

# **Analytics for Hospitals' Health-Care Data**

- Submitted by

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# Project Report

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## CHAPTER 1 INTRODUCTION

### 1.1 : PROJECT OVERVIEW

The terms "heart disease" and "cardiovascular disease" are frequently used interchangeably. Heart disease is a general term that covers a wide range of heart related medical conditions. The irregular health state that directly affects the heart and all of its components is characterized by these medical conditions.

In order to forecast cardiac disease, this study discusses various data mining, big data, and machine learning techniques. Building an important model for the medical system to forecast heart disease or cardiovascular illness requires the use of data mining and machine learning. Our application helps the user in finding out if they have heart disease or not.

They can find out by entering details such as their heart rate, cholesterol, blood pressure etc. A dashboard is also attached along with the results for better understanding where they can compare their blood pressure and similar metrics with other users. This project focuses on Random Forest Classifier. The accuracy of our project is 87% for which is better than most other systems in terms of achieving accuracy quickly.

### 1.2 : PURPOSE

This project's goal is to determine, depending on the patient's medical characteristics—such as gender, age, chest pain, fasting blood sugar level, etc.—whether they are likely to be diagnosed with any cardiovascular heart illnesses. The leading cause of death in the developed world is heart disease. Heart disease cases are rising quickly every day, thus it's crucial and worrisome to predict any potential illnesses in advance. This diagnosis is a challenging task that requires accuracy and efficiency.

Therefore, there needs to be work done to help prevent the risks of having a heart attack or stroke. It is the main factor in adult deaths. By using a person's medical history, our initiative can identify those who are most likely to be diagnosed with a cardiac condition. It can assist in identifying disease with less medical tests and effective therapies, so that patients can be treated appropriately. It can identify anyone who is experiencing any heart disease symptoms, such as chest pain or high blood pressure.

Around the world, machine learning is applied in many different fields. There is no exception in the healthcare sector. Machine learning may be crucial in determining whether locomotor disorders, heart illnesses, and other conditions are present or absent. If foreseen well in advance, such information can offer valuable insights to doctors, who can then customise their diagnosis and course of care for each patient.

## CHAPTER 2 LITERATURE SURVEY

### 2.1 EXISTING PROBLEM

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

### 2.2 REFERENCES

Kenneth Tan et al [1] suggested to forecast the duration of stay using heart-rate readings and physiological ratings. They suggested a model for the heart rate based on the Markov chain model and estimated transition probabilities using the maximum likelihood estimator and the patient population from McMaster Hospital's Neonatal Intensive Care Unit. Using physiological measures and transition probabilities, they then developed maximum likelihood estimators for LOS. Training and test data sets were utilised to validate the linear and nonlinear estimators that were present.

Keijiro Nakamura et al[2] a deep learning model with weighted predictors is created to predict hospitalisation cost and duration of stay using electronic health records. Through 5-fold cross validation, the suggested model outperforms linear regression in terms of prediction accuracy.

Sneha Grampurohit et al[3] proposed effort to develop a Decision Support System to aid clinicians in predicting inpatient hospital length of stay utilising regression models Linear, Ridge, Lasso, and ElasticNet. Mean Absolute Error was used as the evaluative tool for comparing the outcomes of various regressors. The suggested work has produced a graphical user interface as its application.

P.H. Millard et al [4]presented a model-based technique to extracting high-level length-of-stay trends of long-term care residents from a regularly collected administrative social care dataset. It is an expansion of prior work by the authors to include characteristics of inhabitants. Two applications

using data given by an English local government were shown to illustrate the potential use of this method. Stephane Sanchez et al [5] contrasted machine learning-based hospital length of stay (LOS) predictions with and without clinical indicators given in text. Two random forests predicted LOS. The first was unstructured EHR text (EHRs). EHR data was assessed using a UMLS-based word-embedding method with precise matching confined to patient-centric affirmation phrases. The second model used structured data from ICD-10 diagnoses and triage codes (CCMU/GEMSA classifications). The model using unstructured data had a 75.0% accuracy compared to 74.1% for the model containing structured data. The two models produced a similar prediction in 86.6% of cases. developed a unique methodological framework based on predictive data mining to estimate LOS (Length Of Stay) in an emergency department (ED). Sondès Chaabane et al [6] Utilized supervised learning, compact models were constructed in terms of predictor characteristics. The objective was to determine the elements (variables) influencing LOS in EDs in order to develop models for LOS prediction. We discovered two linear regression-based models. Validated models were effectively applied to the categorization and prediction of LOS in the paediatric emergency department (PED) at the regional medical centre in Lille, France.

## CHAPTER 3 IDEATION & PROPOSED SOLUTION

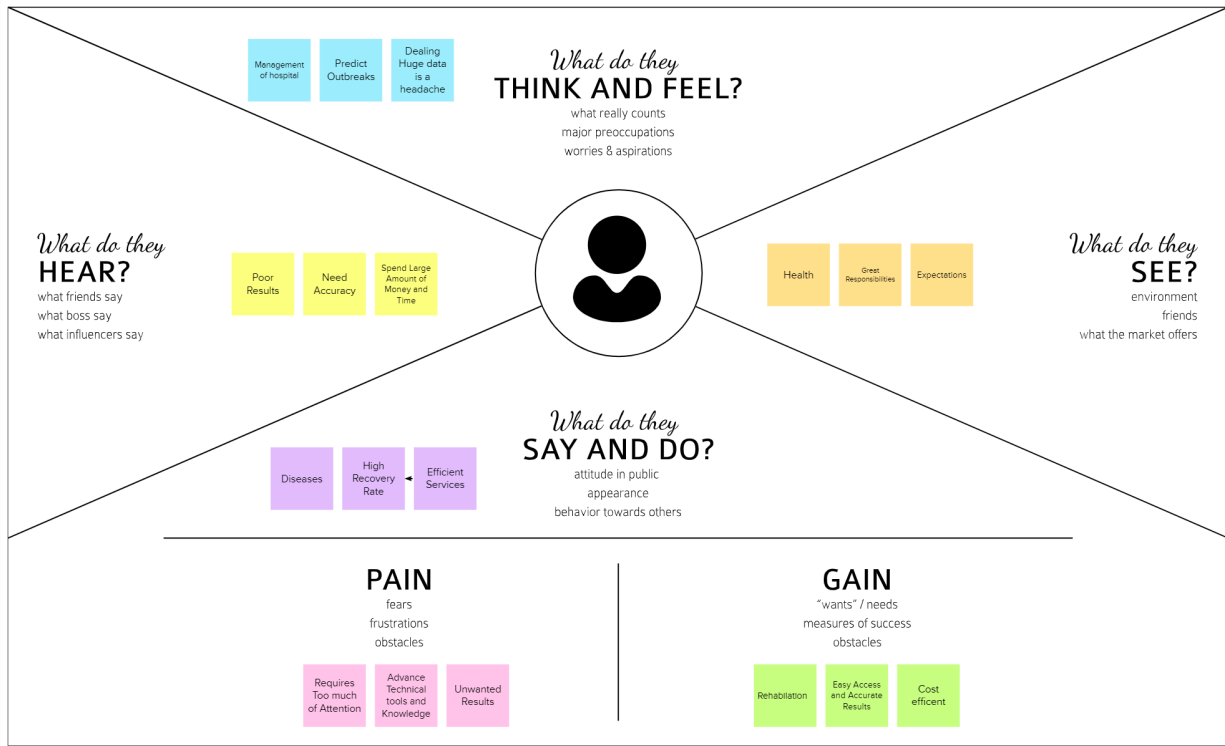
### 3.1 EMPATHY MAP CANVAS

# Empathy Map Canvas

Gain insight and understanding on solving customer problems.

1

Build empathy and keep your focus on the user by putting yourself in their shoes.



## 3.2 IDEATION AND BRAINSTORMING

PRANAV G - TEAM LEADER

1. IDENTIFY PATIENTS OF HIGH LOR RISK
2. OPTIMAL RESOURCE ALLOCATION CAN BE FACILITATED
3. MAKE TIE UPS WITH NGOS
4. PROPOSE A PLAN THAT ATTRACTS MANY HOSPITALS
5. DEVELOP A WEBSITE THAT RUNS 24\*7

## VARSHA K

ANALYSE VARIOUS HOSPITAL'S IMPACT BECAUSE OF LENGTH OF STAY

ANALYSE HOW COMMON PEOPLE'S COST OF LIVING GETS AFFECTED  
BECAUSE OF HIGH LOS

INSUFFICIENT BEDS AND SUPPLIES LEAD TO MORE DEATH  
RATES - VISUALISATION

## HIRTHIK

PREDICT A PRE DEFINED LOS BASED ON DISEASE

SORT HOSPITALS BASED ON LOS

DASHBOARD FOR AGE WISE AND  
DEPARTMENT WISE PATIENTS



## GADAM PRANAV

- The model is packaged using a container for use in different target environments.

Duties typically include using analytics to determine if resources are being allocated appropriately in a hospital network

### PRICING FOR PROJECT=AZURE CALCULATOR

Azure Pricing Calculator saved estimate. This estimate is configured to show the estimated upfront and monthly costs, for a basic implementation that runs 9am-5pm Monday through Friday.

### 3.3 PROPOSED SOLUTION

**Proposed Solution Template:**

Project team shall fill the following information in proposed solution template.


S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	Latest Covid-19 Pandemic has raised worries about one of the most neglected areas of focus: Healthcare Administration. While data science has a variety of applications in healthcare management, patient length of stay is one of the most important parameters to watch and anticipate in order to enhance hospital healthcare management efficiency.
2.	Idea / Solution description	<p>This project intends to calculate the length of stay in a particular hospital</p> <p>The key attributes that will be considered for making the decisions are Department ,Ward Type , Severity of Illness etc</p> <p>For determining the % of acceptance, we will be using various ML models such as Logistic Regression, Multiple Linear Regression, Decision Tree &amp; Random Forest and assess which model gives the highest accuracy with the help of performance metrics like accuracy score, precision and recall.</p>
3.	Novelty / Uniqueness	The web-app will predict the length of stay in a particular hospital . It is beneficial for patients, beneficial for the quality of care they get, and beneficial for the financial health of the institution.


4.	Social Impact / Customer Satisfaction	Extended periods of stay have a detrimental effect on hospitals as well. They contribute to a rise in expenses and are often associated with inefficiency, which is an indication that some procedures may need reevaluation. In a similar vein, the duration of stay has a direct influence on bed management, which in turn reduces
		<p>turnover and affects income. When a patient is held in a bed for a longer period of time than they need, it may mean that the bed is not accessible for another patient who requires it more urgently. This implies that hospitals may not be able to satisfy the demands of their patients.</p> <p>A shorter amount of time spent receiving therapy directly correlates to a shorter overall duration of stay. It is beneficial for patients, beneficial for the quality of care they get, and beneficial for the financial health of the institution.</p>
5.	Business Model (Revenue Model)	<p>1. Advertisements of different hospitals could be placed in the web-app to generate revenue through ads.</p> <p>2. A separate premium plan could be created where the patients and doctors can input certain details and get information about the length of the stay</p>
6.	Scalability of the Solution	A future update could have chat space where Patients , doctors , administration officials of the hospital can interact .
3.4 PROBLEM SOLUTION FIT		

## Problem-Solution fit canvas 2.0

Purpose / Vision

Define CS, fit into	<b>1. CUSTOMER SEGMENT(S)</b> <small>Who is your customer?</small>  <b>HOSPITALS WHO WISH TO IMPROVE THEIR HEALTHCARE MANAGEMENT SYSTEM</b>	<b>6. CUSTOMER</b> <small>What constraints prevent your customers from taking action or limit their choices of solutions? i.e. spending power, budget, no cash, network connection, available devices.</small>  <b>CUSTOMERS MIGHT NOT TRUST THE ACCURACY OF THE PREDICTOR AND THEY MIGHT FEAR DATA MISUSE. THIS MIGHT PREVENT THEM FROM USING</b>	<b>5. AVAILABLE SOLUTIONS</b> <small>Which solutions are available to the customers when they face the problem or need to get the job done? What have they tried in the past? What pros &amp; cons do these solutions have? i.e. pen and paper is an alternative to digital notetaking</small>  <b>APART FROM FACTORS LIKE INFECTION RATE AND WARD TYPE OTHER FACTORS SHOULD ALSO BE CONSIDERED TO ENHANCE RELIABILITY</b>	Explore AS.
	<b>2. JOBS-TO-BE-DONE / PROBLEMS</b> <small>Which jobs-to-be-done (or problems) do you address for your customers? There could be more than one, explore different sides.</small>  <b>DATA COLLECTION IS ONE OF THE MOST IMPORTANT STEP IN DESIGNING THE PREDICTOR' HENCE IT SHOULD BE DONE PROPERLY</b>  <b>CUSTOMERS SHOULD BE ASSURED OF OPTIMUM DATA SECURITY IN ORDER TO HAVE THEM RETAIN THEIR TRUST IN OUR PREDICTOR</b>	<b>9. PROBLEM ROOT CAUSE</b> <small>What is the real reason that this problem exists? What is the back story behind the need to do this job? i.e. customers have to do it because of the change in regulations.</small>  <b>THE RELIABILITY OF THE PREDICTOR IS AFFECTED IF THE DATA COLLECTED IS INACCURATE. CUSTOMERS MIGHT REFRAIN FROM USING IF THEY FIND IT TO BE PRONE TO CYBER ATTACKS</b>	<b>7. BEHAVIOUR</b> <small>What does your customer do to address the problem and get the job done? i.e. directly related: find the right solar panel installer, calculate usage and benefits; indirectly associated: customers spend free time on volunteering work (i.e. Greenpeace)</small>  <b>THE MOST IMPORTANT ASPECT OF THE PREDICTOR IS THE ACCURACY WHICH IS IMPORTANT TO ENHANCE HOSPITAL MANAGEMENT SYSTEM DATA SHOULD BE STORED SECURELY</b>	
<b>3. TRIGGERS</b> <small>What triggers customers to act? i.e. seeing their neighbour installing solar panels, reading about a more efficient solution in the news.</small> <b>CUSTOMERS CAN BE PROVIDED WITH COMPARISON OF LENGTH OF STAY AS PREDICTED BY MODEL AND THE ACTUAL LENGTH OF STAY</b>	<b>10. YOUR SOLUTION</b> <b>DESIGN A PREDICTOR WITH GOOD AMOUNT OF ACCURACY AND ENSURE THAT THE DATA COLLECTED IS SECURE</b>	<b>8. CHANNELS OF BEHAVIOUR</b> <small>8.1 ONLINE</small> <small>What kind of actions do customers take online? Extract online channels from #7</small>  <b>CUSTOMERS MIGHT SEARCH FOR RELIABLE PREDICTORS THAT ARE AVAILABLE ONLINE AND RATE THEM BASED ON LIKING HOSPITALS MIGHT DISCUSS ABOUT THE PREDICTORS WITH OTHER HOSPITALS AND IF THEY FIND IT RELIABLE, THEY WOULD SPREAD A WORD ABOUT IT.</b>	Extract online & offline CH of BE	
<b>4. EMOTIONS: BEFORE / AFTER</b> <b>USERS WOULD FEEL THEY ARE IN COMPLETE CONTROL IN PREDICTING THE LENGTH OF STAY SINCE THEY CAN WHOLEHEARTEDLY TRUST THE PREDICTOR</b>				


 Problem-Solution fit canvas is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 license. Created by Daria Nepriakhina / Amaltama.com


**AMALTAMA**

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## CHAPTER 4 REQUIREMENT ANALYSIS

### 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
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	User Details	Submit the documents <ul style="list-style-type: none"> <li>Ward type</li> <li>Severity of illness</li> <li>Department</li> </ul>
FR-4	User Requirements	<ul style="list-style-type: none"> <li>Upload all the relevant details in the appropriate location in the website</li> <li>Based on the uploads, the system would scrape all the necessary information</li> <li>The length of stay will be predicted based on the scraped information</li> </ul>

## 4.2 NON-FUNCTIONAL REQUIREMENTS

### Non-functional Requirements:

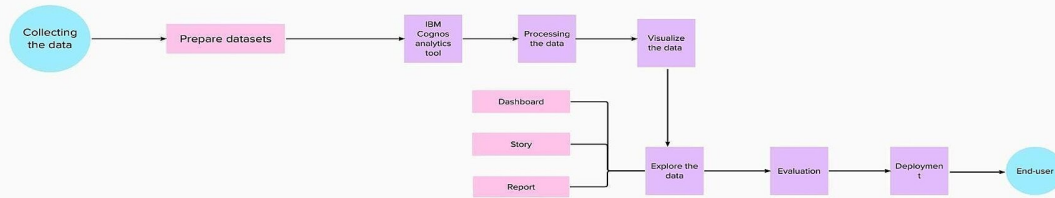
Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	<b>Usability</b>	<ul style="list-style-type: none"><li>• The system doesn't expect any technical pre-requisite from the user i.e.; even the naïve user can access it.</li><li>• User friendly.</li><li>• Reduced focus on Short Term memory load Focus on Internal Locus of Control.</li><li>• The page would not take a lot of time to load the content and display them (&lt; 30 seconds).</li></ul>
NFR-2	<b>Security</b>	<ul style="list-style-type: none"><li>• Only the authenticated user would be able to utilize the services of the site.</li><li>• Database should be backed up every hour</li></ul>
NFR-3	<b>Reliability</b>	<ul style="list-style-type: none"><li>• The system would always strive for maximum reliability due to the importance of data and damages that could be cause by</li></ul>

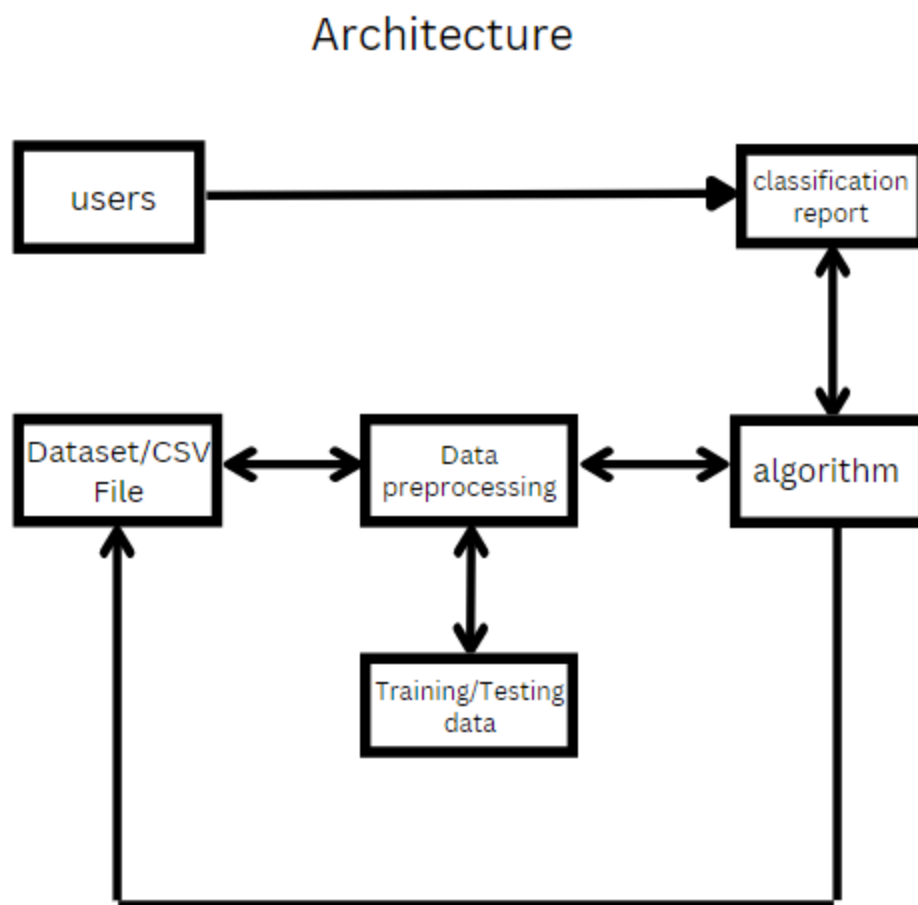
## CHAPTER 5 PROJECT DESIGN

### Data Flow Diagrams ,Solution & Technical Architecture

5.1 Data Flow Diagrams: A Data Flow Diagram (DFD) is a graphical representation of the flow of data in a business information system. It describes the processes that are involved in a system to transfer data from the input to the file storage and reports generation. It shows how data enters and leaves the system, what changes the information, and where data is stored.



## 5.2 Solution and Architecture diagram:



Solution Architecture: Solution architecture is a complex process – with many sub-processes – that bridges the gap between business problems and technology solutions. Its goals are to:

- Find the best tech solution to solve existing business problems.
- Describe the structure, characteristics, behavior, and other aspects of the software to project

stakeholders.

- Define features, development phases, and solution requirements.
- Provide specifications according to which the solution is defined, managed, and delivered.

### 5.3 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
Hospitals		USN-1	By providing my email address, a password, and a password confirmation, I can register for the program as a user.	I can access my account / dashboard	High	Sprint-1
		USN-2	When I register for the application as a user, I will get a confirmation email.	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	Using this algorithm both cost and time can be estimated by providing user details	Can be compared with previous length of stay	Medium	Sprint-1

## 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 are collected.	20	High	2 Members

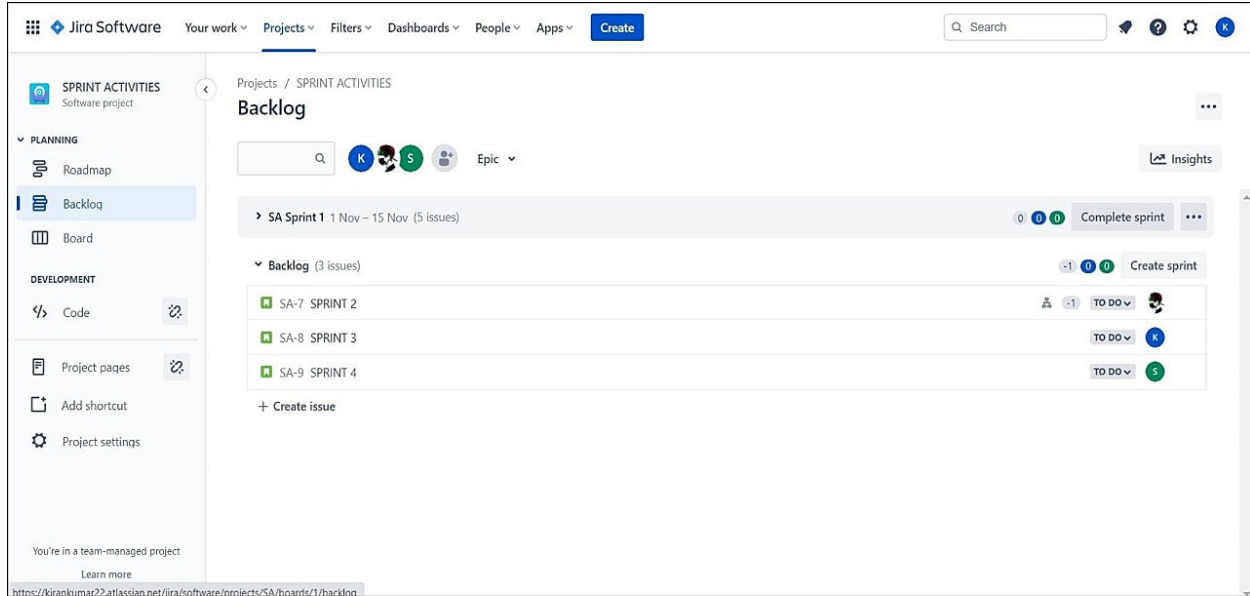
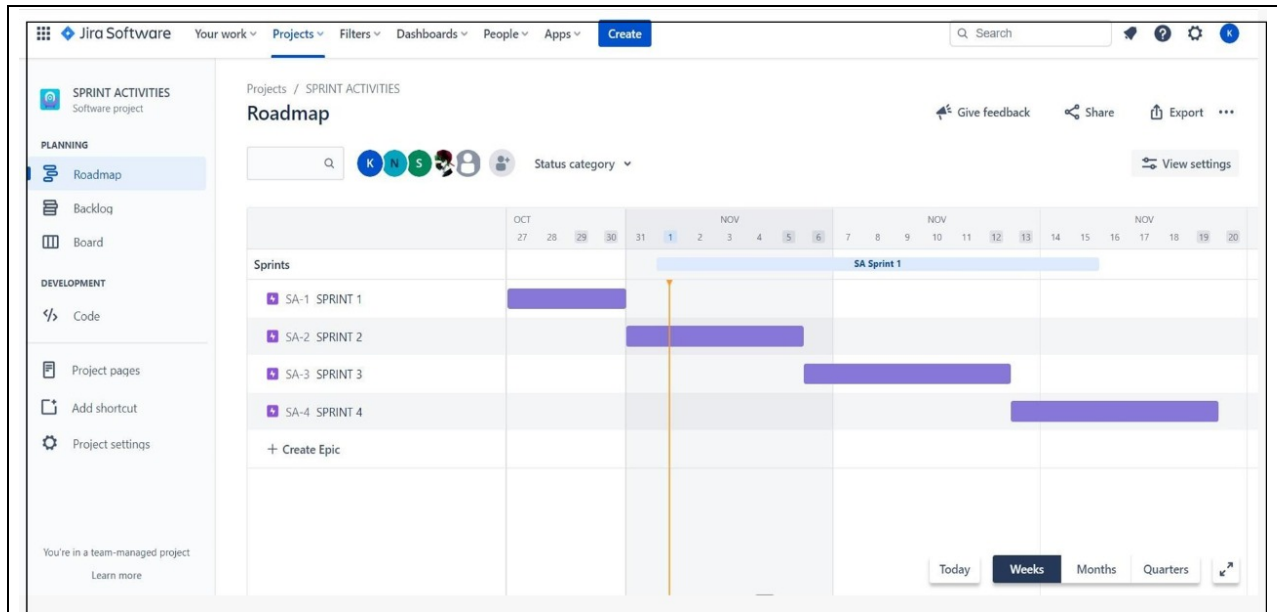
Sprint-2	Analyze	USN-2	As a health care provider all the data that are collected is cleaned and uploaded in the database or IBM cloud.	20	Medium	2 Members
Sprint-3	Dashboard	USN-3	As a health care provider I can use my account in my dashboard for uploading dataset.	10	Medium	2 Members
Sprint-3	Visualization	USN-4	As a health care provider I can prepare data for Visualization.	10	High	2 Members
Sprint-4	Visualization	USN-5	As a health care provider I can present data in my dashboard.	10	High	2 Members
Sprint-4	Prediction	USN-6	As a health care provider I can predict the length of stay	10	High	2 Members

## 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

:  
REPORTS FROM JIRA:





## CHAPTER 7 CODING & SOLUTIONING

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```

```
"2      X      2 anesthesia \n",
```

```
"3      Y      2 radiotherapy \n",
```

```
"4      Y      2 radiotherapy \n",
```

```
"\n",
```

```
" Ward_Type Ward_Facility_Code Bed Grade patientid City_Code_Patient \\n",
```

```
"0    R      F    2.0  31397      7.0  \n",
```

```
"1    S      F    2.0  31397      7.0  \n",
```

```
"2    S      E    2.0  31397      7.0  \n",
```

```
"3    R      D    2.0  31397      7.0  \n",
```

```
"4    S      D    2.0  31397      7.0  \n",
```

```
"\n",
```

```
" Type of Admission Severity of Illness Visitors with Patient Age \\n",
```

```
"0    Emergency      Extreme      2 51-60 \n",
```

```
"1    Trauma      Extreme      2 51-60 \n",
```

```
"2    Trauma      Extreme      2 51-60 \n",
```

```
"3    Trauma      Extreme      2 51-60 \n",
```

```
"4    Trauma      Extreme      2 51-60 \n",
```

```
"\n",
```

```
" Admission_Deposit Stay \n",
```

```
"0      4911.0 0-10 \n",
```

```
"1      5954.0 41-50 \n",
```

```
"2      4745.0 31-40 \n",
```

```

"3      7272.0 41-50 \n",
"4      5558.0 41-50 "
]
},
"execution_count": 163,
"metadata": {},
"output_type": "execute_result"
}
],
"source": [
"train.head()"
]
},
{
"cell_type": "code",
"execution_count": 164,
"id": "c096c760",
"metadata": {},
"outputs": [
{
"name": "stdout",
"output_type": "stream",
"text": [
"<class 'pandas.core.frame.DataFrame'>\n",
"RangeIndex: 318438 entries, 0 to 318437\n",
"Data columns (total 18 columns):\n",
"#   Column                                Non-Null Count  Dtype  \n",
"---  ---                                -
0   case_id                               318438 non-null  int64  \n",
1   Hospital_code                         318438 non-null  int64  \n",
2   Hospital_type_code                    318438 non-null  object \n",
3   City_Code_Hospital                    318438 non-null  int64  \n",
4   Hospital_region_code                  318438 non-null  object \n",
5   Available Extra Rooms in Hospital     318438 non-null  int64  \n",
6   Department                            318438 non-null  object \n",
7   Ward_Type                             318438 non-null  object \n",
8   Ward_Facility_Code                    318438 non-null  object \n",
9   Bed Grade                             318325 non-null  float64\n",
10  patientid                             318438 non-null  int64  \n",
11  City_Code_Patient                      313906 non-null  float64\n",
12  Type of Admission                      318438 non-null  object \n",
13  Severity of Illness                    318438 non-null  object \n",

```

```

" 14 Visitors with Patient      318438 non-null int64 \n",
" 15 Age                       318438 non-null object \n",
" 16 Admission_Deposit        318438 non-null float64\n",
" 17 Stay                      318438 non-null object \n",
"dtypes: float64(3), int64(6), object(9)\n",
"memory usage: 43.7+ MB\n"
]
}
],
"source": [
"train.info()"
]
},
{
"cell_type": "code",
"execution_count": 165,
"id": "1483bd67",
"metadata": {},
"outputs": [
{
"data": {
"text/plain": [
"array(['0-10', '41-50', '31-40', '11-20', '51-60', '21-30', '71-80',\n
'      'More than 100 Days', '81-90', '61-70', '91-100'], dtype=object)"
]
},
"execution_count": 165,
"metadata": {},
"output_type": "execute_result"
}
],
"source": [
"train.Stay.unique()"
]
},
{
"cell_type": "code",
"execution_count": 166,
"id": "a7617b2f",
"metadata": {},
"outputs": [
{

```



```

"data": {
  "text/plain": [
    "City_Code_Patient      4532\n",
    "Bed Grade              113\n",
    "Hospital_code          0\n",
    "Admission_Deposit      0\n",
    "Age                    0\n",
    "Visitors with Patient   0\n",
    "Severity of Illness     0\n",
    "Type of Admission       0\n",
    "patientid              0\n",
    "case_id                0\n",
    "Ward_Facility_Code      0\n",
    "Ward_Type              0\n",
    "Department             0\n",
    "Available Extra Rooms in Hospital  0\n",
    "Hospital_region_code    0\n",
    "City_Code_Hospital      0\n",
    "Hospital_type_code      0\n",
    "Stay                   0\n",
    "dtype: int64"
  ]
},
"execution_count": 166,
"metadata": {},
"output_type": "execute_result"
}
],
"source": [
  "train.isnull().sum().sort_values(ascending = False)"
]
},
{
  "cell_type": "code",
  "execution_count": 167,
  "id": "e4321f9d",
  "metadata": {},
  "outputs": [
    {
      "data": {
        "text/plain": [
          "City_Code_Patient      2157\n",

```

```

"Bed Grade          35\n",
"case_id            0\n",
"Age                0\n",
"Visitors with Patient  0\n",
"Severity of Illness  0\n",
"Type of Admission    0\n",
"patientid           0\n",
"Ward_Facility_Code   0\n",
"Hospital_code        0\n",
"Ward_Type            0\n",
"Department           0\n",
"Available Extra Rooms in Hospital  0\n",
"Hospital_region_code 0\n",
"City_Code_Hospital   0\n",
"Hospital_type_code    0\n",
"Admission_Deposit     0\n",
"dtype: int64"
]
},
"execution_count": 167,
"metadata": {},
"output_type": "execute_result"
}
],
"source": [
"test.isnull().sum().sort_values(ascending = False)"
]
},
{
"cell_type": "code",
"execution_count": 168,
"id": "7d9a95fc",
"metadata": {},
"outputs": [
{
"data": {
"text/plain": [
"(318438, 18)"
]
}
},
"execution_count": 168,
"metadata": {},

```

```
"output_type": "execute_result"
}
],
"source": [
  "train.shape"
]
},
{
  "cell_type": "code",
  "execution_count": 169,
  "id": "d8044bf9",
  "metadata": {},
  "outputs": [
    {
      "data": {
        "text/plain": [
          "(137057, 17)"
        ]
      },
      "execution_count": 169,
      "metadata": {},
      "output_type": "execute_result"
    }
  ],
  "source": [
    "test.shape"
  ]
},
{
  "cell_type": "code",
  "execution_count": 170,
  "id": "99650865",
  "metadata": {},
  "outputs": [
    {
      "name": "stdout",
      "output_type": "stream",
      "text": [
        "case_id : 318438\n",
        "Hospital_code : 32\n",
        "Hospital_type_code : 7\n",
        "City_Code_Hospital : 11\n",

```

```

"Hospital_region_code : 3\n",
"Available Extra Rooms in Hospital : 18\n",
"Department : 5\n",
"Ward_Type : 6\n",
"Ward_Facility_Code : 6\n",
"Bed Grade : 4\n",
"patientid : 92017\n",
"City_Code_Patient : 37\n",
"Type of Admission : 3\n",
"Severity of Illness : 3\n",
"Visitors with Patient : 28\n",
"Age : 10\n",
"Admission_Deposit : 7300\n",
"Stay : 11\n"
]
}
],
"source": [
  "for i in train.columns:\n",
  "  print(i, ': ', train[i].nunique())"
]
},
{
  "cell_type": "code",
  "execution_count": 171,
  "id": "9369c3d3",
  "metadata": {},
  "outputs": [],
  "source": [
    "train['Bed Grade'].fillna(train['Bed Grade'].mode()[0], inplace = True)\n",
    "test['Bed Grade'].fillna(test['Bed Grade'].mode()[0], inplace = True)"
  ]
},
{
  "cell_type": "code",
  "execution_count": 172,
  "id": "de00e3ef",
  "metadata": {},
  "outputs": [],
  "source": [
    "train['City_Code_Patient'].fillna(train['City_Code_Patient'].mode()[0], inplace = True)\n",
    "test['City_Code_Patient'].fillna(test['City_Code_Patient'].mode()[0], inplace = True)"
  ]
}

```

```

]
},
{
  "cell_type": "code",
  "execution_count": 173,
  "id": "e155efa5",
  "metadata": {},
  "outputs": [],
  "source": [
    "from sklearn.preprocessing import LabelEncoder\n",
    "le = LabelEncoder()\n",
    "train['Stay'] = le.fit_transform(train['Stay'].astype('str'))"
  ]
},
{
  "cell_type": "code",
  "execution_count": 174,
  "id": "2d7b0d90",
  "metadata": {},
  "outputs": [
    {
      "data": {
        "text/plain": [
          "(455495, 18)"
        ]
      },
      "execution_count": 174,
      "metadata": {},
      "output_type": "execute_result"
    }
  ],
  "source": [
    "test['Stay'] = -1\n",
    "df = pd.concat([train, test])\n",
    "df.shape"
  ]
},
{
  "cell_type": "code",
  "execution_count": 175,
  "id": "0b66cd25",
  "metadata": {},

```

```

"outputs": [],
"source": [
    "for i in ['Hospital_type_code', 'Hospital_region_code', 'Department',\n",
    "        'Ward_Type', 'Ward_Facility_Code', 'Type of Admission', 'Severity of Illness', 'Age']:\n",
    "    le = LabelEncoder()\n",
    "    df[i] = le.fit_transform(df[i].astype(str))"
]
},
{
    "cell_type": "code",
    "execution_count": 176,
    "id": "59971518",
    "metadata": {},
    "outputs": [],
    "source": [
        "train = df[df['Stay']!=1]\n",
        "test = df[df['Stay']==1]"
    ]
},
{
    "cell_type": "code",
    "execution_count": 177,
    "id": "02e21fda",
    "metadata": {},
    "outputs": [],
    "source": [
        "def get_countid_enocde(train, test, cols, name):\n",
        "    temp = train.groupby(cols)['case_id'].count().reset_index().rename(columns = {'case_id':\nname})\n",
        "    temp2 = test.groupby(cols)['case_id'].count().reset_index().rename(columns = {'case_id':\nname})\n",
        "    train = pd.merge(train, temp, how='left', on= cols)\n",
        "    test = pd.merge(test,temp2, how='left', on= cols)\n",
        "    train[name] = train[name].astype('float')\n",
        "    test[name] = test[name].astype('float')\n",
        "    train[name].fillna(np.median(temp[name]), inplace = True)\n",
        "    test[name].fillna(np.median(temp2[name]), inplace = True)\n",
        "    return train, test"
    ]
},
{
    "cell_type": "code",

```

```

"execution_count": 178,
"id": "6060fc4d",
"metadata": {},
"outputs": [],
"source": [
    "train, test = get_countid_enocode(train, test, ['patientid'], name = 'count_id_patient')\n",
    "train, test = get_countid_enocode(train, test, \n",
    "    ['patientid', 'Hospital_region_code'], name =
'count_id_patient_hospitalCode')\n",
    "train, test = get_countid_enocode(train, test, \n",
    "    ['patientid', 'Ward_Facility_Code'], name =
'count_id_patient_wardfacilityCode')
]
},
{
    "cell_type": "code",
    "execution_count": 179,
    "id": "94ae91ea",
    "metadata": {},
    "outputs": [],
    "source": [
        "test1 = test.drop(['Stay', 'patientid', 'Hospital_region_code', 'Ward_Facility_Code'], axis =1)\n",
        "train1 = train.drop(['case_id', 'patientid', 'Hospital_region_code', 'Ward_Facility_Code'], axis =1)"
    ]
},
{
    "cell_type": "code",
    "execution_count": 180,
    "id": "79bffe9b",
    "metadata": {},
    "outputs": [],
    "source": [
        "X1 = train1.drop('Stay', axis =1)\n",
        "y1 = train1['Stay']\n",
        "from sklearn.model_selection import train_test_split\n",
        "X_train, X_test, y_train, y_test = train_test_split(X1, y1, test_size =0.20, random_state =100)"
    ]
},
{
    "cell_type": "code",
    "execution_count": 181,
    "id": "df59b059",

```

```
"metadata": {},
"outputs": [],
"source": [
    "from sklearn.neighbors import KNeighborsClassifier\n",
    "from sklearn.linear_model import LogisticRegression\n",
    "from sklearn.tree import DecisionTreeClassifier"
]
},
{
    "cell_type": "markdown",
    "id": "3c0e8956",
    "metadata": {},
    "source": [
        "# logistic"
    ]
},
{
    "cell_type": "code",
    "execution_count": 182,
    "id": "fca9facd",
    "metadata": {},
    "outputs": [
        {
            "name": "stdout",
            "output_type": "stream",
            "text": [
                "0.35359764474975464\n",
                "0.35279801532470795\n"
            ]
        }
    ],
    "source": [
        "clf = LogisticRegression(max_iter=1000)\n",
        "clf.fit(X_train, y_train)\n",
        "print(clf.score(X_train, y_train))\n",
        "print(clf.score(X_test, y_test))"
    ]
},
{
    "cell_type": "markdown",
    "id": "0bba38a4",
    "metadata": {},
```



```

"source": [
  "# ANN\n"
]
},
{
  "cell_type": "code",
  "execution_count": 183,
  "id": "f194a381",
  "metadata": {},
  "outputs": [
    {
      "name": "stdout",
      "output_type": "stream",
      "text": [
        "Index(['case_id', 'Hospital_code', 'Hospital_type_code', 'City_Code_Hospital',\n",
        "      'Hospital_region_code', 'Available Extra Rooms in Hospital',\n",
        "      'Department', 'Ward_Type', 'Ward_Facility_Code', 'Bed Grade',\n",
        "      'patientid', 'City_Code_Patient', 'Type of Admission',\n",
        "      'Severity of Illness', 'Visitors with Patient', 'Age',\n",
        "      'Admission_Deposit', 'count_id_patient',\n",
        "      'count_id_patient_hospitalCode', 'count_id_patient_wardfacilityCode'],\n",
        "      dtype='object')\n",
        "Index(['case_id', 'Hospital_code', 'Hospital_type_code', 'City_Code_Hospital',\n",
        "      'Hospital_region_code', 'Available Extra Rooms in Hospital',\n",
        "      'Department', 'Ward_Type', 'Ward_Facility_Code', 'Bed Grade',\n",
        "      'patientid', 'City_Code_Patient', 'Type of Admission',\n",
        "      'Severity of Illness', 'Visitors with Patient', 'Age',\n",
        "      'Admission_Deposit', 'count_id_patient',\n",
        "      'count_id_patient_hospitalCode', 'count_id_patient_wardfacilityCode'],\n",
        "      dtype='object')\n"
      ],
    },
    {
      "data": {
        "text/plain": [
          "(318438, 20)"
        ]
      },
      "execution_count": 183,
      "metadata": {},
      "output_type": "execute_result"
    }
  ]
}

```

```

],
"source": [
    "X = train.drop('Stay', axis =1)\n",
    "y = train['Stay']\n",
    "print(X.columns)\n",
    "z = test.drop('Stay', axis = 1)\n",
    "print(z.columns)\n",
    "\n",
    "# Data Scaling\n",
    "from sklearn import preprocessing\n",
    "X_scale = preprocessing.scale(X)\n",
    "X_scale.shape"
]
},
{
    "cell_type": "code",
    "execution_count": 184,
    "id": "6643b9a9",
    "metadata": {},
    "outputs": [],
    "source": [
        "X_train, X_test, y_train, y_test = train_test_split(X_scale, y, test_size =0.20, random_state
=100)"
    ]
},
{
    "cell_type": "code",
    "execution_count": null,
    "id": "416e5289",
    "metadata": {},
    "outputs": [],
    "source": [
        "import keras\n",
        "from keras.models import Sequential\n",
        "from keras.layers import Dense\n",
        "import tensorflow as tf"
    ]
},
{
    "cell_type": "code",
    "execution_count": null,
    "id": "99d79add",

```

```

"metadata": {},
"outputs": [],
"source": [
    "from keras.utils import to_categorical\n",
    "#Sparse Matrix\n",
    "a = to_categorical(y_train)\n",
    "b = to_categorical(y_test)\n",
    "print(scores)"
]
},
{
    "cell_type": "code",
    "execution_count": null,
    "id": "72f0e86b",
    "metadata": {},
    "outputs": [],
    "source": [
        "model = Sequential()\n",
        "model.add(Dense(64, activation='relu', input_shape = (254750, 20))) \n",
        "model.add(Dense(128, activation='relu'))\n",
        "model.add(Dense(256, activation='relu'))\n",
        "model.add(Dense(512, activation='relu'))\n",
        "model.add(Dense(512, activation='relu'))\n",
        "model.add(Dense(11, activation='softmax'))"
    ]
},
{
    "cell_type": "code",
    "execution_count": null,
    "id": "704ad983",
    "metadata": {},
    "outputs": [],
    "source": [
        "model.summary()"
    ]
},
{
    "cell_type": "code",
    "execution_count": null,
    "id": "4fbd2fa0",
    "metadata": {},
    "outputs": [],

```

```

"source": [
  "model.compile(optimizer= 'SGD', \n",
  "    loss='categorical_crossentropy', \n",
  "    metrics=['accuracy'])"
]
},
{
  "cell_type": "code",
  "execution_count": null,
  "id": "42b29be4",
  "metadata": {},
  "outputs": [],
  "source": [
    "callbacks = [tf.keras.callbacks.TensorBoard(\"logs_keras\")]\n",
    "model.fit(X_train, a, epochs=20, callbacks=callbacks, validation_split = 0.2)"
  ]
},
{
  "cell_type": "code",
  "execution_count": null,
  "id": "c529e1c0",
  "metadata": {},
  "outputs": [],
  "source": [
    "!tensorboard --logdir logs_keras"
  ]
},
{
  "cell_type": "code",
  "execution_count": null,
  "id": "7129c66b",
  "metadata": {},
  "outputs": [],
  "source": [
    "model.fit(X_train, a, epochs=4, validation_split = 0.2)\n",
    "print(\"\\n Model Evaluation\\")\n",
    "model.evaluate(X_test,b)"
  ]
},
{
  "cell_type": "markdown",
  "id": "c2efb55d",

```

```

"metadata": {},
"source": [
    "# XgBoost\n"
]
},
{
    "cell_type": "code",
    "execution_count": null,
    "id": "6e9161fc",
    "metadata": {},
    "outputs": [],
    "source": [
        "import xgboost\n",
        "classifier_xgb = xgboost.XGBClassifier(max_depth=4, learning_rate=0.1,\n",
        "n_estimators=800,\n",
        "        objective='multi:softmax', reg_alpha=0.5, reg_lambda=1.5,\n",
        "        booster='gbtree', n_jobs=4, min_child_weight=2, base_score= 0.75)"
    ]
},
{
    "cell_type": "code",
    "execution_count": null,
    "id": "dd5917ee",
    "metadata": {},
    "outputs": [],
    "source": [
        "model_xgb = classifier_xgb.fit(X_train, y_train)"
    ]
},
{
    "cell_type": "code",
    "execution_count": null,
    "id": "aa94a83b",
    "metadata": {},
    "outputs": [],
    "source": [
        "prediction_xgb = model_xgb.predict(X_test)\n",
        "acc_score_xgb = accuracy_score(prediction_xgb,y_test)\n",
        "print(\"Accuracy:\", acc_score_xgb*100)"
    ]
},
{

```

```

"cell_type": "markdown",
"id": "b3679dbc",
"metadata": {},
"source": [
    "# predictions"
]
},
{
"cell_type": "code",
"execution_count": null,
"id": "16a18feb",
"metadata": {},
"outputs": [],
"source": [
    "pred_nb = clf.predict(X_test)\n",
    "result_nb = pd.DataFrame(pred_nb, columns=['Stay'])\n",
    "result_nb['case_id'] = test1['case_id']\n",
    "result_nb = result_nb[['case_id', 'Stay']]
]
},
{
"cell_type": "code",
"execution_count": null,
"id": "5a9976db",
"metadata": {},
"outputs": [],
"source": [
    "result_nb['Stay'] = result_nb['Stay'].replace({0:'0-10', 1: '11-20', 2: '21-30', 3:'31-40', 4: '41-50', 5:
'51-60', 6: '61-70', 7: '71-80', 8: '81-90', 9: '91-100', 10: 'More than 100 Days'})\n",
    "result_nb.head()
]
},
{
"cell_type": "code",
"execution_count": null,
"id": "37ea741c",
"metadata": {},
"outputs": [],
"source": [
    "pred_xgb = classifier_xgb.predict(test1.iloc[:,1:])\n",
    "result_xgb = pd.DataFrame(pred_xgb, columns=['Stay'])\n",
    "result_xgb['case_id'] = test1['case_id']\n",

```

```

    "result_xgb = result_xgb[['case_id', 'Stay']]
  ]
},
{
  "cell_type": "code",
  "execution_count": null,
  "id": "e0a40d4e",
  "metadata": {},
  "outputs": [],
  "source": [
    "result_xgb['Stay'] = result_xgb['Stay'].replace({0:'0-10', 1: '11-20', 2: '21-30', 3:'31-40', 4: '41-50',
5: '51-60', 6: '61-70', 7: '71-80', 8: '81-90', 9: '91-100', 10: 'More than 100 Days'})\n",
    "result_xgb.head()"
  ]
},
{
  "cell_type": "code",
  "execution_count": null,
  "id": "885a0652",
  "metadata": {},
  "outputs": [],
  "source": [
    "test_scale = preprocessing.scale(z)\n",
    "test_scale.shape"
  ]
},
{
  "cell_type": "code",
  "execution_count": null,
  "id": "2851016b",
  "metadata": {},
  "outputs": [],
  "source": [
    "pred = model.predict_classes(test_scale)\n",
    "pred"
  ]
},
{
  "cell_type": "code",
  "execution_count": null,
  "id": "af40cfd9",
  "metadata": {},

```

```

"outputs": [],
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    "result_nn = pd.DataFrame(pred, columns=['Stay'])\n",
    "result_nn['case_id'] = test['case_id']\n",
    "result_nn = result_nn[['case_id', 'Stay']]\"
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        "result_nn['Stay'] = result_nn['Stay'].replace({0:'0-10', 1: '11-20', 2: '21-30', 3:'31-40', 4: '41-50', 5:
'51-60', 6: '61-70', 7: '71-80', 8: '81-90', 9: '91-100', 10: 'More than 100 Days'})\n",
        "result_nn.head()"
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