	7142
Transfer to another hospital	379	444
Deceased in ED	34	106
Refuses hospitalization	0	0
LWBS	2265	1784
Abandon before ED record closure	1794	1701
Discharge to territorial facilities	5383	3594
Dead on arrival	2	10
Length of stay (LOS)		
ED_LOS	44918	30985

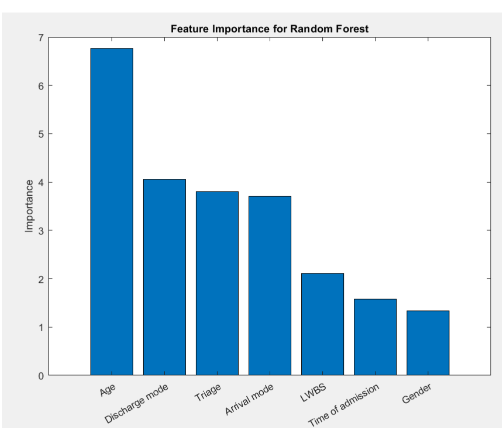

Figure 1: Feature importance of the best LOS binary classification model for year 2019

For 2019 the variables that most influenced the LOS are age and discharge mode, while in 2020 the variable continues to influence the LOS with greater impact but is added to it

3.3 LOS binary classification models for year 2020

The average performance metrics obtained for each classification model are reported in the following table.

The table shows how the best performance are achieved by the RF algorithm. However, conversely to the previous case of binary ED_LOS classification before COVID_19 outbreak, a high specificity is reported for both DT and RF models and a very limited sensitivity is obtained across all the adopted classifiers.

The following table shows the confusion matrix of the best classification model, namely the RF, having proved highest accuracy and F1-score, taken as a balance metrics between precision and recall of the model.

Table 3: Comparison on ED-LOS between the two years

	ED_LOS year 2019 (mean ± standard deviation)	ED_LOS year 2020 (mean ± standard deviation)	p-value
Gender			
M	162,9 ± 306	280,2 ± 710,2	0,000
F	159,6 ± 322,6	244,7 ± 578,3	0,000
Triage code			
White	155,3 ± 504,2	269,3 ± 696,1	0,000
Green	135,2 ± 246,4	265,4 ± 658,1	0,000
Yellow	323,3 ± 469,6	251,1 ± 598,3	0,000
Red	277,8 ± 478,4	228,5 ± 512,9	0,299
Arrival mode			
Autonomous	142,9 ± 268,4	197,7 ± 426,6	0,000
Via ambulance	361,5 ± 585	723,6 ± 1374	0,000
Time of admission			
0:00 - 6:00	159,6 ± 363,2	266,3 ± 663,4	0,000
6:00 - 12:00	168,4 ± 308,9	245,3 ± 549,7	0,000
12:00 - 18:00	165,1 ± 327,2	284,8 ± 713,8	0,000
18:00 - 0:00	151,5 ± 288,7	261,6 ± 688,3	0,000
Age			
Under 18	89,9 ± 398	118 ± 485,7	0,001
18 < Age<40	126,4 ± 223,6	170,1 ± 349,3	0,000
40 < Age < 65	155,8 ± 235,6	254,1 ± 609,4	0,000
Over 65	252,2 ± 398	443,1 ± 927,1	0,000
Discharge mode			
Discharge to home	141,2 ± 248,1	189,8 ± 337,7	0,000
Hospitalization	237 ± 380	392,1 ± 825,7	0,000
Transfer to another hospital	328 ± 335,2	1788,1 ± 2379,2	0,000
Deceased in ED	359,9 ± 400,5	1988,6 ± 2770,8	0,001
Refuses hospitalization	-	-	-
LWBS	198,4 ± 705,8	213,5 ± 716,6	0,501
Abandon before ED record closure	160,2 ± 308	220 ± 462,3	0,000
Discharge to territorial facilities	119,2 ± 175,5	147,9 ± 270,5	0,000
Dead on arrival	18,5 ± 6,4	46,9 ± 53,8	0,489
Length of stay (LOS)			
ED_LOS	161,3 ± 313,9	263,6 ± 652,3	0,000

Table 4: Performance metrics comparison of LOS binary classification models for year 2019

Classifier	Accuracy	Sensitivity	Specificity	F1-score
KNN	0.57	0.61	0.53	0.63
DT	0.66	0.79	0.51	0.67
RF	0.67	0.80	0.49	0.67

Table 5: Confusion matrix of the best LOS binary classification model for year 2019

		Predicted	
		ED_LOS below threshold	ED_LOS above threshold
True	ED_LOS below threshold	2046	474
	ED_LOS above threshold	984	984

Table 6: Performance metrics comparison of LOS binary classification models for year 2020.

Classifier	Accuracy	Sensitivity	Specificity	F1-score
KNN	0.60	0.51	0.66	0.54
DT	0.67	0.50	0.80	0.65
RF	0.67	0.48	0.82	0.67

Table 7: Confusion matrix of the best LOS binary classification model for year 2020.

		Predicted	
		ED_LOS below threshold	ED_LOS above threshold
True	ED_LOS below threshold	828	1015
	ED_LOS above threshold	469	1957

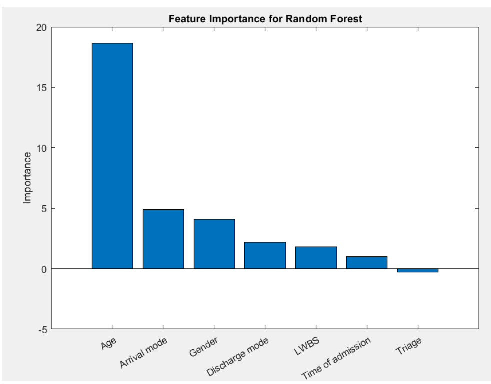

Figure 2: Feature importance of the best LOS binary classification model for year 2020.

By analyzing the impact of the predictors on the best classification model, the following figure, displaying the feature importance bar chart, allows a preliminar investigation of the model decision-making process based on each the predictors' weight.
Compared to Figure 1, by modeling the data recorded in year 2020, i.e., across the COVID-19 pandemic, it emerged that the most influencing variable is the age, followed by and arrival mode and gender, which were less influencing in the previous case (Figure 1). Furthermore, triage code has a surprisingly lowest impact on the predicatability, almost reversing the output displayed in Figure 1.

4 DISCUSSION AND CONCLUSIONS

The study examined variations in length of stay (LOS) among patients hospitalized to Nola Hospital's emergency room (Italy). The comparison's two years are:

- Year 2019: Pre-COVID 19 era;
- Year 2020: COVID 19 pandemic era.

These modifications have been assessed using the Lean Six Sigma (LSS) methodology, more especially the DMAIC cycle. In the Measure Phase, the CTQ computation was used to assess the 2019 database (prior to COVID-19), and the patient population was categorized into groups according to variables such age, gender, hospitalization duration, mode of arrival, and discharge procedures. In the Control phase, the same study was done for the year 2020 (COVID-19 era). The t-test statistical test was used to do the comparison.

The results showed that ED-LOS significantly extended in 2020. This particular result is indicated explicitly for patients older than 40, for all hospital stays, and for patients with triage codes of white, green, and yellow. only for patients with LWBS discharge method; the findings did not indicate an increase in LOS. The main theory explaining the tendency to stay longer is that hospital management's modified flow, which includes policies like accepting longer admissions. Furthermore, the ML results showed that the best classification algorithm is Random Forest. For 2019 the variables that most influenced the LOS are age and discharge mode, while in 2020 the patient age continues to influence the LOS with greater impact but the mode arrive variable is added to it.

In future research, it is essential to clarify the patient flow and used techniques. Overcoming these constraints will require additional work and may require the use of sophisticated data analysis methods [23–30], such as simulation models [30, 40].

REFERENCES

[1] Antony, J., & Banuelas, R. (2002). Key ingredients for the effective implementation of Six Sigma program. Measuring Business Excellence, 6(4), 20-27.
[2] Dusharme, D. (2007). Why Lean Fails. Quality Digest.
[3] Womack, J. P., & Jones, D. T. (2003). Lean thinking: Banish waste and create wealth in your corporation. Simon and Schuster.
[4] George, M. L., Rowlands, D., Price, M., & Maxey, J. (2005). Lean Six Sigma: Combining Six Sigma Quality with Lean Production Speed. McGraw-Hill Education.
[5] Pande, P. S., Neuman, R. P., & Cavanagh, R. R. (2000). The Six Sigma Way: How GE, Motorola, and Other Top Companies are Honing Their Performance. McGraw-Hill Education.
[6] Pyzdek, T., & Keller, P. A. (2014). The Six Sigma Handbook: A Complete Guide for Green Belts, Black Belts, and Managers at All Levels. McGraw-Hill Education.
[7] Antony, J., & Banuelas, R. (2002). Key ingredients for the effective implementation of Six Sigma program. Measuring Business Excellence, 6(4), 20-27.
[8] Harry, M. J., & Schroeder, R. (2000). Six Sigma: The breakthrough management strategy revolutionizing the world's top corporations. Currency Doubleday.
[9] George, M. L., Rowlands, D., Price, M., & Maxey, J. (2005). Lean Six Sigma: Combining Six Sigma Quality with Lean Production Speed. McGraw-Hill Education.
[10] Pyzdek, T., & Keller, P. A. (2014). The Six Sigma Handbook: A Complete Guide for Green Belts, Black Belts, and Managers at All Levels. McGraw-Hill Education.
[11] Schroeder, R. G., Goldstein, S. M., & Rungtusanatham, M. J. (2013). Operations Management in the Supply Chain: Decisions and Cases. McGraw-Hill Education

[12] Womack, J. P., Jones, D. T., & Roos, D. (1990). The Machine That Changed the World: The Story of Lean Production–Toyota's Secret Weapon in the Global Car Wars That Is Now Revolutionizing World Industry. Free Press.
[13] George, M. L. (2003). Lean Six Sigma: Combining Six Sigma Quality with Lean Production Speed. McGraw-Hill Education.
[14] Pande, P. S., Neuman, R. P., & Cavanagh, R. R. (2000). The Six Sigma Way: How GE, Motorola, and Other Top Companies Are Honing Their Performance. McGraw-Hill Education.
[15] Rother, M., & Shook, J. (1999). Learning to See: Value Stream Mapping to Add Value and Eliminate MUDA. Lean Enterprise Institute.
[16] Antony, J. (2004). Design for Six Sigma: A Practical Approach through Innovation. Springer.
[17] Ahmed, S.: Integrating DMAIC approach of Lean Six Sigma and theory of constraints toward quality improvement in healthcare. Rev. Environ. Health 34(4), 427–434 (2019).
[18] Breyfogle III, F. W. (1999). Implementing Six Sigma: Smarter Solutions Using Statistical Methods. Wiley.
[19] Eckes, G. (2001). Making Six Sigma Last: Managing the Balance Between Cultural and Technical Change. Wiley.
[20] Cesarelli, G., Montella, E., Scala, A., Raiola, E., Triassi, M., Improta, G.: DMAIC approach for the reduction of healthcare-associated infections in the neonatal intensive care unit of the university hospital of Naples 'Federico II.' In: Jarm, T., Cvetkoska, A.,Mahni˘c-Kalamiza,
[21] Ferraro, A., Centobelli, P., Cerchione, R., Cicco, M. V. D., Montella, E., Raiola, E., … & Improta, G. (2020). Implementation of lean practices to reduce healthcare associated infections. International Journal of Healthcare Technology and Management, 18(1-2), 51-72.
[22] Trunfio, T.A., Scala, A., Borrelli, A., Sparano, M., Triassi, M., Improta, G.: Application of the Lean Six Sigma approach to the study of the LOS of patients who undergo laparoscopic cholecystectomy at the San Giovanni di Dio and Ruggi d'Aragona university hospital. In: 2021 5th International Conference on Medical and Health Informatics (ICMHI 2021). Association for Computing Machinery, New York, NY, USA, pp. 50–54 (2021).
[23] Brasel, K.J., Lim, H.J., Nirula, R., Weigelt, J.A.: Length of stay: an appropriate quality measure? Arch Surg. 142(5), 461–466 (2007).
[24] Scala, Arianna, Anna Borrelli, and Giovanni Improta. "Predictive analysis of lower limb fractures in the orthopedic complex operative unit using artificial intelligence: The case study of AOU Ruggi." Scientific Reports 12.1 (2022): 22153.
[25] Scala, Arianna, Teresa Angela Trunfio, and Giovanni Improta. "Classification and regression model to manage the hospitalization for laparoscopic cholecystectomy." Scientific Reports 13.1 (2023): 14700.
[26] Ponsiglione, A.M., Trunfio, T.A., Amato, F. and Improta, G., 2023. predictive analysis of hospital stay after caesarean section: A single-center study. Bioengineering, 10(4), p.440.
[27] Trunfio, T. A., Maria Ponsiglione, A., Ferrara, A., Borrelli, A., & Gargiulo, P. (2021, May). A comparison of different regression and classification methods for predicting the length of hospital stay after cesarean sections. In Proceedings of the 5th International Conference on Medical and Health Informatics (pp. 63-67).
[28] Maria Ponsiglione, A., Majolo, M., Longo, G., Russo, G., Triassi, M., Raiola, E., & Improta, G. (2021, August). Analysis of voluntary departures from the Emergency Department of the hospital AORN "A. Cardarelli". In 2021 International Symposium on Biomedical Engineering and Computational Biology (pp. 1-4).
[29] Improta, G., Colella, Y., Rossi, G., Borrelli, A., Russo, G., & Triassi, M. (2021, October). Use of machine learning to predict abandonment rates in an emergency department. In Proceedings of the 2021 10th International Conference on Bioinformatics and Biomedical Science (pp. 153-156).
[30] Giglio, C., De Lauri, C., Della Vecchia, A., Borrelli, A., Russo, G., Triassi, M., & Improta, G. (2021, August). Investigation of factors increasing waiting times in the Emergency Departments of "San Giovanni di Dio e Ruggi d'Aragona" Hospital through machine learning. In 2021 International Symposium on Biomedical Engineering and Computational Biology (pp. 1-5).
[31] Majolo, M., Ponsiglione, A. M., Longo, G., Russo, G., Triassi, M., Raiola, E., & Improta, G. (2021, October). Studying length of stay in the Emergency Department of AORN "Antonio Cardarelli" of Naples. In Proceedings of the 2021 10th International Conference on Bioinformatics and Biomedical Science (pp. 144-147).
[32] Cesarelli, M., Romano, M., Bifulco, P., Improta, G., & D'Addio, G. (2012, August). An application of symbolic dynamics for FHRV assessment. In MIE (pp. 123-127).
[33] Ponsiglione, A.M., Amato, F., Romano, M.: Multiparametric investigation of dynamics in fetal heart rate signals. Bioengineering 9(1), 8 (2021)
[34] Ponsiglione, A.M., Cosentino, C., Cesarelli, G., Amato, F., Romano, M.: A comprehensive review of techniques for processing and analyzing fetal heart rate signals. Sensors 21(18), 6136 (2021)
[35] Improta, G., Mazzella, V., Vecchione, D., Santini, S., & Triassi, M. (2020). Fuzzy logic–based clinical decision support system for the evaluation of renal function in post-Transplant Patients. Journal of evaluation in clinical practice, 26(4), 1224-1234.
[36] Cesarelli, M., Romano, M., Bifulco, P., Improta, G. and D'Addio, G., 2013. Prognostic decision support using symbolic dynamics in CTG monitoring. EFMI-STC, 186, pp.140-144.
[37] Ponsiglione, A.M., Amato, F., Cozzolino, S., Russo, G., Romano, M., Improta, G.: A hybrid analytic hierarchy process and likert scale approach for the quality assessment of medical education programs. Mathematics 10(9), 1426 (2022)
[38] Scala, A., Loperto, I., Triassi, M. and Improta, G., 2022. Risk factors analysis of surgical infection using artificial intelligence: A single center study. International Journal of Environmental Research and Public Health, 19(16), p.10021.
[39] Montella, E., Ferraro, A., Sperlì, G., Triassi, M., Santini, S. and Improta, G., 2022. Predictive analysis of healthcare-associated blood stream infections in the neonatal intensive care unit using artificial intelligence: a single center study. International Journal of Environmental Research and Public Health, 19(5), p.2498.
[40] D'Addio, G., Donisi, L., Pagano, G., Improta, G., Biancardi, A. and Cesarelli, M., 2019, July. Agreement between opal and G-walk wearable inertial systems in gait analysis on normal and pathological subjects. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 3286-3289). IEEE.