Available online at: http://www.advancedscientificjournal.com
http://www.krishmapublication.com
IJMASRI, Vol. 1, issue 1, pp. 144-147, Apr. -2025
https://doi.org/10.53633/ijmasri

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY ADVANCED SCIENTIFIC RESEARCH AND INNOVATION (IJMASRI)

ISSN: 2582-9130 **IBI IMPACTFACTOR 1.5** **DOI: 10.53633/IJMASRI**

RESEARCH ARTICLE

PREDICT HOSPITAL ADMISSIONS FROM THE EMERGENCY DEPARTMENT USING DATA MINING

Monisha S[1] N Vennila S[2] and Sathya R[3]

[1]*PG & Research Department, Department of Computer Science, St.Ann's College of Arts and Science, Tindivanam.*
Email: monishasuresh19@gmail.com

[2]*Principal & Head of the Department, PG & Research Department of Computer Science, St.Ann's College of Arts and Science Tindivanam*
Email: sathiyaat@gmail.com

[3]*Assistant Professor & Head, Department of Computer Science, St.Ann's College of Arts and Science Tindivanam.*
Email: moulikrishna19@gmail.com

Abstract

Overcrowding in the emergency department (ED) can lead to adverse patient outcomes. Therefore, EDs should investigate new ways to improve patient flow and prevent overcrowding. One potential approach is to use machine learning techniques for data mining to predict ED admission. This paper uses routine administrative records (120,600 records) from two emergency hospitals in Northern Ireland to compare machine learning algorithms to predict the risk of ED admission. We use three algorithms to build a predictive model: 1) logistic regression; 2) decision trees; GBM outperformed decision trees (Accuracy = 80.31%,AUC-ROC=0.859) (Accuracy = 80.06%, AUC-ROC = 0.824) and logistic regression model (Accuracy = 79.94%, AUC- ROC = 0.849). Using logistic regression, we identified various factors associated with admission, including hospital location, age, arrival type, triage category, care team, access in the previous month, and previous access. This paper presents the potential applications of three types of machine learning algorithms in predicting patient admissions. The effectiveness of the model developed in this paper in the decision support tool will provide a picture of the estimated time of admission of the ED, issue rules for advance resource planning and avoiding inpatient admissions, and enable comparison of predicted and actual admission costs. Emergency clinics should consider logistic regression models in cases where interpretation is important; However, GBM can be useful in situations where accuracy is important.

Keywords: ED, Data mining

Introduction

In recent years, we have seen the growth of electronic health records, including many electronic medical records (EMRs) that record patients, diagnoses, clinical trials, imaging studies, genomics, treatments, outcomes, practices, financial information, medical procedures, and best practices [1]. Physicians are increasingly asking: What can we do with this wealth of information? How can we analyse this data to gain insights that will improve quality of care and reduce costs? Health care must encompass the full spectrum, including scientific knowledge and data-driven analysis [2]. Working knowledge of a knowledge base that includes research articles, published clinical trial results, medical journals, textbooks, and clinical protocols. Traditionally, the gold standard of evidence in medicine has been generated through the process of randomized controlled trials. Patients arriving at the emergency department are first selected based on the severity of their condition, thus prioritizing those who need immediate treatment. This classification process is called "triage" and is usually performed by nursing staff based on the patient's demographics, complaints, and vital signs. Medical staff then consult with the patient, develop an initial careplan, and finally agree on a course of action, in this case simply admitting or discharging [3,4]. Data mining tools to solve complex problems ranging from targeted genome analysis to decision support development. Algorithms generally fall into two categories: unsupervised algorithms and supervised algorithms. Unsupervised machine learning algorithms are often used to group large amounts of data. Un supervised algorithms can be used to generate hypotheses and are therefore often used before supervised algorithms. The study of machine learning algorithms begins with a prior hypotheses and sets. These results are used to make predictions based on data from out-of-sample studies where the outcome of interest is not yet known.

Existing System

The existing system uses data mining technology to estimate the number of emergency department visits. Previous studies have not determined which data mining techniques can provide more reliable and accurate information to make appropriate treatment decisions for the care unit. The useof hospital-based information and knowledge discovery during emergency hospitalizations is challenging.

1. Although hospitals provide thesame service, the quality of service is not the same.
2. No previous study has determined which data mining techniques can provide greater confidence in finding solutions to predict emergency department visits.
3. More time consuming to use hospital database system.

Proposed System:

Predict hospitalizations from emergency departments. Single Data Use in Emergency Response Research Access is a data measurement tool that provides a baseline for all data used to predict emergency department visits. Predict emergency department visits from data using the same data mining techniques used for hospitalizations, to investigate whether data- only procedures can provide equivalent (or better) results with reasonable results Predict emergency department through analysis. Using hybrid data mining techniques to predict emergency room hospitalizations, to create a more accurate picture of all hybrid data mining processes in the process Yes, emergency room. Using the same hybrid data mining Figure1 techniques to predict hospitalizations as hospitalizations, to investigate whether hybrid data can achieve the same (or better) results in identifying appropriate patients) Problem solving results Predicting the number of emergency room admissions.

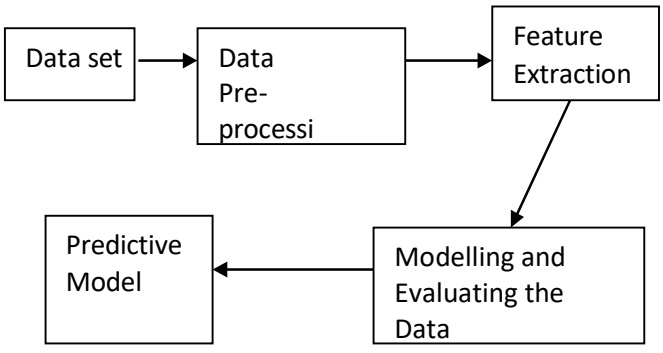
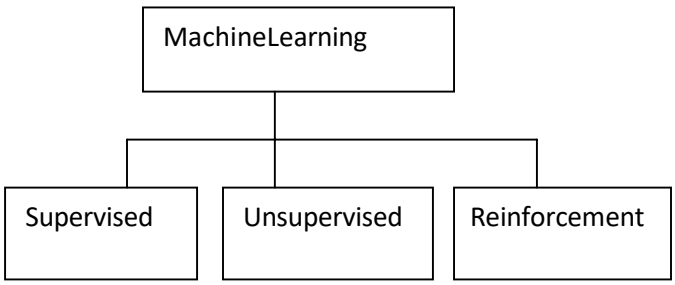


Figure:1

Distributed server farm arrangement that uses virtualization, innovation, and connectivity to data storage.



S.No	Algorithms	Accuracy
1	decisiontrees	80.06%,
2	logisticregression	79.94%,
3	GBM outperformed decisiontrees	80.31%

Table:1

Machine Learning Algorithms and performs

Three machine learning algorithms are used for training purpose in this model: 1) Gradient Boosting machine 2) Random

Advantages

1. Hybrid data mining techniques are used in choosing the appropriate to predict the number of emergency room admissions.

2. It takes less time. Performance and accuracy. In this section, we will cover several of the topics that are available. Distributed storage is generally considered as a Forest, and (3) Decision Tree. Boosting is a class of parallel learning techniques for classification problems. The goal is to create a group of weak learners to create strong learners. Gradient boosting technology is a tree-based algorithm. GBM produces multiple weak decision trees that are combined to obtain a final prediction. It is also called the boosted model. The second algorithmis 3. Random Forest. The algorithm also uses a learning algorithm for classification by creating multiple decision trees for the training process. The next algorithm is the decision tree, which is specifically recursive partitioning. Unless a good model is obtained, the algorithm separates the data based on the differences that separate the data [1]. Since decision trees work on a single tree, random forests and gradient boosting work on a set of trees, these packages help in improving usability. The CARET package is used to train and tune machine learning algorithms. This library provides a good basis for training and debugging models. The performance of a machine learning algorithm is measured by various metrics such as accuracy, Cohens Kappa, sensitivity and specificity.

Conclusions and Future Work

The general study includes the study of various methods used for hospitalization prediction models. This study also compared three different types of learning machines, namely decision trees, random forests, and gradient boosting machines, to predict access to the emergency department. In general, random forests outperform decision trees and gradient boosting techniques. Using these models can help hospital decision makers plan and manage hospital services based on patient flow. This will help reduce overcrowding in the emergency department. It can also combine different algorithms. Demographic Differences Can Be Considered As Predictors.

References

1. Wright SP, Verouhis D, Gamble G, SwedbergK,Sharpe N, Doughty RN. Factors influencing the length ofhospital stay of patients with heart failure. Eur J Heart Fail. 2003;5(2):201–209.
2. Gomez V, Abasolo JE. Using data mining to describelong hospital stays. Paradigma. 2009; 3(1):1–10.
3. Lim A, Tongkumchum P. Methods for analysing hospital length of stay with application to inpatients dyingin Southern Thailand. GlobJ HealthSci. 2009;1(1):27–38. [4]. Chang KC, Tseng MC, Weng HH, LinYH, LiouCW,Tan TY. Prediction of length

of stay of first-ever ischemicstroke. Stroke. 2002; 33(11):2670–2674.

4. Jiang X, Qu X, Davis L. Using datamining to analyse patient discharge data for an urban hospital. In :Proceedings of the 2010 International Conference on Data, Mining; 2010 Jul 12-15; Las Vegas, NV. p. 139–144.
5. IskenMW, RajagopalanB. Data mining to support simulation modeling of patient flow in hospitals. J MedSyst. 2002; 26(2):179– 197.
6. Walczak S, Scorpio R J, Pofahl W E.In: Cook D J, editor. Predicting hospital length of stay with neural networks. Proceeding so the Eleventh International FLAIRS Conference; 1998 May 18-20; Sanibel Island, F L. Menlo Park, CA: AAAI Press; 1998. p. 333–337.
7. Rowan M, Ryan T, Hegarty F, O'Hare N. The use ofartificial neural networks to stratify the length of stay ofcardiac patients based on preoperative and initialpostoperative factors. ArtifIntell Med. 2007; 40(3):211–221.
8. Robinson GH, Davis LE, Leifer RP. Prediction ofhospital length of stay. Health Serv Res. 1966; 1(3):287–300.
9. [10]. Arab M, Zarei A, Rahimi A, Rezaiean F, Akbari F.Analysis of factors affecting lengthofstayinpublichospitals inLorestanProvince, Iran. Hakim Res J. 2010;12(4):27–32.

******