| | |
|---|---|
| Project Title | **stock-market** |
| Tools | Python, ML, SQL, Excel |
| Domain | Data Analyst |
| Project Difficulties level | intermediate |

Dataset : Dataset is available in the given link. You can download it at your convenience.

[Click here to download data set]

**About Dataset**

Given historical stock price data for Apple, Microsoft, Netflix and Google over the past three months, your task is to analyze and compare the performance of these companies in the stock market using various data science techniques.

Specifically, the goal is to identify trends and patterns in stock price movements, calculate moving averages and volatility for each company, and conduct correlation analysis to examine the relationships between different stock prices.

You can also download the latest data using the finance API instead of using the provided dataset.

Here’s a detailed guide on how to carry out a Market Analysis project using machine learning, including a step-by-step explanation and Python code example:

**Project Overview**

Objective: To analyze market trends and predict future market behavior using machine learning techniques.

**Steps to Follow:**

1. **Define the Scope and Objective**:
    - Identify the market or industry you want to analyze.
    - Define the specific objectives of your analysis (e.g., predicting market growth, understanding consumer behavior, etc.).
2. **Data Collection**:
    - Gather relevant data from various sources (e.g., financial reports, market research reports, government databases, etc.).
    - Common data points include market size, market share, growth rates, consumer demographics, competitive analysis, etc.
3. **Data Preparation**:
    - Clean the data to remove any inconsistencies or errors.
    - Combine data from different sources into a single dataset.
    - Use tools like Pandas for data cleaning and preparation.
4. **Exploratory Data Analysis (EDA)**:
    - Perform EDA to understand the data distribution and identify patterns.
    - Use visualization tools like Matplotlib and Seaborn to visualize the data.
5. **Feature Engineering**:
    - Create new features from existing data that might be useful for the machine learning model.

   - Normalize or standardize the data if necessary.
6. **Model Selection**:
   - Choose appropriate machine learning algorithms based on the problem (e.g., linear regression, decision trees, random forest, etc.).
   - Split the data into training and testing sets.
7. **Model Training and Evaluation**:
   - Train the machine learning model on the training set.
   - Evaluate the model's performance on the testing set using appropriate metrics.
8. **Model Tuning and Optimization**:
   - Tune the model's hyperparameters to improve performance.
   - Use techniques like cross-validation to ensure the model is not overfitting.
9. **Deployment**:
   - Deploy the model using tools like Flask or Django for web applications.
   - Use the model to make predictions on new data.

**Detailed Python Code Example**

**Step-by-Step Implementation**

1. **Data Collection**:
   - Assume you have a dataset named `market_data.csv` with columns like `Year`, `Market_Size`, `Growth_Rate`, `Company`, `Revenue`, `Profit`, etc.

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
```

```
from sklearn.metrics import mean_squared_error, r2_score

# Load the dataset
data = pd.read_csv('market_data.csv')

# Display the first few rows of the dataset
print(data.head())
```

2. **Data Preparation**:

```
# Handle missing values
data = data.dropna()

# Convert categorical columns to numerical (if any)
data = pd.get_dummies(data, drop_first=True)

# Split the data into features and target variable
X = data.drop('Market_Size', axis=1)
y = data['Market_Size']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Standardize the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

3. **Exploratory Data Analysis (EDA)**:

```
# Visualize the distribution of the target variable
sns.histplot(y, kde=True)
plt.title('Distribution of Market Size')
plt.show()

# Visualize correlations between features
```

```
plt.figure(figsize=(10, 8))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

4. **Model Selection and Training**:

**SAMPLE REPORT**

## 📈 EDA On 🚀Stock Market Dataset📈

IMPORTING LIBRARIES

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from pandas_profiling import ProfileReport
import warnings
warnings.filterwarnings('ignore')
from sklearn.neighbors import LocalOutlierFactor
import numpy as np
import pandas as pd
from numpy import ma
import pandas as pd
import math
```

```
import matplotlib
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
from matplotlib import ticker, cm
import matplotlib.gridspec as gridspec
import matplotlib.colors as colors
%matplotlib inline

import seaborn as sns

from scipy.stats import multivariate_normal
from sklearn.metrics import f1_score, confusion_matrix,
classification_report, precision_recall_fscore_support
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from scipy.stats import multivariate_normal
from sklearn import preprocessing
from sklearn.preprocessing import MinMaxScaler

from keras import layers
from keras.models import Sequential
from keras.layers import Flatten, Dense
from keras.layers import Embedding
from keras.utils import np_utils, to_categorical
from keras.datasets import imdb
#from keras import preprocessing
from keras.preprocessing.text import Tokenizer
from keras import models, regularizers, layers, optimizers,
losses, metrics
from keras.optimizers import Adam

from keras.callbacks import Callback,ModelCheckpoint
from keras.models import Sequential,load_model
from keras.layers import Dense, Dropout, GlobalAveragePooling1D
from keras.wrappers.scikit_learn import KerasClassifier
import keras.backend as K
import pandas_profiling
```

```
/opt/conda/lib/python3.10/site-packages/numba/core/decorators.py:262: NumbaDeprecationWarning: numba.generated_jit is deprecated. Please see the documentation at: https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-of-generated-jit for more information and advice on a suitable replacement.
  warnings.warn(msg, NumbaDeprecationWarning)
/opt/conda/lib/python3.10/site-packages/visions/backends/shared/nan_handling.py:51: NumbaDeprecationWarning: The 'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The implicit default value for this argument is currently False, but it will be changed to True in Numba 0.59.0. See https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-of-object-mode-fall-back-behaviour-when-using-jit for details.
  def hasna(x: np.ndarray) -> bool:
/tmp/ipykernel_20/3109876753.py:6: DeprecationWarning: `import pandas_profiling` is going to be deprecated by April 1st. Please use `import ydata_profiling` instead.
  from pandas_profiling import ProfileReport
```

## IMPORTING DATA

In [2]:

```
data = pd.read_csv('/kaggle/input/stock-market-analysis-data/stocks.csv')
```

## EDA

In [3]:

```
data.head(10)
```

Out[3]:

| | Ticker | Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|---|---|
| 0 | AAPL | 2023-02-07 | 150.639999 | 155.229996 | 150.639999 | 154.649994 | 154.414230 | 83322600 |
| 1 | AAPL | 2023-02-08 | 153.880005 | 154.580002 | 151.169998 | 151.919998 | 151.688400 | 64120100 |
| 2 | AAPL | 2023-02-09 | 153.779999 | 154.330002 | 150.419998 | 150.869995 | 150.639999 | 56007100 |
| 3 | AAPL | 2023-02-10 | 149.460007 | 151.339996 | 149.220001 | 151.009995 | 151.009995 | 57450700 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 4 | AAPL | 2023-02-13 | 150.949997 | 154.259995 | 150.919998 | 153.850006 | 153.850006 | 62199000 |
| 5 | AAPL | 2023-02-14 | 152.119995 | 153.770004 | 150.860001 | 153.199997 | 153.199997 | 61707600 |
| 6 | AAPL | 2023-02-15 | 153.110001 | 155.500000 | 152.880005 | 155.330002 | 155.330002 | 65573800 |
| 7 | AAPL | 2023-02-16 | 153.509995 | 156.330002 | 153.350006 | 153.710007 | 153.710007 | 68167900 |
| 8 | AAPL | 2023-02-17 | 152.350006 | 153.000000 | 150.850006 | 152.550003 | 152.550003 | 59144100 |
| 9 | AAPL | 2023-02-21 | 150.199997 | 151.300003 | 148.410004 | 148.479996 | 148.479996 | 58867200 |

In [4]:

```
data['Ticker'].unique()
```

Out[4]:

```
array(['AAPL', 'MSFT', 'NFLX', 'GOOG'], dtype=object)
```

In [5]:

```
data.describe()
```

Out[5]:

| | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|
| count | 248.000000 | 248.000000 | 248.000000 | 248.000000 | 248.000000 | 2.480000e+02 |
| mean | 215.252093 | 217.919662 | 212.697452 | 215.381674 | 215.362697 | 3.208210e+07 |
| std | 91.691315 | 92.863023 | 90.147881 | 91.461989 | 91.454750 | 2.233590e+07 |
| min | 89.540001 | 90.129997 | 88.860001 | 89.349998 | 89.349998 | 2.657900e+06 |
| 25 | 135.23 | 137.44 | 134.82 | 136.34 | 136.34 | 1.714180 |

| | | | | | | |
|---|---|---|---|---|---|---|
| % | 5004 | 0004 | 2495 | 7498 | 7498 | e+07 |
| 50% | 208.764999 | 212.614998 | 208.184998 | 209.920006 | 209.920006 | 2.734000e+07 |
| 75% | 304.177505 | 307.565002 | 295.437500 | 303.942505 | 303.942505 | 4.771772e+07 |
| max | 372.410004 | 373.829987 | 361.739990 | 366.829987 | 366.829987 | 1.133164e+08 |

In [6]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 248 entries, 0 to 247
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Ticker     248 non-null    object 
 1   Date       248 non-null    object 
 2   Open       248 non-null    float64
 3   High       248 non-null    float64
 4   Low        248 non-null    float64
 5   Close      248 non-null    float64
 6   Adj Close  248 non-null    float64
 7   Volume     248 non-null    int64  
dtypes: float64(5), int64(1), object(2)
memory usage: 15.6+ KB
```

In [7]:

```
data.shape
```

Out[7]:

```
(248, 8)
```

In [8]:

```
data.dtypes
```

Out[8]:

```
Ticker        object
Date          object
Open         float64
High         float64
Low          float64
Close        float64
Adj Close    float64
Volume         int64

dtype: object
```

In [9]:

```
data.describe
```

Out[9]:

```
<bound method NDFrame.describe of     Ticker        Date
Open        High         Low       Close  \
0     AAPL  2023-02-07  150.639999  155.229996  150.639999
154.649994
1     AAPL  2023-02-08  153.880005  154.580002  151.169998
151.919998
2     AAPL  2023-02-09  153.779999  154.330002  150.419998
150.869995
3     AAPL  2023-02-10  149.460007  151.339996  149.220001
151.009995
4     AAPL  2023-02-13  150.949997  154.259995  150.919998
153.850006
..     ...         ...         ...         ...         ...
...
243   GOOG  2023-05-01  107.720001  108.680000  107.500000
107.709999
244   GOOG  2023-05-02  107.660004  107.730003  104.500000
105.980003
245   GOOG  2023-05-03  106.220001  108.129997  105.620003
106.120003
246   GOOG  2023-05-04  106.160004  106.300003  104.699997
105.209999
247   GOOG  2023-05-05  105.320000  106.440002  104.738998
106.214996

      Adj Close    Volume
0    154.414230  83322600
1    151.688400  64120100
2    150.639999  56007100
3    151.009995  57450700
4    153.850006  62199000
..          ...       ...
243  107.709999  20926300
244  105.980003  20343100
245  106.120003  17116300
246  105.209999  19780600
```

```
247  106.214996  20705300


[248 rows x 8 columns]>
```

In [10]:

```
data.isnull().any()
```

Out[10]:

```
Ticker       False
Date         False
Open         False
High         False
Low          False
Close        False
Adj Close    False
Volume       False

dtype: bool
```

In [11]:

```
data.isnull().sum()
```

Out[11]:

```
Ticker       0
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
```

```
Volume       0

dtype: int64
```

In [12]:

```
data.corr()
```

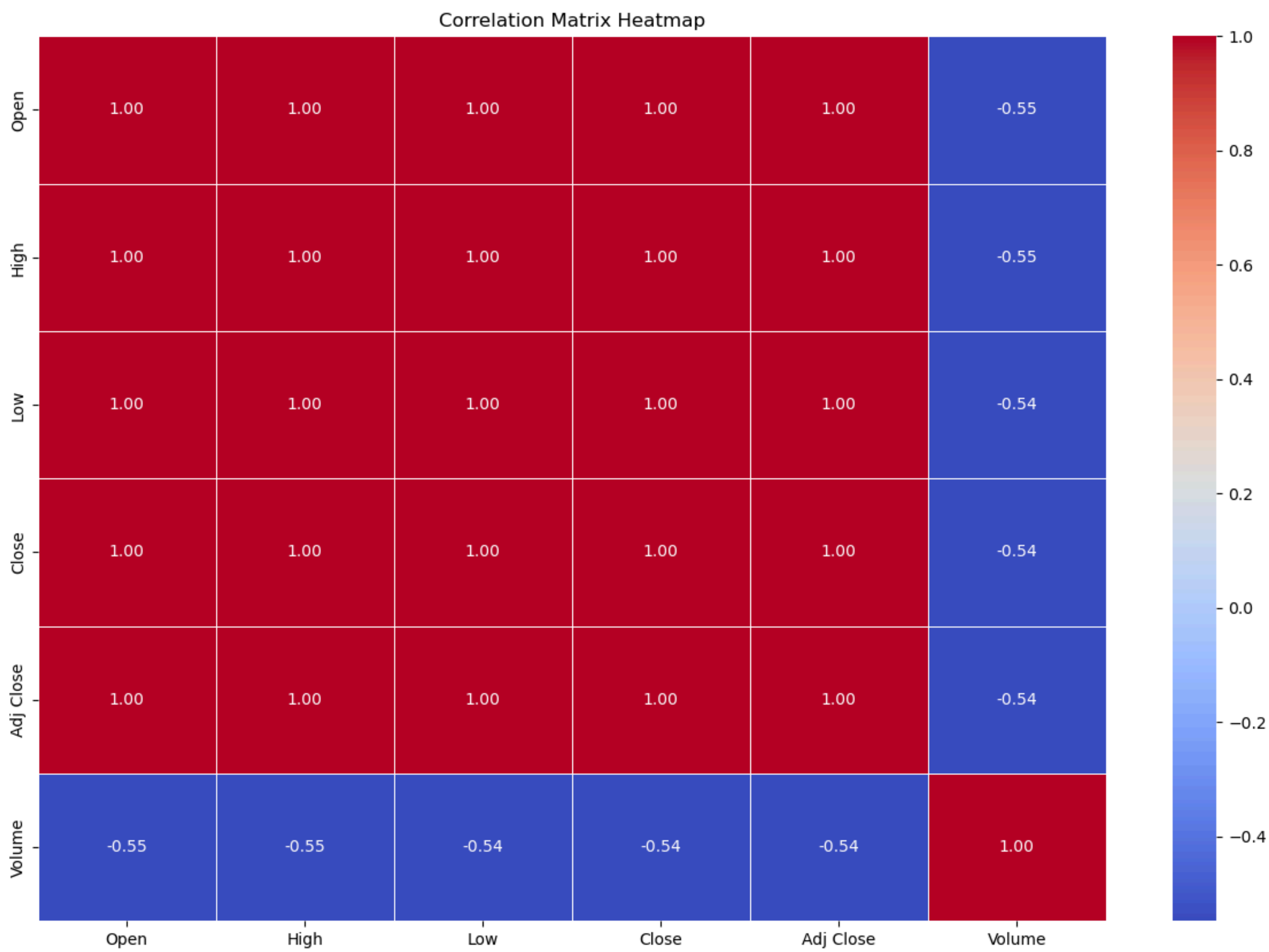
Out[12]:

| | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|
| Open | 1.000000 | 0.999626 | 0.999650 | 0.999176 | 0.999173 | -0.547741 |
| High | 0.999626 | 1.000000 | 0.999654 | 0.999644 | 0.999640 | -0.546175 |
| Low | 0.999650 | 0.999654 | 1.000000 | 0.999663 | 0.999661 | -0.544590 |
| Close | 0.999176 | 0.999644 | 0.999663 | 1.000000 | 0.999999 | -0.544194 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Adj Close | 0.999173 | 0.999640 | 0.999661 | 0.999999 | 1.000000 | -0.544370 |
| Volume | -0.547741 | -0.546175 | -0.544590 | -0.544194 | -0.544370 | 1.000000 |

In [13]:

```
correlation_matrix = data.corr()
plt.figure(figsize=(15, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
linewidths=0.5, fmt='.2f')
plt.title("Correlation Matrix Heatmap")
plt.show()
```




## PANDAS PROFILING

In [14]:

```
profile= ProfileReport(data, title="Stock Market Analysis")
```

In [15]:

```
profile
```

```
Summarize dataset: 100%

53/53 [00:20<00:00, 2.97it/s, Completed]

Generate report structure: 100%

1/1 [00:05<00:00, 5.29s/it]

Render HTML: 100%

1/1 [00:01<00:00, 1.80s/it]
```

Out[15]:

In [16]:

```
data['Date'] = pd.to_datetime(data['Date'])
```

## DATA VISUALIZATIONS

In [17]:

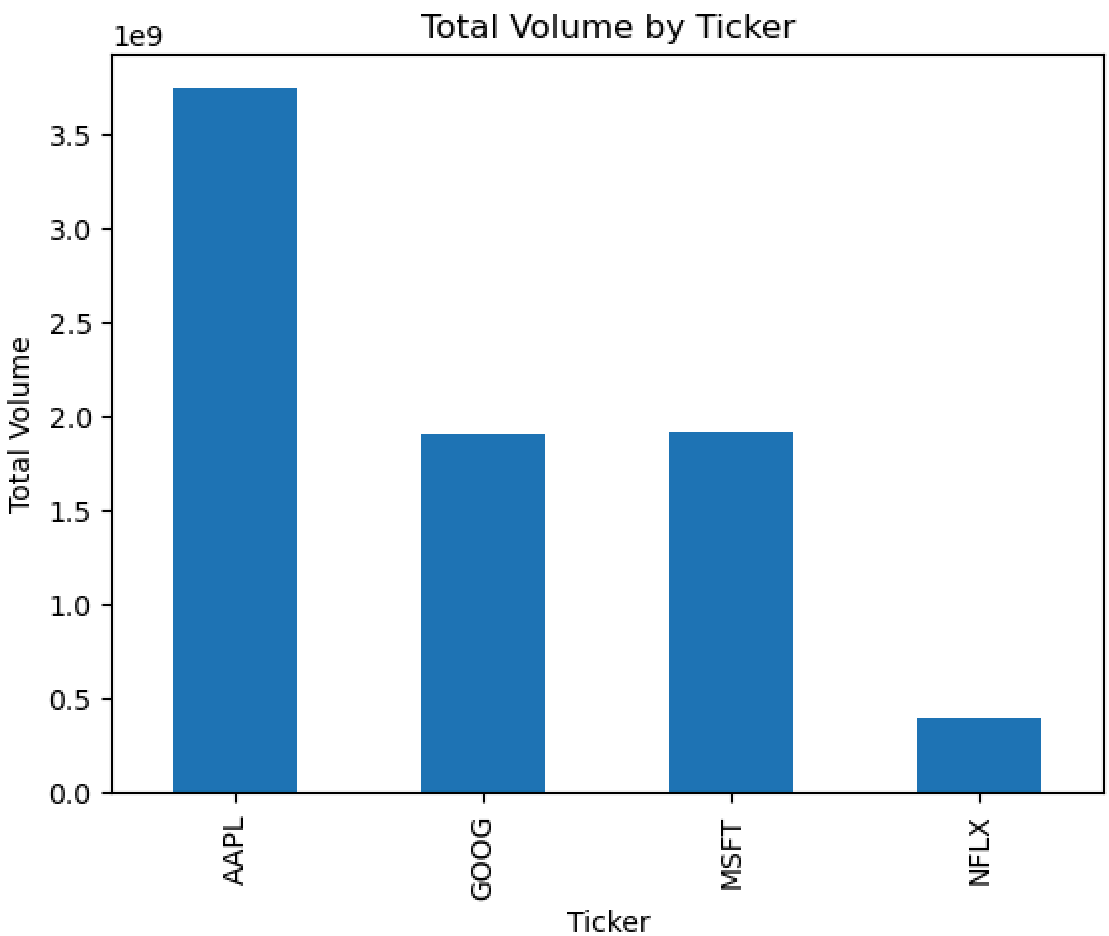
```
# the distribution of the closing prices to understand their range and frequency.
plt.hist(data['Close'], bins=20)
plt.xlabel('Closing Price')
plt.ylabel('Frequency')
plt.title('Closing Price Distribution')
plt.show()
```


In [18]:

```
#the cumulative volume traded over time to observe any trends or spikes.
ticker_volume = data.groupby('Ticker')['Volume'].sum()
ticker_volume.plot(kind='bar')
plt.xlabel('Ticker')
plt.ylabel('Total Volume')
plt.title('Total Volume by Ticker')
```

Out[18]:

```
Text(0.5, 1.0, 'Total Volume by Ticker')
```




In [19]:

```
#Exploring the relationship between volume and closing prices,
to identify any correlations.
plt.scatter(data['Volume'], data['Close'])
plt.xlabel('Volume')
plt.ylabel('Closing Price')
plt.title('Volume vs. Closing Price')
plt.show()
```


In [20]:

```
#Illustrating the distribution of the closing prices, including
the median, quartiles, and outliers.
plt.boxplot(data['Close'])
plt.ylabel('Closing Price')
plt.title('Closing Price Distribution')
plt.show()
```


In [21]:

```
data.head(5)
```

Out[21]:

| | Ticker | Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|---|---|
| 0 | AAPL | 2023-02-07 | 150.639999 | 155.229996 | 150.639999 | 154.649994 | 154.414230 | 83322600 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1 | AAPL | 2023-02-08 | 153.880005 | 154.580002 | 151.169998 | 151.919998 | 151.688400 | 64120100 |
| 2 | AAPL | 2023-02-09 | 153.779999 | 154.330002 | 150.419998 | 150.869995 | 150.639999 | 56007100 |
| 3 | AAPL | 2023-02-10 | 149.460007 | 151.339996 | 149.220001 | 151.009995 | 151.009995 | 57450700 |
| 4 | AAPL | 2023-02-13 | 150.949997 | 154.259995 | 150.919998 | 153.850006 | 153.850006 | 62199000 |

linkcode

Thanks for reading my Notebook😁✌️

Reference link