Enhanced encryption scheme for collecting the documents in Cloud Computing

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ABSTRACT

The patients may experience inconvenience whenever there is crowding in Emergency Departments (EDs). The quality of health care is affected due to crowding of ED. To avoid the adverse effects of inconvenience and improve patient care, there is a need to explore ideas and innovative technology methods for predictions of admissions in ED. The analysis of data gathered from hospitals like the patient age, previous history, month of the year, day of the week and time of the day in which the patient was admitted in the ED for health care work as the key for predictions of future admissions using data mining techniques with the help of some machine learning algorithms. The usage of data mining techniques combined with the following three techniques logistic regression, decision trees, and (GBM) Gradient Boosted Machines give the final method for predictions of patient admission in ED. The advantages of using data mining techniques for prediction are, hospitals can be more resourceful in managing health care. The combination of logistic regression method and decision tree models give an interpretation of patients in ED. The GBM model gives the accurate value, hence used when accuracy is the priority.

Keywords

Data Mining, Decision trees, Emergency Department, Gradient Boosted Machines, logistic regression, Machine learning.

I Introduction

While most emergency department (ED) visits end in discharge, EDs represent the largest source of hospital admissions [1]. Upon arrival to the ED, patients are first sorted by acuity in order to prioritize individuals requiring urgent medical intervention. This sorting process, called "triage", is typically performed by a member

of the nursing staff based on the patient's demographics, chief complaint, and vital signs. Subsequently, the patient is seen by a medical provider who creates the initial care plan and ultimately recommends a disposition, which this study limits to hospital admission or discharge.

Prediction models in medicine seek to improve patient care and increase logistical efficiency [2]. For example, prediction models for sepsis or acute coronary syndrome are designed to alert providers of potentially life-threatening conditions, while models for hospital utilization or patient-flow enable resource optimization on a systems level [4]. Early identification of ED patients who are likely to require admission may enable better optimization of hospital resources through improved understanding of ED patient mixtures [9]. It is increasingly understood that ED crowding is correlated with poorer patient outcomes [11]. Notification of administrators and inpatient teams regarding potential admissions may help alleviate this problem [12]. From the perspective of patient care in the ED setting, a patient's likelihood of admission may serve as a proxy for acuity, which is used in a number of downstream decisions such as bed placement and the need for emergency intervention [14].

Numerous prior studies have sought to predict hospital admission at the time of ED triage. Most models only include information collected at triage such as demographics, vital signs, chief complaint, nursing notes, and early diagnostics [19], while some models include additional features such as hospital usage statistics and past medical history [23]. A few models built on triage information have been formalized into clinical decision rules such as the Sydney Triage to Admission Risk Tool and the Glasgow Admission Prediction Score [25]. Notably, a progressive modeling approach that uses information available at later time-points, such as lab tests ordered, medications given, and diagnoses entered by the ED provider during the patient's current visit, has been able to achieve high predictive power and indicates the utility of these features [20,21]. We hypothesized that extracting such features from a patient's previous ED visits would lead to a robust model for predicting admission at the time of triage. Prior models that incorporate past medical history utilize simplified chronic disease categories such as heart disease or diabetes [9] while leaving out rich historical information accessible from the electronic health record (EHR) such as outpatient medications and historical labs and vitals, all of which are routinely reviewed by providers when evaluating a patient. As a recent work showed that using all elements of the electronic health record can robustly predict in-patient outcomes [26], a prediction model for admission built on comprehensive elements of patient history may improve on prior models.

Furthermore, many prior studies have been limited by technical factors, where continuous variables are often reduced to categorical variables through binning or to binary variables encoding presence or missing-ness of data due to the challenges of imputation [9]. Logistic regression and Naive Bayes are commonly used [22], with few studies using more complex algorithms like random-forests, artificial neural networks, and support vector machines [18]. While gradient boosting and deep neural networks have been shown to be powerful tools for predictive modeling, neither has been applied to the task of predicting admission at ED triage to date.

Expanding on prior work [12], we build a series of binary classifiers on 560,486 patient visits, with 972 variables extracted per visit from the EHR, including previous

healthcare usage statistics, past medical history, historical labs and vitals, prior imaging counts, and outpatient medications, as well as fine demographic details such as insurance and employment status. We use gradient boosting and deep neural networks, two of the best performing algorithms in classification tasks, to model the nonlinear relationships among these variables. Moreover, we test whether we have achieved maximum performance for our feature set by measuring performance across models trained on increasing fractions of our data. Lastly, we identify variables of importance using information gain as our metric and present a low-dimensional model amenable to implementation as clinical decision support.

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 chromic 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 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.

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.

SYSTEM ARCHITECTURE

The system architecture consists of five steps:

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.

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.

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.

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.

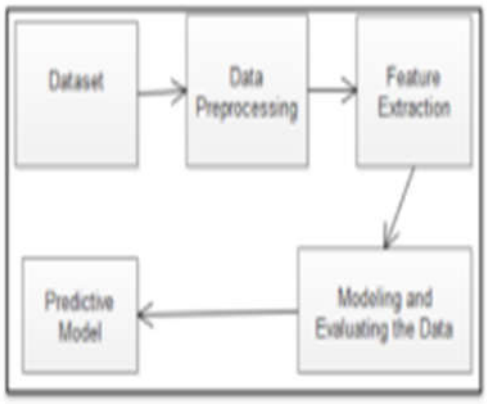
f) ADMISSION-FROM-ED: Total Emergency Department visits by type, resulting in an inpatient admission.

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.

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.

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.

	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

Discussion

This study used a data mining approach to develop and assess three machine learning algorithms to predict the probability of admission at the point of triage. Overall, the results show that the GBM performed best, although the decision tree and logistic regression models only performed slightly less well, thus making all three models potential candidates for implementation. Although the GBM was the most accurate of the three models, in scenarios where interpretability is important logistic regression model may be the most promising candidate for implementation due to its simplicity and ease of interpretation. This follows the process recommended by Kuhn and Johnson [15]. They propose three steps for identifying an implementable model: 1. Build the potentially most accurate model using complex and less interpretable models; 2. Build simpler models using more interpretable algorithms; 3. If the accuracy of the simpler model is sufficient compared to the more complex model consider this model for implementation. In this study, the simpler models (logistic regression and the decision tree) compare quite well with the more complex GBM. The logistic regression model is also straightforward to interpret and understand and clearly articulates how different factors are contributing to the prediction, which may assist with clinician buy in and confidence in the prediction. Whilst decision trees can be interpreted, they can be unstable with small changes in the data potentially drastically changing the structure of the tree [14]. Ensembles of decision trees, such as GBM's, can be similarly difficult to interpret as they combine multiple single decision trees to derive the final predictions. However, in scenarios where accuracy is paramount, the GBM would be the optimal choice for implementation.

The models presented in this study have higher levels of accuracy when compared to several other studies presented in the literature. For example, using logistic regression to model data held on the hospital administrative systems about patients aged over 75, LaMantia *et al.* [9] achieved an AUC-ROC of 0.73. They postulate that their model is not accurate enough by itself to make an individual level admission decision. Using logistic regression, Sun *et al.* [8] achieved similar accuracy to the

models presented here, with an AUC-ROC of 0.849. It is notable that Sun *et al.* [8] do not achieve higher accuracy than the models presented here despite including data about pre-existing conditions. They found that admission was more likely for patients with diabetes, hypertension and dyslipidaemia.

However, Cameron *et al.* [11] achieved a slightly higher accuracy using a logistic regression model, with an AUC-ROC of 0.8774. They included two variables which were unavailable in this study: the national early warning score (NEWS), which is not used in Northern Ireland; and the referral source, which isn't always captured at the point of triage in Northern Ireland. They also covered a larger geographical area, and consequently had a larger sample, which could also have improved the accuracy of their model.

The analysis of the descriptive statistics and logistic regression model also highlights some important patterns in data. Admissions are linked to the patient's age, arrival mode, triage category, care group, previous admissions, the hospital and to a lesser extent temporal variables. Although the results show that admission is more likely with more severe triage categories, the descriptive statistics also highlight the potential for admission across the categories. Potential explanations for this could be that patients deteriorate after being triaged, or that additional information relating to their condition becomes available, resulting in an admission.

The logistic regression model also highlights that admission is more likely when patients arrive by ambulance. This may be due to the increased propensity for patients to call an ambulance for more serious conditions. This compares similarly to other studies which have also identified a positive relationship between arrival by ambulance and admission to hospital [8], [11]. Similarly, the care group and triage category are likely to be proxies for the severity of the patient's condition. It is also possible that patients with different types of conditions attend different ED's at different times, which could account for the significance of temporal and site differences. Although these relationships are interesting and useful in informing the model development process, the overall aim of the study was not to gain inference, but to develop predictive models. Further research would therefore be required to confirm any underlying causal mechanisms.

There are several practical applications of the models developed in this study. The predictions from the models can be automated and displayed in near real time in a clinical or performance management dashboard to assist with decision making. From a performance management and improvement perspective, the models can be used to compare the predicted decision to admit with the clinician's decision, thereby identifying patients who may have been admitted unnecessarily, or patients who typically would have been admitted. Auditing these cases could help to evaluate performance. At an aggregated level, predictions can be used as a performance indicator alongside other commonly used indicators such as risk adjusted mortality an length of stay.

Another benefit of implementing the model developed here is that it can help to improve planning and resource allocation in hospitals [8], [10]. Bed managers in the hospital would have advance information about the number of patients in the ED department who are likely to be admitted, which can be compared to bed availability to identify any potential shortfalls, which could

result in delays to admission and hence longer stays in the ED department and overcrowding. Advance warning of hospital admissions can also provide the opportunity to make bed requests and preparations in advance of the admission [26]. This is important for both the patient's experience, and from a performance management perspective. ED crowding, delays, and long waits in the ED department have been found to be associated with adverse patient outcomes such as increased morbidity and mortality [3], [22]. From a performance management perspective, ED wait time is a key target which hospitals must deliver against in the UK, and one which Northern Ireland hospitals regularly fail to meet [14], [15]. One advantage of the methodological approach taken in this study, compared with much of the existing literature, is the comparison of models built using multiple machine learning algorithms. This approach allows us to compare models and to identify the most accurate approaches, whilst also taking into consideration the feasibility of implementation and use as a decision support tool. This approach is in contrast to some other studies, which have focused on a narrower range of machine learning and statistical techniques [8], [9], [11]. Moreover, no examples of the use of GBM's in this context were found in the literature. Another benefit of the model presented here is that it is simple to calculate, and uses a small number of variables usually collected and recorded on administrative systems at or before the point of triage.

Whilst the model will be useful in supporting a range of decisions, it does have a level of error and should therefore be used in conjunction with clinical judgement when making individual admission decisions. Caution should therefore be taken when implementing the model to reduce the risk of reserving a bed for a patient who ends up not being admitted [22]. In this light, the application of the model for patient level decision making can be viewed more as a decision support tool, providing clinicians with a double check automated triage scale, rather than a prescriptive decision. However, the accuracy of the model would also lend itself well for use as a planning and performance management tool.

Although the aim of this study was to use readily available routine data available at the point of triage, the incorporation of additional data could potentially increase accuracy. For example, clinical data such as pre-existing conditions, blood pressure, test results, and heart rate may be useful in improving accuracy. Similarly, the incorporation of social care data, or data collected from primary and community care may improve predictive accuracy. Some previous research has incorporated a limited range of social care data, with mixed results. Caplan *et al.* [39] find that dependence on certain daily activities is positively associated with the risk of a hospital admission. However, Cameron *et al.* [11] fail to find a significant relationship between whether the person lives alone and their probability of admission. Although electronic systems in health and social care often hold data on more clinically focused variables as well as data relating to social care, the data often resides in silos within or across the organisations involved in the provision of care. This can make accessing and combining the data difficult to achieve in practice, depending on the maturity of the organisations IT infrastructure.

The increasing digitization of textual data, such as clinical notes, could create the opportunity for future studies to incorporate textual data into the machine learning models, alongside the administrative data,

which may increase predictive accuracy further. Some inroads into the use of textual data in predicting admissions has been reported in the literature [27].

Future studies should also consider whether the accuracy of the model is generalizable to other contexts. This can be investigated by applying the models presented here to data collected from other contexts, and comparing the results to models developed directly on that data. It would also be interesting for future studies to consider whether accuracy varies across different sub populations, or to what extent accuracy degrades over time.

Whilst the aims of this study focused more on the development of an implementable tool, and therefore used reliable and well-tested algorithms, future studies could also consider evaluating the use and accuracy of additional machine learning algorithms against the models presented in this study. Potential candidates for future research could include random forests, support vector machines or artificial neural networks. In particular, deep learning has been successful in several machine learning tasks [43]. Combining multiple algorithms in an ensemble may also help to increase the accuracy of the tool, as may the use of techniques such as multi-view learning. However, care should be taken in that some of these techniques are more computationally expensive, difficult to interpret and difficult to implement in production systems.

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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