FINAL DELIVERABLES

TEAM ID	**PNT2022TMID13550**
PROJECT NAME	**ANAYTICS FOR HOSPITALS HEALTH -CARE DATA**

TEAM MEMBERS:

Muneeswari M - 95191902062
Prathika P – 95191902076
Nivetha K – 95191902068
Priya P – 95191902077
Ragamathi M G --95191902079

CHAPTER 1

INTRODUCTION

This project deals with the analytics for hospital's health care data using data analytics. Data analytics (DA) is the process of examining data sets in order to find trends and draw conclusions about the information they contain. Increasingly, data analytics is done with the aid of specialized systems and software. Data analytics technologies and techniques are widely used in commercial industries to enable organizations to make more-informed business decisions.

PROJECT OVERVIEW:

Recent Covid-19 Pandemic has raised alarms over one of the most overlooked areas to focus: Healthcare Management.

While healthcare management has various use cases for using data science, patient length of stay is one critical parameter to observe and predict if one wants to improve the efficiency of the healthcare management in a hospital.

This parameter helps hospitals to identify patients of high LOS-risk (patients who will stay longer) at the time of admission. Once identified, patients with high LOS risk can have their treatment plan optimized to minimize LOS and lower the chance of staff/visitor 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 — a not for profit organization dedicated to manage the functioning of Hospitals in a professional and optimal manner

PURPOSE:

Data analytics in health care is vital. It helps health care organizations to evaluate and develop practitioners, detect anomalies in scans and predict

outbreaks in illness, per the Harvard Business School. Data analytics can also lowercosts for health care organizations and boost business intelligence. Hospital data analytics can look over patient data and any prescribed medication to alert doctors and patients of incorrect dosages or wrong prescriptions, which lessens human error and the cost to your hospital. This in turn helps in gaining better insights and also enables healthcare practitioners to make well-informed decisions.

CHAPTER 2

LITERATURE SURVEY

The main aim of this paper is to provide a deep analysis on the research field of healthcare data analytics. This paper is analyzing the previous studies and works in this research area, as well as highlighting some of guidelines and gaps. This studyhas used seven popular databases and selected most relevant papers, in order to conduct this paper. The paper has listed some data analytics tools and techniques that have been used to improve healthcare performance in many areas such as: medical operations, reports, decision making, and prediction and prevention system. Moreover, the systematic review has showed an interesting demographic of fields of publication, research approaches, as well as outlined some of the possible reasons and issues associated with healthcare data analytics, based on geographical distribution theme[1].

This part deals with the advanced analytical methods focused on healthcare. This includes the clinical prediction models, temporal data mining methods, and visual analytics. Integrating heterogeneous data such as clinical and genomic data is essential for improving the predictive power of the data that will also be discussed. Information retrieval techniques that can enhance the quality of biomedical search will be presented. Data privacy is an extremely important concern in healthcare. Privacy-preserving data publishing techniques will therefore be presented.[2].

One of the promises of the growing critical mass of clinical data accumulating in electronic health record (EHR) systems is secondary use (or re-use) of the data for other purposes, such as quality improvement and clinical research.1 The growth of such data has increased dramatically in recent years due to incentives for EHR adoption in the US funded by the Health Information Technology for Economic and Clinical Health (HITECH) Act.2-3 In the meantime, there has also seen substantial growth in other kinds of health-related data, most notably through efforts to sequence genomes and other biological structures and functions.4 The analysis of this data is usually called analytics (or data analytics). This chapter will define the terminology of this field, provide an overview of its promise, describe what work has been accomplished, and list the challenges and opportunities going forward[3].

Clinicians, healthcare providers-suppliers, policy makers and patients are experiencing exciting opportunities in light of new information deriving from the analysis of big data sets, a capability that has emerged in the last decades. Due to the rapid increase of publications in the healthcare industry, we have conducted a structured review regarding healthcare big data analytics. With reference to the resource-based view theory we focus on how big data resources are utilized to create organization values/capabilities, and through content analysis of the selected publications we discuss: the classification of big data types related to healthcare, the associate analysis techniques, the created value for stakeholders, the platforms

and tools for handling big health data and future aspects in the field. We present anumber of pragmatic examples to show how the advances in healthcare were made possible. We believe that the findings of this review are stimulating and provide valuable information to practitioners, policy makers and researchers while presenting 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 data are the need of the hour. Data analytics is becoming a future escalating tool of all industries including medicine, robotics, etc. This article briefly explains how data analytics is used in healthcare systems. Health care is the process of maintaining and improving the health of an individual by preventing, diagnosing and treating the diseases, illness and other physical and mental imbalances in people. Data analytics is classified into four types and they are descriptive, diagnostic, predictive and prescriptive analysis. Health care makes use of prescriptive analysis to arrive atthe best results and make better decisions. Big data plays a major role in data analytics. It helps the data analysts to collect data from the patients and store them efficiently. After the completion of this whole article, the reader will be able to getthe collective idea about health care analytics.[5]

EXISTING PROBLEM

> The already existing model is trained with minimal parameters

- Low accuracy in prediction
- No feature extraction done
- High complexity

REFERENCES

[1]. Mohammad Alkhatib , Amir Talaei-Khoei (University of Nevada,Reno)Amir Talaei-Khoei University of Nevada, Reno | UNR · Department of Accounting and Information Systems PhD of Information Systems-Amir Ghapanchi

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

[3]. From: Hoyt,RE,Yoshihashi,A,Eds.(2014).Health Informatics:Practical Guide for Healthcare and formation Technology Professionals,Sixth Edition.Pensacola,FL,Lulu.com.

[4]. Panagiota Galetsia , Korina Katsaliakia , Sameer Kumarb,⁎ a School of Economics, Business Administration & Legal Studies, International Hellenic University, 14th km Thessaloniki-N. Moudania, Thessaloniki, 57001, Greece b Opus College of Business, University of St. Thomas Minneapolis Campus, 1000 LaSalle Avenue, Schulze Hall 435, Minneapolis, MN 55403, USA

[5]. from"n book: Innovative Data Communication Technologies and Application (pp.83-96)" P. Nagaraj-Professor (Assistant) at Kalasalingam University

[6]. Yang J.-J., Li J., Mulder J., Wang Y., Chen S., Wu H., Wang Q., Pan H. Emerginginformation technologies for enhanced healthcare.Comput.ind.2015;69:3-11.doi:10.1016/j.compimd.2015.01.012. [CrossRef] [Google Scholar]

[7]. Cortada J.W., Gordon D., Lenihan B. The Value of Analytics in Healthcare. IBM Institute for Business Value; Armonk, NY, USA: 2012. Report No.: GBE03476- USEN-

00. [Google Scholar].

[8]. Makary M.A., Daniel M. Medical error-the third leading cause of death in the US.Br. Med. J. 2016;353:i2139. doi: 10.1136/bmj.i2139. [PubMed] [CrossRef] [Google Scholar].

[9]. Prokosch H.-U., Ganslandt T. Perspectives for medical informatics. Methods Inf. Med. 2009;48:38–44. doi: 10.3414/ME9132. [PubMed] [CrossRef] [Google Scholar].

[10]. Simpao A.F., Ahumada L.M., Gálvez J.A., Rehman M.A. A review of analytics andclinical informatics in health care. J. Med. Syst. 2014;38:45. doi: 10.1007/s10916- 014-0045-x. [PubMed] [CrossRef] [Google Scholar].

[11]. Ghassemi M., Celi L.A., Stone D.J. State of the art review: The data revolution incritical care. Crit. Care. 2015;19:118. doi: 10.1186/s13054-015-0801-4. [PMC free article] [PubMed] [CrossRef] [Google Scholar].

[12]. Tomar D., Agarwal S. A survey on Data Mining approaches for Healthcare. Int. J. Bio-Sci. Bio-Technol. 2013;5:241–266. doi: 10.14257/ijbsbt.2013.5.5.25. [CrossRef] [Google Scholar]

[13]. K. Jee and G. H. Kim, "Potentiality of big data in the medical sector: Focus on how to reshape the healthcare system," Healthc. Inform. Res., vol. 19, no. 2, pp. 79–85, Jun. 2013. doi: 10.4258/hir.2013.19.2.79.

[14]. J. King, V. Patel, and M. F. Furukawa, "Physician adoption of electronic health record technology to meet meaningful use objectives: 2009–2012," The Office of the National Coordinator for Health Information Technology, Tech. Rep., Dec. 2012.

[15]. V. Mayer-Schönberger and K. Cukier, Big Data: A Revolution That Will Transform How We Live, Work, and Think. Eamon Dolan, 2014.

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

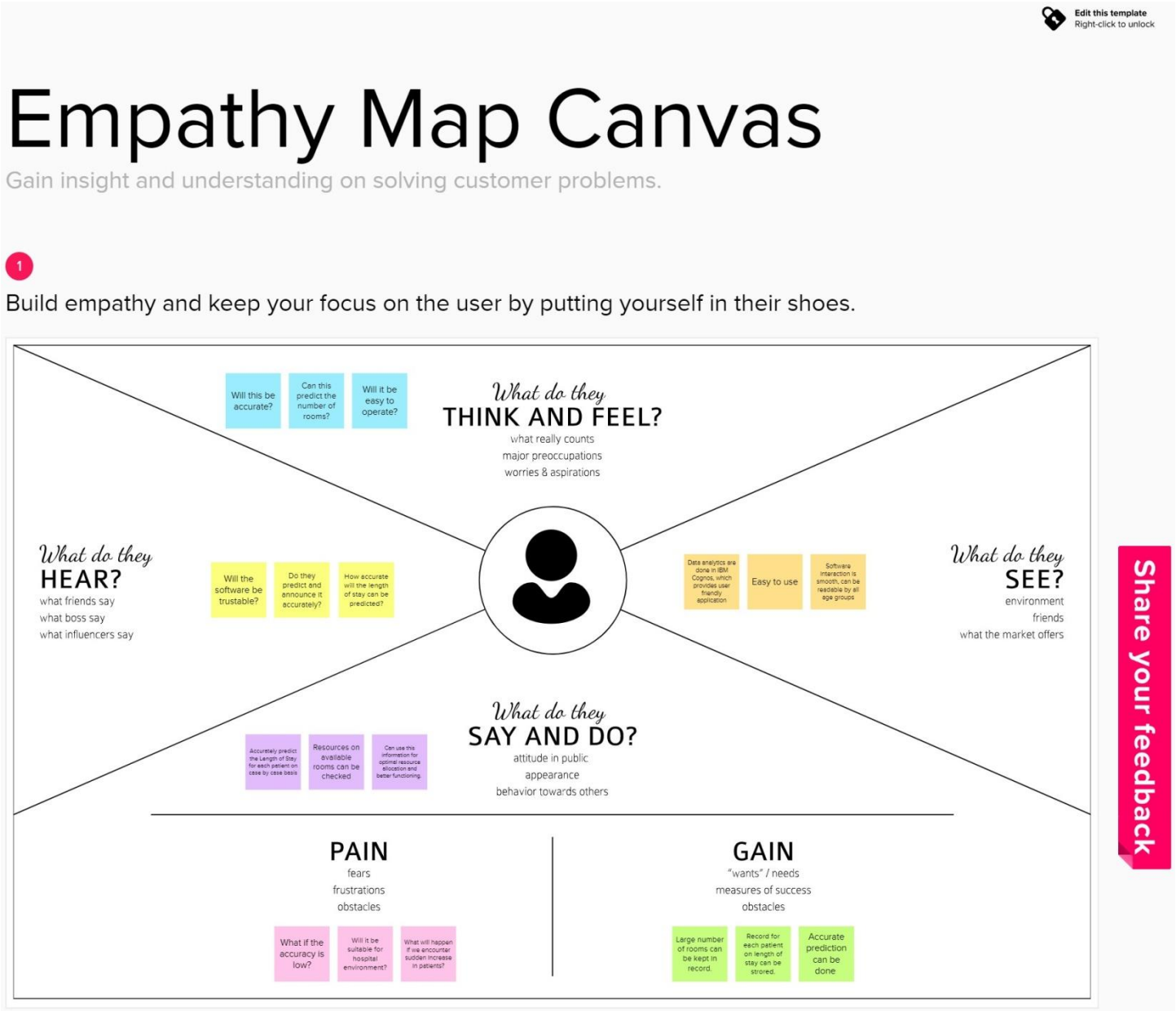
PROBLEM STATEMENT AND DEFINITION

- The aim is to accurately predict the Length of Stay for each patient on case by case basis so that the Hospitals can use this information for optimal resource allocation and better functioning.
- The length of stay is divided into 11 different classes ranging from 0-10 days to more than 100 days.

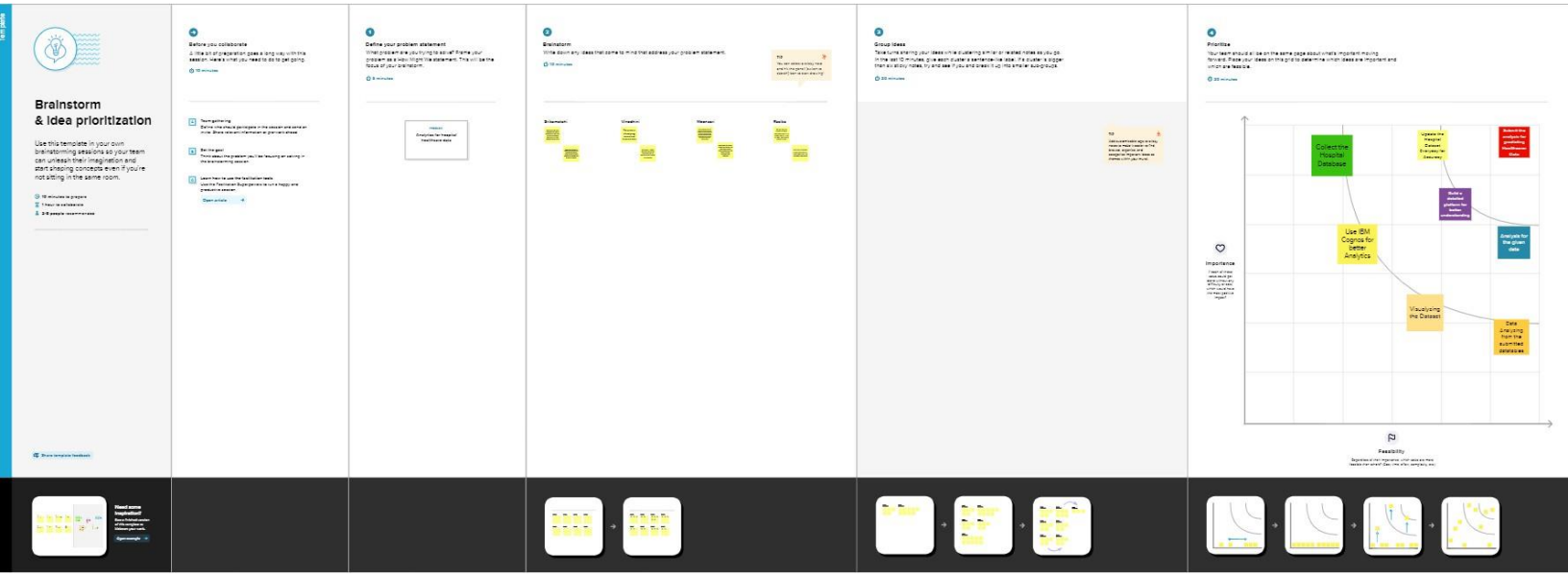
CHAPTER 3

IDEATION & PROPOSED SOLUTION

EMPATHY MAP CAMPUS



IDEATION & BRAINSTORMING



PROPOSED SOLUTION

Predict the length of stay of patients.

The length of the stay can be predicted using either Random forest or

Decision Tree for more accuracy.

Certain parameters like age, stage of the
diseases, disease diagnosis, severity of illness, type of admission, facilities allocated, etc., are used for prediction.

IBM Cognos will be used for data analytics.

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	Analytics for Hospitals' Health Care Data. To analyse the Length Of Stay (LOS) of patient. To have a better allocation of beds for patients.
2.	Idea / Solution description	Developing an project for Hospitals to analyse the Length Of Stay for the current patients. And allocate the bed for further patients. By using the machine learning techniques, the Length Of Stay can be predicted accurately
3.	Novelty / Uniqueness	There are many applications that analyse the Length Of Stay of a patient. Our focus is to propose the machine learning technique. And use the recent algorithms which predict accurately. Analyse based on up to date, data of the patient.
4.	Social Impact / Customer Satisfaction	For example, in critical situation like covid, it is useful for hospitals to analyse the Length Of Stay and allocate beds for the patients. It will be useful to overcome the difficulty faced by the patients and the hospitals.
5.	Business Model (Revenue Model)	Right now the application is profitless but in future we might add an option of premium plans for advanced learning.
6.	Scalability of the Solution	Based on the situation the patients visiting the hospitals may change. This project is scalable for all hospitals in any kind of situation.

PROBLEM SOLUTION FIT

Problem-Solution fit canvas 2.0

Analytics for hospitals' health-care data

1. CUSTOMER SEGMENT(S) — CS

- Sales executives
- Managers
- Representatives
- Common people

6. CUSTOMER — CC

- **Anxiety-**customer began to get anxious when they still no idea about what they have found.
- **Mysteries-**they might Called it mysteries which they can't able to conclude it (founded thing) and give up.

5. AVAILABLE SOLUTIONS — AS

- By analyzing the data using excel analysis.
- By gathering the information from the past experience and learning etc…

Explore AS,

e CS, fit into

2. JOBS-TO-BE-DONE / PROBLEMS — J&P

- Analyzing the data and providing the visualization as user understandable.
- Giving the necessary information for particular thing which needs for customer

9. PROBLEM ROOT CAUSE — RC

- Lack of study in the relationship between attributes.
- Unaware of the analysis.
- Limited analytical thinking.

7. BEHAVIOUR — BE

When the user Don't have the knowledge about data analysis this kind of situation occurs.

Focus on J&P, t

Focus on J&P, tap

3. TRIGGERS — TR

- Seeking for self-gratification by data analysis
- To help peoples to get extra knowledge about thedata analytics.

4. EMOTIONS: BEFORE / AFTER — EM

- Before : Not sure about the accuracy of the data
- After: Having an accurately predicted and analyzed data.

10. YOUR SOLUTION — SL

8.

This system is built by using the Data analysis with the help of IBM cognos.

The goal is to accurately predict the Length of Stay for each patient on case by case basis so that the Hospitals can use this information for resource allocation and better functioning.

CHANNELS of BEHAVIOUR — CH

8.1 ONLINE

- Online websites
- Social media platforms

8.2 OFFLINE

- Customer throw words

Identify strong TR & EM

ne & offline CH of BE

CHAPTER 4

Project Design Phase-II
Solution Requirements (Functional & Non-functional)

Date	03 October 2022
Team ID	PNT2022TMID13550
Project Name	Project-Analytics for Hospital Health -care Data
Maximum Marks	4 Marks

Functional Requirements:

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail Registration through LinkedIN
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	Operability	Transmit patient information and make it compatible between the administration
FR-4	Accuracy	Predicting length of stay will be possible using the dashboard. Depending on various combinations of the input sources in a precise manner
FR-5	Adherence	The object is meant to be used in a hospital, therefore any forms of data need not be kept secret.
FR-6	Productivity	According to expectations, the dashboard would enhance Length of Stay, therefore generating a situation where offering a more effective remedy

NON FUNCTIONAL REQUIREMENT

Non-functional Requirements:

Following are the non-functional requirements of the proposed solution.

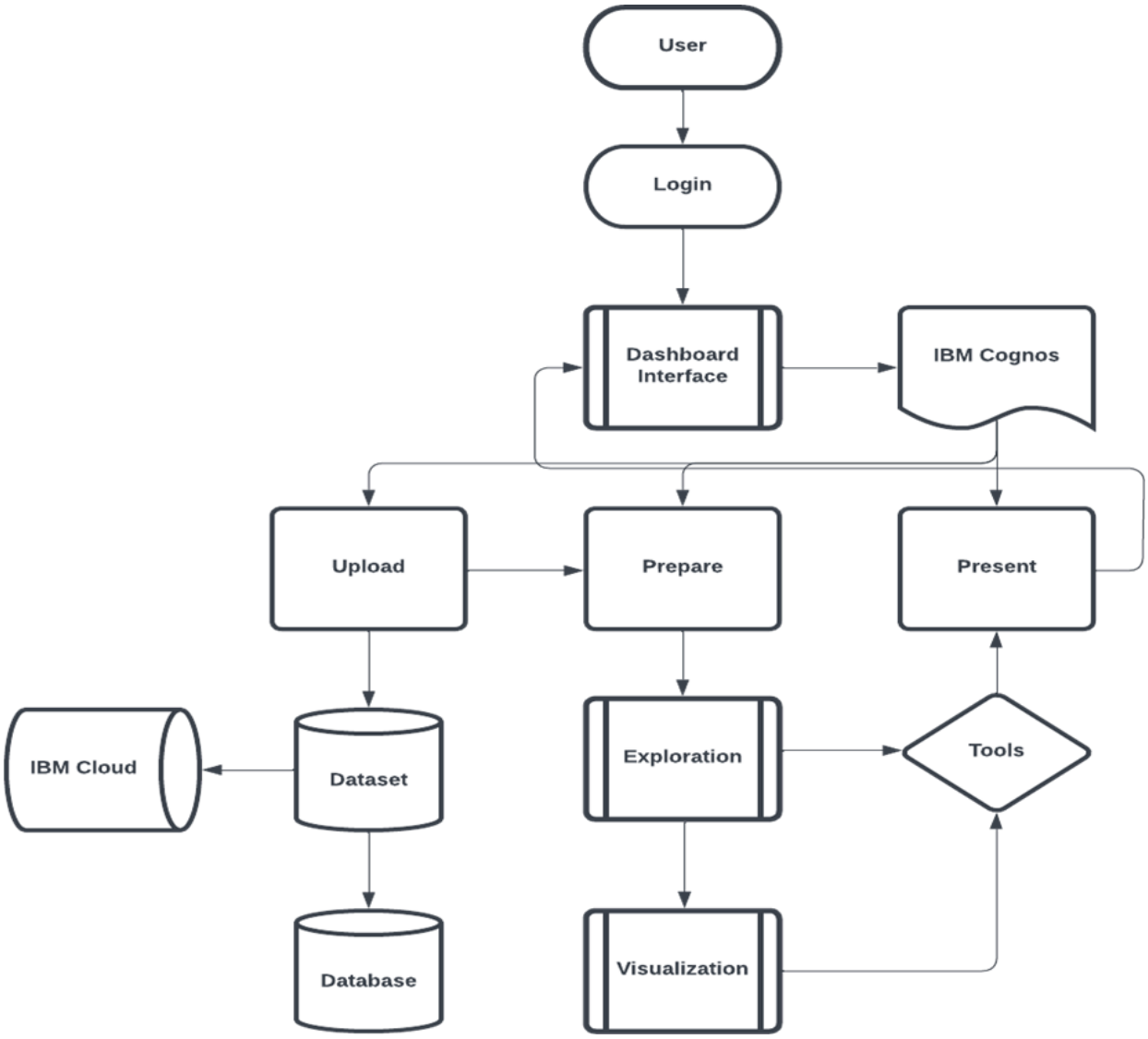
FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	The efficiency, productivity, and contentment with which certain people are capable of a particular set of tasks performed in a certain setting.
NFR-2	**Security**	This method of preventing unwanted access to data access and data corruption during the course of its life
NFR-3	**Reliability**	Error rates are lower with systems that are very reliable. Potential mistakes in processes that could hurt patients
NFR-4	**Performance**	Among the performance metrics are Effective and high-quality patient care Cost of medical services Performance inequalities results of care

NFR-5	**Availability**	The platform can be made available to users upon request. Timely manner, it also aids in providing information that is required for the user's dataset
NFR-6	**Scalability**	The capacity of a medical assistance to effective when used carefully or under strict control expanding the circumstances under actual world conditions to increase the percentage of the while maintaining effectiveness, to the eligible population

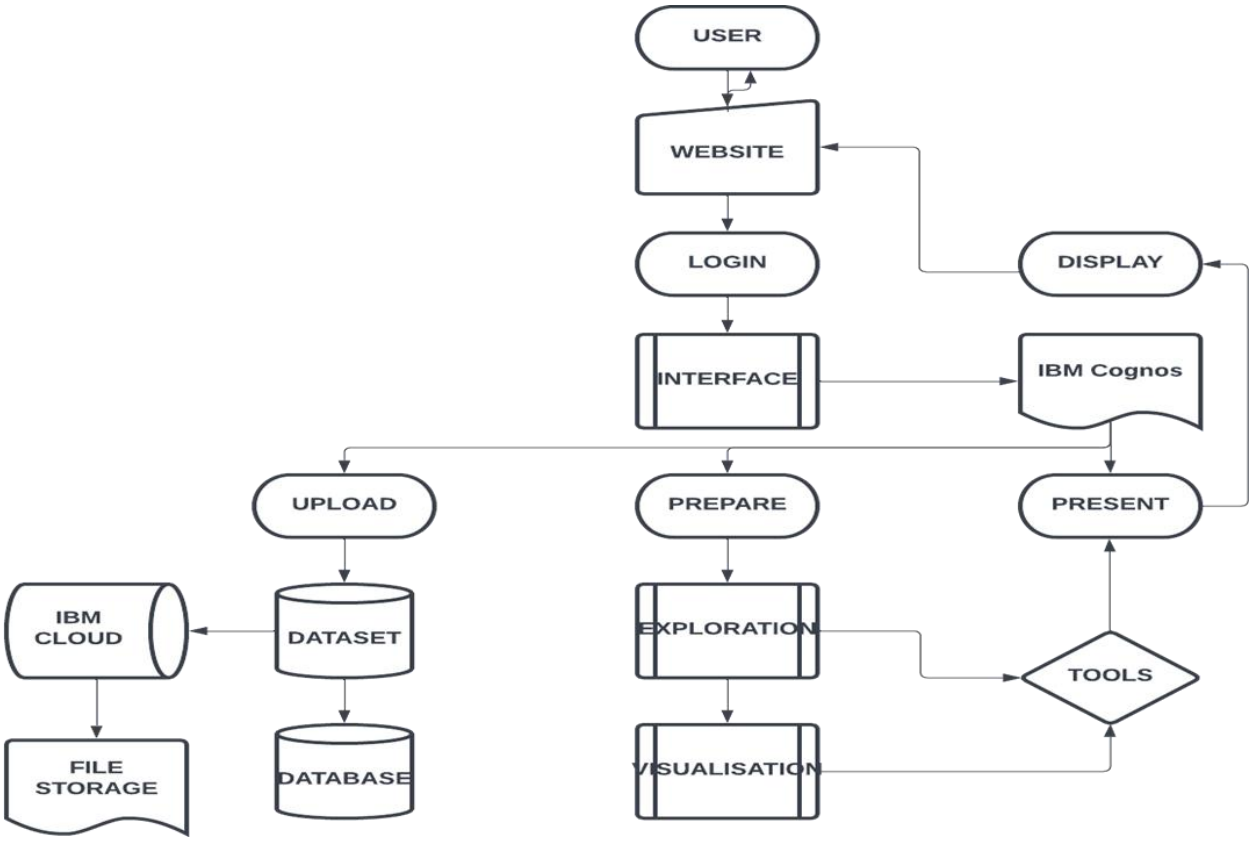
CHAPTER 5

PROJECT DESIGN

DATA FLOW DIAGRAMS



SOLUTION & TECHNICAL ARCHITECTURE



USER STORIES :

User Type	Functional	User Story	User Story / Task	Acceptance criteria	Priority	Release
Customer	Requirement (Epic)	Number	As a user, I can register for the dashboard by entering my email, and password, and confirming my password.	I can access my account in the dashboard	High	Sprint-1
(Mobile user)	Registration	USN-1	As a user, I will receive a confirmation email once I have registered for the dashboard	I can receive a	High	Sprint-1
		USN-2	As a user, I can register for the dashboard through Social Media	confirmation email & click confirm	Low	Sprint-2
		USN-3	As a user, I can register for the dashboard through Gmail	I can register & access the dashboard with Social Media Login	Medium	Sprint-1
		USN-4	As a user, I can log into the application by entering email & password	I can register and access dashboard with Gmail	High	Sprint-1
	Login	USN-5	As a user ,I can use my account in my dashboard for uploading dataset.	I can login to the account in my email login.	Medium	Sprint-1
	Dashboard	USN-6	As a user ,I can use my dashboard in website	I can login to the account for uploading dataset.	Medium	Sprint-2
Customer (Web user)	Website	USN-7	As a user ,I can contact Customer care Executive for my login.	I can login into the dashboard by visiting website.	High	Sprint-2
Customer Care Executive		USN-8	As a user ,I can contact administrator for my queries.	I can contact customer executive for my login.	High	Sprint-2
Administrator		USN-9	As a user, I can prepare data by using Exploration Techniques.	I can contact administrator for solving my queries.	High	Sprint-1
Exploration	Dashboard	USN-10	As a user, I can Present data in my dashboard.	I can prepare data by using Exploration Techniques.	High	Sprint-2

CHAPTER 6
PROJECT PLANNING & SCHEDULING

SPRINT PLANNING & ESTIMATION

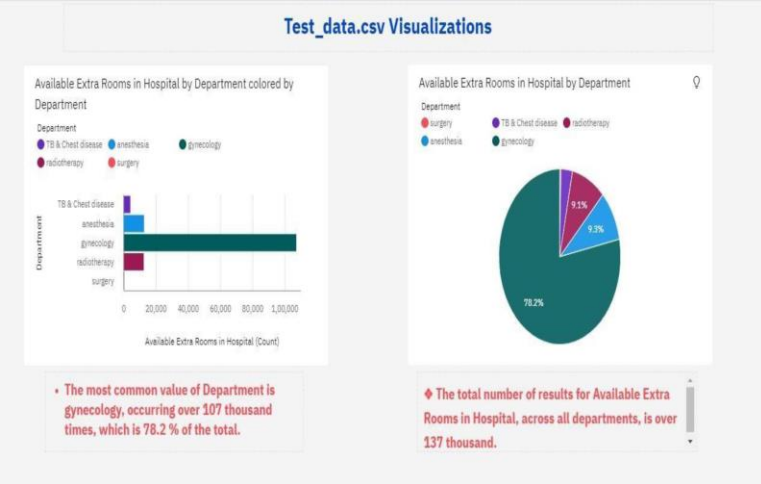
Sprint	Functional Requirement(Epic)	User Story Number	User Story / Task	Story Points	Priority	Team members
Sprint-1	Registration	USN-1	As a health care provider I can create account in IBM cloud and the data are collected.	20	High	Nivetha Prathika
Sprint-2	Analyse	USN-2	As a health care provider all the data that are collected is cleaned and uploaded in the database or IBM cloud.	20	Medium	Priya Nivetha
Sprint-3	Dashboard	USN-3	As a health care provider I can use my account in my dashboard for uploading dataset.	20	Medium	Prathika Ragamathi
Sprint-3	Visualization	USN-4	As a health care provider I can prepare data for Visualization.	10	High	Nivetha Ragamathi
Sprint-4	Visualization	USN-5	As a health care provider I can present data in my dashboard.	10	High	Muneeswari Priya
Sprint-4	Prediction	USN-6	As a health care provider I can predict the length of stay	10	High	Muneeswari Prathika

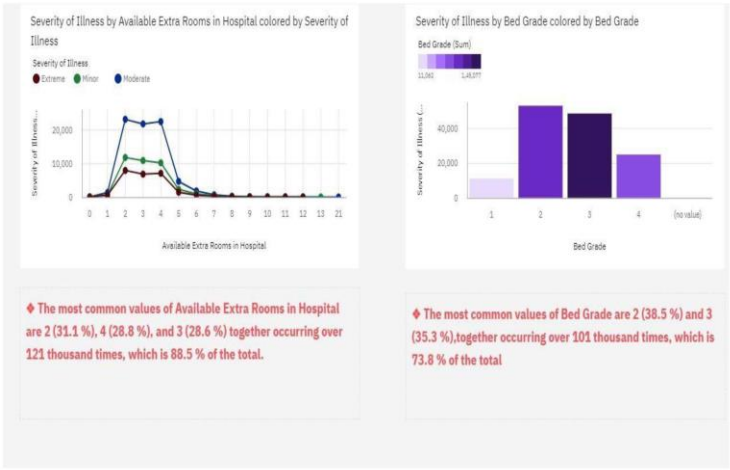
KAGGLE API :

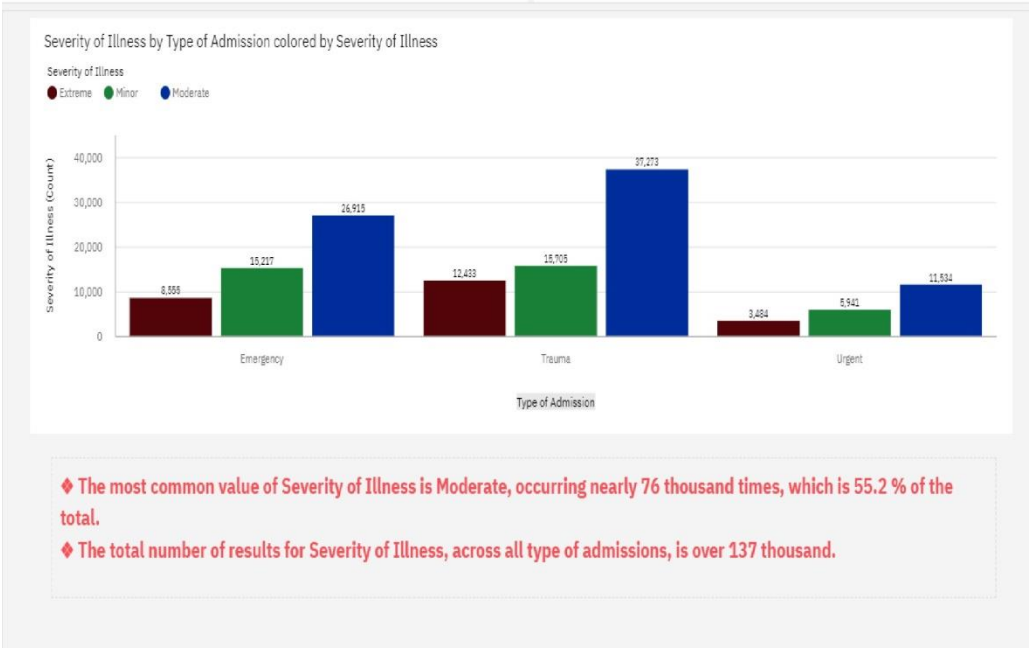

FAIL
Gmail
Compose
Inbox
Starred
Snoozed
Sent
Drafts
More
Labels
1-Download your dataset using Kaggle API

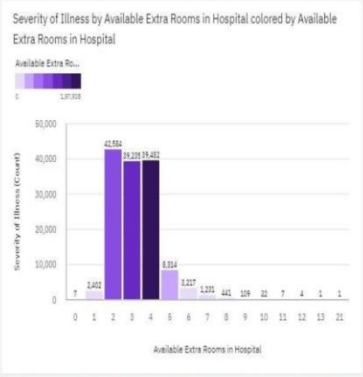
CHAPTER 7
CODING & SOLUTIONING

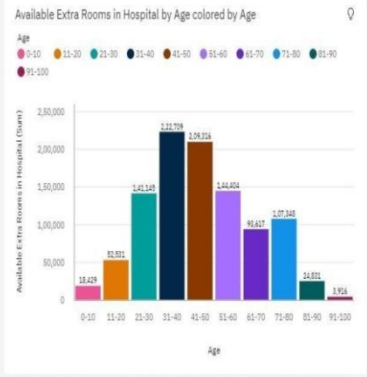
FEATURE 1





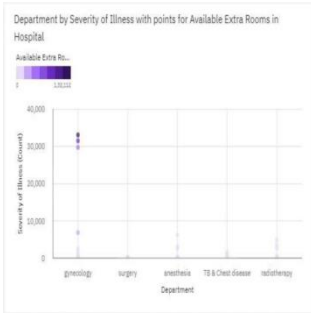




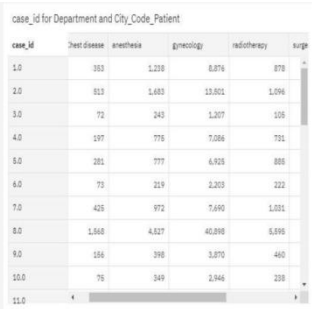


♦ The most common values of Available Extra Rooms in Hospital are 2 (31.1 %), 4 (28.8 %), and 3 (28.6 %), together occurring over 121 thousand times, which is 88.5 % of the total.

♦ Available Extra Rooms in Hospital is most unusual when the combinations of Age and Age are 31-40 and 31-40, 41-50 and 41-50 and 91-100 and 91-100.

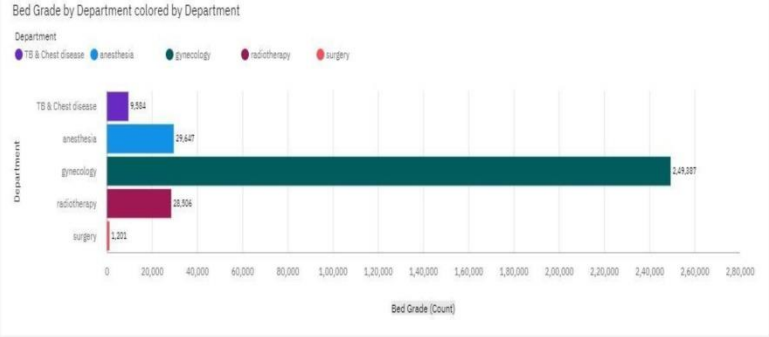


♦ The most common value of Department is gynecology, occurring over 107 thousand times, which is 78.2 % of the total.



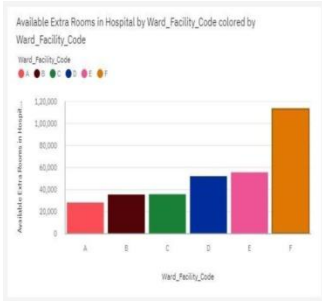
♦ The most common values of City_Code_Patient are 23.0 (3.2 %), 20.0 (3.2 %), 16.0 (3.2 %), 15.0 (3.2 %), and 14.0 (3.2 %), together occurring 25 times, which is 16.2 % of the total.

Train_data.csv Visualizations

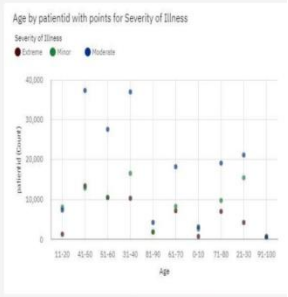


♦ The total number of results for Bed Grade, across all departments, is over 318 thousand.

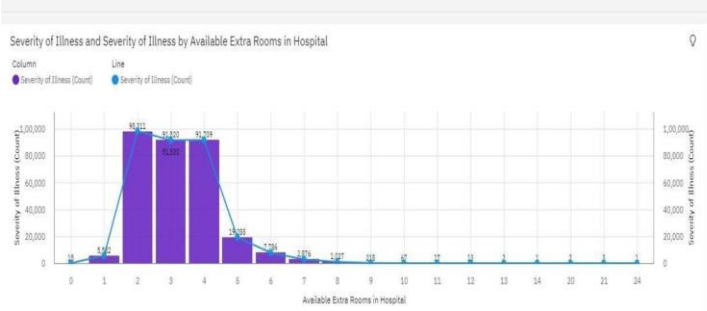
♦ The most common value of Department is gynecology,occurring over 249 thousand times, which is 78.3 % of the total



♦ The most common value of Ward_Facility_Code is F, occurring nearly 113 thousand times, which is 35.4 % of the total.

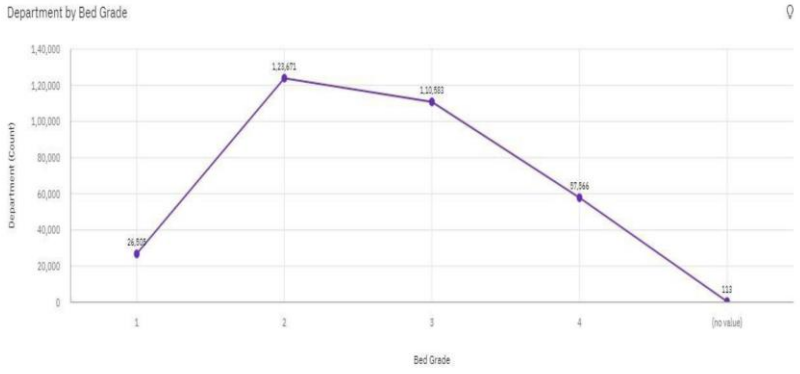


♦ The most common values of Age are 41-50 (20 %) and 31-40 (20 %),together occurring over 127 thousand times, which is 40 % of the total.



♦ The total number of results for Severity of Illness, across all available extra rooms in hospitals, is over 318 thousand.

♦ The most common values of Available Extra Rooms in Hospital are 2 (30.9 %), 4 (28.8 %), and 3 (28.7 %), together occurring nearly 282 thousand times, which is 88.4 % of the total.

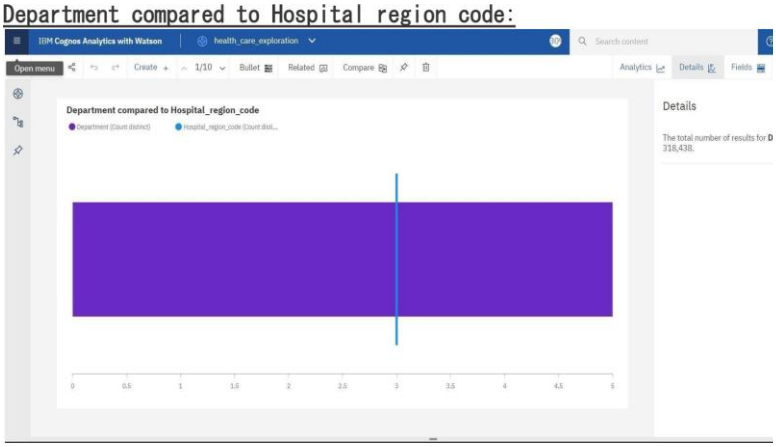


♦ The most common values of Bed Grade are 2 (38.8 %) and 3 (34.7 %),together occurring over 234 thousand times, which is 73.6 % of the total.

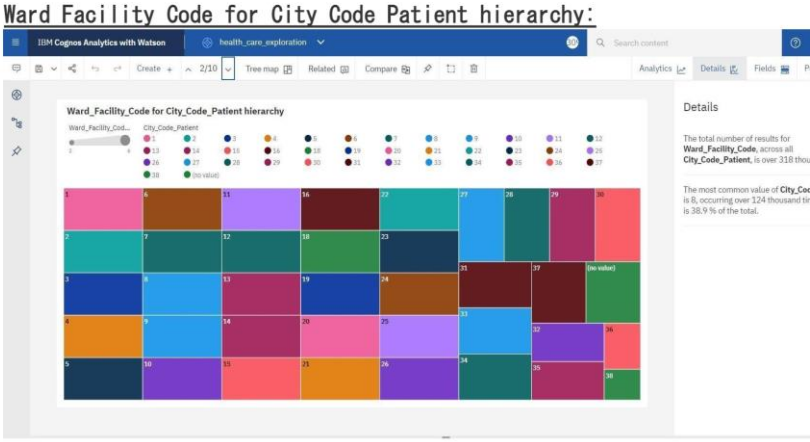
♦ The total number of results for Department, across all bed grades, is over 318 thousand.

FEATURE 2

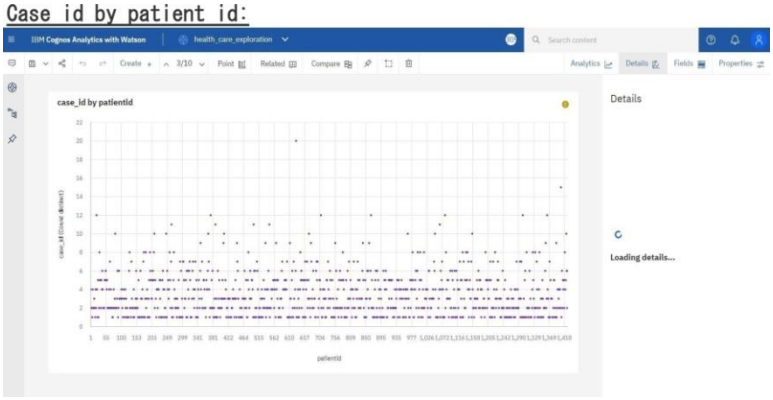
Department compared to Hospital region code:



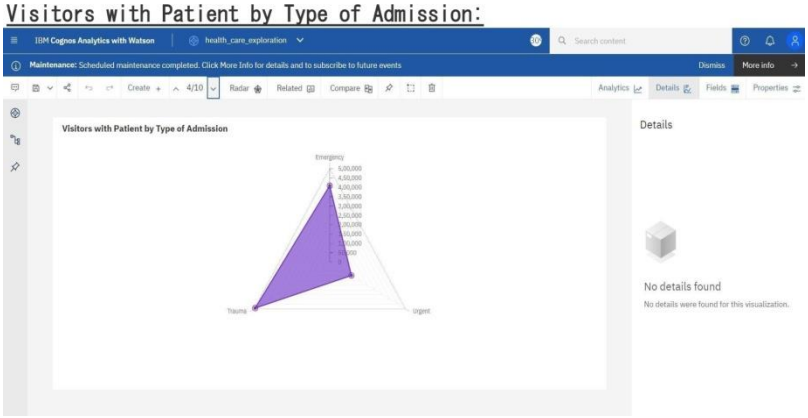
Ward Facility Code for City Code Patient hierarchy:



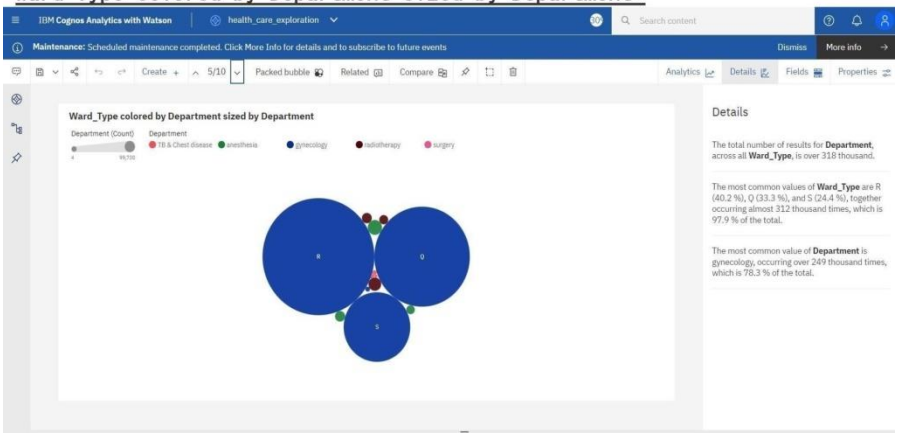
Case id by patient id:



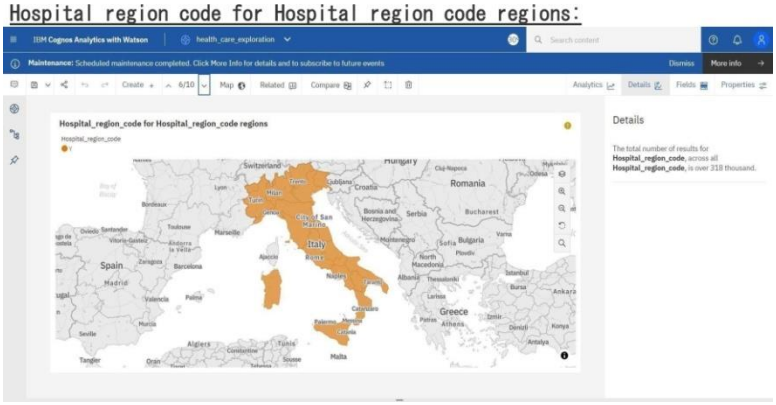
Visitors with Patient by Type of Admission:



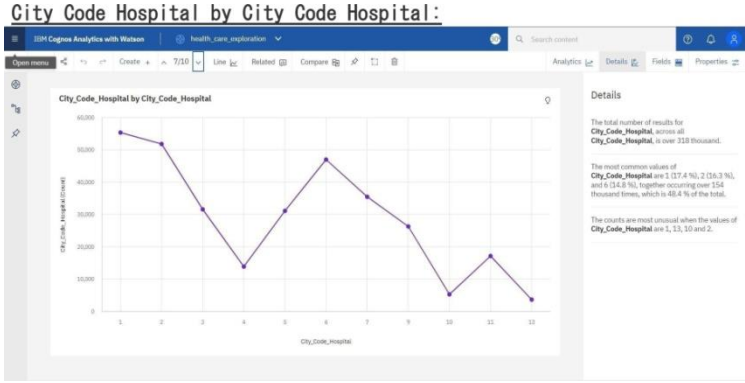
Ward Type colored by Department sized by Department:



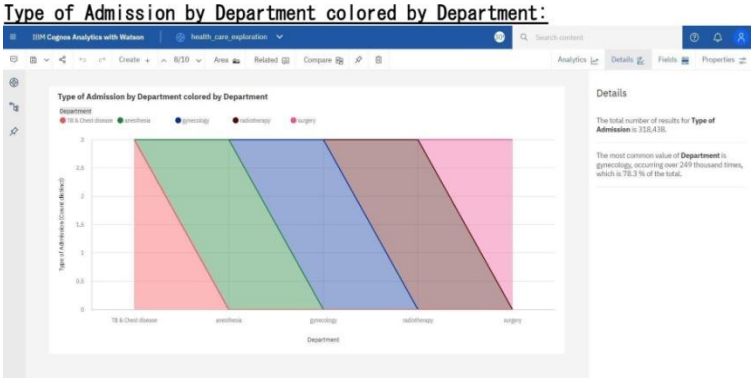
Hospital region code for Hospital region code regions:



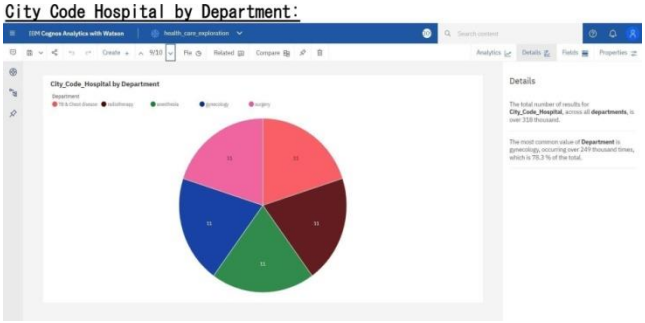
City Code Hospital by City Code Hospital:

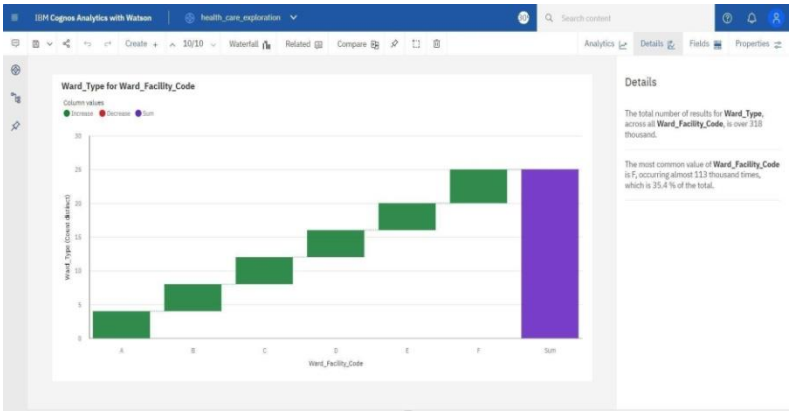


Type of Admission by Department colored by Department:



City Code Hospital by Department:





CHAPTER 8

TESTING

TEST CASES

- verify user is able to see home page
- verify user is able to see dashboard page
- verify user is able to naivigate to story page
- verify filters are working

8.1 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

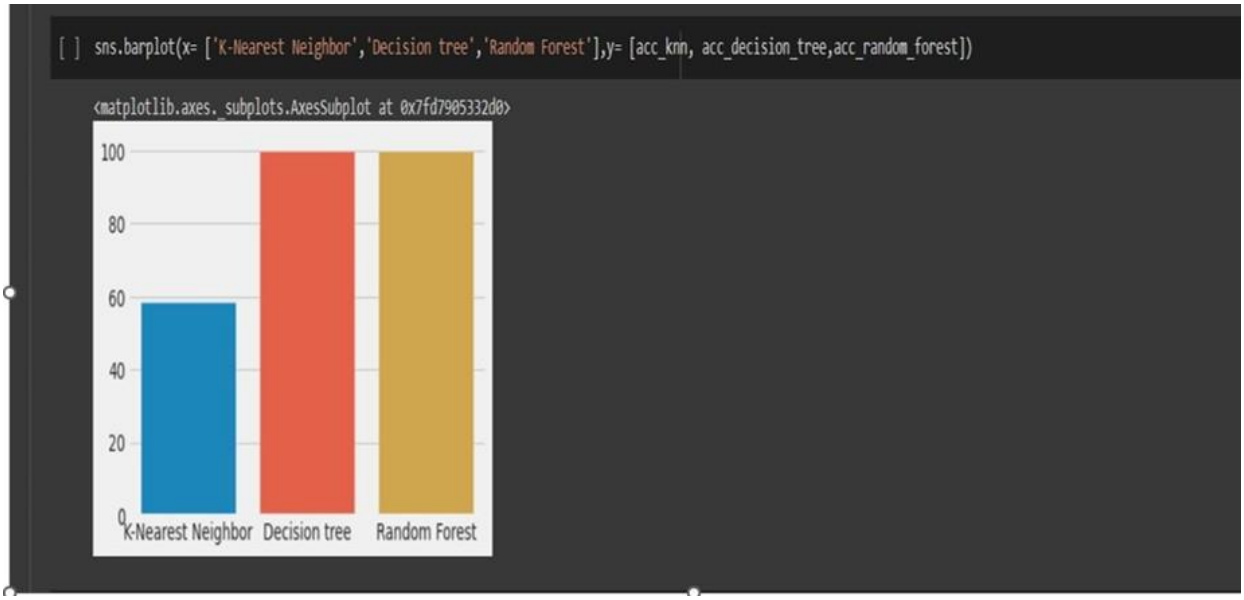
This report shows the number of test cases that have passed, failed, and untested

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
Exception Reporting	9	0	0	9
Final Report Output	10	0	0	10
Version Control	1	0	0	1

CHAPTER 9

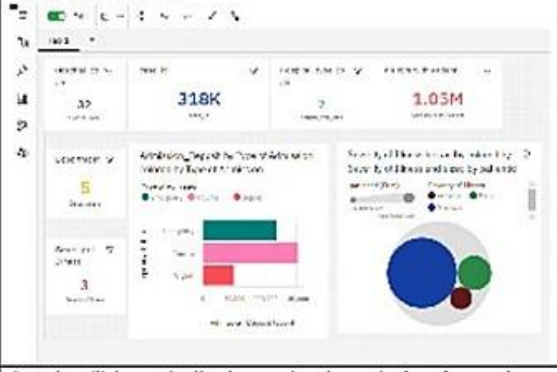
RESULTS

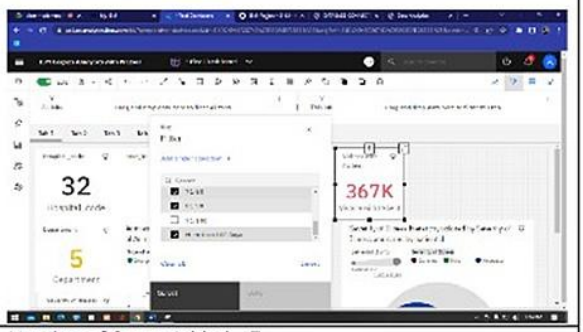
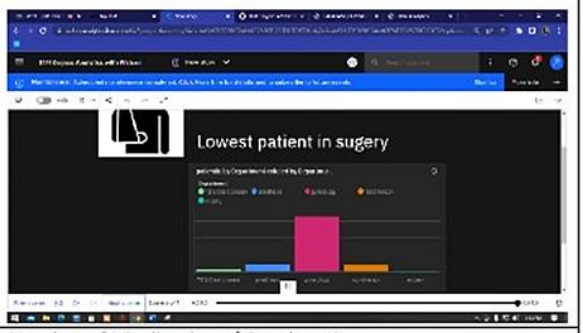
PERFORMANCE METRICS

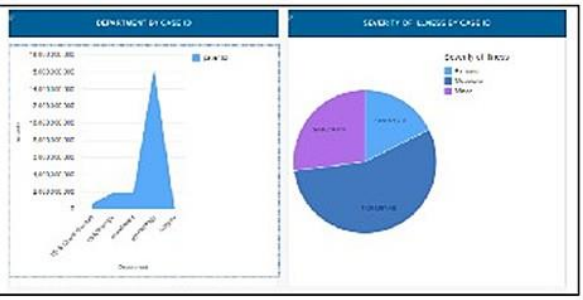


Model Performance Testing:

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 – 5 
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 efficiency of healthcare
- benefit areas like emergency preparation, charting, administration, compliance, and financial management.
- Analysing clinical data to improve medical research
- Using patient data to improve health outcomes
- Gaining operational insights from healthcare provider data
- Improved staffing 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:

REPLACING MEDICAL PERSONNEL:

Application of technology in every sphere of human life is improving the way things are done. These technologies are are also posing some threat to world of works. Robotics are replacing human labour.

DATA SAFETY:

Data security is another challenge in applying big data in healthcare. Big datastorage is usually targets of hackers. This endangers the safety of medical data. Healthcare organisations are very much concerned about the safety of patients' sensitive personal data. For this, all healthcare applications must meet the requirement for data security and be HIPAA compliant before they can be deployed for healthcare services.

PRIVACY:

One of the major drawbacks in the application of big data in healthcareindustry is the issue of lack of privacy. Application of big data technologies involves monitoring of patient's data, tracking of medical inventory and assets, organizing collected data, and visualization of data on the dashboard and the reports. So visualization of sensitive medical data especially that of the patients creates negative impression of big data as it violets privacy

MAN POWER:

Applying big data solutions in healthcare requires special skills, and such kills are scarce. Handling of big data requires the combination of medical, technological and statistical knowledge.

CHAPTER 11

CONCLUSIO

N

The impact of data analytics in healthcare has already made a substantial difference in the ability of healthcare providers to offer patients high-quality care inan efficient, cost-effective manner. However, the role of data analytics in improving patient outcomes and healthcare processes continues to grow and expand as moretypes of data become available and new tools are developed that make the results of the analytics clear and easy for healthcare professionals to access.

Realizing the potential of data analytics to transform the healthcare industry begins by understanding how the technology can be applied to address healthcare providers' challenges, including staff recruitment and utilization, operational efficiencies, and enhanced patient experiences. Patient-centered healthcare depends on knowing what patients want and need. Data analytics holds the key to unlocking this vital information.

CHAPTER 12

FUTURE SCOPE

Artificial Intelligence (AI) will play a significant role in data analytics in healthcare for the next decade. For example, the field of AI-enabled clinical decision support is just emerging. This type of support can compare patients who fit similar profiles within a system, then it can alert doctors to trends in data that may have been overlooked. The use of big data in healthcare will include testing for drug interactions that small studies are unlikely to catch and prevent patients from taking harmful drug combinations.

Decisions made by physicians, like what test or treatments to give a particular patient, makeup 80-90% of all healthcare spending, so using artificial intelligence to make more educated decisions will bring down healthcare costs. It's crucial 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>
  <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 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     Team ID : PNT2022TMID13550      </b></i></h4></center>

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

   <tbody>
     <tr>
       <td>Team Leader</td>
       <td>Muneeswari M          </td>

     </tr>
     <tr>
       <td>Team member</td>
       <td>Prathika P</td>

     </tr>
     <tr>
       <td>Team member</td>
       <td>Priya P          </td>

     </tr>
   <tr>
       <td>Team member</td>
       <td>Ragamathi M G       </td>

   </tr>
   <tr>
       <td>Team member</td>
       <td>Nivetha K     </td>

   </tr>
```

```
    </tbody>
  </table>
</body>
</html>
```

About Page :

```
<!DOCTYPEhtml>
<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>
  <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 class="active"><a href="index.html">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="container">
<b>Analytics For Hospitals' Health-Care Data</b>
<br>
```

Recent Covid-19 Pandemic has raised alarms over one of the most overlooked areas to focus: HealthcareManagement.
While healthcare management has various use cases for using data science, patient length of stay is one critical parameter to observe and predict if one wants to improve the efficiency of the healthcare management in a hospital.
This parameter helps hospitals to identify patients of high LOS-risk (patients who will stay longer) at the time

of admission. Once identified, patients with high LOS risk can have their treatment plan optimized to minimize LOS and lower the chance of staff/visitor 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 a not for profit organization dedicated to manage the functioning of Hospitals in a professional and optimal manner.

```
<br><br>
<b>Goal:</b>
```

The goal is to accurately predict the Length of Stay for each patient on case by case basis so that the Hospitals can use this information for optimal resource allocation and better functioning. The length of stay is divided into 11 different classes ranging from 0-10 days to more than 100 days.

```
<br><br>

<b>Technical Architecture:</b>
<br>
<img src="pic.JPG">




</div>
</body>
</html>
```

DASHBOARD PAGE :

```
<!DOCTYPEhtml>
<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>
 <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 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_folders%2FDashboard%
2FHealth%2BCare%2BData%2BAnalytics&amp;closeWindowOnLastView=true&amp;ui_appbar=false&amp
;ui_navbar=false&amp;shareMode=embedded&amp;action=view&amp;mode=dashboard&amp;subView=mo
del0000018476584e12_00000000"width="1100" height="600"frameborder="0"gesture="media"
allow="encrypted-media"allowfullscreen=""></iframe>
</div>

</body>
</html>
```

REPORT PAGE :

```
<!DOCTYPEhtml>
<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>
  <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 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%2FHealth%2BCare%2BData%2B
Analytics%2BReport&amp;closeWindowOnLastView=true&amp;ui_appbar=false&amp;ui_navbar=false&am
p;shareMode=embedded&amp;action=run&amp;format=HTML&amp;prompt=false"width="1000"
height="900"frameborder="0"gesture="media" allow="encrypted-media"allowfullscreen=""></iframe>
</br>

</div>

</body>
</html>
```

STORY :

```
<!DOCTYPEhtml>
<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>
 <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&amp;pathRef=.my_folders%2FStory%2FHealth
%2Bcare%2Bdata%2Banalytics%2Bstory&amp;closeWindowOnLastView=true&amp;ui_appbar=false&amp;
ui_navbar=false&amp;shareMode=embedded&amp;action=view&amp;sceneId=model000001847a5e7043_00
000001&amp;sceneTime=0"width="1000"  height="900"frameborder="0"gesture="media"  allow="encrypted-
media"allowfullscreen=""></iframe>
</br>

</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.(
1	2	2	c	5	Z	2	radiotherapy	S	F	2.(
2	3	10	e	1	X	2	anesthesia	S	E	2.(
3	4	26	b	2	Y	2	radiotherapy	R	D	2.(
4	5	26	b	2	Y	2	radiotherapy	S	D	2.(

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

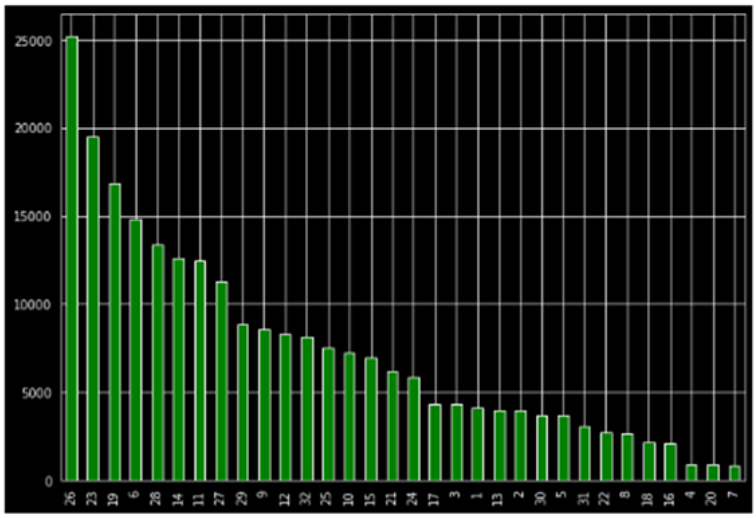
Distribution of values

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
```

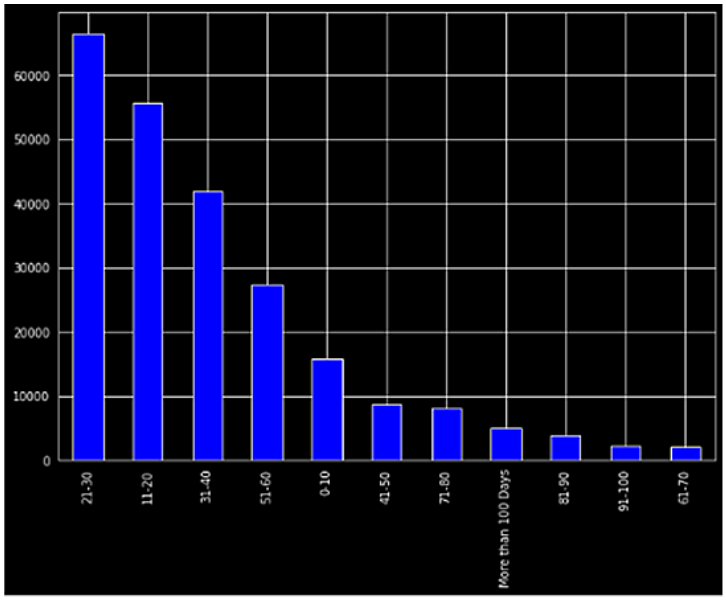
```
plt.figure(figsize=(10,7))
train.Hospital_code.value_counts().plot(kind="bar", color = ['green'])
```



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
```



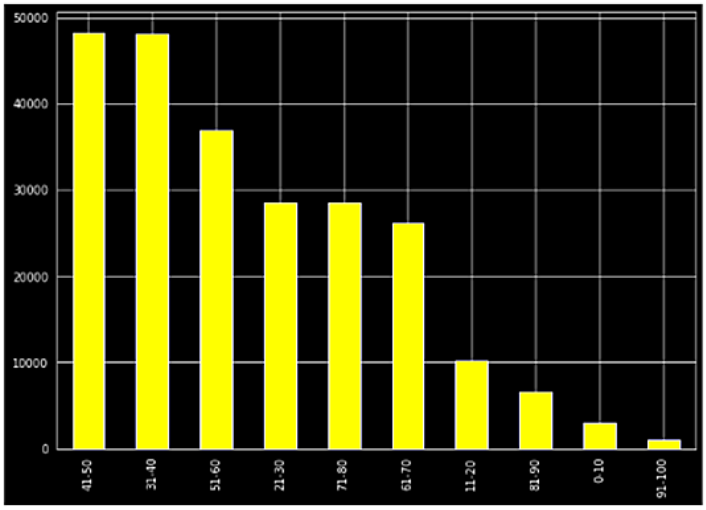
Age

```
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'])
```



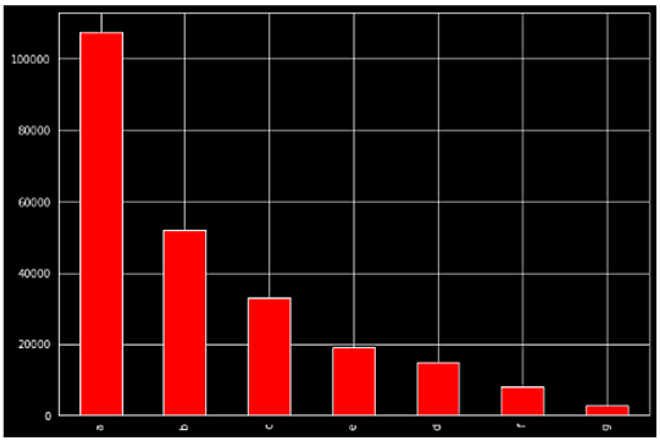
Hospital_type_code

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

```
a    107545
b     51925
```

```
c      32995
e      19105
d      14833
f       8166
g       2740
Name: Hospital_type_code, dtype: int64
```

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

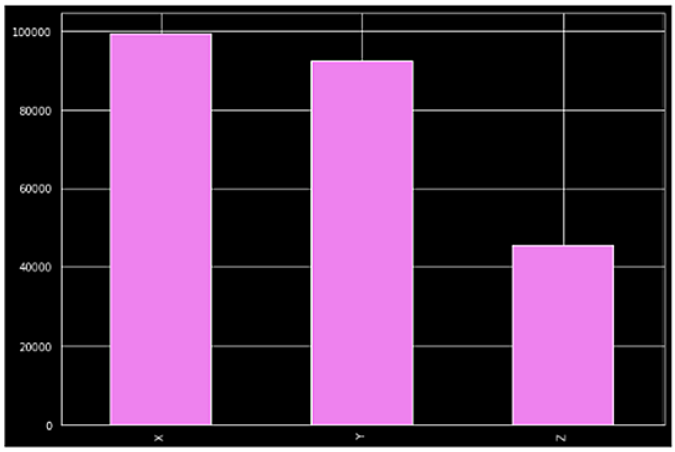


Hospital_region_code

```
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'])
```



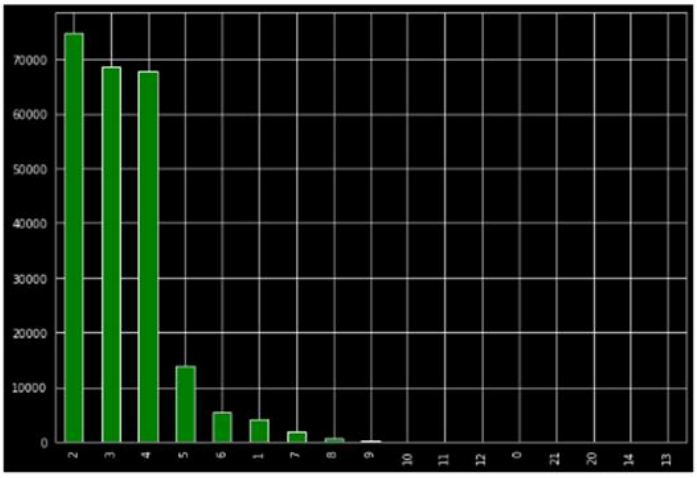
Available_Extra_Rooms_in_Hospital

```
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'])
```



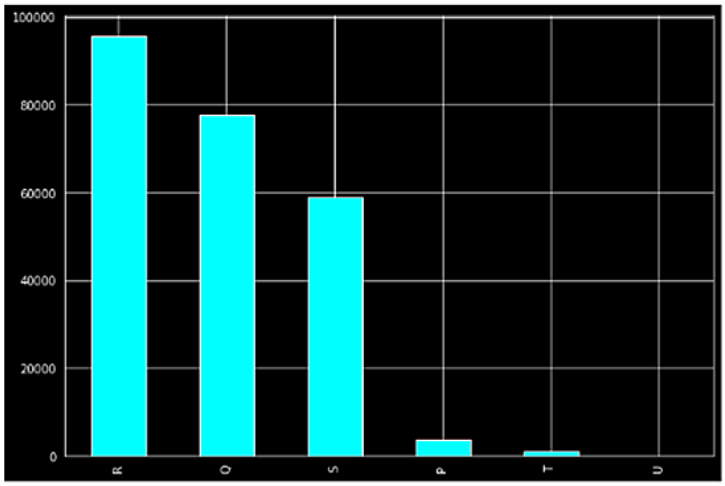
Department

```
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'])
```



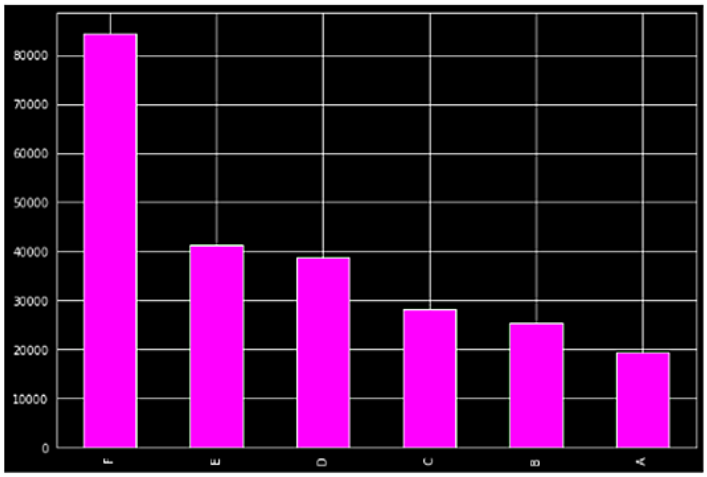
Ward_Facility_Code

```
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'])
```



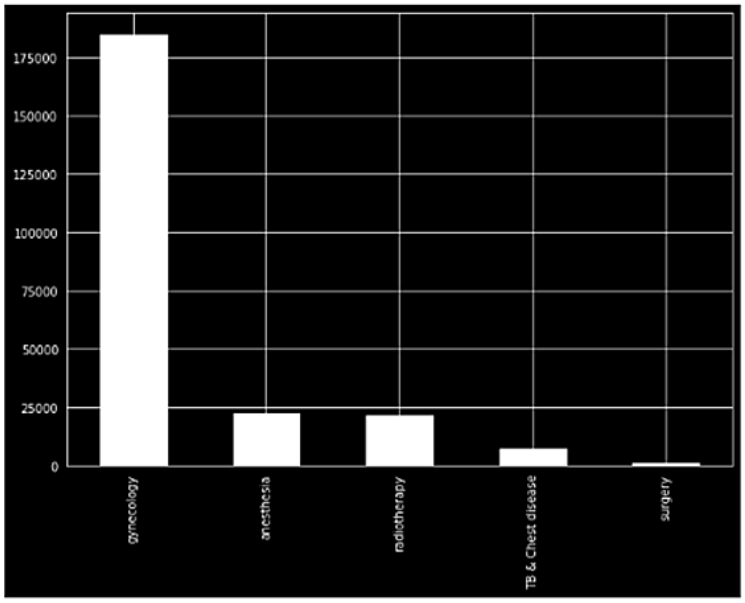
Visitors_with_Patient

```
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'])
```

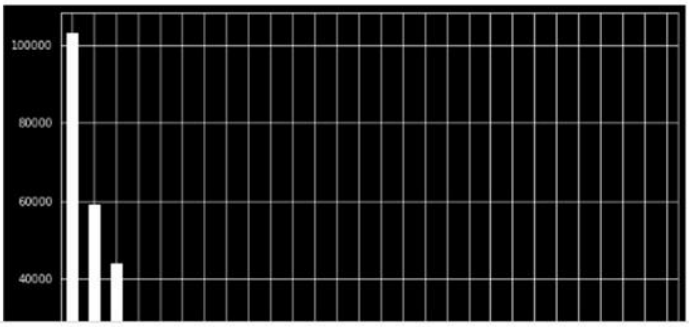


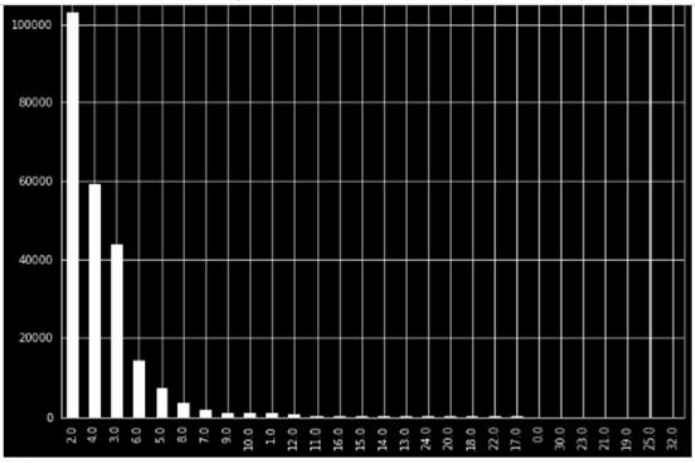
Ward_Type

```
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'])
```



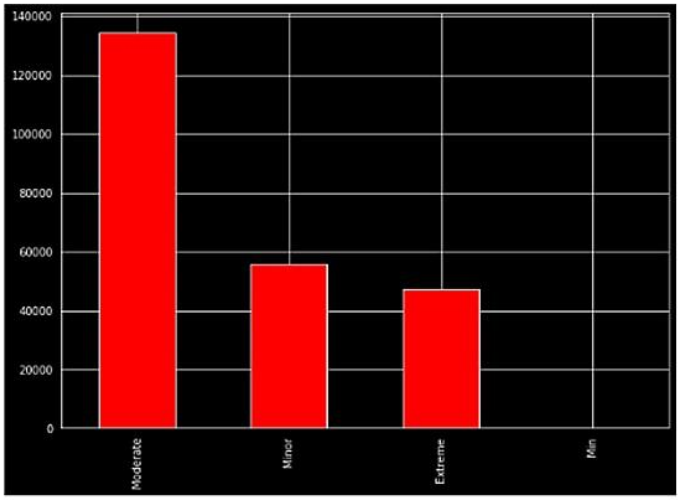


Severity of Illness

```
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

```
for features in train.columns:
    print('*---------------------------------------------------------------------------------------------------*')
    print(' Unique Values for {}'.format(features))
    print(train[features].unique())
    print('*---------------------------------------------------------------------------------------------------*')
    print()
```

```
*---------------------------------------------------------------------------------------------------*
 Unique Values for case_id
[     1      2      3 ... 237307 237308 237309]
*---------------------------------------------------------------------------------------------------*
```

```
*---------------------------------------------------------------------------------------------------*
 Unique Values for Hospital_code
[ 8  2 10 26 23 32  1 22 16  9  6 29 12  3 21 28 27 19  5 14 13 31 24 17
 25 15 11 30 18  4  7 20]
*---------------------------------------------------------------------------------------------------*

*---------------------------------------------------------------------------------------------------*
 Unique Values for Hospital_type_code
['c' 'e' 'b' 'a' 'f' 'd' 'g']
*---------------------------------------------------------------------------------------------------*

*---------------------------------------------------------------------------------------------------*
 Unique Values for City_Code_Hospital
[ 3  5  1  2  6  9 10  4 11  7 13]
*---------------------------------------------------------------------------------------------------*

*---------------------------------------------------------------------------------------------------*
 Unique Values for Hospital_region_code
['Z' 'X' 'Y']
*---------------------------------------------------------------------------------------------------*

*---------------------------------------------------------------------------------------------------*
 Unique Values for Available_Extra_Rooms_in_Hospital
[ 3  2  1  4  6  5  7  8  9 10 12  0 11 20 14 21 13]
*---------------------------------------------------------------------------------------------------*

*---------------------------------------------------------------------------------------------------*
 Unique Values for Department
['radiotherapy' 'anesthesia' 'gynecology' 'TB & Chest disease' 'surgery']
*---------------------------------------------------------------------------------------------------*

*---------------------------------------------------------------------------------------------------*
 Unique Values for Ward_Type
['R' 'S' 'Q' 'P' 'T' 'U']
*---------------------------------------------------------------------------------------------------*

*---------------------------------------------------------------------------------------------------*
 Unique Values for Ward_Facility_Code
['F' 'E' 'D' 'B' 'A' 'C']
*---------------------------------------------------------------------------------------------------*

*---------------------------------------------------------------------------------------------------*
 Unique Values for Bed_Grade
[ 2.  3.  4.  1. nan]
*---------------------------------------------------------------------------------------------------*

*---------------------------------------------------------------------------------------------------*
 Unique Values for patientid
[31397 63418  8088 ... 37502 73756 21763]
*                                                                                                   *
```

```
*-----------------------------------------------------------------------------------------------------------*
 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
...                   ...                ...                 ...
237304                  F             Trauma             Extreme
237305                  C          Emergency             Extreme
```

```
237306                  F         Emergency              Minor
237307                  A         Emergency              Minor
237308                  E            Trauma                Min

        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

```
# 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])
```

```
# 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'])
```

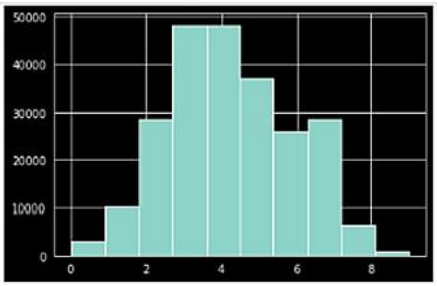
```
combined[0]
```

	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	

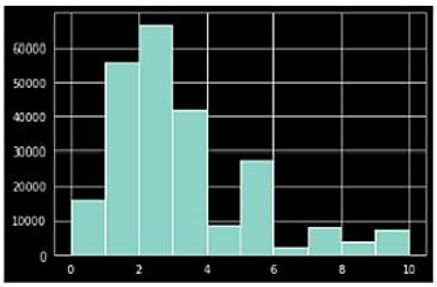
237309 rows × 14 columns

```
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	



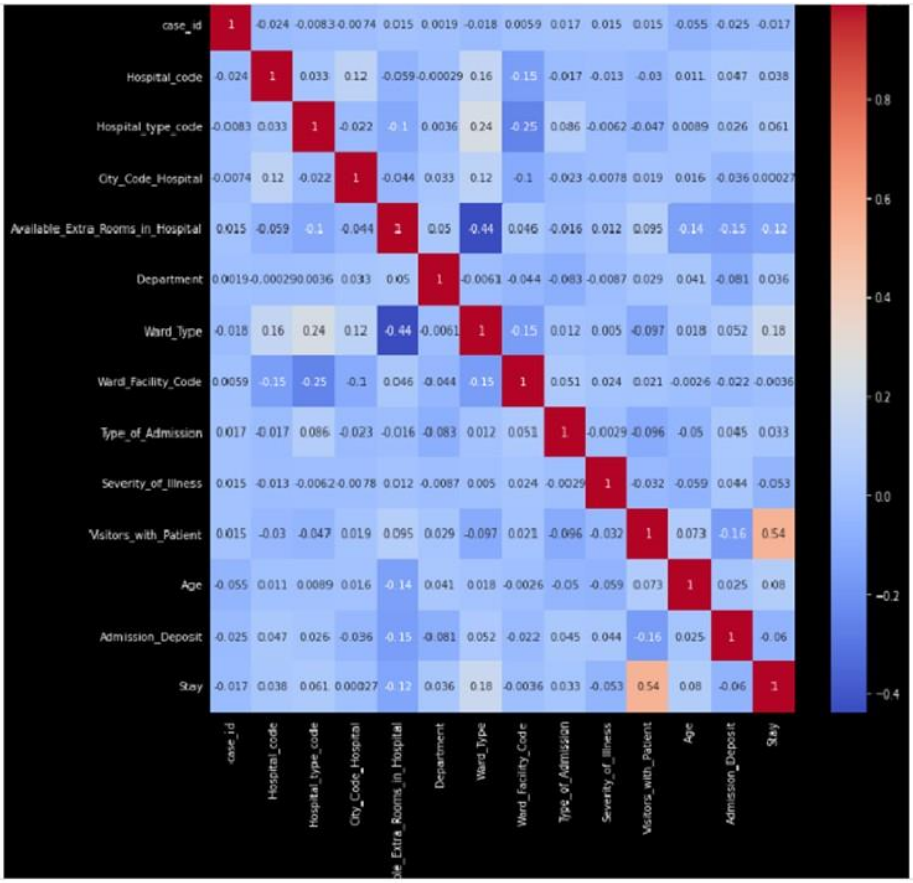

```
combined[0].Stay.hist()
```



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

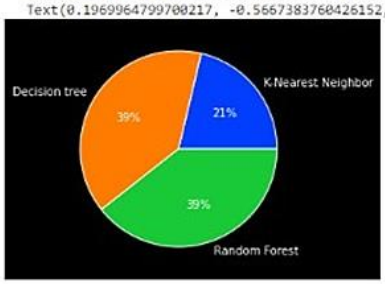
```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(X_train, Y_train)
Y_pred = random_forest.predict(X_test)
random_forest.score(X_train, Y_train)
acc_random_forest = round(random_forest.score(X_train, Y_train) * 100, 2)
acc_random_forest
```

```
99.76
```

Prediction accuracy comparison

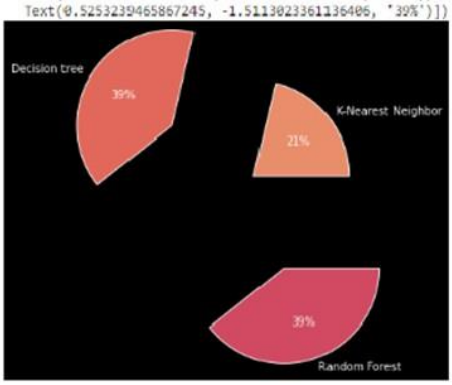
```
palette_color = sns.color_palette('bright')
data=[acc_knn, acc_decision_tree,acc_random_forest]
keys=['K-Nearest Neighbor','Decision tree','Random Forest']

#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, 0.682277842548633, 'K-Nearest Neighbor'),
  Text(-0.9277499083745313, 0.590999244932723, 'Decision tree'),
  Text(0.36116021327837317, -1.0390203560781281, 'Random Forest')],
 [Text(0.4706412895980693, 0.3721515504810725, '21%'),
  Text(-0.5060454045679261, 0.322363224508758, '39%'),
  Text(0.1969964799700217, -0.5667383760426152, '39%')])
```




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

```
 ],
[Text(0.8706863857564283, 0.6884803683899842, 'K-Nearest Neighbor'),
 Text(-1.771158915987741, 1.1282712857806532, 'Decision tree'),
 Text(0.689487679895875, -1.0835843161491535, 'Random Forest')],
[Text(0.47848531109137044, 0.37835407632242374, '21%'),
 Text(-1.3494544121811365, 0.859635265356688, '39%'),
 Text(0.5253239465867245, -1.5113023361136406, '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
```

GitHub & Project Demo Links:

GithHub link: IBM-EPBL/**IBM-Project-36286-1660293946**