EASWARI ENGINEERING COLLEGE

TEAM ID: PNT2022TMID09674

CRUDE OIL PRICE PREDICTION

TEAM MEMBERS

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1. INTRODUCTION

1.1. Project overview

Oil demand is inelastic, therefore the rise in price is good news for producers because they will see an increase in their revenue. Oil importers, however, will experience increased costs of purchasing oil. Because oil is the largest traded commodity, the effects are quite significant. A rising oil price can even shift economic/political power from oil importers to oil exporters. The crude oil price movements are subject to diverse influencing factors.
This Project mainly focuses on applying Neural Networks to predict the Crude Oil Price. This decision helps us to buy crude oil at the proper time. Time series analysis is the best option for this kind of prediction because we are using the Previous history of crude oil prices to predict future crude oil. So we would be implementing RNN(Recurrent Neural Network) with LSTM(Long Short Term Memory) to achieve the task.

1.2. Purpose

Crude oil price fluctuations have a far reaching impact on global economies and thus price forecasting can assist in minimising the risks associated with volatility in oil prices. Price forecasts are very important to various stakeholders: governments, public and private enterprises, policymakers, and investors. According to economic theory, the price of crude oil should be easily predictable from the equilibrium between demand and supply, wherein demand forecasts are usually made from GDP, exchange rates and domestic prices, and supply is predicted from past production data and reserve data. Predicting demand for oil is usually straightforward, however supply is heavily affected by political activity such as cartelisation by OPEC to regulate prices, technological advances leading to the extraction of higher amounts of oil, and wars and other conflicts which can affect supply unpredictably.

2. LITERATURE SURVEY

2.1. Existing problem

Numerous studies have used traditional and statistical econometric models to forecast crude oil prices. These methods are usually able to handle only linear time series data. However, crude oil market is the most volatile commodities market. Therefore, forecasting oil price via nonlinear models is the appropriate choice. ANN is the most popular nonlinear AI model used to predict crude oil price earlier. Therefore, this approach was used. Finally, we presented the existing literature on forecasting crude oil price using ANNs models. As conclusions drawn from these studies, neural network approach has shown a strong predictive ability, in this field of research. So we have used RNN and LSTM instead of the traditional ANN method.

2.2. References

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2.3. Problem statement definition

1. Supply

Supply and demand has to do with how much oil is available.

Supply has historically been determined by countries that are part of OPEC. But now, the United States is playing a bigger role in supply thanks to booming production from American shale fields. So if major oil-producing countries are pumping out a lot of crude, the supply will be high.

Just look at what happened in 2014.
“Saudi Arabia made the decision that they were not going to cut back production, they were going to continue to produce at record high levels,” said Tamar Essner, senior energy director at Nasdaq IR Solutions.
“At the same time, you had very robust output from the United States, and from other producers around the world.”
Oil prices fell sharply as producers pumped more than the world could consume.
OPEC was largely blamed for the free fall in oil prices because it refused to cut down its production. But OPEC said U.S. shale drillers were to blame for pumping too much, and should cut their production first.
In 1973, Arab members of OPEC put an embargo against the United States as a retaliatory measure for U.S. support of Israel during the Yom Kippur War. After the embargo, the oil supply in the U.S. was so scarce and the demand was so high, it drove the price of crude to the point that gas stations began rationing gasoline.

2. Demand
Demand on the other hand is determined by how much need there is for oil at a given time. That need is often for things like heat, electricity and transportation. The more economic growth a region sees, the more demand there will be for oil.
“Economies around the world have picked up since the financial crisis, and growth has gotten stronger so people have been using more energy,” Essner said.
And then there’s the question of how the market will react to renewable energy.
“A lot of this will be impacted by public policy, but at the end of the day renewable can only displace hydrocarbons if it’s economically feasible,” Essner said.
“Right now, renewables are still more expensive than hydrocarbons, so consumers aren’t going to voluntarily make the switch.”

3.Geopolitics
Since supply is determined by the big oil-producing countries, tension with one of those nations can cause major problems. So if there’s war or conflict in an oil-producing region, crude inventories could seem threatened, and that could ultimately alter the price of oil.
“Geopolitics has traditionally been a factor in the oil price,” Essner said.
“Particularly when situations in the Middle East or other oil-rich regions of the world would flare up and there would be conflict, you would generally speaking see a little bit of an uptick in the price of oil as a result, just by virtue of the risk of supply being disrupted, or of means of transportation being disrupted, such as a canal or pipeline or workers going on protest, things like that.”
Just think back to the Gulf War of 1991. Oil production fell, which caused prices to rise.
And in 2003, oil prices soared after the U.S. invaded Iraq. That Middle Eastern nation produces a lot of oil, and with instability in the region, people weren’t immediately sure what would happen to the supply.
“That’s what makes the oil markets so fascinating, is that it’s really a very interesting interplay of financial markets, the economy, and those are two very different things, the currency market, geopolitics and the environment,” Essner said.

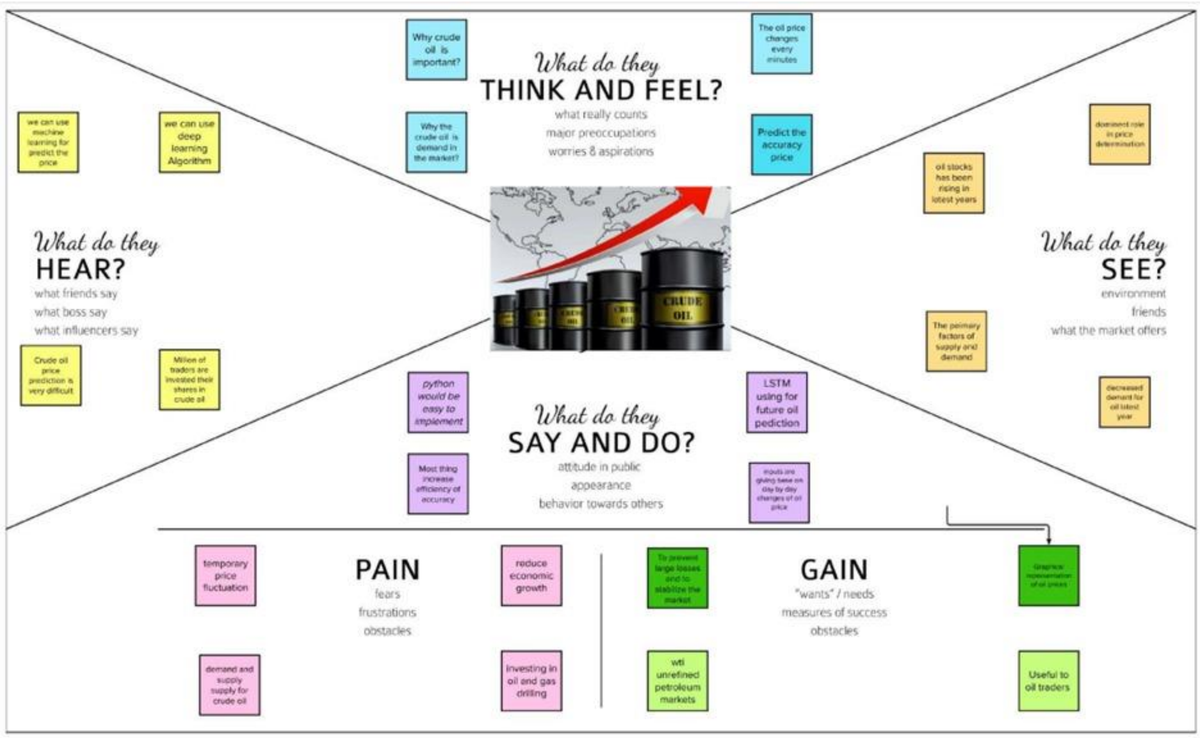
The energy industry is sure to evolve, and experts are watching to see what role oil will play in the future. But for now, the oil markets remain a powerful force in the world of economics, geopolitics and your commuting budget.

3. IDEATION AND PROPOSED SOLUTION

3.1. Empathy Map Canvas

An empathy map is a simple, easy-to-digest visual that captures knowledge about a user's behaviours and attitudes.

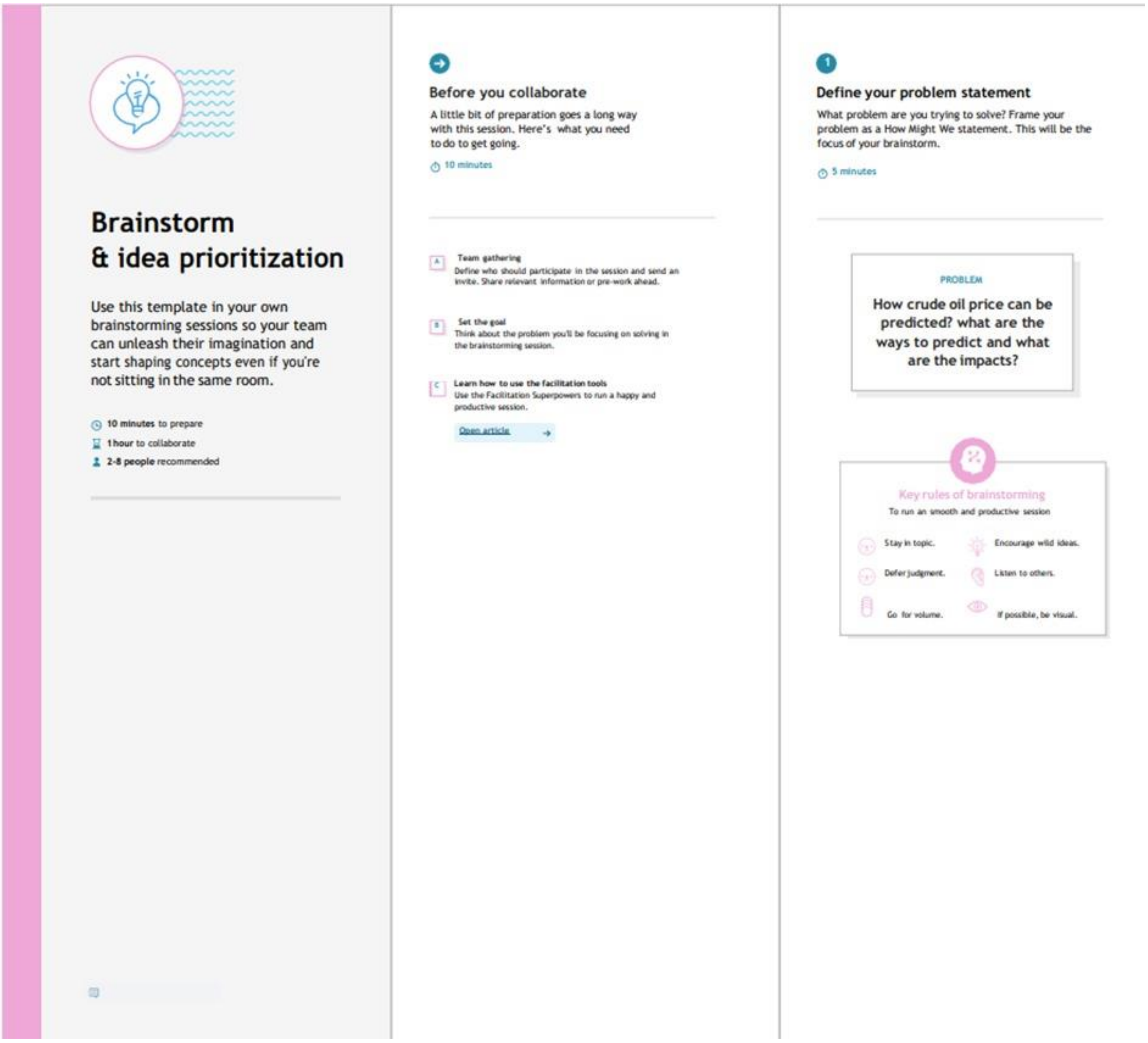
It is a useful tool to helps teams better understand their users.
Creating an effective solution requires understanding the true problem and the person who is experiencing it. The exercise of creating the map helps participants consider things from the user's perspective along with his or her goals and challenges.



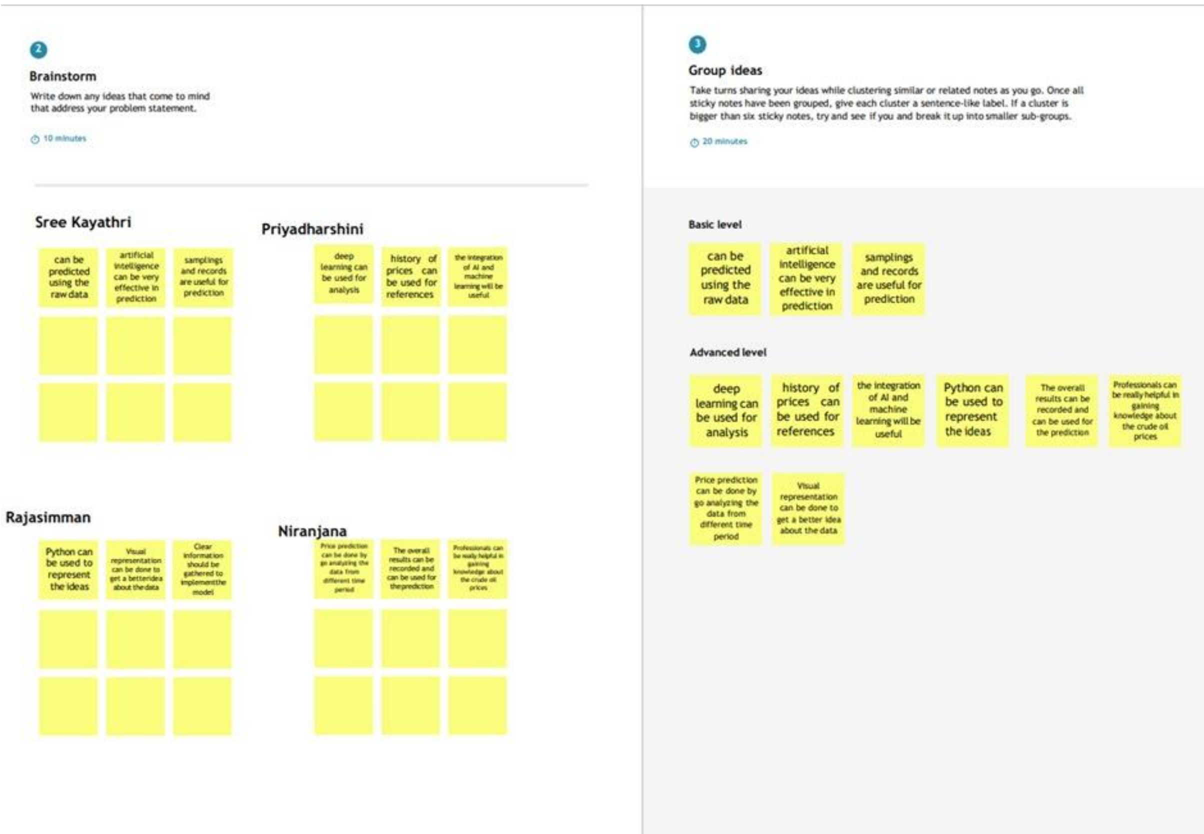
3.2. Ideation and Brainstorming

Brainstorming provides a free and open environment that encourages everyone within a team to participate in the creative thinking process that leads to problem solving. Prioritizing volume over value, out-of-the-box ideas are welcome and built upon, and all participants are encouraged to collaborate, helping each other develop a rich amount of creative solutions.

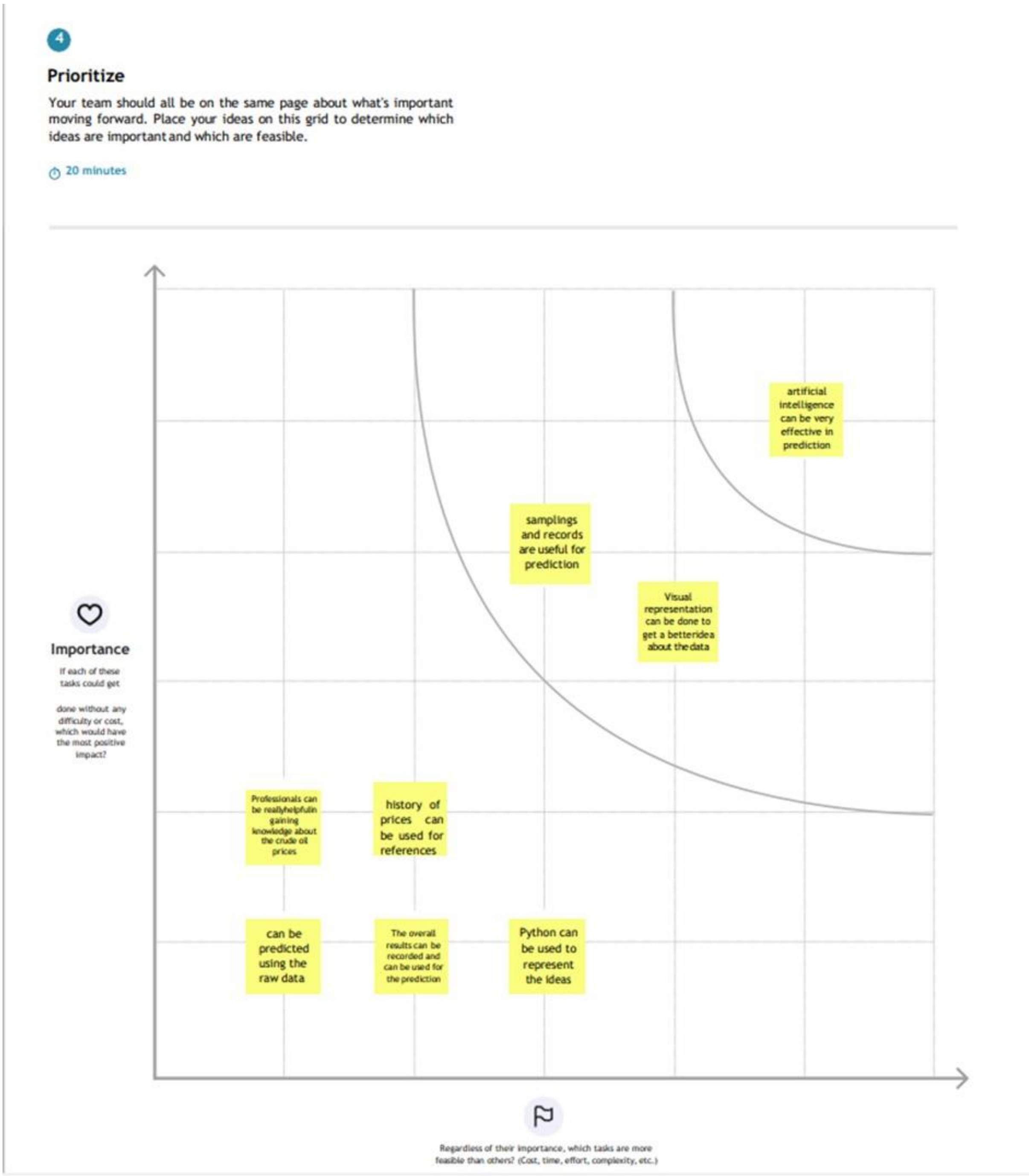
Step-1: Team Gathering, Collaboration and Select the Problem Statement



Step-2: Brainstorm, Idea Listing and Grouping



Step-3: Idea Prioritization

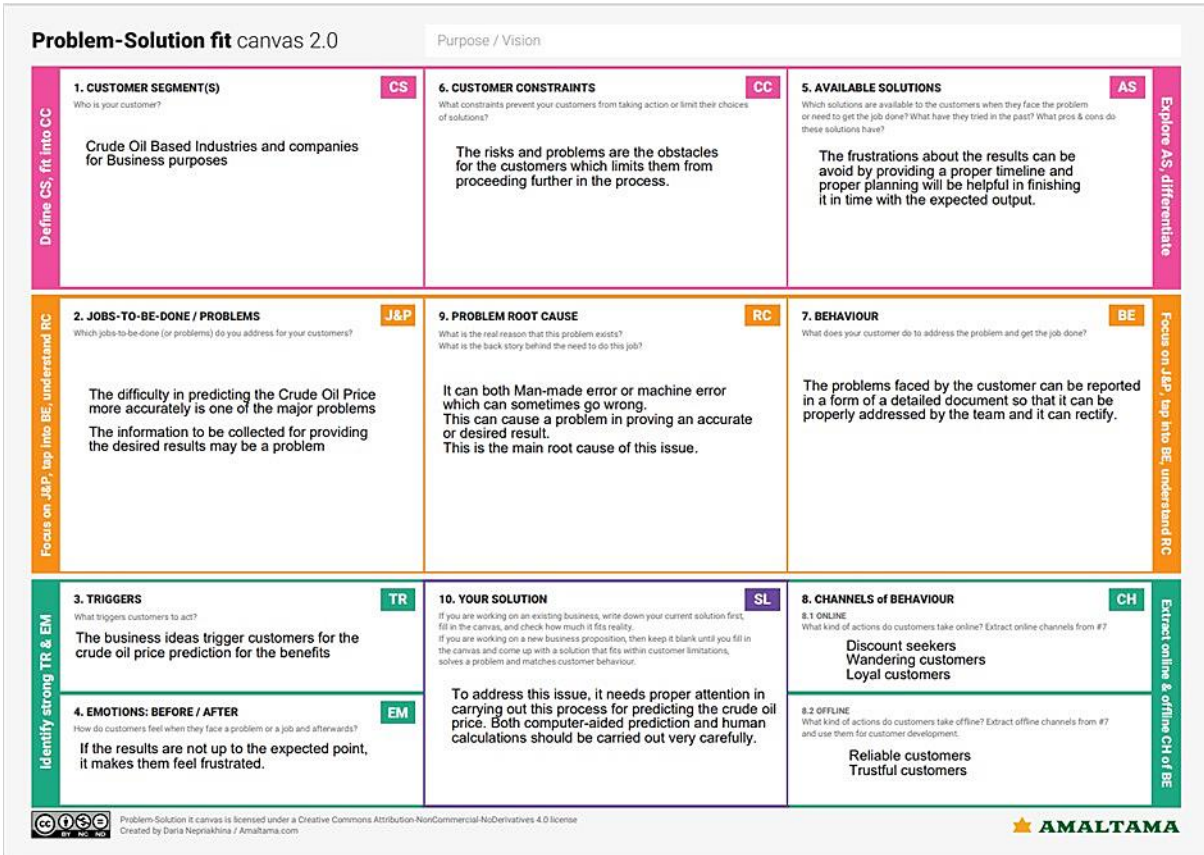


3.3. Proposed Solution:

S.No.	Parameter	Description
	Problem Statement (Problem to be solved)	As with the erratic changes in supply and demand and also the influence of geopolitics, it is very hard to predict the value of crude oil prices in the global market.

	Idea / Solution description	We are going to collect the dataset of the past oil prices with time so that by feeding those to the model and training it and compiling it and when it's achieved the optimal state we can implement it in the web application.
	Novelty / Uniqueness	It may be a traditional idea but the implementation of periodic training will have a better effect on it.
	Social Impact / Customer Satisfaction	By using the web app customer can gain knowledge of the crude oil price and get benefits financially.
	Business Model (Revenue Model)	It will be used by every individual at ease so that they can have an idea of the crude price so, that the use of the crude will be stable in the market
	Scalability of the Solution	The idea we proposed it take the input in the periodic and adjust and train through these so, that it will adapt to very different situations.

3.4. Problem Solution Fit



4. REQUIREMENT ANALYSIS

4.1.Functional requirement

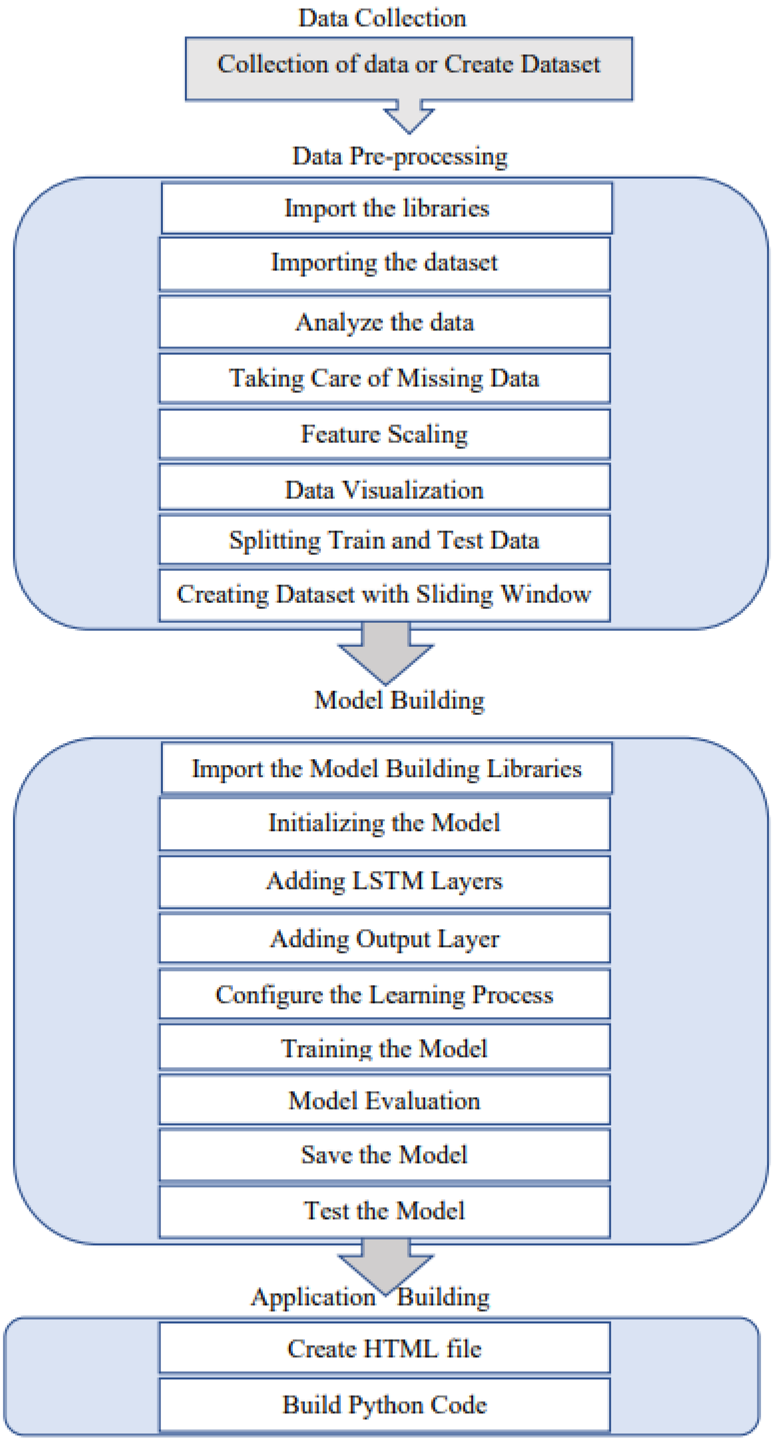
FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	Graph	Showing graph by obtaining the data from the dataset
FR-4	Support	Providing answers for the queries asked by users.
FR-5	News	Information of the oil prices will be updated by admin
FR-6	Notification	Notification will be sent for the users price alert
Fr-7	Database	Information of the User will be stored

4.2. Non-Functional Requirements

FR No.	Non-Functional Requirement	Description
NFR-1	Usability	It can use by wide variety of client as it is very simple to learn and not complex to proceed.
NFR-2	Security	We are using login for the user and the information will be hashed so that it will be very secure to use.
NFR-3	Reliability	It will be reliable that it can update with very time period so that the accuracy will be good.
NFR-4	Performance	It will be perform fast and secure even at the lower bandwidth.
NFR-5	Availability	Prediction will be available for every user but only for premium user news,database and price alert will be alert.
NFR-6	Scalability	It is scalable that we are going to use data in kb so that the quite amount of storage is satisfied.

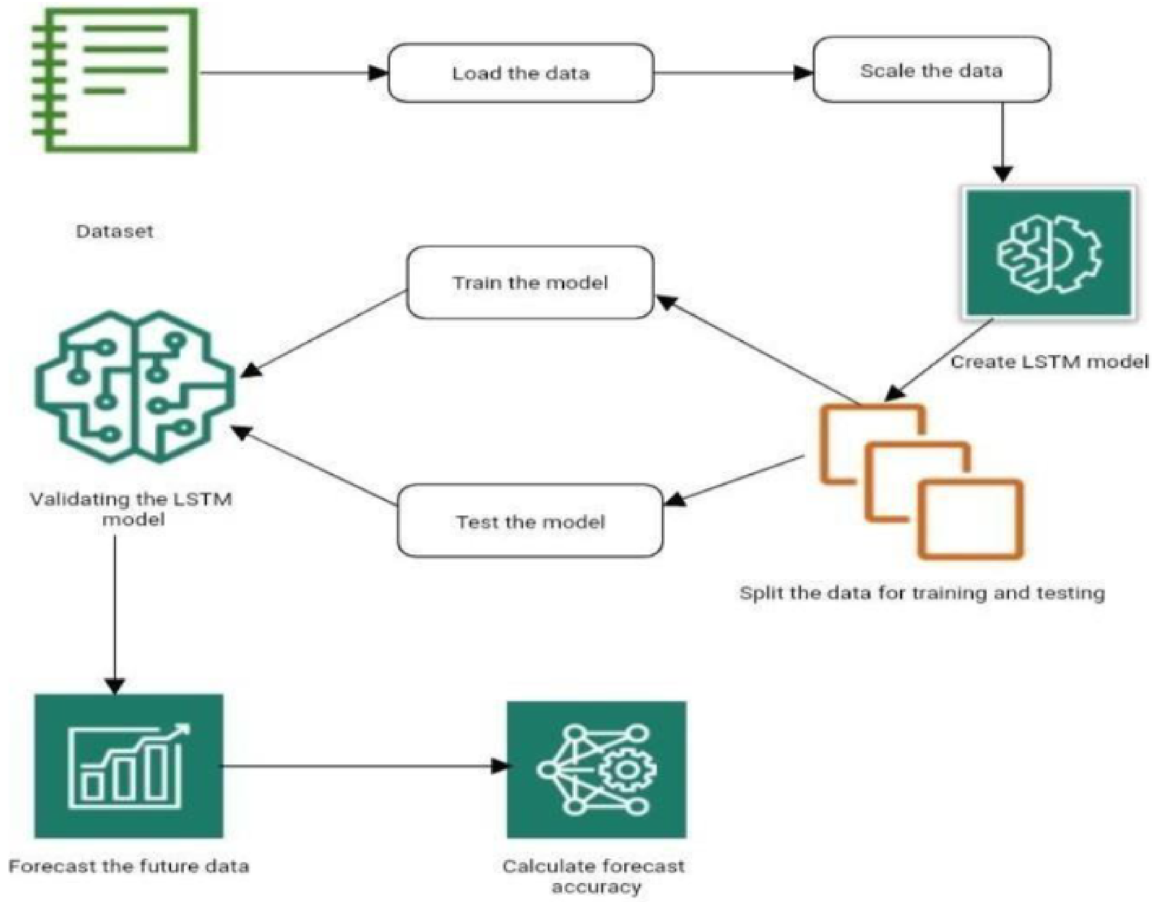
5. Project Design

5.1. Project Flow Diagrams

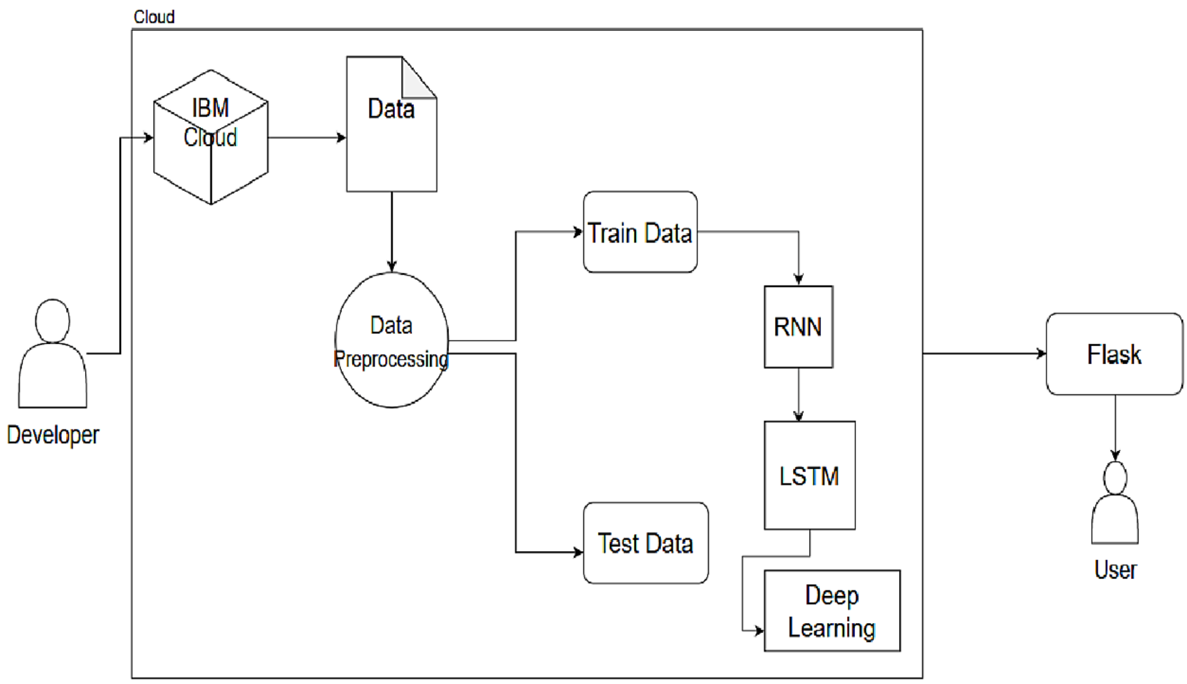


5.2. Solution & Technical Architecture

Solution Architecture



Technical Architecture



5.3. User Stories

User Type	Functional Requirement (Epic)	User Story Number	User Story/ Task	Acceptance criteria	Priority	Release
Customer (Mobile User)	Registration	USN-1	As a user,I can register for the application by entering my email,password,and confirming my password.	I can access my account/ Displays Line gragh / Bar gragh.	High	Sprint-1
		USN-2	As a user,I will receive confirmation email onceI have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	As a user,I can register for the application through Facebook	I can register & access the my Account	Low	Sprint-2
		USN-4	As a user,I can register for the application through Gmail	I can register through already logged in gmail account.	Medium	Sprint-1
	Login	USN-5	As a user,I can log into the application by entering email & password	After registration, I can log in by only email & password.	High	Sprint-1
	Line\Bar gragh		After entering the inputs,the model will display predictions in Line\Bar Gragh Format.	I can get the expected prediction in various formats.	High	Sprint-3
Customer (Web user)	Login	USN-1	As the web user,I can login simply by using Gmailor Facebook account.	Already created gmail can be used for Login.	Medium	Sprint-2

Customer Care Executive	Support		The Customer care service will provide solutions for any FAQ and also provide ChatBot.	I can solve the problems arised by Support.	Low	Sprint-3
Administrator	News		Admin will give the recentnews of OilPrices.	Provide the recent oil prices.	High	Sprint-4
	Notification		Admin will notify when the oil prices changes.	Notification by Gmail.	High	Sprint-4
	Access Control		Admin can control the access of users.	Access permission for Users.	High	Sprint-4
	Database		Admin can store the details of users.	Stores User details.	High	Sprint-4

6. PROJECT PLANNING & SCHEDULING

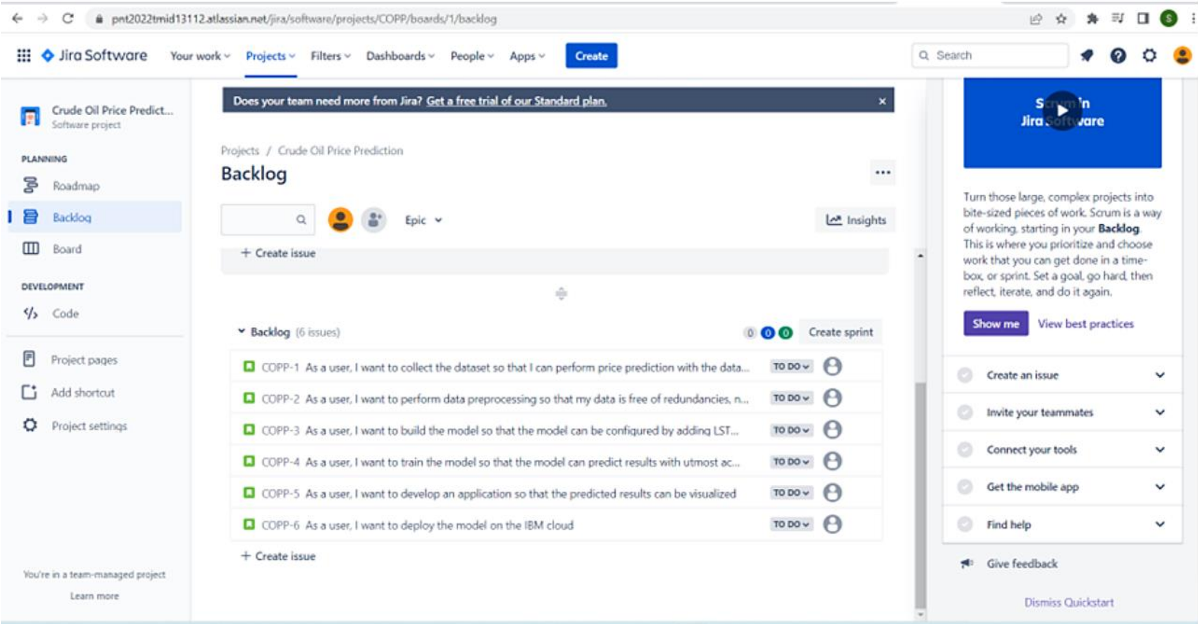
6.1. Sprint Planning & Estimation

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date(Planned)	Story Points Completed (as on PlannedEnd 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	18 Nov 2022

6.2. Sprint Delivery Schedule

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Registration	USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	10	High	SREE KAYATHRI S
Sprint-1		USN-2	As a user, I will receive confirmation email once I have registered for the application	10	High	PRIYADHARSHINI T K
Sprint-1	Login	USN-3	As a user, I can log into the application by entering email & password.	15	High	RAJASIMMAN R
Sprint-2	Input Necessary Details	USN-4	As a user, I can give Input Details to Predict Likeliness of crude oil	15	High	NIRANJANA R
Sprint-2	Data Pre-processing	USN-5	Transform raw data into suitable format for prediction.	15	High	NIRANJANA R
Sprint-3	Prediction of Crude Oil Price	USN-6	As a user, I can predict Crude oil using machine learning model.	20	High	SREE KAYATHRI S
Sprint-3		USN-7	As a user, I can get accurate prediction of crude oil	5	Medium	RAJASIMMAN R
Sprint-4	Review	USN-8	As a user, I can give feedback of the application.	20	High	PRIYADHARSHINI T K

6.3. Reports from JIRA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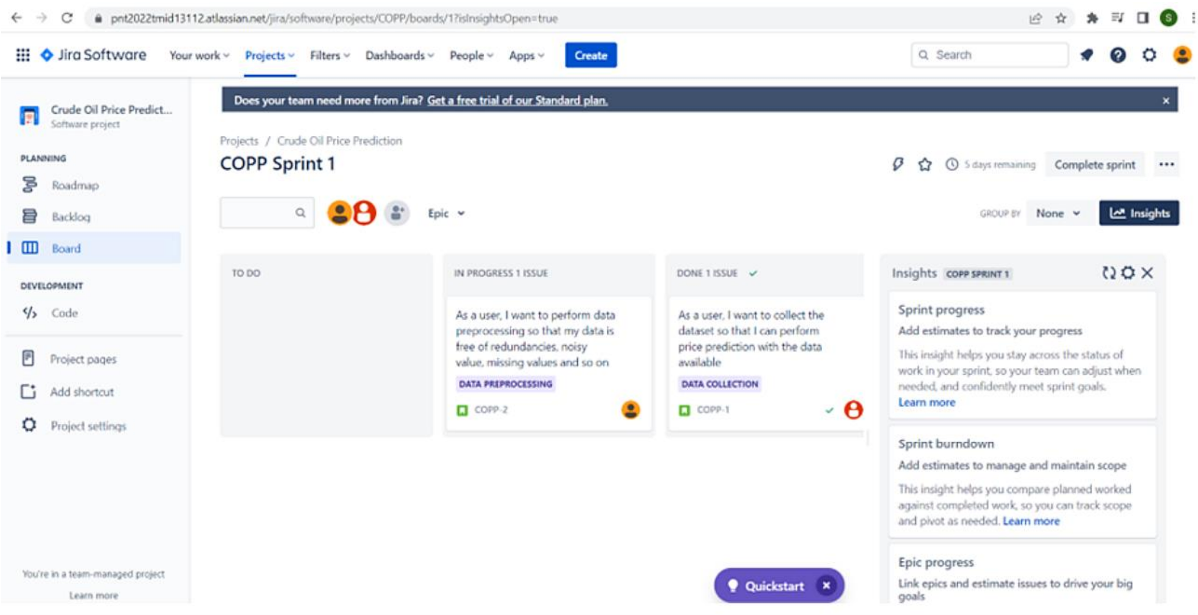
Jira Software
Your work
Projects
Filters
Dashboards
People
Apps
Create
Search
Crude Oil Price Predict...
Software project
PLANNING
Roadmap
Backlog
Board
DEVELOPMENT
Code
Project pages
Add shortcut
Project settings
You're in a team-managed project
Learn more
Does your team need more from Jira? Get a free trial of our Standard plan.
Projects / Crude Oil Price Prediction
Backlog
Epic
Insights
+ Create issue
Backlog (6 issues)
Create sprint
COPP-1 As a user, I want to collect the dataset so that I can perform price prediction with the data...
COPP-2 As a user, I want to perform data preprocessing so that my data is free of redundancies, n...
COPP-3 As a user, I want to build the model so that the model can be configured by adding LST...
COPP-4 As a user, I want to train the model so that the model can predict results with utmost ac...
COPP-5 As a user, I want to develop an application so that the predicted results can be visualized
COPP-6 As a user, I want to deploy the model on the IBM cloud
TO DO
+ Create issue
Turn those large, complex projects into bite-sized pieces of work. Scrum is a way of working, starting in your Backlog. This is where you prioritize and choose work that you can get done in a time-box, or sprint. Set a goal, go hard, then reflect, iterate, and do it again.
Show me
View best practices
Create an issue
Invite your teammates
Connect your tools
Get the mobile app
Find help
Give feedback
Dismiss Quickstart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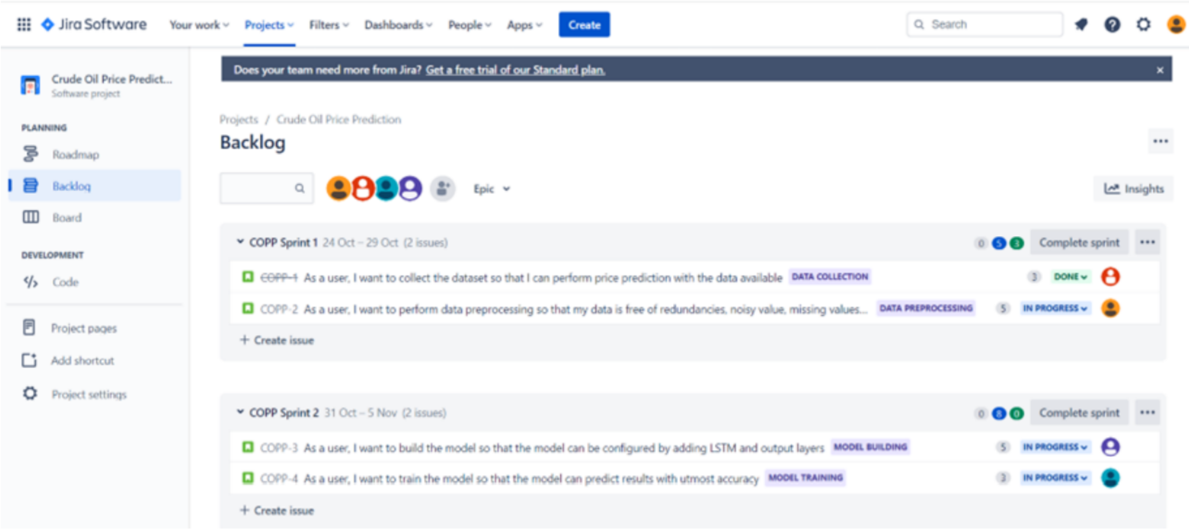
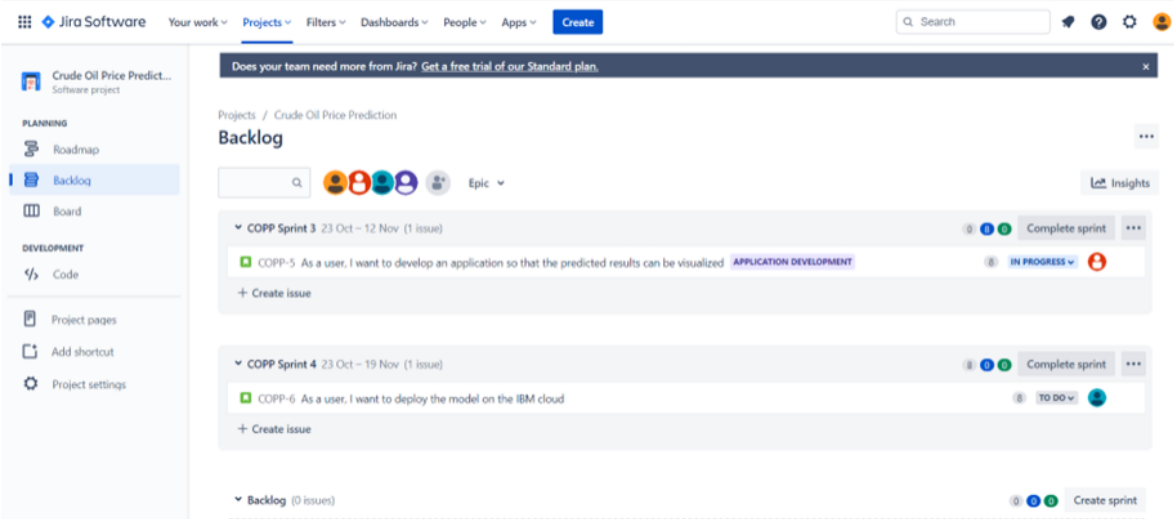
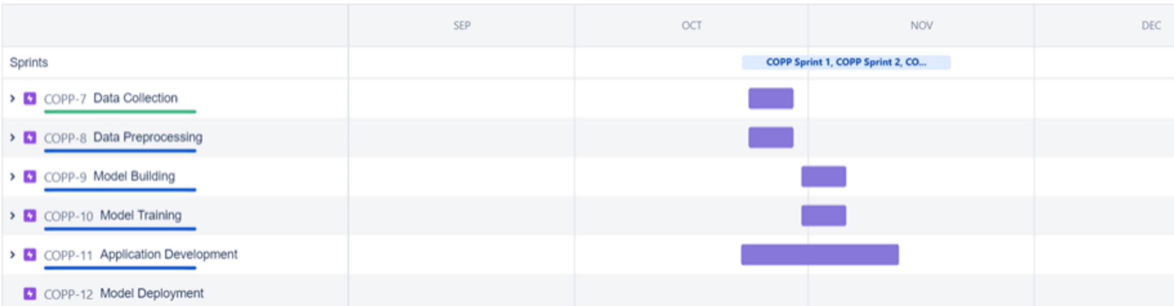
Jira Software
Your work
Projects
Filters
Dashboards
People
Apps
Create
Search
Crude Oil Price Predict...
Software project
PLANNING
Roadmap
Backlog
Board
DEVELOPMENT
Code
Project pages
Add shortcut
Project settings
You're in a team-managed project
Learn more
Does your team need more from Jira? Get a free trial of our Standard plan.
Projects / Crude Oil Price Prediction
COPP Sprint 1
Complete sprint
Epic
GROUP BY
None
Insights
TO DO
IN PROGRESS 1 ISSUE
DONE 1 ISSUE
As a user, I want to perform data preprocessing so that my data is free of redundancies, noisy value, missing values and so on
DATA PREPROCESSING
COPP-2
As a user, I want to collect the dataset so that I can perform price prediction with the data available
DATA COLLECTION
COPP-1
Insights
COPP SPRINT 1
Sprint progress
Add estimates to track your progress
This insight helps you stay across the status of work in your sprint, so your team can adjust when needed, and confidently meet sprint goals.
Learn more
Sprint burndown
Add estimates to manage and maintain scope
This insight helps you compare planned worked against completed work, so you can track scope and pivot as needed. Learn more
Epic progress
Link epics and estimate issues to drive your big goals
Quickstart







7. CODING & SOLUTIONING

7.1. Feature 1

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:

```
from google.colab import files
uploaded = files.upload()
```

In [3]:

```
import io
ds = pd.read_excel(io.BytesIO(uploaded['Crude Oil Prices Daily.xlsx']))
ds.head()
ds[:10]
```

Out[3]:

	Date	Closing Value
0	1986-01-02	25.56
1	1986-01-03	26.00
2	1986-01-06	26.53
3	1986-01-07	25.85
4	1986-01-08	25.87
5	1986-01-09	26.03
6	1986-01-10	25.65
7	1986-01-13	25.08
8	1986-01-14	24.97
9	1986-01-15	25.18

In [4]:

```
ds.isnull().sum()
```

Out[4]:

```
Date             0
Closing Value    7
dtype: int64
```

In [5]:

```
ds.dropna(axis=0,inplace=True)
```

In [6]:

```
ds.isnull().sum()
```

Out[6]:

```
Date             0
Closing Value    0
dtype: int64
```

In [7]:

```
data=ds.reset_index()['Closing Value']
data
```

Out[7]:

```
0       25.56
1       26.00
2       26.53
3       25.85
4       25.87
        ...
8211    73.89
```

```
8212    74.19
8213    73.05
8214    73.78
8215    73.93
Name: Closing Value, Length: 8216, dtype: float64
```

In [8]:

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
data=scaler.fit_transform(np.array(data).reshape(-1,1))
```

In [9]:

```
data
```

Out[9]:

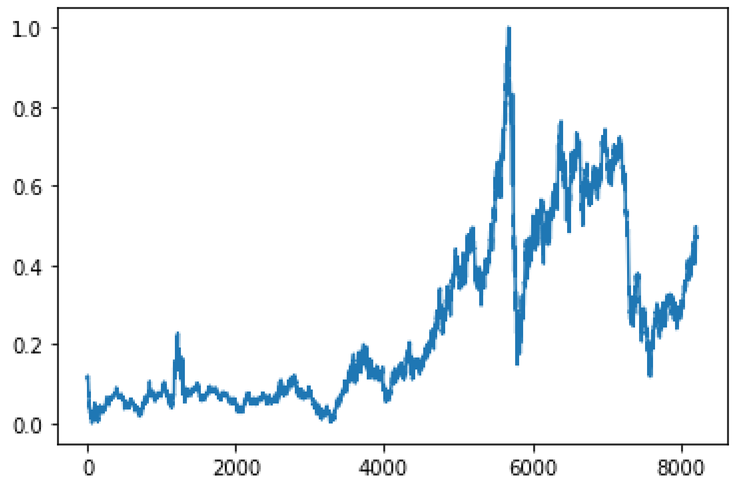
```
array([[0.11335703],
       [0.11661484],
       [0.12053902],
       ...,
       [0.46497853],
       [0.47038353],
       [0.47149415]])
```

In [10]:

```
plt.plot(data)
```

Out[10]:

```
[<matplotlib.lines.Line2D at 0x7f9e733ad2d0>]
```



In [11]:

```
training_size=int(len(data)*0.65)
test_size=len(data)-training_size
train_data,test_data=data[0:training_size,:],data[training_size:len(dat
a),:1]
```

In [12]:

```
training_size,test_size
```

Out[12]:

```
(5340, 2876)
```

In [13]:

```
train_data.shape
```

Out[13]:

```
(5340, 1)
```

In [14]:

```
def create_dataset(dataset,time_step=1):
  dataX,dataY=[],[]
  for i in range(len(dataset)-time_step-1):
    a=dataset[i:(i+time_step),0]
    dataX.append(a)
```

```
    dataY.append(dataset[i+time_step,0])
  return np.array(dataX),np.array(dataY)
```

In [15]:

```
time_step=10
x_train,y_train=create_dataset(train_data,time_step)
x_test,y_test=create_dataset(test_data,time_step)
```

In [16]:

```
print(x_train.shape),print(y_train.shape)
```

```
(5329, 10)
(5329,)
```

Out[16]:

```
(None, None)
```

In [17]:

```
print(x_test.shape),print(y_test.shape)
```

```
(2865, 10)
(2865,)
```

Out[17]:

```
(None, None)
```

In [18]:

```
x_train
```

Out[18]:

```
array([[0.11335703, 0.11661484, 0.12053902, ..., 0.10980305, 0.1089886
,
        0.11054346],
       [0.11661484, 0.12053902, 0.11550422, ..., 0.1089886 ,
0.11054346,
        0.10165852],
       [0.12053902, 0.11550422, 0.1156523 , ..., 0.11054346,
0.10165852,
        0.09906708],
       ...,
       [0.36731823, 0.35176958, 0.36080261, ..., 0.36391234,
0.37042796,
        0.37042796],
       [0.35176958, 0.36080261, 0.35354657, ..., 0.37042796,
0.37042796,
        0.37879461],
       [0.36080261, 0.35354657, 0.35295424, ..., 0.37042796,
0.37879461,
        0.37916482]])
```

In [19]:

```
x_test
```

Out[19]:

```
array([[0.38005331, 0.36872501, 0.37324152, ..., 0.3537687 ,
0.35465719,
        0.3499926 ],
       [0.36872501, 0.37324152, 0.38205242, ..., 0.35465719, 0.3499926
,
        0.3465867 ],
       [0.37324152, 0.38205242, 0.38042352, ..., 0.3499926 , 0.3465867
,
        0.34355101],
       ...,
       [0.40604176, 0.41218718, 0.41041019, ..., 0.46794017,
0.47297497,
        0.47119799],
       [0.41218718, 0.41041019, 0.43513994, ..., 0.47297497,
0.47119799,
```

```
        0.47341922],
       [0.41041019, 0.43513994, 0.4417296 , ..., 0.47119799,
0.47341922,
        0.46497853]])
```

In [20]:

```
x_train1=x_train.reshape(x_train.shape[0],x_train.shape[1],1)
x_test=x_test.reshape(x_test.shape[0],x_test.shape[1],1)
```

In [21]:

```
x_train1
```

Out[21]:

```
array([[[0.11335703],
        [0.11661484],
        [0.12053902],
        ...,
        [0.10980305],
        [0.1089886 ],
        [0.11054346]],

       [[0.11661484],
        [0.12053902],
        [0.11550422],
        ...,
        [0.1089886 ],
        [0.11054346],
        [0.10165852]],

       [[0.12053902],
        [0.11550422],
        [0.1156523 ],
        ...,
        [0.11054346],
        [0.10165852],
        [0.09906708]],

       ...,

       [[0.36731823],
        [0.35176958],
        [0.36080261],
        ...,
        [0.36391234],
        [0.37042796],
        [0.37042796]],

       [[0.35176958],
        [0.36080261],
        [0.35354657],
        ...,
        [0.37042796],
        [0.37042796],
        [0.37879461]],

       [[0.36080261],
        [0.35354657],
        [0.35295424],
        ...,
        [0.37042796],
```

```
        [0.37879461],
        [0.37916482]]])
```

In [22]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM
```

INITIALIZING THE MODEL

In [23]:

```
model=Sequential()
```

ADDING LSTM AND OUTPUT LAYERS

In [24]:

```
model.add(LSTM(50,return_sequences=True,input_shape=(10,1)))
model.add(LSTM(50,return_sequences=True))
model.add(LSTM(50))
```

In [25]:

```
model.add(Dense(1))
```

In [26]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 10, 50)            10400

lstm_1 (LSTM)                (None, 10, 50)            20200

lstm_2 (LSTM)                (None, 50)                20200

dense (Dense)                (None, 1)                 51

=================================================================
Total params: 50,851
Trainable params: 50,851
Non-trainable params: 0
_________________________________________________________________
```

CONFIGURING THE LEARNING PROCESS

In [27]:

```
model.compile(loss='mean_squared_error',optimizer='adam')
```

MODEL TRAINING

In [28]:

```
model.fit(x_train,y_train,validation_data=(x_test,y_test),epochs=3,batc
h_size=64,verbose=1)
```

```
Epoch 1/3
84/84 [==============================] - 9s 39ms/step - loss: 0.0017 -
val_loss: 8.1129e-04
Epoch 2/3
84/84 [==============================] - 2s 24ms/step - loss: 1.2676e-
04 - val_loss: 7.8078e-04
Epoch 3/3
84/84 [==============================] - 2s 23ms/step - loss: 1.2624e-
04 - val_loss: 7.7794e-04
```

Out[28]:

```
<keras.callbacks.History at 0x7f9e150bd650>
```

MODEL EVALUATION

In [29]:

```
##Transformback to original form
train_predict=scaler.inverse_transform(train_data)
test_predict=scaler.inverse_transform(test_data)
### Calculate RMSE performance metrics
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(train_data,train_predict))
```

Out[29]:

```
29.347830443269938
```

MODEL SAVING

In [30]:

```
from tensorflow.keras.models import load_model
```

In [31]:

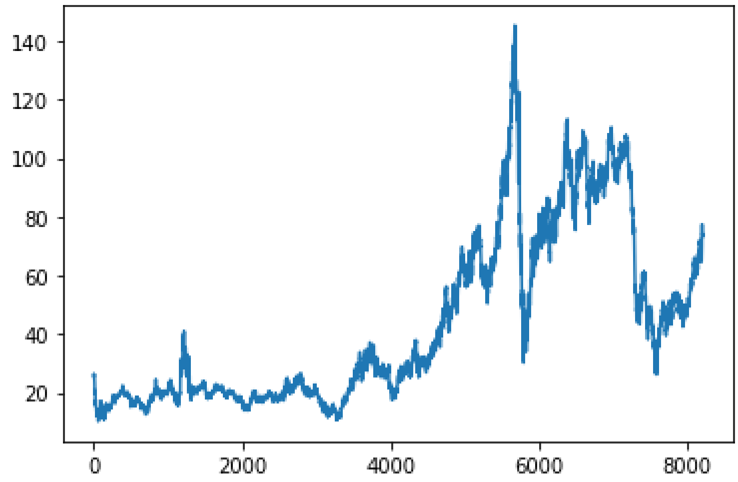
```
model.save("crude_oil.hs")
```

```
WARNING:absl:Found untraced functions such as lstm_cell_layer_call_fn,
lstm_cell_layer_call_and_return_conditional_losses,
lstm_cell_1_layer_call_fn,
lstm_cell_1_layer_call_and_return_conditional_losses,
lstm_cell_2_layer_call_fn while saving (showing 5 of 6). These
functions will not be directly callable after loading.
```

MODEL TESTING

In [32]:

```
### Plotting
look_back=10
trainpredictPlot = np.empty_like(data)
trainpredictPlot[:, :]= np.nan
trainpredictPlot[look_back:len(train_predict)+look_back, :] =
train_predict
# shift test predictions for plotting
testPredictplot = np.empty_like(data)
testPredictplot[:,: ] = np.nan
testPredictplot[look_back:len(test_predict)+look_back, :] =
test_predict
# plot baseline and predictions
plt.plot(scaler.inverse_transform(data))
plt.show()
```



In [33]:

```
len(test_data)
```

Out[33]:

```
2876
```

In [34]:

```
x_input=test_data[2866:].reshape(1,-1)
x_input.shape
```

Out[34]:

```
(1, 10)
```

In [35]:

```
temp_input=list(x_input)
temp_input=temp_input[0].tolist()
```

In [36]:

```
temp_input
```

Out[36]:

```
[0.44172960165852215,
0.4811195024433585 5,
0.4972604768251147 6,
0.4679401747371539,
0.4729749740855915,
0.47119798608026064,
0.4734192210869242 5,
0.4649785280616022,
0.4703835332444839,
0.4714941507478158 7]
```

In [37]:

```
lst_output=[]
n_steps=10
i=0
while(i<10):
    if(len(temp_input)>10):
#print(temp_input)
        x_input=np.array(temp_input[1:])
        print("{} day input {}".format(i,x_input))
        x_input=x_input.reshape(1,-1)
        x_input = x_input.reshape((1, n_steps, 1)) #print(x_input)
        yhat = model.predict(x_input, verbose=0)
        print("{} day output {}".format(i,yhat))
        temp_input.extend(yhat[0].tolist())
        temp_input=temp_input[1:] #print(temp_input)
        lst_output.extend(yhat.tolist())
        i=i+1
    else:
        x_input = x_input.reshape((1, n_steps,1))
        yhat = model.predict(x_input, verbose=0)
        print(yhat[0])
        temp_input.extend(yhat[0].tolist())
        print(len(temp_input))
        lst_output.extend(yhat.tolist())
        i=i+1
[0.4805713]
11
1 day input [0.4811195  0.49726048 0.46794017 0.47297497 0.47119799
0.47341922
0.46497853 0.47038353 0.47149415 0.4805713 ]
1 day output [[0.4844224]]
2 day input [0.49726048 0.46794017 0.47297497 0.47119799 0.47341922
0.46497853
0.47038353 0.47149415 0.4805713  0.48442239]
2 day output [[0.4833879]]
3 day input [0.46794017 0.47297497 0.47119799 0.47341922 0.46497853
0.47038353
0.47149415 0.4805713  0.48442239 0.48338789]
```

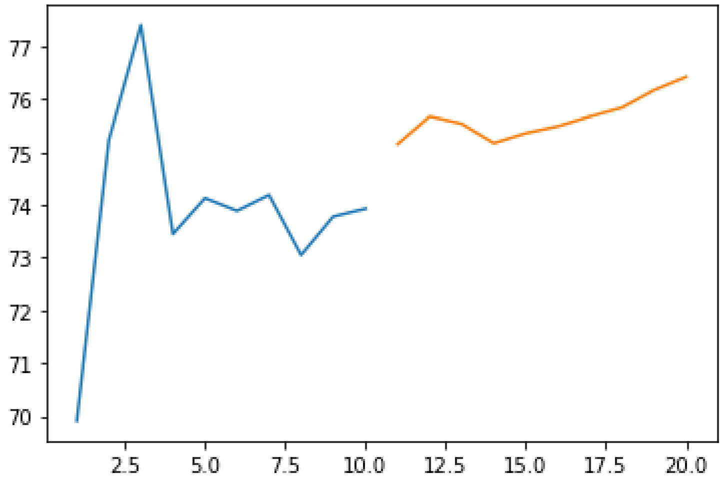
```
3 day output [[0.48069027]]
4 day input [0.47297497 0.47119799 0.47341922 0.46497853 0.47038353
0.47149415
0.4805713  0.48442239 0.48338789 0.48069027]
4 day output [[0.4820817]]
5 day input [0.47119799 0.47341922 0.46497853 0.47038353 0.47149415
0.4805713
0.48442239 0.48338789 0.48069027 0.48208171]
5 day output [[0.48304394]]
6 day input [0.47341922 0.46497853 0.47038353 0.47149415
0.4805713  0.48442239
0.48338789 0.48069027 0.48208171 0.48304394]
6 day output [[0.48441863]]
7 day input [0.46497853 0.47038353 0.47149415 0.4805713  0.48442239
0.48338789
0.48069027 0.48208171 0.48304394 0.48441863]
7 day output [[0.48566842]]
8 day input [0.47038353 0.47149415 0.4805713  0.48442239 0.48338789
0.48069027
0.48208171 0.48304394 0.48441863 0.48566842]
8 day output [[0.48811078]]
9 day input [0.47149415 0.4805713  0.48442239 0.48338789 0.48069027
0.48208171
0.48304394 0.48441863 0.48566842 0.48811078]
9 day output [[0.48995987]]
```

In [38]:

```
day_new=np.arange(1,11)
day_pred=np.arange(11,21)
len(data)
plt.plot(day_new, scaler.inverse_transform(data[8206:]))
plt.plot(day_pred, scaler.inverse_transform(lst_output))
```

Out[38]:

```
[<matplotlib.lines.Line2D at 0x7f9e151ef6d0>]
```

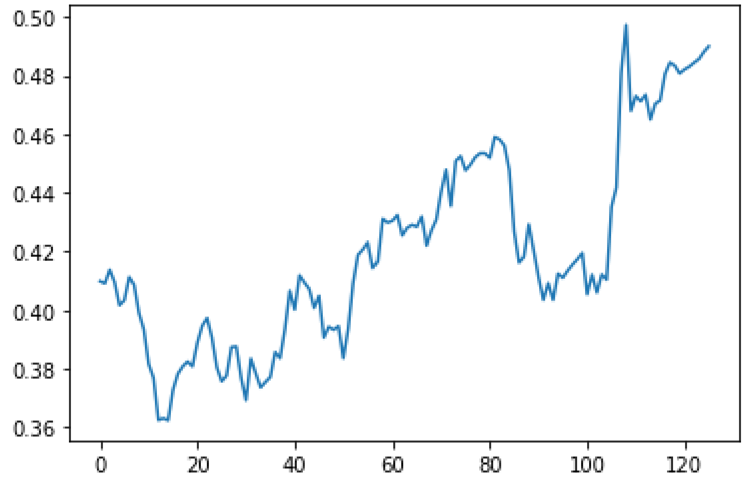


In [39]:

```
df3=data.tolist()
df3.extend(lst_output)
plt.plot(df3[8100:])
```

Out[39]:

```
[<matplotlib.lines.Line2D at 0x7f9e10cc3d10>]
```

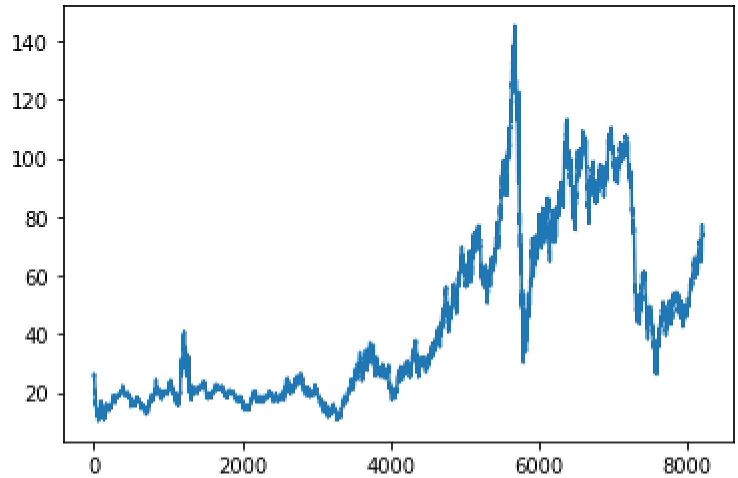


In [40]:

```
df3=scaler.inverse_transform(df3).tolist()
plt.plot(scaler.inverse_transform(data))
```

Out[40]:

```
[<matplotlib.lines.Line2D at 0x7f9e10f89e10>]
```



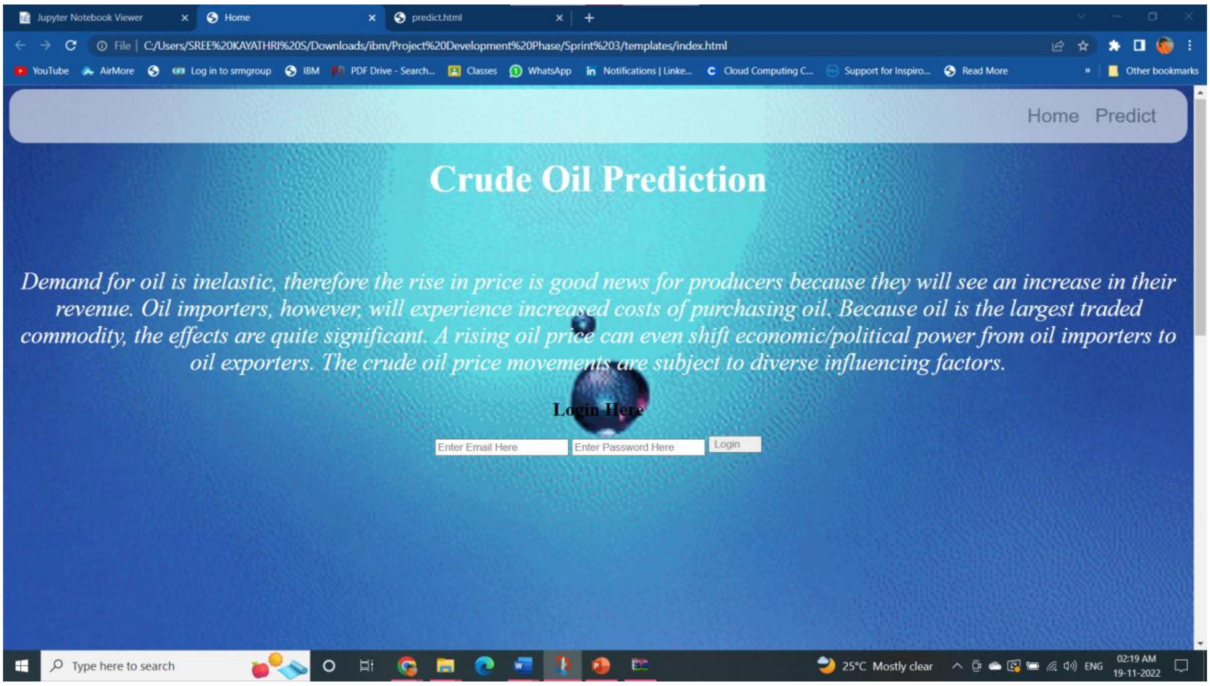
7.2 Feature 2

index.html

```
<!DOCTYPE html>
<html lang="en">
<head>
   <meta name="viewport" content="width=device-width, initial-scale=1.0">
   <title>Home page</title>
   <link rel="stylesheet" href="style.css">
</head>
<body>

   <div class="main">
      <div class="navbar">
         <div class="icon">
            <h2 class="logo">CRUDE OIL</h2>
         </div>
```

```
        <div class="menu">
          <ul>
            <li><a href="#">HOME</a></li>
            <li><a href="#">ABOUT</a></li>
            <li><a href="#">SERVICE</a></li>
            <li><a href="#">CONTACT</a></li>
          </ul>
        </div>

        <div class="search">
          <input class="srch" type="search" name="" placeholder="Type To text">
          <a href="#"> <button class="btn">Search</button></a>
        </div>

      </div>
      <div class="content">
        <h1>Crude Oil<br><span>Price Prediction</span><br></h1>
        <p class="par"> Crude oil means a mixture of hydrocarbons that exists in
liquid phase in<br>
          natural underground reservoirs and remains liquid <br>at atmospheric
pressure
          after passing through <br>surface separating facilities.</p>

          <button class="cn"><a href="register.html">JOIN US</a></button>

          <div class="form">
            <h2>Login Here</h2>
            <input type="email" name="email" placeholder="Enter Email Here">
            <input type="password" name="" placeholder="Enter Password Here">
            <button class="btnn"><a href="#">Login</a></button>

            <p class="link">Don't have an account<br>
            <a href="#">Sign up </a> here</a></p>
            <p class="liw">Log in with</p>

            <div class="icons">
              <a href="#"><ion-icon name="logo-facebook"></ion-icon></a>
              <a href="#"><ion-icon name="logo-google"></ion-icon></a>
            </div>

          </div>
            </div>
          </div>
      </div>
    </div>
    <script src="https://unpkg.com/ionicons@5.4.0/dist/ionicons.js"></script>
</body>
```

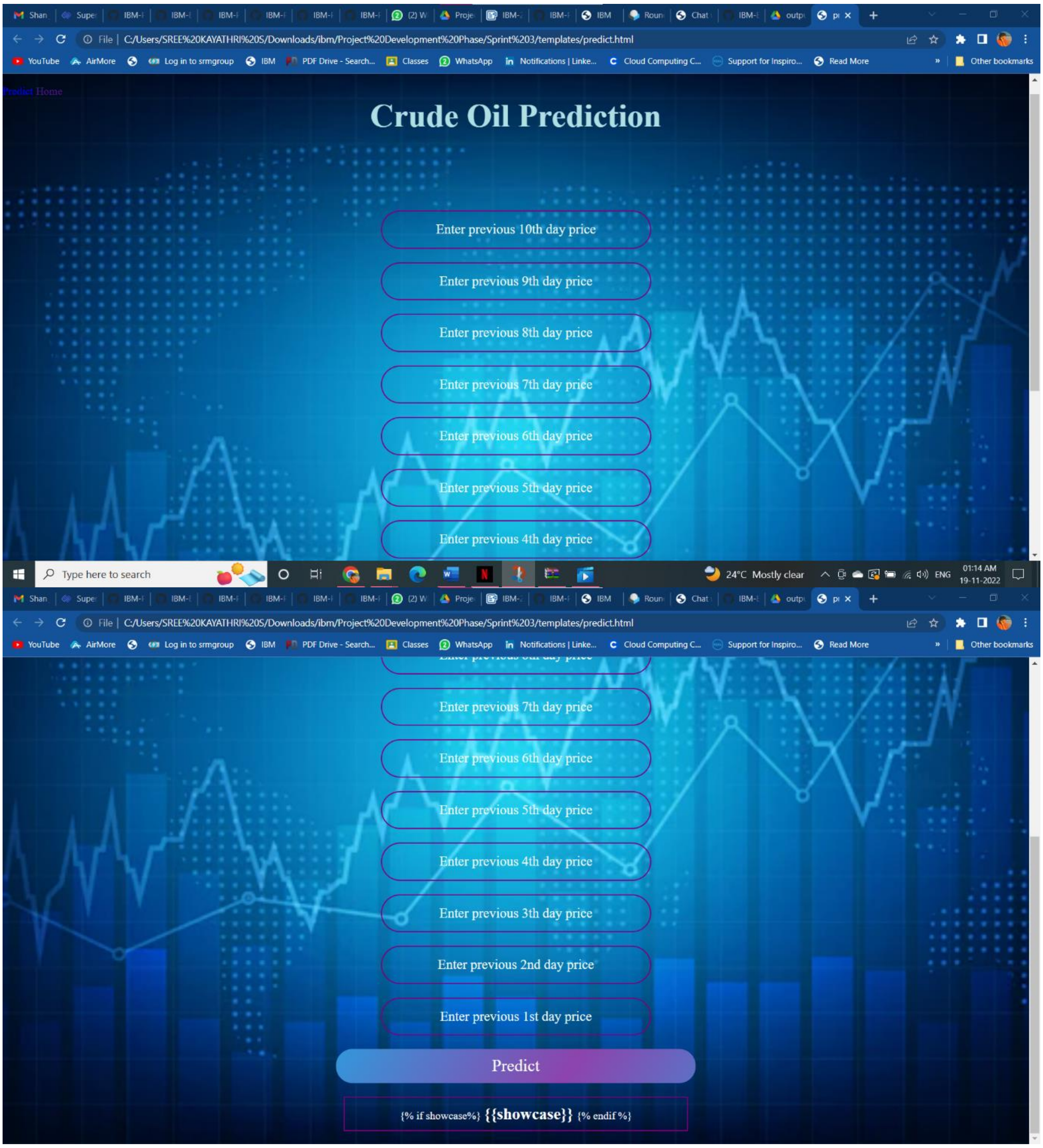
```
</html>
```



predict.html

```
<!DOCTYPE html>
<html>
   <head>
      <title>Registration Form</title>
      <link rel="stylesheet"
      href="register.css" type="text/css">
   </head>
   <body>
      <div class="main">
         <div class="register">
            <h2>Register Here</h2>
            <form id="register" method="post">
               <label>First Name : </label>
               <br>
               <input type="text" name="fname"
               id="name" placeholder="Enter Your First Name">
               <br><br>
               <label>Last Name : </label>
               <br>
               <input type="text" name="lname"
               id="name" placeholder="Enter Your last Name">
               <br><br>
               <label>Your Age : </label>
               <br>
               <input type="number" name="age"
```

```
            id="name" placeholder="How Old Are You">
            <br><br>
            <label>Email : </label>
            <br>
            <input type="email" name="email"
            id="name" placeholder="Enter Your Valid Email">
            <br><br>
            <label>Gender : </label>
            <br>
                 
            <input type="radio" name="gender"
            id="male">
             
            <span id="male">Male</span>
                 
            <input type="radio" name="gender"
            id="female">
             
            <span id="female">Female</span>
            <br><br>
            <input type="submit" value="Submit"
            name="submit" id="submit">
          </form>
        </div>
      </div>
    </body>
</html>
```



8. TESTING

8.1 Test Cases

Test case analysis This report shows the number of test cases that have passed, failed, and untested.

Section	Total Cases	Not Tested	Fail	Pass
ML Model	4	0	0	4
Flask Application	4	0	0	4

IBM cloud	4	0	0	4
Exception Reporting	2	0	0	2
Final Report output	4	0	0	4

8.2 User Acceptance Testing

The purpose is to briefly explain the test coverage and open issues of the crude oil price prediction project at the time of the release to user acceptance testing

Defect Analysis:

Not Reproduced	0	0	0	0	0
Skipped	0	0	0	0	0
Won't fix	0	0	0	1	1
Totals	8	0	2	2	12

Test case analysis

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

Section	Total Cases	Not Tested	Fail	Pass
ML Model	4	0	0	4
Flask Application	4	0	0	4
IBM Cloud	4	0	0	4
Exception Reporting	2	0	0	2
Final Report Output	4	0	0	4

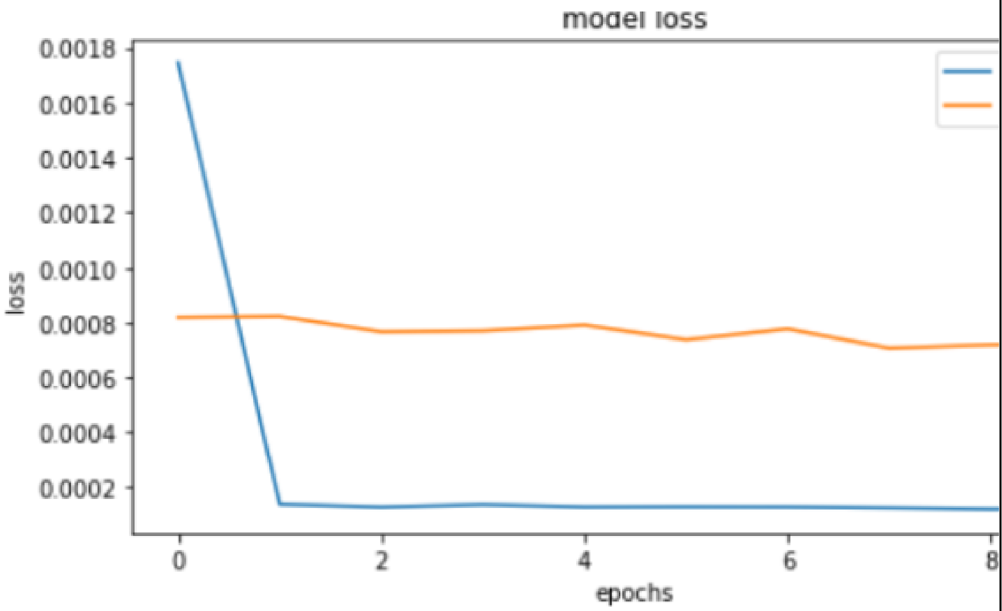
The report shows the number of resolved and closed bugs at each severity level and how they were resolved

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	3	0	0	0	3
Duplicate	1	0	1	0	2
External	0	0	0	0	0
Fixed	4	0	1	1	6

9. RESULTS

9.1 Performance Metrics

S.No	Parameters	Values	Screenshot
1.	Model Summary		Model: "sequential_1" ____ Layer (type) Output Shape == lstm_3 (LSTM) (None, 10, 50) lstm_4 (LSTM) (None, 10, 50) lstm_5 (LSTM) (None, 50) dense_1 (Dense) (None, 1) == Total params: 50,851 Trainable params: 50,851 Non-trainable params: 0

2.	Accuracy		Train Mean Absolute Error: 1.0278217422906264 Train Root Mean Squared Error: 1.42852486399340 Test Mean Absolute Error: 2.780526920817909 Test Root Mean Squared Error: 3.63482344665237З 

10. ADVANTAGES & DISADVANTAGES

Advantages:

- Prediction of crude oil price can help the importers to choose the right time to buy as they wait for the prices to fall down
- Prediction of crude oil prices can help the exporters to increase the demand
- It can even help in shifting the political powers
- can assist in minimizing the risks associated with volatility in oil prices

Disadvantages

- The prediction results may lack accuracy
- Volatility in prices may be misleading

11. CONCLUSION

LSTM network is better than other traditional neural networks for forecasting prices as it aims in using a back propagation model. Traditional neural networks such as CNN on the other hand predicts the next outgoing but doesn't necessarily save the previous data or connection which is based on feed-forwarding, in the sense the previous data is not necessary to predict the future data. LSTM focuses on storing the previous data and prediction which is rather encouraging and more approximate. The outcomes derived are relatively encouraging. The results show that large lookups do not necessarily improve the accuracy of the predictions of crude oil prices. Hence it can be concluded, the model with a single LSTM model is definitely the most accurate.

12. FUTURE SCOPE

The project's future potential is enormous. The project can be implemented with the real-time functionalities that are necessary.Because it is quite versatile in terms of expansion, the project can be upgraded in the near future as and when the need arises. The complete prediction value can be increased in a much better, accurate,and error-free manner with the proposed approach. The project can be enhanced with real time data.

13. APPENDIX

Source Code

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [ ]:

```
from google.colab import files
uploaded = files.upload()
```

In [ ]:

```
import io
ds = pd.read_excel(io.BytesIO(uploaded['Crude Oil Prices Daily.xlsx']))
ds.head()
ds[:10]
```

Out[ ]:

	Date	Closing Value
0	1986-01-02	25.56
1	1986-01-03	26.00
2	1986-01-06	26.53
3	1986-01-07	25.85
4	1986-01-08	25.87
5	1986-01-09	26.03
6	1986-01-10	25.65

7	1986-01-13	25.08
8	1986-01-14	24.97
9	1986-01-15	25.18

In [ ]:

```
ds.isnull().sum()
```

Out[ ]:

```
Date             0
Closing Value    7
dtype: int64
```

In [ ]:

```
ds.dropna(axis=0,inplace=True)
```

In [ ]:

```
ds.isnull().sum()
```

Out[ ]:

```
Date             0
Closing Value    0
dtype: int64
```

In [ ]:

```
data=ds.reset_index()['Closing Value']
data
```

Out[ ]:

```
0       25.56
1       26.00
2       26.53
3       25.85
4       25.87
        ...
8211    73.89
8212    74.19
8213    73.05
8214    73.78
8215    73.93
Name: Closing Value, Length: 8216, dtype: float64
```

In [ ]:

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
data=scaler.fit_transform(np.array(data).reshape(-1,1))
```

In [ ]:

```
data
```

Out[ ]:

```
array([[0.11335703],
       [0.11661484],
       [0.12053902],
       ...,
       [0.46497853],
       [0.47038353],
       [0.47149415]])
```

In [ ]:

```
plt.plot(data)
```

Out[ ]:

```
[<matplotlib.lines.Line2D at 0x7f9e733ad2d0>]
```

In [ ]:

```
training_size=int(len(data)*0.65)
test_size=len(data)-training_size
train_data,test_data=data[0:training_size,:],data[training_size:len(dat
a),:1]
```

In [ ]:

```
training_size,test_size
```

Out[ ]:

```
(5340, 2876)
```

In [ ]:

```
train_data.shape
```

Out[ ]:

```
(5340, 1)
```

In [ ]:

```
def create_dataset(dataset,time_step=1):
  dataX,dataY=[],[]
  for i in range(len(dataset)-time_step-1):
    a=dataset[i:(i+time_step),0]
    dataX.append(a)
    dataY.append(dataset[i+time_step,0])
  return np.array(dataX),np.array(dataY)
```

In [ ]:

```
time_step=10
x_train,y_train=create_dataset(train_data,time_step)
x_test,y_test=create_dataset(test_data,time_step)
```

In [ ]:

```
print(x_train.shape),print(y_train.shape)
(5329, 10)
(5329,)
```

Out[ ]:

```
(None, None)
```

In [ ]:

```
print(x_test.shape),print(y_test.shape)
(2865, 10)
(2865,)
```

Out[ ]:

```
(None, None)
```

In [ ]:

```
x_train
```

Out[ ]:

```
array([[0.11335703, 0.11661484, 0.12053902, ..., 0.10980305, 0.1089886
,
         0.11054346],
       [0.11661484, 0.12053902, 0.11550422, ..., 0.1089886 ,
0.11054346,
         0.10165852],
       [0.12053902, 0.11550422, 0.1156523 , ..., 0.11054346,
0.10165852,
         0.09906708],
       ...,
       [0.36731823, 0.35176958, 0.36080261, ..., 0.36391234,
0.37042796,
         0.37042796],
       [0.35176958, 0.36080261, 0.35354657, ..., 0.37042796,
0.37042796,
         0.37879461],
       [0.36080261, 0.35354657, 0.35295424, ..., 0.37042796,
0.37879461,
         0.37916482]])
```

In [ ]:

```
x_test
```

Out[ ]:

```
array([[0.38005331, 0.36872501, 0.37324152, ..., 0.3537687 ,
0.35465719,
        0.3499926 ],
       [0.36872501, 0.37324152, 0.38205242, ..., 0.35465719, 0.3499926
,
        0.3465867 ],
       [0.37324152, 0.38205242, 0.38042352, ..., 0.3499926 , 0.3465867
,
        0.34355101],
       ...,
       [0.40604176, 0.41218718, 0.41041019, ..., 0.46794017,
0.47297497,
        0.47119799],
       [0.41218718, 0.41041019, 0.43513994, ..., 0.47297497,
0.47119799,
        0.47341922],
       [0.41041019, 0.43513994, 0.4417296 , ..., 0.47119799,
0.47341922,
        0.46497853]])
```

In [ ]:

```
x_train1=x_train.reshape(x_train.shape[0],x_train.shape[1],1)
x_test=x_test.reshape(x_test.shape[0],x_test.shape[1],1)
```

In [ ]:

```
x_train1
```

Out[ ]:

```
array([[[0.11335703],
        [0.11661484],
        [0.12053902],
        ...,
        [0.10980305],
        [0.1089886 ],
        [0.11054346]],

       [[0.11661484],
        [0.12053902],
        [0.11550422],
        ...,
        [0.1089886 ],
        [0.11054346],
        [0.10165852]],

       [[0.12053902],
        [0.11550422],
        [0.1156523 ],
        ...,
        [0.11054346],
        [0.10165852],
        [0.09906708]],

       ...,

       [[0.36731823],
        [0.35176958],
        [0.36080261],
        ...,
```

```
        [0.36391234],
        [0.37042796],
        [0.37042796]],

       [[0.35176958],
        [0.36080261],
        [0.35354657],
        ...,
        [0.37042796],
        [0.37042796],
        [0.37879461]],

       [[0.36080261],
        [0.35354657],
        [0.35295424],
        ...,
        [0.37042796],
        [0.37879461],
        [0.37916482]]])
```

In [ ]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM
```

INITIALIZING THE MODEL

In [ ]:

```
model=Sequential()
```

ADDING LSTM AND OUTPUT LAYERS

In [ ]:

```
model.add(LSTM(50,return_sequences=True,input_shape=(10,1)))
model.add(LSTM(50,return_sequences=True))
model.add(LSTM(50))
```

In [ ]:

```
model.add(Dense(1))
```

In [ ]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 10, 50)            10400

lstm_1 (LSTM)                (None, 10, 50)            20200

lstm_2 (LSTM)                (None, 50)                20200

dense (Dense)                (None, 1)                 51

=================================================================
Total params: 50,851
Trainable params: 50,851
Non-trainable params: 0
_________________________________________________________________
```

CONFIGURING THE LEARNING PROCESS

In [ ]:

```
model.compile(loss='mean_squared_error',optimizer='adam')
```

MODEL TRAINING

In [ ]:

```
model.fit(x_train,y_train,validation_data=(x_test,y_test),epochs=3,batc
h_size=64,verbose=1)
```

```
Epoch 1/3
84/84 [==============================] - 9s 39ms/step - loss: 0.0017 -
val_loss: 8.1129e-04
Epoch 2/3
84/84 [==============================] - 2s 24ms/step - loss: 1.2676e-
04 - val_loss: 7.8078e-04
Epoch 3/3
84/84 [==============================] - 2s 23ms/step - loss: 1.2624e-
04 - val_loss: 7.7794e-04
```

Out[ ]:

```
<keras.callbacks.History at 0x7f9e150bd650>
```

MODEL EVALUATION

In [ ]:

```
##Transformback to original form
train_predict=scaler.inverse_transform(train_data)
test_predict=scaler.inverse_transform(test_data)
### Calculate RMSE performance metrics
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(train_data,train_predict))
```

Out[ ]:

```
29.347830443269938
```

MODEL SAVING

In [ ]:

```
from tensorflow.keras.models import load_model
```

In [ ]:

```
model.save("crude_oil.hs")
```

```
WARNING:absl:Found untraced functions such as lstm_cell_layer_call_fn,
lstm_cell_layer_call_and_return_conditional_losses,
lstm_cell_1_layer_call_fn,
lstm_cell_1_layer_call_and_return_conditional_losses,
lstm_cell_2_layer_call_fn while saving (showing 5 of 6). These
functions will not be directly callable after loading.
```

MODEL TESTING

In [ ]:

```
### Plotting
look_back=10
trainpredictPlot = np.empty_like(data)
trainpredictPlot[:, :]= np.nan
trainpredictPlot[look_back:len(train_predict)+look_back, :] =
train_predict
# shift test predictions for plotting
testPredictplot = np.empty_like(data)
testPredictplot[:,: ] = np.nan
testPredictplot[look_back:len(test_predict)+look_back, :] =
test_predict
# plot baseline and predictions
plt.plot(scaler.inverse_transform(data))
plt.show()
```

In [ ]:

```
len(test_data)
```

Out[ ]:

```
2876
```

In [ ]:

```
x_input=test_data[2866:].reshape(1,-1)
x_input.shape
```

Out[ ]:

```
(1, 10)
```

In [ ]:

```
temp_input=list(x_input)
temp_input=temp_input[0].tolist()
```

In [ ]:

```
temp_input
```

Out[ ]:

```
[0.44172960165852215,
0.48111950244335855,
0.49726047682511476,
0.4679401747371539,
0.4729749740855915,
0.47119798608026064,
0.47341922108692425,
0.4649785280616022,
0.4703835332444839,
0.47149415074781587]
```

In [ ]:

```
lst_output=[]
n_steps=10
i=0
while(i<10):
    if(len(temp_input)>10):
#print(temp_input)
        x_input=np.array(temp_input[1:])
        print("{} day input {}".format(i,x_input))
        x_input=x_input.reshape(1,-1)
        x_input = x_input.reshape((1, n_steps, 1)) #print(x_input)
        yhat = model.predict(x_input, verbose=0)
        print("{} day output {}".format(i,yhat))
        temp_input.extend(yhat[0].tolist())
        temp_input=temp_input[1:] #print(temp_input)
        lst_output.extend(yhat.tolist())
        i=i+1
    else:
        x_input = x_input.reshape((1, n_steps,1))
        yhat = model.predict(x_input, verbose=0)
        print(yhat[0])
        temp_input.extend(yhat[0].tolist())
        print(len(temp_input))
        lst_output.extend(yhat.tolist())
        i=i+1
[0.4805713]
11
1 day input [0.4811195  0.49726048 0.46794017 0.47297497 0.47119799
0.47341922
0.46497853 0.47038353 0.47149415 0.4805713 ]
1 day output [[0.4844224]]
2 day input [0.49726048 0.46794017 0.47297497 0.47119799 0.47341922
0.46497853
0.47038353 0.47149415 0.4805713  0.48442239]
2 day output [[0.4833879]]
3 day input [0.46794017 0.47297497 0.47119799 0.47341922 0.46497853
```

```
0.47038353
0.47149415 0.4805713  0.48442239 0.48338789]
3 day output [[0.48069027]]
4 day input [0.47297497 0.47119799 0.47341922 0.46497853 0.47038353
0.47149415
0.4805713  0.48442239 0.48338789 0.48069027]
4 day output [[0.4820817]]
5 day input [0.47119799 0.47341922 0.46497853 0.47038353 0.47149415
0.4805713
0.48442239 0.48338789 0.48069027 0.48208171]
5 day output [[0.48304394]]
6 day input [0.47341922 0.46497853 0.47038353 0.47149415
0.4805713  0.48442239
0.48338789 0.48069027 0.48208171 0.48304394]
6 day output [[0.48441863]]
7 day input [0.46497853 0.47038353 0.47149415 0.4805713  0.48442239
0.48338789
0.48069027 0.48208171 0.48304394 0.48441863]
7 day output [[0.48566842]]
8 day input [0.47038353 0.47149415 0.4805713  0.48442239 0.48338789
0.48069027
0.48208171 0.48304394 0.48441863 0.48566842]
8 day output [[0.48811078]]
9 day input [0.47149415 0.4805713  0.48442239 0.48338789 0.48069027
0.48208171
0.48304394 0.48441863 0.48566842 0.48811078]
9 day output [[0.48995987]]
```

In [ ]:

```
day_new=np.arange(1,11)
day_pred=np.arange(11,21)
len(data)
plt.plot(day_new, scaler.inverse_transform(data[8206:]))
plt.plot(day_pred, scaler.inverse_transform(lst_output))
```

Out[ ]:

```
[<matplotlib.lines.Line2D at 0x7f9e151ef6d0>]
```

In [ ]:

```
df3=data.tolist()
df3.extend(lst_output)
plt.plot(df3[8100:])
```

Out[ ]:

```
[<matplotlib.lines.Line2D at 0x7f9e10cc3d10>]
```

In [ ]:

```
df3=scaler.inverse_transform(df3).tolist()
plt.plot(scaler.inverse_transform(data))
```

Out[ ]:

```
[<matplotlib.lines.Line2D at 0x7f9e10f89e10>]
```

7.2 Feature 2

index.html

```
<!DOCTYPE html>
<html lang="en">
<head>
```

```
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Home page</title>
    <link rel="stylesheet" href="style.css">
</head>
<body>

    <div class="main">
        <div class="navbar">
            <div class="icon">
                <h2 class="logo">CRUDE OIL</h2>
            </div>

            <div class="menu">
                <ul>
                    <li><a href="#">HOME</a></li>
                    <li><a href="#">ABOUT</a></li>
                    <li><a href="#">SERVICE</a></li>
                    <li><a href="#">CONTACT</a></li>
                </ul>
            </div>

            <div class="search">
                <input class="srch" type="search" name="" placeholder="Type To text">
                <a href="#"> <button class="btn">Search</button></a>
            </div>

        </div>
        <div class="content">
            <h1>Crude Oil<br><span>Price Prediction</span><br></h1>
            <p class="par"> Crude oil means a mixture of hydrocarbons that exists in
liquid phase in<br>
                natural underground reservoirs and remains liquid <br>at atmospheric
pressure
                after passing through <br>surface separating facilities.</p>

                <button class="cn"><a href="register.html">JOIN US</a></button>

                <div class="form">
                    <h2>Login Here</h2>
                    <input type="email" name="email" placeholder="Enter Email Here">
                    <input type="password" name="" placeholder="Enter Password Here">
                    <button class="btnn"><a href="#">Login</a></button>

                    <p class="link">Don't have an account<br>
                    <a href="#">Sign up </a> here</a></p>
                    <p class="liw">Log in with</p>

                    <div class="icons">
```

```
                <a href="#"><ion-icon name="logo-facebook"></ion-icon></a>
                <a href="#"><ion-icon name="logo-google"></ion-icon></a>
              </div>

            </div>
              </div>
            </div>
        </div>
    </div>
    <script src="https://unpkg.com/ionicons@5.4.0/dist/ionicons.js"></script>
</body>
</html>
```

predict.html

```
<!DOCTYPE html>
<html>
    <head>
        <title>Registration Form</title>
        <link rel="stylesheet"
        href="register.css" type="text/css">
    </head>
    <body>
        <div class="main">
            <div class="register">
                <h2>Register Here</h2>
                <form id="register" method="post">
                    <label>First Name : </label>
                    <br>
                    <input type="text" name="fname"
                    id="name" placeholder="Enter Your First Name">
                    <br><br>
                    <label>Last Name : </label>
                    <br>
                    <input type="text" name="lname"
                    id="name" placeholder="Enter Your last Name">
                    <br><br>
                    <label>Your Age : </label>
                    <br>
                    <input type="number" name="age"
                    id="name" placeholder="How Old Are You">
                    <br><br>
                    <label>Email : </label>
                    <br>
                    <input type="email" name="email"
                    id="name" placeholder="Enter Your Valid Email">
                    <br><br>
                    <label>Gender : </label>
                    <br>
```

```html
                 
            <input type="radio" name="gender"
            id="male">
             
            <span id="male">Male</span>
                 
            <input type="radio" name="gender"
            id="female">
             
            <span id="female">Female</span>
            <br><br>
            <input type="submit" value="Submit"
            name="submit" id="submit">
          </form>
        </div>
      </div>
  </body>
</html>
```

index.css

```css
h1 {
	text-align: center;
	color: floralwhite;
	font-size: 50px;
	font-family: roboto;
}

p {
	font-family: roboto;
	color: ghostwhite;
	margin-right: 30px;
	margin-left: 30px;
	text-align: center;
	font-size: 20px;
	font-weight: bold;
}

body {
	background: url(index.png);
	background-repeat: no-repeat;
	background-size: cover;
}

.button {
	display: inline-block;
	border-radius: 4px;
	background-color: black;
	border: none;
	color: #FFFFFF;
```

```
        text-align: center;
        font-size: 20px;
        padding: 12px;
        width: 100px;
        transition: all 0.5s;
        cursor: pointer;
        margin: 5px;
}

a {
        font-size: 20px;
        font-family: roboto;
        color: ghostwhite;
        margin-right: 30px;
        margin-left: 30px;
        text-align: center;
        font-size: 20px;
        font-weight: bold;
}

table {
        background: slateblue;
        opacity: 0.8;
   margin-left:auto;
   margin-right:auto;
   margin-bottom: 0px;
}

th,
td {
        text-align: left;
        color: black;
        font-size: 30px;
        font-family: roboto;
}
```

Predict.css

```
body{
   background: url(index.png);
   background-repeat: no-repeat;
   background-size: cover;
}
```

App.py:

```
from flask import Flask, render_template, request, redirect import numpy as np
# from tensorflow.k

from keras.saving.save import load_model
app = Flask(   name   ,template_folder='template')
```

```
@app.route('/', methods=["GET"]) def index():
return render_template('index.html')

@app.route('/predict.html', methods=["POST", "GET"])@app.route('/method',
methods=["POST", "GET"])
def method():
if request.method == "POST": string = request.form['val'] string = string.split(',')
temp_input = [eval(i) for i in string]

x_input = np.zeros(shape=(1, 10))x_input.shape

lst_output = [] n_steps = 10
i = 0
while (i < 10):
if (len(temp_input) > 10):
x_input = np.array(temp_input[1:])x_input = x_input.reshape(1, -1)
x_input = x_input.reshape((1, n_steps, 1)) yhat = model.predict(x_input, verbose=0)
temp_input.extend(yhat[0].tolist()) temp_input = temp_input[1:]
lst_output.extend(yhat.tolist())
i = i + 1

else:
x_input = x_input.reshape((1, n_steps, 1)) yhat = model.predict(x_input, verbose=0)
temp_input.extend(yhat[0].tolist()) lst_output.extend(yhat.tolist())
i = i + 1
val = lst_output[9]
return render_template('predict.html', prediction=val)

if request.method == "GET”:
return render_template('predict.html')

if enamel == "     main   ":
model =load_model(r'crudeoilprediction.h5') app.run(debug=True)

#cloud deployment code in ml model

!pip installibm_watson_machine_learning

from ibm_watson_machine_learning importAPIClient wml_credentials = (
"url" : "https://us-south.ml.cloud.ibm.com",
"apikey" : "cRkqykhsnLO1 Ogs_xoYjgLkNTtTS1QxyioMn1GSIQ1P5" client=
APIClient(wml_credentials)
#for creatinga deployment phase
def guid_from_space_name(client, space_name): space=client.spaces.get_details()
#print(space)
return(next(item for item in space['resources'] if item['entity'][‘name'] ==
space_name)['metadata']['id'])
```

```
space_uid = guid_from_space_name(client,'models') print("Space UID = "+space_uid)
client.set.default_space(space_uid) client.software_specifications.list()
software_spec_uid=
client.software_specifications.get_uid_by_name("tensorflow_rt22.1-py3.9")
software_spec_uid
```

GitHub Link
https://github.com/IBM-EPBL/IBM-Project-26174-1660020097

Project Demo
https://drive.google.com/file/d/1P2XSYQK9BnEc5Yrwbznijk3aIBR6dnzA/view?usp=sharing