

# Crude Oil Price Prediction Using IBM Watson Studio

## **1. INTRODUCTION**

### **1.1 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.

### **1.2 Purpose**

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.

## **2. LITERATURE SURVEY**

### **2.1 Existing problem**

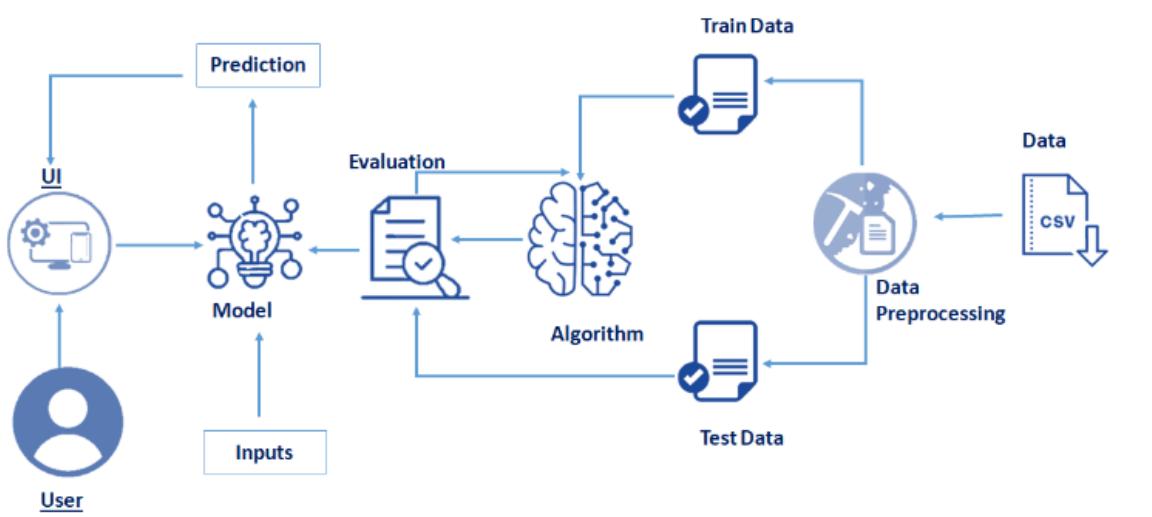
The internal and external environment of the oil market is changing, and the influencing factors have become diverse and complex. As the factors affecting international oil prices become more and more complex, it becomes difficult to capture practical factors and predict oil prices. Oil demand is inelastic, 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.

### **2.2 Proposed solution**

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.

### 3. THEORITICAL ANALYSIS

#### 3.1 Block Diagram



#### 3.2 Hardware / Software designing

##### Software Requirements:

- Anaconda Navigator
- Tensor flow
- Keras
- Flask

##### Hardware Requirements:

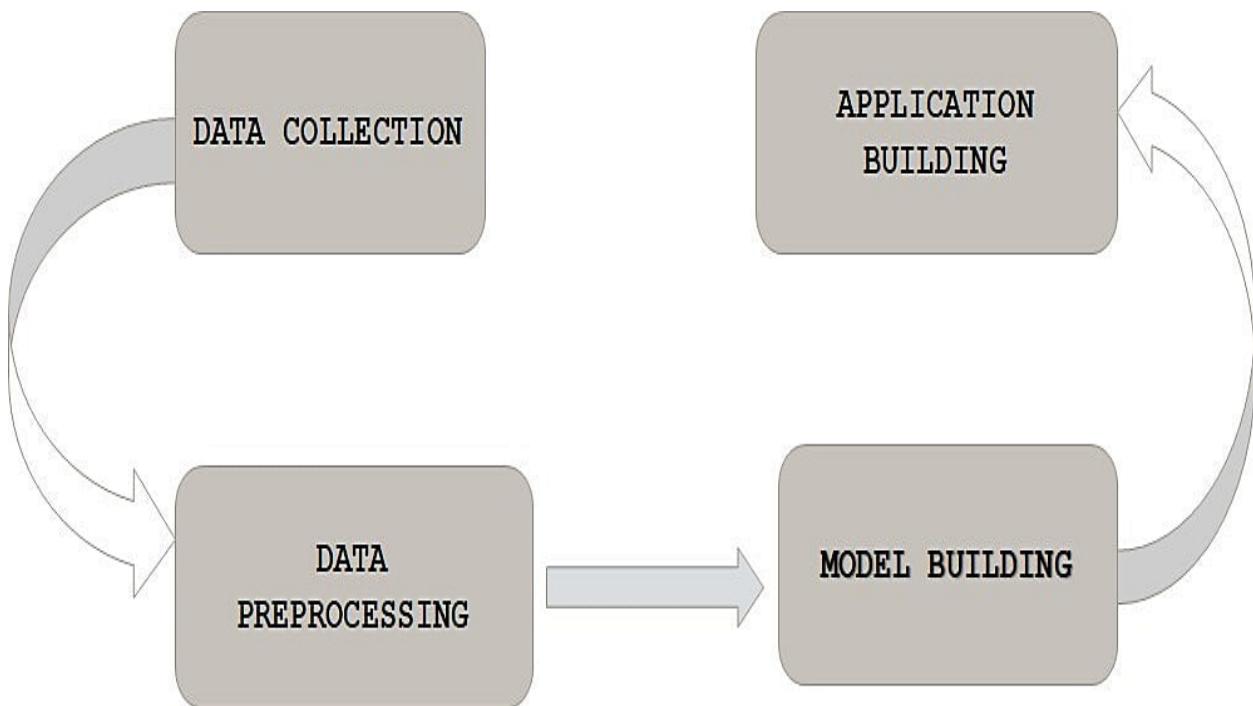
- Processor : Intel Core i3
- Hard Disk Space : Min 100 GB

- Ram : 4 GB
- Display : 14.1 “Color Monitor(LCD, CRT or LED)
- Clock Speed : 1.67 GHz

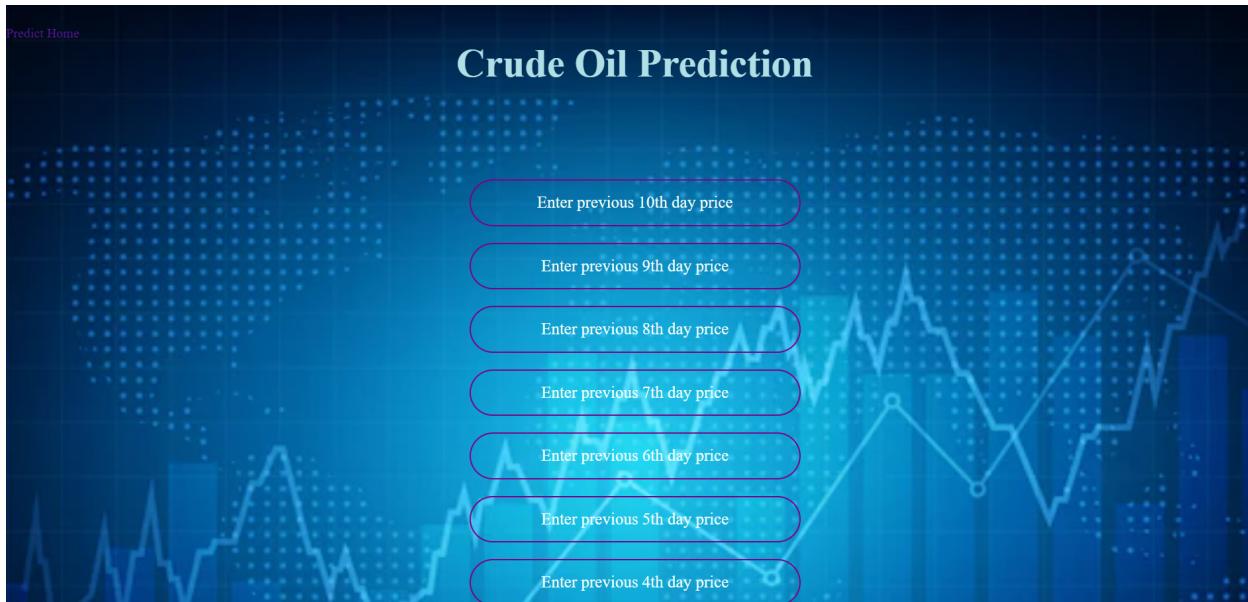
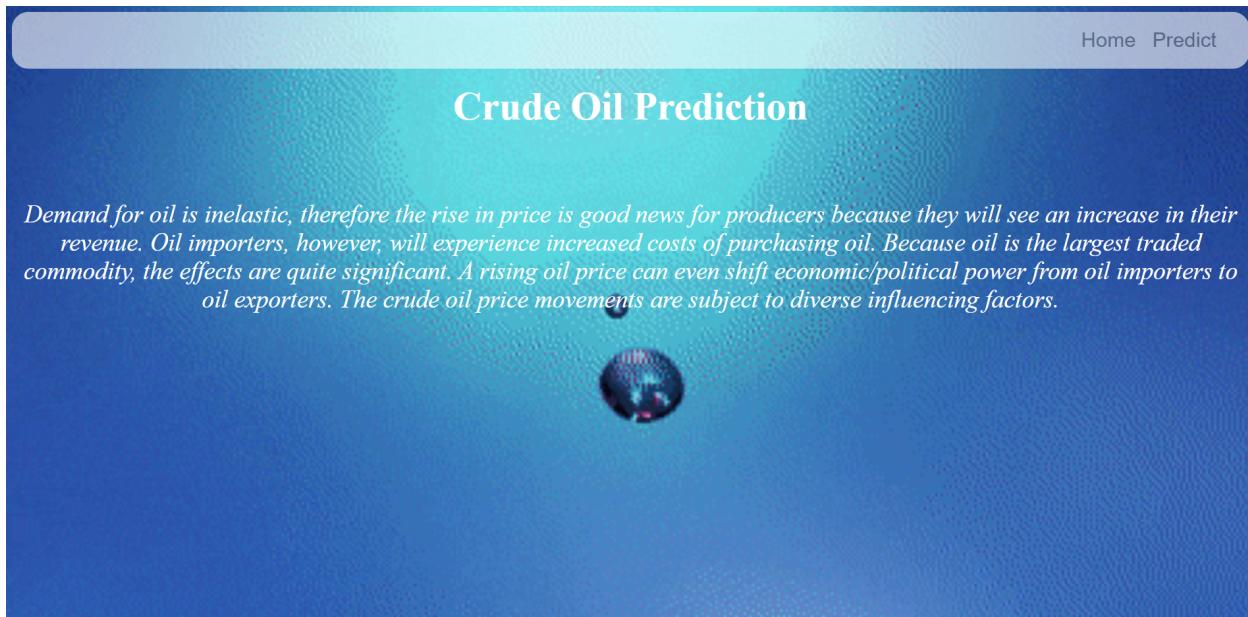
## 4. EXPERIMENTAL INVESTIGATIONS

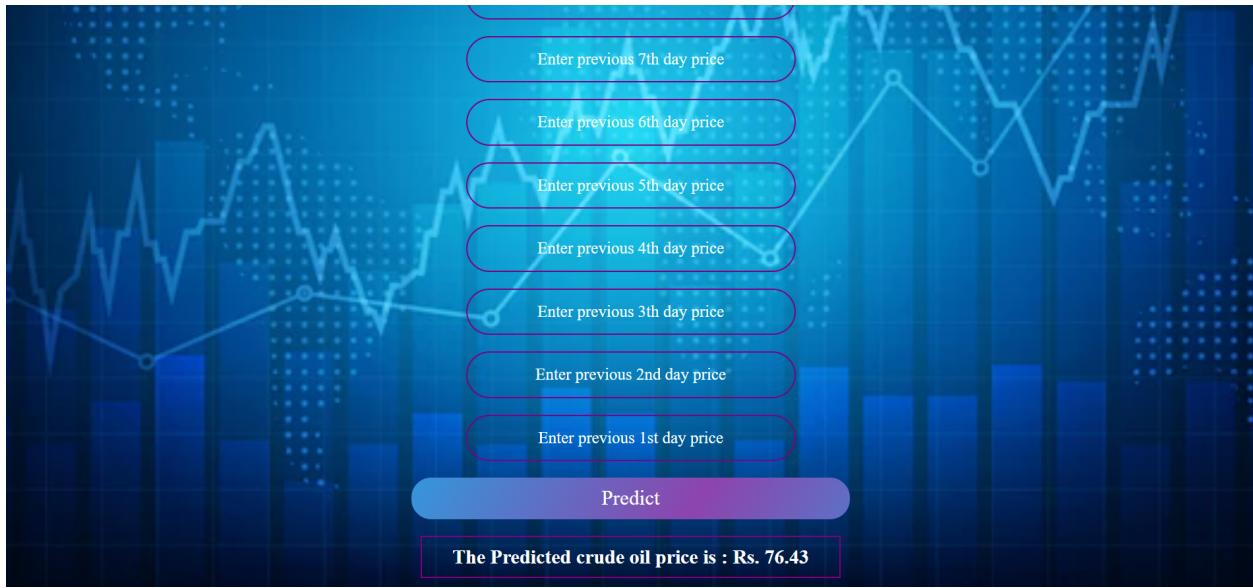
Study shows that it provide with different price of crude Oil from past days, the model detects, and prediction of given prices. When click in to the predict button then it will shows the predicted output.

## 5. FLOWCHART



## 6. RESULT





## 7. ADVANTAGES & DISADVANTAGES

### **Advantages:**

- Increased accuracy for crude oil price prediction.
- Reduce the time complexity.

### **Disadvantages:**

- Data mining techniques does not help to provide effective decision making.

## **8. APPLICATIONS**

- Neural Network technology is considered as one of the key technology used to predict the crude oil price.
- It using the Previous history of crude oil prices to predict future crude oil.

## **9. CONCLUSION**

In this project, we are using the Previous history of crude oil prices to predict future crude oil based on the IBM Watson Studio. 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.

## **10. FUTURE SCOPE**

The project can be further enhanced by deploying the deep learning model obtained using a web application and larger dataset cloud be used for prediction to give higher accuracy and produce better result.

## **11. BIBILOGRAPHY**

- Abdullah, S. N. and Zeng, X. (2010) „„Machine learning approach for crude oil price prediction with Artificial Neural Networks-Quantitative (ANN-Q) model““ Proceedings

of the International Joint Conference on Neural Networks (IJCNN'2010), 1-8.

- Alizadeh, A. and Mafinezhad, K (2010) „„Monthly Brent Oil Price Forecasting Using Artificial Neural Networks and A Crisis Index““ Proceedings of the International Conference On Electronics And Information Engineering (ICEIE'2010), 2, 465-468
- Aloui, C. Hamdi, M., Mensi, W. and Nguyen, D. Y. (2012) „„Further evidence on the timevarying efficiency of crude oil markets““ Energy Studies Review 19(2), 38-51.

## 12.APPENDIX

### Source Code

```
jupyter Crudeoil_price_prediction_using_LSTM Last Checkpoint: Last Monday at 6:26 PM (autosaved)
File Edit View Insert Cell Kernel Widgets Help
Not Trusted Python 3 (pykernel) O
File + % Run C Markdown
```

### Crude oil price prediction using LSTM

1.we will collect the data  
2.preprocess the data  
3.create an LSTM model  
4.predict the test data and plot the output  
5.predict the future 30 days and plot the output

Dataset link <https://www.kaggle.com/rockbottom73/crude-oil-prices>

#### importing necessary libraries

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow.keras
import pickle
```

#### Importing dataset

1.Since data is in form of excel file we have to use pandas read\_excel to load the data 2.After loading it is important to check the complete information of data as it can indication many of the hidden infomation such as null values in a column or a row 3.Check whether any null values are there or not. if it is present then following can be done, a.Imputing data using Imputation method in sklearn b.Filling NaN values with mean, median and mode using fillna() method  
4.Describe data --> which can give statistical analysis

```
In [2]:
```

```
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It includes your credentials.
# You might want to remove those credentials before you share the notebook.
client_2c12594bc3394700b42a3e64f17b2b8 = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='7Rwv80eqh1HRA9Gch7XU8ibz37EVjsEnptxoh83yH15',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.private.us.cloud-object-storage.appdomain.cloud')

body = client_2c12594bc3394700b42a3e64f17b2b8.get_object(Bucket='crudeoil-donotdelete-pr-h4uozk1hs6snux',Key='Crude Oil Prices [1986-01-01 to 2016-06-24].xlsx')
data = pd.read_excel(body.read())
data.head()
```

```
Out[2]:
```

	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

## Data Preprocessing

### Checking or null values

```
In [5]: data.isnull().sum()
```

```
Out[5]:
```

Date	Closing Value
0	0
1	7

dtype: int64

```
In [6]: data.dropna(axis=0,inplace=True)
```

```
In [7]: data.isnull().sum()
```

```
Out[7]:
```

Date	Closing Value
0	0
1	0

dtype: int64

```
In [8]: data.shape
```

```
Out[8]: (8216, 2)
```

### Selecting Closing value column for prediction

```
In [9]: data_oil=data.reset_index()['Closing Value']
```

```
In [10]: data_oil
```

```
Out[10]:
```

	0	25.56
1	26.00	~ ~ ~

### Selecting Closing value column for prediction

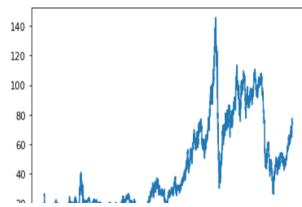
```
In [9]: data_oil=data.reset_index()['Closing Value']

In [10]: data_oil
```

```
Out[10]: 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 [11]: plt.plot(data_oil)

Out[11]: [
```



### Create the Stacked LSTM model

```
In [23]: #tensorflow :open source used for both ML and DL for computation
from tensorflow.keras.models import Sequential#it is a plain stack of layers
from tensorflow.keras.layers import Dense#Dense layer is the regular deeply connected neural network layer
from tensorflow.keras.layers import LSTM #Long Short Term Memory
```

```
In [24]: model=Sequential()
model.add(LSTM(50,return_sequences=True,input_shape=(10,1)))
model.add(LSTM(50,return_sequences=True))
model.add(LSTM(50))
model.add(Dense(1))
model.compile(loss='mean_squared_error',optimizer='adam')
```

```
In [25]: 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
```

```
In [26]: #Training the model
model.fit(X_train,y_train,validation_data=(X_test,ytest),epochs=50,batch_size=8)

Epoch 1/50
667/667 [=====] - 18s 18ms/step - loss: 264.9510 - val_loss: 3117.7952
Epoch 2/50
667/667 [=====] - 11s 16ms/step - loss: 171.1041 - val_loss: 2526.8098
Epoch 3/50
667/667 [=====] - 11s 17ms/step - loss: 57.7536 - val_loss: 1433.7810
Epoch 4/50
667/667 [=====] - 11s 16ms/step - loss: 17.5767 - val_loss: 971.1276
Epoch 5/50
667/667 [=====] - 11s 17ms/step - loss: 6.2937 - val_loss: 737.6458
Epoch 6/50
667/667 [=====] - 11s 16ms/step - loss: 3.1081 - val_loss: 605.8196
Epoch 7/50
667/667 [=====] - 11s 17ms/step - loss: 1.8348 - val_loss: 516.5406
Epoch 8/50
667/667 [=====] - 11s 17ms/step - loss: 1.2188 - val_loss: 449.3754
Epoch 9/50
667/667 [=====] - 11s 16ms/step - loss: 1.1672 - val_loss: 407.3385
Epoch 10/50
667/667 [=====] - 11s 16ms/step - loss: 0.8811 - val_loss: 378.0981
Epoch 11/50
667/667 [=====] - 11s 16ms/step - loss: 0.8022 - val_loss: 360.6334
Epoch 12/50
667/667 [=====] - 11s 17ms/step - loss: 0.7800 - val_loss: 341.1000
Epoch 13/50
667/667 [=====] - 11s 17ms/step - loss: 0.7666 - val_loss: 331.3139
Epoch 14/50
667/667 [=====] - 11s 17ms/step - loss: 0.7724 - val_loss: 318.3911
Epoch 15/50
667/667 [=====] - 11s 17ms/step - loss: 0.8337 - val_loss: 309.7038
Epoch 16/50
667/667 [=====] - 11s 17ms/step - loss: 0.7343 - val_loss: 304.2457
Epoch 17/50
```

```
test_predict=model.predict(X_test)
```

```
In [28]: a1 = model.predict([[46,47,48,50,51,52,54,43,44,47]])
```

```
In [29]: np.round(a1[0][0],2)
```

```
Out[29]: 46.35
```

### model evaluation

```
In [30]: ### Calculate RMSE performance metrics
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(y_train,train_predict))
```

```
Out[30]: 0.9475632335882856
```

```
In [31]: ### Test Data RMSE
math.sqrt(mean_squared_error(ytest,test_predict))
```

```
Out[31]: 16.716945182249823
```

```
In [32]: model.save("crude_oil.h5")
```

```
In [33]: !tar -zcvf Crude_oil_ibm.tgz crude_oil.h5
crude_oil.h5
```

```
In [34]: ls-1
```

```
crude_oil.h5
Crude_oil_ibm.tgz
```

## IBM Deployment

```
In [35]: !pip install ibm_watson_machine_learning
```

```
Requirement already satisfied: ibm_watson_machine_learning in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (1.0.232)
Requirement already satisfied: pandas<1.4.0,>=0.24.2 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_
machine_learning) (1.3.4)
Requirement already satisfied: requests in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_
learning) (2.26.0)
Requirement already satisfied: packaging in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_
learning) (21.3)
Requirement already satisfied: lmomond in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_
learning) (0.3.3)
Requirement already satisfied: tabulate in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_
learning) (0.8.9)
Requirement already satisfied: urllib3 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_
learning) (1.26.7)
Requirement already satisfied: ibm-cos-sdk==2.11.* in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_m
achine_learning) (2.11.0)
Requirement already satisfied: importlib-metadata in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_ma
chine_learning) (4.8.2)
Requirement already satisfied: certifi in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_learni
ng) (2022.6.15)
Requirement already satisfied: ibm-cos-sdk-s3transfer==2.11.0 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from i
bm-cos-sdk==2.11.*->ibm_watson_machine_learning) (2.11.0)
Requirement already satisfied: jmespath<1.0.0,>=0.7.1 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm-cos-s
dk==2.11.*->ibm_watson_machine_learning) (0.10.0)
Requirement already satisfied: ibm-cos-sdk-core==2.11.0 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm-cos-
sdk==2.11.*->ibm_watson_machine_learning) (2.11.0)
Requirement already satisfied: python-dateutil<3.0.0,>=2.1 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm-
cos-sdk-core==2.11.0->ibm-cos-sdk==2.11.*->ibm_watson_machine_learning) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from pandas<1.4.0,>=0.2
4.2->ibm_watson_machine_learning) (2021.3)
Requirement already satisfied: numpy<1.17.3 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from pandas<1.4.0,>=0.2
4.2->ibm_watson_machine_learning) (1.20.3)
```

```
spark-mllib_2.4-scala_2.11      55a70f99-7320-4be5-9fb9-9edb5a443af5  base
spark-mllib_3.0                  5c1b0ca2-4977-5c2e-9439-ffd44ea8ffe9  base
autoai-obm_2.0                  5c2e37fa-80b8-5e77-840f-d912469614ee  base
spss-modeler_18.1                5c3cad7e-507f-4b2a-a9a3-ab53a21dee8b  base
cuda-py3.8                      5d3232bf-c86b-5df4-a2cd-7b08701cd4de  base
autoai-kb_3.1-py3.7              632db422-10aa-5180-88f0-f52dfb6444d7  base
pytorch-onnx_1.7-py3.8            634d3cdc-b562-5bf9-a2d4-ea90a478456b  base
spark-mllib_2.3-r_3.6              6586b9e3-ccd6-4f92-900f-0f8cb2bd6f0c  base
tensorflow_2.4-py3.7              65e171d7-72d1-55d9-8eb8-f813d620c9b0  base
spss-modeler_18.2                687eddc9-028a-4117-b9dd-e57b36f1efa5  base
pytorch-onnx_1.2-py3.6            692a6ad4-2c4d-45ff-a1ed-b167ee55469a  base
spark-mllib_2.3-scala_2.11        7963efe5-bbec-417e-92cf-0574e21b4e8d  base
-----
Note: Only first 50 records were displayed. To display more use 'limit' parameter.
```

```
In [42]: software_space_uid = client.software_specifications.get_uid_by_name('tensorflow_rt22.1-py3.9')
```

```
Out[42]: 'acd9c798-6974-5d2f-a657-ce06e986df4d'
```

```
In [43]: model_details = client.repository.store_model(model='Crude_oil_ibm.tgz',
                                                       meta_props={
                                                       client.repository.ModelMetaNames.NAME:'crude_oil_prediction',
                                                       client.repository.ModelMetaNames.SOFTWARE_SPEC_UID:software_space_uid,
                                                       client.repository.ModelMetaNames.TYPE:'tensorflow_2.7'
                                                       })
```

```
In [44]: model_id = client.repository.get_model_id(model_details)
model_id
```

```
Out[44]: 'cddf1594-c497-4877-92d9-d0dbcdd729cd'
```

```
In [ ]:
```