Team id: PNT2022TMID53212

Project Report
Analytics for Hospitals' Health-Care Data

1. Introduction
1.1 Project overview :

Healthcare organizations are under increasing pressure to improve patient care outcomes and achieve better care. While this situation represents a challenge, it also offers organizations an opportunity to dramatically improve the quality of care by leveraging more value and insights from their data. Health care analytics refers to the analysis of data using quantitative and qualitative techniques to explore trends and patterns in the acquired data. While healthcare management uses various metrics for performance, a patient's length of stay is an important one.

Being able to predict the length of stay (LOS) allows hospitals to optimize their treatment
plans to reduce LOS, to reduce infection rates among patients, staff, and visitors.

1.2. Purpose
The goal of this project is to accurately predict the Length of Stay for each patient so that
the hospitals can optimize resources and function better.

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.

2.2. References

- Janatahack: Healthcare Analytics II - Analytics Vidhya - Link
- What Is Naive Bayes Algorithm in Machine Learning? - Rohit Dwivedi - Link
- Naive Bayes for Machine Learning – From Zero to Hero - Anand Venkataraman - Link
- XGBoost Parameters - XGBoost Documentation - Link
- Predicting Heart Failure Using Machine Learning, Part 2- Andrew A Borkowski - Link
- How to Tune the Number and Size of Decision Trees with XGBoost in Python-JasonBrownlee - Link
- Big Data Analytics in Healthcare That Can Save People - Sandra Durcevic - Link
- Learning Process of a Neural Network – Jordi Torres - Link

2.3. Problem statement

The task 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.

3. Ideation & proposed solution

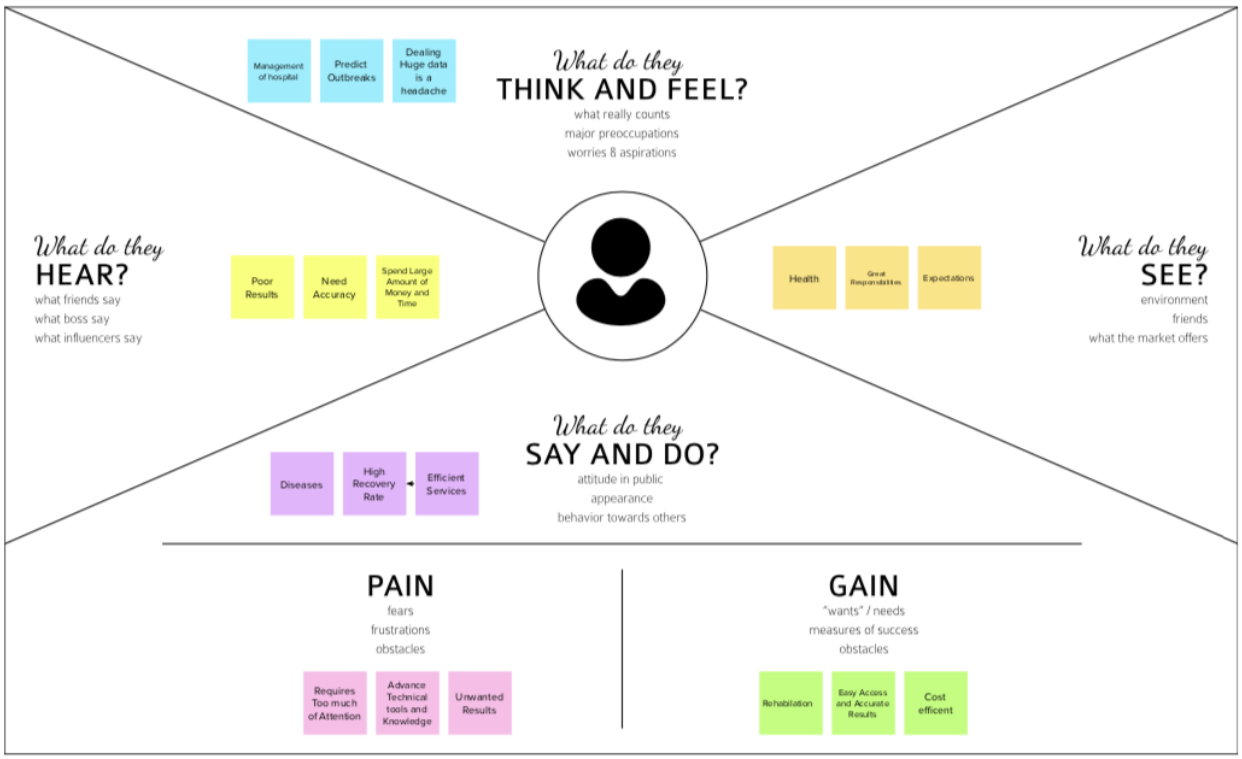
3.1 Empathy map Canvas

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.



1

Define your problem statement

What problem are you trying to solve? Frame your problem as a How Might We statement. This will be the focus of your brainstorm.

5 minutes

Public hospitals has some main challenges such as deficient infrastructure, deficient manpower, unmanageable patient load and etc.,so peoples can be benefitted if these problems are solved adhering to certain software or some notes to maintain all.
Govt Hospitals facing data management due to lack of IT trained staffs.

Private/Small Health sectors cannot store and analyze large data set it consumes lots of money and time.

Researchers faces issues when they are dealing with large datasets as there is Depicting a diversity of opinions and experiences embedded within patient-generated information(not standard data).

Health Researchers and Students are not able to Extract useful Information's due to lack of data's made available publicly as Many hospitals are not sharing health care data being mindful with patients privacy.

Issues with system functionality, including poor user interfaces and fragmented displays, delayed care delivery. Issues with system access, system configuration, and software updates also delayed care.

2

Brainstorm

Write down any ideas that come to mind that address your problem statement.

10 minutes

TIP

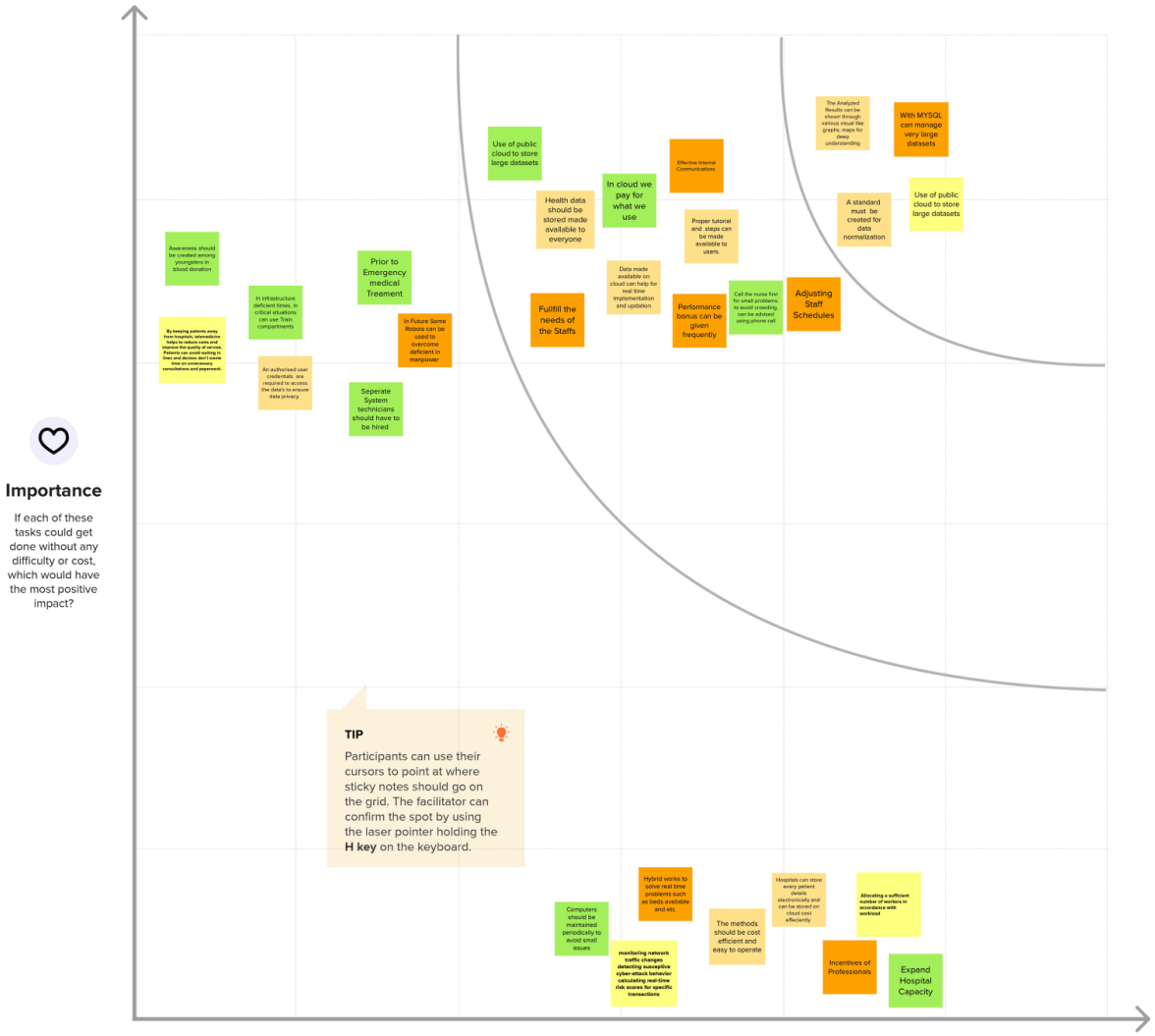
You can select a sticky note and hit the pencil [switch to sketch] icon to start drawing!

4

Prioritize

Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible.

20 minutes

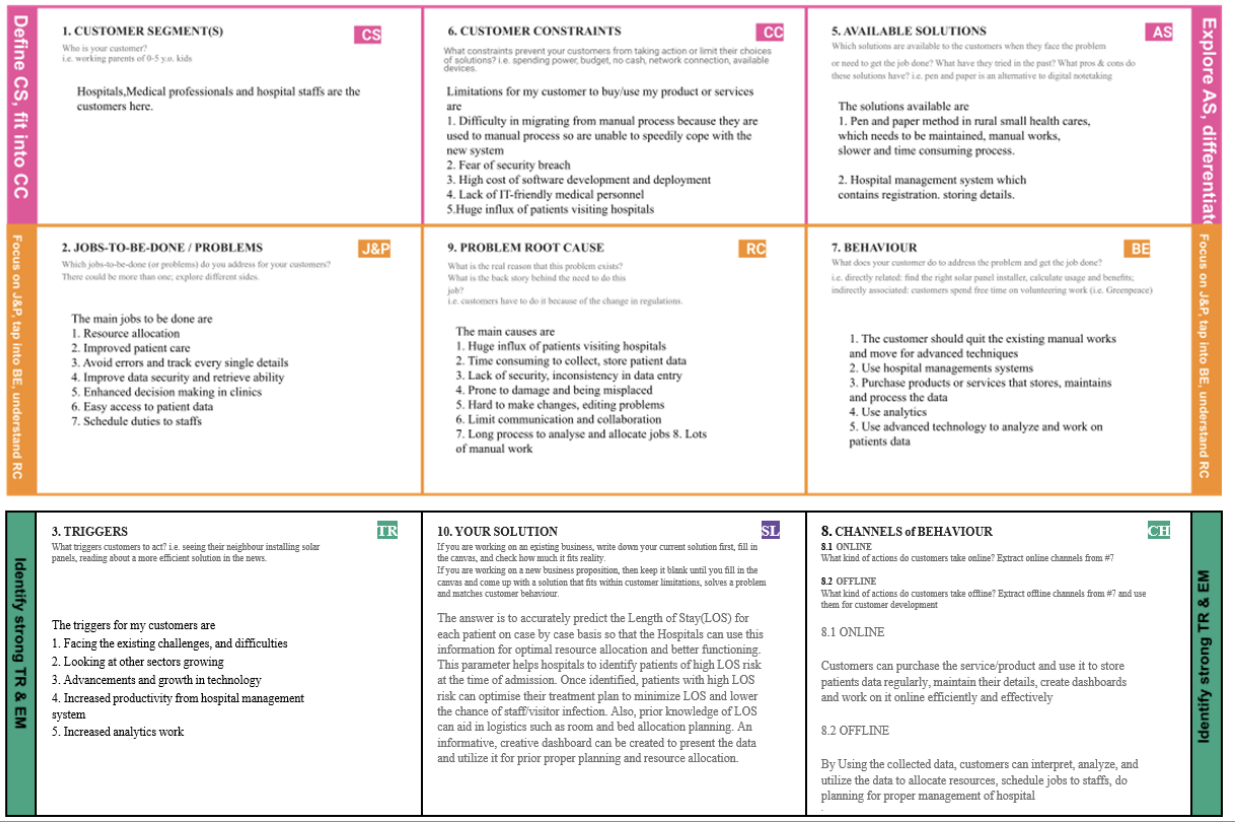


3.3 Proposed solution

S. No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	The task 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.
2.	Idea / Solution description	Naïve Bayes is a classification technique that works on the principle of Bayes theorem with an assumption of independence among the variables. Here the goal is to predict Length of Stay i.e., “Stay” column (Target Variable) and it is classified into 11 levels. We must find the probabilityof each patient’s length of stay using feature variables, which contain the patient’s condition and hospital-level information. These feature variables are ordinal and naïve Bayes is a perfect multilevel classifier.

3.	Novelty / Uniqueness	Accurate understanding of the factors associating with the LOS and progressive improvements in processing and monitoring may allow more efficient management of the LOS of inpatients
4.	Social Impact / Customer Satisfaction	A shorter LOS reduces the risk of acquiring staph infections and other healthcare-related conditions, frees up vital bed spaces, and cuts overall medical expenses
5.	Business Model (Revenue Model)	The length of stay (LOS) is an important indicator of the efficiency of hospital management. Reduction in the number of inpatient days results in decreased risk of infection and medication side effects, improvement in the quality of treatment, and increased hospital profit with more efficient bed management
6.	Scalability of the Solution	Remote patient monitoring systems enabling effective distance treatment. Patient portals that allow people to better manage their health themselves;

3.4 Problem solution fit



1. **Requirements analysis**

4.1 Functional requirements

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	Share patient data and make it interoperable among the management
FR-4	Accuracy	The dashboard will be able to predict length of stay based on multiple combinations based on input sources with a n accuracy of upto 85%
FR-5	Compliance	The product is to be used within the hospital so any form of data need not be hidden
FR-6	Productivity	The dashboard is believed to improve the predictions of Length of Stay and thereby creating a scenario of providing better solution

1. **Nonfunctional requirements**

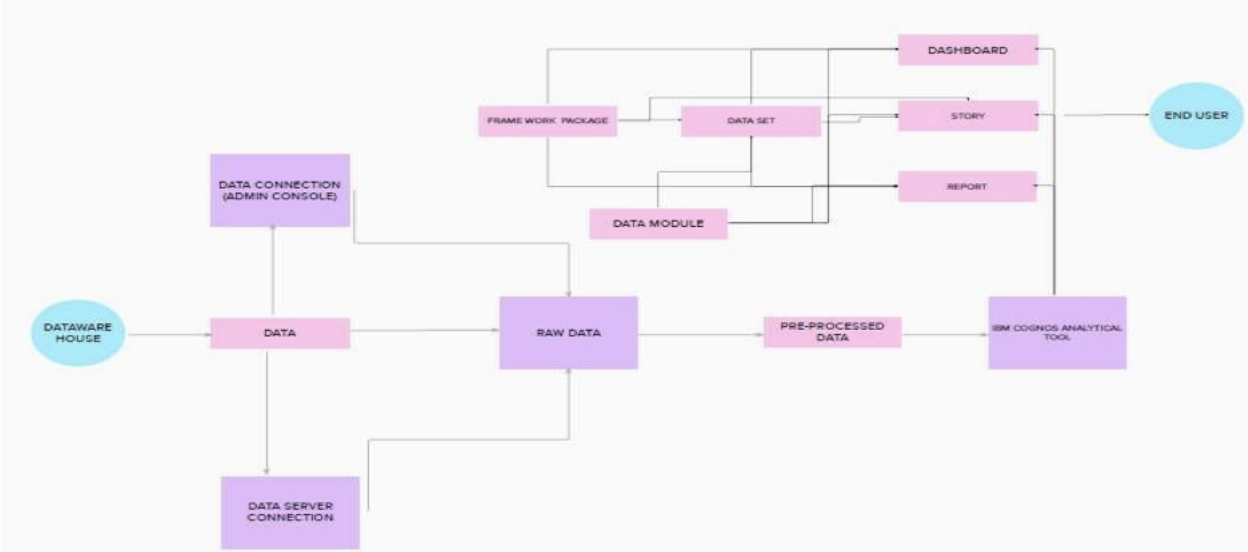
FR No.	**Non-Functional Requirement**	**Description**
NFR-1	**Usability**	This Dashboards are designed to offer a comprehensive overview of patient's LOS,

		and do so through the use of data visualization tools like charts and graphs.
NFR-2	**Security**	General industry level security shall be provided
NFR-3	**Reliability**	This dashboard will be consistent and reliable to the users and helps the user to use in effective, efficient and reliable manner.
NFR-4	**Performance**	The dashboard reduces the time needed for analysing data and has an automated system for that which improves the performance
NFR-5	**Availability**	The dashboard can available to meet user's demand in timely manner and it is also helps to provide necessary information to the user's dataset
NFR-6	**Scalability**	It is a multi-tenant system which is capable of rimming on lower-level systems as well.

5. PROJECT DESIGN

5.1 Data Flow Diagrams

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leaves the system, what changes the information, and where data is stored.



5.2 Solution & Technical Architecture

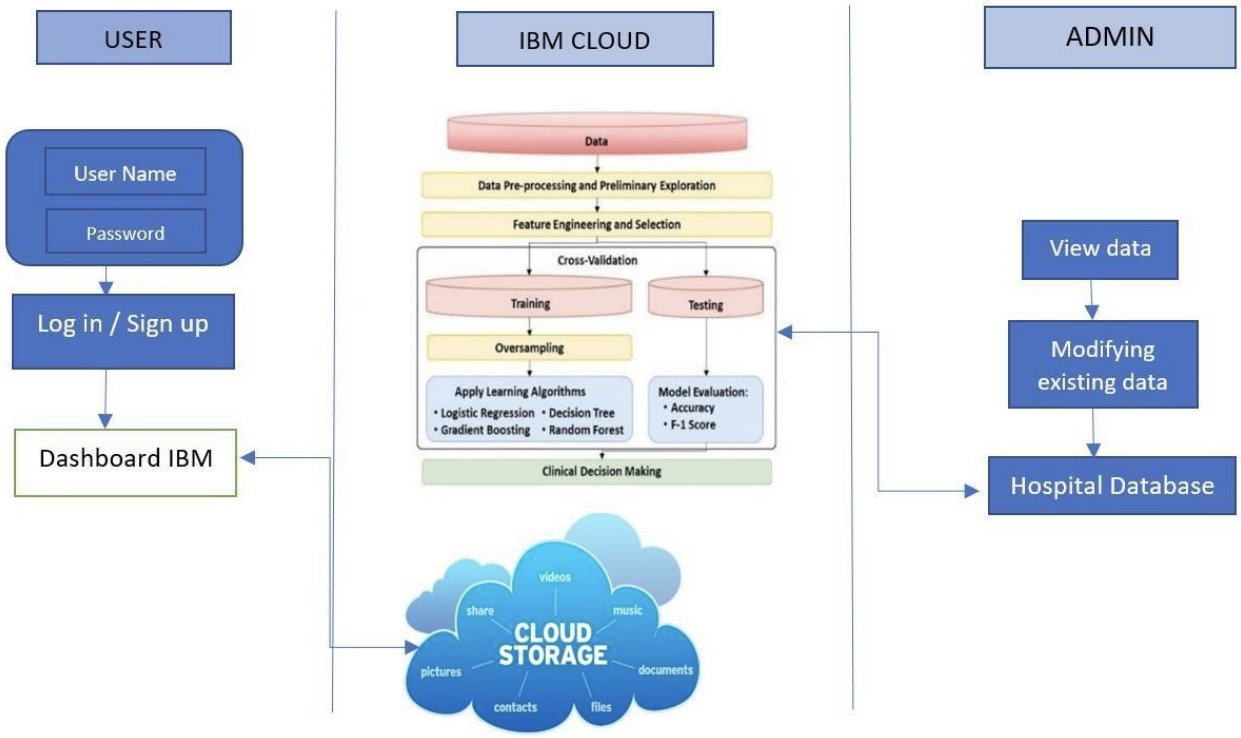


Table1: Components & Technologies:

S. No	Component	Description	Technology
1.	User Interface	How user interacts with application e.g., Web UI, Mobile App, Chatbot etc.	HTML, CSS, JavaScript / Angular Js / React Js etc…
2.	Application Logic-1	Logging in as a patient / user in the application	Python
3.	Application Logic-2	Logging in as an admin in the application	IBM Watson Assistant
5.	Database	All the data about patients such as disease, address and etc.	MySQL, NoSQL, etc.

6.	Cloud Database	IBM Watson cloud is used for storage, Cloud	IBM DB2, IBM Cloud ant etc.
7.	External API-1	Purpose of External API used in the application	Aadhar API, etc.
8.	Machine Learning Model	Purpose of Machine Learning Model	Regression Model, etc.
9.	Infrastructure (Server / Cloud)	Application Deployment on Local System / Cloud Local Server Configuration, Cloud Server Configuration	Local, Cloud Foundry, Kubernetes, etc.

Table-2: Application Characteristics:

S. No	**Characteristics**	**Description**	**Technology**
1.	Open-Source Frameworks	List the open-source frameworks used	Python
2.	Security Implementations	List all the security / access controls implemented, use of firewalls etc.	Encryption.
3.	Scalable Architecture	Justify the scalability of architecture (3 – tier, Micro-services)	Can supports higher workloads
4.	Availability	Justify the availability of application (e.g.	Highly available

		use of load balancers, distributed servers etc.)	
5.	Performance	Design consideration for the performance of the application (number of requests per sec, use of Cache, use of CDN's) etc.	It performs good uses various tools and ideas in a scientific manner to meet the desired outcomes

5.3 User Stories

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer	Dashboard	USN 1	As a user, I can upload the datasets to the dashboard	I can access various operations	Medium	Sprint-4
	View	USN 2	As a user, I can view the	I can view the visual data	Medium	Sprint-3

			patient details	and the result after the predicti on		
Admin	Analyse	USN 3	As an admin, I will analys e the given dataset	I can analyse the dataset	High	Sprint-2
	Predict	USN 4	As an admin, I will predict the length of stay	I can predict the length of stay	High	Sprint-1

6 Project planning & scheduling

6.1 Sprint Planning & Estimation

Spri nt	Function al Require	User Stor y	User Stor	Sto ry	Prior ity	Team Members

	ment (Epic)	Number	y / Task	Points		
Sprint-1	Data Collection	USN-1	The User needs a complete data about the patients admitted in the hospital and a dataset should be prepared.	2	Medium	Duvicksha,jaikishore
Sprint-1	Data Exploration	USN-2	As a user, I need nicely visualized dashboard of number of beds occupied and number of free beds in hospital.	4	High	**Chitiprolu Pratyusha,jaikishore,kapireddy charitha**
Sprint-2	Track of patient visit of Hospital	USN-3	Tracking a patient Health care over years of visit and Screening of data they have in hospital.	2	Medium	Kapireddy charitha,Duvicksha

Sprint -2	Dashboard	USN - 4	As a user, I want the interactive dashboard to analyse the data. Have the data in terms of Graph.	4	High	chitiprolu prathyusha,jaikishore,duvicksha
Sprint-3	Detailed EHR's of patient	USN -5	Provided greater details in the EHR's of individual patient with clear idea of what to do.	2	Medium	Chitiprolu Prathyusha,kapireddy charitha
Sprint- 3	Story Creation	USN -6	As a user, I need the story animation of the data set with insights	4	High	Kapireddy charitha ,jaikishore
Sprint-4	Predict LOS	USN -7	As a user, I want the flawless system to predict the length of stay of the patients	4	High	chitiprolu prathyusha,jaikishore,duvicksha
Sprint-4	Using ML algorithm for Prediction	USN -8	As a user, I need prior knowledge of LOS can aid in logistics such as room and	4	High	Duvicksha,chitiprolu Pratyusha,kapireddy charitha

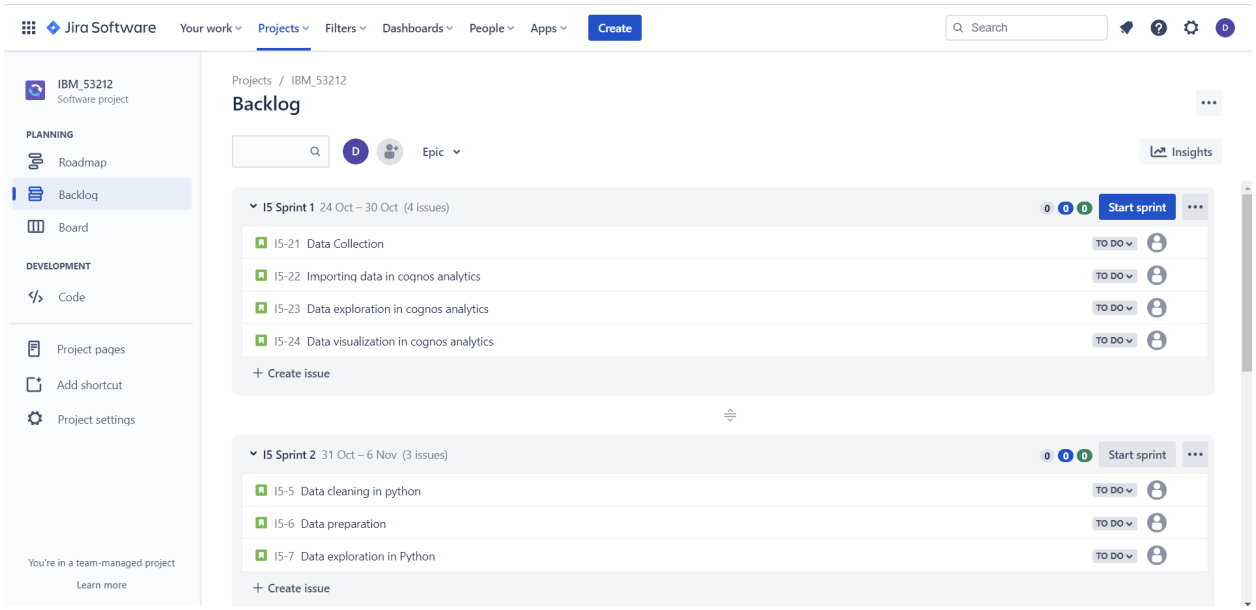
			bed allocation planning.			

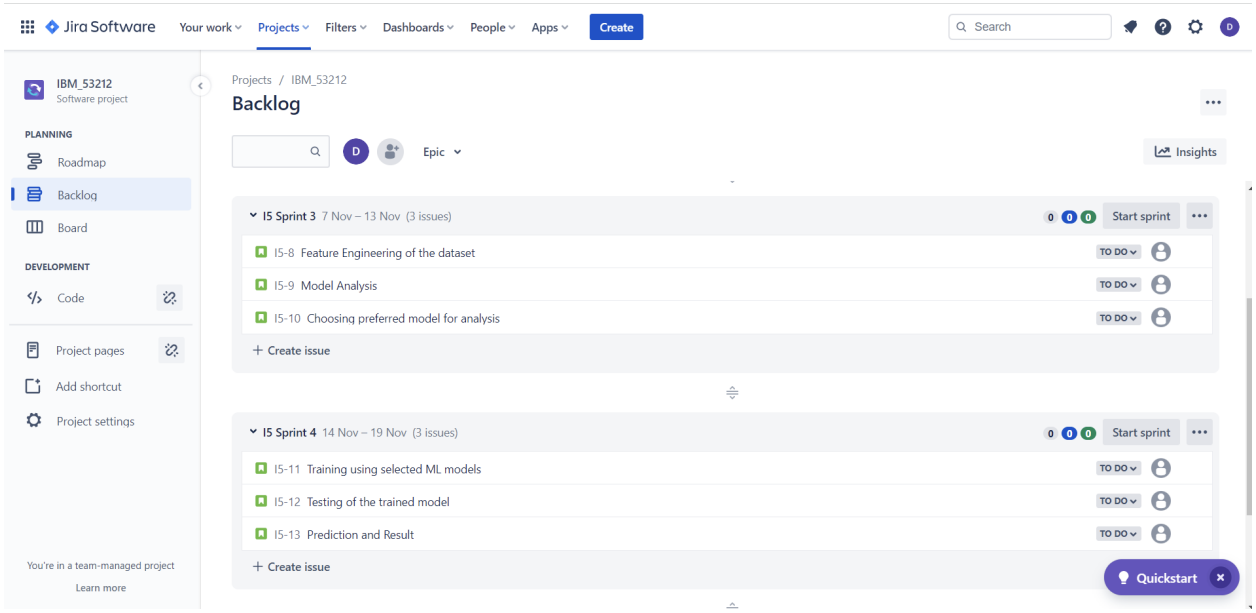
5.2 Sprint Delivery Schedule

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	30Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	06 Nov 2022	20	05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	13 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

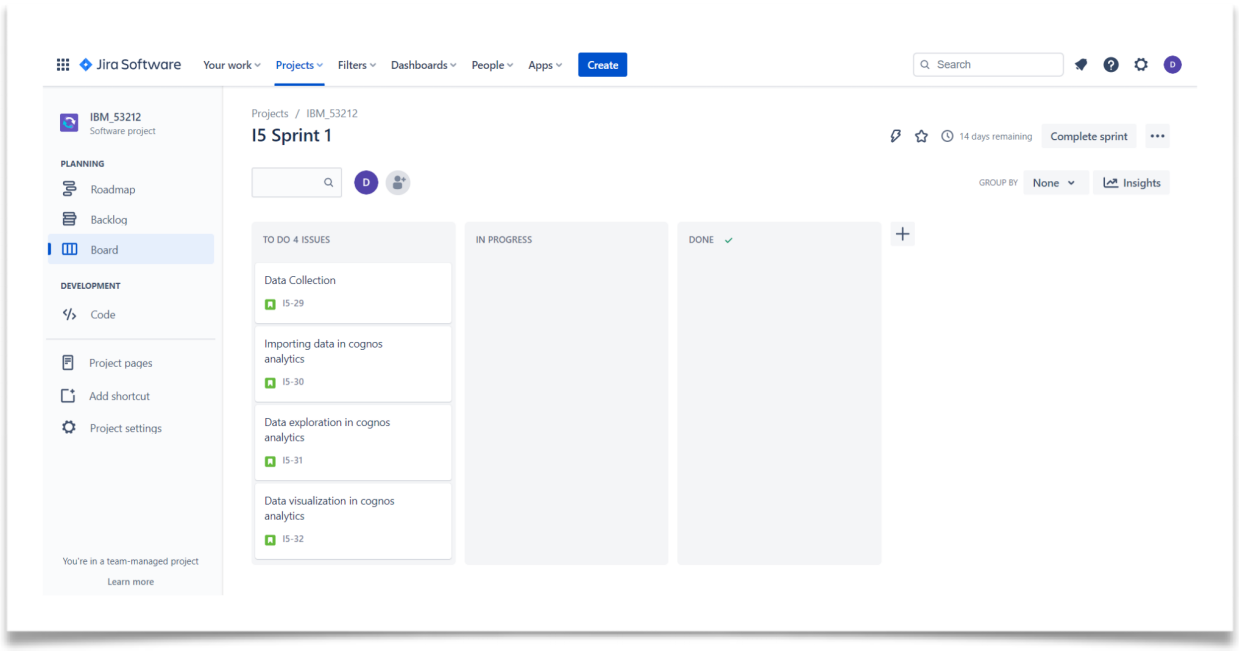
1. **Reports from JIRA**

Jira Sprints

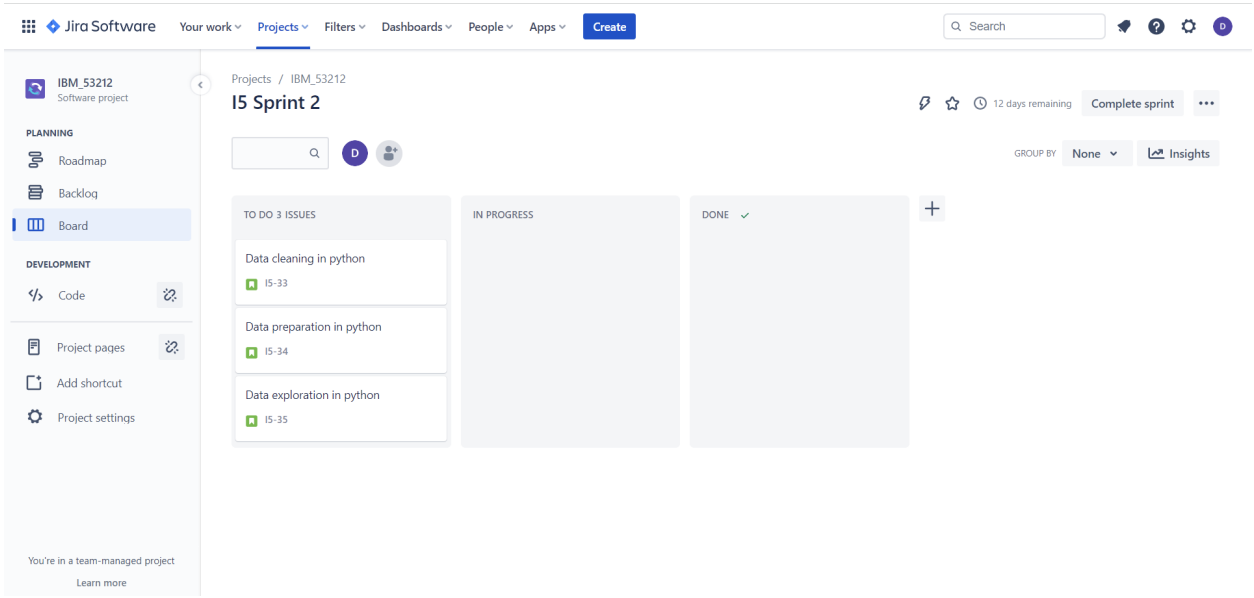

Jira Software
Your work
Projects
Filters
Dashboards
People
Apps
Create
Search
IBM_53212
Software project
PLANNING
Roadmap
Backlog
Board
DEVELOPMENT
Code
Project pages
Add shortcut
Project settings
You're in a team-managed project
Learn more
Projects / IBM_53212
Backlog
Epic
Insights
I5 Sprint 1 24 Oct – 30 Oct (4 issues)
Start sprint
I5-21 Data Collection
I5-22 Importing data in cognos analytics
I5-23 Data exploration in cognos analytics
I5-24 Data visualization in cognos analytics
TO DO
Create issue
I5 Sprint 2 31 Oct – 6 Nov (3 issues)
I5-5 Data cleaning in python
I5-6 Data preparation
I5-7 Data exploration in Python


Jira Software
Your work
Projects
Filters
Dashboards
People
Apps
Create
Search
IBM_53212
Software project
PLANNING
Roadmap
Backlog
Board
DEVELOPMENT
Code
Project pages
Add shortcut
Project settings
You're in a team-managed project
Learn more
Projects / IBM_53212
Backlog
Epic
Insights
I5 Sprint 3 7 Nov – 13 Nov (3 issues)
Start sprint
I5-8 Feature Engineering of the dataset
I5-9 Model Analysis
I5-10 Choosing preferred model for analysis
TO DO
Create issue
I5 Sprint 4 14 Nov – 19 Nov (3 issues)
I5-11 Training using selected ML models
I5-12 Testing of the trained model
I5-13 Prediction and Result
Quickstart

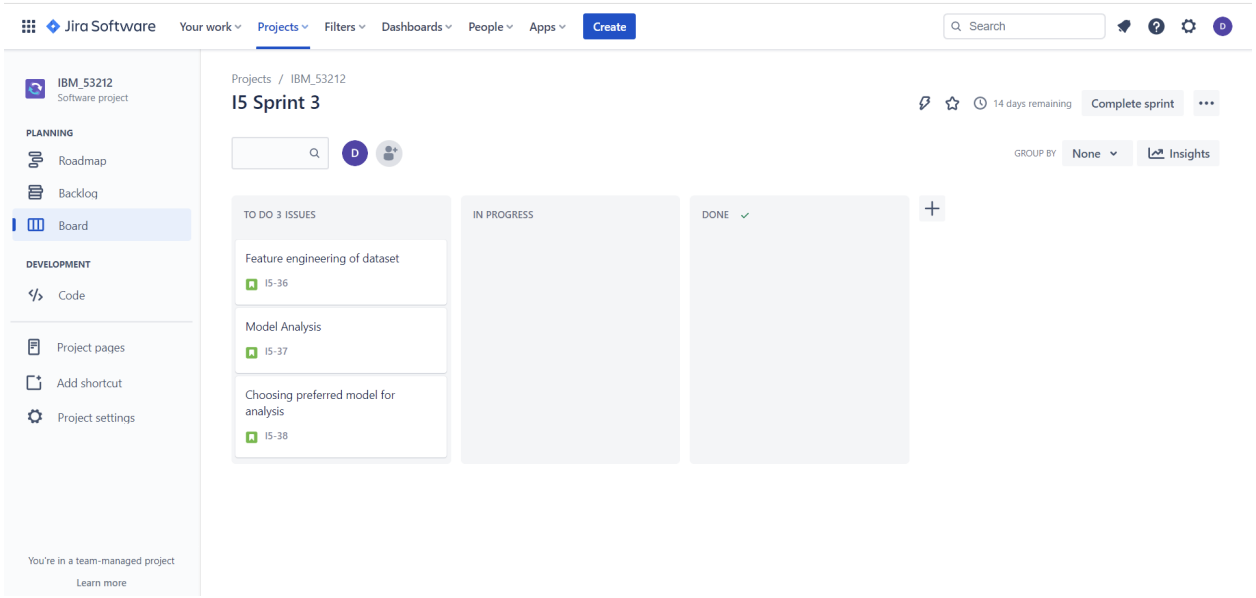
Sprint 1 Dashboard



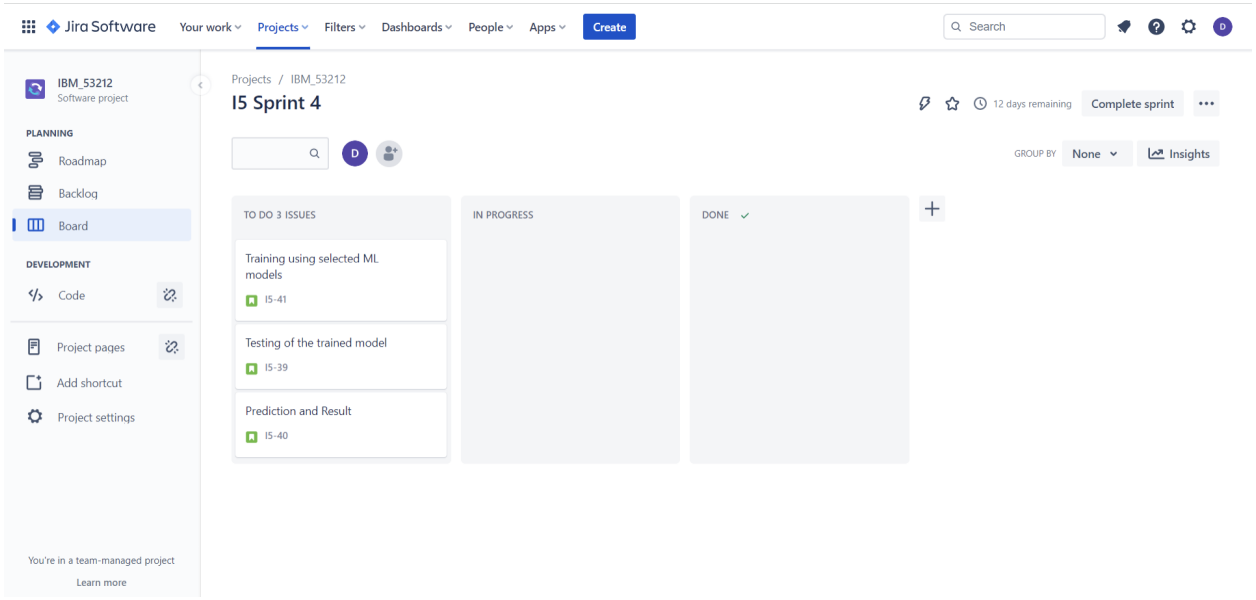
Sprint 2 Dashboard



Sprint 3 Dashboard



Sprint 4 Dashboard



7 . Coding & solutioning

ML Models

Naive Bayes Model

In Bayes theorem, given a Hypothesis H and Evidence E, it states that the relation between the probability of Hypothesis P(H) before getting Evidence and probability of hypothesis after getting Evidence P(H|E)

$$P(H \mid E) = [\, \boldsymbol{P}\,(\boldsymbol{E} \mid \boldsymbol{H}) \,/\, \boldsymbol{P}(\boldsymbol{E})]\, P(H)$$

When we apply Bayes Theorem to our data it represents as follows.

- P(H) is the prior probability of a patient's length of stay (LOS).
- P(E) is the probability of a feature variable.
- P(E|H) is the probability of a patient's LOS given that the features are true. • P(H|E) is the probability of the features given that patient's LOS is true.

Model is trained using Gaussian Naïve Bayes classifier, partitioned train data is fed to the model in array format then the trained model is validated using validation data.

This model gives an accuracy score of 34.55% after validating.

2) XGBoost Model

Boosting is a sequential technique that works on the principle of an ensemble. At any instant T, the model outcomes are weighed based on the outcomes of the previous instant (T -1). It combines the set of weak learners and improves prediction accuracy. Tree ensemble is a set of classification and regression trees. Trees are grown one after another, and they try to reduce the misclassification rate. The final prediction score of the model is calculated by summing up each and individual score.

Before feeding train data to the XGB Classifier model, booster parameters must be tuned. Tunning the model can prevent overfitting and can yield higher accuracy. In this XGBoost model, we have used the following parameters for tunning,

- learning_rate = 0.1 - step size shrinkage used to prevent overfitting. After each boosting step, we can directly get the weights of new features, and eta shrinks the feature weights to make the boosting process more conservative.
- max_depth = 4 – Maximum depth of the tree. This value describes the complexity of the model. Increasing its value results in overfitting.
- n_estimators = 800 – Number of gradient boosting trees or rounds. Each new tree attempts to model and correct for the errors made by the sequence of

previous trees. Increasing the number of trees can yield higher accuracy but the model reaches a point of diminishing returns quickly.

- objective = 'multi:softmax' – this parameter sets XGBoost to do multiclass classification using the softmax objective because the target variable has 11 Levels.
- reg_alpha = 0.5 - L1 regularization term on weights. Increasing this value will make the model more conservative.
- reg_lambda = 1.5 - L2 regularization term on weights and is smoother than L1 regularization. Increasing this value will model more conservative.
- min_child_weight = 2 - Minimum sum of instance weight needed in a child.

Once the model was trained and validated, it yields an accuracy score of 43.04%. This model nearly took 25 minutes to get trained but when compared to the Naïve Bayes model it gave an 8.5% improvement.

3) Neural Network Model

Neural Networks are built of simple elements called neurons, which take in a real value, multiply it by weight, and run it through a non-linear activation function. The process records one at a time and learns by comparing their classification of the record with the known actual classification of the record. The errors from the initial classification of the first record are fed back into the network and used to modify the network's algorithm for further iterations.In this neural network model, there are **six** dense layers, the final layer is an output layer with an activation function "**SoftMax**". SoftMax is used here because each patient must be classified in one of the 11 levels in the Stay variable.

In this model, increasing the number of neurons from each layer to the other layer, will increase the hypothetical space of the model and try to learn more patterns from the data. There are a total of **442,571** trainable parameters. Every layer is activated using "**relu**" activation function because it overcomes the vanishing gradient problem, allowing models to learn faster and perform better.

Finally, evaluating the model with a test set yields an accuracy score of **41.79%**. Neural Networks supposedly performs better than any other models. But because

of the smaller dataset, it was not able to learn more accurately than the XGBoost model. It nearly took 20 minutes to train the model.

In the Naive Bayes model, patients are more likely to be misclassified. This model is biased towards the duration of 21-30 days, it has classified 72,206 patients for this level.
Whereas the other two models XGBoost and Neural Networks are predicting mostly similar Length of Stay for the patient
Examining these predictions, many of the patients are staying in the hospital for 21-30 days and very few people are staying for 61-70 days. As far as the distribution of Length of Stay is concerned, 13% of the patients are discharged from the hospital within 20 days and 1% of the overall patients are staying in the hospital for more than 60 days.

9) Results

9.1 Performance metrics

Finally, evaluating the model with a test set yields an accuracy score of **42.05%**. Neural Networks supposedly performs better than any other models. But because of the smaller dataset, it was not able to learn more accurately than the XGBoost model.

In the Naïve Bayes model, patients are more likely to be misclassified. This model is biased towards the duration of 21-30 days, it has classified 72,206 patients for this level

Length of Stay	Predicted Observations from Naïve Bayes	Predicted Observations from XGBoost	Predicted Observations from Neural Network
0-10 Days	2598	4373	4517
11-20 Days	26827	39337	35982
21-30 Days	**72206**	58261	61911
31-40 Days	15639	12100	8678
41-50 Days	469	61	26
51-60 Days	13651	19217	21709
61-70 Days	92	16	1
71-80 Days	955	302	248
81-90 Days	296	1099	1165
91-100 Days	2	78	21
More than 100 Days	4322	2213	2799

Whereas the other two models XGBoost and Neural Networks are predicting mostly similar Length of Stay for the patient, we can see this similarity for the first five cases. In we can see that the observations classified by both these models are marginally similar.

case_ id	Length of Stay predicted	Length of Stay predicted	Length of Stay predicted

	from Naïve Bayes	from XGBoost	from Neural Networks
318439	21-30	0-10	0-10
318440	51-60	51-60	51-60
318441	21-30	21-30	21-30
318442	21-30	21-30	21-30
318443	31-40	51-60	51-60

Examining these predictions, many of the patients are staying in the hospital for 21-30 days and very few people are staying for 61-70 days. As far as the distribution of Length of Stay is concerned, 13% of the patients are discharged from the hospital within 20 days and 1% of the overall patients are staying in the hospital for more than 60 days.

10) Advantages:

11) Conclusion

In this project, different variables were analyzed that correlate with Length of Stay by using patient-level and hospital-level data.

By predicting a patient's length of stay at the time of admission helps hospitals to allocate resources more efficiently and manage their patients more effectively. Identifying factors that associate with LOS to predict and manage the

number of days patients stay, could help hospitals in managing resources and in the development of new treatment plans. Effective use of hospital resources and reducing the length of stay can reduce overall national medical expenses.

12) Future insights

- **Smart Staffing & Personnel Management:** having a large volume of quality data helps health care professionals in allocating resources efficiently. Healthcare professionals can analyze the outcomes of checkups among individuals in various demographic groups and determine what factors prevent individuals from seeking treatment.
- **Advanced Risk & Disease Management:** Healthcare institutions can offer accurate, preventive care. Effectively decreasing hospital admissions by digging into insights such as drug type, conditions, and the duration of patient visits, among many others.
- **Real-time Alerting: Clinical Decision Support (CDS):** applications in hospitals analyzes patient evidence on the spot, delivering recommendations to health professionals when they make prescriptive choices. However, to prevent unnecessary in-house procedures, physicians prefer people to stay away from hospitals
- **Enhancing Patient Engagement:** Every step they take, heart rates, sleeping habits, can be tracked for potential patients (who use smart wearables). All this information can be correlated with other trackable data to identify potential health risks.

Appendix:

Code:
Feature engineering:

```
def get_countid_enocde(train, test, cols, name):
  temp = train.groupby(cols)['case_id'].count().reset_index().rename(columns =
{'case_id': name})
  temp2 = test.groupby(cols)['case_id'].count().reset_index().rename(columns =
{'case_id': name})
  train = pd.merge(train, temp, how='left', on= cols)
  test = pd.merge(test,temp2, how='left', on= cols)
  train[name] = train[name].astype('float')
  test[name] = test[name].astype('float')
  train[name].fillna(np.median(temp[name]), inplace = True)
  test[name].fillna(np.median(temp2[name]), inplace = True)
  return train, test

train, test = get_countid_enocde(train, test, ['patientid'], name = 'count_id_patient')
train, test = get_countid_enocde(train, test,
                          ['patientid', 'Hospital_region_code'], name =
'count_id_patient_hospitalCode')
train, test = get_countid_enocde(train, test,
                          ['patientid', 'Ward_Facility_Code'], name =
'count_id_patient_wardfacilityCode')


# Droping duplicate columns
test1 = test.drop(['Stay', 'patientid', 'Hospital_region_code', 'Ward_Facility_Code'],
axis =1)
train1 = train.drop(['case_id', 'patientid', 'Hospital_region_code',
'Ward_Facility_Code'], axis =1)

# Splitting train data for Naive Bayes and XGBoost
X1 = train1.drop('Stay', axis =1)
y1 = train1['Stay']
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X1, y1, test_size =0.20,
random_state =100)
```

Models

Naïve bayes Model

```
from sklearn.naive_bayes import GaussianNB
target = y_train.values
features = X_train.values
classifier_nb = GaussianNB()
model_nb = classifier_nb.fit(features, target)

prediction_nb = model_nb.predict(X_test)
from sklearn.metrics import accuracy_score
acc_score_nb = accuracy_score(prediction_nb,y_test)
print("Acurracy:", acc_score_nb*100)
```

XGBoost model

```
import xgboost
classifier_xgb = xgboost.XGBClassifier(max_depth=4, learning_rate=0.1,
n_estimators=800,
                        objective='multi:softmax', reg_alpha=0.5, reg_lambda=1.5,
                        booster='gbtree', n_jobs=4, min_child_weight=2, base_score=
0.75)

model_xgb = classifier_xgb.fit(X_train, y_train)

prediction_xgb = model_xgb.predict(X_test)
acc_score_xgb = accuracy_score(prediction_xgb,y_test)
print("Accuracy:", acc_score_xgb*100)
```

Neural Network

```
X = train.drop('Stay', axis =1)
y = train['Stay']
print(X.columns)
z = test.drop('Stay', axis = 1)
print(z.columns)

# Data Scaling
from sklearn import preprocessing
X_scale = preprocessing.scale(X)
X_scale.shape

X_train, X_test, y_train, y_test = train_test_split(X_scale, y, test_size =0.20,
random_state =100)

import keras
from keras.models import Sequential
from keras.layers import Dense
import tensorflow as tf

from keras.utils import to_categorical
#Sparse Matrix
a = to_categorical(y_train)
b = to_categorical(y_test)

model = Sequential()
model.add(Dense(64, activation='relu', input_shape = (254750, 20)))
model.add(Dense(128, activation='relu'))
model.add(Dense(256, activation='relu'))
model.add(Dense(512, activation='relu'))
model.add(Dense(512, activation='relu'))
model.add(Dense(11, activation='softmax'))

model.compile(optimizer= 'SGD',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

```
callbacks = [tf.keras.callbacks.TensorBoard("logs_keras")]
model.fit(X_train, a, epochs=20, callbacks=callbacks, validation_split = 0.2)
```

GitHub link: https://github.com/IBM-EPBL/IBM-Project-17196-1659630236