

Hospital Admission Prediction: A Technology Survey

Twinkle L. Chauhan¹, Mukta S. Takalikar², Anil kumar Gupta³

^{1,2}Dept. of Computer Engineering, PICT, Pune, Maharashtra, India.

³CDAC HPC I&E, Pune, Maharashtra, India.

Abstract - Overcrowding in Emergency Departments (ED's) has a great impact on the patients along with negative consequences. Therefore it gets important to find innovative methods to improve patient flow and prevent overcrowding. This can be done with the help of different machine learning techniques to predict the hospital admissions from ED. This will help in resource planning of hospital as well. The paper consists of survey of the different methods used for prediction. The paper also consist the implementation result of three different methods of the machine learning techniques along with its results comparison.

Key Words: Data Mining, Health Care, Machine Learning.

1. INTRODUCTION

Emergency department in hospitals has main function to treat patients who are suffering from injuries which may lead to severe complications or acute serious illness. Emergency departments are not for treating patients with regular ongoing care. For ensuring that the sickest patients get seen first, a sorting mechanism called triage process is used to categorize patients. According to the patient's symptoms, the patient is categorized into three levels of triage process. In this, critical patients are given first importance and non-critical patients are given a waiting time according to their symptoms to get treated by doctors.

Patients waiting in the EDs lead to crowding and this may have negative impacts on management, patients, etc. Therefore, there is a need to explore methods which will help to improve patient flow, prevent overcrowding and reduce waiting time involved in triage process. Identifying patients which are at high risk of getting admissions from emergency department to hospital will help to reduce the crowding and also help in resource management. This can be done with the help of different machine learning techniques by predicting the patient's admission.

2. Literature Survey

Byron Graham. [1] developed a prediction model in which machine learning techniques such as Logistic Regression, Decision Tree and Gradient Boosted Machine were used. The most important predictors in there model were age, arrival mode, triage category, care group, admission in past-month, past-year. In which the gradient boosted

machine outperforms and focus on avoiding the bottleneck in patient flow. Jacinta Lucke. [2] and team has designed the predictive model by considering age as main attribute, where the age is categorized in two category below 70 years and above 70 years. They observed that the category of people below 70 years was less admitted in compare with the category of people above 70 years. Younger patient had higher accuracy while the older patient had high risk of getting admitted to hospital. The decision of prediction was based on the attributes such as age, sex, triage category, mode of arrival, chief complaint, ED revisits, etc. Xingyu Zhang [3] in there predictive model, they have used logistic regression and multilayer neural network. This methods were implemented using the natural language processing and without natural language processing. The accuracy of model with natural language processing is more than the model without natural language processing.

Boukenze. [4] with his team created a model using decision tree C4.5 for predicting admissions which overall gave a good accuracy and less execution time. The author has used the prediction model for predicting a particular disease that is chronic kidney disease. Dinh and his team [5], developed a model which uses multivariable logistic regression for prediction. For the prediction the two main attributes were demographics and triage process, which helped to increase the accuracy. Davood. [6] developed a model for reducing emergency department boarding using the logistic regression and neural network, were a set of thumb rules were developed to predict the hospital admissions. The prediction model used as decision support tool and helped to reduce emergency department boarding. The set of thumb rules were found by examining the importance of eight demographic and clinical factors such as encounter reason, age, radiology exam type, etc. of the emergency department patient's admission. Xie. [7] and his teams model consist of coxian phase type distribution (PH Model) and logistic regression where the PH model has out performs than logistic regression.

Peck and his teams [8] created a model for predicting the inpatient for same-day to improve patient flow. The model uses Naive Bayes and linear regression with logit link function, the result of the model was accurate even though it had less number of independent variables. Sun. [9] and his team uses logistic regression for creating the model

Table 1. Literature Survey

<i>Paper No.</i>	<i>Methods</i>	<i>Description</i>	<i>Advantages</i>	<i>Disadvantages</i>
[1]	Logistic Regression, Decision Tree and Gradient Boosted Machine	Avoid bottleneck in patient flow and allowing hospital resource planning	GBM outperforms from rest two algorithms due to the important predictors.	GBM outperforms bit more time than rest two algorithms.
[2].	Multivariable Logistic Regression	Younger patient had higher accuracy while older patient has high risk of getting admitted to hospital.	Age and triage category plays an important role.	People with above 55 age also has moderate risk of getting admitted to hospital.
[3].	Logistic Regression, Multilayer Neural Network	With the help of NLP the predictive accuracy increased than without NLP.	Demographics help in NLP.	Logistic regression is time consuming.
[4].	Decision Tree C4.5	Good accuracy and less execution time.	Categorical attributes in dataset.	Over fitting and pruning may require as the dataset gets larger.
[5].	Multivariable Logistic Regression	Demographics and triage process increased the accuracy.	Deep analysis of decision making nodes.	The outpatient record was not maintained.
[6].	Logistic Regression, Neural Network	A set of thumb rules were developed to predict hospital admissions.	Demographics and clinical factors help to set the rules.	Small change in data leads to drastic change in model.
[7].	Coxian Phase type distribution (PH Model) , Logistic Regression	PH model has more accuracy than Logistic regression.	PH model provide more information regarding possible timing of patient.	Risk of over fitting.
[8].	Naive Bayes and Linear Regression with a logit link function	The model was accurate even though it had less number of readily available independent variables.	Resources management on early basis.	Model needs to recalibrate when changes occur in data.
[9].	Logistic Regression	Early prediction at the triage process helped for patient admission.	Demographics such as PAC diagnosis helped for making decision.	Important factor were missing such as present symptoms, the vital signs of patients.
[10].	Time Series Regression, Exponential Smoothing	Performs well than linear regression.	Highly informative model.	Patient acuity, minimum staffing regulations and clinician satisfaction such factors were not taken into consideration.

with the help of triage process which plays an important role for early prediction of hospital admission.

The factors which were considered for prediction are age, sex, emergency visit in preceding three months, arrival mode, patient acuity category, coexisting chronic diseases. Jones. [10] with his team developed a predictive model for forecasting the daily patient volumes in emergency department. The model uses regression which is actually a time series regression and exponential smoothing where time series regression performs better than linear regression.

3. METHODOLOGY

As the patient arrives in the emergency department, a triage process is carried out. If the patient is critical then directly that patient is given emergency medicine if that patient can get cure with it or else taken to surgery. In mean time the relatives of the patient fill the causality papers where that patient gets the admission number which refers to the admission in the emergency department .If that patient symptoms are not critical but need to cure as soon as possible then such patients are given waiting time of around 10 to 15 minutes. If the

patient has acute illness then such patients are kept waiting for around 30 to 45 minutes. So, in overall triage process each patient has to wait for some time at least. This makes the emergency department crowded.

When an unknown patient arrives, such as through some road accident, or anything such critical where the identity of that patient can't be recognized. That time the patient is labeled unknown and a MLC is registered. MLC is MedicoLegal Complaint where a complaint is registered which is carried out by the police for identification of the patient. One more case is handled by the ED is that when certain patient arrives in emergency department as during the triage process if patient is declared to be dead, then those patients directly death certificate process starts without admission in the emergency department.

The working of model is such that, as soon as the patient arrives in the emergency department, a casualty officer does the triage of the patient and mean while s/he checks the past history of the patient. If the patient is old, then according to the medical history of the patient, the officer decides whether the patient will get admitted to hospital or not as the records contain the complete history such as last time when the patient got admitted, what disease does that patient is suffering, etc. So as the patient is being get treated by the doctor, in that time the inpatient bed is made ready for that patient. If the patient is new then, its record are added to the database of hospital patients and triage is done.

3.1. SYSTEM ARCHITECTURE

The system architecture consists of five steps:

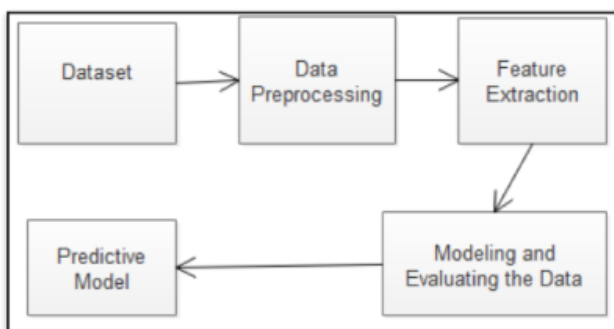


Figure 1: System Architecture

- 1) Dataset: A hospital dataset is taken for the further processing. This is the raw data in the comma separated value (csv) format. The dataset consist of 10 attributes such as ED-level, acuity, etc.
- 2) Data Preprocessing: The second step is data preprocessing in which all the null values, missing values are removed. Removal of extra value is also done. Format the attributes in correct format.
- 3) Feature Extraction: In this step, a particular number of features are extracted for the model. Such features are

selected which are important and which help in predicting.

- 4) From the 10 attributes, main attributes are selected. Here five main attributes are selected.
 - a) OSHPD-ID: A unique 10 digit number assigned to each patient.
 - b) ED-LEVEL: Hospital services providing immediate initial evaluation and treatment to patients on a 24hrs basis.
 - c) EMSA-TRAUMA-LEVEL: Emergency Medical
 - d) Services Agency trauma center designation level.
 - e) ACUITY: Emergency Department type of visit.
 - f) ADMISSION-FROM-ED: Total Emergency Department visits by type, resulting in an inpatient admission.
- 5) Modeling the data: The complete dataset is divided into two parts, training and testing. In this step the training dataset is used. Using different machine learning techniques, the model is trained. The trained model obtained in previous step is now used to evaluate. For evaluating the testing dataset is used.
- 6) Predictive Model: Now after the number of times training and evaluating the model, it is ready for the prediction purpose where external data is given as input.

3.2. MACHINE LEARNING ALGORITHMS AND PERFORMANCE

In this model three machine learning algorithms are used for training purpose: (1) Gradient Boosted Machine, (2) Random Forest and (3) Decision Tree. Boosting is a class of ensemble learning techniques for classification problems. It aims to build a set of weak learners to create one strong learner. The gradient boosted machine is that algorithm which is a tree based ensemble technique. GBM creates multiple weakly associated decision trees that are combined to get the final prediction. It is also known as boosting model. The second algorithm is the Random forest. This algorithm also uses an ensemble learning approach for classification while training process by creating number of decision trees. The next algorithm is the decision tree which is specifically recursive partitioning. The algorithm splits the data at each node based on the variable that separates the data unless an optimal model is not obtained [1].

Using RPART, CARET packages the implementation of the above algorithm is done. As decision tree works on single tree and the random forest and gradient boosted machine works on ensemble of trees this packages are helpful to implement. The CARET package was used to train and tune the machine learning algorithms. This library provides a consistent framework to train and tune models. The performances of the machine learning algorithms are evaluated by the range of measures such as Accuracy, Cohens Kappa, Sensitivity and Specificity.

Table 2: Model Performance.

	Accuracy	Kappa	Specificity	Sensitivity
GBM	0.9352	0.855	0.9631	0.7881
Decision Tree	0.9488	0.8885	0.9742	0.7942
Random Forest	0.9795	0.9561	0.9906	0.9304

4. RESULTS AND DISCUSSION

For the evaluation of the methods accuracy, kappa, sensitivity and specificity this performance metrics are used. As shown in table, the Random forest performs best across all performance measures. A small difference is observed the remaining two methods decision tree and gradient boosted machine. Here it is seen that decision tree is performing better than the gradient boosted machine.

This study gives a broad spectrum of different methods of machine learning used in the field of healthcare. The prediction of the hospital admission from emergency department helps the hospital management for resource planning. This also reduces the waiting time of the patient which is carried while the triage process. For admission of any patient through the emergency department the triage process plays an important role.

5. CONCLUSION AND FUTURE WORK

The overall study involved a survey of different methods used for the prediction model of hospital admission. Along with this study it also has comparison of three different machine learning algorithms namely, decision tree, random forest and gradient boosted machine which are used for predicting the hospital admission from emergency department. Overall the random forest performs better when compared to the decision tree and gradient boosted machine. Implementation of these models could help the hospital decision makers for planning and managing the hospital resources based on the patient flow. This would help for reducing the emergency department crowding.

In future, different algorithms regarding deep learning and machine learning can used to implement the model. Even ensemble of different algorithms can also be done. Different demographics as predictor can be taken into consideration.

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