PROJECT REPORT

<u>CRUDE OIL PRICE PREDICITION</u>

Submitted by

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TABLE OF CONTENTS

CHAPTER 1
INTRODUCTION

1.1 PROJECT OVERVIEW

Machine Learning and Deep Learning play an important role in computer technology and artificial intelligence. With the use of deep learning and machine learning, human effort can be reduced in recognizing, learning, predictions and in many more areas. 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

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. Given the important role price of the crude oil plays, it becomes extremely important for managers to predict future oil price while making operational decisions such as: when to purchase material, how much to produce and what modes of transportation to use.

CHAPTER 2
LITERATURE SURVEY

2.1 EXISTING PROBLEM

We use two types of oil price data to evaluate the accuracy of different oil price prediction models. The first one is the U.S. refiner acquisition cost for crude oil imports, which is the weighted average cost of all oil imported into the U.S. The second one is a model trained with artificial neural networks (ANN), which is a classical machine learning model for oil price prediction.

2.2 REFERENCES

YEAR	TITLE	AUTHOR	TECHNIQUE	PROBLEM STATEMENT	PROS AND CONS
2018	Low salinity water flooding form a length and time scale perspective	W.Bartels and H.Mahani	EOR,SCAL, micro-CT, micro-model	The field application of low salinity water flooding is the improvement of oil recovery by acceleration of production “Oil faster compared to conventional high salinity brine injection.	**PROS:** Microscopic sweep efficiency is standard reservoir engineering terminology and related to areal and volumetric sweep it is related to the overall result of the oil recovery process **CONS:** Ground soil quality gets under 30>.
2019	Text-based crude oil price forecasting	Xuerong lii shaupang Wang	Econometric model and CNN model	The novel crude oil price forecasting method based on online media test mining with the aim of the capturing the more immediate market antecedents of price fluctuation specifically early attempt to apply deep learning	**PROS:** Oil price forecasting, financial market, online news, text Analysis convolutional neural network. Our emperical Forecasting in accurate crude oil price.

				technique of crude oil forecasting and extract hidden pattern on online new media CNN. They need to grouped for according greater forecasting method is LDA topic model optimized input variable lag order selection	
2020	A new hybrid model for forecasting Brent crude oil price.	H. Abdollahi and S.B. Ebrahimi	Adaptive Neuro Fuzzy Inference System (ANFIS) and Auto regressive Fractionally Integrated Moving Average (ARFIMA) and Markov-Switching model	Oil price forecasting remains a challenging Issue due to the particular characteristics of oil price and its impact on various economic sectors. Motivated by this issue the author aim to introduce a robust hybrid model for reliable forecasting of Brent oil price.	**PROS:** The specific weights are assigned to each model to achieve an accurate prediction of the empirical time series. Robustness of results and prediction quality of the hybrid model compared **CONS:** Reliable forecasting of crude oil prices is especially beneficial to producer and imposter nations to optimize their production and order rates and mitigate the adverse effects of possible shocks.
2021	Towards predictive Crude Oil Purchase	Jen-Yulee and Tien-Think Ngugen	Auto regressive Integrated Moving average (ARIMA) and Sessional Auto regressive integrated moving average	Crude oil price impact volatility global economy in general as well as the economy of Europe and us particular supremely difficult to describes to tendency precisely. Hence it is used to forecast methodology	**PROS:** We further estimated the forecasts of the oil prices at a monthly level based on our yearly forecast of oil prices from our best

			(SARIMA)	To approach autoregressive cope with predictive crude oil.	**CONS:** forecasting the price of oil accurately is difficult across various time period as there are a multitude of factors that can affect the prices of oil.
2018	Online media sources to forecast the crude oil price	Elshendy , and M., Fronzetti colladon	GDELT and ARIMAX	This slay looks for signals of economic awareness on online social media and test this significance in economic predictions the study analyses over a period of two years the relationship between West Texas intermediate daily crude oil price and multiple predicators extracted from twitter google trends ,Wikipedia and the global data on events, language and Tone database.	**PROS:** Advantages of integrating information from Different platforms, to relative the predicative model, neural network based models.
2018	Crude Oil Price Prediction using LSTM networks	Varun Gupta, Ankit Pandey	RNN,LSTM	In this paper, we have tried to predict crude oil prices is using LSTM based RNN. We have tried to experiment with different types of models using different epochs, lookbacks and other tuning methods. The results obtained are promising and presented a reasonably accurate prediction for the price of crude oil in near future.	**PROS:** All the input to the proposed network were normalised to achieve the best results. **CONS:** Increase in lookback, accuracy of the Network decreased.

2019	Hybrid Approach and econometric models	Rajesh Prasad	Hybrid approach model, AI approach DMA model, SSL.	Crude oil price prediction is a wide area of research that has been for a very long time in history and numerous approaches have been proposed in predicting crude oil price. The Econometric models Cover many familiar models. LSTM is applied on the extracted dataset to train and test the models. At the end the prediction of crude oil Prices is evaluated with a view to discovering knowledge.	**PROS:** DMA model provides better proxy of expected Spot price than future price. **CONS:** However prediction using powerful AI tool like the LSTM of the DL is very rare.
2020	Crude oil price prediction Using LSTM	Nidhi Motra, Priya Raj, Sanidhya Saxena, Rohit Kumar	RNN,LSTM, Backpropagation ,CNN	This is the attempt mode to forecast price prediction using LSTM neural network We have come across Testing different various version of model using various lookback and alternative turning methods. The conclusion derived from this study are promising and represent and more precise prediction for the crude oil price in coming days.	**PROS:** LSTM network is better than other tradition neural network for forecasting prices. **CONS:** Large look ups do not necessarily improve the accuracy of the prediction of crude oil prices.
2020	The prediction of Brent crude oil trend using LSTM and Facebook prophet.	Cruleryuz. D, Oxden. E	RNN,LSTM, Facebook Prophet	In this study, to increase the accuracy and stability, the Long Short Term Memory and Facebooks prophet were applied to foresee future tendencies in	**PROS:** LSTM and Facebook prophet Can predict the 349 weeks without needing the actual price of the previous period.

				Brent Oil Prices considering their previous prices.	
2021	Crude oil price forecast based on Dup Transfer Learning	Ahao deng, Liang Ma and Taishan	RNN, LSTM And Transfer Learning	This paper proposes using Long Short Term Memory Network based on transfer learning to predict the price of crude oil in Shanghai. The basic idea is to take advantage of the Correlation between Brent crude oil for training in the early stage and the use Shanghai crude oil to fine –tune the network.	**PROS:** The proposed T-LSTM can accuracy predict the crude oil price of Shanghai and the model has strong generalization ability and higher Predication.
2021	Crude oil price based on the variable selection-LSTM integrated model	Shaelong sun	BTNA, and LASSO-LSTM	This paper assesses and selects are influence factors with the elastic-net regularized linear model (GLMNET), spike-slab laser model and Bayesian model average (BSA). The influence factors of crude oil price into price supply and demand finance factor.	**PROS:** BMA-LSTM Integrated models are the best compared with other techniques **CONS:** Hard to learn LSTM

2018	Crude oil price forecasting based on support vector machine	Lean yu	ARIMA, SVM, BPNN (Back Propagation Neural Network)	A new SVM based method for time series forecasting and its application in crude oil price prediction are presented. We first introduce a basic theory of the support vector machine model, and then present the new SVM based methods for time series forecasting.	**PROS:** The support vector machine can perform very well on time series forecasting. **CONS:** It does not execute well when the data set as more sound, target class are overlapping.

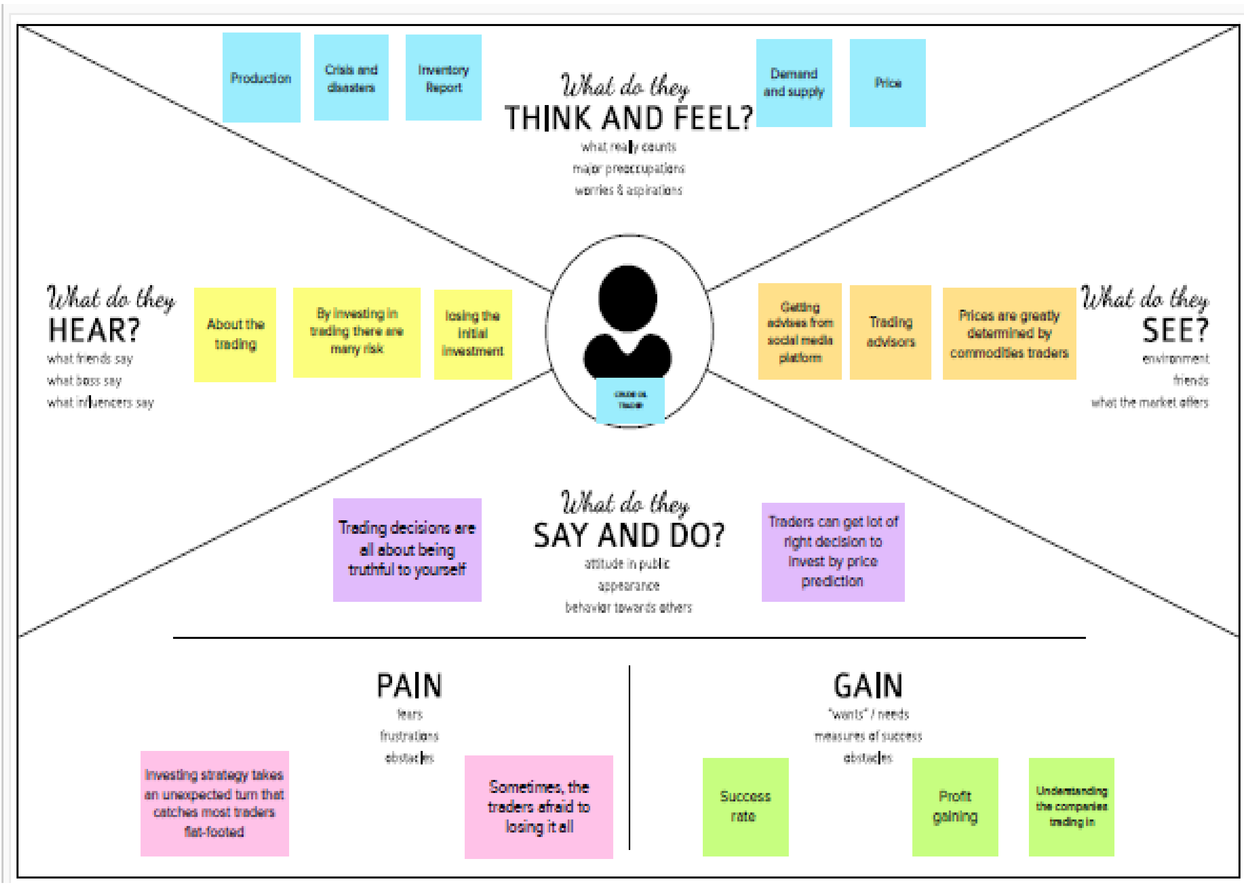
2.3 PROBLEM STATEMENT DEFINITION

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 Guided 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.

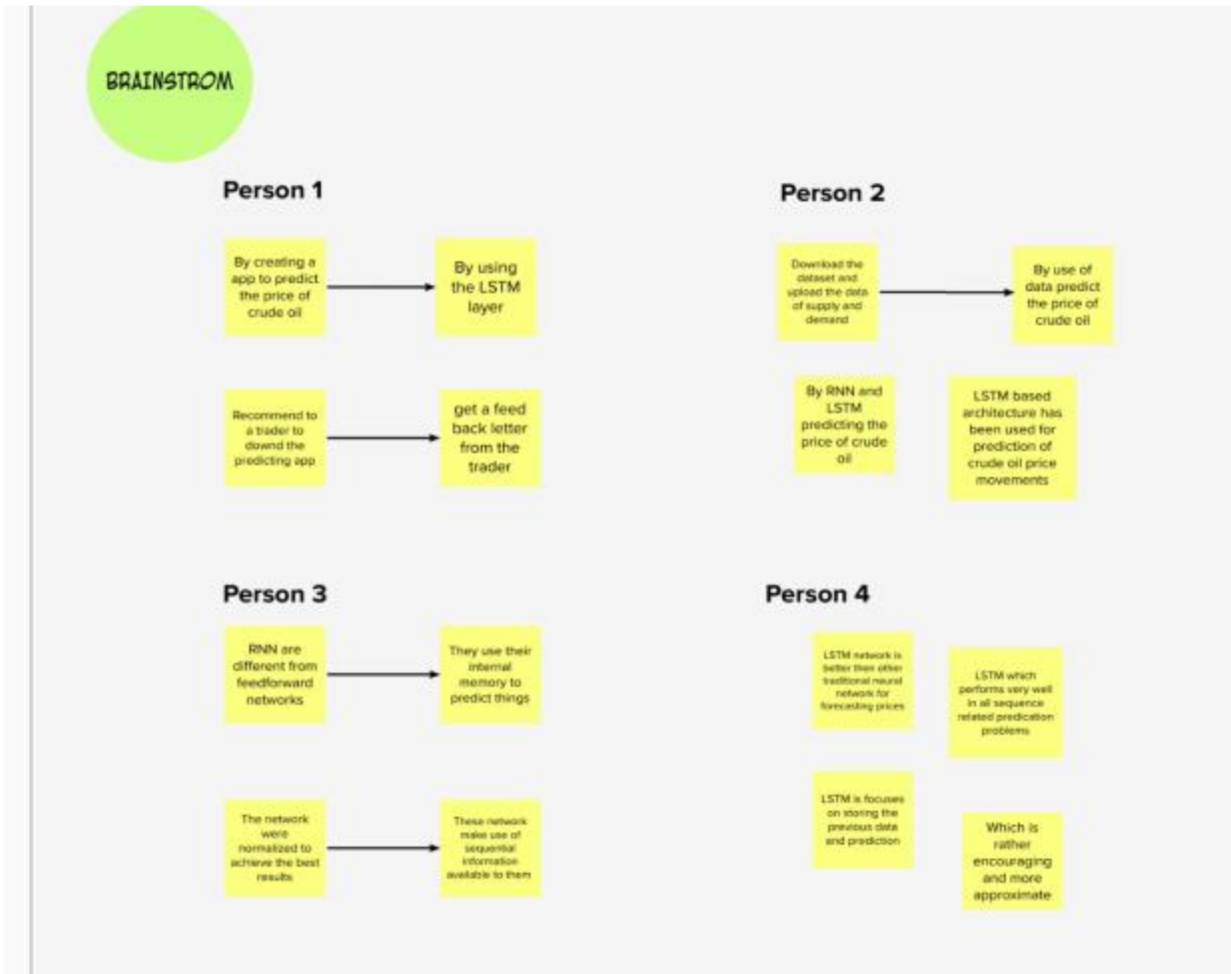
CHAPTER 3
IDEATION AND PROPOSED SOLUTION

3.1 EMPATHY MAP CANVAS

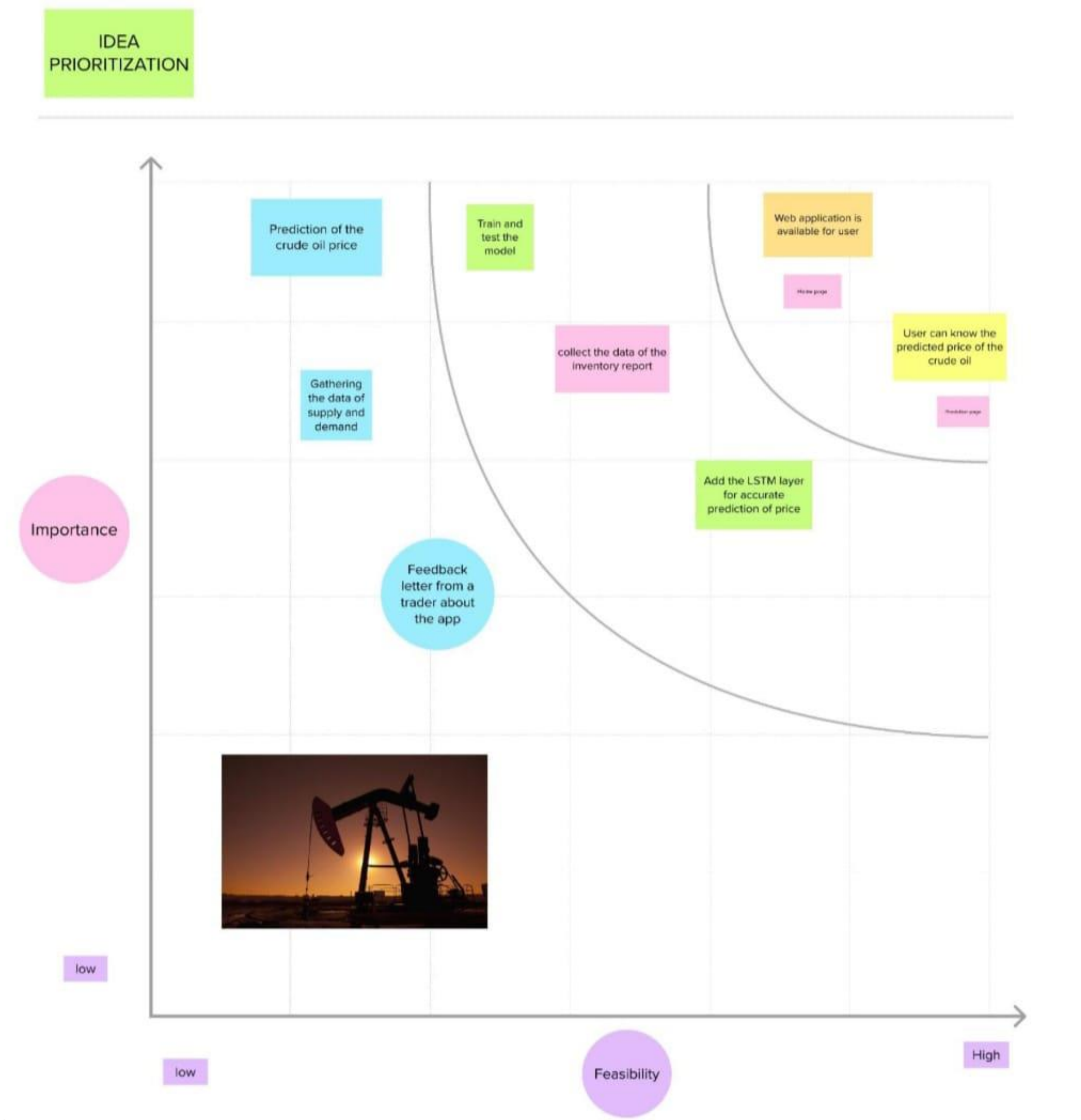


3.2 IDEATION & BRAINSTORMING

BRAINSTORM



IDEA PRIORITIZATION



3.3 PROPOSED SOLUTION

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 Guided 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.

SOLUTION DESCRIPTION:

Recurrent Neural Networks: RNN are different from feedforward networks. They use their internal memory to predict things. They are very good at tasks at which humans are not good at such as handwriting recognition and speech recognition. They were initially developed in 1980. These networks make use of sequential information available to them. Traditionally, we assumed that inputs do not depend on each other. But that was not a valid assumption. As if we want to predict the next words in a sentence, we must know the previous words. They can be thought of having a memory which stores the information for future use. There exist various extensions of RNN. One of them is the Bidirectional RNN. In these networks, output at time t may depend on future inputs as well. The other popular variant of the RNN is the deep RNN. In these recurrent networks, there exist multiple layers per time step.

LSTM Networks:

The most popular and widely used type of RNN is the LSTM and these types of recurrent networks have been used for this study. These networks learn order dependence in sequence prediction problem. The LSTM networks are able to solve two major issues encountered in RNN i.e., vanishing gradients and exploding gradients. The key to the solution of these problems were the internal structure that has been used in LSTM. In this, there exists one input layer, one hidden layer and one output layer. This most simple architecture of LSTM networks is known as vanilla LSTM which performs very well in all sequence related prediction problems.

Data retrieval and pre-processing:

In data retrieval, datasets can be fetched such of news data, black gold price data and market data. Dataset from news can be retrieved through headlines as it is easier to obtain and justifies in one line. Factors that affect the prediction are export business, stock market and later business.

Methodology:

LSTM based architecture has been used for prediction of crude oil price movements. The proposed architecture consists of four layers of LSTM layers followed by a dense layer with ten neurons and at the end dense layer with only one neuron. All the inputs to the proposed network were normalized to achieve the best results.

Libraries Required:

Make sure that the following libraries are installed on your working machine before proceeding further • Koras • Tensor flow • Jumpy • Pandas

NOVELTY:

In the era of big data, deep learning for predicting crude oil price has become even more popular than before. We collected 2 years of data from world global data and proposed a comprehensive customization of feature engineering and deep learning-based model for predicting price of crude oil. The proposed solution is comprehensive as it includes pre-processing of the crude oil dataset, utilization of multiple feature engineering techniques, combined with a customized deep learning-based system for crude price prediction. We conducted comprehensive evaluations on frequently used machine learning models and conclude that our proposed solution outperforms due to the comprehensive feature engineering that we built. The system achieves overall high accuracy for crude oil price prediction. With the detailed design and evaluation of prediction term lengths, feature engineering, and data pre-processing methods, this work contributes to the stock analysis research community both in the financial and technical domains.

SOCIAL IMPACT:

Crude oil price prediction has long been the subject of research because of the importance of accuracy of prediction and the difficulty in forecasting. Traditionally, forecasting has involved linear models such as LSTM and RNN using standardized numerical data such as corporate financial data and crude oil price data. However, we know little about which characteristics of crude oil price affect the accuracy of predictions and to what extent. The purpose is to analyse the effects of crude oil price characteristics on crude oil price prediction via RNNs. To this end, we define the characteristics of crude oil price and identify significant differences in prediction performance for each characteristic. The results reveal that the accuracy of prediction is improved by utilizing solid lines, colour, and a single image without axis marks. Based on these findings, we describe the implications of making predictions only with which are unstructured data, without using large amounts of standardized data. Finally, we identify issues for future research.

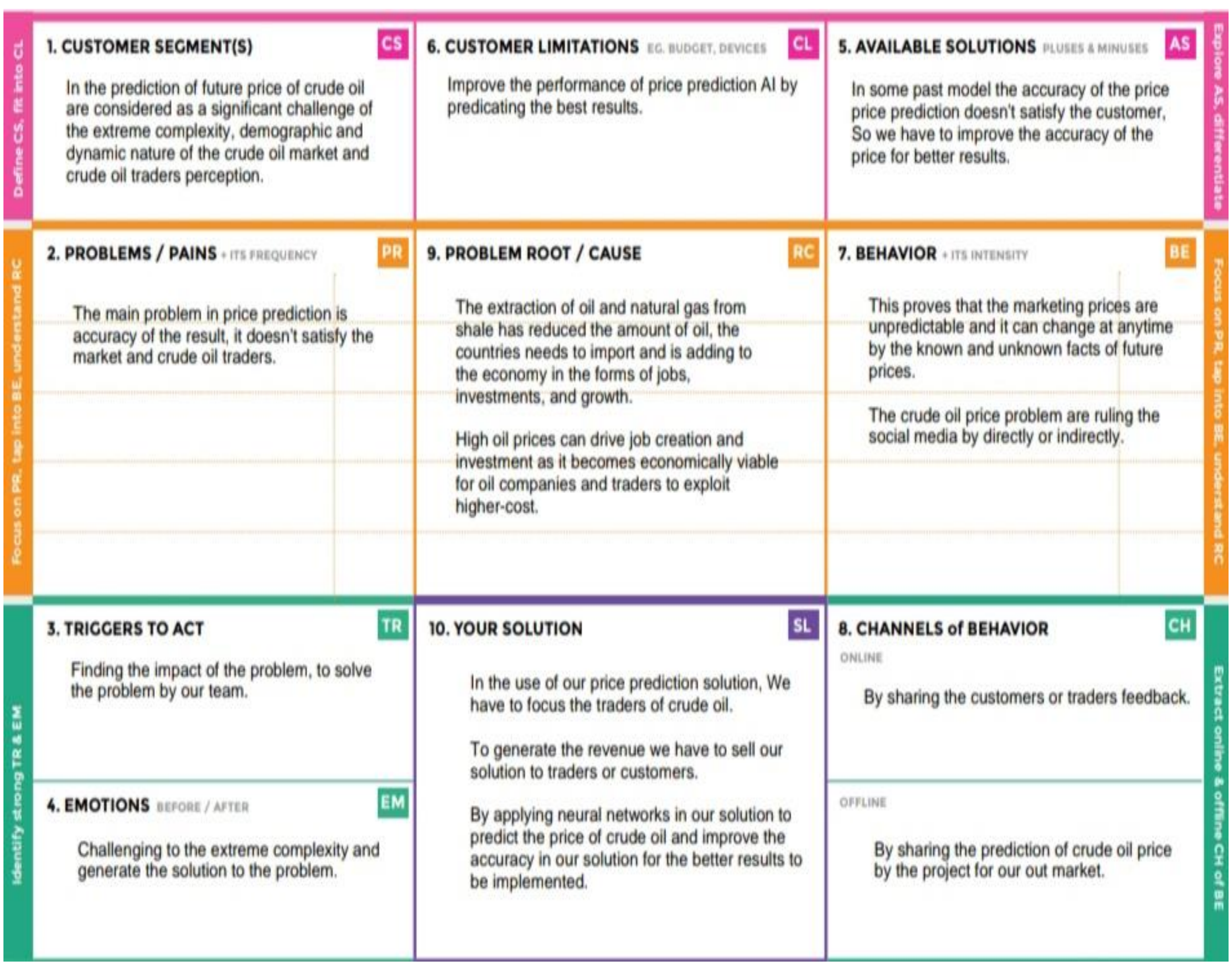
BUSINESS MODEL:

Crude oil price prediction is of course based on data, but when using AI, you are delving into the world of big data. That means that you have more data and more detail to your data. You are then able to take into account each customer's specific individual behaviour and therefore have a more precise price prediction. Learning from mistakes is one of the most valuable things you can do as a human. The thing is that, when it comes to predicting, AI is much better at learning and adjusting than we are. This is not only due to the speed with which a computer can understand and re-evaluate data but also because it is unbiased. Model management (which is minimizing the gap between reality and predicating) is a key element to a good AI-powered crude oil price prediction. When we analyse the prediction and reality we might compare and adjust a tenfold of combinations. With AI the number of combinations that can be made between result data and predicting data. It is therefore concluded that AI creates more and better improvements than we could do manually.

SCALABILITY OF SOLUTION:

Crude oil price forecasting plays a significant role in world economy and its accurate prediction has significant benefits for the economic conditions of a country. In this direction, an effort has been in this paper. This paper has proposed an LSTM based network for better prediction of crude oil prices. The results obtained from the work are quite encouraging. The results indicate that large lookups do not necessarily improve the accuracy of the predictions of crude oil prices. It has been found that lookups up to the value of 10 are ideal for crude oil price prediction purposes. It has also been found that just increasing the number of LSTM layers do not have much impact on the accuracy of the results. Here it can be 90% accurate in price prediction. In future work, current market and political conditions can also be taken into consideration in crude oil price forecasting for even better results.

3.4 PROBLEM SOLUTION FIT



CHAPTER 4
REQUIREMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENTS

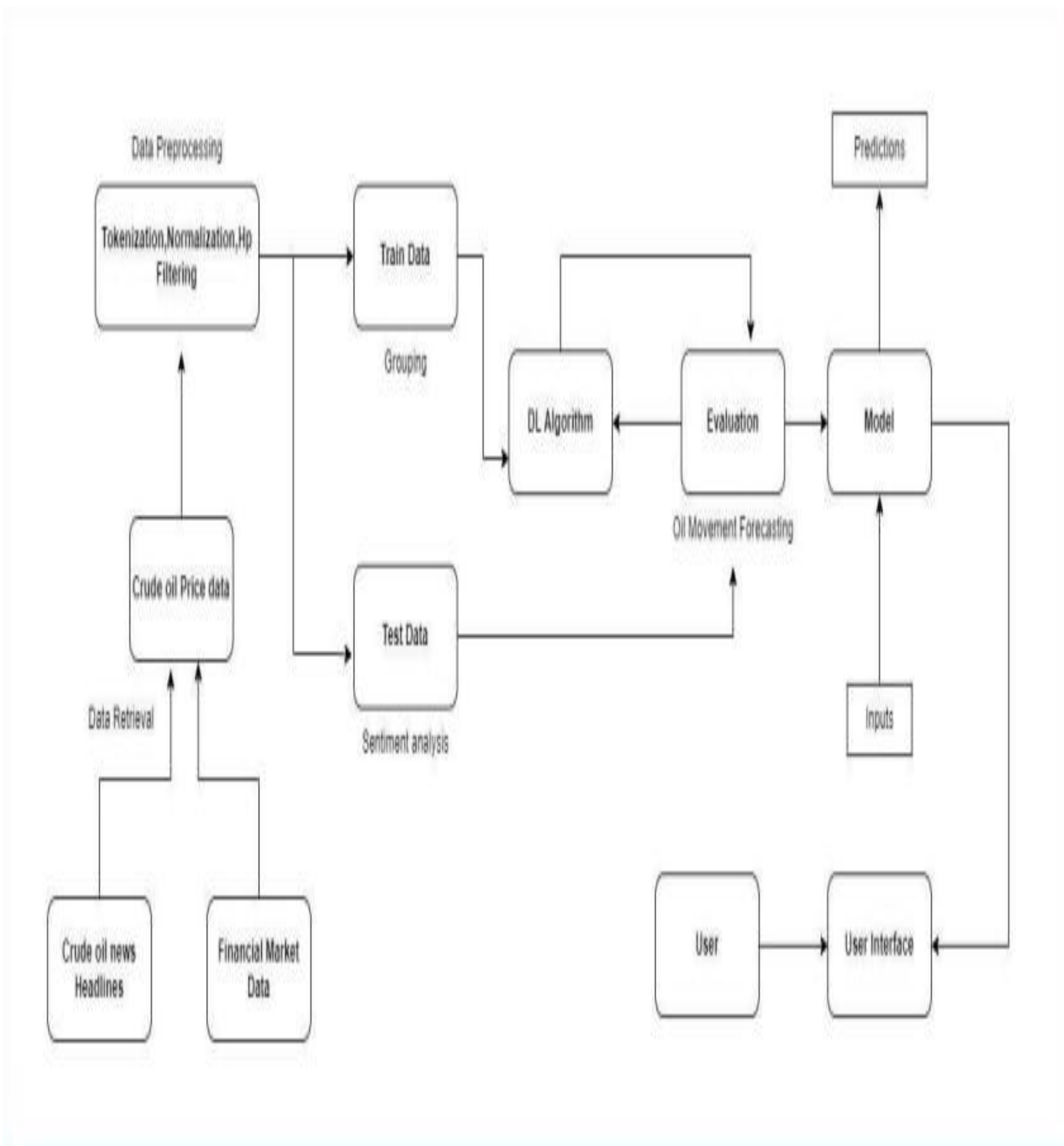
FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	Graph	Obtaining the data from the dataset to show the graph
FR-4	Customer Support	Providing answers for the queries asked by users.
FR-5	Database	User’s information will be stored
FR-6	Price information	Information of the oil prices will be updated by admin
FR-7	Notification	Price alert are sends to user by notification

4.2 NON FUNCTIONAL REQUIREMENTS

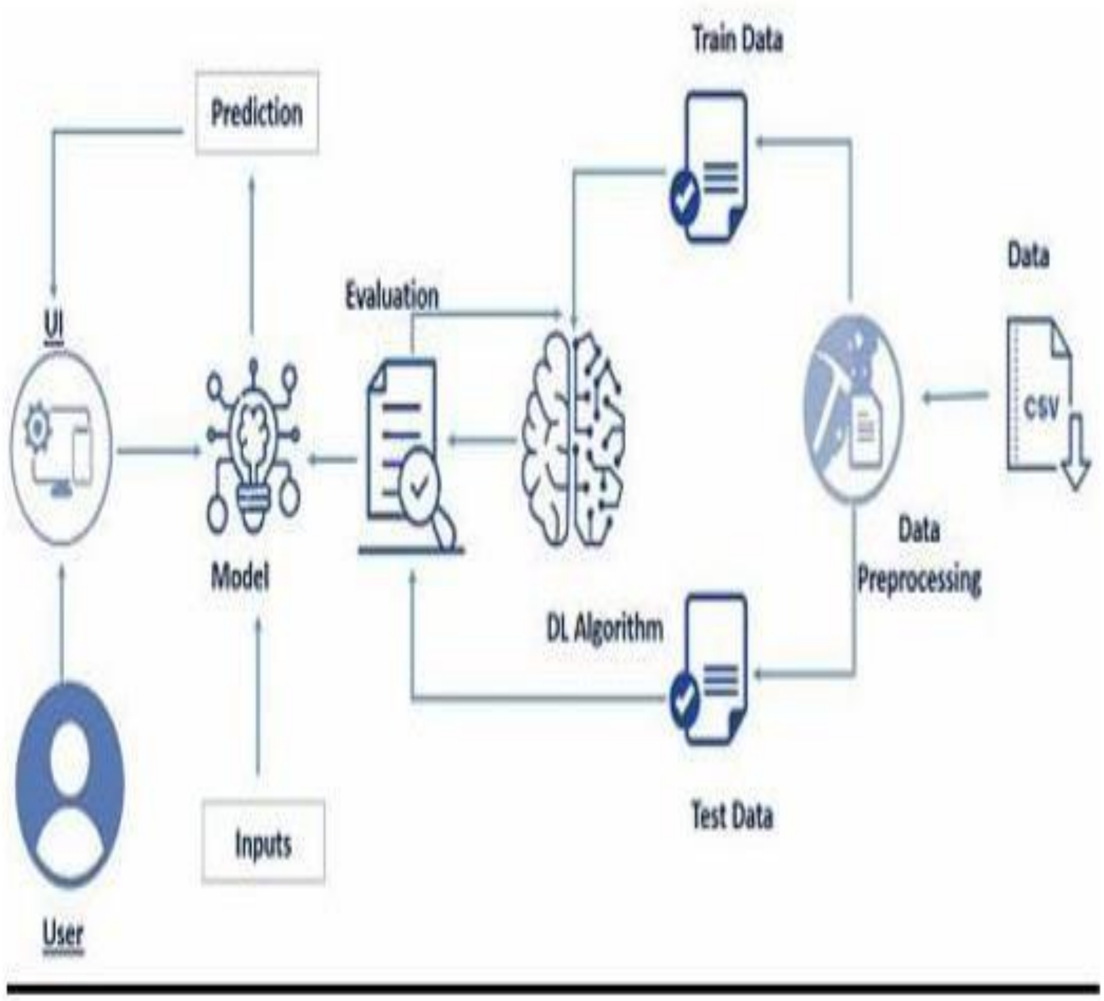
FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	It can use by wide variety of user, it is very simple to learn and not complex to proceed.
NFR-2	**Security**	In this model we are using login for the user and the information will be secured, so that it will be very secure to use
NFR-3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

CHAPTER 5
PROJECT DESIGN

5.1 DATA FLOW DIAGRAM



5.2 SOLUTION & TECHNICAL ARCHITECTURE



5.3 USER STORIES

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Web user)	Dataset	USN-1	Importing dataset of crude oil to the model	Model has the dataset to predict the price	High	Sprint-1
	Input Necessary Details	USN-2	As a user, I can give Input Details to Predict Likeliness of crude oil	User has to give the input	High	Sprint-2
	Data Pre-processing	USN-3	Transforming the raw data into suitable format for price prediction.	Model has to convert the given input.	High	Sprint-2
	Crude oil price prediction	USN-4	As a user, I can predict Crude oil using the model.	User can Predict the price using the model.	High	Sprint-3
		USN-5	As a user, I can get accurate prediction of crude oil	After prediction user can get accurate price.	Medium	Sprint-3
	Feedback	USN-6	As a user, I can give feedback of the application.	I can get the prediction in various format.	High	Sprint-4

CHAPTER 6
PROJECT PLANNING AND SCHEDULING

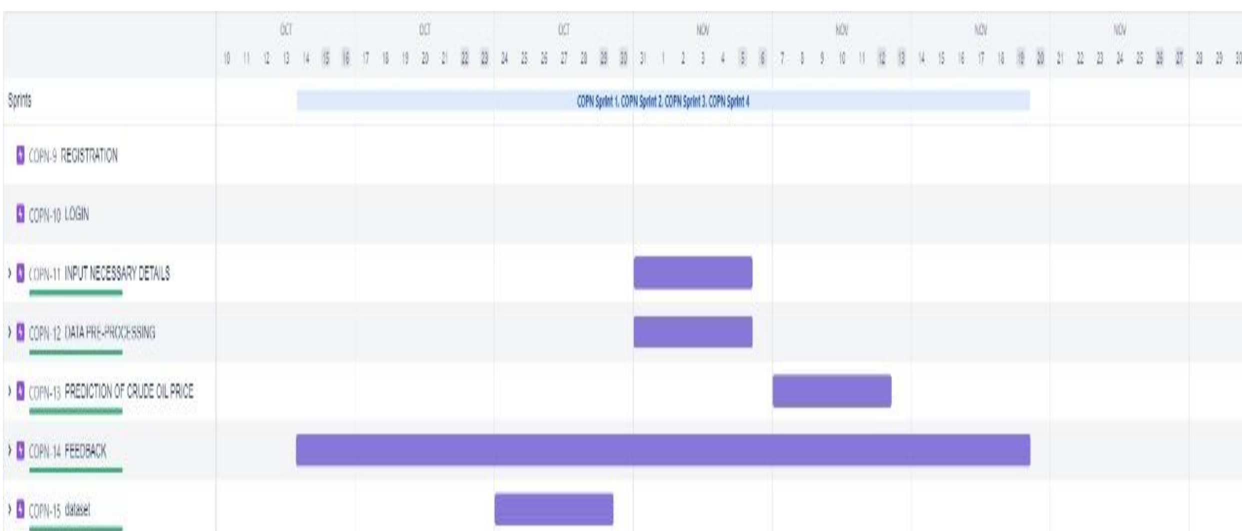
6.1 SPRINT PLANNING AND ESTIMATION

Sprint	**Functional Requirement (Epic)**	**User Story Number**	**User Story / Task**	**Story Points**	**Priority**	**Team Members**
Sprint-1	Dataset	USN-1	Importing dataset of crude oil to the model	20	High	MANISHA.R
Sprint-2	Input Necessary Details	USN-2	As a user, I can give Input Details to Predict Likeliness of crude oil	10	High	BHAVESHRAJ.A
Sprint-2	Data Pre-processing	USN-3	Transforming the raw data into suitable format for price prediction.	10	High	PRAVEEN.D
Sprint-3	Crude oil price prediction	USN-4	As a user, I can predict Crude oil using the model.	10	High	SHERINVINCY.C
Sprint-3		USN-5	As a user, I can get accurate prediction of crude oil	10	Medium	BHAVESHRAJ.A
Sprint-4	Feedback	USN-6	As a user, I can give feedback of the application.	20	High	MANISHA.R

6.2 SPRINT DELIVERY SCHEDULE

Sprint	**Total Story Points**	**Duration**	**Sprint Start Date**	**Sprint End Date (Planned)**	**Story Points Completed (as on Planned End Date)**	**Sprint Release Date (Actual)**
Sprint-1	20	6 Days	24 Oct 2022	29 Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	20	05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

6.3 Reports from JIRA



CHAPTER 7

CODING & SOLUTIONING

```python
from flask import Flask,render_template,request,redirect
import numpy as np
from tensorflow import keras
from keras.models import load_model
import joblib
import scipy


app = Flask(__name__)
model = load_model(r'C:\Users\sreen\Desktop\New folder\Flask\crude_oil.h5')

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


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


        sc = joblib.load(r'C:\Users\sreen\Desktop\New folder\Flask\scaler.save')

        x_input = sc.fit_transform(np.array(x_input).reshape(-1,1))

        x_input = np.array(x_input).reshape(1,-1)

        x_input = x_input.reshape(1,-1)
        x_input = x_input.reshape((1,10,1))
        print(x_input.shape)
```

```python
        model = load_model(r'C:\Users\sreen\Desktop\New folder\Flask\crude_oil.h5')
        output = model.predict(x_input)
        print(output[0][0])

        val = sc.inverse_transform(output)

        return render_template('web.html' , prediction = val[0][0])
    if request.method=="GET":
        return render_template('web.html')

if __name__=="__main__":
    app.run(debug=True)
```

CHAPTER 8
TESTING

8.1 TEST CASES

Test case ID	Feature Type	Component	Test Scenario	Expected Result	Actual Result	Status
HP_TC_001	UI	Home Page	Verify UI elements in the Home Page	The Home page must be displayed properly	Working as expected	PASS
HP_TC_002	UI	Home Page	Check if the UI elements are displayed properly in different screen sizes	The Home page must be displayed properly in all sizes	The UI is not displayed properly in screen size 2560 x 1801 and 768 x 630	PASS
HP_TC_003	Functional	Web Page	Check if user can enter the past days price	The input price should be updated to the application successfully	Working as expected	PASS
WP_TC_001	Functional	Web Page	Check if user cannot enter any number as price	The application should not allow user to enter any number as price	User is able to enter any price	FAIL
WP_TC_002	Functional	Web Page	Check if the page redirects to the result page once the input is given	The page should redirect to the results page	Working as expected	PASS

8.2 USER ACCEPTANCE TESTING

8.2.1 DEFECT ANALYSIS

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Total
By Design	1	0	1	0	2
Duplicate	0	0	0	0	0
External	0	0	2	0	2
Fixed	4	1	0	1	6
Not Reproduced	0	0	0	1	1
Skipped	0	0	0	1	1
Won't Fix	1	0	1	0	2
Total	6	1	4	3	14

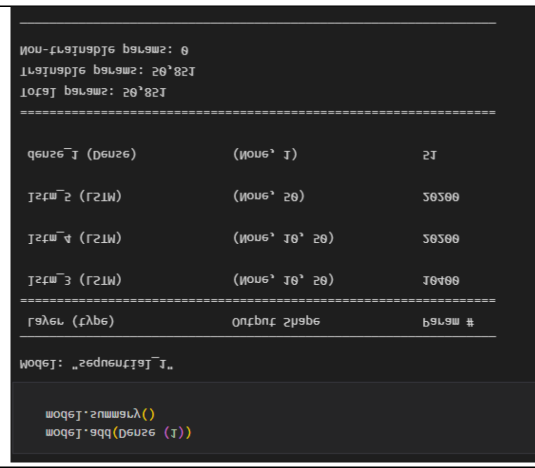
8.2.2 TEST CASE ANALYSIS

Section	Total Cases	Not Tested	Fail	Pass
Client Application	10	0	3	7
Security	2	0	1	1
Performance	3	0	1	2
Exception Reporting	2	0	0	2
Print Engine	2	0	0	2
Final Report Output	2	0	0	2

CHAPTER 9

RESULTS

9.1 PERFORMANCE METRICS

<table>
<tr><th>S.No.</th><th>Parameter</th><th>Values</th><th>Screenshot</th></tr>
<tr><td>1.</td><td>Model Summary</td><td>Total params: 50,851 Trainable params: 50,851 Non-trainable params: 0</td><td>
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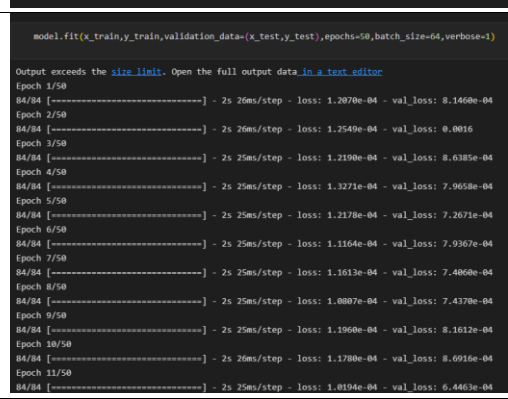
<tr><td>2.</td><td>Accuracy</td><td></td><td>
</td></tr>
<tr><td>3.</td><td>Confidence Score</td><td>Class Detected-9

Confidence Score9</td><td></td></tr>
</table>

CHAPTER 10
ADVANTAGES & DISADVANTAGES

ADVANTAGES

- With Price of falling up full to its lowest level in consumer will spend to gasoline in government estimate.
- Tepid inflation declining energy price lamp down inflation.
- Lowest oil prices economy energy producing in US, Iran, Venereal.
- The plunge in oil price is roiling market worldwide.
- Increase fuel mileage for passenger can seemed expensive

DISADVANTAGES

- Falling oil prices hurt a key sector of stock market.
- Less business spending automation of energy and equipment firms.
- Sagging economics higher supply mayor reason for oil drop, investor worry persistent declines.
- Less business spending automation of energy and equipment forms. These facilities high demand of actuator and values

CHAPTER 11
CONCLUSION

LSTM network is better than other traditional neural network for forecasting prices as it aims in using back propagation model. Traditional neural network such as RNN 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 outcome derived are relatively encouraging. The results show that large look ups do not necessarily improve the accuracy of the predictions of crude oil prices. Hence it can be concluded, the model with single LSTM model is definitely the most accurate.

CHAPTER 12
FUTURE SCOPE

- This work is carried out on the closing price of crude oil; however, there are various other factors which also affect the crude oil prices like change in the prices and quantities (demand and supply), change in the economy and current affairs as shown by the media.
- The main advantage of this research is in capturing the changing pattern of these prices.
- In the coming future, fundamental indicators and market trends have been planned to be incorporated into a model which help the proposed model perform more efficiently.

APPENDIX

SOURCE CODE

MODEL CREATION

MODEL BUILDING :

IMPORTING THE MODEL BUILDING LIBRARIES

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

INITIALIZING THE MODEL

```
model = Sequential()
```

ADDING LSTM LAYERS

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

FLASK APP

```python
from flask import Flask,render_template,request,redirect
import numpy as np
from tensorflow import keras
from keras.models import load_model
import joblib
import scipy


app = Flask(__name__)
model = load_model(r'C:\Users\sreen\Desktop\New folder\Flask\crude_oil.h5')

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def home():
    return render_template('index.html')


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


        sc = joblib.load(r'C:\Users\sreen\Desktop\New folder\Flask\scaler.save')

        x_input = sc.fit_transform(np.array(x_input).reshape(-1,1))

        x_input = np.array(x_input).reshape(1,-1)

        x_input = x_input.reshape(1,-1)
        x_input = x_input.reshape((1,10,1))
        print(x_input.shape)
```

```python
        model = load_model(r'C:\Users\sreen\Desktop\New folder\Flask\crude_oil.h5')
        output = model.predict(x_input)
        print(output[0][0])

        val = sc.inverse_transform(output)

        return render_template('web.html' , prediction = val[0][0])
    if request.method=="GET":
        return render_template('web.html')

if __name__=="__main__":
    app.run(debug=True)
```

RECOGNIZER

```python
x_input = [eval(i) for i in string]


sc = joblib.load(r'C:\Users\sreen\Desktop\New folder\Flask\scaler.save')

x_input = sc.fit_transform(np.array(x_input).reshape(-1,1))

x_input = np.array(x_input).reshape(1,-1)

x_input = x_input.reshape(1,-1)
x_input = x_input.reshape((1,10,1))
print(x_input.shape)

model = load_model(r'C:\Users\sreen\Desktop\New folder\Flask\crude_oil.h5')
output = model.predict(x_input)
print(output[0][0])

val = sc.inverse_transform(output)
```

HOME PAGE (HTML)

```html
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <title>Homepage</title>
    <link href="https://fonts.googleapis.com/css2?family=Poppins:wght@400;700&display=swap" rel="stylesheet">
    <link href="https://fonts.googleapis.com/css2?family=Ubuntu&display=swap" rel="stylesheet">
    <link rel="stylesheet" href="{{url_for('static',filename='css/style.css')}}">
</head>
<body>
    <header>
        <div>
                <ul class="menu">
                    <li><a href="{{url_for('home')}}">Home</a></li>
                    <li><a href="{{url_for('home')}}">About</a></li>
                </ul>
            </div>
        <div class="banner-text">
            <h1>CRUDE OILL<span> PRICE PREDICTION</span></h1>
            <p>Crude oil is composed of hydrocarbons, which are mainly hydrogen (about 13% by weight) and carbor
            <a href="{{url_for('predict')}}">PREDICT</a>
        </div>
    </header>

</body>
</html>
```

HOME PAGE (CSS)

```css
* {
    margin: 0;
    padding: 0;
}
body {
    font-family: 'Poppins', sans-serif;
}
.wrapper {
    width: 1170px;
    margin: auto;
}
header {
```

```
    background: linear-gradient(rgba(0, 0, 0, 0.8), rgba(0, 0, 0, 0.8)),
url(1.jpg);
    height: 100vh;
    -webkit-background-size: cover;
    background-size: cover;
    background-position: center center;
    position: relative;
}
.menu {
    float: right;
    list-style: none;
    margin-top: 30px;
}
.menu li {
    display: inline-block;
}
.menu li a {
    color: #fff;
    text-decoration: none;
    padding: 5px 20px;
    font-family: 'Poppins', sans-serif;
    font-size: 16px;
    text-transform: uppercase;
}
.menu li a:hover {
    background: #fff;
    color: #333;
}
.logo {
    float: left;
}
.logo img {
    width: 100%;
    padding: 15px 0;
}
.banner-text {
    position: absolute;
    width: 600px;
    height: 300px;
    margin: 20% 30%;
    text-align: center;
}
.banner-text h1 {
    text-align: center;
    color: #fff;
    text-transform: uppercase;
    font-size: 60px;
}
        .banner-text p {
    font-family: 'Ubuntu', sans-serif;
    font-size: 16px;
    line-height: 1.5;
    color: #ddd;
}
.banner-text h1 span {
    color: purple;
}
.banner-text a {
    border: 1px solid #fff;
    padding: 10px 25px;
```

```
    text-decoration: none;
    text-transform: uppercase;
    font-size: 14px;
    margin-top: 20px;
    display: inline-block;
    color: #fff;
}
.banner-text a:hover {
    background: #fff;
    color: #333;
}
/*resposive*/

@media (max-width:600px) {
    .wrapper {
        width: 100%;
    }
    .logo {
        float: none;
        width: 50%;
        text-align: center;
        margin: auto;
    }
    .menu {
        float: none;
        margin-top: 0;
    }
    .menu li a {
        padding: 5px;
        font-size: 11px;
    }
    .menu {
        text-align: center;
    }
    .banner-text {
        width: 100%;
        height: auto;
        margin: 15% 0;
    }
    .banner-text h1 {
        font-size: 30px;
    }
}
```

WEB PAGE (HTML)

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta http-equiv="X-UA-Compatible" content="IE=edge">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Web Page</title>
    <link rel="stylesheet" href="{{url_for('static',filename='css/web.css')}}">
    <style>
        input[type=text]{
```

```
            width: 100%;
            border: 2px solid #aaa;
            border-radius: 4px;
            margin: 8px 0;
            outline: none;
            padding: 8px;
            box-sizing: border-box;
            transition: 3s;
        }
        input[type=text]:focus{
            border-color: purple;;
            box-shadow: 0 0 8px 0  purple;;
        }
    </style>
</head>
<body>
    <header class="homepage" >
        <div class="navbar">
                        <div class="nav-list">
                 <ul>
                   <li><a href="{{url_for('home')}}">Home</a></li>
                <ul>
            </div>
                    </div>
        <div class="Div">
            <h1><span>Crude</span>oil<span>Price</span>Prediction</h1>
            <p>
                Enter past 10 days price...!!! <br> To predict the current crude
oil price
            </p>
            <form action="/predict" method="POST" enctype = "multipart/form-
data">
                <input type="text" name="val" placeholder="Enter the crude oil
price for first 10 days" >
                 <br> <br> <br>
                <input type="submit" class="button-class" placeholder="Predict">
            </form><br> <br>
            <div>
                <h4>Predicted price is: {{prediction}}</h4>

            </div>




        </div>

    </header>

</body>
</html>
```

WEB PAHE (CSS)

```
*{
    margin: 0;
    padding: 0;
    text-decoration: none;
    list-style: none;
}
```

```css
body{
    font-family: 'poppins', sans-serif
}
.homepage{
    min-height: 100vh;
    width: 100%;
    position: relative;
    background: linear-gradient(rgba(0, 0, 0, 0.8), rgba(0, 0, 0, 0.8)),
url(1.jpg);;
    background-size: cover;
    background-position: center;
    z-index: 1;
}
.homepage::after{
    content: '';
    position: absolute;
    left:0;
    top:0;
    height: 100%;
    width: 100%;
    background-color: rgb(34,33,33);
    opacity: .3;
    z-index: -2;
}
.navbar{
    position: absolute;
    padding: 40px 40px;
    display: flex;
    justify-content: space-between;
    width: 100%;
    box-sizing: border-box;
    align-items: center;
}
.navbar a{
    color: white;
}
.navbar h1{
    font-size: 38px;
}
.navbar span{
    color: purple;
}
.navbar h1:hover{
    transform: scale(1.1);
}
.nav-list ul{
    display: flex;
}
.nav-list ul li{
    margin: 0 25px;
    font-size: 20px;
}
.nav-list ul li a::after{
    content: '';
    display: block;
    width: 0%;
    height: 2px;
    transition: width 0.3s ease;
    background: whitesmoke;
}
```

```
.nav-list ul li a:hover::after{
    width: 100%;
}
.menu-icon{
    width: 40px;
    height:50px;
    position: absolute;
    top:45px;
    right:50px;
    cursor: pointer;
    display: none;
}
.Div{
    color:white;
    margin: 0;
    padding: 0;
    position: absolute;
    top:50%;
    left: 50%;
    transform: translateX(-50%) translateY(-35%);
    text-align: center;
    z-index: -1;
}
.Div h1{
    text-align: center;
    font-size: 40px;
}
.Div h1 span{
    color: purple;
}
.Div p{
    margin: 1.6% 0;
    font-size: 20px;
    font-weight: 500;
}
.Div .btn{
    display: inline-block;
    padding: 10px 20px;
    color: white;
    background-color: purple;
    border: 3px solid purple;
    border-radius: 7px;
    letter-spacing: .2px;
    margin-top: 17px;

}
.Div .btn:hover{
    border: 2px solid #ffffe0;
    transform: scale(1.1);
}
.Div .btn:active{
    transform: scale(0.9);
}
@media screen  and (max-width:750px){
    .menu-icon{
       display: block;
    }
    .navbar{
        padding: 0;
```

```
    }
    .nav-list{
        top: 0;
        left: 0;
        position: absolute;
        background-color: rgba(28, 26, 26, 0.2);
        backdrop-filter: blur(15px);
        width: 100%;
        height:100vh;
        display:flex;
        justify-content: center;
        align-items: center;
        margin-left: -100%;
    }
    .nav-list ul{
        display: flex;
        flex-direction: column;
        align-items: center;
    }
    .nav-list ul li{
        margin: 25px 0;
        font-size: 25px;
    }
    .navbar a h1{
        position: absolute;
        top: 40px;
        left: 50px;
    }
    .menu-mobile{
        margin-left: 0;
    }
}
@media screen and (max-width:350px){
     .navbar a h1{
           position: absolute;
        top: 50px;
        left: 10px;
        font-size: 30px;
     }
     .menu-icon{
        right:10px;
     }
     .Div h1 {
        font-size: 30px;
     }
     .Div p{
        font-size: 15px;

     }
     .Div .btn{
        padding: 5px 10px;
     }
}

.button-class{
    position: relative;
    display: inline-block;
    padding: 12px 36px;
    margin:10px 0;
    color: #fff;
```

```
    text-decoration: none;
    text-transform: uppercase;
    font-size: 18px;
    letter-spacing: 2px;
    border-radius: 40px;
    background: purple;;

}

.button-class:hover{
    background-color: white;
}
```

GITHUB

https://github.com/IBM-EPBL/IBM-Project-31534-1660201626