

PREDICTION OF PATIENT ADMISSIONS TO EMERGENCY DEPARTMENT WARDS IN HOSPITALS USING A MACHINE LEARNING BASED APPROACH

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ABSTRACT

Patient overcrowding in Emergency Departments (ED) in hospitals sounds to be a demanding factor in delivering qualitative medical services for the patients. This occurs as an effect of lack of needed resources, improper patient flow, lack of quality staffs and lack of inpatient beds. Data mining methods were used before to avoid the problems caused by ED crowding. To improve the performance of the ED system, a prediction model is developed to avoid ED crowding in hospitals. The prediction model developed predicts the likelihood for the number of patients to get admitted to the ED ward each time. The proposed model is implemented using decision tree algorithm. The model is trained and tested using MIT MIMIC-III dataset. The prediction model involves finding the disease based on the symptoms and predicting the admission status for the patients based on their severity condition. The predicted result can be used to make necessary arrangements like resuscitation area, necessary emergency medicines with inpatient beds and sufficient emergency room staffs in the ED ward in advance. The developed model can be implemented in hospitals and can be used to check if sufficient resources are available for the proper functioning of the emergency departments. The prediction model built achieves an overall accuracy of above 80%.

KEYWORDS: Emergency department overcrowding, Resuscitation area, Prediction model, Severity condition, Resource allocation.

I. INTRODUCTION

Hospitals must ensure to provide utmost care and better treatment for their patients. Such type of effective care and treatment can be provided only if the hospitals are well equipped with proper resources and facilities. Emergency Department (ED) in hospitals are specialized in providing efficient medication for the patients in emergency situations. Most of the patient cases will be occurring without prior appointment. ED overcrowding is a regular and concerning story. Since the nature of patient inflow to the ward is unplanned, proper facilities and resources must always be available. Adverse effects will have to be encountered if proper resources are not available. In such cases, it can lead to patient overcrowding in the wards. Severe consequences have to be faced if there is an increase in patient overcrowding. Some of the reasons that lead to patient overcrowding are: increased waiting time, ambulance delays, lack of bed resources and so on.

Previous works have shown that emergency department overcrowding seems to be a serious problem leading the hospital management to make important decisions to overcome the problem. Other reasons for overcrowding of patients include higher number of patient attendances in ED, lack of maintenance, reduced number of alternative treatments, ED managers shortages and closing of other local ED wards. The main reason apart from all of these is the inability to shift patients to an inpatient bed. This brings the necessity for the hospitals to manage patient inflow and also to realize the capacity and demand for the bed resources. Data mining techniques could be helpful to reduce emergency ward crowding and to enhance the outcome of patient flow. These techniques could be helpful in finding and segregating the patients with more seriousness and allows the proper measures to be taken to avoid problems in the hospital system. Many data mining based models have been developed for predicting hospital admissions in ED wards and the performances of those models were also measured. Each model has got their own advantages as well as the disadvantages. ED overcrowding can also be prevented if the length of stay of each patients could be predicted. If the length of stay could be predicted, necessary

arrangements especially the bed resources can be properly allocated for the patients who are likely to get admitted. This helps in effective scheduling of ED rooms for the new patients. But uncertainty in length of stay information can be serious problem. Some of the reasons that lead to uncertainty can be the clinician's estimates on patient's stay and then a change in that decision. So in such cases it could be better if the prediction model is developed also to predict length of stay of patients. Studies have claimed that machine learning based approaches can be used to build efficient and accurate models for predicting ED admissions.

A machine learning based prediction model has been developed for predicting the future patient admissions that could occur in an emergency department. The model developed is mainly useful for making necessary arrangements in the emergency department before the patient gets admitted. Sufficient inpatient beds is one of the important resources that need to be maintained in the ED ward. The model developed will be helpful in the cases if beds are not available. Necessary bed arrangements can be made in advance before the patient gets admitted to the emergency department. The machine learning based model that is built is found to be more efficient than the previously built data mining based models.

The contributions in this paper are as follows. Section II describes the related works explaining various prediction models developed. Section III explains the proposed machine learning based prediction model. Section-IV presents the experimental evaluation and the analysis of the results obtained. Section V concludes the paper and provides future directions.

II. RELATED WORKS

Patient overcrowding in emergency wards can cause a serious bad impact in effectively monitoring and providing better medication for the patients. One of the major problems is the lack of inpatient beds in ED wards. Several prediction models has been built earlier to avoid these problems. This section briefly describes about the previously developed models by different researchers.

Jordan S. Peck et. al. [1] proposed a method for characterizing the value of predictive analytics in facilitating hospital patient flow. Discrete event simulation is applied to characterize the patient flow affects of using admission predictions and current state information generated in an Emergency Department (ED). The information includes crowding levels and total expected bed need. The result obtained is that sharing prediction and crowding information to influence inpatient staff priorities by using specific information sensitivity schedules can lead to statistically significant ($p < 0.05$) reductions in boarding time (between 11.69% and 18.38% compared to baseline performance). The range of improvement depends on varying simulated hospital configurations. Zhang W. et. al. [2] proposed a method of using multiple data sources for the prediction of the number of asthma-related emergency department (ED) visits. The preliminary findings show that the developed model can predict the number of asthma ED visits based on near-real-time environmental and social media data with approximately 70% precision. These results are helpful for public health surveillance and ED preparedness. Xie Y. et. al. [3] developed a method using large-scale health insurance claims data for predicting the number of hospitalization days in a population. Regression decision tree algorithm was utilized along with insurance claim data from 242,075 individuals for three years. This provides predictions of number of days in hospital in the third year, depending on hospital admissions and procedure claims data from the first two years. Results demonstrate that the proposed method improves predictions over two established baseline methods. A reasonable predictive accuracy (AUC = 0.843) was obtained for the whole population.

Alexey V. et. al. [4] developed a simulation model containing two - component and the estimate of the load of four departments is made with this model. The results obtained is that linear dependency between patients mean arrival gap and the number of patients in the departments is none. The model can be used to plan reorganization of departments in the hospital. Davood et. al. [5] proposed a prediction model that can be used as a decision support tool and to help reduce ED overcrowding. This model proves that an admission prediction model depending on demographic and clinical determinant factors can accurately estimate the likelihood of patient admission and also decreases ED boarding and congestion problems. Lucini F.R. et. al [6] developed a text mining based prediction model. In the prediction module, eight text mining methods were used and NuSupport Vector Machine was found to be the text mining method with the best overall performance. Its average F1-score

in predicting hospitalization was found to be 77.70% with a standard deviation (SD) of 0.66%. Hongteng Xu et. al. [7] developed a new discriminative learning algorithm for improving the prediction of transition events. Simultaneous feature selection and learning by adding a group-lasso regularizer to the ADMM algorithm is achieved. By testing on real-world data, it was shown that the proposed method obtains better performance in terms of accuracy of predicting the destination of care unit transition and duration of each care unit occupancy. Krishan L. Katri et. al. [8] developed an artificial neural network based classifier using multilayer perceptron with back propagation algorithm to predict peak demand days of patients with respiratory diseases like Asthma. The precision and recall rate for peak class were 77.1% and 78.0% and the obtained rates for non peak events were 83.9% and 83.2% respectively. The overall accuracy of the system is found to be 81.0%.

Miguel Monteiro et. al. [9] developed a model for ischemic stroke patients. Machine learning techniques are used as a solution to the problem of predicting the functional outcome of ischemic stroke patients three months after admission. A pure machine learning approach achieves only a slightly superior AUC (0.808 ± 0.085) than that of the best score (0.771 ± 0.056) while using the features available at admission. It is observed that by progressively adding features available at further points in time, the AUC to a value above 0.90 can be significantly increased. The results obtained can be used to check the use of the scores at the time of admission. The papers [10], [11], [12] and [13] proposed many prediction models for patient admission prediction based on neural networks. The methods proposed in these literatures are found to have both merits and demerits. Alternative methods including machine learning techniques must be proposed to build efficient and effective prediction models.

III. A NEW MACHINE LEARNING BASED PROPOSED MODEL

Emergency ward is an important area where necessary resources are to be updated frequently. ED wards in the hospital must always ensure to provide good medication for the patients. Patients in the emergency departments can be treated with effective and better medical care only if the resources are sufficient in it. Lack of sufficient resources, improper facilities, staffing shortages and lack of sufficient inpatient beds can lead to patient overcrowding in emergency wards. Such type of emergency department overcrowding can bring adverse effects. To reduce Emergency Department (ED) overcrowding in hospitals, a machine learning algorithm called Decision Tree has been used to develop a prediction model. The prediction model built can be used to predict the number of patient admissions that could occur in the ED ward of the hospital. The model can be used to check for necessary and sufficient amount of resources for the ED ward to treat the expected (predicted) number of patients. This model mainly helps the ED ward managers to know in advance that how many patients are likely to get admitted in the ED room. The proposed system is implemented as follows. This system mainly involves two stages.

A. Building the prediction model using Decision Tree

- (1) Data extraction
- (2) Data split into training and testing sets
- (3) Model tuning using the training set
- (4) Make predictions based on testing set

B. Two phases

- (1) Disease Prediction.
- (2) Predicting the admission status based on disease and condition.

The aforementioned stages are explained in detail below.

A. Building the prediction model using Decision Tree

The prediction model is developed using decision tree algorithm. This involves the following stages.

- (1) Data extraction

- (2) Data split into training and testing sets
- (3) Model tuning using the training set
- (4) Make predictions based on testing set

(1) Data Extraction

The first stage in building a model is data extraction. Two datasets are taken here to build the prediction model. One dataset consists of various symptoms and their corresponding diseases. The other dataset consists of the list of various diseases, their severity condition (severe or mild) and the admission status (admit or not admit). These datasets are in .csv formats. Data extraction stage involves extracting these files in a supporting format.

(2) Data split into training and testing sets

Datasets are split into training and as testing data. 70% of the data is taken as training and the remaining 30% is taken as testing data. The datasets are split in random by the algorithm.

(3) Model tuning using the training set

The decision tree algorithm trains the classifier model using the training set. Tuning refers to the process of training the model to predict accurate results when a new input is given. The training phase is like what output must the model produce, when an test input with the same properties from the training dataset is given.

(4) Make predictions based on testing set

Fig. 1 illustrates the process in developing the prediction model. Initially the dataset will be extracted from .csv file format as excel file. The extracted data will be split as training and testing data. The decision tree algorithm is used to train the model with the training data. Once the model has been trained, the input data selected from the testing dataset will be given to the model. The model gives the output which is the admission status of the patient.

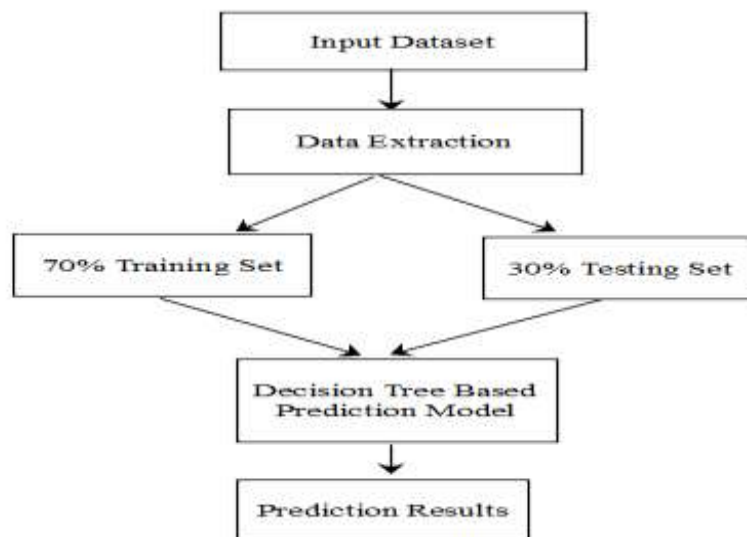


Fig-1: Decision Tree Based Prediction Model for Predicting Patient Admission in Emergency Departments

This is the final stage in building a prediction model. After the training phase has completed, a new input data is given to the trained model from the testing set. The model makes predictions as the output. The overall accuracy for the decision tree based model is above 80%.

B. Two Phases

The hospital managements can implement the developed prediction model in the hospitals to predict the possibility of future admission of patients to the ED ward. This allows to know in advance whether the resources such as bed are sufficiently available for the number of patients predicted. This helps to reduce long queues in

hospitals and especially the patient overcrowding in ED wards. The patient need not wait for a long time to get admitted. If the system determines that more patients are likely to get admitted and if the hospital has no sufficient beds, then alternative arrangements can be made as soon as possible before the admission stage.

The implementation in hospital involves two phases.

- (1) Disease Prediction.
- (2) Predicting the admission status based on disease and condition.

(1) Disease Prediction

The system has been developed to implement two phases. Disease prediction is the first phase. Fig. 2 illustrates the disease prediction stage. Initially the patient arrives at the hospital and waits for the triage stage. Triage is the process where the patient will be assisted with a nurse to consult the doctor about the disease. After consultation, if the patient is likely to get admitted in the hospital, the developed prediction model will be used. The patient’s symptoms will be entered as input to the developed prediction model. Based on the symptoms given, the model predicts the disease.

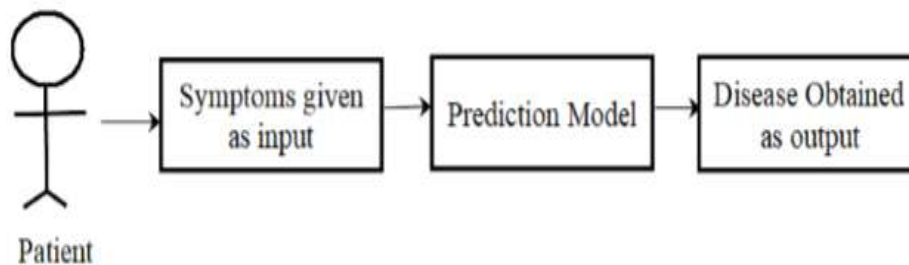


Fig-2: Disease Prediction Phase

(2) Predicting the admission status based on disease and condition

This is the second phase in the model implementation. Fig. 3 illustrates the admission status prediction stage. Once the model predicts the disease, the disease predicted will be taken as one of the inputs in this stage. Along with the disease, the condition of the patient will also be given as input to the model. The condition will be like either severe or mild. Based on the inputs given, the model predicts whether admission is needed or no admission needed. Then the hospital can cross check with the ED ward for the availability of resources. If more resources are needed, the ward managers can make necessary arrangements. In this way, patients overcrowding in the ED departments can be reduced.



Fig-3: Admission Status Prediction Phase

The main advantage of this model is that the clinician’s decision may change at times depending on the patient’s condition. This model built can help to make necessary arrangements in advance instead of making arrangements at the moment. Fig. 4 represents the overall process flow of the developed prediction model.

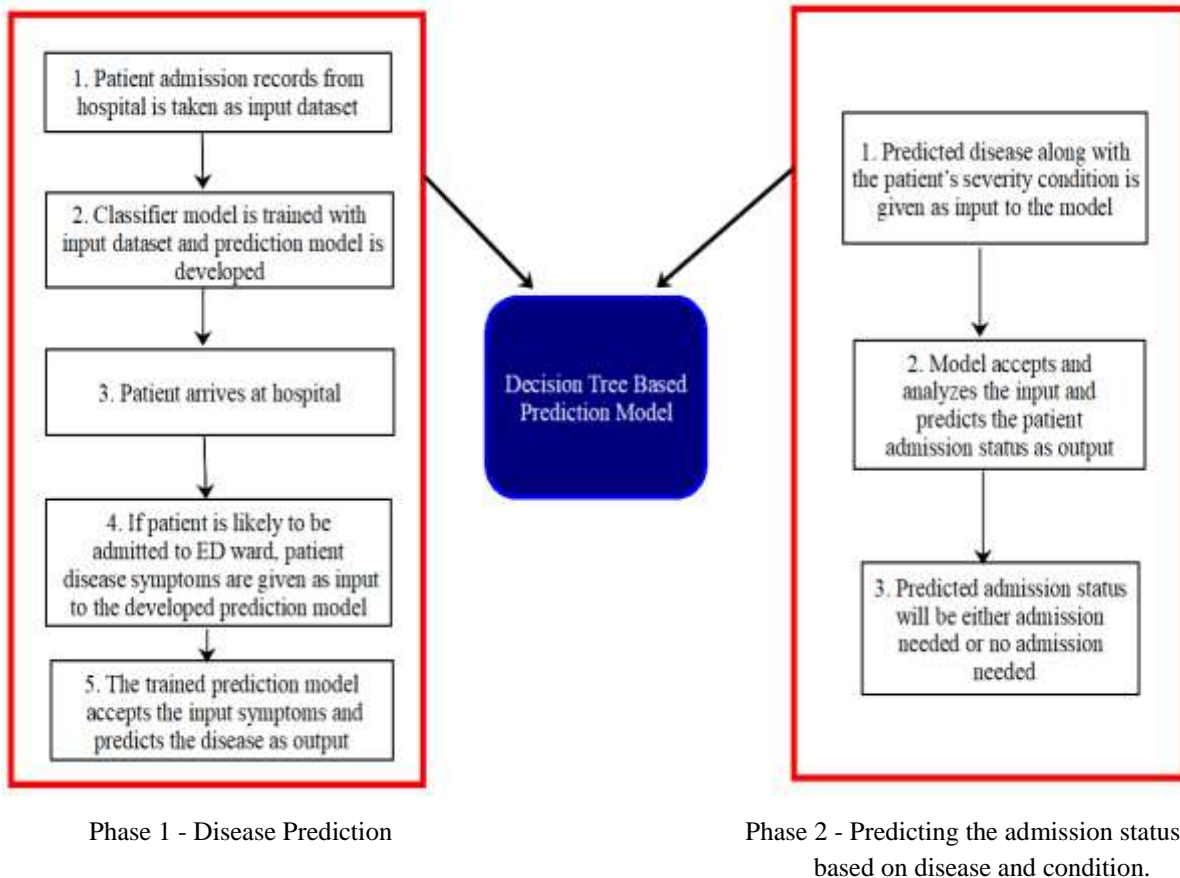


Fig-4: Architecture of Patient Admission Prediction to Emergency Departments in Hospitals Using Machine Learning

IV. RESULTS AND DISCUSSION

A. Experimental Setting

The system was implemented using Python standard library packages. XAMPP control panel was used for creating local web server. The model was run on a desktop with intel Core i3 7th gen processor and 4 GB RAM.

B. Dataset Description

The dataset used for the implementation is based on a real world hospital dataset. The dataset includes disease symptoms, diseases, severity condition and admission status of the patient based on the severity condition.

C. Data Acquisition and Processing

Two datasets were collected for implementing the model. One of the datasets consist of a list of symptoms with its corresponding diseases. This dataset is used in disease prediction phase. Another dataset consists of a list of diseases and admission status based on severity condition. This is used in admission prediction phase. The newly developed prediction model serves as an important factor for reducing the patient overcrowding in hospitals especially in emergency wards. The implemented decision tree based prediction model will be useful in advance resource planning in hospitals, arranging for appropriate staffs and reducing staff shortages. The prediction model built achieved an overall accuracy of above 80%. The model seems to be better and efficient than the models developed in the existing literatures. The result analysis of the model can be represented as a case study. The case study is for two phases. First phase is disease prediction and the second phase is the admission prediction. The case study is as follows.

Table-1: Results of Disease Prediction Phase

Symptom 1 (Input)	Symptom 2 (Input)	Symptom 3 (Input)	Predicted Disease (Output)
Itching	Skin rash	Nodal skin eruptions	Fungal infection
Belly pain	Toxic look (Typhos)	Diarrhoea	Typhoid
Yellowish skin	High fever	Weight loss	Jaundice

Table 1. describes the result of the initial phase disease prediction. The patient symptoms like itching, skin rash and nodal skin eruptions are given as input to the model. The disease given as output by the model is fungal infection. The disease displayed is given as input in the next phase.

Table-2: Results of Admission Status Prediction Phase

Disease (Input)	Condition (Input)	Admission Status (Result)
Fungal infection	Severe	Admission Needed
Typhoid	Mild	No Admission Needed
Jaundice	Severe	Admission Needed

Table 2. describes the result of the next phase admission status prediction. The predicted disease and the severity condition of the patient is taken as input by the model in this phase. The output predicted is admission needed.

D. Results of Disease Prediction Stage

The symptoms of the disease caused for the patient is given as input in this stage. The model will be trained and tested based on the dataset using the decision tree algorithm. The corresponding disease for the symptoms given is predicted as output by the model.

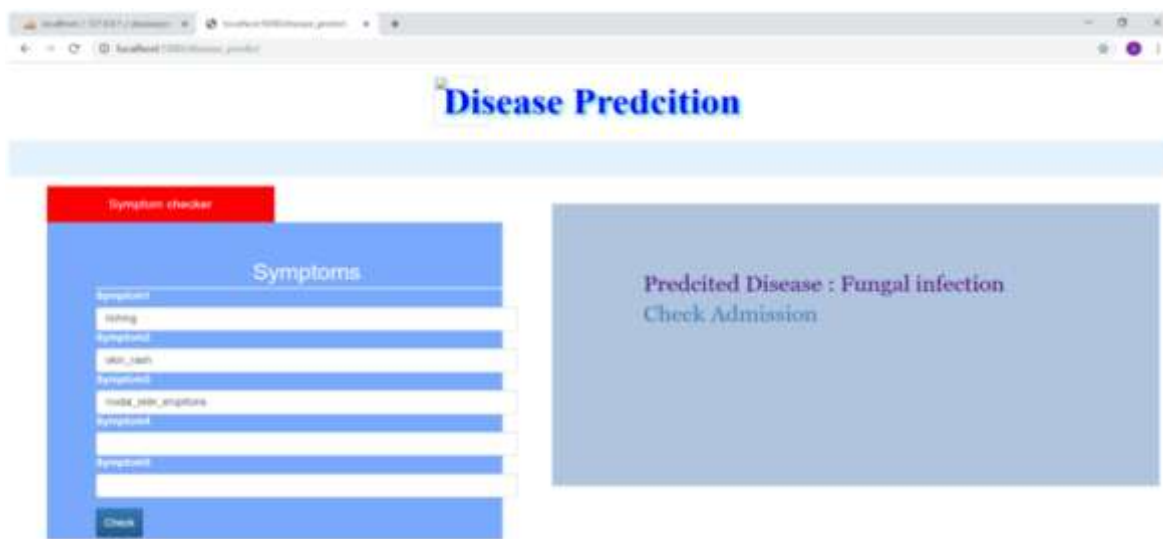


Fig-5: Output of Disease Prediction Phase

E. Results of Admission Status Prediction Stage

The predicted disease and the severity condition of the patient (severe/mild) are given as input in this stage. The model will be trained and tested based on the second dataset. The output predicted will be whether the patient needs admission or do not require admission.



Fig.-6: Checking for Admission Status



Fig-7: Output of Admission Status Phase

V. CONCLUSION

A prediction model has been developed using decision tree algorithm for predicting the chance for the number of patients to get admitted in the emergency ward. Frequently monitoring these kind of informations each time will be very useful for the hospital administration. The hospital management can make necessary arrangements for the patients in advance. The ED ward managers can make advance resource planning in the ED ward. This helps to reduce long queues and overcrowding of patients in the emergency ward. The developed prediction model achieves an overall accuracy of above 80%. The future scope of this work is that extra features for predicting the cancer admissions could be added as another module to the system. The system can be implemented to add more input details of patients. The algorithms which are better than decision tree can be implemented as an alternative for building the prediction model. Alternative algorithms include Gradient Boosting, Support Vector Machine (SVM) and Random Forests.

ACKNOWLEDGEMENTS

We would like to express our special gratitude to Dr. S. Suresh Babu, Head of our Institution and our colleagues who have supported us in this research work.

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