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Intelligent Decision Support in Beds Management and Hospital Planning

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Abstract

Worldwide, due to the constant overcrowding experienced in hospitals, hospital beds are one of the most needed resources, proving to be an extremely important feature in hospitalization planning and management, since the main purpose is to optimize their occupancy rate. This study aims to predict the future flow of patients after admission to a particular inpatient specialty to allow a more assertive planning based on demographic data. All data sources were made available by the Centro Hospitalar do Tâmega e Sousa (CHTS) and are relative to a 5-year period, 2017 to 2021. From the results achieved with the Machine Learning (ML) models developed was possible to conclude that these can prove to be an asset for the hospital, since being known the flow of patients allows a more informed and careful management of the management of beds.

Keywords: Type your keywords here, separated by semicolons ;

1. Introduction

Currently, the continuous increase of these expenditures is irrefutable, which accentuates the importance given to the management of resources, in the ability to achieve methods and models to optimize them [1]. Another aspect is the huge amount of data generated by several hospital processes, which makes it difficult to search and obtain useful

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information for decision making, such as information regarding the clinical status of patients that end up being forgotten.

In Healthcare, Data Mining (DM) has been proving to be an asset in several sectors, being used, for example, to evaluate the effectiveness of a treatment [2], in hospital resource management [3] and in reducing fraud in health insurance [4].

Thus, being bed management one of the aspects to be considered in an efficient hospital planning, this study aims to predict the future flow of patients, i.e., which is the next specialty to which they will be admitted or if they will be discharged. With these insights, Health professionals will be able to estimate the future flow of patients, being expected an optimization of hospital resources, as well as cost reduction.

2. Background

2.1. Resources Planning in Hospital Settings

Hospital beds are one of the most needed resources in hospitals. The importance associated of a good planning and management of these beds is evident, since this management is reflected both in the quality of service provided and in the efficiency and effectiveness of the various services [5].

Besides this, the volume of records generated daily is also a problem, due to the difficulty of understanding them. The application of DM in this sector has proven to be an asset, since it allows the achievement of crucial information for decision making [6].

Therefore, a decision support tool may be viable in helping professionals develop a more assertive hospital bed management planning. For this purpose, this tool needs to consider several processes, such as admission forecasts, Length of Stay (LOS), future flows and hospital discharges. However, in the present study, the focus is directed to the prediction of the future flow of patients in CHTS.

2.2. Related Works

The application of ML techniques is increasingly notorious to generate useful information for decision making in bed management and hospital planning, thus providing an optimization of both.

In 2002, Steven Walczak et al. [7] developed a decision support tool using artificial neural network for hospital bed management planning. According to the author, one of the key aspects for successful planning is the accurate prediction of patients' LOS, and the project focused on two types of patients, namely, pediatric trauma patients and patients with acute pancreatitis. For the development of the DM models, all available data in the first ten minutes after the patient's arrival at the hospital were used. It was concluded that a combination of two artificial neural networks, a primary one used to indicate the LOS of patients and a secondary one serving as a signal to identify patients with more severe injuries or diseases, increased by 5% the predictions of perfect LOS for patients with acute pancreatitis, thus allowing the development of a decision support tool capable of assisting physicians and hospital administrators in determining the need and allocation of critical hospital resources [E1].

In 2011, Teow el al. [8] dedicated themselves to identifying the patterns behind the overcrowding of beds in various specialties at the National University Hospital (NUH) in Singapore, using statistical approaches such as Data Mining. From this study, a better understanding of the problem was made possible, concluding that, with the knowledge collected, the hospital will be more informed to develop strategies capable of reducing this overcrowding, thus ensuring a better quality of service provided to the patient. For example, one of the points verified was that there were not enough beds per specialty to meet demand, while others had a greater number of beds than needed, leading to occupation in other services, and thus to uncontrolled overcrowding [E2].

In 2014, Oliveira et al. [9] predicted the number of weekly discharges of patients in four specialties (Orthopedics, Obstetrics, Delivery Room and Nursery), based on data provided by the Centro Hospitalar do Porto, over a 4-year period. For this, a classification approach was followed, where the Support Vector Machine (SVM) technique stood out as having a better performance than the Decision Trees (DT) and Naïve Bayes (NB) techniques. This study revealed that an accurate discharge forecast allows for a better management of available beds for the following weeks [E3].

Should be highlighted that, for a correct bed management and bed planning there are some indicators to be considered, LOS the most investigated factor. For this reason, from a different perspective, the present research will focus on predicting the next path to be taken by the patient, which may be a new specialty or even hospital discharge.

3. Materials and Methods

For the development of this project, two methodologies were used, one for the development of this research and the other to support the DM project, which are the DSR (Design Science Research) and CRISP-DM (Cross Industry Standard Process for Data Mining) methodologies, respectively. The DSR consists on six activities [10], which are: Understanding the Problem (1), Suggestion (2), Development (3), Evaluation (4), Conclusion (5), and Communication (6).

The CRISP-DM methodology describes a DM project life cycle and supported the development of all DM techniques. Consist on a set of 6 phases [11]: Business Understanding (1), Data Understanding (2), Data Preparation (3), Modeling (4), Evaluation (5), and Implementation (6). This paper discusses only the first 5 phases, since the implementation can be developed in future work.

4. Case Study

This section presents the processes and decisions made in the first 5 phases of the CRISP-DM methodology. As previously mentioned, this study aims to predict the next specialty where a patient will be admitted or if will be discharged.

4.1. Business Understanding

The primary goal of this research is to achieve improved efficiency in hospital bed planning and management by predicting future patient flow at CHTS.

4.2. Data Understanding

All data sources were made available by the CHTS, containing data regarding admissions, discharges, transfers between specialties and patient demographics over a 5-year period.

4.3. Data Preparation

In a first phase, the attributes of greatest interest for the predictive models were selected. Later, using the selected attributes, we derived new variables, where we developed the attribute age, based on the patient's date of birth, and at the level of the medical record, two new attributes were introduced, identifying the number of services performed in the hospitalization in question and the number of previous hospitalizations associated with the patient.

A set of classes were defined that include the specialty codes of the inpatient service, along with a code identifying the hospital discharge.

The integration of all data sources was performed to model a single data set, used as input in the developed ML algorithms. All attributes were properly anonymized and coded.

4.4. Modelation

The ML techniques applied were Decision Tree (DT), Random Forest (RF), K-Nearest Neighbors (KNN) and Gradient Boosting (GB), being adopted the Cross Validation K-fold (CV) technique for sampling and validation of results, since it allows the use of all data for training and testing, ensuring greater confidence in the results achieved

[12]. Furthermore, it became evident that the classes were not balanced, which led to the need to balance them, and for this an oversampling method was applied.

4.5. Evaluation

To evaluate the developed models and check whether they are aligned with the objective under study, the evaluation metrics were selected, namely, Accuracy (AC), Precision (PC), Recall (RC), F1-Score (F1), Kappa (KP) and Area Under the ROC Curve (AUC), according to the approach applied. Success criteria were defined for each evaluation metric:

- AC, PC, RC, F1, AUC ≥ 85%;
- KP ≥ 80%.

5. Results And Discussion

Table 1 present the results obtained in all models for the defined target, considering the metrics under evaluation.

Table 1. ML Table Results

	DT	RF	KNN
AC	86.80	86.88	63.07
PC	87.46	87.55	92.07
RC	86.80	86.88	63.07
F1	86.48	86.58	70.45
KP	86.37	86.46	61.88
AUC	99.63	99.63	85.66

Is possible to verify the good performance presented by the DT and RF models, according to the defined metrics. The RF model is slightly better, which is justified by the fact that this technique is based on Bootstrap aggregation (Bagging), combining several ML algorithms, allowing predictions with better accuracy.

6. Conclusions

This study proved the possibility to predict future patient flow upon admission to a given specialty, based on patient demographics and the patient's medical record.

Among a set of applied techniques, RF was the one that, according to the defined evaluation metrics, showed the best predictive results, with an accuracy of 86.88%.

Therefore, it should be induced that the application of the developed model will allow a more accurate hospital planning since the set of information obtained through it will allow more informed decisions to be made, leading to a more adjusted hospital discharge planning and consequently to a better quality of the service provided to the patient.

As future work, new algorithms will be studied that allow optimizing the results obtained. In addition, we intend to implement an Adaptive Business Intelligence (ABI) system, helping professionals in decision making involving all hospital planning processes [13].

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