Predictive Models of Ward Admissions from the Emergency Department

Laiene Azkue[1,2][a], Jon Kerexeta[1,3][b], Jorge Sampedro[4], Moisés Espejo[4] and Nekane Larburu[1,3][c]
[1]*Vicomtech Foundation, Basque Research and Technology Alliance, (BRTA), 20009 Donostia, Spain*
[2]*Biomedical Engineering Department, Mondragon Unibertsitatea, 20500 Mondragón, Spain*
[3]*Biodonostia Health Research Institute, 20014 San Sebastián, Spain*
[4]*Asunción Klinika, 20400 Tolosa, Spain*

Keywords: Emergency Department, Ward Admission, Predictive Models, Machine Learning, Artificial Intelligence.

Abstract: The demand for emergency department (ED) care has increased significantly in recent years, mainly due to factors such as the increase in chronic diseases, aging population and urban population growth. The large influx of patients can lead to overcrowding and resource allocation problems, which impact the quality of care. A new tool to improve patient severity classification systems could improve ED care and avoid inappropriate admissions. Therefore, we propose the development of an artificial intelligence model to predict ED ward admissions. The proposed model uses electronic medical records from the Asunción Klinika in Spain and environmental data. Three models are created at different stages of ED: *arrival model* which predicts admission upon patient arrival, *triage model* which predicts admission after clinicians' triage and the last one, *laboratory model* which make use of triage model data and laboratory analysis to estimate the risk among the most critical patients. The arrival model achieved an AUC of 0.801, the triage model achieved an AUC of 0.854, and the laboratory model achieved an AUC of 0.781. These models provide valuable information for efficient patient management and resource allocation in the ED, contributing to improved patient care and the adequacy of hospital admissions.

1 INTRODUCTION

The demand for emergency department (ED) care has increased considerably worldwide in recent years. During the pandemic, it is evident that due to COVID-19 there has been a disproportionate increase in demand on EDs, leaving them overwhelmed (WHS, 2023). However, regardless of the pandemic, there is a considerable increase due to factors such as an aging population, increase in chronic diseases, lack of access to primary care, urban population growth, and changes in lifestyles (McKenna et al., 2019),(Lowthian et al., 2011) .

Hospital management is affected by the increasing demand for ED care. The high influx of patients can lead to overcrowding, long waiting times, and challenges in resource allocation, which can impact quality of care and patient satisfaction (Sun et al., 2013). Rapid identification of the worst-off patients to prioritise patient care could improve it.

Clinicians' triage plays a crucial role in today's EDs. It is a patient stratification system that allows the identification and prioritization of patients requiring immediate medical attention. The triage evaluates parameters such as vital signs, symptomatology, and initial clinical assessment (Yancey and O'Rourke, 2023). This task involves the intervention of the clinical caregivers, which can be costly. Artificial intelligence (AI) can provide rapid and improved evaluation when assessing patients according to their severity.

To address this issue, we propose the development of three AI models capable of predicting ward admissions from the ED in three different

[a] https://orcid.org/0009-0009-2266-7985
[b] https://orcid.org/0000-0002-6516-8619
[c] https://orcid.org/0000-0003-0248-7783

Azkue, L., Kerexeta, J., Sampedro, J., Espejo, M. and Larburu, N.
Predictive Models of Ward Admissions from the Emergency Department.
DOI: 10.5220/0012202700003657

In *Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2024) - Volume 2*, pages 277-284
ISBN: 978-989-758-688-0; ISSN: 2184-4305

sequential stages. Each stage requires different grades of clinical involvement and clinical tests. Thus, the models may detect high risk patients, which faster the process without clinical involvement. These models are based on various clinical factors, including the patient's health status, diagnostic test results, severity of the medical condition, and environmental factors which differ in each stage.

Previously, we have conducted the following systematic review, (Larburu et al., 2023), focusing on predictive models for ED ward admission. This review showed that logistic regression is the most used algorithm, along with the gradient boosting algorithm. The most frequently used variables are triage and age. It is worth noting that all the reviewed articles have an unbalanced nature. The systematic review cover articles published between 2011 and 2022, with sample sizes ranging from 2,476 to 3,189,204 number of patients. The highest performance was achieved by (Hong et al., 2018) with the XGBoost algorithm, obtaining an AUC of 0.92 (95% CI 0.92-0.93).

The article is structured as follows: dataset section summarizes the databases used and the general characteristics of the database. Later, in the methodology section, the models to be created and the methodology carried out are exposed. Finally, the results are presented, together with a discussion and conclusions in the following two sections.

2 DATASET

Two types of data are used: electronic health records (*EHR*), and *environmental* data.

EHR: The data used for analysis were obtained from Asunción Klinika of Tolosa, Basque Country, Spain. Once the study was approved by the committee, the necessary data for the analysis were provided. These retrospective data include vital signs, laboratory results, details of performed tests, demographic information, and more. The data covers a period from January 1, 2004, to December 31, 2022, encompassing a total of 284,503 emergency cases involving 75,913 unique patients. It also includes the target variable, which indicates whether the patient is admitted to the ward or not. This variable is unbalanced since 16.4% are admitted to the ward.

Environmental: Environmental data is extracted from (Open-Meteo, 2023), an open-source weather API service. This API provides access to meteorological data from around the world. The data come from various governmental meteorological services and research organizations. The data covers the period from January 1, 2004 to December 31, 2022 and they are from Tolosa. The environmental data collected include the variables of temperature, wind chill, solar radiation, precipitation, evaporation, relative humidity, pressure, wind speed and gusts.

The two datasets are unified and a database with 196,659 instances and 255 predictor variables, since EDs have been reduced to the year range 2010 to 2022, as triage was implemented in 2010. The target variable is unbalanced, since the number of patients not admitted to the ward is greater than the number of patients admitted to the ward.

A total of 255 predictor variables can be classified into the following categories (Table 1): demographic (2), triage information (16), clinical and laboratory findings (199), environmental (19) and others, that is, uncategorized EHR variable (19).

Table 1: Description of predictor variables.

	Quantity	type
Demographic	**2**	-
Sex	-	Categorical
Female	45.4%	
Male	54.6%	
Unknown	0.001%	
Age (50.76±23.77)	-	Numerical
-20	11.34%	
20-40	24.05%	
40-60	26.41%	
+60	38.2%	
Triage information	**16**	-
Triage	-	Ordinal categorical
0 – Non-urgent	0.006%	
1 – Minor Urgent	0.95%	
2 – Urgent	3.45%	
3 – Emergency	18.51%	
4 – Critical emergency	66.55%	
5 – Immediate Life Threatening	7.33%	
NaN	3.2%	
Vital signs		Numerical
Clinical and laboratory findings	**199**	-
Laboratory data	64	Numerical
tests performed	135	Categorical
Environmental	**19**	Numerical
Others	**19**	-
ED data	18	Numerical / Categorical
Cause of attendance	1	Categorical
Common Disease	68.69%	
Personal Accident	20.05%	
Laboral Accident	5.7%	
Sports Accident	2.13%	
Traffic Accident	1.77%	
School Accident	1.34%	
Pregnancy	0.18%	
Professional disease	0.134%	
Undetermined	0.006%	

3 METHODS

This section discusses the methodology to be carried out for the creation of predictive models. The objective is the prediction of ward admissions from the ED. For this purpose, with the data provided by Asunción Klinika and acquired by Open-Meteo, three models are created at three different stages of the ED attendance (Figure 1):

Arrival Model: Model able to predict ward admission from the ED upon patient arrival. This model is trained with data prior to triage, such as demographic data and environmental variable data.

Triage Model: Model capable of predicting ward admission from the ED after triage. This model is trained with data available at triage, such as, demographic data, environmental variables data and data obtained at triage: the triage value and vital signs acquired at triage.

Laboratory Model: Model able to predict ward admission from the ED for patients undergoing laboratory tests after triage (smaller population). This model is trained with post-laboratory test data, such as demographic data, environmental variable data, triage data and laboratory test data.

These three models are an efficient and fast way to classify urgent patients from non-urgent patients from the first moment of care. As new tests/analyses are carried out in the ED, more accurate models will be used as they make use of this new information. First, on arrival at the ED, we will have a result of the *arrival model* to be able to estimate the patient's risk. Secondly, after clinicians triage the patient, we will be able to obtain the updated risk with this new variable (*triage model*). Finally, in case the patient has not yet been discharged and laboratory tests have been conducted, the risk will be updated with these tests (*laboratory model*).

3.1 Data Preprocessing

To ensure the data is clean and suitable for predictive modelling, several preprocessing steps are applied. Initially, One-Hot Coding is performed to transform the categorical variables into numerical ones. Subsequently, missing values are imputed using the KNN (K-Nearest Neighbors) method (Juna et al., 2022). Finally, the classes of the target variable are balanced, but only in the training database (70%) using the random undersampling technique.

3.2 Feature Selection

The most related variables with the admission in ward are estimated using a combination of the Boruta method and the importance of the dependent feature of the XGBoost model. On the one hand, the Boruta method is a feature selection technique that helps to identify the most relevant variables in a dataset (Kursa and Rudnicki, 2010). On the other hand, the importance of the dependent feature of the XGBoost model allows to evaluate the degree of influence that each variable has on the prediction of the model. The variables selected by both techniques have been selected as the relevant ones for the predictive models.

This methodology is carried out on the triage model, since this is the model that has been given more importance. This is because in the state of the art it is the most studied model, that is, all models use the triage variable and focus on the instant after triage. Then, among these variables, the clinicians' triage related variables are discarded for arrival model training. Similarly, the laboratory model is trained with the variables selected for the triage model, plus variables acquired after triage.

3.3 Predictive Models

The predictive models implemented include the following algorithms: Logistic Regression, K-NN, Gaussian Naives Bayes, Bernoulli Naives Bayes, Decision Tree Classification, Random Forest

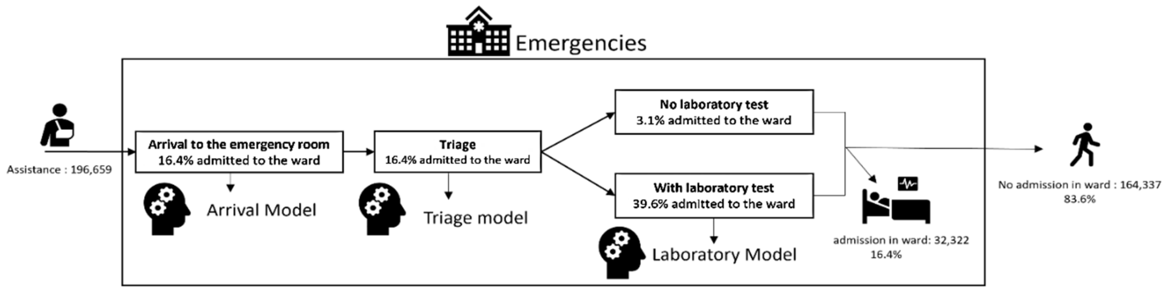

Figure 1: Predictive system workflow for the emergency department.

Classification, Gradient Boosting Classifier (GBC), eXtreme Gradient Boosting (XGBoost), AdaBoost (Adaptive), CatBoosting (Categorical), LightGBM (Light Gradient Boosting Machine), MLP (Multilayer Perceptron) (Juna, 2022; Theng, 2020; Kelleher, 2020; Natras, 2022).

3.4 Evaluation Methods

For model evaluation, the database is divided into training (70%) and validation (30%). The best hyperparameters are searched in the training set using GridSearch. Finally, a 10-fold cross-validation is used during the training phase (Browne, 2000). The evaluation metrics used to assess the model's performance in both the validation set and during cross-validation training are as follows (Hossin and Sulaiman, 2015): confusion matrix, ROC-AUC, accuracy, precision, recall and F1.

4 RESULTS

This section presents the results obtained from each of the three models (see Figure 1), along with their optimal hyperparameters.

4.1 Triage Model

The triage model is the model that predicts ward admission after the clinical caregivers have conducted the triage. Hence, it makes use of triage information for the prediction.

4.1.1 Training Triage Model

After the feature importance (see Section 3.2), it was observed that triage, cause of attendance, age, and sex are the main variables.

Table 2: Result of algorithm XGBoost in the training of model triage.

	XGBoost
AUC	0.854(95% IC 0.849-0.858)
Accuracy	0.773(95% IC 0.768-0.777)
Precision	0.757(95% IC 0.750-0.763)
Recall	0.803(95% IC 0.796-0.810)
F1	0.779(95% IC 0.775-0.784)

With these variables, predictive models were created using the 10-fold cross validation technique with 70% of the database.
XGBoost algorithm obtained the best results with an AUC value of 0.854 (95% CI 0.849-0.858) (Table 2).

4.1.2 Triage Model Validation Results

Validation is performed with the XGBoost algorithm at the default threshold of 0.5. The model is validated with the remaining 30% of the database. This model obtains an AUC of 0.858. This model classifies 74.29% of the negative class correctly, in addition to classifying 81.22% of the positive class correctly.

Table 3 shows that the value of precision and F1 score decreases due to the imbalance of the validation dataset.

Table 3: Triage model comparison in training and validation.

	Training	Validation
AUC	0.854	0.858
Accuracy	0.773	0.755
Precision	0.757	0.384
Recall	0.803	0.812
F1	0.779	0.521

4.2 Arrival Model

The arrival model is the model that predicts ward admissions at the time of arrival at the ED, before the triage. Therefore, an estimate of the triage or patient status could be made with the output of the arrival model, since clinicians have not yet get involved and this model can help them in their decision making.

4.2.1 Training Arrival Model

For this model we have used the same variables as in the triage model, except from triage information, which has been removed, since this model aims to predict the risk of ward admission before the triage. Hence, the cause of attendance, age and sex are solely used. With these variables, predictive models were created using the 10-fold cross validation technique with 70% of the database.

The best performing model is Gradient boosting with an AUC value of 0.801 (95% CI 0.796-0.806) (Table 4).

Table 4: Result of algorithm Gradient Boosting in the training of model arrival.

	Gradient Boosting
AUC	0.801(95% IC 0.796-0.806)
Accuracy	0.731(95% IC 0.726-0.735)
Precision	0.721(95% IC 0.716-0.725)
Recall	0.753(95% IC 0.748-0.757)
F1	0.736(95% IC 0.732-0.741)

4.2.2 Arrival Model Validation Results

The Gradient Boosting model was validated with the 0.5 threshold. The model obtained an AUC value of 0.805. It predicts well 76.82% of patients admitted to the ward and 70.45% of those not admitted to the ward.

Table 5 shows the difference between the training and validation results. In general, all the metrics have maintained their training value in the validation, except the accuracy, and therefore, the f1 score. This is because the training dataset is balanced, and the validation dataset is not.

Table 5: Arrival model comparison in training and validation.

	Training	Validation
AUC	0.801	0.805
Accuracy	0.731	0.715
Precision	0.721	0.338
Recall	0.753	0.768
F1	0.736	0.469

4.3 Laboratory Model

Laboratory model is the model which predicts ward admission from the ED for patients after triage and with laboratory tests. The database used in this model is reduced from 196,659 emergencies to 71,982 emergencies since those were the ones that had laboratory information. This is the 36.6% from previous cases. The imbalance of the data changes: from the total number of these cases (n=71,982), 39.59% are admitted to the ward.

4.3.1 Training Laboratory Model

In this model we used triage variables, cause of attendance, age, sex, laboratory data (red blood cells, hemoglobin, hematocrit, MCV, MCH, MCHC, etc), vital signs and environmental variables (temperature, thermal sensation, precipitation, etc). The Gradient boosting model obtains the best results with an AUC value of 0.788 (95% CI 0.785-0.792) (Table 6).

Table 6: Result of algorithm Gradient Boosting in the training of model laboratory.

	Gradient Boosting
AUC	0.788 (95% IC 0.785-0.792)
Accuracy	0.715 (95% IC 0.712-0.718)
Precision	0.719 (95% IC 0.716-0.723)
Recall	0.705 (95% IC 0.699-0.711)
F1	0.712 (95% IC 0.709-0.716)

4.3.2 Laboratory Model Validation Results

The selected model has been validated and the results of the Table 7 are obtained. Considering that the population has been reduced by discarding patients who are initially in the best condition (n=71,982), it is understandable that the predictive ability decreases among the severe patients. Therefore, we have applied the triage model in this reduced cohort to compare whether the use of laboratory data improves the predictive ability.

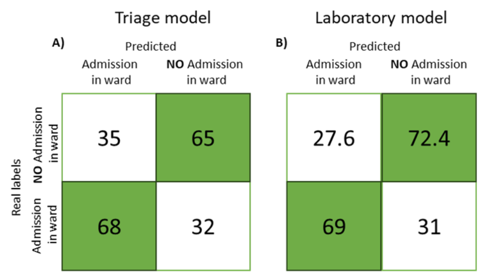

Figure 2: Confusion matrices (in %) to compare the triage model (a) and the laboratory model (b) in the validation set of the reduced data.

Table 7: Laboratory model comparison in training and validation with the triage model in the reduced database.

	Training	Validation	Triage model
AUC	0.781	0.779	0.728
Accuracy	0.711	0.710	0.662
Precision	0.622	0.622	0.561
Recall	0.691	0.685	0.680
F1	0.654	0.652	0.615

The results of the laboratory model based on laboratory data outperform both in validation and training the results of the triage model in the reduced database, as shown in the Table 7. A comparison of the classification of laboratory model (b) and the triage model in this cohort (a) can be seen in Figure 2 For positive predictions, laboratory model improves by 1.08% over the triage model. In the case of negative predictions, it improves by 7.33%, taking into account that this class is the majority class.

5 DISCUSSION

Promising results were obtained using three predictive models at different times during emergency care: arrival model, triage model and laboratory model. These three models predict ward admission, but at different stages of Emergency

Department (ED): arrival model predicts admission to the ward on arrival of the ED, whereas the triage model predicts it after triage has been performed. Finally, laboratory model predicts ward admission for patients undergoing laboratory tests, that is, it is a model trained with a smaller population than the other two models.

These models benefit healthcare personnel in patient management by providing the ability to evaluate ward admission at different points of care. The accuracy of the models improves with an increased number of tests conducted. Consequently, the laboratory model demonstrates greater predictive capacity compared to the arrival model. In addition, the arrival model proves valuable in estimating potential ward admissions prior to triage. Thus, during periods of high demand, it may be possible to create two care pathways: one with patients with a high probability of admission and the other with patients with a low probability of admission. This approach could minimize the collapse in the ED and enhance overall management. These models are useful tools for the effective management of patients according to their needs and can avoid unnecessary admissions, improving not only the quality of care but also patient safety. The following Table 8 shows the results obtained for each model.

Table 8: Results of the ED workflow.

	Nº Var	n	AUC
Arrival model	3	196,659	0.805
Triage model	4	196,659	0.858
Laboratory model	55	71,982	0.779

There are 196,659 emergency room attendances. The arrival model has obtained an AUC value of 0.805, with the use of 3 predictor variables (cause of attendance, age and sex) and the Gradient Boosting model.

Afterwards, the patient is triaged by nursing and with this evaluation, another model (triage model) is created to improve the capacity of the initial model (arrival model). The triage model makes use of the XGBoost algorithm and uses 4 variables, which are the same as those used in the arrival model, together with the triage value. An AUC value of 0.858 and a precision of 0.440 is obtained. A low precision value is obtained since the data are unbalanced (83.6% negative class and 16.4% positive class). This implies that the model has a tendency to predict the majority (negative) class more frequently due to the higher number of examples in the dataset. As a result, the model accuracy is affected. But actually, the model is able to correctly predict 72.70% of the positive class and to incorrectly predict 18.13% of the negative class. However, having the database unbalanced the number of patients in the 18.13% of the negative class is higher than the 72.70% of the positive class, which lowers the accuracy result.

Finally, an additional model (laboratory model) is developed with the aim of predicting the need for ward admission for those patients undergoing laboratory tests. It is important to note that these patients, in general, present a more severe health condition compared to those who do not undergo such tests. Therefore, this model is trained with a reduced database (n=71,982) with the gradient boosting algorithm, of which 39.6% are admitted to the ward. In this model the 4 variables of the previous arrival model used together with laboratory results data, vital signs data and environmental data, obtaining an AUC value of 0.781. The AUC decreases with respect to the triage model, but this model is not the best model to compare whether the AUC has improved. This is because the two models have been trained with different databases, that is, the triage model has been trained with a database of 196,659 urgencies, including those in best condition, and the laboratory model with a database of 71,982 urgencies, which are supposed to be the most severe patients. Therefore, these results have been compared with a new triage model, which makes use of the same reduced database, but only with triage model variables, i.e. without laboratory tests information. As for the AUC value, the value of this new triage model is 0.728 and the laboratory model obtains a value of 0.781, thus improving predictivity. This model does not greatly increase the correct prediction of the positive class, but it reduces the number of false positives.

6 CONCLUSION

Three machine learning models have been developed to predict ward admissions from the ED at various stages during the emergency care process. In these three models triage, age and cause of care variables are the most important ones in terms of prediction. In addition, the best performing models are XGBoost and Gradient boosting. The arrival model is useful for identifying patients who may require ward admission from the beginning of their ED care, without triage. The triage model, with the inclusion of the triage value, improves predictive ability later in the process. On the other hand, laboratory model focuses on patients undergoing laboratory tests, offering greater predictive accuracy for this specific group.

Regarding the results obtained and the results of the systematic review by (Larburu et al., 2023) which summarizes the articles dealing with predictive models of ward admissions, it can be seen that even without the clinicians triage variable, the arrival model exceeds a quarter of the articles in the systematic review, which make use of variables at triage. Therefore, this initial model, achieves results comparable with the literature but without the need of clinician's involvement.

In the case of the triage model, we observe that three studies demonstrate superior results in terms of AUC: 0.92 (Hong et al., 2018), 0.89 (Cusidó et al., 2022), and 0.877 (Cameron et al., 2015). It is worth noting that these three articles have been trained on much larger databases, consisting of 560 thousand, 3 million, and 255 thousand instances, respectively. We have identified six articles that achieve similar AUC value (confidence intervals overlap), generally characterized by a comparable database size (Sun et al., 2011; Martinez et al., 2012; Zlotnik et al., 2016; Graham et al., 2018; Lucke et al., 2018; De Hond et al., 2021). Lastly, our model outperforms five articles, all of which, except for one (more than a million instances), make use of much smaller databases (Noel et al., 2019; Parker et al., 2019; Brink et al., 2020; Feretzakis, Karlis, et al., 2022; Feretzakis, Sakagianni, et al., 2022).

Finally, it is important to note that the laboratory model cannot be directly compared with the models in the systematic review. This is because the laboratory model is trained on a small population consisting specifically of patients undergoing laboratory tests in the ED, patient in worse condition.

These machine learning models offer an opportunity to improve the management and efficiency of emergency departments from a clinical perspective. These models can help prioritize and allocate resources more effectively, streamlining floor admission processes and optimizing patient care, as well as achieving more efficient management of available resources, ensuring timely and appropriate care for each patient, and thus improving clinical outcomes in the ED setting. Additionally, these models can play a relevant role in reducing hospital admission inadequacy, which directly translates into improvements in patient safety (Puig et al., 2004).

However, it is important to mention some limitations of the study. One important limitation to consider is the applicability of the model to different clinical contexts or settings. Since machine learning models are trained with data specific to a particular institution or context, it is possible that their performance and predictive ability may be affected when applied in other settings with different characteristics. The variables used in the model may be related to clinical practice and procedures specific to the home institution, which could limit its usefulness elsewhere where the relevant variables may vary.

ACKNOWLEDGEMENTS

The authors would like to thank INVIZA-Asunción Klinica and STT Systems for their support in the INURGE project. This work has been funded by the research project INURGE (ZL-2022/00571) of the Basque Government's HAZITEK programme from the public agency SPRI.

ETHICAL COMMITEE

The study was conducted in accordance with the Declaration of Helsinki and approved by the Research Ethics Committee of the Gipuzkoa Health Area (protocol code SAMURG-2022-01, 6 February 2023).

REFERENCES

Brink, A., Alsma, J., Brink, H. S. et al. (2020). Prediction admission in the older population in the Emergency Department: the CLEARED tool. *Neth J Med 78*, 357–367

Browne, M. W. (2000). Cross-Validation Methods. *J Math Psychol 44*, 108–132. https://doi.org/10.1006/jmps.1999.1279.

Cameron, A., Rodgers, K., Ireland, A. et al. (2015). A simple tool to predict admission at the time of triage. *Emerg Med J 32*, 174–179

Cusidó, J., Comalrena, J., Alavi, H. et al. (2022). Predicting Hospital Admissions to Reduce Crowding in the Emergency Departments. *Appl Sci 12*, 10764

De Hond, A., Raven, W., et al. (2021). Machine learning for developing a prediction model of hospital admission of emergency department patients: Hype or hope? *Int J Med Inf 152*, 104496

Feretzakis, G., Karlis, G., et al. (2022). Using machine learning techniques to predict hospital admission at the emergency department. *J Crit Care Med 8*, 107–116

Feretzakis, G., Sakagianni, A., Loupelis, E. et al. (2022). Predicting Hospital Admission for Emergency Department Patients: A Machine Learning Approach. *Stud Health Technol Inf*, 297–300

Graham, B., Bond, R., et al. (2018). Using data mining to predict hospital admissions from the emergency department. *IEEE Access 6*, 10458–10469

Hong, W. S., Haimovich, A. D. and Taylor, R. A. (2018). Predicting hospital admission at emergency department triage using machine learning. *PloS One 13*, e0201016

Hossin, M. and Sulaiman, M. N. (2015). A review on evaluation metrics for data classification evaluations. *Int J Data Min Knowl Manag Process 5*, 1

Juna, A., Umer, M., Sadiq, S. et al. (2022). Water quality prediction using KNN imputer and multilayer perceptron. *Water 14*, 2592

Kelleher, J. D., Namee, B. M. and D'Arcy, A. (2020). *Fundamentals of Machine Learning for Predictive Data Analytics, second edition: Algorithms, Worked Examples, and Case Studies*. MIT Press.

Kursa, M. B. and Rudnicki, W. R. (2010). Feature Selection with the Boruta Package. *J Stat Softw 36*, 1–13. https://doi.org/10.18637/jss.v036.i11.

Larburu, N., Azkue, L. and Kerexeta, J. (2023). Predicting Hospital Ward Admission from the Emergency Department: A Systematic Review. *J Pers Med 13*, 849. https://doi.org/10.3390/jpm13050849.

Lowthian, J. A., Curtis, A. J., Cameron, P. A. et al. (2011). Systematic review of trends in emergency department attendances: an Australian perspective. *Emerg Med J 28*, 373–377. https://doi.org/10.1136/emj.2010.099226.

Lucke, J. A., de Gelder, J., et al. (2018). Early prediction of hospital admission for emergency department patients: a comparison between patients younger or older than 70 years. *Emerg Med J 35*, 18–27

Martinez, E., Fernández, C., et al. (2012). Prediction model for in-hospital admission in patients arriving in the emergency department. In *Anales del Sistema Sanitario de Navarra* (207–217)

McKenna, P., Heslin, S. M., et al. (2019). Emergency department and hospital crowding: causes, consequences, and cures. *Clin Exp Emerg Med 6*, 189–195. https://doi.org/10.15441/ceem.18.022.

Natras, R., Soja, B. et.al. (2022). Ensemble Machine Learning of Random Forest, AdaBoost and XGBoost for Vertical Total Electron Content Forecasting. *Remote Sens 14*, 3547. https://doi.org/10.3390/rs14153547.

Noel, G., Bonte, N., et al. (2019). Real-time estimation of inpatient beds required in emergency departments. *Eur J Emerg Med 26*, 440–445

Open-Meteo (2023). Open-Meteo. Available at: https://openmeteo.substack.com/embed [Accessed December 22, 2023].

Parker, C. A., Liu, N., Wu, S. X. et al. (2019). Predicting hospital admission at the emergency department triage: A novel prediction model. *Am J Emerg Med 37*, 1498–1504

Puig, C., Carrasco, G., et al. (2004). Factores asociados a la inadecuación de los ingresos por urgencias en un hospital privado de tercer nivel. *Rev Calid Asist 19*, 363–369. https://doi.org/10.1016/S1134-282X(04)77725-8.

Sun, B. C., Hsia, R. Y., et al. (2013). Effect of emergency department crowding on outcomes of admitted patients. *Ann Emerg Med 61*, 605-611.e6. https://doi.org/10.1016

Sun, Y., Heng, B. H., Tay, S. Y. et al. (2011). Predicting hospital admissions at emergency department triage using routine administrative data. *Acad Emerg Med 18*, 844–850

Theng, M. and Theng, D. (2020). *Machine Learning Algorithms for Predictive Analytics: A Review and New Perspectives*. https://doi.org/10.37896/HTL26.06/1159.

WHS (2023). *World health statistics 2023: monitoring health for the SDGs, sustainable development goals*.

Yancey, C. C. and O'Rourke, M. C. (2023). Emergency Department Triage. In *StatPearls*. Treasure Island (FL): StatPearls Publishing. Available at: http://www.ncbi.nlm.nih.gov/books/NBK557583/ [Accessed June 23, 2023].

Zlotnik, A., Alfaro, M. C., et al. (2016). Building a decision support system for inpatient admission prediction with the Manchester triage system and administrative check-in variables. *CIN Comput Inform Nurs 34*, 224–230