

# READMISSION OF PATIENTS IN HOSPITAL (Analysis of Enterprise Data)

## PROJECT REPORT

SUBMITTED FOR THE COURSE: Storage Technology(ITE--2009)

Under the Guidance of-Prof. Siva Rama Krishnan

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## **LITERATURE RIVIEW:**

M. Karaolis et al. [5] develop a data mining system using association rule analysis based on the apriori algorithm for the assessment of heart event related risk factors. While T.A. Jilani et al.[28] use data mining techniques to investigate factors that contribute significantly to enhancing the risk of acute coronary syndrome. They assume that the dependent variable is diagnosis – with dichotomous values showing presence or absence of disease and then apply binary regression to the factors affecting the dependent variable. F. I. Dakheel et al. [31] used data mining techniques to identify outlier patients who are using large amount of drugs over a long period of time. They use three techniques for finding the drug utilization for cardiac patients. First they apply a clustering technique, followed by measuring of clustering validity, and finally they apply a decision tree as classification algorithm. C.Yang et al. [12] present a DM approach to better identify patients at high risk of early renal failure, and to understand the factors that lead to fast progression of the disease using support vector machines (SVMs) and Cox proportional hazards regression (CHR).

Besides using and comparing classic DM techniques, some of the studies present new techniques, which improve old ones, such as [39] where J.Gao et al. present CoLe (Cooperative Learning), a model for cooperative agents for mining knowledge from heterogeneous data, which allows for the cooperation of different mining agents and the combination of the mined knowledge into knowledge structures that no individual mining agent can produce alone. CoLe organizes the work in rounds so that knowledge discovered by one mining agent can help others in the next round. They implement a multi-agent system based on CoLe for mining diabetes data, including an agent using a genetic algorithm for mining event sequences, an agent with improvements to the PART algorithm and a combination agent with methods to produce hybrid rules containing conjunctive and sequence conditions. Other new techniques presented are hybridizations of well-known ones such as: K.S.Kavitha et al.[8] model and design an evolutionary neural network for heart disease detection by applying hybridization to train the neural network using Genetic algorithm. Sung Ho Ha and Seong Hyeon Joo [11] suggest a hybrid data mining method for the medical classification of chest pain. They used an Apriori algorithm to identify lab tests and a C5.0 algorithm to generate a classification rule base for the classification of chest pain, which can help physicians to make clinical decisions faster and more accurately. R. Parvathi and S. Palaniammal [30] present a new technique that employs image mining, to find spatial association rules, namely the detection of associations between spatial objects , an effective method for discovering diseases from the symptoms

**KEYWORDS:** Machine Learning, Artificial Intelligence, Machine Learning Techniques

## **ABSTRACT**

The need to improve our understanding of readmission of Overall, the readmission rates in the adult population vary patients to hospitals after discharge is becoming increasingly from 5% to 29% . Although the evidence to explain recognised. Hospital admission and readmission rates have this variation is limited, these discrepancies appear to be due increased over the last few decades. It is reported that to a lack of uniformity in defining readmission and the absence readmissions may be responsible for up to half of all hospital of precision in the measurements used. The definitions of admissions . The rise in readmission rates is not unique a readmission varied from readmission within 2 weeks, 1 to western countries, as studies from the developing world month, 3 months, 6 months or 1 year from the time of the indicate a similar trend . The cost of multiple age of the population studied differed from study to study. admissions to the patients and their relatives, in terms of While no association of readmission with age has been found distress, morbidity and mortality, is immeasurable. It has [13], the elderly were the focus of study in many papers been reported that hospital admission, particularly of elderly published on readmission.

## **INTRODUCTION**

Readmission rates have received considerable attention in the literature for a number of reasons. Economic concerns resulted in publications designed to monitor the impact of changes in health care systems, including the effect of various payment/reimbursement schemes on readmission rates [3, 10,11], while several studies examined the use of readmission as a measure of outcome of the quality of care delivered in hospital [12–14].

It is claimed that a significant number of readmissions are avoidable and potentially preventable [5,15]. The interest in readmission is driven by the assumption that improvement in hospital care can result in a reduction in readmissions and medical care costs [16]. This editorial aims to provide an overview of the major issues raised by the literature on readmission, to stimulate further debate and to identify areas for future research.

A review of the literature on readmission of adults reveals a considerable variation in the probable causes for the increase in readmission rates. Previous studies have identified factors which might lead to repeated admissions such as hospital admission during the most recent year, premature discharge, poor patient compliance, age of the patient, male sex, chronic disability, patient living alone, unavoidable relapse, inadequate medical management, poor self-rated general health, in- adequate rehabilitation and poor discharge planning [1,17,18, 20]. In addition, patients with specific diagnostic categories such as chronic heart failure and chronic obstructive pulmonary disease are said to be at greater risk of readmission [8]. However, there is no general agreement about the underlying causes of readmission. Although some conditions occur repeatedly, in many cases diagnostic subgroups may be a marker for other factors associated with readmission including the organisation and quality of care [8].

## **IMPLEMENTATION: SURVEY(DATASET)**

The screenshot shows a web browser window with the following details:

- Title Bar:** Search the web...
- Address Bar:** File | C:/Users/Ankush/Downloads/LAPTOP%20%20(Responses)%20-%20Form%20Responses%201.pdf
- Toolbar:** Apps, New Tab, Geeks For Geeks, InterviewBit.
- Content Area:** A table titled "LAPTOP (Responses)" with 1/2 page displayed. The table has 13 columns corresponding to survey questions. The columns are:
  - Timestamp
  - 1Patient ID
  - 2Patient Name
  - 3Patient Number
  - 4Patient age
  - 5Prior food service
  - 6Urticaria syringe access? 7Patient treatment delay 8Improper hospital stay
  - 9Chicken water
  - 10Exposition of water w/11Improper ventilation 12Plan co-operative Act 13Readmitted
- Bottom Status Bar:** DHill\_232\_s99 (1).doc, DHill\_232\_s99.doc, hierarchical-based...ppt, hierarchical-based.ppt, Activate Windows, Go to Settings to activate Windows, Show all, 9:04 PM, 3/28/2019, battery icon.



## **SQL IMPLEMENTATION ON THE DATA COLLECTED FROM THE SURVEY:**

### **1) We will create table in the database with the data collected from survey.**

```
SQL> create table response(patient_id number(7) primary key,
  2 patient_name varchar(30),
  3 mobile_number number(10),
  4 patient_age number(3),
  5 poor_food_service number(2),
  6 unclean_syringe_scissor number(2),
  7 patient_treatment_delay number(2),
  8 improper_hospitality number(2),
  9 unclean_water number(2),
10 deposition_of_waste number(2),
11 improper_ventilation number(2),
12 non_coordinative_doctor number(2),
13 time timestamp(0),
14 readmitted number(2));
```

Table created.

### **2) Description of the table**

```
SQL> desc response;
Name          Null?    Type
-----          -----
PATIENT_ID      NOT NULL NUMBER(7)
PATIENT_NAME    VARCHAR2(30)
MOBILE_NUMBER   NUMBER(10)
PATIENT_AGE     NUMBER(3)
POOR_FOOD_SERVICE NUMBER(2)
UNCLEAN_SYRINGE_SCISSOR NUMBER(2)
PATIENT_TREATMENT_DELAY NUMBER(2)
IMPROPER_HOSPITALITY NUMBER(2)
UNCLEAN_WATER   NUMBER(2)
DEPOSITION_OF_WASTE NUMBER(2)
IMPROPER_VENTILATION NUMBER(2)
NON_COORDINATIVE_DOCTOR NUMBER(2)
TIME           TIMESTAMP(0)
READMITTED     NUMBER(2)
```

### 3) Inserting the values in the Table:

```
SQL> insert into response values(12345,'Nirbhay',9159742131,19,0,1,1,1,1,1,1,1,'26-FEB-2019 8:19:59',1);
1 row created.

SQL> insert into response values(1221,'Kushal',9888555468,19,1,1,1,1,0,0,1,1,'26-FEB-2019 8:44:07',1);
1 row created.

SQL> insert into response values(1234,'SHIV',9131239406,20,0,0,0,0,1,0,0,0,'26-FEB-2019 9:37:19',1);
1 row created.

SQL> insert into response values(1466,'Priyank',9827010221,19,1,1,1,0,0,1,1,1,'27-FEB-2019 2:26:53',0);
1 row created.

SQL>
SQL> insert into response values(1788,'Shivam',9457723651,19,1,1,1,1,1,1,1,1,'27-FEB-2019 2:28:57',1);
1 row created.
```

```
SQL> insert into response values(1723,'Shera',1234567890,20,1,1,1,1,1,1,1,1,'27-FEB-2019 3:39:44',0);
1 row created.
```

```
SQL>
SQL> insert into response values(1936,'Jay',9850890401,19,0,1,1,0,1,1,0,0,'28-FEB-2019 10:13:22',1);
1 row created.

SQL> insert into response values(1333,'Brajesh',9234653679,43,1,0,1,0,1,1,0,0,'28-FEB-2019 10:13:16',1);
1 row created.

SQL> insert into response values(1611,'John',0987654321,55,1,0,1,1,0,1,1,0,'28-FEB-2019 10:18:56',1);
1 row created.

SQL>
SQL> insert into response values(1892,'Zoya',8772652112,6,1,1,1,1,1,1,1,1,'28-FEB-2019 12:18:33',1);
1 row created.

SQL> insert into response values(1672,'Amerul',9892118262,20,0,0,0,0,1,0,1,0,'28-FEB-2019 12:18:33',0);
1 row created.
```

#### 4) Displaying the values in the table

```
SQL> select * from response;

PATIENT_ID PATIENT_NAME          MOBILE_NUMBER PATIENT_AGE
----- -----
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
-----
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
-----
NON_COORDINATIVE_DOCTOR
-----
TIME
-----
READMITTED
-----
12345 Nirbhay                  9159742131      19

PATIENT_ID PATIENT_NAME          MOBILE_NUMBER PATIENT_AGE
----- -----
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
-----
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
-----
NON_COORDINATIVE_DOCTOR
-----
TIME
-----
READMITTED
-----
0                      1          1

PATIENT_ID PATIENT_NAME          MOBILE_NUMBER PATIENT_AGE
----- -----
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
-----
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
-----
NON_COORDINATIVE_DOCTOR
-----
TIME
-----
READMITTED
-----
1                      1          1          1

PATIENT_ID PATIENT_NAME          MOBILE_NUMBER PATIENT_AGE
----- -----
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
-----
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
-----
NON_COORDINATIVE_DOCTOR
-----
TIME
-----
READMITTED
-----
1
```

PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT AGE
-----	POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	-----
-----	IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE	IMPROPER_VENTILATION	-----
NON_COORDINATIVE_DOCTOR	-----	-----	-----
TIME	-----	-----	-----
READMITTED	-----	-----	-----
26-FEB-19 08.19.59 AM	-----	-----	-----
PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT AGE
-----	POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	-----
-----	IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE	IMPROPER_VENTILATION	-----
NON_COORDINATIVE_DOCTOR	-----	-----	-----
TIME	-----	-----	-----
READMITTED	-----	-----	-----
1	-----	-----	-----

PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT AGE
-----	POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	-----
-----	IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE	IMPROPER_VENTILATION	-----
NON_COORDINATIVE_DOCTOR	-----	-----	-----
TIME	-----	-----	-----
READMITTED	-----	-----	-----
1221 Kushal	9888555468	19	-----
PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT AGE
-----	POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	-----
-----	IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE	IMPROPER_VENTILATION	-----
NON_COORDINATIVE_DOCTOR	-----	-----	-----
TIME	-----	-----	-----
READMITTED	-----	-----	-----
1	1	1	-----
PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT AGE
-----	POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	-----
-----	IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE	IMPROPER_VENTILATION	-----
NON_COORDINATIVE_DOCTOR	-----	-----	-----
TIME	-----	-----	-----
READMITTED	-----	-----	-----
1	0	0	1

PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT_AGE
POOR_FOOD_SERVICE	UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	
IMPROPER_HOSPITALITY	UNCLEAN_WATER	DEPOSITION_OF_WASTE	IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR			
TIME			
READMITTED			
	1		

PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT_AGE
POOR_FOOD_SERVICE	UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	
IMPROPER_HOSPITALITY	UNCLEAN_WATER	DEPOSITION_OF_WASTE	IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR			
TIME			
READMITTED			
26-FEB-19 08.44.07 AM			

PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT_AGE
POOR_FOOD_SERVICE	UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	
IMPROPER_HOSPITALITY	UNCLEAN_WATER	DEPOSITION_OF_WASTE	IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR			
TIME			
READMITTED			
	1		

PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT_AGE
POOR_FOOD_SERVICE	UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	
IMPROPER_HOSPITALITY	UNCLEAN_WATER	DEPOSITION_OF_WASTE	IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR			
TIME			
READMITTED			
1234	SHIV	9131239406	20
PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT_AGE
POOR_FOOD_SERVICE	UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	
IMPROPER_HOSPITALITY	UNCLEAN_WATER	DEPOSITION_OF_WASTE	IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR			
TIME			
READMITTED			
0	0	0	0
PATIENT_ID	PATIENT_NAME	MOBILE_NUMBER	PATIENT_AGE
POOR_FOOD_SERVICE	UNCLEAN_SYRINGE_SCISSOR	PATIENT_TREATMENT_DELAY	
IMPROPER_HOSPITALITY	UNCLEAN_WATER	DEPOSITION_OF_WASTE	IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR			
TIME			
READMITTED			
0	1	0	0

```
PATIENT_ID PATIENT_NAME MOBILE_NUMBER PATIENT_AGE
-----+
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR
-----
TIME
READMITTED
-----
0
PATIENT_ID PATIENT_NAME MOBILE_NUMBER PATIENT_AGE
-----+
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR
-----
TIME
READMITTED
26-FEB-19 09.37.19 AM
PATIENT_ID PATIENT_NAME MOBILE_NUMBER PATIENT_AGE
-----+
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR
-----
TIME
READMITTED
1
```

```
PATIENT_ID PATIENT_NAME MOBILE_NUMBER PATIENT_AGE
-----+
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR
-----
TIME
READMITTED
-----
1466 Priyank 9827010221 19
PATIENT_ID PATIENT_NAME MOBILE_NUMBER PATIENT_AGE
-----+
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR
-----
TIME
READMITTED
-----
1 1 1
```

```
PATIENT_ID PATIENT_NAME MOBILE_NUMBER PATIENT_AGE
-----+
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR
-----
TIME
READMITTED
-----
0 0 1 1
```

```
PATIENT_ID PATIENT_NAME           MOBILE_NUMBER PATIENT_AGE
----- -----
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR
-----
TIME
READMITTED
-----
1

PATIENT_ID PATIENT_NAME           MOBILE_NUMBER PATIENT_AGE
----- -----
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR
-----
TIME
READMITTED
-----
27-FEB-19 02.26.53 AM

PATIENT_ID PATIENT_NAME           MOBILE_NUMBER PATIENT_AGE
----- -----
POOR_FOOD_SERVICE UNCLEAN_SYRINGE_SCISSOR PATIENT_TREATMENT_DELAY
IMPROPER_HOSPITALITY UNCLEAN_WATER DEPOSITION_OF_WASTE IMPROPER_VENTILATION
NON_COORDINATIVE_DOCTOR
-----
TIME
READMITTED
-----
0
```

##### **5) To count the number of readmission of the patients:**

```
SQL> select count(readmitted) from response where readmitted=1;
COUNT(READMITTED)
-----
8
```

**6) Quarries to find the number of readmission from each category:**

**a) Poor food services:**

```
SQL> select count(readmitted) from response where poor_food_service=1 and readmitted=1;  
COUNT(READMITTED)  
-----  
5
```

**b) Unclean syringes and scissors:**

```
SQL> select count(readmitted) from response where unclean_syringe_scissor=1 and readmitted=1;  
COUNT(READMITTED)  
-----  
5
```

**c) Patient treatment delay:**

```
SQL> select count(readmitted) from response where patient_treatment_delay=1 and readmitted=1;  
COUNT(READMITTED)  
-----  
7
```

**d) Improper hospitality:**

```
SQL> select count(readmitted) from response where improper_hospitality=1 and readmitted=1;  
COUNT(READMITTED)  
-----  
5
```

e) **Unclean water:**

```
SQL> select count(readmitted) from response where unclean_water=1 and readmitted=1;  
COUNT(READMITTED)  
-----  
6
```

f) **Deposition of waste:**

```
SQL> select count(readmitted) from response where deposition_of_waste=1 and readmitted=1;  
COUNT(READMITTED)  
-----  
6
```

g) **Improper ventilation:**

```
SQL> select count(readmitted) from response where improper_ventilation=1 and readmitted=1;  
COUNT(READMITTED)  
-----  
5
```

h) **Non co-ordinative doctor:**

```
SQL> select count(readmitted) from response where non_coordinative_doctor=1 and readmitted=1;  
COUNT(READMITTED)  
-----  
4
```

## 7)Quaries to calculate average or percentage of each category—

### a) Poor food Services:

```
SQL> select avg(poor_food_service) from response where readmitted=1;  
AVG(POOR_FOOD_SERVICE)  
-----  
       .625
```

### b) Unclean syringes and scissors:

```
SQL> select avg(unclean_syringe_scissor) from response where readmitted=1;  
AVG(UNCLEAN_SYRINGE_SCISSOR)  
-----  
       .625
```

### c)Patient treatment delay:

```
SQL> select avg(patient_treatment_delay) from response where readmitted=1;  
AVG(PATIENT_TREATMENT_DELAY)  
-----  
       .875
```

### d) Improper hospitality:

```
SQL> select avg(improper_hospitality) from response where readmitted=1;  
AVG(IMPROPER_HOSPITALITY)  
-----  
       .625
```

**e) Unclean Water:**

```
SQL> select avg(unclean_water) from response where readmitted=1;  
AVG(UNCLEAN_WATER)  
-----  
      .75
```

**f) Deposition of waste:**

```
SQL> select avg(deposition_of_waste) from response where readmitted=1;  
AVG(DEPOSITION_OF_WASTE)  
-----  
      .75
```

**g) Improper Ventilation:**

```
SQL> select avg(improper_ventilation) from response where readmitted=1;  
AVG(IMPROPER_VENTILATION)  
-----  
      .625
```

**8) Non co-ordinative doctor:**

```
SQL> select avg(non_coordinative_doctor) from response where readmitted=1;  
AVG(NON_COORDINATIVE_DOCTOR)  
-----  
      .5
```

**IMPLEMENTATION THROUGH MACHINE LEARNING ALGORITHMS:**  
**APPLYING VARIOUS ALGORITHMS ON OUR DATASET AND**  
**FINDING THE ACCURACY AND THEN COMPARING THEM**

**PROPOSED APPROACH**

First I took survey from various patients who visited hospital for various reasons regarding the various environmental problems in the hospital which they faced and can be a crucial reason behind their readmission. The survey was astonishing ,the results we obtained were ridiculous. We found that there were many patients who were readmitted . Then we took the responses and feeded it into various classifiers inorder to find their respective accuracy.I normally took 70% of the data as training data and 30% of the data as testing data .Then I found their accuracy.And the results would be shown in the upcomming pages.

**EXPERIMENTAL RESULTS**

**LOGISTIC REGRESSION**

Training Data	Testing Data	Optimiser Used	Accuracy
70.00%	30.00%	Logistic regression	57.00%

**APPLYING DECISION TREE**

Training Data	Testing Data	Optimiser Used	Accuracy
70.00%	30.00%	Decision tree	60.00%

**APPLYING RANDOM FOREST**

Training Data	Testing Data	Optimiser Used	Accuracy
70.00%	30.00%	Random forest	68.00%

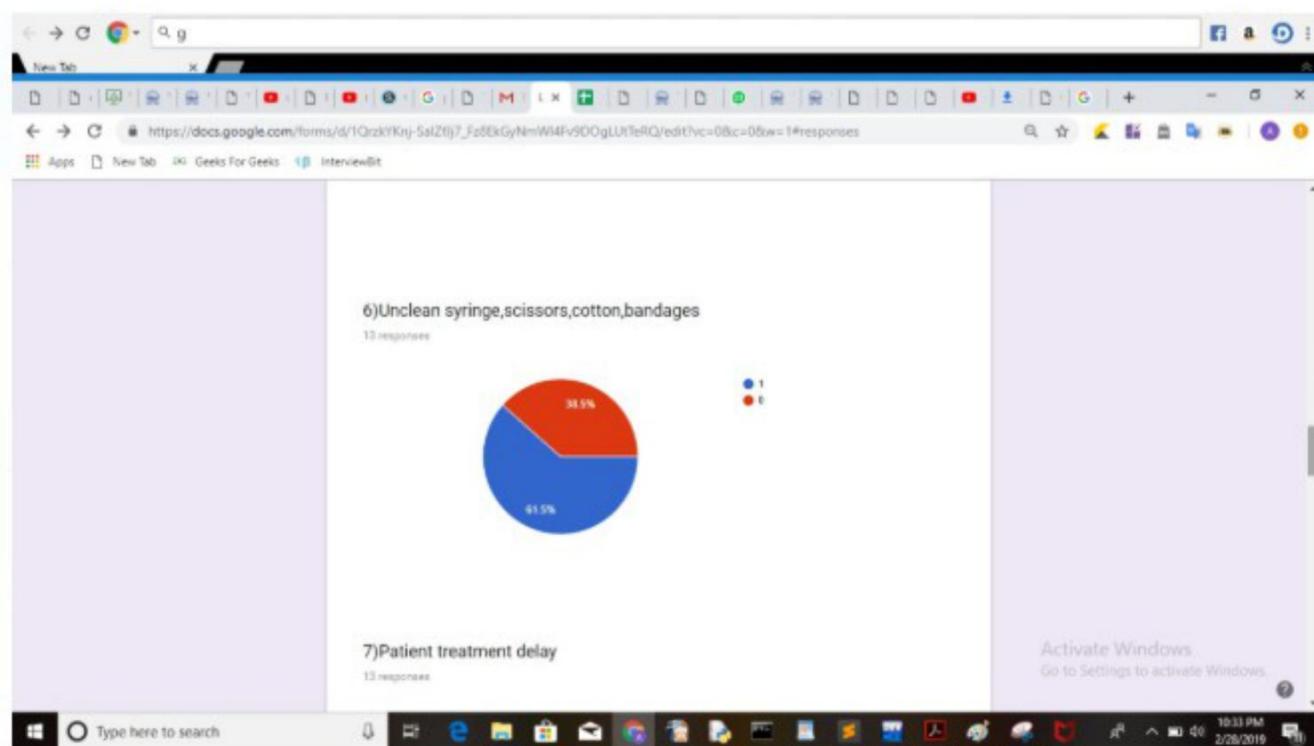
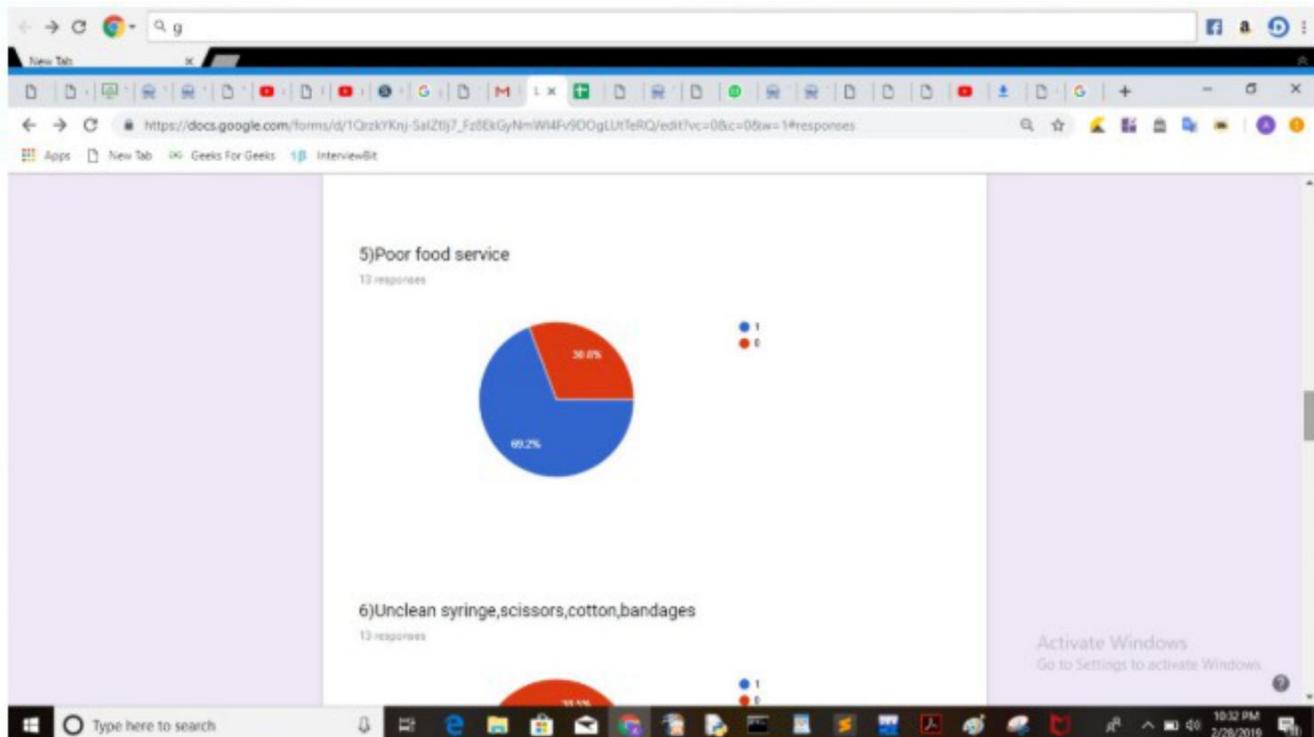
**APPLYING K NEAREST NEIGHBOUR**

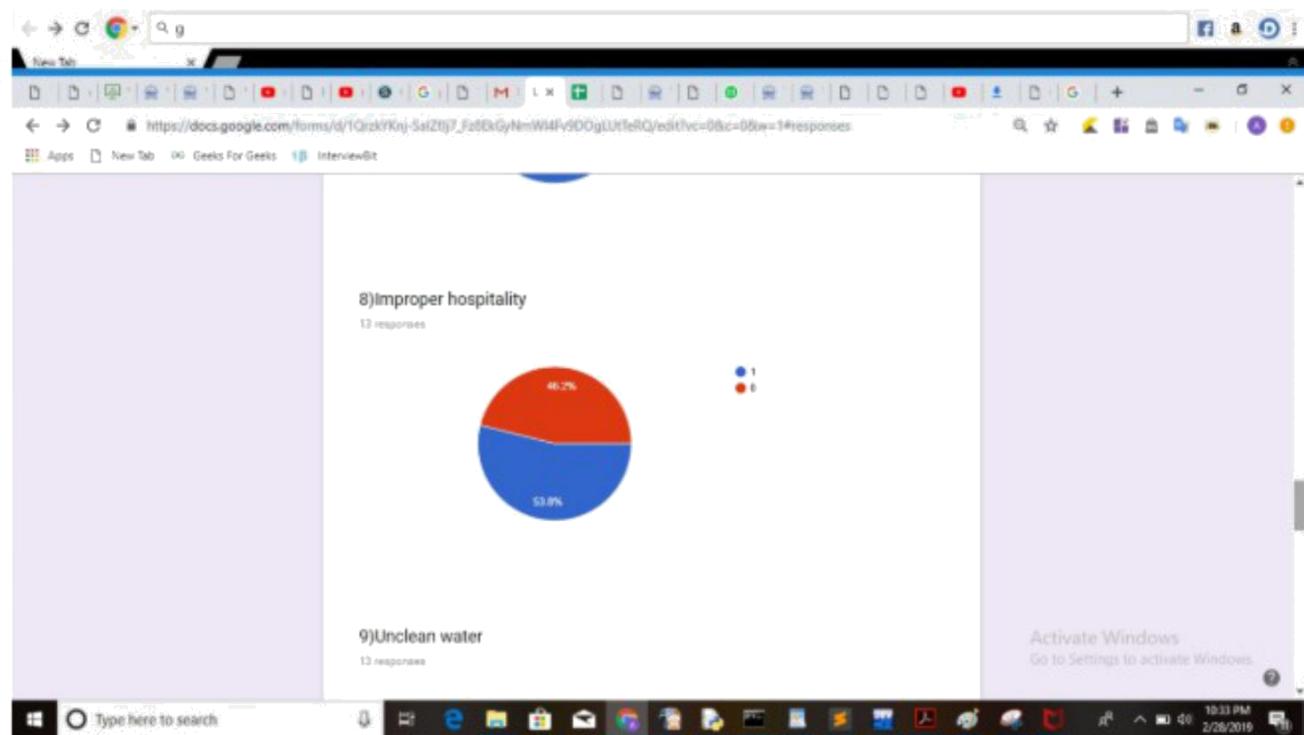
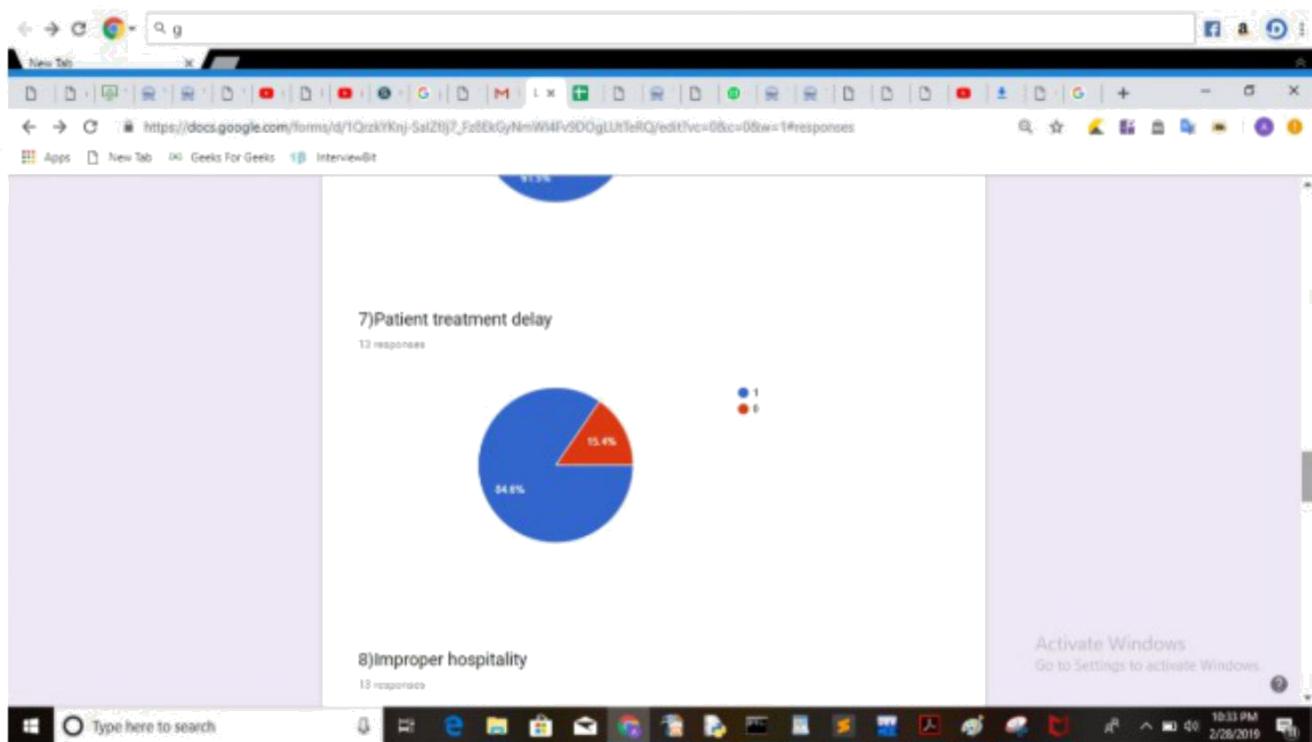
Training Data	Testing Data	Optimiser Used	Accuracy
75.00%	25.00%	K nearest neighbour	77.00%

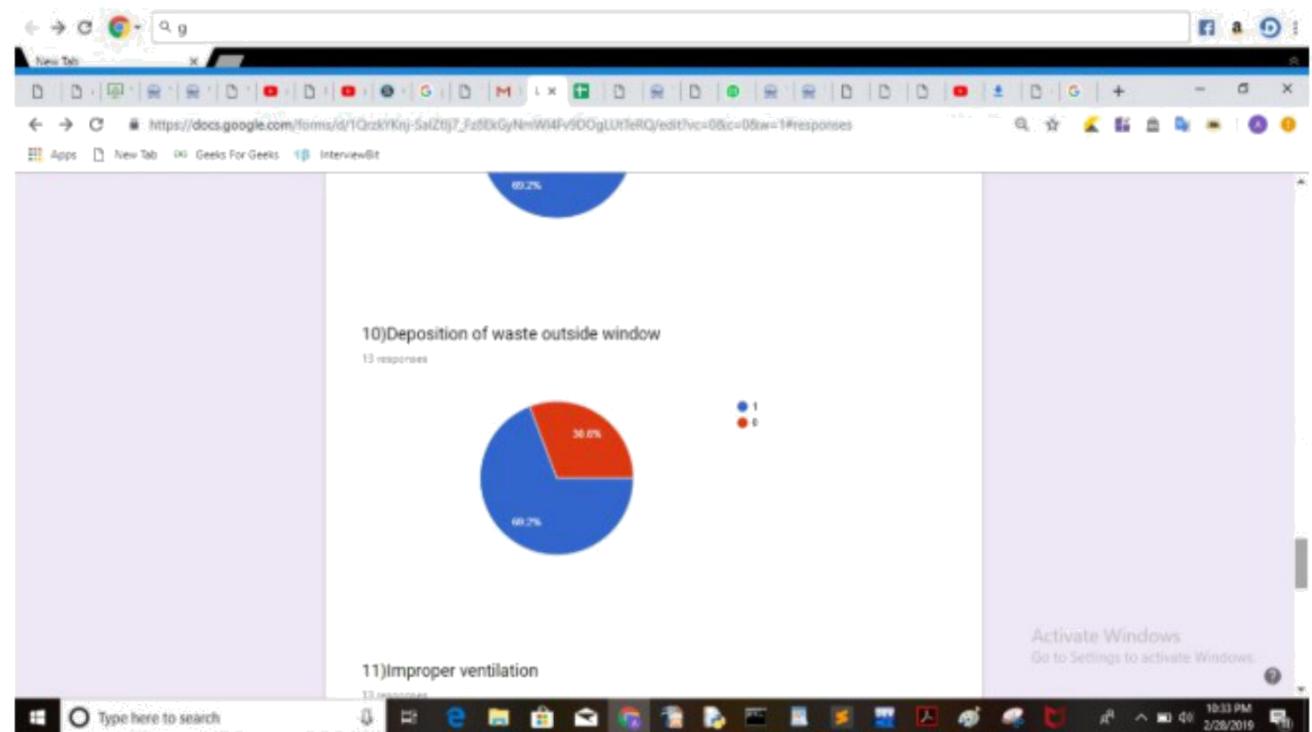
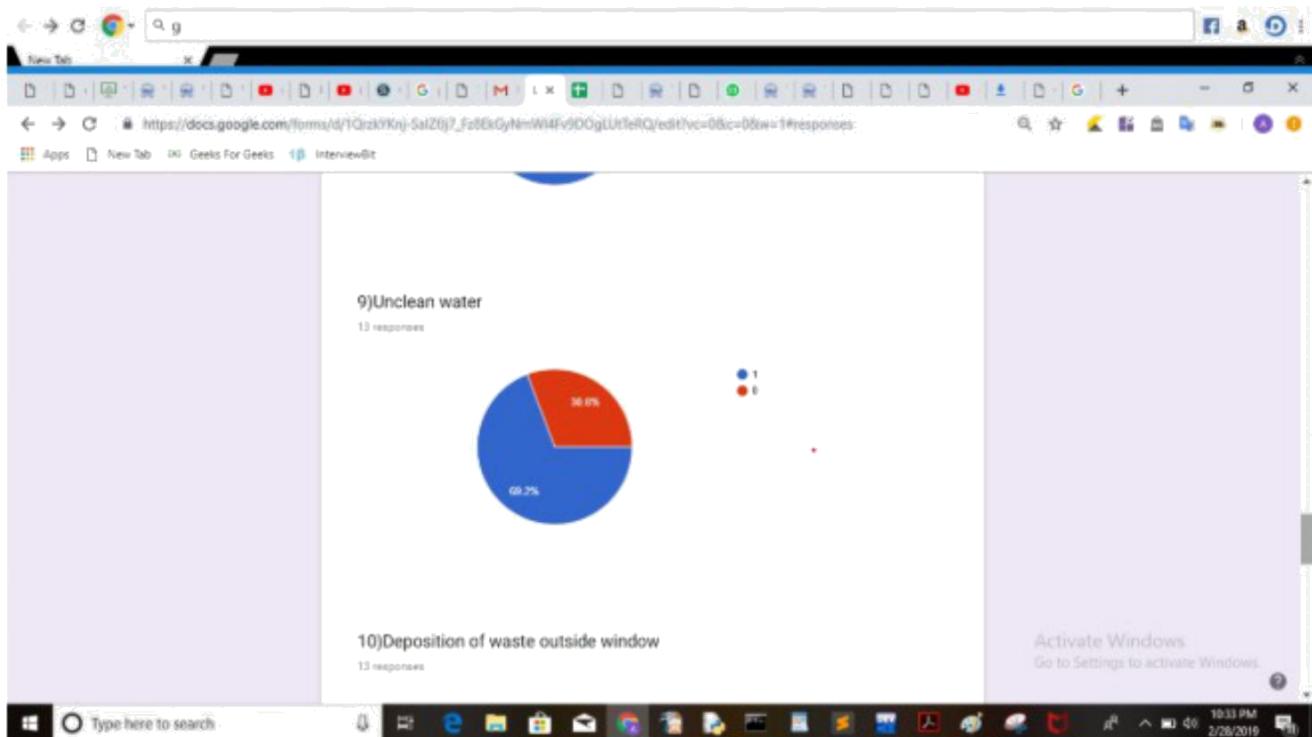
**APPLYING SVM WITH GRID SEARCH**

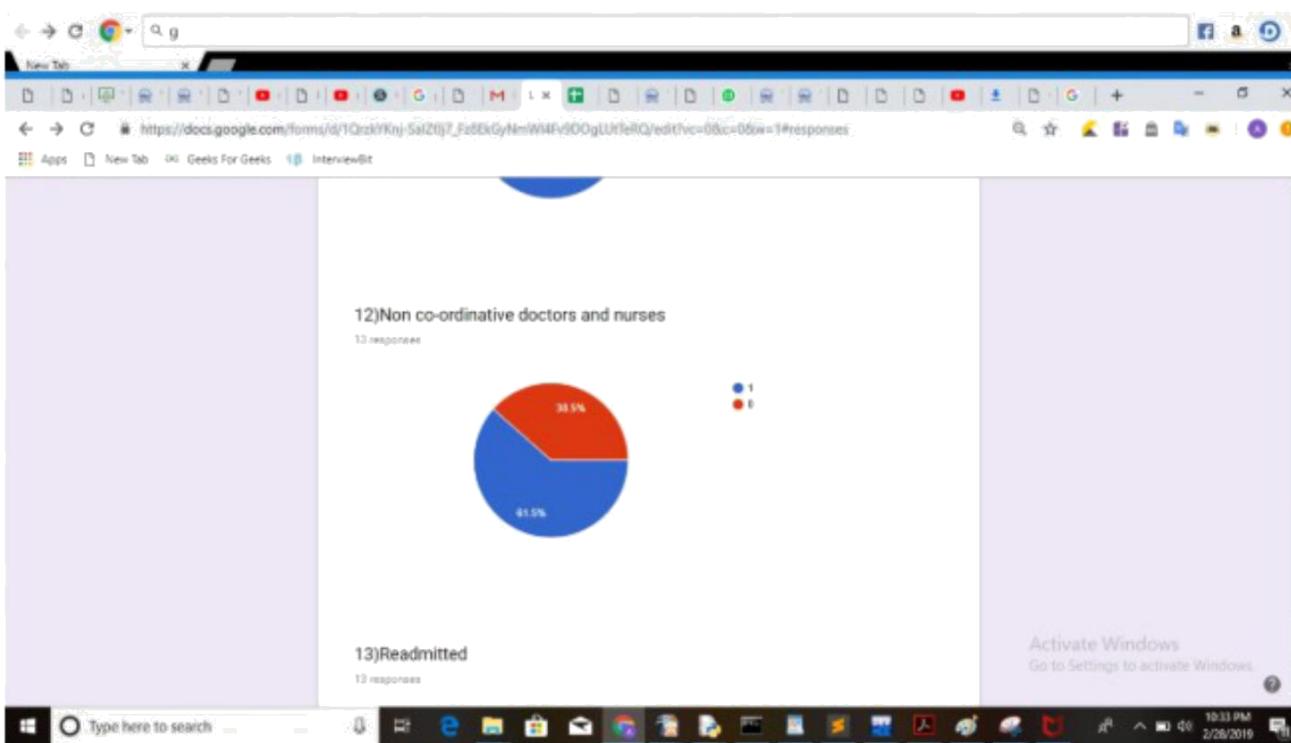
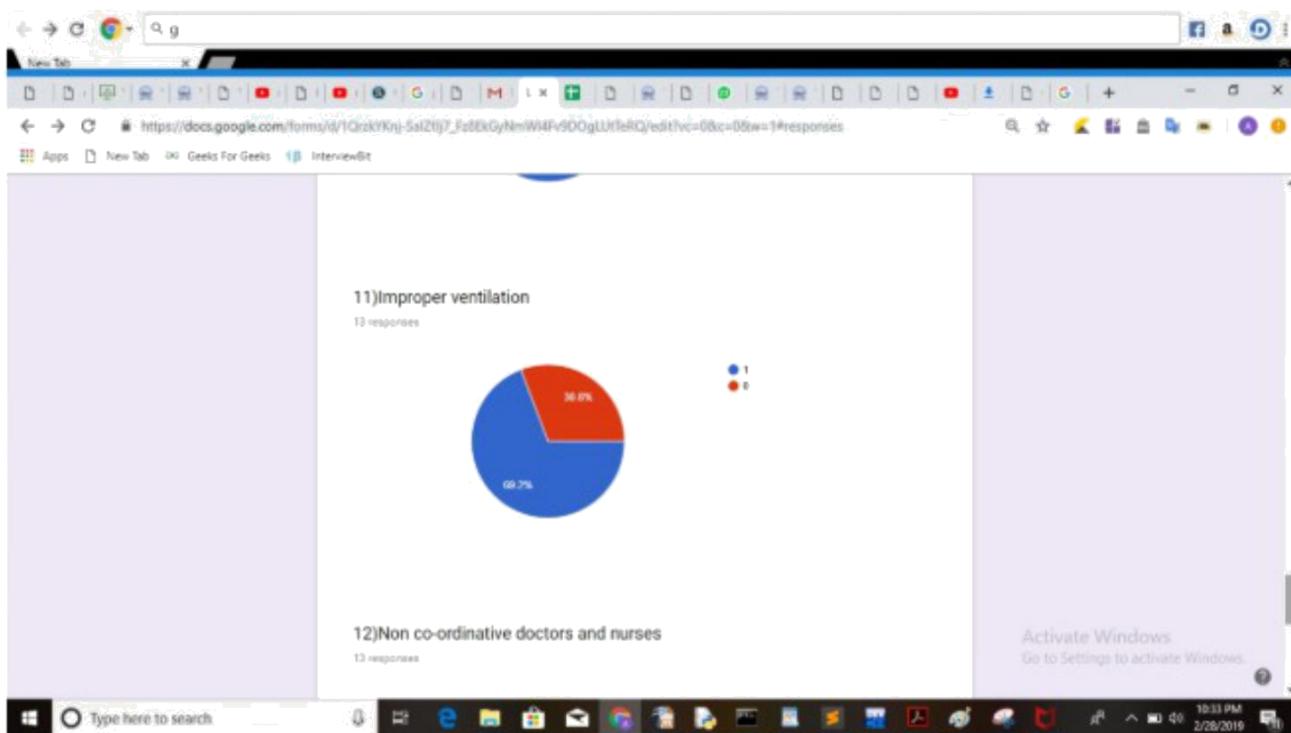
Training Data	Testing Data	Optimiser Used	Accuracy
70.00%	30.00%	SVM	63.00%

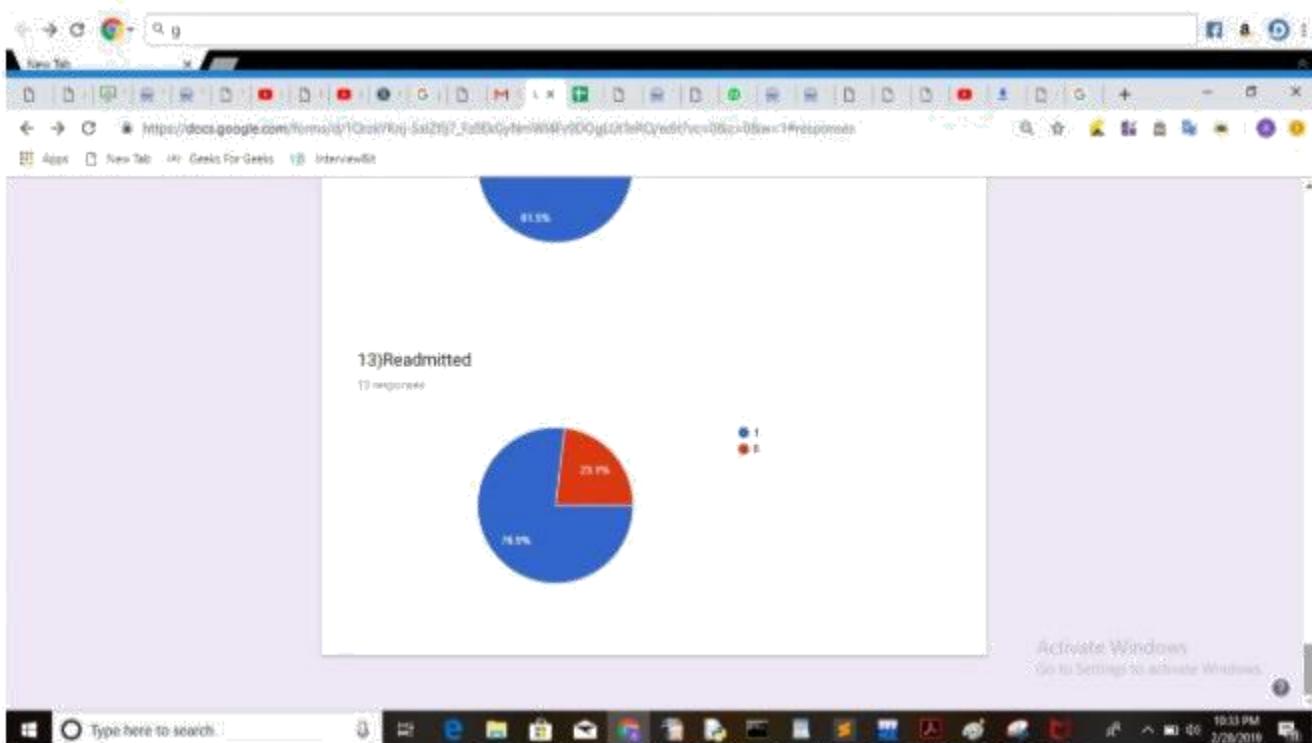
## OUTPUT - SERVEY











## MACHINE LEARNING CODE

### Applying Logistic Regression

```
In [270]: from sklearn.linear_model import LogisticRegression
In [271]: logmodel = LogisticRegression()
In [272]: logmodel.fit(X_train,y_train)
          C:\Users\Satin\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:432: FutureWarning: to 'lbfgs' in 0.22. Specify a solver to silence this warning.
Out[272]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                           intercept_scaling=1, max_iter=100, multi_class='warn',
                           n_jobs=None, penalty='l2', random_state=None, solver='warn',
                           tol=0.0001, verbose=0, warm_start=False)
In [273]: predictions = logmodel.predict(X_test)
In [274]: from sklearn.metrics import classification_report,confusion_matrix
In [275]: print(classification_report(y_test,predictions))
           precision    recall  f1-score   support

```

```
In [273]: predictions = logmodel.predict(X_test)
```

```
In [274]: from sklearn.metrics import classification_report,confusion_matrix
```

```
In [275]: print(classification_report(y_test,predictions))
```

	precision	recall	f1-score	support
0	0.25	0.14	0.18	7
1	0.70	0.82	0.76	17
micro avg	0.62	0.62	0.62	24
macro avg	0.47	0.48	0.47	24
weighted avg	0.57	0.62	0.59	24

```
In [276]: print(confusion_matrix(y_test,predictions))
```

```
[[ 1  6]
 [ 3 14]]
```

## Applying Decision Tree

```
In [368]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=101)
```

```
In [369]: from sklearn.tree import DecisionTreeClassifier
```

```
In [370]: dtree = DecisionTreeClassifier()
```

```
In [371]: dtree.fit(X_train,y_train)
```

```
Out[371]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
          max_features=None, max_leaf_nodes=None,
          min_impurity_decrease=0.0, min_impurity_split=None,
          min_samples_leaf=1, min_samples_split=2,
          min_weight_fraction_leaf=0.0, presort=False, random_state=None,
          splitter='best')
```

```
In [372]: predictions = dtree.predict(X_test)
```

```
In [373]: from sklearn.metrics import classification_report,confusion_matrix
```

```
In [374]: print(classification_report(y_test,predictions))
```

```
In [372]: predictions = dtree.predict(X_test)

In [373]: from sklearn.metrics import classification_report,confusion_matrix

In [374]: print(classification_report(y_test,predictions))
```

	precision	recall	f1-score	support
0	0.38	0.50	0.43	10
1	0.71	0.60	0.65	20
micro avg	0.57	0.57	0.57	30
macro avg	0.55	0.55	0.54	30
weighted avg	0.60	0.57	0.58	30

```
In [189]: print(confusion_matrix(y_test,predictions))
```

```
[[ 5  5]
 [ 8 12]]
```

## Applying Random Forest

```
In [225]: from sklearn.ensemble import RandomForestClassifier

In [226]: rfc = RandomForestClassifier(n_estimators=50)

In [227]: rfc.fit(X_train, y_train)

Out[227]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                                 max_depth=None, max_features='auto', max_leaf_nodes=None,
                                 min_impurity_decrease=0.0, min_impurity_split=None,
                                 min_samples_leaf=1, min_samples_split=2,
                                 min_weight_fraction_leaf=0.0, n_estimators=50, n_jobs=None,
                                 oob_score=False, random_state=None, verbose=0,
                                 warm_start=False)

In [228]: rfc_pred = rfc.predict(X_test)

In [229]: print(confusion_matrix(y_test,rfc_pred))

[[ 4  6]
 [ 3 17]]
```

```
In [227]: rfc.fit(X_train, y_train)

Out[227]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                                 max_depth=None, max_features='auto', max_leaf_nodes=None,
                                 min_impurity_decrease=0.0, min_impurity_split=None,
                                 min_samples_leaf=1, min_samples_split=2,
                                 min_weight_fraction_leaf=0.0, n_estimators=50, n_jobs=None,
                                 oob_score=False, random_state=None, verbose=0,
                                 warm_start=False)

In [228]: rfc_pred = rfc.predict(X_test)

In [229]: print(confusion_matrix(y_test,rfc_pred))

[[ 4  6]
 [ 3 17]]

In [230]: print(classification_report(y_test,rfc_pred))

          precision    recall  f1-score   support

           0       0.57      0.40      0.47      10
           1       0.74      0.85      0.79      20

      macro avg       0.70      0.62      0.69      30
      weighted avg       0.68      0.70      0.68      30
```

## Applying K Nearest Neighbours Algorithm

```
In [317]: X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.25)

In [318]: from sklearn.neighbors import KNeighborsClassifier

In [319]: knn = KNeighborsClassifier(n_neighbors=1)

In [320]: knn.fit(X_train,y_train)

Out[320]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                               metric_params=None, n_jobs=None, n_neighbors=1, p=2,
                               weights='uniform')

In [321]: pred = knn.predict(X_test)

In [322]: from sklearn.metrics import classification_report,confusion_matrix

In [323]: print(confusion_matrix(y_test,pred))

[[ 4  2]
 [ 5 14]]
```

```
In [321]: pred = knn.predict(X_test)

In [322]: from sklearn.metrics import classification_report,confusion_matrix

In [323]: print(confusion_matrix(y_test,pred))

[[ 4  2]
 [ 5 14]]
```

---

```
In [324]: print(classification_report(y_test,pred))
```

	precision	recall	f1-score	support
0	0.44	0.67	0.53	6
1	0.88	0.74	0.80	19
micro avg	0.72	0.72	0.72	25
macro avg	0.66	0.70	0.67	25
weighted avg	0.77	0.72	0.74	25

### Applying SVM with Grid Search

```
In [334]: param_grid = {'C': [0.1, 1, 10, 100, 1000], 'gamma': [1, 0.1, 0.01, 0.001, 0.0001], 'kernel': ['rbf']}

In [335]: from sklearn.model_selection import GridSearchCV

In [336]: grid = GridSearchCV(SVC(),param_grid,refit=True,verbose=3)

In [337]: grid.fit(X_train,y_train)
```

C:\Users\Satin\Anaconda3\lib\site-packages\sklearn\model\_selection\\_split.py:1943: FutureWarning: You should specify a value for 'cv' instead of relying on the default value. The default value will change from 3 to 5 in version 0.22.  
warnings.warn(CV\_WARNING, FutureWarning)  
[Parallel(n\_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

Fitting 3 folds for each of 25 candidates, totalling 75 fits

```
[CV] C=0.1, gamma=1, kernel=rbf .....
```

```
[CV] ..... C=0.1, gamma=1, kernel=rbf, score=0.625, total= 0.0s
```

```
[CV] C=0.1, gamma=1, kernel=rbf .....
```

```
[CV] ..... C=0.1, gamma=1, kernel=rbf, score=0.625, total= 0.0s
```

```
[CV] C=0.1, gamma=1, kernel=rbf .....
```

```
[CV] ..... C=0.1, gamma=1, kernel=rbf, score=0.625, total= 0.0s
```

```
[CV] C=0.1, gamma=1, kernel=rbf .....
```

```
[CV] ..... C=0.1, gamma=0.1, kernel=rbf, score=0.625, total= 0.0s
```

```
[CV] C=0.1, gamma=0.1, kernel=rbf .....
```

```
[CV] ..... C=0.1, gamma=0.1, kernel=rbf, score=0.625, total= 0.0s
```

```
[CV] C=0.1, gamma=0.1, kernel=rbf .....
```

```
[CV] ..... C=0.1, gamma=0.1, kernel=rbf, score=0.625, total= 0.0s
```

```
[CV] C=0.1, gamma=0.1, kernel=rbf .....
```

```
[CV] ..... C=0.1, gamma=0.01, kernel=rbf, score=0.625, total= 0.0s
```

Activate Windows  
Go to Settings to activate

```
[CV] ..... C=0.1, gamma=0.001, kernel=rbf, score=0.625, total= 0.0s
[CV] C=0.1, gamma=0.001, kernel=rbf .....
[CV] C=0.1, gamma=0.001, kernel=rbf, score=0.63636363636364, total= 0.0s
[CV] C=0.1, gamma=0.0001, kernel=rbf .....
[CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.625, total= 0.0s
[CV] C=0.1, gamma=0.0001, kernel=rbf .....
[CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.625, total= 0.0s
[CV] C=0.1, gamma=0.0001, kernel=rbf .....
[CV] C=0.1, gamma=0.0001, kernel=rbf, score=0.625, total= 0.0s
```

```
In [338]: grid_predictions = grid.predict(X_test)
```

```
In [339]: print(confusion_matrix(y_test,grid_predictions))
```

```
[[ 2  8]
 [ 2 18]]
```

```
In [340]: print(classification_report(y_test,grid_predictions))
```

	precision	recall	f1-score	support
0	0.50	0.20	0.29	10
1	0.69	0.90	0.78	20
micro avg	0.67	0.67	0.67	30
macro avg	0.60	0.55	0.53	30
weighted avg	0.63	0.67	0.62	30

## CONCLUSION

- 1) Finally we came to the conclusion with the help of the various machine learning algorithms with their accuracy % that they are quiet well in predicting the test cases and future cases. And it will help us a lot to determine which factor is actually causing the patient to readmit. And by knowing that we'll try to fix that issue and the results would be fruitfull.
- 2) We also concluded that we can find the exact reason which is the major factor in the readmission of the patients in the hospital through the implementation of the SQL on the dataset. With the help of the SQL we will be finding the average and the factor which will be having the highest average will be the main reason behind the readmission of the patients in the hospital.

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