# Utilizing machine learning for detecting benchmark abidance for admitted patients to the Emergency Department

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### Abstract

Emergency Department (ED) crowding is a ubiquitous issue around the world with grave consequences to the quality of patient care (Schull, Slaughter, and Redelmeier 2002; Ataman and Sarıyer 2021). However, little research has been done to explore what factors contribute to a patient's length of stay (LOS). This study aims to classify if a patient's LOS meets the national benchmark using machine learning techniques (cta 2017). Such knowledge could help hospitals anticipate overcrowding and identify sources of delay. The data used for this study consists of 99 features collected from the Foothills Medical Center ED in 2017. Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) were used to create the classifiers. The performance of these classifiers were compared and investigated. A Decision Tree was used for feature selection. Our results show that the ANN outperformed the other classifiers using 42 features while achieving an accuracy of 0.726, recall 0.737, and specificity 0.648.

## Introduction

Emergency Department (ED) crowding is a serious issue confronting many hospitals around the world. Literature shows that delays in the ED can result in poor patient care and increase risk of morbid outcomes (Ataman and Sarıyer 2021; Kuo et al. 2020). Comparing a patient's total Length of Stay (LOS) to the national benchmark can be used as an indicator to determine how well EDs handles overcrowding. This national benchmark is based on the Canadian Triage & Acuity Scale (CTAS) which categorizes patients according to the severity of their symptoms (cta 2017).

This study aims to use the data gathered from the Foothills Medical Center (FMC) ED in 2017 and various machine learning techniques to create classifiers that identify whether a patient's LOS will meet the national benchmark according to their CTAS. Correctly classifying if a patient's LOS meets the national benchmark can help hospitals anticipate possible overcrowding and detect inefficiencies in the ED. In addition, identifying which factors affect a patient's delayed LOS can help administrators identify ED setbacks which can create changes that lead to better patient outcomes.



## Dataset Description

This study uses anonymous data obtained from the Foothills Medical Center (FMC) in Calgary Alberta for patients who visited the ED between January 2017 to December 2017. The data contains information like each patient's first contact date with nurse, consultation request, and discharge type. In addition, the shifts for physicians and nurses were collected. A record of each patient's diagnostic imaging, lab request date, and lab request type were also obtained. In total, we collected data for 79000 patients. For more details about the demographics of the data collected please check appendices A.

## Methodology

### Data Pre-processing

Data acquired from FMC was stored in different files and so we combined all the information by joining using patient IDs. After combining, we performed various data cleaning steps. We converted categorical data into individual indicator variables. All the date variables were converted into datetime format. Lastly, any records with null values were removed. This represented around 18% of the data and so the number of data points went from 79000 to 65000.

Following the data cleaning, we derived our own features from the collected data. Below is a list of the features we derived.

- Number of patients in waiting room before arrival
- Number of patients in waiting room after arrival
- Number of patients waiting for discharge/admission
- Number of physicians before/after arrival
- Number of labs ordered before/after arrival
- Number of diagnostic imaging ordered before/after arrival
- Categorical time of arrival (morning, midday, night, late night)
- Categorical age (0-10, 10-20, 20-30, . . ., 90-100, >100)

### Analysis

Figure 1 shows the analysis process followed in this study. Our goal is to collect data gathered upon patient admission and see if the LOS for this patient will abide with national benchmark based on CTAS classification. Those benchmarks were obtained from Wait Time Alliance (wta 2015). We started with 49 features and created three classifiers using Support Vector Machine (SVM), Random Forest (RF), and customized Neural Network (NN).(Pappu and Pardalos 2014) We conducted a feature reduction using a Decision Tree. The final classifier is built with the reduced features and with the algorithm with the best overall accuracy, specificity, and sensitivity.

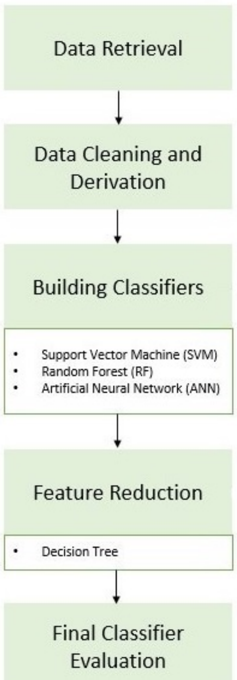


Figure 1: Flowchart of Data Handling and Analysis Process

For training the classifiers we used a balanced 5 fold cross validation approach to make sure we avoid over fitting. As for the NN, the batch size was 50 and the model was trained with 150 epochs. The activation method utilized is the Rectified Linear unit (RELU) sigmoid activation function was utilized for the last layer. The mean square error function was utilized as the loss function for our NN model.

## Results

The SVM classifiers was tested using three kernels namely the linear, polynomial (poly), and radial basis factor (RBF). To evaluate the performance of the models we recorded the accuracy, sensitivity, and specificity of the classifiers in the testing dataset using the original 49 features. Table 1 shows the results achieved. Hence, we find that our customized NN performed overall better than the others. After performing feature reduction using a Decision Tree, we tested our NN model again using 42 features and found the results to be the same as with the original 49 features. The list of features can be found in Appendix B. Additionally, all code and associated data have been published and made publicly available[1].

| | **Accuracy** | **Sensitivity** | **Specificity** |
|---|---|---|---|
| **SVM-Poly** | 69.879 | 62.43 | 67.95 |
| **SVM-Linear** | 66.44 | 56.86 | 69.631 |
| **SVM-RBF** | 70.26 | 62.99 | 69.16 |
| **RF** | 71.66 | 69.07 | 56.13 |
| **ANN** | 72.71 | 73.33 | 65.13 |

Table 1: Metrics measurements for the initial classifiers.

## Conclusion and Future Work

This paper presents an approach for detecting if patient LOS in ED would meet the national benchmark upon arrival using real time data from the FMC hospital. We discussed a set of derived features that could be helpful when conducting such as analysis. Additionally, we demonstrated the effectiveness of our customized NN model when compared with other state of the art classifiers. The results from this project can help researchers investigate and further expand on this research to help ED managers determine factors to prevent overcrowding which can lead to better patient outcomes.

For future work, we would like to test our model on data obtained from other hospitals. Additionally, we want to test our model on data obtained during the COVID pandemic period and further investigate the impact of COVID on ED admissions. Further, we would like to investigate the ability to predict the LOS of a patient upon admission and not just if they will meet the benchmark. Finally, we would like to add an additional step to the analysis to include which access block is causing the delay in patient flow and help manager in making decision faster.

## References

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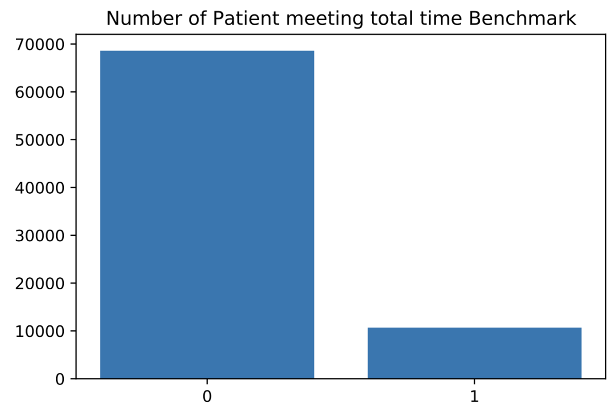
[1]https://github.com/jfosea/AAAI-ED

## Appendix A
## Demographics of Patients at the Foothills Medical Center ED in 2017

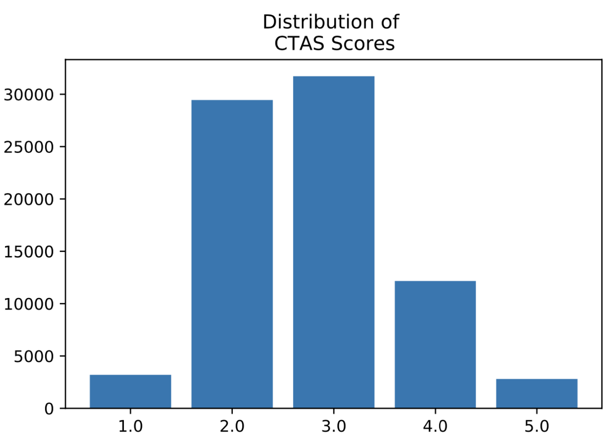
### A.1 Descriptive statistics for various continuous features of Patients at Foothills Medical Center ED in 2017

| Feature | Mean | 25-th | Median | 75-th | Deviation |
|---|---|---|---|---|---|
| Age | 50.09 | 32.33 | 48.66 | 66.08 | 20.69 |
| Physicians at Arrival | 4.7 | 4 | 5 | 6 | 1.63 |
| Labs Per Patient | 4.9 | 0 | 4 | 7 | 6.86 |
| Diagnostic Image Per Patient | 0.95 | 0 | 1 | 1 | 1.37 |
| Patients Waiting for Treatment at Arrival | 0 | 0.01 | 0 | 0 | 0 |
| Patients Waiting for Discharge at Arrival | 18.48 | 15 | 19 | 23 | 6.05 |
| Patients Waiting for Admission at Arrival | 11.76 | 9 | 12 | 15 | 4.5 |

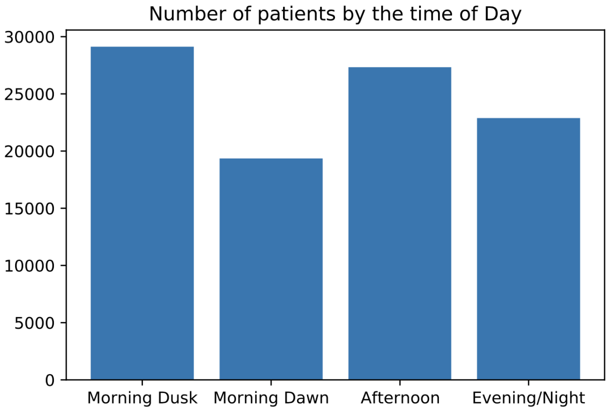
### A.2 Number of Patients at Foothills Medical Center ED in 2017 meeting LOS benchmark



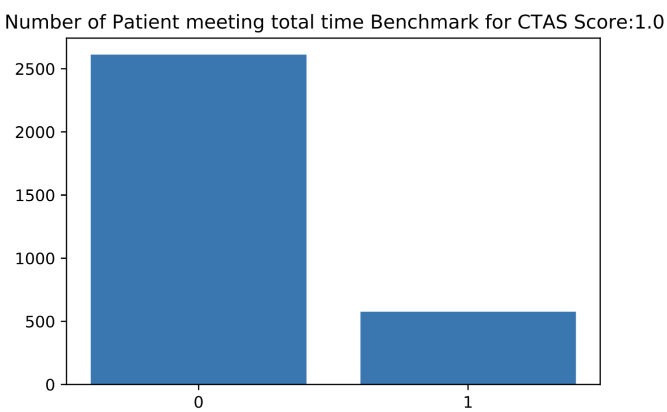

### A.3 Distribution of CTAS Scores of Patients at Foothills Medical Center ED in 2017



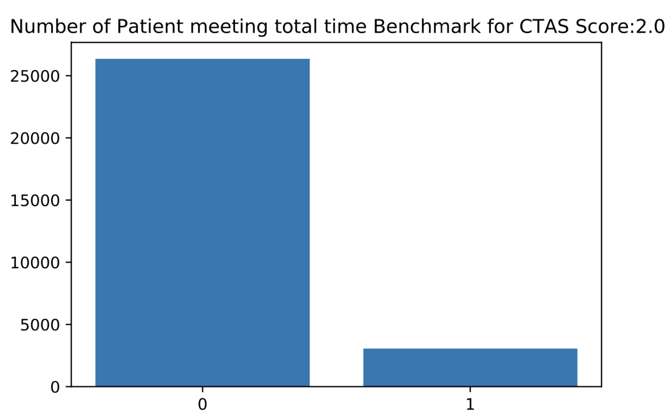
### A.4 Number of Patients at Foothills Medical Center ED in 2017 arriving at various times of day



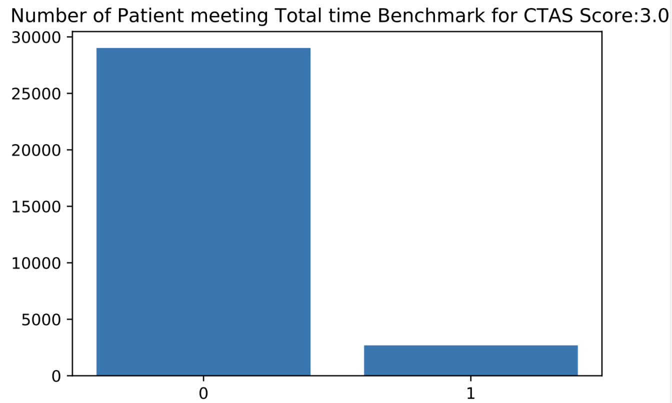

### A.5 Number of Patients with CTAS 1 meeting LOS benchmark



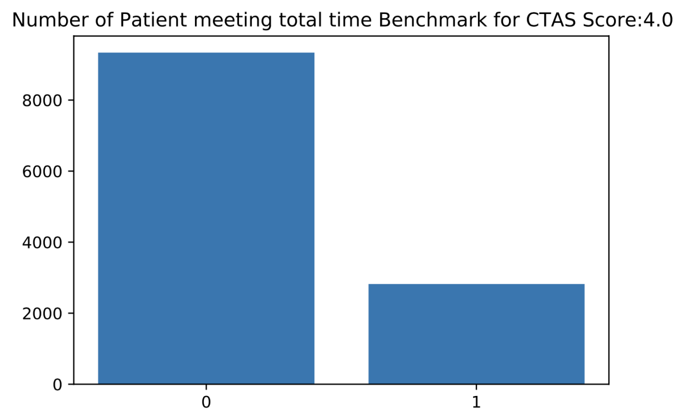

### A.6 Number of Patients with CTAS 2 meeting LOS benchmark



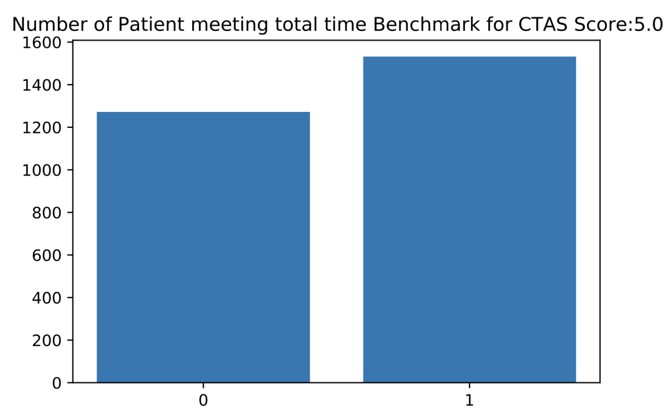

### A.7 Number of Patients with CTAS 3 meeting LOS benchmark




### A.8 Number of Patients with CTAS 4 meeting LOS benchmark




### A.9 Number of Patients with CTAS 5 meeting LOS benchmark



# Appendix B
# Feature Importance Derived from Decision Tree

| Feature | Importance | Feature | Importance |
|---|---|---|---|
| Arrival Mode by Ambulance Indicator | 0 | Initial Location Group Waiting Room - Main | 0.010767 |
| Number of Patients In Waiting Before | 0 | Patient Age 81-90 | 0.010963 |
| Number of Patients In Waiting Before with same CTAS | 0 | Patient Age 71-80 | 0.011645 |
| Patient Age 1-10 | 0.000089 | Patient Age 51-60 | 0.012136 |
| Labs Ordered Hour Before Arrival | 0.00012 | Patient Age 51-60 | 0.012375 |
| Patient Age >100 | 0.000377 | Patient Age 41-50 | 0.012707 |
| Labs Ordered Hour After Arrival | 0.000433 | Male Patient | 0.012986 |
| Initial Location Group Waiting Room Non-ED | 0.000684 | Patient Age 31-40 | 0.013617 |
| Initial Location Group Minor Treatment Area | 0.001913 | Arrival Mode Ground Ambulance | 0.013825 |
| Initial Location Group Intake | 0.001977 | Patient Age 21-30 | 0.014724 |
| Diagnostic Imaging Ordered Hour After Arrival | 0.002257 | Number of Physicians At Arrival | 0.018529 |
| Initial Treatment Location Group Intake | 0.002401 | Number of Physicians 3 Hours Before | 0.020598 |
| Diagnostic Imaging Ordered Hour Before Arrival | 0.002635 | Number of Physicians 1 Hours Before | 0.020727 |
| Time of day of arrival - Morning Dawn | 0.002676 | Number of Physicians 2 Hours Before | 0.021024 |
| Initial Location Group Main | 0.002723 | Number of Physicians 2 Hours After | 0.024403 |
| Patient Age 91-100 | 0.004046 | Number of Physicians 1 Hours After | 0.025071 |
| Time of day of arrival Morning Dusk | 0.0043 | Number of Physicians 3 Hours After | 0.03016 |
| Time of day of arrival Midday | 0.005772 | Initial Treatment Location Group Minor Treatment Area | 0.033458 |
| Time of day of arrival - Night/Evening | 0.006093 | Number of Patients Waiting For Admission CTAS | 0.064415 |
| Initial Location Group Waiting Room in Minor Treatment Area | 0.0062 | Number of Patients Waiting For Discharge CTAS | 0.082542 |
| Arrival Mode No Ambulance | 0.007475 | Number of Patients In Waiting After CTAS | 0.098289 |
| Patient Age 11-20 | 0.00767 | Number of Patients Waiting For Admission | 0.100195 |
| Intial Location Group Main | 0.009096 | Number of Patients Waiting For Discharge | 0.122669 |
| Initial Location Group Waiting Room Intake | 0.009958 | Number of Patients In Waiting After | 0.123156 |
| Female Patient | 0.010122 | | |