



# **Readmission Rate of Diabetic Patients**

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# Problem Statement

- The stakeholder of this project will be the hospital officials who can use the results to figure out which patients have higher readmission chances.
- This will help hospital to save money also improve the healthcare services..
- With this project, the aim is to find the best model for readmission prediction and the factors which most likely affect the readmission.



# Project Flow

**Data  
Collection**

**Data Wrangling(Missing  
values, Data cleaning,  
standardization etc.)**

**EDA &  
Visualizations**

**Modelling:  
Logistic  
Decision Trees  
Random Forest  
AdaBoost Classification**

# Data Description

Medical records in the dataset include 50 attributes that are the risk factors, in addition to a label indicating the readmission status of a patient indicates whether a patient was readmitted to the hospital within 30 days or not.

The dataset encounters satisfy the following conditions:

- It is an inpatient encounter (a hospital admission)
- It is a diabetic encounter, that is, one during which any kind of diabetes was entered to the system as a diagnosis.
- The length of stay was at least 1 day and at most 14 days.
- Laboratory tests were performed during the encounter.
- Medications were administered during the encounter.



# Null Value Handling

**race 2273**  
**weight 98569**  
**payer\_code 40256**  
**medical\_specialty 49949**

**diag\_1 21**  
**diag\_2 358**  
**diag\_3 1423**

- The features having more than 85% null values are been dropped.
- As diagnostic tests (diag\_1, 2,3) and medical\_specialty are either continuous or discrete i have replace null values with “unknown” as the null values are below 10%.

# Feature Engineering

In Healthcare sector service utilization factor plays a key role to know how efficient the hospital is providing services.

```
data['service_utilization'] = data['number_outpatient'] + data['number_emergency'] + data['number_inpatient']
```

## Understanding Diagnostic test Codes:

According to ICD-9-CM- Diagnostic codes are defined with specific terms within interval of numbers. Ref for diagnostic code:

<https://www.findacode.com/code-set.php?set=ICD9>

```
def map_now():  
    listname = [('infections', 139),  
                ('neoplasms', (239 - 139)),  
                ('endocrine', (279 - 239)),  
                ('blood', (289 - 279)),  
                ('mental', (319 - 289)),  
                ('nervous', (359 - 319)),  
                ('sense', (389 - 359)),  
                ('circulatory', (459 - 389)),  
                ('respiratory', (519 - 459)),  
                ('digestive', (579 - 519)),  
                ('genitourinary', (629 - 579)),  
                ('pregnancy', (679 - 629)),  
                ('skin', (709 - 679)),  
                ('musculoskeletal', (739 - 709)),  
                ('congenital', (759 - 739)),  
                ('perinatal', (779 - 759)),  
                ('ill-defined', (799 - 779)),  
                ('injury', (999 - 799))]
```



# Exploratory Data Analysis

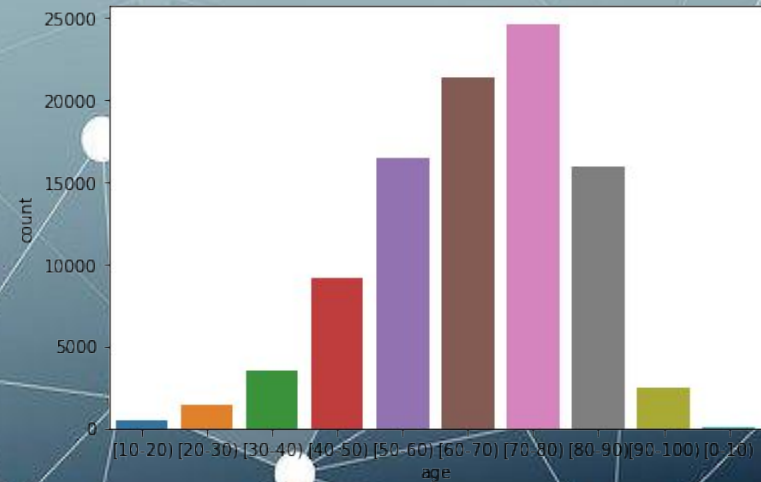
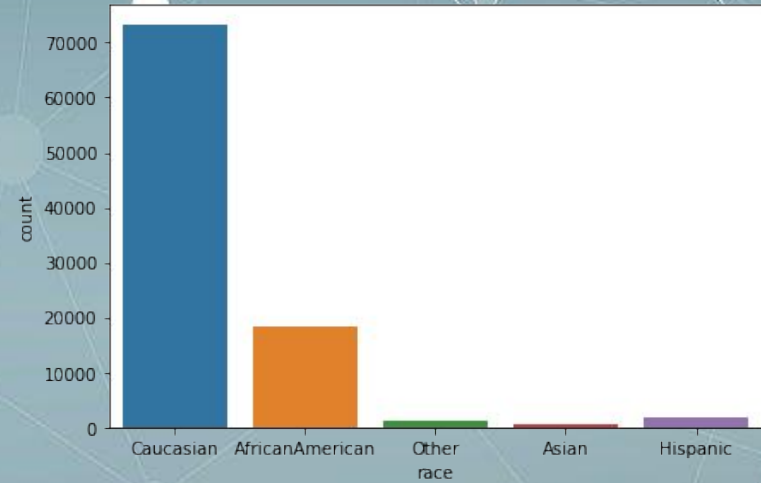
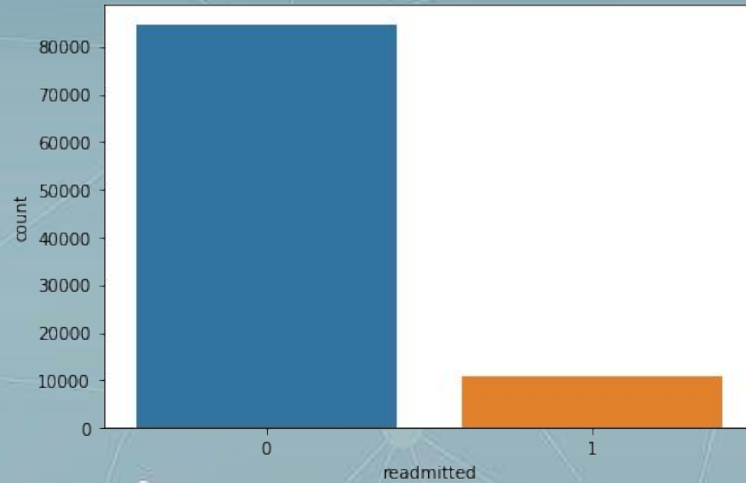
- Analyzing the numerical and categorical data separately.

- This picture discuss about numerical data present in the dataset



# EDA...

This picture discuss about categorical data like Readmitted patients, Race, Gender and Age present in the dataset.



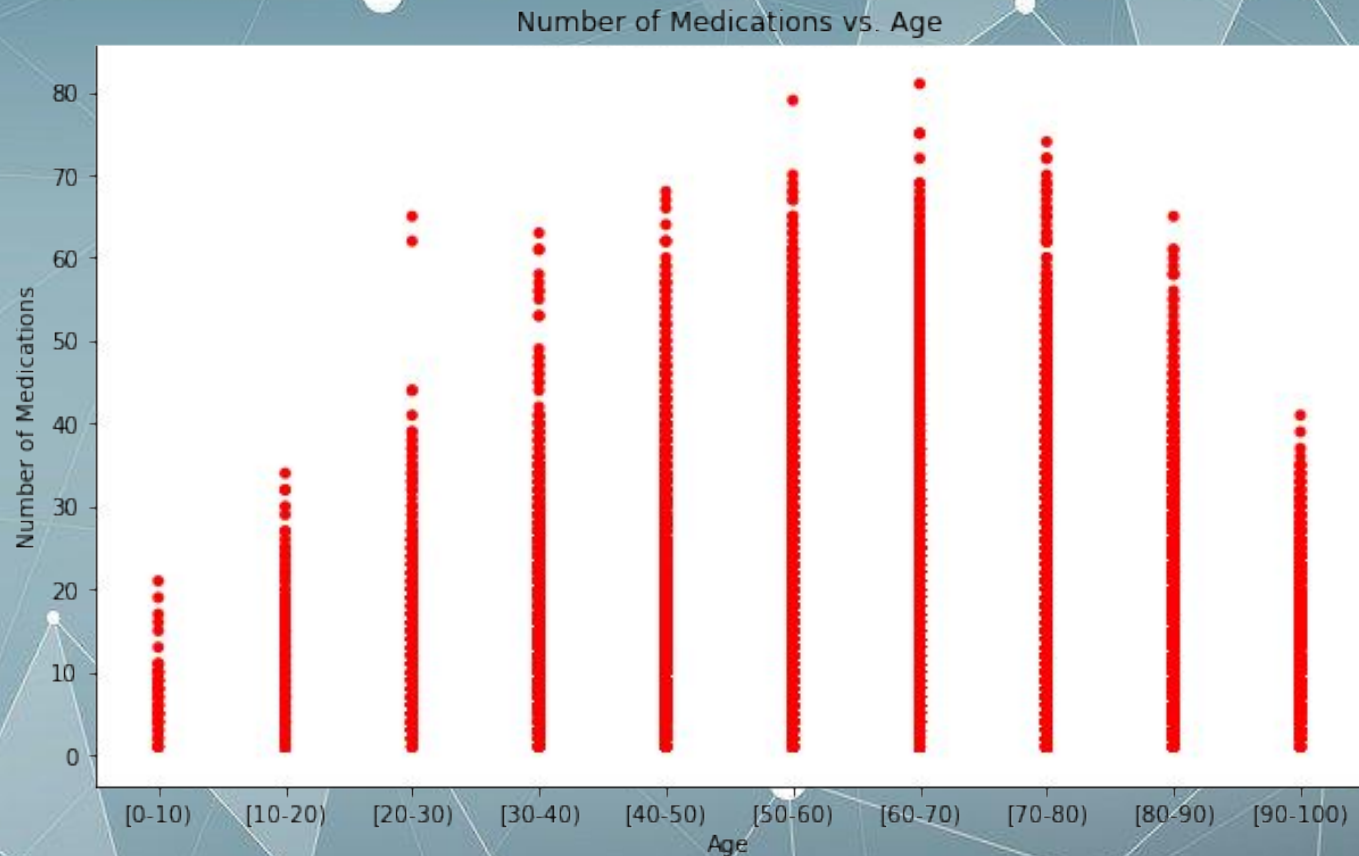


# EDA

This picture discuss about relationship between number of medications provided to the patients who admitted in different departments.



# No.of medications vs age

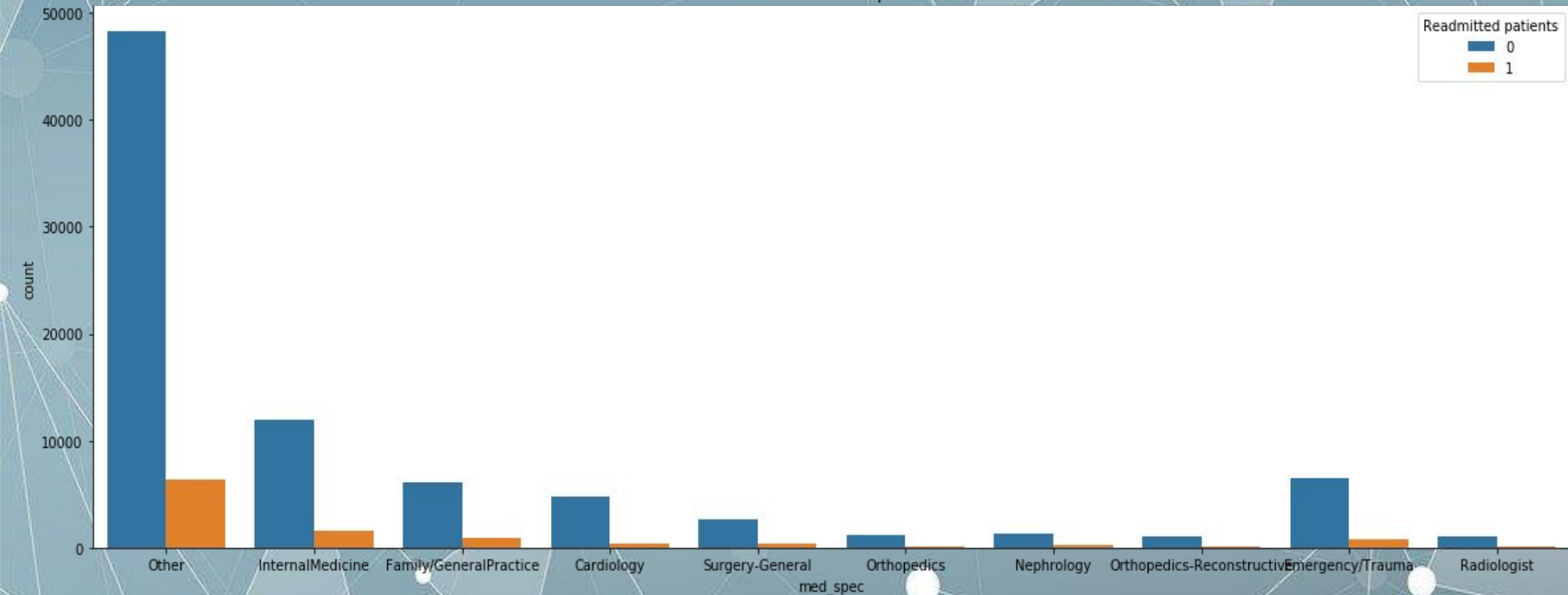


When the doctor gives medicine to patient he considers the patients age according to age he prescribes the power of medicine & no.of medicines.



# No. of Readmission per Department

Readmissions vs Department



The above chart gives the how many patients patients are readmitted per department

# Data Journey

1. Importing All Libraries.
2. Loading dataset and reading it.

## Data Profiling

1. Null handling
2. Check uniques for every feature.
3. Drop null values
4. Drop highly correlated values

## Feature Engineering

1. Encode features
2. Check for categorical features.
3. Check for Numerical features

## EDA

1. Plot categorical & numerical data
2. Analyze medicine vs age.
3. Check service of the hospital

## Feature Analysis

1. Confirm target.F.
2. Analyze corr between Target.F & other features
3. Remove skewness & kurtosis.

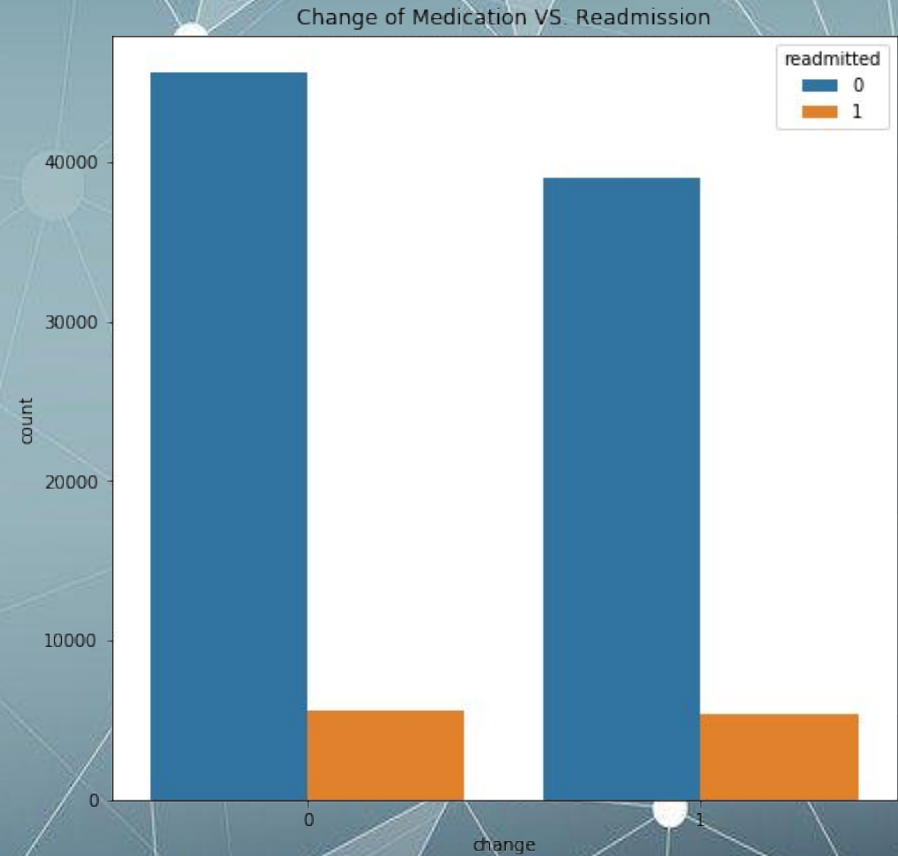
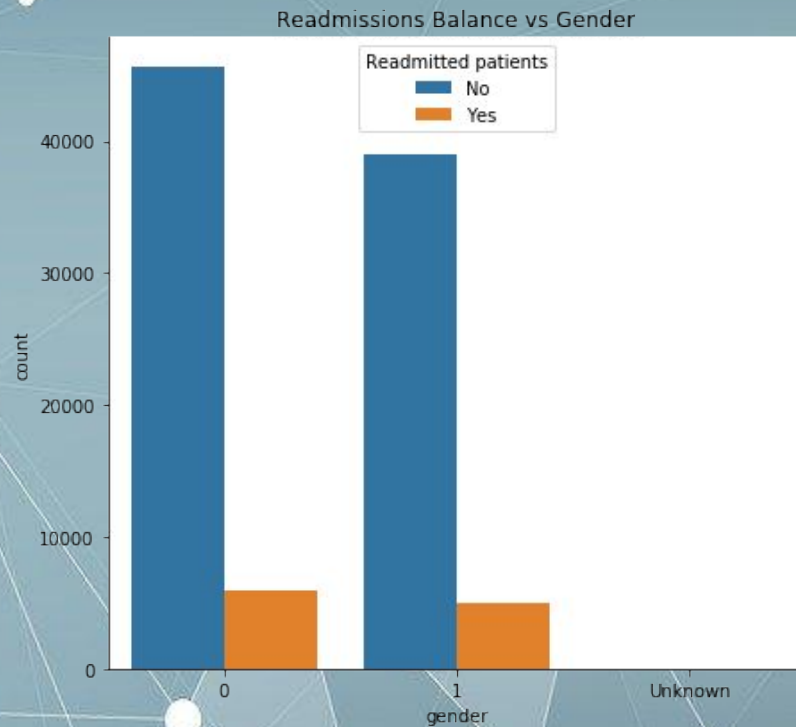
## Modelling

1. Modelling with different classification techniques.
2. Comparing models.

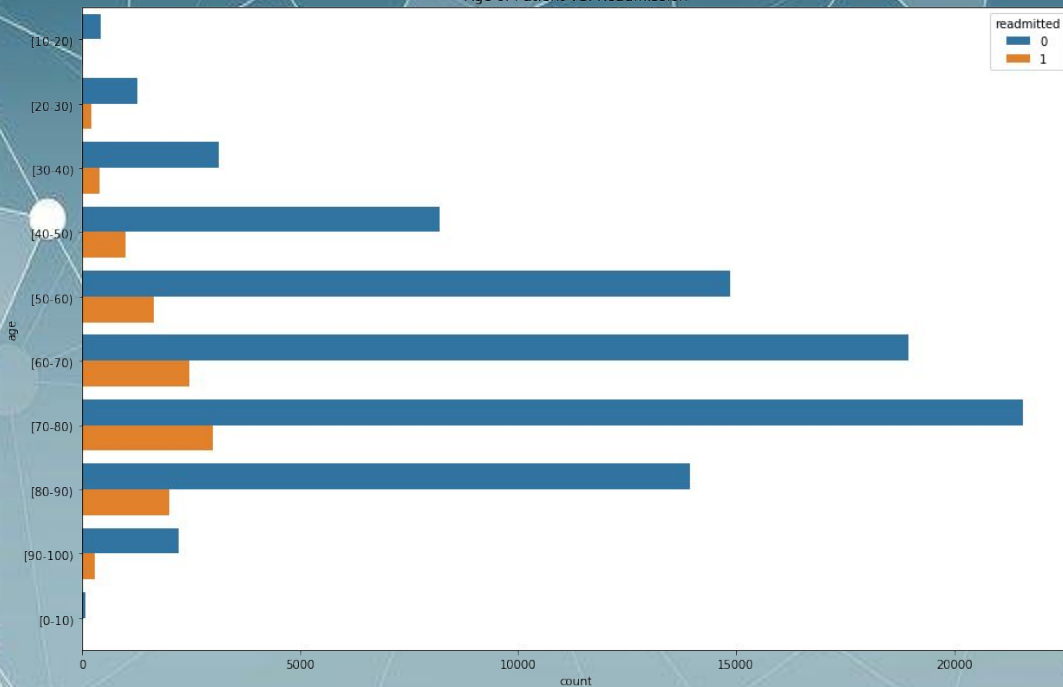


# Feature Analysis

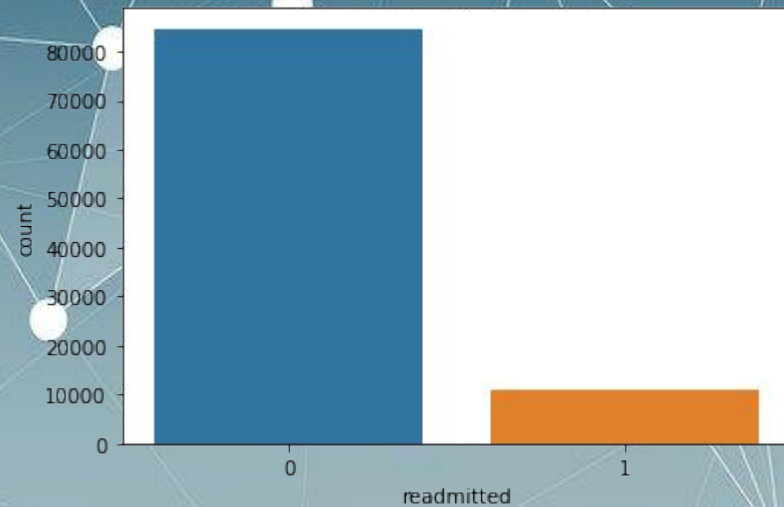
Checking behaviour of each feature with target variable



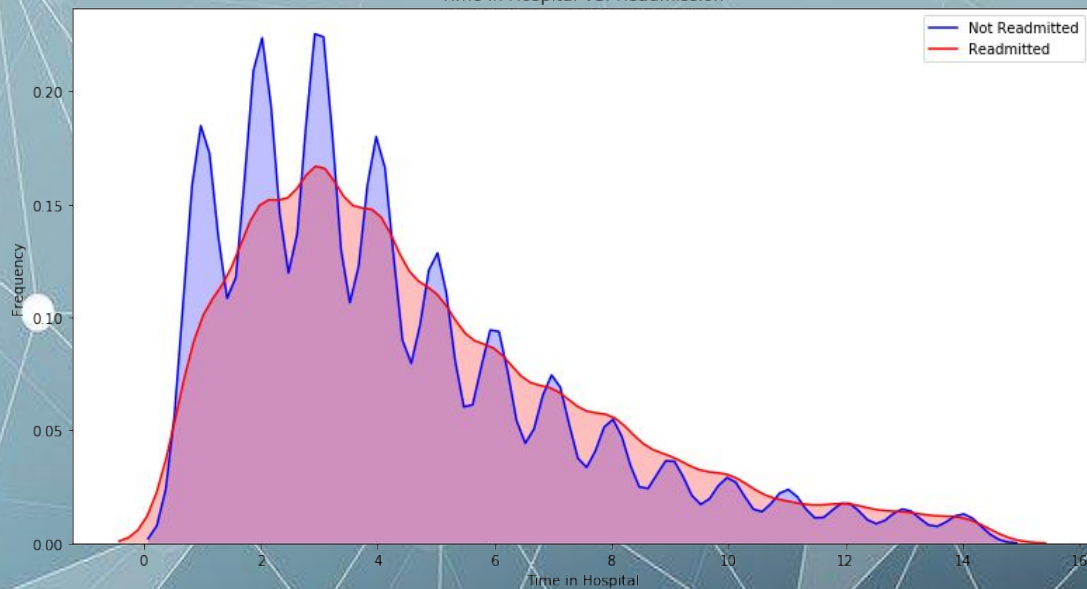
Age of Patient VS. Readmission



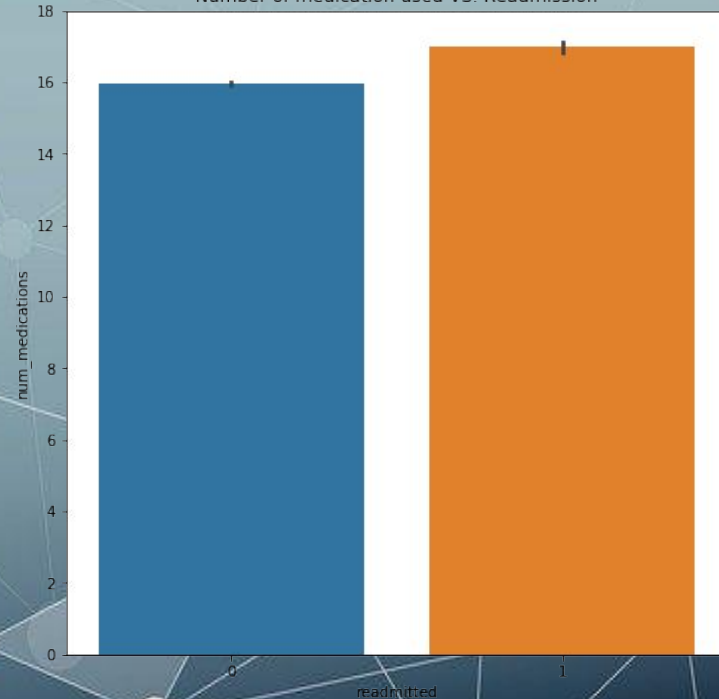
Distribution of Readmission



Time in Hospital VS. Readmission



Number of medication used VS. Readmission





# Modelling

**The Models i have chosen are:**

- **Logistic Regression**
- **Decision Tree**
- **Random Forest**
- **Adaboost Classification**
- **Naive Bayes**
- **Gradient Boost Algorithm**

**As per problem statement (prediction of readmission of diabetic patients) i have selected the above models**

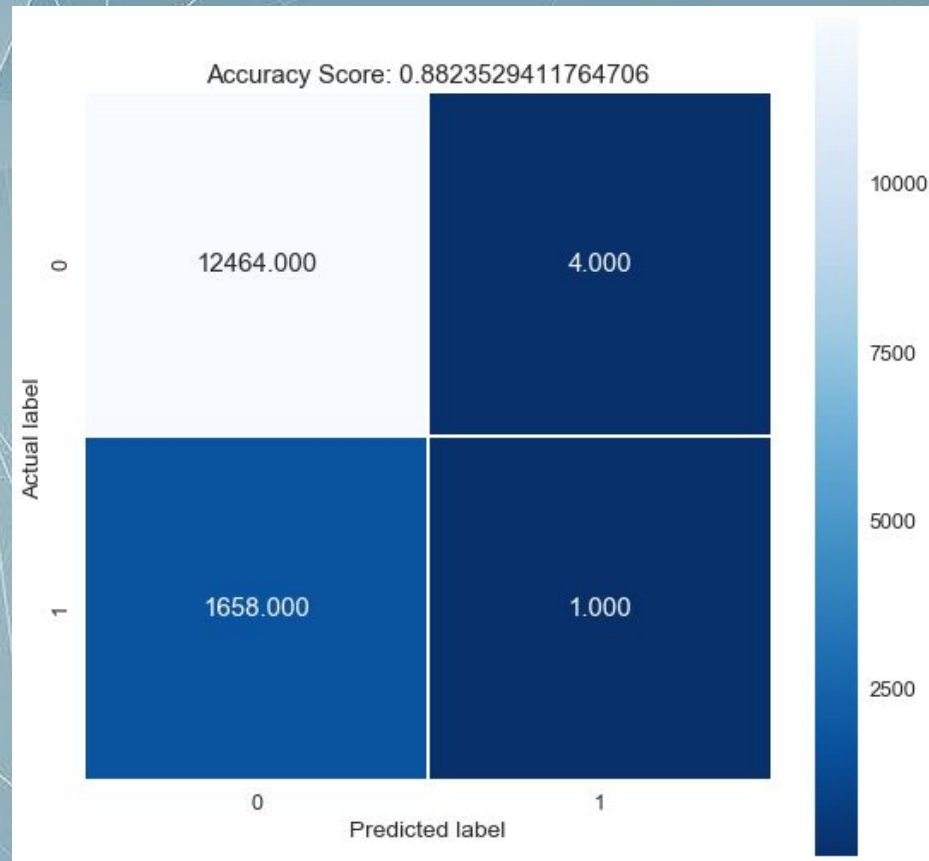
# Evaluation

To evaluate the model performance the following parameters are been used:

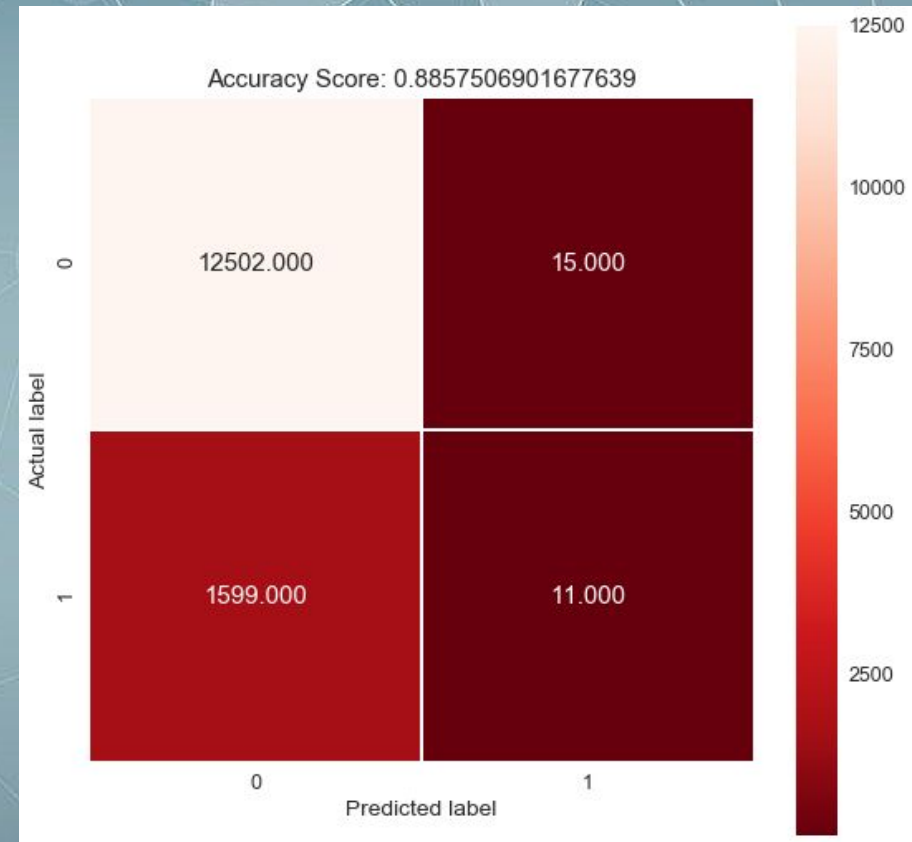
1. Accuracy
2. Precision
3. Recall
4. Confusion Matrix



# Evaluations of Models

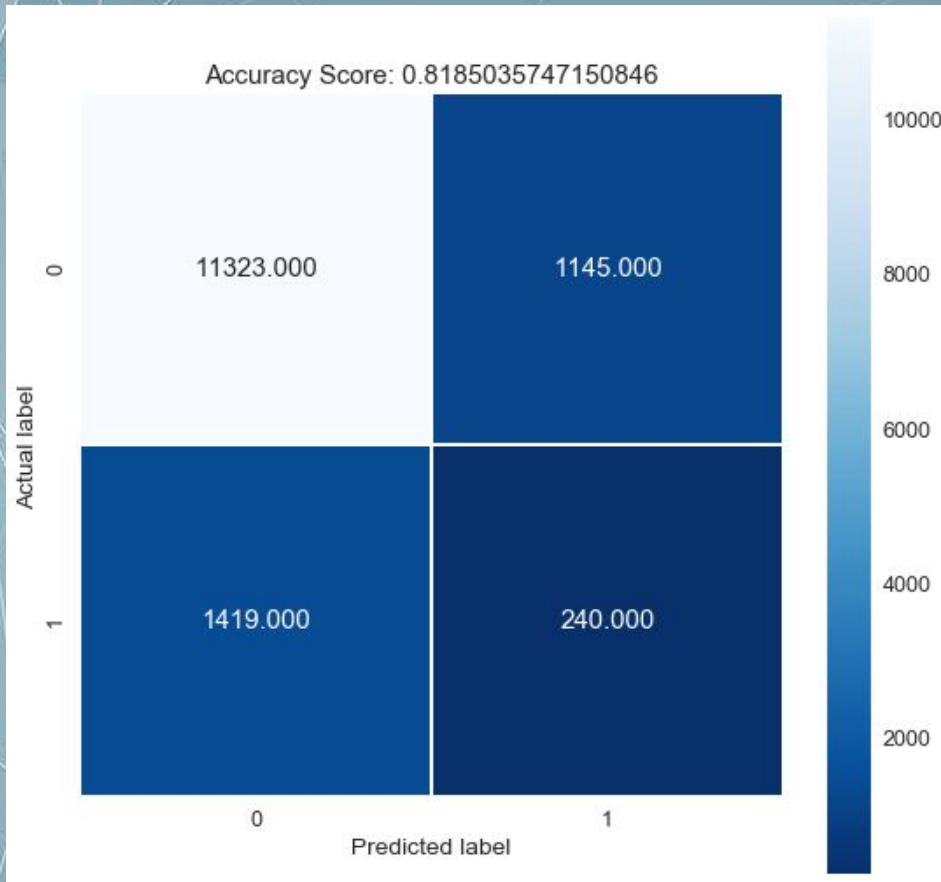


**Confusion Matrix of Logistic Regression**

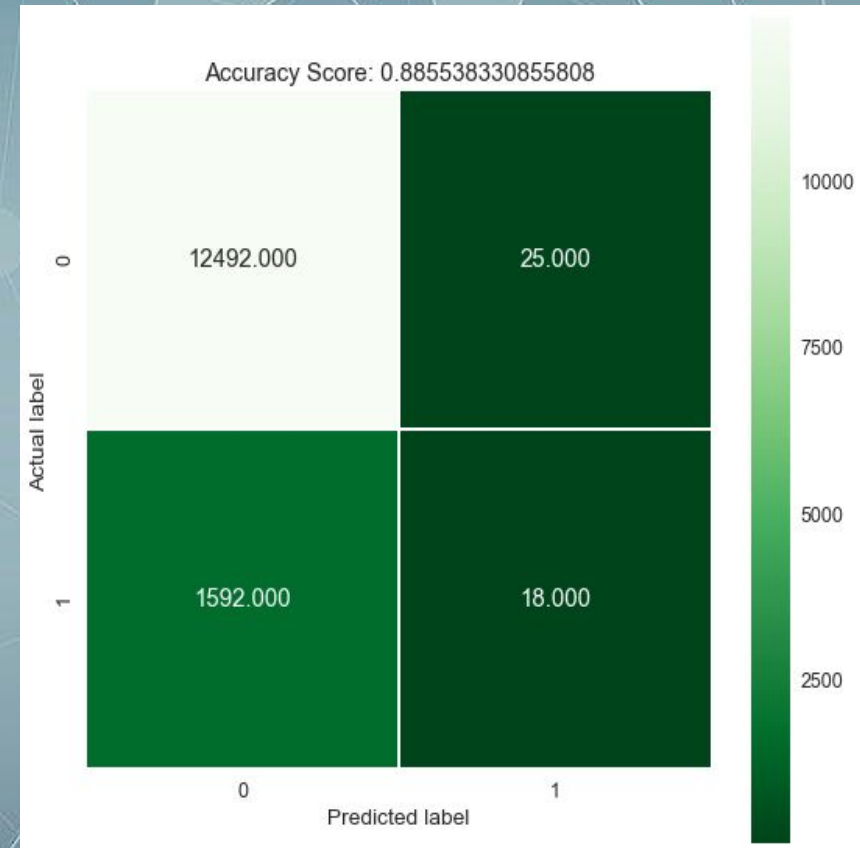


**Confusion Matrix of Random Forest**

# Evaluation of Models



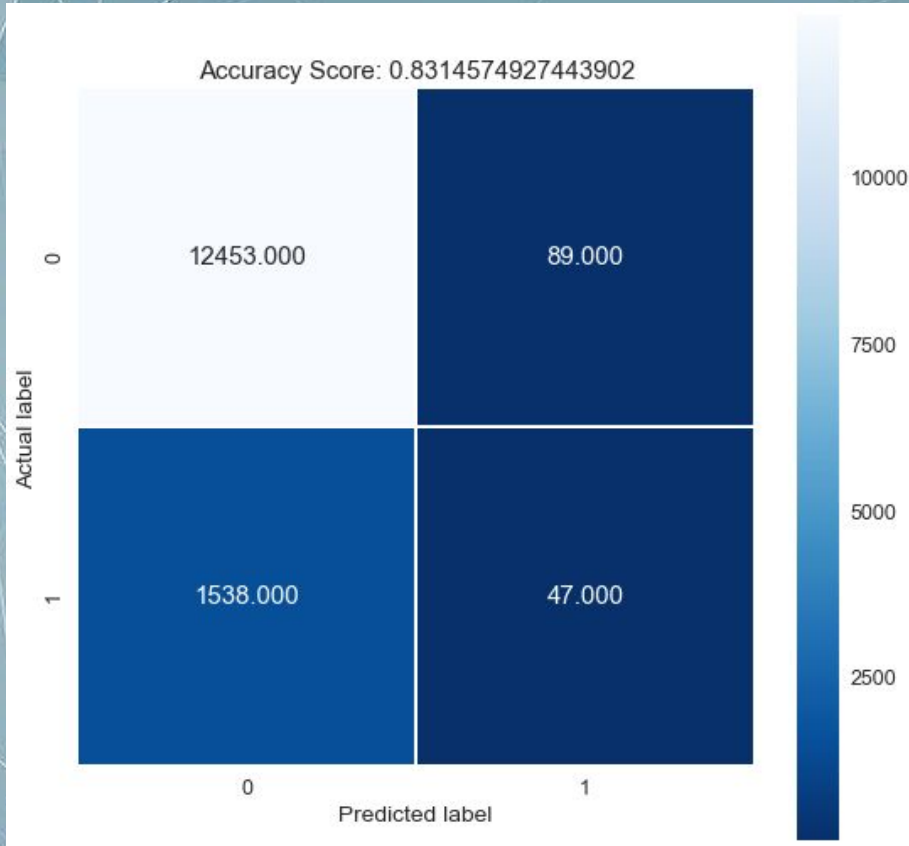
Confusion Matrix of Decision Tree



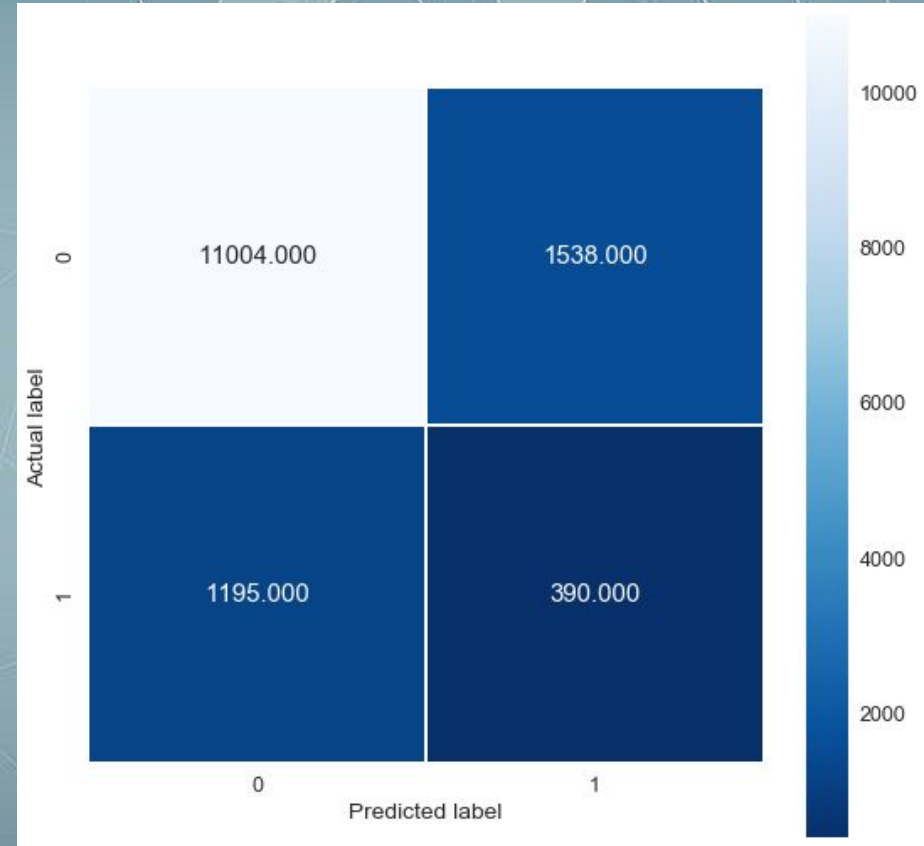
Confusion Matrix of AdaBoost Classification Model



# Evaluation of Models

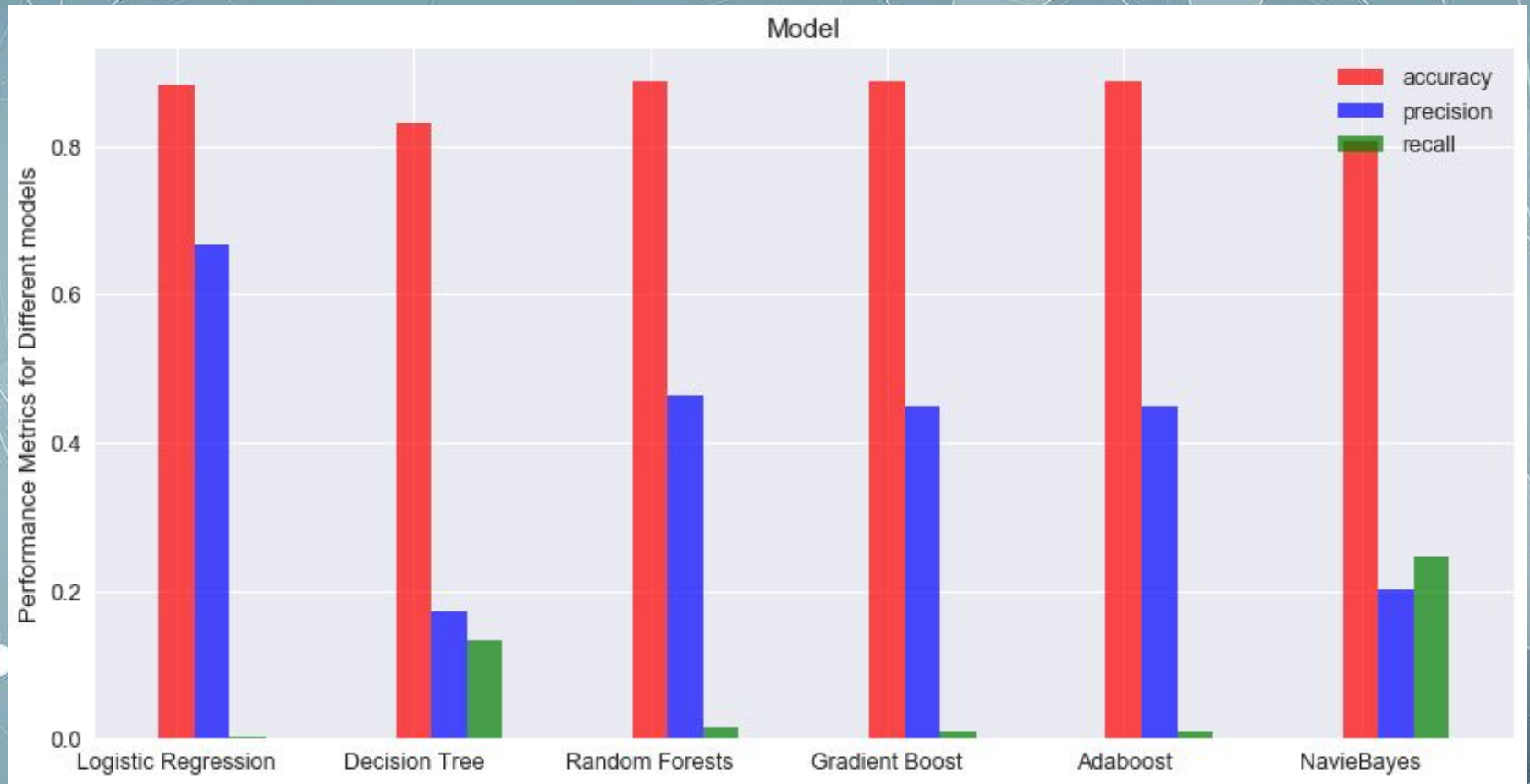


**Confusion Matrix of Gradient Boost Algorithm**



**Confusion Matrix of Naive Bayes Model**

# Comparison of Models





# Business Recommendations

- After processing models we ended having Random Forest is the good model for classification.
- We ended with some of the important features which hospitals have to consider. Therefore hospital authorities know which feature is showing more effect on readmission rate.

