USING DATA MINING TO PREDICT HOSPITAL ADMISSIONS FROM THE EMERGENCY DEPARTMENT

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ABSTRACT

Crowding within emergency departments can have significant negative consequences for patients. ED therefore need to explore the use of innovative methods to improve patient flow and prevent overcrowding. One potential method is the use of data mining using machine learning techniques to predict ED admissions. This paper uses routinely collected administrative data (120 600 records) from two major acute hospitals in Northern Ireland to compare contrasting machine learning algorithms in predicting the risk of admission from the ED. We use three algorithms to build the predictive models: 1) logistic regression; 2) decision trees; and 3) gradient boosted machines (GBM). The GBM performed better (accuracy D 80:31%, AUC-ROC D 0:859) than the decision tree (accuracy D 80:06%, AUC-ROC D 0:824) and the logistic regression model (accuracy D 79:94%, AUC-ROC D 0:849). Drawing on logistic regression, we identify several factors related to hospital admissions, including hospital site, age, arrival mode, triage category, care group, previous admission in the past month, and previous admission in the past year. This paper highlights the potential utility of three common machine learning algorithms in predicting patient admissions. Practical implementation of the models developed in this paper in decision support tools would provide a snapshot of predicted admissions from the ED at a given time, allowing for advance resource planning and the avoidance bottlenecks in patient flow, as well as comparison of predicted and actual admission rates. When interpret ability is a key consideration, EDs should consider adopting logistic regression models, although GBM's will be useful where accuracy is paramount.

1 INTRODUCTION

Emergency Department (ED) crowding can have serious negative consequences for patients and staff, such as increased wait time ,ambulance diversion, reduced staff morale, and cancellation of elective procedures Previous research has shown ED crowding to be a Significant international problem making it crucial that innovative steps are taken to address the problem. There are many possible causes of ED crowding depending on the context, with some of the main reasons including increased ED attendances, inappropriate attendances, a lack of alternative treatment options, Alecko fin patient beds, ED staffing shortages ,and closure of other local ED departments. The most significant of these causes is the in ability to transfer patients to an inpatient bed, making it critical for hospitals to manage patient flow and understand capacity and demand for inpatient beds. One mechanism that could help to reduce ED crowding and improve patient flow is the use of data mining to identify patients at high risk of an inpatient admission, therefore allowing measures to be taken to avoid bottlenecks in the system For example, a model that can accurately predict hospital admissions could be used for inpatient bed management, staff planning and to facilitate specialized work streams with in the ED Cameron et al. [11] also propose that the implementation of the system could help to improve patient satisfaction by providing the patient with advance notice that admission is likely. Such a model could be developed using data mining techniques, which involves examining and analysing data to extract useful information and knowledge on which decisions can be taken.

Literature Survey

This literature survey of the project using data mining to predict hospital admission from the emergency department.

- Sanpathi Indraja Master of Computer Applications Miracle Educational Society Group of Institutions Bhogapuram – Vizianagram-(AP).
- Saragadam Sridhar Master of Computer Applications Miracle Educational Society Group of Institutions Bhogapuram – Vizianagram-(AP).

3 IMPLEMENTATION STUDY

Existing System:

Using a range of clinical and demographic data relating to elderly patients, La Mantia *et al.* used logistic regression to predict admissions to hospital, and ED re-attendance. They predicted admissions with moderate accuracy.Boyle *et al.* used historical data to develop forecast models of ED presentations and admissions. Model performance was evaluated using the mean absolute percentage error (MAPE), with the best attendance model achieving a MAPE of around 7%, and the best admission model achieving a MAPE of around 2% for monthly admissions.

Disadvantages:

They predicted admissions with moderate accuracy, but were unable to predict ED re-attendance accurately. The use of historical data by itself to predict future events has the advantage of allowing forecasts further into the future, but has the disadvantage of not incorporating data captured at arrival and through triage, which may improve the accuracy of short-term forecasting of admissions. Their model was less accurate with an accuracy of 76% for their best model.

Proposed System & alogirtham

This study draws on this data to achieve two objectives. The first is to create a model that accurately predicts admission to hospital from the ED department, and the second is to evaluate the performance of common machine learning algorithms in predicting hospital admissions. We also suggest use cases for the implementation of the model as a decision support and performance management tool.

4.1 Advantages:

This study seeks to contribute to the existing body of knowledge by building machine learning models using a novel dataset and by comparing the performance of less frequently used algorithms with the more traditional logistic regression approach. Moreover, the data used in our study is routinely available at the point of triage, allowing for the potential implementation of a fully automated decision support system based on the models built here.

IMPLEMENTATION

MODULES:

Data Holder:

In this module, the data Holder uploads patient's data to the health server. For the security purpose the data owner keeping one copy of the data and then store in the server.

Data Analyzer:

In this module, he logs in by using his/her user's name and password. After Login receiver will Search for data and Search Patient Records.

Emergency Sector:

In this module, the sector can do following operations such as View All Published Patients Details, View All Emergency Patients and Admit to Hospital, View All Emergency Admitted Patients Count.

Healthcare Server :

The Health service provider manages a server to provide data storage service and can also do the following operations such as View and Authorize Analyser, View and Authorize Data Holder, View Patients Between Ages, Users Patient Search Transaction ,View All Admitted Emergency Patients Details, View Patients Age Limit Results, View Patients Admitted Count.

5 RESULTS AND DISCUSSION

1.2 SCREENSHOTS

1.2.1 HOME SCREEN

FIG.5.1 HOME SCREEN

1.2.2 DATA HOLDER LOGIN PAGE

FIG.5.2 DATA HOLDER LOGIN SCREEN

5.3.3 ADD PATIENT DETAILS

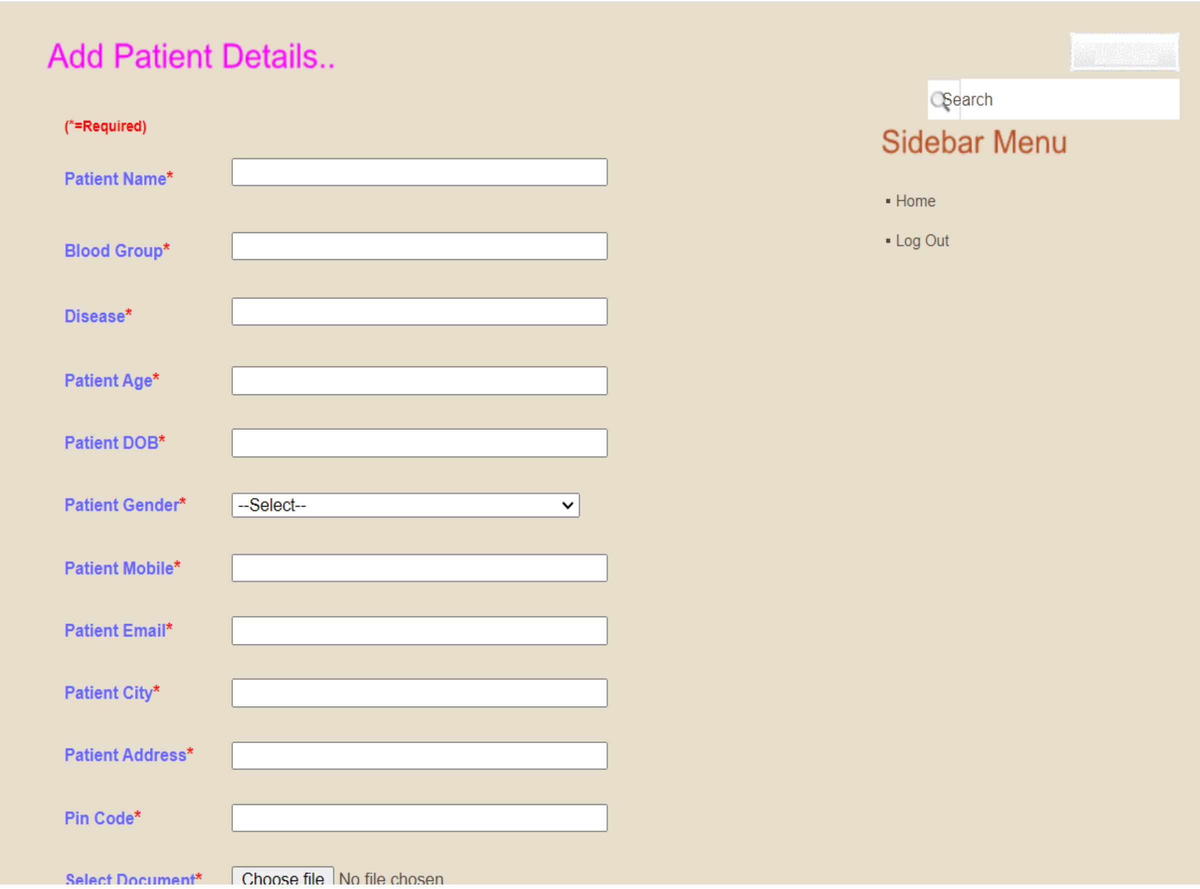
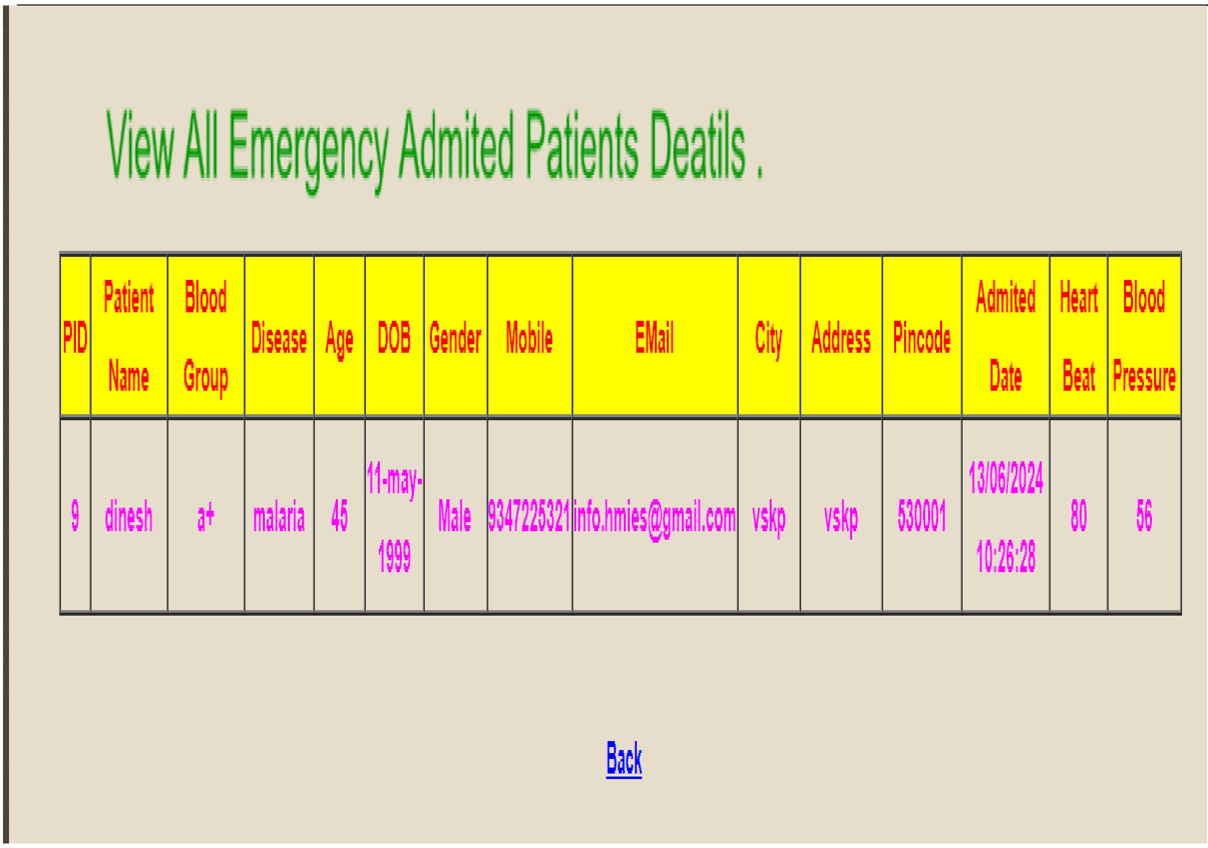


FIG.5.3 ADD PATIENT DETAILS

1.2.3 EDIT DETAILS

FIG.5.4 EDIT DETAILS

5.3.5 VIEW (ED)ADMITED PATIENTS DETAILS



View All Emergency Admited Patients Deatils .

PID	Patient Name	Blood Group	Disease	Age	DOB	Gender	Mobile	EMail	City	Address	Pincode	Admited Date	Heart Beat	Blood Pressure
9	dinesh	a+	malaria	45	11-may-1999	Male	9347225321	info.hmies@gmail.com	vskp	vskp	530001	13/06/2024 10:26:28	80	56

FIG.5.5 VIEW (ED) ADMITED PATIENTS DETAILS

5.3.6 VIEW AUTHORIZE USERS

View and Authorize Users..

ID	User Image	User Name	Email	Phone No.	Address	Status
1		Kadhir	tmksmanju13@gmail.com	9535866270	#78726,14th Cross,Rajajiangar	Authorized
2		tmksmanju	tmksmanju13@gmail.com	9535866270	#7827,14th Cross,Vijayanagar	Authorized
3		Sujan	tmksmanju13@gmail.com	9535866270	#7827,4th Main,Vijayangar	Authorized
4		madhu	info.hmies@gmail.com	9347225321	vskp	Authorized
5		srija	saialapati5@gmail.com	9876543240	vspk	Authorized

FIG.5.6 VIEW AUTHORIZE USERS

5.3.7 VIEW PROFILE

FIG.5.7 VIEW PROFILE

5.3.8 VIEW AND AUTHORIZE DATA HOLDER

View and Authorize Data Holder..

ID	Owner Image	Owner Name	Email	Phone No.	Address	Status
1		Rajesh	tmksmanju13@gmail.com	9535866270	#78267,14th Main,Malleshwaram,Bangalore-21	Authorized
2		Manjunath	tmksmanju13@gmail.com	9535866270	#7827,14th Cross,Malleshwaram,Bangalore-40	Authorized
3		Sugumar	tmksmanju13@gmail.com	9535866270	#43,14th Cross,Rajajiangar	Authorized
4		dinesh	info.hmies@gmail.com	9347225321	vskp	Authorized
5		sravani	sravanialapati4@gmail.com	9963355559	tpg	Authorized

FIG.5.8. VIEW AND AUTHORIZE DATA HOLDER

5.3.9 SEARCH HISTORY

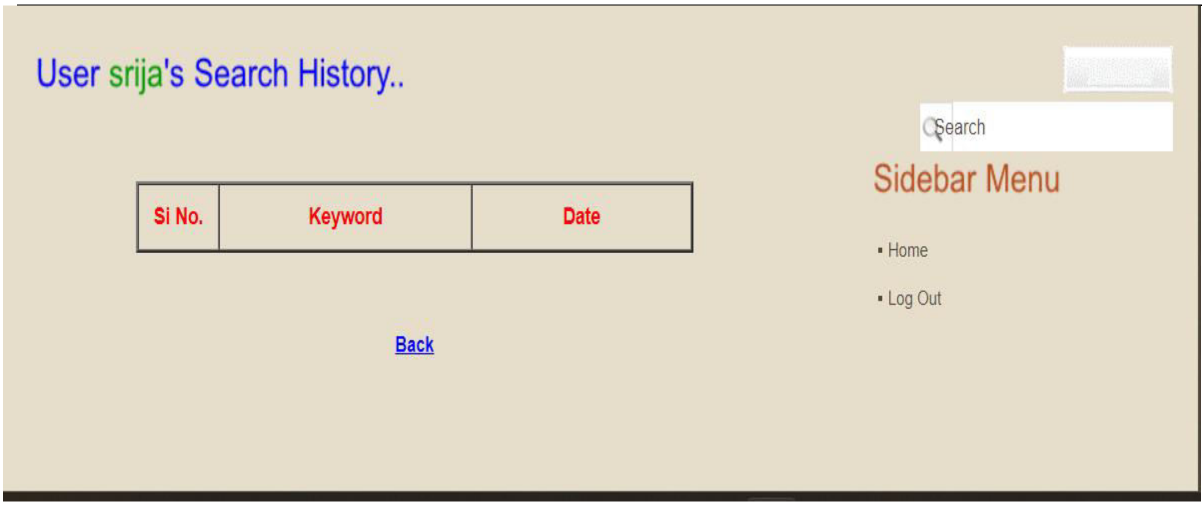


FIG.5.9. SEARCH HISTORY

5.3.10 VIEW BASED ON AGES

FIG.5.10. VIEW BASED ON AGES

5.3.11 PATIENTS RANGES ON AGES

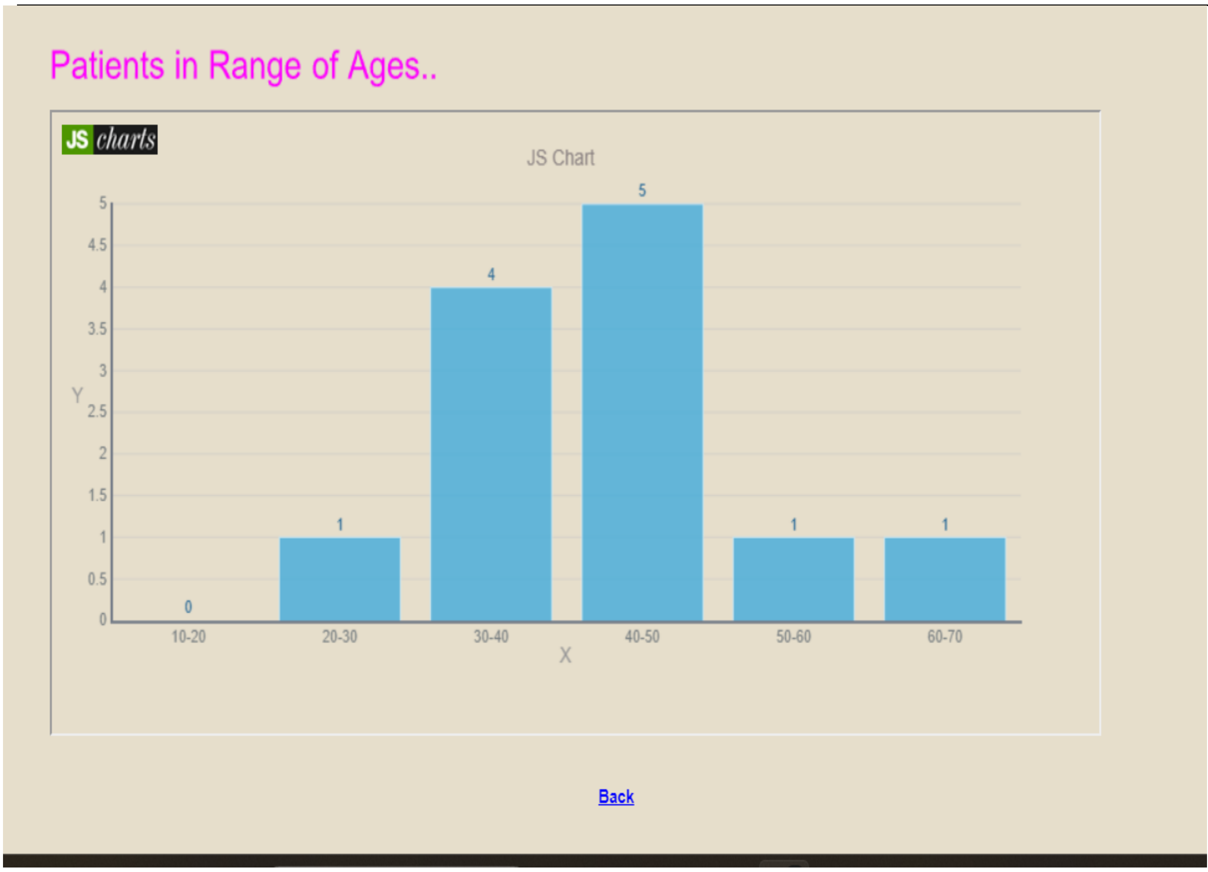


FIG.5.11. PATIENTS RANGES ON AGES

5.3.12 SEARCH TRANSACTION OF PATIENTS

Si No.	User Name	Keyword	Date
1	Kadhir	Sukla	07/12/2018 16:40:34
2	Kadhir	Sukla	07/12/2018 16:40:42
3	Kadhir	Abhinay	07/12/2018 16:40:53
4	Kadhir	Abhinay	07/12/2018 16:43:02
5	Kadhir	Sukla	07/12/2018 16:44:28
6	Kadhir	Sukla	07/12/2018 16:45:17
7	Kadhir	Sukla	07/12/2018 16:45:32
8	Kadhir	Sukla	07/12/2018 16:46:03
9	Kadhir	Sukla	07/12/2018 16:46:23
10	Kadhir	Sukla	07/12/2018 16:47:41
11	Kadhir	Sukla	07/12/2018 16:48:10

FIG.5.12 SEARCH TRANSACTION OF PATIENTS

5.3.13. SEARCH RECORDS

FIG.5.13. SEARCH RECORDS

5.3.14 RECORD FOUND

FIG.5.14.RECORD FOUND

6. CONCLUSION AND FUTURE WORK

CONCLUSION

This study involved the development and comparison of three machine learning models aimed at predicting hospital admissions from the ED. Each model was trained using routinely collected ED data using three different data mining algorithms, namely logistic regression, decision trees and gradient boosted machines. Overall, the GBM performed the best when compared to logistic regression and decision trees,but the decision tree and logistic regression also performed well. The three models presented in this study yield comparable, and in some cases improved performance compared to models presented in other studies. Implementation of the models as a decision support tool could help hospital decision makers to more effectively plan and manage resources based on the expected patient inflow from the ED. This could help to improve patient flow and reduce ED crowding, therefore reducing the adverse effects of ED crowding and improving patient satisfaction. The models also have potential application in performance monitoring and audit by comparing predicted admissions against actual admissions. However, whilst the model could be used to support planning and decision making, individual level admission decisions still require clinical judgement.

7. REFRENCES

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