PROJECT REPORT

TEAM ID	PNT2022TMID27276
PROJECT TITLE	ANALYTICS OF HOSPITAL HEALTH CARE DATA

TEAM MEMBERS:

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Tahsin Ansari I (Team Member 1)

Mohammed Sameer ali (Team Member 2)

dinesh (Team Member 3)

CHAPTER 1

INTRODUCTION

This project is about the anlytics for hospital health care data using data analytics. Data Analytics is the process of examining data sets in order to fnd trends and draw conclusions about the information they contain. The data anlytics is done with the specilized systems and soft ware. Data anlytics technologies and techniques are widely used in commercial industriesto enable organizations to make more informational businees disisions.

1.1 PROJECT OVERVIEW

Recent Covid-19 pandemic has raised alarms over one of the most overlooked
areas to focus
Example: Health care Management

While health care management has various use cases for using datascience,patient length of stay in one critical parameter to observe and predict if one wants to improve the efciencyof health care management in a hospital.

This parameter helps hospitals to identify patients of high LOS risk (patients who stay longer) at the time of admission. once identifed patients with high LOS risk can have their treatment plan optimized to minimizeLOS and lower the chance of staff/visitors infection. Also prior knowledge of Los can aid in logistics such as room and bed allocation planning.

Suppose you have been hired as Data Scientist of Health Man -not for proft organization dedicated to manage the functioning of hospitals in a professional and optimal manner.

1.2 PURPOSE

Data anlytics in health care is vital. It healps healyh care organizations to evaluate and develop practitioners, detect anomalies in scans and predict out breaks in illness, per the Harvard Businees School. Data Analytics can also lower costs for health care organizations and boost business intelligence . Hospital data anlytics can look over patient data and any prescribed medication to alert doctors and patients of incorrect dossages or wrong prescriptions, which lessens human error and the cost to your hosptital. This in turn helps in ganing better insights znd also enables healthcare practitioners to make well-informed decisions

CHAPTER 2

LITERATURE SURVEY

The main aim of this paper is to provide a deep anlytics on the research feild of healthcare data anlytics, This is analyzing the previous studies and works in this research area ,as well as highlighting some of the guidelines and gaps. This study has used seven popular databases and selected most relevent papers ,in order to conduct this paper . The paper has listed some of thedata anlytics tools and techniques that have been used to improve healthcare performance in many areas such as medical operators ,decision making reports ,predction and prevention system. Moreover, the systematic review has showed an interesting demo graphic of felds of publication ,research approaches,as well as outlined some of the possible reasons and issues associate with health care data anlytics ,based on geographical distribution theme[1]

This paper deals with advanced analytical methods to focus on healthcare. This includes the clinical prediction models ,temporal data mining methods,and visual anlytics . Integrating hetrogeneous data such as clinical and geonomic data is essential for improving retrivel techniques that can enhance the quality of biomedical search will be presented . Data publishing techniques that can enhance the quality of biomedical search will be presented. Data privacy is an extreamely important concern in healthcare . Privacy-preserving data techniques will therefore be presented [2].

One of the promises of growing critical mass of clinical data accumulating in electronic health reccord(EHR) system is secondary use or it may be reuse of data for other purpose ,such as quality improvement and clinical research .(1)The growthofsuch data has increased dramatically in recent years due to incentives for EHRadoption in the US funded by the Health Information Technology for EconomicandClinical Health (HITECH) Act (2). In the meantime, there has also seen substantial growth in other kinds of health-related data, most notably through effortstosequence genomes and other biological structures and functions(3). The analysisofthis data is usually called analytics (or data analytics). This chapter will defnetheterminology of this feld, provide an overview of its promise, describe what workhas been accomplished, and list the challenges and opportunities going forward[3].

Clinicians, healthcare providers-suppliers, policy makers and patientsareexperiencing exciting opportunities in light of new information deriving fromtheanalysis of big data sets, a capability that has emerged in the last decades. Duetothe rapid increase of publications in the healthcare industry, we have conductedastructured review regarding healthcare big data analytics. With referencetotheresource-based view theory we focus on how big data resources are utilizedtocreate organization values/capabilities, and through content analysis of the selectedpublications we discuss: the classifcation of big data types related to healthcare, the associate analysis techniques, the created value for stakeholders, the platformsand tools for handling big health data and future aspects in the feld. We present anumber of pragmatic examples to show how the advances in healthcare weremadepossible. We believe that the fndings of this review are stimulating andprovidevaluable information to practitioners, policy makers and researchers whilepresenting them with certain paths for future research[4].

In this modern techno-world, the term data is unavoidable and certainly, nothing is possible without its usage. The trends about how to analyze the dataarethe need of the hour. Data analytics is becoming a future escalating tool of all industries including medicine, robotics, etc. This article briefy explains howdataanalytics is used in healthcare systems. Health care is the process of maintainingand improving the health of an individual by preventing, diagnosing andtreatingthe diseases, illness and other physical and mental imbalances in people. Dataanalytics is classifed into four types and they are descriptive, diagnostic, predictiveand prescriptive analysis. Health care makes use of prescriptive analysis toarriveatthe best results and make better decisions. Big data plays a major roleindataanalytics. It helps the data analysts to collect data from the patients and storethemefciently. After the completion of this whole article, the reader will be abletogetthe collective idea about health care analytics.[5]

2.1 EXISTING SYSTEM

- The already existing model is trained with minimal parameters
- Low accuracy in prediction
- No feature extraction done
- High complexity

2.2 REFERENCES

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[2]. From:"Book of Data Analytics" Chandank Reddy(Wayne State University) CharuC.Aggarwal(Watson Research Center)

[3]. From: Hoyt,RE,Yoshihashi,A,Eds.(2014).Health Informatics:Practical GuideforHealthcare and formation Technology Professionals,SixthEdition.Pensacola,FL,Lulu.com.

[4]. Panagiota Galetsia , Korina Katsaliakia , Sameer Kumarb, a School ofEconomics, Business Administration & Legal Studies, International HellenicUniversity, 14th km Thessaloniki-N. Moudania, Thessaloniki, 57001, GreecebOpusCollege of Business, University of St. Thomas Minneapolis Campus, 1000LaSalleAvenue, Schulze Hall 435, Minneapolis, MN 55403, USA

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[16]. J. Rapoport, D. Teres, Y. Zhao, S. Lemeshow Length of stay data as a guidetohospital economic performance for icu patients Med Care, 41 (3) (2003), pp. 386- 397

2.3 PROBLEM STATEMENT AND DEFINITION

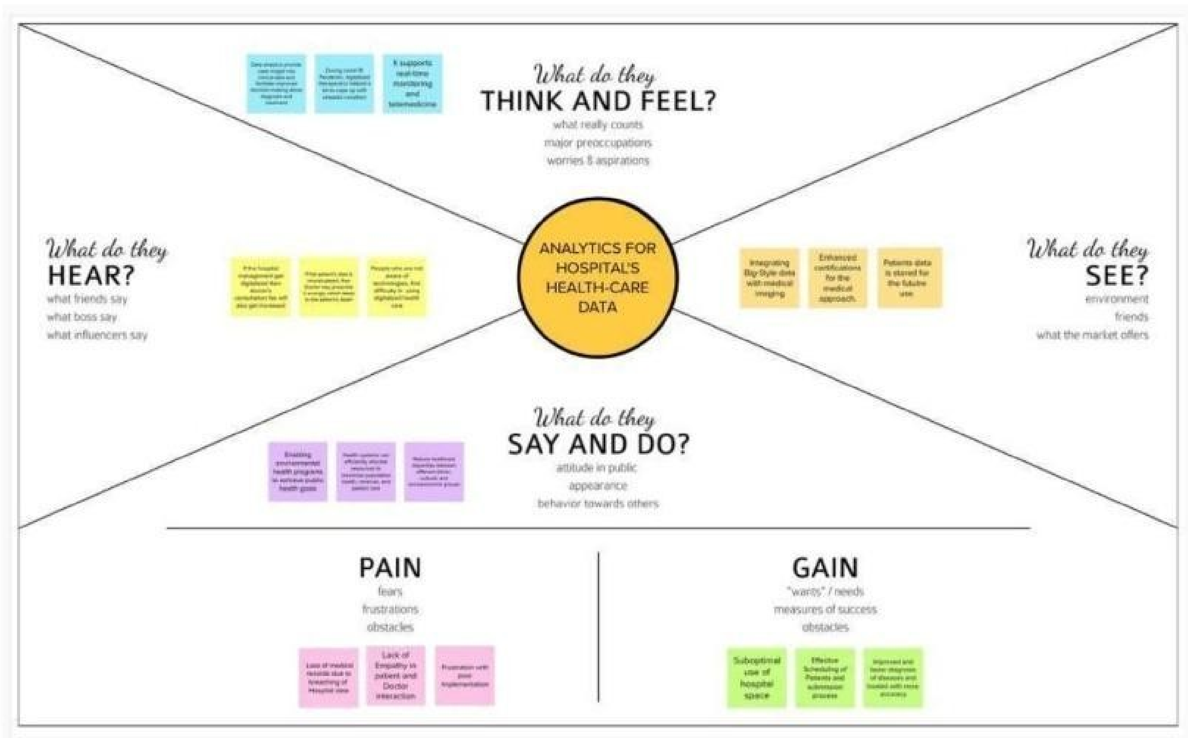
- The aim is to accurately predict the Length of Stay for each patient oncasebycase basis so that the Hospitals can use this information for optimal resourceallocation and better functioning.

- The length of stay is divided into 11 different classes ranging from0-10daysto more than 100 days

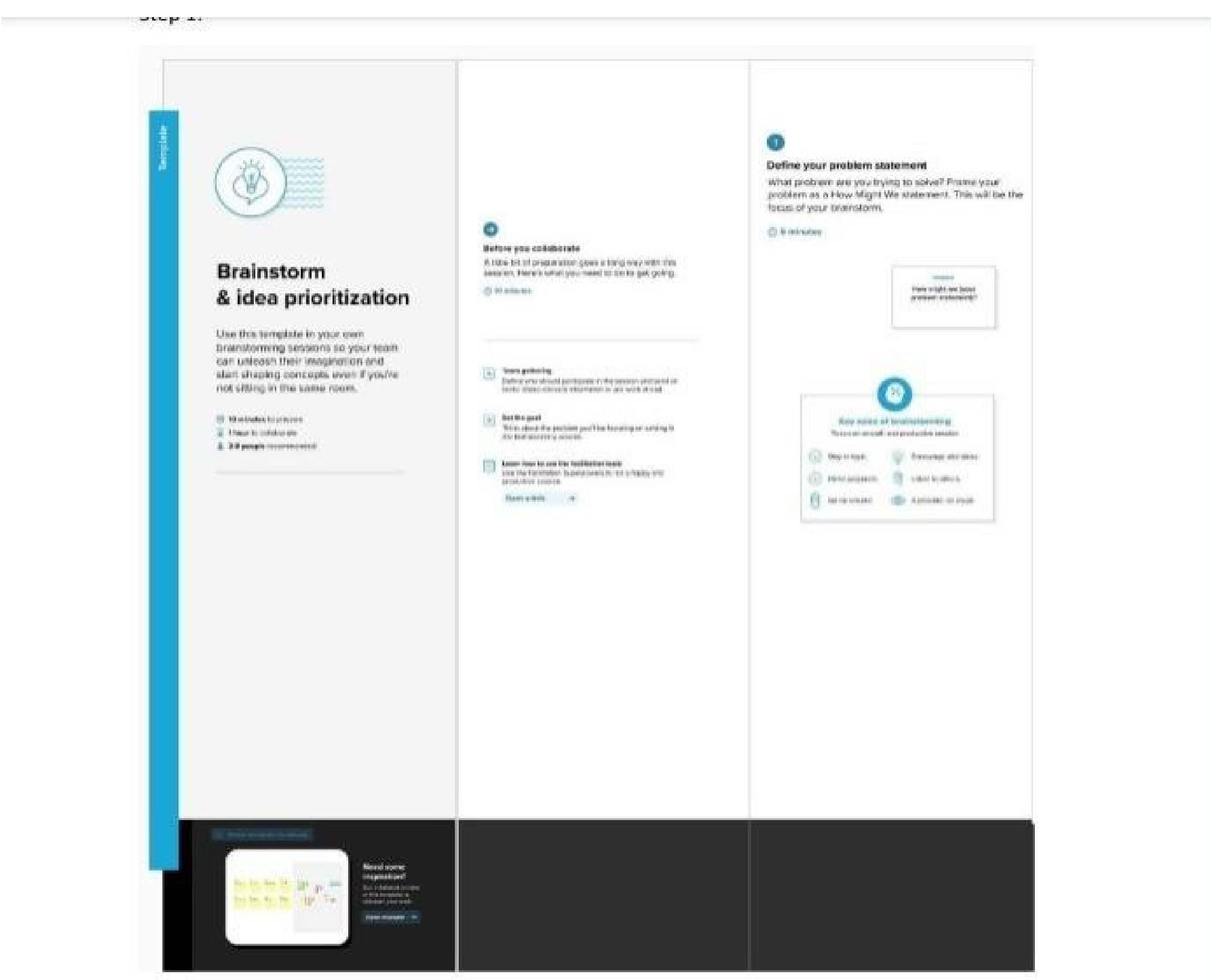
CHAPTER 3

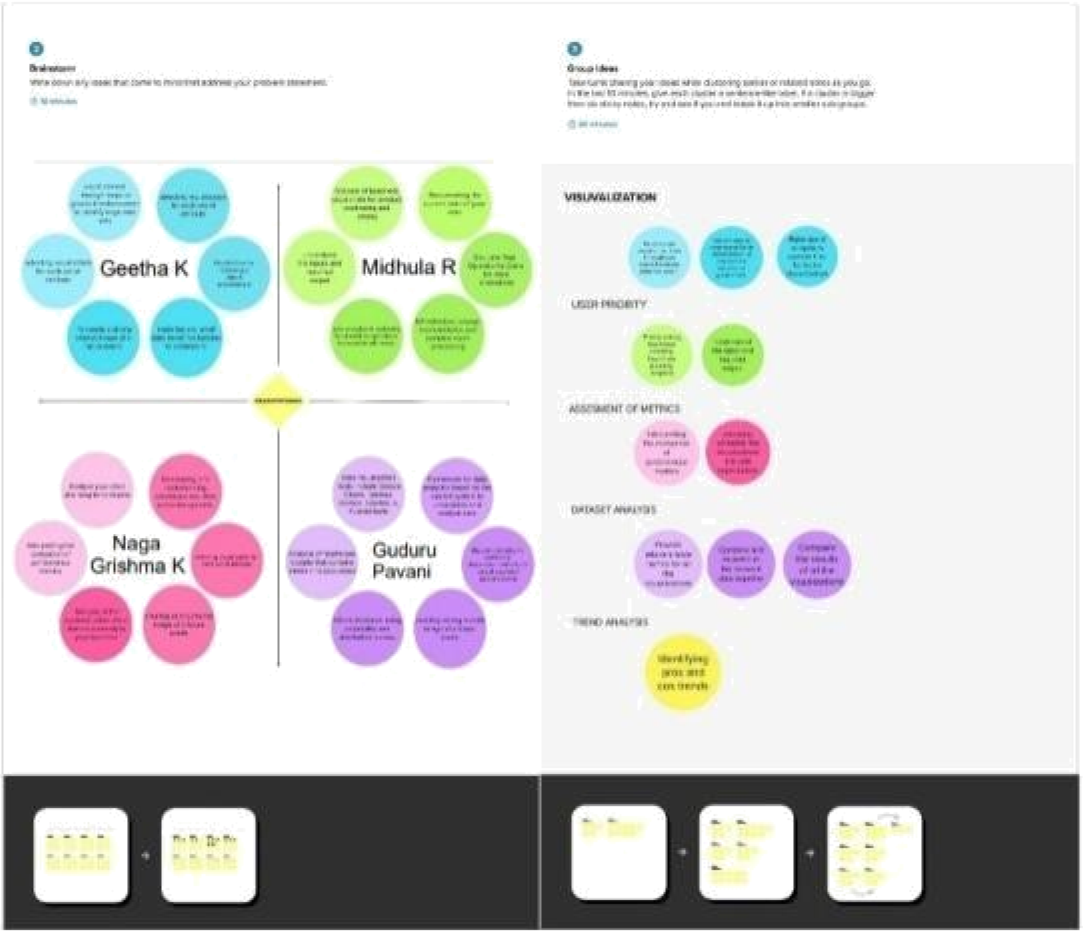
IDEATION & PROPOSED SOLUTION

3.1 EMPATHY MAP CANVAS



3.2 IDEATION & BRAINSTORMING





Brainstorm
Group ideas
Geetha K
Midhula R
Naga Grishma K
Guduru Pavani
VISUVALIZATION
USER PRIORITY
ASSESMENT OF METRICS
DATASET ANALYSIS
TREND ANALYSIS
Identifying pros and cons trends

Prioritize
Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible.
Provide relevant lable names for all the visualizations
Make sure to choose correct attributes such as color for representation
Identifying pros and cons trends
Combine and visualize all the relevant data together
Select the required dashboard needed for visualization
Checking whether the visualizations are upto expectations
Choose the appropriate chart type for the data
Make sure to choose correct attributes such as color for respresentation
Recognize positive and negative movement
Importance
Feasibility
After you collaborate
You can export the mural as an image or pdf to share with members of your company who might find it helpful.
Quick add-ons
Keep moving forward

3.3 PROPOSED SOLUTION

Predicting the length of stay of patients.

The length of the stay can be predicted using either Randomforest orDecision Tree for more accuracy. Certain parameters like age, stageof thediseases, disease diagnosis, severity of illness, type of admission, facilitiesallocated, etc., are used for prediction. IBM Cognos will be used for data analytics.

The model will be trained using colab.It predicts the length of stay (LOS) of the patients with more accuracy. As a result proper resources and therapy canbeprovided.Patients can get proper treatment and better medical care thanbeforewhich helps them for their faster recovery. So the prediction minimizestheoverfow of patients and helps in resource management and optimizetheirresource utilization. Hence this leads to faster recovery and lower the expensesfortreatment. It improves the trust in hospital management**.**

It avoids the major risk of spreading infection among the hospital staff. Thisleads to overall safety of hospital staff and patients. Resource consumptionisoptimized. This model can be used by all government hospitals, private hospitals, and this model is also trained with the real world hospital survey for betterprediction small clinics. Length of the stay will be predicted with more accuracy. This model predictsthe length of the stay for all kinds of patients and predicts with more accuracy

3.4 PROBLEM SOLUTION

1. CUSTOMER SEGMENT(S)

- Patients
- Hospital Management

6. CUSTOMER STATE LIMITATIONS

- Inadequate information about availability of required resource

5. AVAILABLE SOLUTIONS

- Tableau cloud
- Text Mining
- Information Retrieval

2. PROBLEMS / PAINS

- Effective Resource allocation
- Reduce Waiting time for patients in Hospitals

9. ROOT / CAUSE
of every problem

- No proper system or less efficient Prediction System

7. BEHAVIOR

Tracking the information with the available Technologies

3. TRIGGERS TO ACT

- Covid Pandemic
- Emergency Situations

4. EMOTIONS

- BEFORE: Feeling bad & Frustrated
- AFTER: Feeling better &Relaxed

10. YOUR SOLUTION

Existing: ratio of discharges in given period of time to no. of beds in hospital during the time period

Proposing: Using predictive analysis powered by AI

8. CHANNELS OF BEHAVIOR

ONLINE: Use of data from all region(data Exploration)

OFFLINE: Use of data Collect from nearby facilities

CHAPTER 4

REQUIREMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENT

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	Collect data	Data from various sources are collected using different methods in order to provide optimized results.
FR-2	Data Cleaning and Wrangling	When combining multiple data sources, there are many opportunities for data to be duplicated or mislabeled hence we cleanse the data
FR-3	Creating data model	The process of analyzing and defning all the data, as well as the relationships between those bits of data comes under this.
FR-4	Prediction and Analysis	The hidden trends are analyzed and the fnal results are predicted using machine learning and AI algorithms.

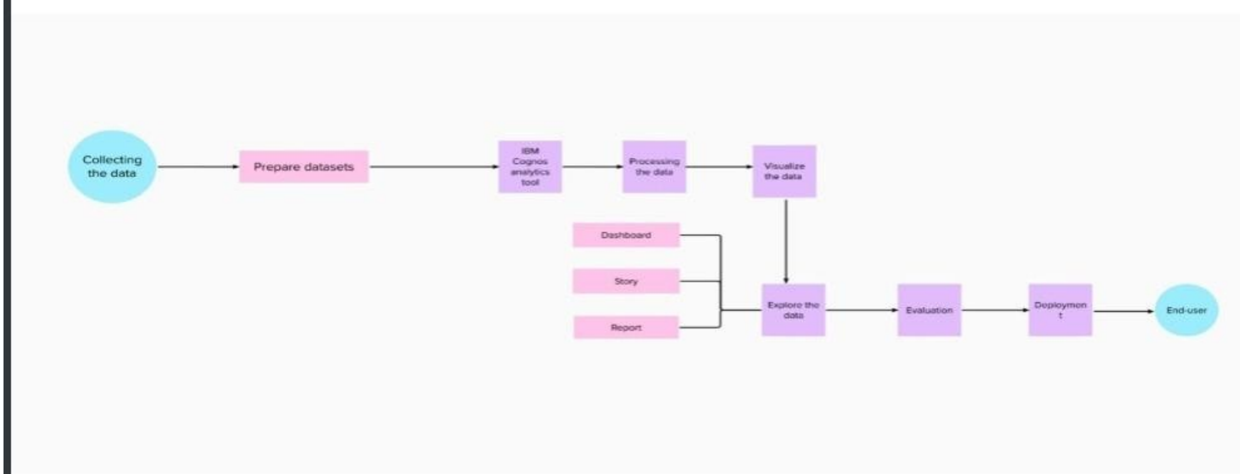
4.2 NON FUNCTIONAL REQUIREMENT

FR No	Non-Functional Requirement	Description
NFR-1	Usability	The project must be easy to use. The user needs to have a good experience while working with the interface.
NFR-2	Security	Every user can access the website only if they posses the password. The database is secured with encryption techniques which provides high levels of security
NFR-3	Reliability	The project must have minimal degree of failure under normal usage and how often does the user get access to this work
NFR-4	Performance	The project must respond quickly to the user's actions or even if the user has to wait the waiting period must be short.
NFR-5	Availability	The project is platform independent. It runs perfectly on almost every platform
NFR-6	Scalability	The project allows multiple users to handle the data at the same time. It is highly scalable since adding features and making advancements in the website is uncomplicated.

CHAPTER 5

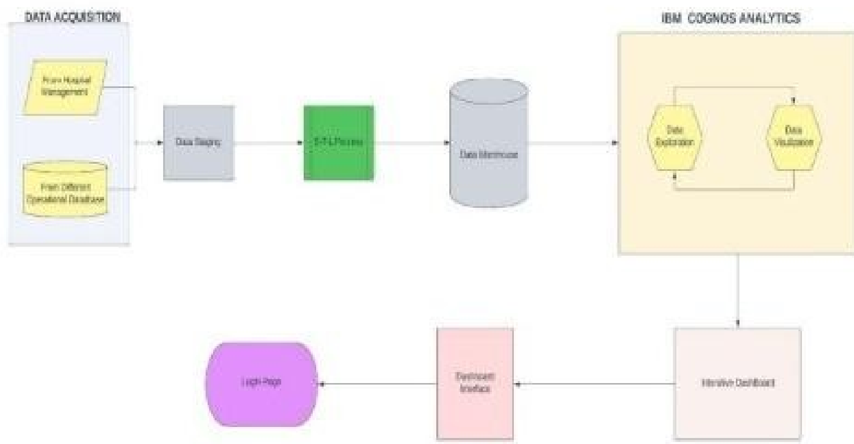
PROJECT DESIGN

5.1 DATA FLOW DIAGRAMS

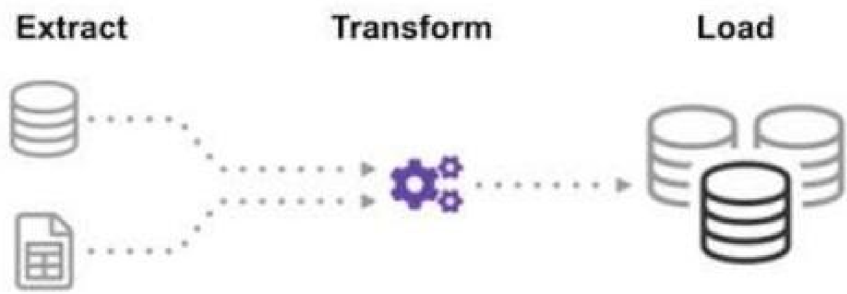


5.2 SOLUTION & TECHNICAL ARCHITECTURE

SYSTEM ARCHITECTURE:



ETL PROCESS (DATA INTEGRATION PROCESS):



5.3 USER STORIES

User Stories

Use the below template to list all the user stories for the product.

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Web user)		USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	I can access my account / dashboard	High	Sprint-1
		USN-2	As a user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	As a user, I can register for the application through Gmail	I can register & access the dashboard	Medium	Sprint-1
	Login	USN-4	As a user, I can log into the application by entering email & password	I can access the dashboard	High	Sprint-1
	Dashboard	USN-5	As a user, I can upload the datasets to the dashboard	I can access various operations	High	Sprint-1
	View	USN-6	As a user, I can view the patient details	I can view the visual data and the result after the prediction	High	Sprint-2
Admin	Analyse	USN-7	As an admin, I will analyse the given dataset	I can analyse the dataset	High	Sprint-2
	Predict	USN-8	As an admin, I will predict the length of stay	I can predict the length of stay	High	Sprint-2

CHAPTER 6

PROJECT PLANNING & SCHEDULING

6.1 SPRINT PLANNING & ESTIMATION

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Registration	USN-1	As a health care provider I can create account in IBM cloud and the data arecollected.	20	High	Geetha K Midhula R
Sprint-2	Analyze	USN-2	As a health care provider all the data thatare collected is cleaned and uploaded in the database or IBM cloud.	20	Medium	Naga grishma K Guduru pavani
Sprint-3	Dashboard	USN-3	As a health care provider I can use my account in my dashboard for uploading dataset.	10	Medium	Midhula R Guduru pavani
Sprint-3	Visualization	USN-4	As a health care provider I can prepare data for Visualization.	10	High	Midhula R Naga grishma K
Sprint-4	Visualization	USN-5	As a health care provider I canpresent data in my dashboard.	10	High	Geetha K Naga grishma K
Sprint-4	Prediction	USN-6	As a health care provider I can predict the length of stay	10	High	Geetha K Guduru pavani

6.2 SPRINT DELIVERY SCHEDULE

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date(Actual)
Sprint-1	20	6 Days	24 Oct 2022	29 Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	20	05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

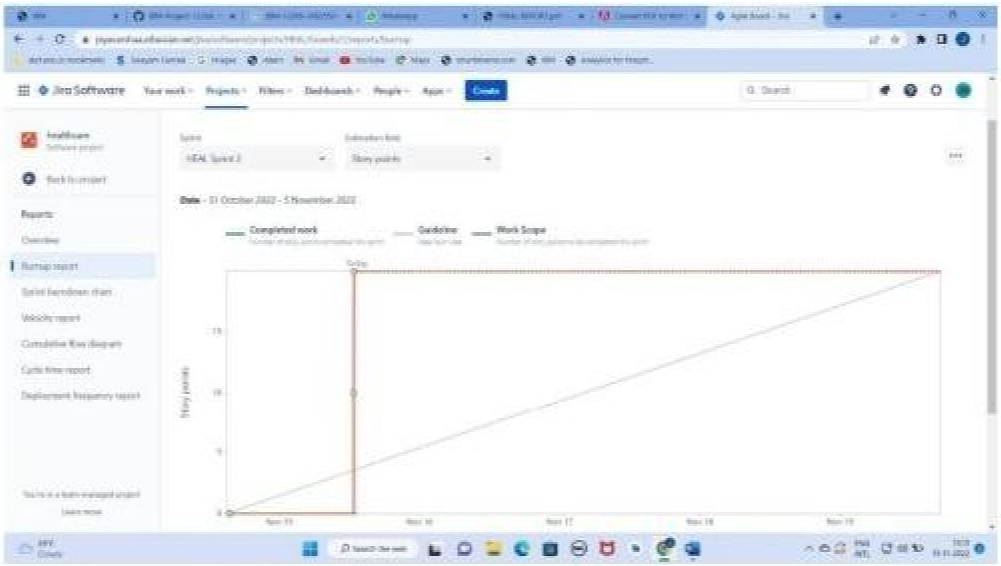
Velocity:

Imagine we have a 10-day sprint duration, and the velocity of the team is 20 (points per sprint). Let's calculate the team's average velocity (AV) per iteration unit (story points per day)

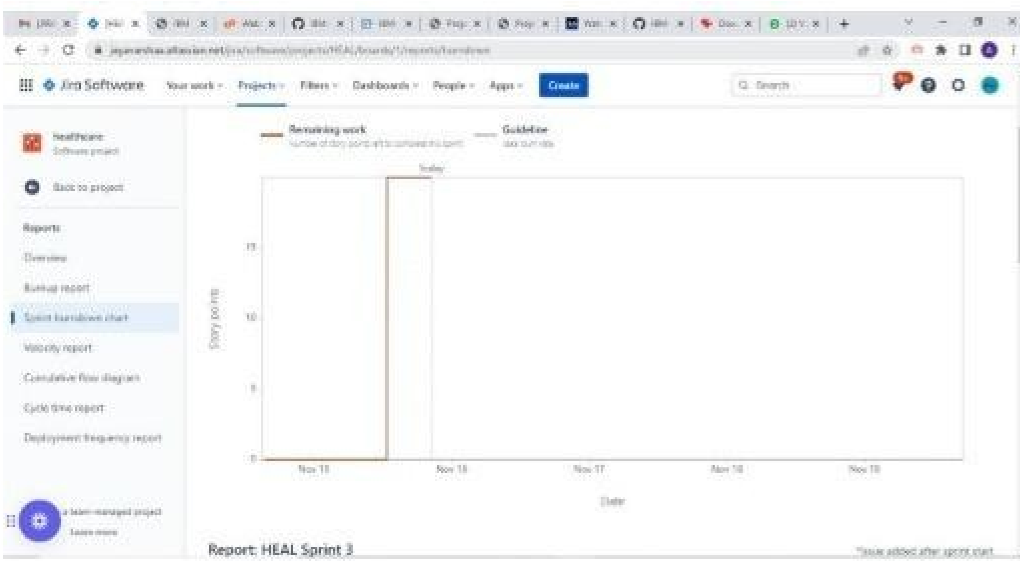
$$AV = \frac{sprint\ duration}{velocity} = \frac{20}{10} = 2$$

6.3 REPORTS FROM JIRA

Burnup chart



Burn down chart



CHAPTER 7

CODING & SOLUTIONING

7.1 FEATURE 1

- Fetched the data from DB2 database.
- Creating responsive dashboard.
- Inserting flter for each chart
- Creating report
- Created reports using multiple graphs and charts

7.2 FEATURE 2

- Creating stories and performed.
- Perform animation render image from website.
- Included graphs and charts.
- Creating web application using bootstrap.
- Embedded the cognos with web application.

7.3 Database Schema

- case_id
- Hospital_code
- Hospital_type_code
- City_Code_Hospital
- Hospital_region_code
- Available Extra Rooms in Hospital
- Department
- Ward_Type
- Ward_Facility_Code
- Bed Grade
- Patient id
- City_Code_Patient
- Type of Admission
- Severity of Illness
- Visitors with Patient
- Age
- Admission_Deposit
- Stay

CHAPTER 8

TESTING

8.1 Test Cases

- ◊ Verify user is able to see Home page.
- ◊ Verify user is able to see Dashboard page.
- ◊ Verify user is able to navigate to Report page.
- ◊ Verify user is able to navigate to story page.
- ◊ Verify flters are working

8.2 User Acceptance Testing

1. Purpose of Document

The purpose of this document is to briefly explain the test coverage and open issues of the [ProductName] project at the time of the release to User Acceptance Testing (UAT).

2. Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and how they were resolved

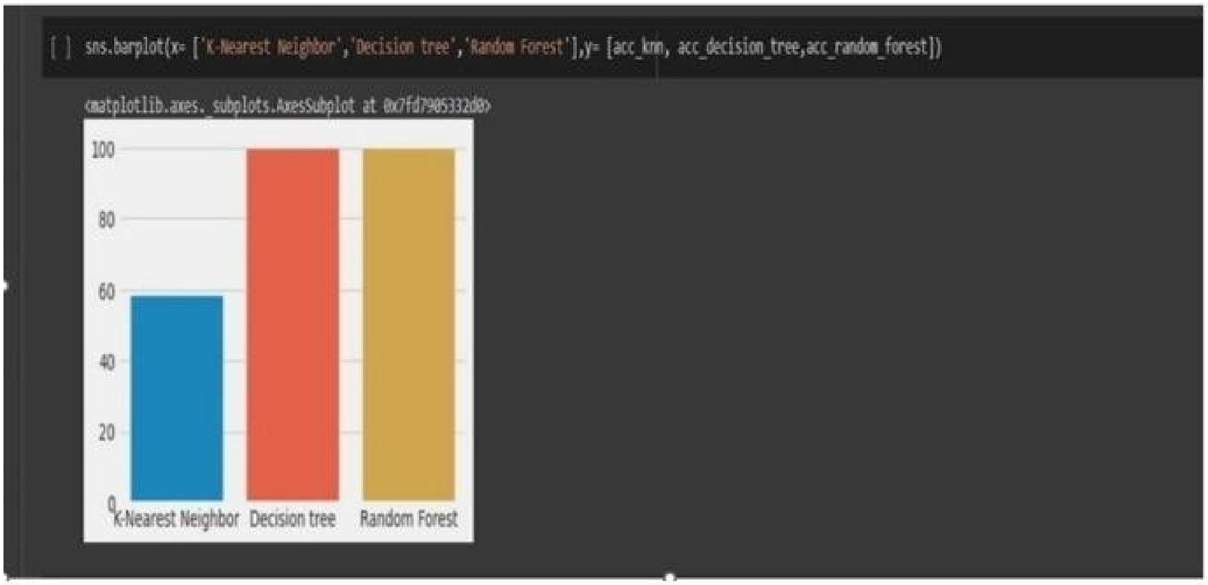
Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	8	5	0	3	16
Duplicate	1	0	5	0	6
External	0	3	2	1	6
Fixed	13	4	3	16	36
Not Reproduced	0	1	0	0	1
Skipped	0	1	0	1	2
Won't Fix	1	4	2	1	8
Totals	23	18	12	22	75

3. Test Case Analysis

This report shows the number of test cases that have passed, failed, and untested

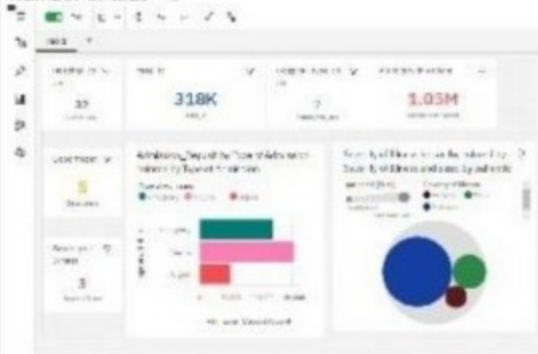
Section	Total Cases	Not Tested	Fail	Pass
Print Engine	9	0	0	9
Client Application	43	0	0	43
Security	1	0	0	1
Outsource Shipping	1	0	0	1

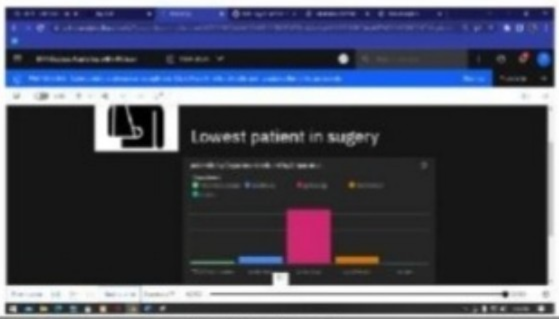
CHAPTER 9
RESULTS
9.1 PERFORMANCE METRICS



Model Performance Testing:

Project team shall fill the following information in model performance testing template.

S.No.	Parameter	Screenshot/ Values
1.	Dashboard design	Number of Visulizations / Graphs – 22 Number of tabs – 8 
2.	Data Responsiveness	Data's will dynamically changed and graph also changed. 
3.	Amount Data to Rendered (DB2 Metrics)	Number of rows read – 318438 Number of rows loaded – 318438 Number of rows rejected – 0 

4.	Utilization of Data Filters	We created filters for Dashboards which is perfectly working. 
5.	Effective User Story	Number of Scene Added – 7 Animations are perfectly displayed. Images are perfectly rendered. 
6.	Descriptive Reports	Number of Visulizations / Graphs – 6

CHAPTER 10

ADVANTAGES AND DISADVANTAGES

ADVANTAGES

- Cost-effective use of technology
- Improved project management
- Sustaining the improvements in the result
- Boosting hospital capacity
- Enhance the quality and efciency of healthcare
- beneft areas like emergency preparation, charting, administration, compliance, and fnancial management.
- Analysing clinical data to improve medical research
- Using patient data to improve health outcomes
- Gaining operational insights from healthcare provider data
- Improved stafng through health business management analytics
- Early detection of disease.
- Prevention of unnecessary doctor's visits.
- Discovery of new drugs.
- More accurate calculation of health insurance rates.

- More effective sharing of patient data

DISADVANTAGES

- Privacy
- Replacing Doctors
- Frustration with poor implementation.
- Cybersecurity risks
- Healthcare Regulatory Changes.
- Healthcare Stafng Shortages

CHAPTER 11
CONCLUSION

The impact of data analytics in healthcare has already made a substantial difference in the ability of healthcare providers to offer patients high-quality careinan efcient, cost-effective manner.

However, the role of data analytics in improvingpatient outcomes and healthcare processes continues to grow and expandas moretypes of data become available and new tools are developed that make the resultsof the analytics clear and easy for healthcare professionals to access.

Realizing the potential of data analytics to transform the healthcare industrybegins by understanding how the technology can be applied to address healthcareproviders' challenges, including staff recruitment and utilization, operational efciencies, and enhanced patient experiences. Patient-centered healthcaredepends on knowing what patients want and need. Data analytics holds thekeytounlocking this vital information.

CHAPTER 12
FUTURE SCOPE

Artifcial Intelligence (AI) will play a signifcant role in data analyticsinhealthcare for the next decade. For example, the feld of AI-enabled clinical decisionsupport is just emerging.

This type of support can compare patients who ft similarprofles within a system, then it can alert doctors to trends in data that mayhavebeen overlooked. The use of big data in healthcare will include testingfor druginteractions that small studies are unlikely to catch and prevent patients fromtaking harmful drug combinations.

Decisions made by physicians, like what test or treatments to giveaparticular patient, makeup 80-90% of all healthcare spending, so usingartifcial intelligence to make more educated decisions will bring down healthcare costs. It'scrucial to have informed leaders at the vanguard of these innovations in healthcare.

CHAPTER 13
APPENDIX

SOURCE CODE

HOME PAGE

```
<!DOCTYPE
html>
<html lang="en">
<head>
    <title>Data Analytics</title>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width, initial-scale=1"> <link rel="stylesheet"

href="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/css/bootstrap.min.css"> <script
    src="https://ajax.googleapis.com/ajax/libs/jquery/3.6.0/jquery.min.js">< <script
    src="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/js/bootstrap.min.js
</head>
<body>

<nav class="navbar navbar-inverse">
    <div class="container-fluid">
        <div class="navbar-header">
            <a class="navbar-brand" href="#">Analytics for Hospitals' Health-Care Data</ </div>

        <ul class="nav navbar-nav">
            <li class="active"><a href="#">Home</a></li>
            <li><a href="dashboard.html">Dashboard</a></li>
            <li><a href="report.html">Report</a></li>
            <li><a href="story.html">Story</a></li>
        </ul>
    </div>
</nav>

<div class="jumbotron">
  <center> <h4><i><b>Team ID : PNT2022TMID28558</b></i></h4></center>

</div>
<table class="table table-bordered">

        <tbody>
            <tr>
                <td>Team Leader</td>
                <td>Pradeep rajal</td>

            </tr>
            <tr>
```

```
            <td>Team member</td>
            <td>Tahsin Ansari I </td>

          </tr>
          <tr>
            <td>Team member</td>
            <td>Mohammed Sameer ali</td>

          </tr>
              <tr>
            <td>Team member</td>
            <td> dinesh m</td>

          </tr>
        </tbody>
    </table>
</body>
</htm
```

DASHBOARD

<!DOCTYPE html>

```
<!DOCTYPE html>
<html lang="en">
<head>
<title>Data Analytics</title>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width, initial-scale=1">
    <link         rel="stylesheet"         href="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/css         <script
    src="https://ajax.googleapis.com/ajax/libs/jquery/3.6.0/jquery.min.js"><                              <script
    src="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/js/bootstrap.min.js
</head>
<body>

<nav class="navbar navbar-inverse ">
    <div class="container-fluid">
        <div class="navbar-header">
            <a class="navbar-brand" href="#">Analytics for Hospitals' Health-Care Data</ </div>

        <ul class="nav navbar-nav">
```

```
<li><a href="index.html">Home</a></li>
<li class="active"><a href="#">Dashboard</a></li>
<li><a href="report.html">Report</a></li>
<li><a href="story.html">Story</a></li>
</ul>
</div>
</nav>

<div class="container">
<iframe

src="https://us1.ca.analytics.ibm.com/bi/?perspective=dashboard&amp;pathRef=.my_fo
00184774a03ac_00000002"
width="1500" height="1000" frameborder="0" gesture="media" allow="encrypted-medi </div>
```

REPORT

```
<!DOCTYPE
html>
<html lang="en">
<head>
<title>Data Analytics</title>
<meta charset="utf-8">
<meta name="viewport" content="width=device-width, initial-scale=1">
<link rel="stylesheet" href="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/css <script
src="https://ajax.googleapis.com/ajax/libs/jquery/3.6.0/jquery.min.js">< <script
src="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/js/bootstrap.min.js
</head>
<body>

<nav class="navbar navbar-inverse ">
<div class="container-fluid">
<div class="navbar-header">
<a class="navbar-brand" href="#">Analytics for Hospitals' Health-Care Data</ </div>

<ul class="nav navbar-nav">
<li><a href="index.html">Home</a></li>
<li><a href="dashboard.html">Dashboard</a></li>
<li class="active"><a href="#">Report</a></li>
<li><a href="story.html">Story</a></li>
</ul>
</div>
```

```
</nav>

<div class="container">
    <iframe

src="https://us1.ca.analytics.ibm.com/bi/?pathRef=.my_folders%2FReport%2FFinal%2BR ;action=edit"

        width="1550" height="1500" frameborder="0" gesture="media" allow="encrypted-me </br>


</div>

</body>
</html>
```

STORY

```
<!D
    OCT
    YPE
    htm
    l>
    <html lang="en">
    <head>
    <title>Data Analytics</title>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width, initial-scale=1">
    <link rel="stylesheet" href="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/css/bootstrap.m
    <script src="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/js/bootstrap.min.js"></script>
    </head>
    <body>
    <nav class="navbar navbar-inverse ">
    <div class="container-fluid">
    <div class="navbar-header">
    <a class="navbar-brand" href="#">Analytics for Hospitals' Health-Care Data</a> </div>

    <ul class="nav navbar-nav">
    <li><a href="index.html">Home</a></li>
    <li><a href="dashboard.html">Dashboard</a></li>
    <li><a href="report.html">Report</a></li>
    <li class="active"><a href="#">Story</a></li>
    </ul>
```

</div>

</nav>

<div class="container">

<iframe
src="https://us1.ca.analytics.ibm.com/bi/?perspective=story&pathRef=.my_folders%2Fstory%0000002&sceneTime=0"
width="1500" height="1000" frameborder="0" gesture="media" allow="encrypted-media"
allowfullscreen=""></iframe>

</div>

</body>

</html>

Importing required Packages

In [72]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
sns.set_style("darkgrid")
plt.style.use("dark_background")
```

Importing the dataset

In [73]:

```
train = pd.read_csv('/content/input/training_data.csv')
test = pd.read_csv('/content/input/testing_data.csv')
Paramters_Description = pd.read_csv('/content/input/parameter_description.csv')
sample = pd.read_csv('/content/input/testing_target.csv')
```

Viewing dataset

In [74]:

```
train.head(5)
```

Out[74]:

	case_id	Hospital_code	Hospital_type_code	City_Code_Hospital	Hospital_region_code	Available_Extra_Rooms_in_Hospital	Department	Ward_Type	Ward_Facility_Code	Bed_Grade
0	1	8	c	3	Z	3	radiotherapy	R	F	2.0
1	2	2	c	5	Z	2	radiotherapy	S	F	2.0
2	3	10	e	1	X	2	anesthesia	S	E	2.0
3	4	26	b	2	Y	2	radiotherapy	R	D	2.0
4	5	26	b	2	Y	2	radiotherapy	S	D	2.0

Dataset Column Description

```
Paramters_Description
```

	Column	Description
0	case_id	It is identity number given by hospital admini...
1	Hospital_code	It is the code (identity number) given to the ...
2	Hospital_type_code	It is the unique code given to the type of hos...
3	City_Code_Hospital	It is the code given to the city where the hos...
4	Hospital_region_code	It is the code given to the region where the h...
5	Available_Extra_Rooms_in_Hospital	It will display the number of rooms that are s...
6	Department	The department that is overlooking the patient...
7	Ward_Type	The unique code given to the type of ward to w...
8	Ward_Facility_Code	The unique code given to the facility in the w...
9	Bed_Grade	It is the quality or condition of the bed in t...
10	patientid	It is the unique identity value given to the p...
11	City_Code_Patient	It is the unique identity code given to the ci...
12	Type_of_Admission	It is the admission type registered in the hos...
13	Severity_of_Illness	It is the severity level of the patients' illn...
14	Visitors_with_Patient	Number of the visitors with the patients to ta...
15	Age	It is the age of patients. It is given in peri...
16	Admission_Deposit	It is the deposit amount that the patient paid...
17	Stay	It is the Length Of Stay (LOS) of patients. I...

Analysis of dataset

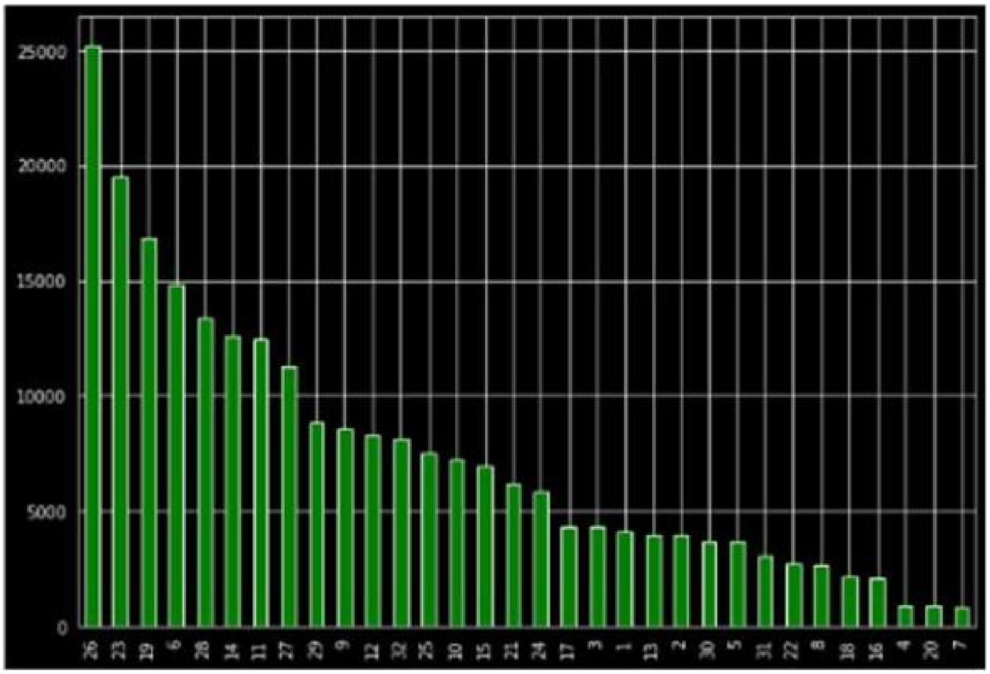
Distribution of values

Hospital_code

```
train.Hospital_code.value_counts()
```

```
26    25225
23    19505
19    16825
6     14847
28    13341
14    12594
11    12454
27    11312
29     8828
9      8558
12     8312
32     8166
25     7529
10     7257
15     6965
21     6226
24     5863
17     4319
3      4308
1      4111
13     3974
2      3940
30     3707
5      3684
31     3051
22     2740
8      2679
18     2164
16     2119
4       937
20      905
7       864
Name: Hospital_code, dtype: int64
```

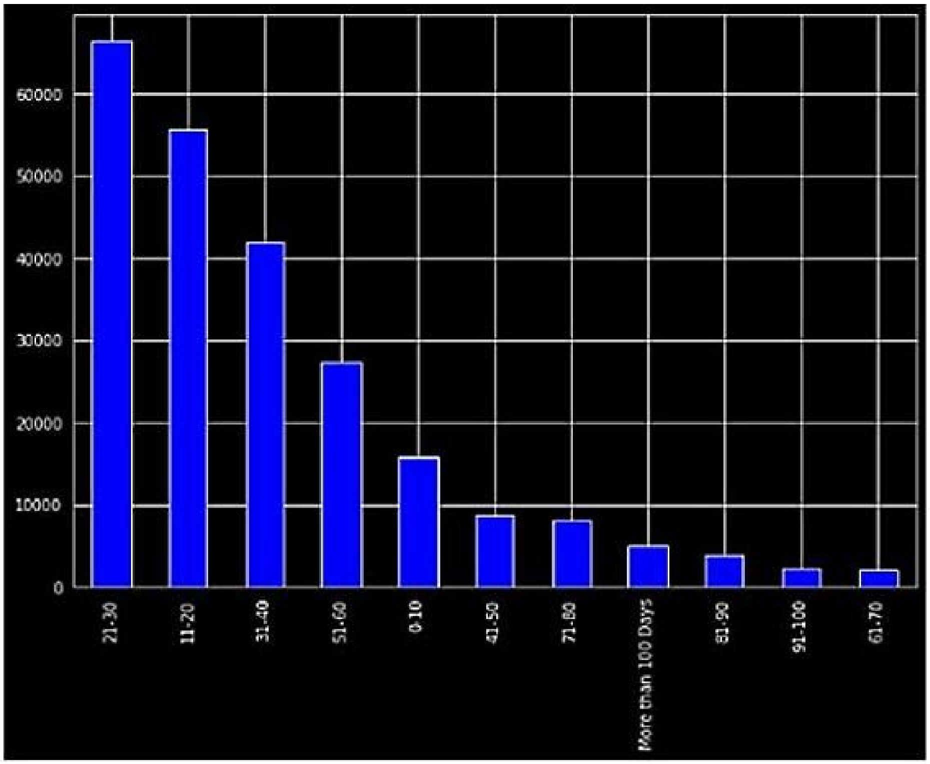
```
plt.figure(figsize=(10,7))
train.Hospital_code.value_counts().plot(kind="bar", color = ['green'])
```



Stay

```
train.Stay.value_counts()
```

```
21-30                 66497
11-20                 55691
31-40                 41951
51-60                 27458
0-10                  15866
41-50                  8665
71-80                  8061
More than 100 Days     5029
81-90                  3821
91-100                 2179
61-70                  2090
Name: Stay, dtype: int64
```



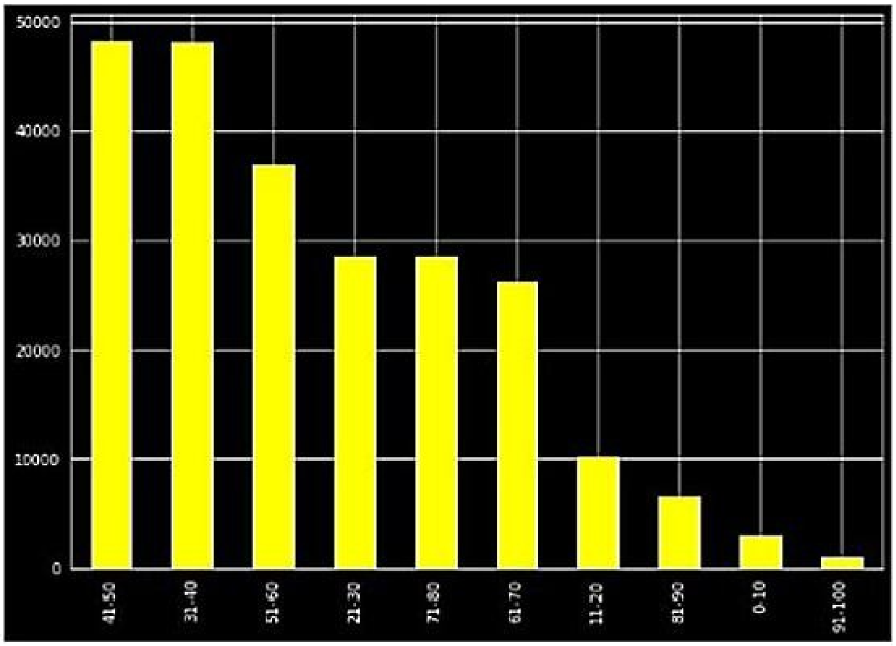
Age

```
train.Age.value_counts()
```

```
41-50     48272
31-40     48106
51-60     36969
21-30     28555
71-80     28552
61-70     26139
11-20     10141
```

```
81-90      6578
0-10       3030
91-100      966
Name: Age, dtype: int64
```

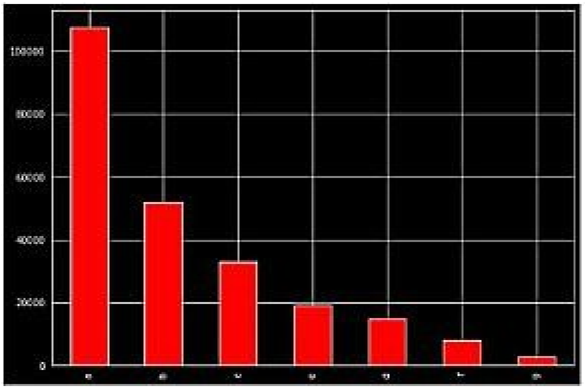
```
#Age distribution
plt.figure(figsize=(10,7))
train.Age.value_counts().plot(kind="bar", color = ['Yellow'])
```



Hospital_type_code

```
train.Hospital_type_code.value_counts()
```

```
a    107545
b     51925
```

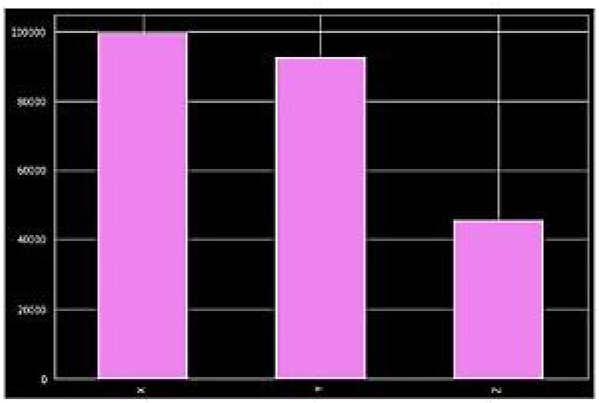


Hospital_region_code

```
train.Hospital_region_code.value_counts()
```

```
X    99568
Y    92214
Z    45527
Name: Hospital_region_code, dtype: int64
```

```
#Hospital_region_code distribution
plt.figure(figsize=(10,7))
train.Hospital_region_code.value_counts().plot(kind="bar", color = ["Violet"])
```



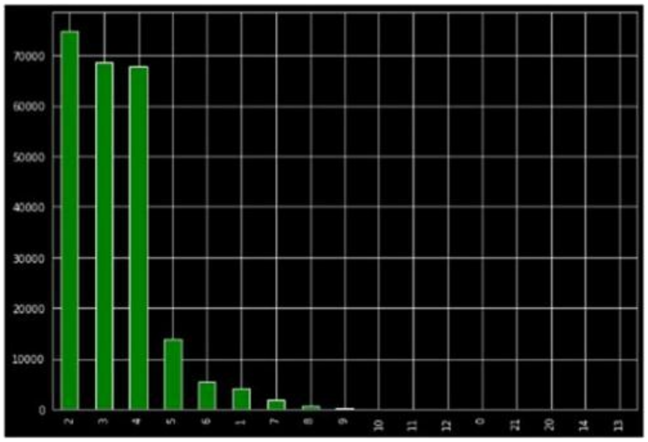
Available_Extra_Rooms_in_Hospital

```
train.Available_Extra_Rooms_in_Hospital.value_counts()
```

```
2     74877
3     68517
4     67756
5     13879
6      5344
1      4208
7      1876
8       622
9       144
10       46
```

```
11       13
12       11
0        11
21        2
20        1
14        1
13        1
Name: Available_Extra_Rooms_in_Hospital, dtype: int64
```

```
#Available_Extra_Rooms_in_Hospital distribution
plt.figure(figsize=(10,7))
train.Available_Extra_Rooms_in_Hospital.value_counts().plot(kind="bar", color = ['green'])
```



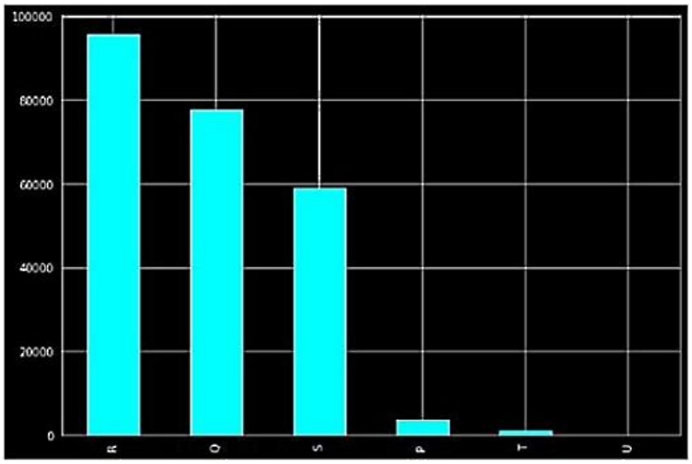
Department

```
train.Department.value_counts()
```

```
gynecology          185062
```

```
R    95788
Q    77707
S    59022
P     3691
T     1092
U        9
Name: Ward_Type, dtype: int64
```

```
#Ward_Type distribution
plt.figure(figsize=(10,7))
train.Ward_Type.value_counts().plot(kind="bar", color = ['cyan'])
```



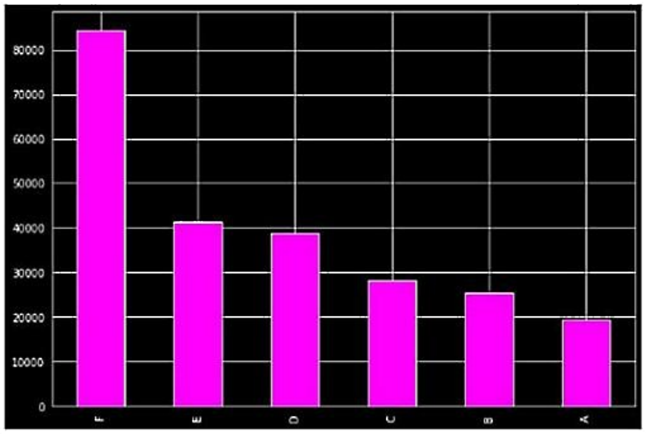
Ward_Facility_Code

```
train.Ward_Facility_Code.value_counts()
```

```
F    84438
E    41246
```

```
D    38584
C    28137
B    25493
A    19411
Name: Ward_Facility_Code, dtype: int64
```

```
#Ward_Facility_Code distribution
plt.figure(figsize=(10,7))
train.Ward_Facility_Code.value_counts().plot(kind="bar", color = ['magenta'])
```



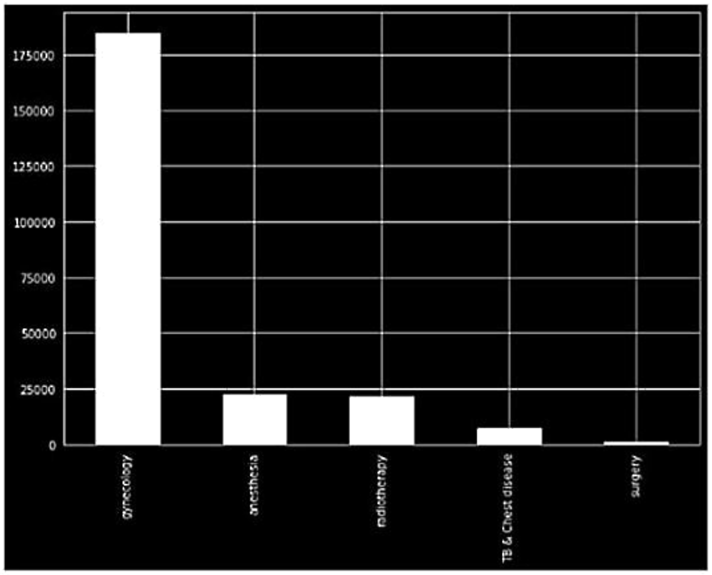
Visitors_with_Patient

```
train.Visitors_with_Patient.value_counts()
```

```
2.0     103037
4.0      59068
3.0      43860
6.0      14211
5.0       6992
```

```
anesthesia             22557
radiotherapy           21725
TB & Chest disease      7017
surgery                  948
Name: Department, dtype: int64
```

```
#Department distribution
plt.figure(figsize=(10,7))
train.Department.value_counts().plot(kind="bar", color = ['white'])
```

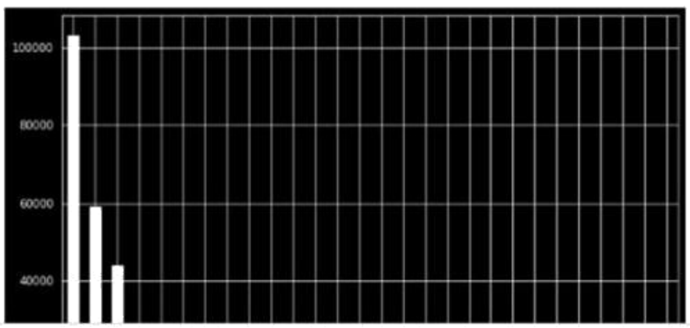


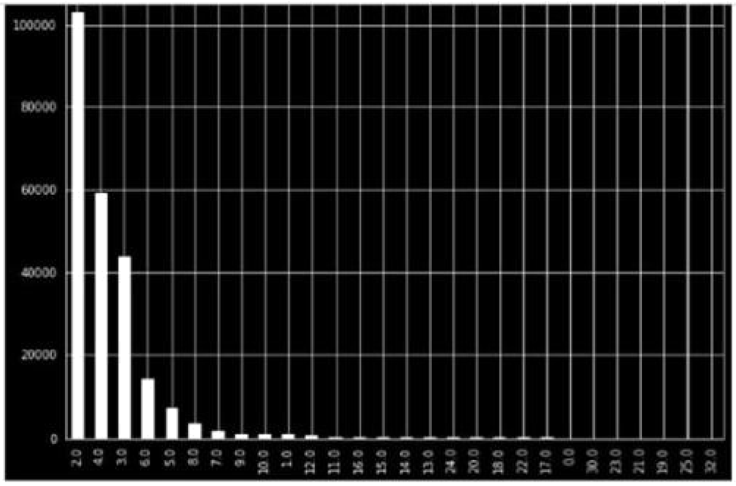
Ward_Type

```
train.Ward_Type.value_counts()
```

```
8.0       3662
7.0       1888
9.0       1024
10.0       882
1.0        871
12.0       757
11.0       242
16.0       220
15.0       146
14.0       138
13.0        84
24.0        63
20.0        46
18.0        35
22.0        16
17.0        15
0.0         13
30.0         9
23.0         8
21.0         8
19.0         6
25.0         6
32.0         1
Name: Visitors_with_Patient, dtype: int64
```

```
#Visitors_with_Patient distribution
plt.figure(figsize=(10,7))
train.Visitors_with_Patient.value_counts().plot(kind="bar", color = ['white'])
```



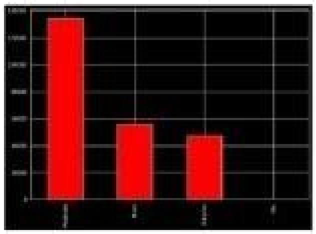


Severity of Illness

```
train.Severity_of_Illness.value_counts()
```

```
Moderate    134324
Minor        55665
Extreme      47319
Min              1
Name: Severity_of_Illness, dtype: int64
```

```
#Severity_of_Illness distribution
plt.figure(figsize=(10,7))
train.Severity_of_Illness.value_counts().plot(kind="bar", color = ['red'])
```



Unique values of columns

[illegible]

```
*------------------------------------------------------------------------------------------*
 Unique Values for City_Code_Patient
[ 7.  8.  2.  5.  6.  3.  4.  1.  9. 14. nan 25. 15. 12. 10. 28. 24. 23.
 20. 11. 13. 21. 18. 16. 26. 27. 22. 19. 31. 34. 32. 30. 29. 37. 33. 35.
 36.]
*------------------------------------------------------------------------------------------*

*------------------------------------------------------------------------------------------*
 Unique Values for Type_of_Admission
['Emergency' 'Trauma' 'Urgent']
*------------------------------------------------------------------------------------------*

*------------------------------------------------------------------------------------------*
 Unique Values for Severity_of_Illness
['Extreme' 'Moderate' 'Minor' 'Min']
*------------------------------------------------------------------------------------------*

*------------------------------------------------------------------------------------------*
 Unique Values for Visitors_with_Patient
[ 2.  4.  3.  8.  6.  7. 13.  5.  1. 10. 15. 11. 12.  9. 24. 16. 14. 20.
  0. 19. 18. 17. 23. 21. 32. 30. 22. 25. nan]
*------------------------------------------------------------------------------------------*

*------------------------------------------------------------------------------------------*
 Unique Values for Age
['51-60' '71-80' '31-40' '41-50' '81-90' '61-70' '21-30' '11-20' '0-10'
 '91-100' nan]
*------------------------------------------------------------------------------------------*

*------------------------------------------------------------------------------------------*
 Unique Values for Admission_Deposit
[4911. 5954. 4745. ... 2710. 2236.   nan]
*------------------------------------------------------------------------------------------*

*------------------------------------------------------------------------------------------*
 Unique Values for Stay
['0-10' '41-50' '31-40' '11-20' '51-60' '21-30' '71-80'
 'More than 100 Days' '81-90' '61-70' '91-100' nan]
*------------------------------------------------------------------------------------------*
```

Data Preprocessing & Feature Engineering

The following features may have relevance with the Length of Stay of a patient

Department: It Relates to the type of disease. Hence it will have impact on the length of stay of the patients

Type of Admission: It Relates to patients' reason of admission to the hospital and definitely it will have impact on length of stay opf the patients

Severity of Illness: It Relates to the curability of disease

Age: Relates to the curability of diseaseThe following features may have relevance with the Length of Stay of a patient

Department: It Relates to the type of disease. Hence it will have impact on the length of stay of the patients

Type of Admission: It Relates to patients' reason of admission to the hospital and definitely it will have impact on length of stay opf the patients

Severity of Illness: It Relates to the curability of disease

Age: Relates to the curability of disease

Ward_Type: Relates to the curability of disease

\

The following features doesn't have relevance with the Length Of Stay(LOS) of Patients

Hospital_region_code: It is code given to the hospital region which is irrelevent to the Length of Stay.

Bed Grade: It is the grade given to the quality of the bed in ward it is also irrelevent to the length of stay.

patientid: it is the identity number or code given for the identification of the patient which is irrelevant to the length of stay.

City_Code_Patient: It is the city code and irrelevant to the length of stay of patients.

```
"""
as 'Hospital_region_code', 'Bed_Grade', 'patientid', 'City_Code_Patient' are irrelevant to the health or
length of stay of patients so lets drop these parameters from training and testing dataset to improve the performace of model (high accurracy)
by reducing the complexity
"""
train = train.drop(['Hospital_region_code', 'Bed_Grade', 'patientid', 'City_Code_Patient'], axis = 1)
test = test.drop(['Hospital_region_code', 'Bed_Grade', 'patientid', 'City_Code_Patient'], axis = 1)
```

```
# Combine test and train dataset for processing
combined = [train, test]
combined
```

```
[        case_id  Hospital_code Hospital_type_code  City_Code_Hospital  \
 0             1              8                  c                   3
 1             2              2                  c                   5
 2             3             10                  e                   1
 3             4             26                  b                   2
 4             5             26                  b                   2
 ...         ...            ...                ...                 ...
 237304   237305             23                  a                   6
 237305   237306             19                  a                   7
 237306   237307              8                  c                   3
 237307   237308             21                  c                   3
 237308   237309              5                  a                   1

         Available_Extra_Rooms_in_Hospital    Department Ward_Type  \
 0                                       3  radiotherapy         R
 1                                       2  radiotherapy         S
 2                                       2    anesthesia         S
 3                                       2  radiotherapy         R
 4                                       2  radiotherapy         S
 ...                                   ...           ...       ...
 237304                                  3    gynecology         R
 237305                                  2    gynecology         R
 237306                                  5    gynecology         Q
 237307                                  4  radiotherapy         S
 237308                                  3    gynecology         Q

        Ward_Facility_Code Type_of_Admission Severity_of_Illness  \
 0                       F         Emergency             Extreme
 1                       F            Trauma             Extreme
 2                       E            Trauma             Extreme
 3                       D            Trauma             Extreme
 4                       D            Trauma             Extreme
```

```
        Visitors_with_Patient    Age  Admission_Deposit   Stay
0                         2.0  51-60             4911.0   0-10
1                         2.0  51-60             5954.0  41-50
2                         2.0  51-60             4745.0  31-40
3                         2.0  51-60             7272.0  41-50
4                         2.0  51-60             5558.0  41-50
...                       ...    ...                ...    ...
237304                    5.0  41-50             4298.0  51-60
237305                    4.0  41-50             4165.0  31-40
237306                    4.0  31-40             5075.0  21-30
237307                    2.0  31-40             5179.0  11-20
237308                    NaN    NaN                NaN    NaN

[237309 rows x 14 columns],
        case_id  Hospital_code Hospital_type_code  City_Code_Hospital  \
0        318439             21                  c                   3
1        318440             29                  a                   4
2        318441             26                  b                   2
3        318442              6                  a                   6
4        318443             28                  b                  11
...         ...            ...                ...                 ...
137052   455491             11                  b                   2
137053   455492             25                  e                   1
137054   455493             30                  c                   3
137055   455494              5                  a                   1
137056   455495              6                  a                   6

        Available_Extra_Rooms_in_Hospital    Department Ward_Type  \
0                                       3    gynecology         S
1                                       2    gynecology         S
2                                       3    gynecology         Q
3                                       3    gynecology         Q
4                                       2    gynecology         R
...                                   ...           ...       ...
137052                                  4    anesthesia         Q
137053                                  2  radiotherapy         R
137054                                  2    anesthesia         R
137055                                  2    anesthesia         R
137056                                  3    gynecology         Q

       Ward_Facility_Code Type_of_Admission Severity_of_Illness  \
0                       A         Emergency            Moderate
1                       F            Trauma            Moderate
2                       D         Emergency            Moderate
3                       F            Trauma            Moderate
4                       F            Trauma            Moderate
...                   ...               ...                 ...
137052                  D         Emergency               Minor
137053                  E         Emergency            Moderate
137054                  A            Urgent               Minor
137055                  E            Trauma               Minor
137056                  F            Trauma             Extreme

        Visitors_with_Patient    Age  Admission_Deposit
0                           2  71-80               3095
1                           4  71-80               4018
2                           3  71-80               4492
3                           3  71-80               4173
4                           4  71-80               4161
...                       ...    ...                ...
137052                      4  41-50               6313
137053                      2   0-10               3510
137054                      2   0-10               7190
137055                      2  41-50               5435
137056                      5  51-60               4702

[137057 rows x 13 columns]]
```

Lets encode the categorical data for traning the model

```python
# Encoding Department
from sklearn.preprocessing import LabelEncoder

for dataset in combined:
    label = LabelEncoder()
    dataset['Department'] = label.fit_transform(dataset['Department'])
combined[1].Department.unique()
```

```
array([2, 1, 0, 3, 4])
```

```python
# Encoding Ward Type, Hospital_type_code, Ward_Facility_Code, Type_of_Admission, Severity_of_Illness
for dataset in combined:
    label = LabelEncoder()
    dataset['Hospital_type_code'] = label.fit_transform(dataset['Hospital_type_code'])
    dataset['Ward_Facility_Code'] = label.fit_transform(dataset['Ward_Facility_Code'])
    dataset['Ward_Type'] = label.fit_transform(dataset['Ward_Type'])
    dataset['Type_of_Admission'] = label.fit_transform(dataset['Type_of_Admission'])
    dataset['Severity_of_Illness'] = label.fit_transform(dataset['Severity_of_Illness'])
```

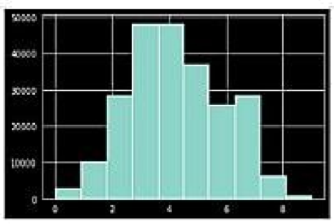
```python
combined[0]
```

	case_id	Hospital_code	Hospital_type_code	City_Code_Hospital	Available_Extra_Rooms_in_Hospital	Department	Ward_Type	Ward_Facility_Code	Type_of_Admission	Severi
0	1	8	2	3	3	3	2	5	0	
1	2	2	2	5	2	3	3	5	1	
2	3	10	4	1	2	1	3	4	1	
3	4	26	1	2	2	3	2	3	1	
4	5	26	1	2	2	3	3	3	1	
...	...	...	...	...	...	...	...	...	...	
237304	237305	23	0	6	3	2	2	5	1	
237305	237306	19	0	7	2	2	2	2	0	
237306	237307	8	2	3	5	2	1	5	0	
237307	237308	21	2	3	4	3	3	0	0	
237308	237309	5	0	1	3	2	1	4	1	

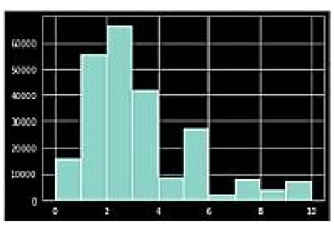
237309 rows × 14 columns

```
combined[1]
```

	case_id	Hospital_code	Hospital_type_code	City_Code_Hospital	Available_Extra_Rooms_in_Hospital	Department	Ward_Type	Ward_Facility_Code	Type_of_Admission	Severi
0	318439	21	2	3	3	2	3	0	0	
1	318440	29	0	4	2	2	3	5	1	
2	318441	26	1	2	3	2	1	3	0	



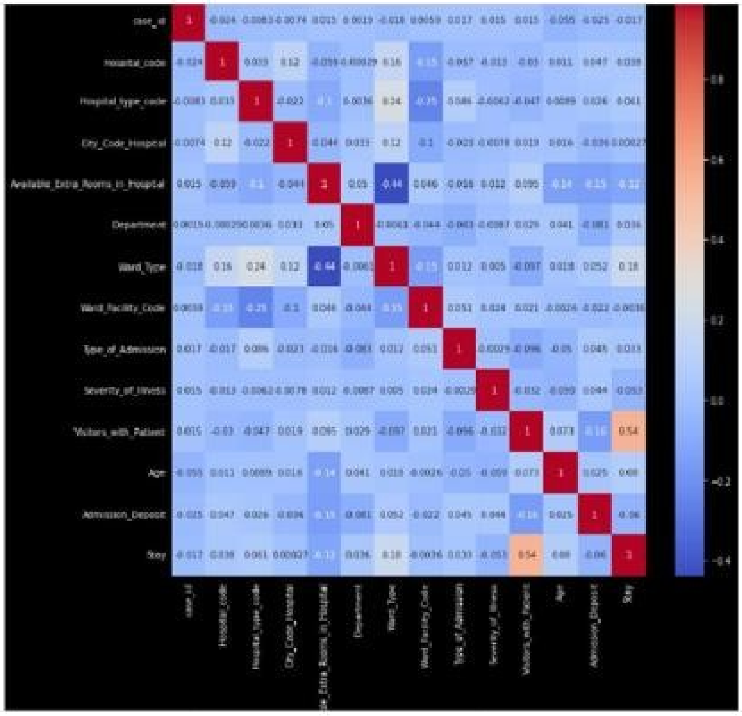

```
combined[0].Stay.hist()
```



shape of combined (train data, test data) dataset

```
for dataset in combined:
    print(dataset.shape)
```

```
(237309, 14)
(137057, 13)
```




```
combined[1]
```

	case_id	Hospital_code	Hospital_type_code	City_Code_Hospital	Available_Extra_Rooms_in_Hospital	Department	Ward_Type	Ward_Facility_Code	Type_of_Admission	Severi
0	318439	21	2	3	3	2	3	0	0	
1	318440	29	0	4	2	2	3	5	1	
2	318441	26	1	2	3	2	1	3	0	
3	318442	6	0	6	3	2	1	5	1	
4	318443	28	1	11	2	2	2	5	1	
...	...	...	...	...	...	...	...	...	...	
137052	455491	11	1	2	4	1	1	3	0	
137053	455492	25	4	1	2	3	2	4	0	
137054	455493	30	2	3	2	1	2	0	2	
137055	455494	5	0	1	2	1	2	4	1	
137056	455495	6	0	6	3	2	1	5	1	

137057 rows × 13 columns

Training the model

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
```

```
train = combined[0]
test = combined[1]
```

```
X_train = train.drop(['case_id', 'Stay'], axis=1)
Y_train = train["Stay"]
X_test  = test.drop("case_id", axis=1).copy()
```

```
X_train.shape
```

```
(237309, 12)
```

```
Y_train.shape
```

```
(237309,)
```

```
X_test.shape
```

```
(137057, 12)
```

```
X_test.columns
```

```
Index(['Hospital_code', 'Hospital_type_code', 'City_Code_Hospital',
       'Available_Extra_Rooms_in_Hospital', 'Department', 'Ward_Type',
       'Ward_Facility_Code', 'Type_of_Admission', 'Severity_of_Illness',
       'Visitors_with_Patient', 'Age', 'Admission_Deposit'],
      dtype='object')
```

```
Y_train
```

```
0         0.0
1         4.0
2         3.0
3         4.0
4         4.0
         ...
237304    5.0
237305    3.0
237306    2.0
237307    1.0
237308    NaN
Name: Stay, Length: 237309, dtype: float64
```

```
X_train.fillna(0,inplace=True)
Y_train.fillna(0,inplace=True)
X_test.fillna(0,inplace=True)
```

K-Nearest Neighbor Algorithm

```
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(X_train, Y_train)
Y_pred = knn.predict(X_test)
acc_knn = round(knn.score(X_train, Y_train) * 100, 2)
acc_knn
```

```
53.99
```

Descision Tree Algorithm

```
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, Y_train)
Y_pred = decision_tree.predict(X_test)
acc_decision_tree = round(decision_tree.score(X_train, Y_train) * 100, 2)
acc_decision_tree
```

```
99.76
```

Random Forest Algorithm

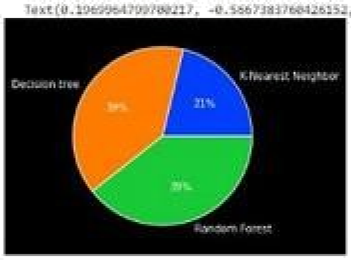
```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(X_train, Y_train)
Y_pred = random_forest.predict(X_test)
random_forest.score(X_train, Y_train)
acc_random_forest = round(random_forest.score(X_train, Y_train) * 100, 2)
acc_random_forest
```

```
99.76
```

Prediction accuracy comparison

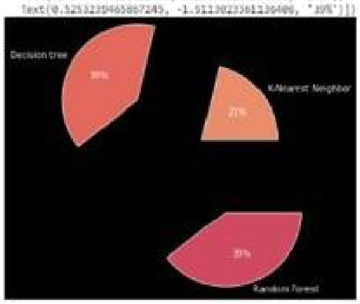
```
palette_color = sns.color_palette('bright')
data=[acc_knn, acc_decision_tree,acc_random_forest]
keys=['K-Nearest Neighbor','Decision tree','Random Forest']

#getting the algorithm with highest accuracy
max_accuracy=max(data)
index=[0,0,0]
j=0;
for i in data:
  if(i==max_accuracy):
    index[j]=1
    j=j+1
  else:
    index[j]=0.01
    j=j+1

plt.pie(data, labels=keys, colors=palette_color, autopct='%.0f%%')
```

```
([,
  ,
  ],
 [Text(0.8628423642631272, 0.6822778425408633, 'K-Nearest Neighbor'),
  Text(-0.9277499083745313, 0.590999244932723, 'Decision tree'),
  Text(0.36116021327837317, -1.0398203560781281, 'Random Forest')],
 [Text(0.4706412895080693, 0.3721515504810725, '21%'),
  Text(-0.5060454045679261, 0.322363224508758, '39%'),
  Text(0.1969964709780217, -0.5667383760426152, '39%')])
```




```
palette_color = sns.color_palette('flare')
plt.pie(data, labels=keys, colors=palette_color,explode=index, autopct='%.0f%%')
```

```
 ],
 [Text(0.8706863857564283, 0.6884803683859842, 'K-Nearest Neighbor'),
  Text(-1.7711580915987434, 1.1282712857806532, 'Decision tree'),
  Text(0.6804876798095076, -1.9835843161491535, 'Random Forest')],
 [Text(0.4784853110913704, 0.3783540763224374, '21%'),
  Text(-1.3494544121811365, 0.8596352653566608, '39%'),
  Text(0.3253235465867245, -1.5113023361130406, '39%')])
```




```
output = pd.DataFrame({
        "case_id": test["case_id"],
        "Stay": Y_pred
})
```

```
output['Stay'] = output['Stay'].replace(stay_labels.values(), stay_labels.keys())
```

```
output.to_csv('LOS_Prediction.csv', index = False)
```

```
output
```

	case_id	Stay
0	318439	0-10
2	318441	21-30
3	318442	11-20
4	318443	31-40
...	...	...
137052	455491	0-10
137053	455492	0-10
137054	455493	21-30
137055	455494	21-30
137056	455495	51-60

137057 rows × 2 columns

```
data=np.array([[29,0,4,2,2,3,5,1,2,4,7,4018]])
p=random_forest.predict(data)
p
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted wi
th feature names
  "X does not have valid feature names, but"
```

```
array([5.])
```

```
def prediction(p):
  if(p[0]==0):
    print("The predicted LOS of patient is : 0-10")
  elif(p[0]==1):
    print("The predicted LOS of patient is : 11-20")
  elif(p[0]==2):
    print("The predicted LOS of patient is : 21-30")
  elif(p[0]==3):
    print("The predicted LOS of patient is : 31-40")
  elif(p[0]==4):
    print("The predicted LOS of patient is : 41-50")
  elif(p[0]==5):
    print("The predicted LOS of patient is : 51-60")
  elif(p[0]==6):
    print("The predicted LOS of patient is : 61-70")
  elif(p[0]==7):
    print("The predicted LOS of patient is : 71-80")
  elif(p[0]==8):
```

```
  elif(p[0]==8):
    print("The predicted LOS of patient is : 81-90")
  elif(p[0]==9):
    print("The predicted LOS of patient is : 91-100")
  elif(p[0]==10):
    print("The predicted LOS of patient is : More than 100 Days")
```

```
data=np.array([[29,0,4,2,2,3,5,1,2,4,7,4018]])
p=random_forest.predict(data)
print(p)
```

```
prediction(p)
```

```
The predicted LOS of patient is : 51-60
```

GIT HUB LINK : https://github.com/IBM-EPBL/IBM-Project-22276-1659845740