PROJECT OVERVIEW

Project Title: Stock Price Prediction

Problem Definition: The problem is to build a predictive model that forecasts stock prices based on historical market data. The goal is to create a tool that assists investors in making well-informed decisions and optimizing their investment strategies. This project involves data collection, data preprocessing, feature engineering, model selection, training, and evaluation.

Dataset Link: https://www.kaggle.com/datasets/prasoonkottarathil/microsoft-lifetime-stocks-dataset

Design Thinking:

1.Data Collection: Collect historical stock market data, including features like date, open price, close price, volume, and other relevant indicators.

2.Data Preprocessing: Clean and preprocess the data, handle missing values, and convert categorical features into numerical representations.

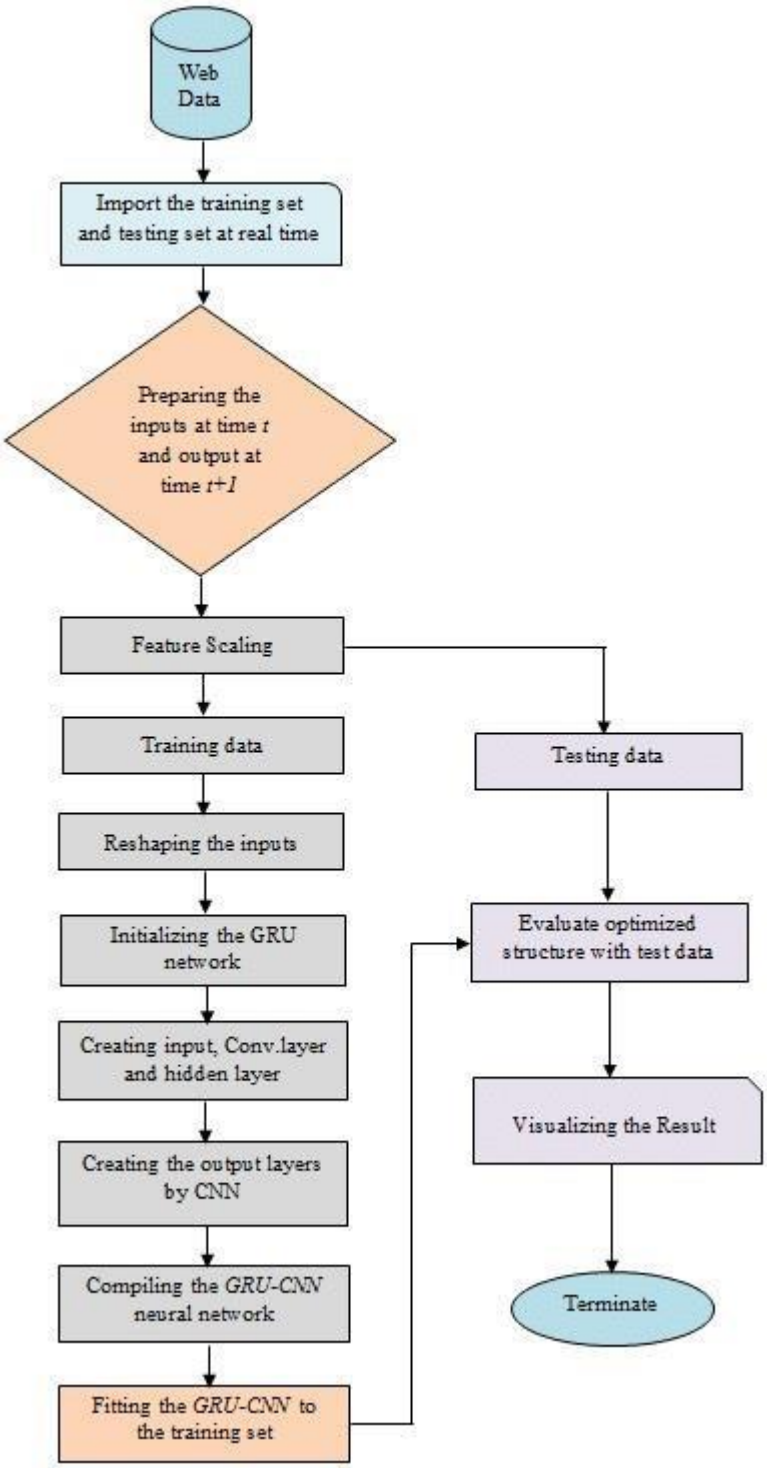
3. **Feature Engineering:** Create additional features that could enhance the predictive power of the model, such as moving averages, technical indicators, and lagged variables.

4. **Model Selection:** Choose suitable algorithms for time series forecasting (e.g., ARIMA, LSTM) to predict stock prices.

5. **Model Training:** Train the selected model using the preprocessed data.

6. **Evaluation:** Evaluate the model's performance using appropriate time series forecasting metrics (e.g., Mean Absolute Error, Root Mean Squared Error).

FLOWCHART:


Web Data
Import the training set and testing set at real time
Preparing the inputs at time t and output at time t+1
Feature Scaling
Training data
Reshaping the inputs
Initializing the GRU network
Creating input, Conv.layer and hidden layer
Creating the output layers by CNN
Compiling the GRU-CNN neural network
Fitting the GRU-CNN to the training set
Testing data
Evaluate optimized structure with test data
Visualizing the Result
Terminate

Stock price prediction analysis involves several steps. Here's a detailed breakdown:

1. Define Objective:
- Clearly outline the goal of the analysis, such as short-term or long-term predictions, sectorspecific predictions, or specific stock predictions.

2. Data Collection:
- Gather historical stock price data, financial reports, economic indicators, and any other relevant data sources.

3. Data Cleaning:
- Handle missing values, outliers, and inconsistencies in the data. Ensure data is in a format suitable for analysis.

4. Feature Selection/Engineering:
- Identify relevant features that could impact stock prices (e.g., historical prices, trading volumes, news sentiment).
- Create new features that might enhance predictive power (e.g., moving averages, technical indicators).

5. **Data Splitting:**
- Split the dataset into training and testing sets to evaluate the model's performance on unseen data.

6. Model Selection:
- Choose a suitable algorithm for prediction. Common choices include linear regression, decision trees, support vector machines, and neural networks.

7. Model Training:
- Train the chosen model using the training dataset. Adjust parameters to optimize performance.

8. Model Evaluation:

- Assess the model's performance on the testing dataset using metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), or accuracy, depending on the nature of the prediction.

9. Hyperparameter Tuning:
- Fine-tune the model by adjusting hyperparameters to improve accuracy.

10. Validation:
- Validate the model using a separate dataset, if available, to ensure robustness.

11. Prediction:
- Apply the trained model to new or unseen data to make predictions.

12. Evaluate Results:
- Assess the accuracy of predictions against actual outcomes. If the model performs well, proceed to deployment; otherwise, revisit previous steps for refinement.

13. Deployment:
- Implement the model in a production environment for real-time predictions. This could involve integrating the model into a trading algorithm or a user interface.

14. Monitoring and Maintenance:
- Continuously monitor the model's performance in real-world conditions. Retrain or update the model as needed to adapt to changing market conditions.

15. Documentation:
Document the entire process, including data sources, preprocessing steps, model details, and results. This facilitates future maintenance and improvements.

Stock price prediction is inherently uncertain due to the dynamic nature of financial markets. Machine learning models are valuable tools, but they

should be used cautiously, and predictions should be interpreted with an understanding of the associated risk

For machine learning algorithms to work, it's necessary to convert **raw data** into a **clean data** set, which means we must convert the data set to **numeric data**. We do this by encoding all the **categorical labels** to column vectors with binary values. **Missing values**, or NaNs (not a number) in the data set is an annoying problem. You have to either drop the missing rows or fill them up with a mean or interpolated values.

Preprocess data in Python – Step by step:

1. Load data in Pandas.
2. Drop columns that aren't useful.
3. Drop rows with missing values.
4. Create dummy variables.
5. Take care of missing data.
6. Convert the data frame to NumPy.
7. Divide the data set into training data and test data.

1.Load data in Pandas:

To work on the data, you can either load the CSV in Excel or in Pandas. For the purposes of

this tutorial, we'll load the CSV data in Pandas.

```
import pandas as pd
df = pd.read_csv('MSFT.csv')
```

Let's take a look at the data format below:

```
[3]  df.info()

     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 8525 entries, 0 to 8524
     Data columns (total 7 columns):
      #   Column     Non-Null Count  Dtype
     ---  ------     --------------  -----
      0   Date       8525 non-null   object
      1   Open       8525 non-null   float64
      2   High       8525 non-null   float64
      3   Low        8525 non-null   float64
      4   Close      8525 non-null   float64
      5   Adj Close  8525 non-null   float64
      6   Volume     8525 non-null   int64
     dtypes: float64(5), int64(1), object(1)
     memory usage: 466.3+ KB
```

2. **Drop Columns That Aren't Useful:**Let's try to drop some of the columns which won't

contribute much to our machine learning model. We'll start with Date and Open.

```
[4]  cols = ['Date','Open']
     df = df.drop(cols, axis=1)

     df.info()

     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 8525 entries, 0 to 8524
     Data columns (total 5 columns):
      #   Column     Non-Null Count  Dtype
     ---  ------     --------------  -----
      0   High       8525 non-null   float64
      1   Low        8525 non-null   float64
      2   Close      8525 non-null   float64
      3   Adj Close  8525 non-null   float64
      4   Volume     8525 non-null   int64
     dtypes: float64(4), int64(1)
     memory usage: 333.1 KB
```

3. **Drop Rows With Missing Values:** Next we can drop all rows in the data that have missing

values (NaNs). Here's how:

```
[6]  df = df.dropna()

     df.info()

     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 8525 entries, 0 to 8524
     Data columns (total 5 columns):
      #   Column     Non-Null Count  Dtype
     ---  ------     --------------  -----
      0   High       8525 non-null   float64
      1   Low        8525 non-null   float64
      2   Close      8525 non-null   float64
      3   Adj Close  8525 non-null   float64
      4   Volume     8525 non-null   int64
     dtypes: float64(4), int64(1)
     memory usage: 333.1 KB
```

4. Creating Dummy Variables

Instead of wasting our data, let's convert the Pclass, Sex and Embarked to columns in Pandas and drop them after conversion.

```
[8]  dummies = []
     cols = ['High', 'Low']
     for col in cols:
        dummies.append(pd.get_dummies(df[col]))
```

Then..

```
[9]  MSFT_dummies = pd.concat(dummies, axis=1)
```

Finally we **concatenate** to the original data frame, column-wise:

```
[10] df = pd.concat((df,MSFT_dummies), axis=1)
```

Now that we converted High and Low values into columns, we drop the redundant columns from the data frame.

```
[11] df = df.drop(['High','Low'], axis=1)
```

Let's take a look at the new data frame:

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8525 entries, 0 to 8524
Columns: 9265 entries, Close to 158.330002
dtypes: float64(2), int64(1), uint8(9262)
memory usage: 75.5 MB
```

5. Take Care of Missing Data

Let's compute a median or interpolate() all the ages and fill those missing age values.

Pandas has an interpolate() function that will replace all the missing NaNs to interpolated values.

```
[13] df['Close'] = df['Close'].interpolate()
```

Now let's observe the data columns. Notice 'Close' is now interpolated with imputed new values.

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8525 entries, 0 to 8524
Columns: 9265 entries, Close to 158.330002
dtypes: float64(2), int64(1), uint8(9262)
memory usage: 75.5 MB
```

6. Convert the Data Frame to NumPy: Now that we've converted all the data to integers, it's time to prepare the data for machine learning models. This is where scikit-learn and NumPy come into play: X= Input set with 14 attributes y = Small y output, in this case Survived

Now we convert our data frame from Pandas to NumPy and we assign input and output:

```
[15] X = df.values
     y = df['Adj Close'].values
```

still has Adj Close values in it, which should not be there. So we drop in the NumPy

column, which is the first column.

X

```
X = np.delete(X, 1, axis=1)
```

7. Divide the Data Set Into Training Data and Test Data

Now that we're ready with X and y, let's split the data set: we'll allocate 70 percent for training and 30 percent for tests using scikit model_selection.

```
2s
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=
```

FEATURE ENGINEERING:

Feature engineering is the process of selecting, creating, or transforming variables in a dataset to improve the performance of machine learning models. It involves tasks like selecting relevant features, handling missing data, and creating new variables. Effective feature engineering can significantly impact model accuracy and predictive power, making it a crucial step in data analysis and machine learning.

We are planning to create window statistics of 1 week, 2 week, 1 month and 1 year and so on. Use common and simple statistics like mean, median, max, min and exponentially weighted mean.

```
BASE_FEATURES = [ 'returnsOpenPrevMktres10', 'returnsOpenPrevRaw10',
'open', 'close']
```

To generate the ratio between these features and market mean.

```
def add_market_mean_col(market_df):
daily_market_mean_df = market_df.groupby('time').mean()
daily_market_mean_df = daily_market_mean_df[['volume', 'close']]
merged_df = market_df.merge(daily_market_mean_df, left_on='time',
right_index=True, suffixes=("",'_market_mean'))
merged_df['volume/volume_market_mean'] = merged_df['volume'] /
merged_df['volume_market_mean']
merged_df['close/close_market_mean'] = merged_df['close'] /
merged_df['close_market_mean']
return merged_df.reset_index(drop = True)
```

```
BASE_FEATURES = BASE_FEATURES + ['volume',
'volume/volume_market_mean',
'close/close_market_mean']
```

In a similar context, the ratio of opening price and closing price should tell us more than just raw closing/opening price

```
def generate_open_close_ratio(df):
df['open/close'] = df['open'] / df['close']
```

```
BASE_FEATURES = BASE_FEATURES + ['open/close']
```

Likewise, we can generate the ratio of raw return values to its current opening/closing prices. Note that this is not a duplicate of residual return columns which are the returns after movement of the market as a whole has been accounted for, leaving only movements inherent to the instrument. The generated ratio is not adjusted by market movements it is just a ratio of its price delta versus its price.

```
open_raw_cols = ['returnsOpenPrevRaw1',
'returnsOpenPrevRaw10']
close_raw_cols = ['returnsClosePrevRaw1', 'returnsClosePrevRaw10']
```

```
def raw_features_to_ratio_features(df):
for col in open_raw_cols:
df[col + '/open' ] = df[col] / df['open'] for col in
close_raw_cols:
df[col + '/close'] = df[col] / df['close']

BASE_FEATURES = BASE_FEATURES +
['returnsClosePrevRaw1/close',
'returnsClosePrevRaw10/close', 'returnsOpenPrevRaw1/open'
'returnsOpenPrevRaw10/open']
```

The previously mentioned window statistics feature is generated based on the BASE_FEATURES we gathered. And merged on time and assetCode(which is like the id column of the market data)

```
new_df = generate_features(market_train_df)
market_train_df = pd.merge(market_train_df, new_df, how =
'left', on = ['time', 'assetCode'])
```

‘Microsoft Corp’ has related ‘assetCodes’ of ‘{‘MSFT.O’, ‘MSFT.F’, ‘MSFT.DE’, ‘MSFT.OQ’}’. These codes are just Microsoft stocks on different stock exchanges. So now it is clear that if one news is related to an asset name all related asset codes will be affected. Also merging table on ‘assetName’ is practically much easier because it is single name of an asset in both market and news data (On the contrary market data has ‘assetCode’ which has a single asset code and news data has ‘assetCodes’ which has more than one asset codes). So now let’s transform sentiment column accordingly and merge market and news data.

```
def merge_with_news_data(market_df, news_df):
news_df['firstCreated'] = news_df.firstCreated.dt.hour
news_df['assetCodesLen'] = news_df['assetCodes'].map(lambda x:
len(eval(x))) news_df['asset_sentiment_count'] =
news_df.groupby(['assetName',
'sentimentClass'])['firstCreated'].transform('count') kcol =
['time', 'assetName'] news_df = news_df.groupby(kcol,
as_index=False).mean() market_df = pd.merge(market_df,
news_df, how='left', on=kcol, suffixes=("", "_news")) return
market_df
 market_train_df = merge_with_news_data(market_train_df,
news_train_df)
```

MODEL TRAINING:

Model training in stock price prediction involves using historical stock market data to train a machine learning model that can make predictions about future stock prices. Here is a step-by-step explanation of the process:

Data collection:

Gather historical stock market data, including variables such as stock prices, trading volume, technical indicators, news sentiment, and macroeconomic factors for a given time period.

Data preprocessing:

Clean the collected data, handle missing values, and remove outliers. Normalize or scale the data as needed.

Feature engineering:

Select or create relevant features that may have an impact on stock prices. This can involve transforming or combining existing variables to extract meaningful information. For example, using moving averages or creating lagged variables.

Train-test split:

Split the dataset into two parts: a training set and a test set. The training set will be used to train the model, while the test set will be used to evaluate its performance.

Model selection:

Choose an appropriate machine learning algorithm or model for stock price prediction. Some commonly used models include linear regression, support vector machines (SVM), random forests, or deep neural networks.

Hyperparameter tuning:

Fine-tune the model by selecting the best hyperparameters. Hyperparameters are settings that control the learning process of the model, such as learning rate, regularization strength, or the number of hidden layers in a neural network.

Model training:

Fit the chosen model to the training data using the selected features. The model will learn patterns and relationships present in the training data.

Model evaluation:

Assess the performance of the trained model by evaluating its predictions on the test set. Metrics such as mean squared error (MSE), mean absolute error (MAE), or root mean squared error (RMSE) can be used to measure prediction accuracy.

Model refinement:

If the model's performance is not satisfactory, additional steps can be taken to improve it. This may include experimenting with different algorithms, adjusting hyperparameters, adding new features, or gathering more data.

Model deployment:

Once the model is trained and evaluated, it can be deployed to make predictions on new, unseen data. This can involve automating the prediction process and updating the model periodically with new data to enhance its accuracy.

CODE:

```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

```
[10] data=pd.read_csv('/content/MSFT.csv')
```

```
[11] training_set=data.iloc[:,1:2].values
```

```
[12] from sklearn.preprocessing import MinMaxScaler
     scaler=MinMaxScaler(feature_range=(0,1))
     scaled_training_set=scaler.fit_transform(training_set)
     scaled_training_set
```

```
array([[0.00000000e+00],
       [5.44673742e-05],
       [7.62543239e-05],
       ...,
       [9.92909264e-01],
       [9.85128179e-01],
       [9.99184307e-01]])
```

```
X_train=[]
y_train=[]
for i in range(60,1258):
 X_train.append(scaled_training_set[i-60:i,0])
 y_train.append(scaled_training_set[i,0])
X_train=np.array(X_train)
y_train=np.array(y_train)
```

```
[14] print(X_train.shape)
```

```
(1198, 60)
```

```
[15] from keras.models import Sequential
     from keras.layers import LSTM
     from keras.layers import Dense
     from keras.layers import Dropout
```

```
15] from keras.models import Sequential
    from keras.layers import LSTM
    from keras.layers import Dense
    from keras.layers import Dropout

16] regressor=Sequential()
    regressor.add(LSTM(units=50,return_sequences=True,input_shape=(X_train.shape[1],1)))
    regressor.add(Dropout(0.2))
    regressor.add(LSTM(units=50,return_sequences=True))
    regressor.add(Dropout(0.2))
    regressor.add(LSTM(units=50,return_sequences=True))
    regressor.add(Dropout(0.2))
    regressor.add(LSTM(units=50))
    regressor.add(Dropout(0.2))
    regressor.add(Dense(units=1))
```

```
[17] regressor.compile(optimizer='adam',loss='mean_squared_error')
     regressor.fit(X_train,y_train,epochs=10,batch_size=32)

     Epoch 1/10
     38/38 [==============================] - 10s 84ms/step - loss: 3.2573e-05
     Epoch 2/10
     38/38 [==============================] - 3s 80ms/step - loss: 3.7207e-06
     Epoch 3/10
     38/38 [==============================] - 3s 85ms/step - loss: 3.4982e-06
     Epoch 4/10
     38/38 [==============================] - 4s 96ms/step - loss: 3.4549e-06
     Epoch 5/10
     38/38 [==============================] - 3s 80ms/step - loss: 2.9047e-06
     Epoch 6/10
     38/38 [==============================] - 3s 74ms/step - loss: 1.9501e-06
     Epoch 7/10
     38/38 [==============================] - 3s 78ms/step - loss: 1.1707e-06
     Epoch 8/10
     38/38 [==============================] - 3s 91ms/step - loss: 6.0697e-07
     Epoch 9/10
     38/38 [==============================] - 3s 82ms/step - loss: 4.9459e-07
     Epoch 10/10
     38/38 [==============================] - 3s 78ms/step - loss: 6.1307e-07
     <keras.src.callbacks.History at 0x785b64137850>

[18] import pandas as pd
     data_test=pd.read_csv('/content/MSFT.csv')
     actual_stock_price=data_test.iloc[:,1:2].values
```

EVALUTION:

Stock price prediction is an important aspect of financial analysis. It involves using various techniques and models to forecast the future price movements of a stock or a group of stocks. There are several methods and metrics that can be used to evaluate the accuracy and effectiveness of stock price prediction models. Here are some key evaluation measures:

Mean Squared Error (MSE):

MSE provides a measure of the average squared difference between the predicted and actual stock prices. Lower MSE values indicate better accuracy in predicting stock prices.

Root Mean Squared Error (RMSE):

RMSE is the square root of the MSE and provides a measure of the average difference between the predicted and actual stock prices. It is useful for comparing models across different datasets.

It's important to note that stock price prediction is a challenging task, as it depends on various factors such as market conditions, investor behaviour, and unexpected events. Therefore, it's crucial to apply critical thinking and use multiple evaluation measures to assess the performance of a prediction model. Additionally, backtesting and out-of-sample testing can provide insights into the model's robustness and generalizability.

CODE:

```
[26] def calculate_rmse(y_true,y_pred):
         rmse=np.sqrt(np.mean((y_true-y_pred)**2))
         return rmse
```