GURU TEGH BAHADUR INSTITUTE OF TECHNOLOGY

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Subject:- Advances in Machine Learning

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Experiment 6

Aim: Understand the interpretability of ML models by using LIME or SHAP to explain model Predictions.

Theory:

SHAP and LIME are model-agnostic techniques used to interpret machine learning predictions by explaining how individual features contribute to a model's output. SHAP (SHapley Additive exPlanations) assigns each feature an importance value based on Shapley values from game theory, ensuring a fair and consistent attribution by considering all possible combinations of features. LIME (Local Interpretable Model-agnostic Explanations) explains a specific prediction by approximating the complex model locally with a simple, interpretable model—like linear regression—after perturbing the input data to see how changes affect the output. Both methods aim to increase transparency and trust in machine learning models by providing insights into how input features influence predictions.

About the Dataset:

The Heart Failure Clinical Records Dataset is a medical dataset used for predicting patient survival following heart failure. It comprises clinical and laboratory data from patients, focusing on attributes that are significant indicators of heart health. The key attributes include:

- **Age**: The patient's age in years, which can influence heart failure risk.
- **Anaemia**: A binary indicator (1 or 0) showing whether the patient has anaemia, affecting oxygen transport in the body.
- **Creatinine Phosphokinase (CPK)**: Levels of the CPK enzyme in the blood (measured in mcg/L), with elevated levels indicating potential muscle damage, including heart muscle.
- **Diabetes**: A binary indicator of diabetes presence, which is a risk factor for heart disease.

- **Ejection Fraction**: The percentage of blood leaving the heart each time it contracts, measured in percentage; lower values suggest weakened heart function.
- **High Blood Pressure**: A binary indicator of hypertension, a common risk factor for heart failure.
- **Platelets**: Platelet count in the blood (measured in kiloplatelets/mL), important for blood clotting and can reflect underlying health issues.

This dataset is valuable for building machine learning models to predict outcomes like mortality or hospitalization due to heart failure. By applying interpretability methods like LIME and SHAP, we can analyze how each attribute influences the model's predictions on a per-patient basis. For example, SHAP can quantify the contribution of high blood pressure to the risk prediction for an individual, while LIME can provide a localized explanation highlighting the most influential features for a specific prediction. This insight aids clinicians in understanding the model's decision-making process, leading to better-informed clinical decisions and personalized patient care.

Code:

```
[34]
import numpy as np # linear algebra
import pandas as pd
```

```
import warnings
from numba import NumbaDeprecationWarning
warnings.filterwarnings("ignore", category=NumbaDeprecationWarning)

# Data Standardization and Encoding
from sklearn.preprocessing import RobustScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

# Modelling
from sklearn import model_selection, metrics
from sklearn.model_selection import train_test_split

# Visualization Library, matplotlib and seaborn
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.ticker import FuncFormatter

# Hide convergence warning for now
import warnings
from sklearn.exceptions import ConvergenceWarning
warnings.filterwarnings("ignore", category=ConvergenceWarning)

# Oversampling technique
from imblearn.over_sampling import SMOTE

# Random Forest
from sklearn.linear_model import LogisticRegression

import xgboost as xgb
```

```
from sklearn.model_selection import RandomizedSearchCV

# Additional packages
from pandas.api.types import is_numeric_dtype
from scipy.stats import randint as sp_randint


# Model Explanation
import shap
from sklearn.inspection import permutation_importance



import random
```

2.2. Load the Data

```
[36] # Read the data
     df_heart = pd.read_csv('/content/heart_failure_clinical_records_dataset.csv')
     print('No. of row: {}, no. of columns: {}'.format(df_heart.shape[0], df_heart.shape[1]))
```

```
No. of row: 299, no. of columns: 13
```

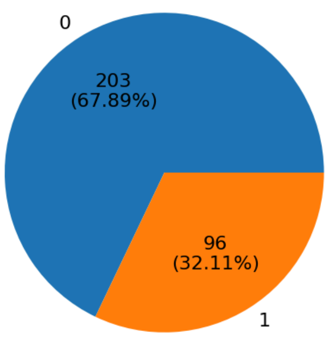
```
[37] # Basic information about the dataset
     df_heart.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   age                       299 non-null    float64
 1   anaemia                   299 non-null    int64  
 2   creatinine_phosphokinase  299 non-null    int64  
 3   diabetes                  299 non-null    int64  
 4   ejection_fraction         299 non-null    int64  
 5   high_blood_pressure       299 non-null    int64  
 6   platelets                 299 non-null    float64
 7   serum_creatinine          299 non-null    float64
 8   serum_sodium              299 non-null    int64  
 9   sex                       299 non-null    int64  
 10  smoking                   299 non-null    int64  
 11  time                      299 non-null    int64  
 12  DEATH_EVENT               299 non-null    int64  
dtypes: float64(3), int64(10)
memory usage: 30.5 KB
```

```
def auto_fmt (pct_value):
    return '{:.0f}\n({:.2f}%)'.format(df_heart['DEATH_EVENT'].value_counts().sum()*pct_value/100,pct_value)

df_death_count = df_heart['DEATH_EVENT'].value_counts().rename_axis('Death Event').reset_index(name='Case Count')

fig = plt.gcf()
fig.set_size_inches(6,6)
plt.pie(x=df_death_count['Case Count'], labels=df_death_count['Death Event'], autopct=auto_fmt, textprops={'fontsize': 16
plt.title('Distribution of Target Label (i.e. Death Event)',  fontsize = 16)
```

```
Text(0.5, 1.0, 'Distribution of Target Label (i.e. Death Event)')
```

Distribution of Target Label (i.e. Death Event)



3.2. Missing Value Handling / Replacement

```
] df_null_value = df_heart.isnull().sum().rename_axis('Feature').reset_index(name='No of Null Value')

# Check if there are features with null value
df_null_value[df_null_value['No of Null Value']>0]
```

Feature	No of Null Value

ervation: there is no missing value in the data set.

```
# Split the data into train and test data
y = df_heart['DEATH_EVENT']
X = df_heart.drop(['DEATH_EVENT'], axis = 1)

# Splitting 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)

print('No. of rows in X: {}, X_train: {}, and X_test: {}'.format(df_heart.shape[0], X_train.shape[0], X_test.shape[0]))
```

```
No. of rows in X: 299, X_train: 239, and X_test: 60
```

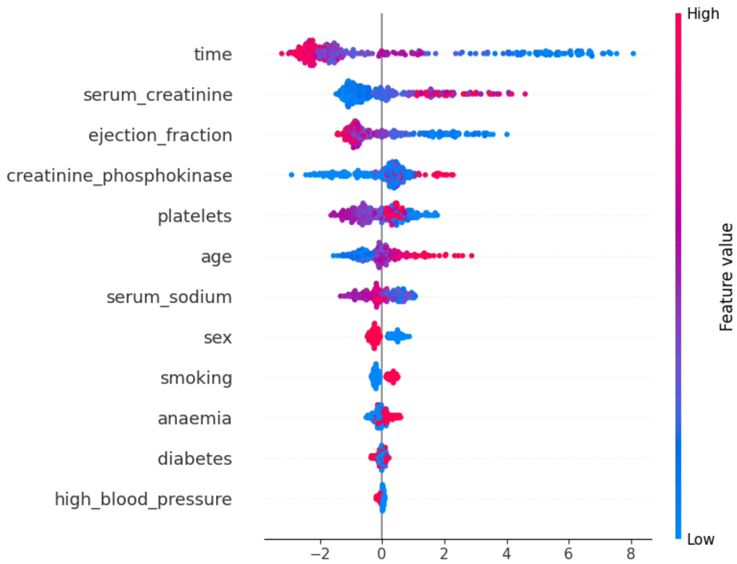
```
# XGBoost
model = xgb.XGBClassifier()
model.fit(X_train, y_train)
```

```
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

```
[48] # Prediction and accuracy score
y_pred = model.predict(X_test)
y_pred_prob = model.predict_proba(X_test)
print(metrics.classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.76      0.89      0.82        35
           1       0.79      0.60      0.68        25

    accuracy                           0.77        60
   macro avg       0.77      0.74      0.75        60
weighted avg       0.77      0.77      0.76        60
```

```
explainer = shap.Explainer(model, X)

# Calculate SHAP values for all instances
shap_values = explainer(X)

# Visualize global feature importance using summary plot
shap.summary_plot(shap_values, X)
```



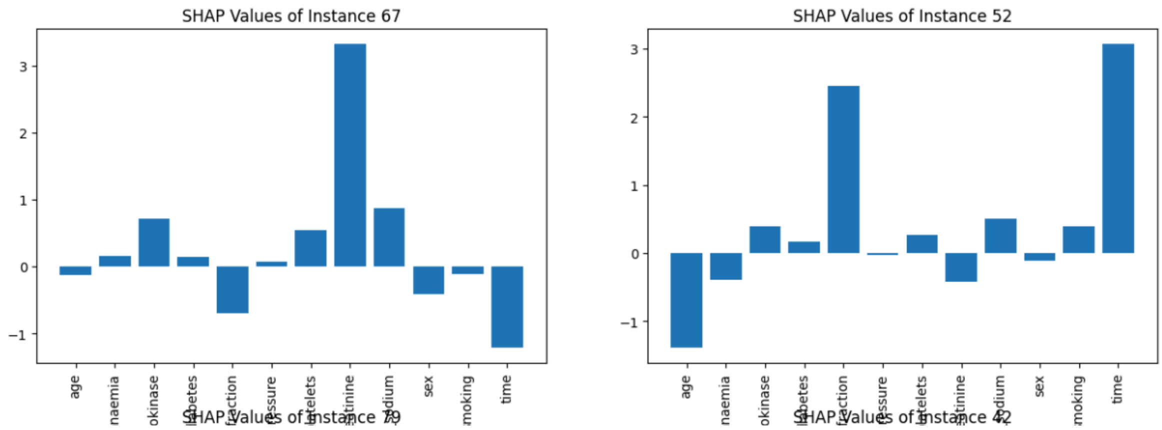
The Local Importance of SHAP exhibits what features are crucial factors in prediction.

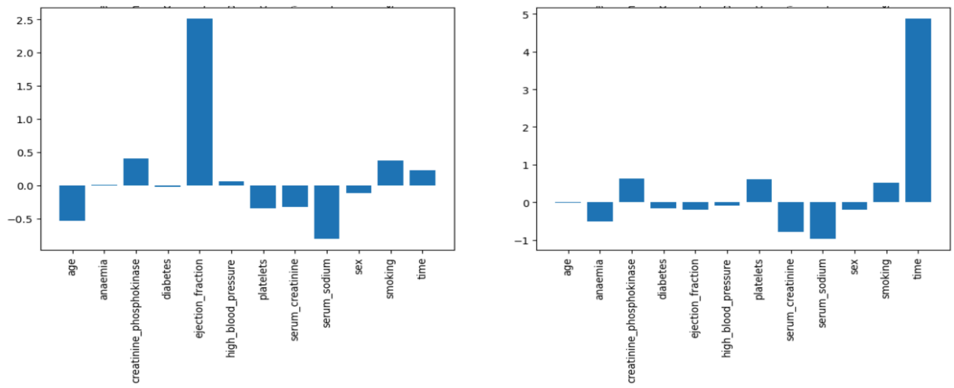
```
# The SHAP library provides TreeExplaier for all tree-based algorithms, like LGBM and XGBoost
explainer = shap.TreeExplainer(model)

# Output the shap values of individual instances in a array format
shap_values = explainer.shap_values(X)
```

```
[51] # Setup the dataframe for the Shap values
df_shap = pd.DataFrame(shap_values, columns=X_test.columns)
df_shap.head(5)
```

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	platelets	serum_creatinine	serum_sodium	sex	s
0	0.572182	-0.225883	0.747439	0.271055	1.530564	-0.060201	-0.363379	1.145880	0.622181	-0.180388	-0.
1	-0.194135	-0.317300	0.868684	0.249230	-0.007776	0.015902	-0.429873	-0.233223	0.437601	-0.209444	-0.
2	0.236991	-0.274458	0.557530	0.100305	1.533030	0.050292	0.445368	-0.082821	0.707721	-0.193354	0.
3	-0.550786	0.412682	-0.029820	0.159871	1.299968	0.018217	0.331563	1.137865	-1.032761	-0.167951	-0.
4	0.269116	0.277795	1.035377	-0.235638	1.349784	0.050292	0.040142	0.774017	0.574824	0.392428	-0.

```
[58] # Manually select some instances with high variance for illustration purpose
idx =[67, 52, 79, 42]

# Select the row corresponding to instance 0
instances = df_pred_shap_1.drop(['pred','index'], axis=1)
# print(instance)

# Create a bar chart of the feature values
fig, ax = plt.subplots(2, 2, figsize=(15,10))

# Create a bar chart in the first subplot

ax[0, 0].bar(instances.iloc[idx[0],:].index.tolist(), instances.iloc[idx[0],:].values.tolist())
ax[0, 1].bar(instances.iloc[idx[1],:].index.tolist(), instances.iloc[idx[1],:].values.tolist())
ax[1, 0].bar(instances.iloc[idx[2],:].index.tolist(), instances.iloc[idx[2],:].values.tolist())
ax[1, 1].bar(instances.iloc[idx[3],:].index.tolist(), instances.iloc[idx[3],:].values.tolist())

# ax.bar(instance.index, instance.values, ax[0][0])

# # Set labels and title
# ax.set_xlabel('Feature')
# ax.set_ylabel('Value')

# Set title for the first subplot
ax[0, 0].set_title('SHAP Values of Instance ' + str(idx[0]))
ax[0, 1].set_title('SHAP Values of Instance ' + str(idx[1]))
ax[1, 0].set_title('SHAP Values of Instance ' + str(idx[2]))
ax[1, 1].set_title('SHAP Values of Instance ' + str(idx[3]))

# Rotate x-axis labels if needed
# Rotate x-axis labels if needed
ax[0, 0].tick_params(axis='x', rotation=90)
ax[0, 1].tick_params(axis='x', rotation=90)
ax[1, 0].tick_params(axis='x', rotation=90)
ax[1, 1].tick_params(axis='x', rotation=90)

# Show the plot
plt.show()
```





Conclusion:

In this experiment, LIME and SHAP were utilized to interpret the predictions of a machine learning model trained on the Heart Failure Clinical Records Dataset. By focusing on critical attributes such as age, anaemia status, creatinine phosphokinase levels, diabetes presence, ejection fraction, high blood pressure, and platelet counts, we aimed to predict patient outcomes related to heart failure.

Applying LIME allowed us to generate local explanations for individual predictions, helping us understand which features most influenced the model's decisions on a case-by-case basis. SHAP provided both local and global interpretability by quantifying the contribution of each feature to the model's output across all instances.

The use of these interpretability techniques enhanced our understanding of the model's behavior, making its predictions more transparent and trustworthy. This is particularly important in the medical domain, where insights into feature importance can support clinicians in making informed decisions and potentially improve patient care by highlighting key risk factors associated with heart failure.

Experiment 7

Aim: Use AutoML and Hyperparameter tuning tools to automate the model selection and optimization process.

Theory:

AutoML (Automated Machine Learning) and hyperparameter tuning tools automate the selection and optimization of machine learning models by handling tasks like data preprocessing, model selection, and parameter tuning automatically. This reduces the need for manual experimentation and expertise, making the model development process faster and more efficient. By streamlining these steps, these tools make machine learning more accessible and enable practitioners to build high-performing models with less effort.

About the Dataset:

The dataset used in this experiment is the **Bike Sharing Demand Dataset**, which provides historical data of bike rentals in a city. It includes various attributes that can influence the demand for bike sharing, making it suitable for predictive modeling using AutoML and hyperparameter tuning tools.

Key Attributes:

- **datetime:** The date and time of each bike rental record.
- **season:** The season of the year (1: Spring, 2: Summer, 3: Fall, 4: Winter).
- **holiday:** Whether the day is a holiday (1) or not (0).
- **workingday:** Whether the day is a working day (1) or a weekend/holiday (0).
- **weather:** Categorical variable representing weather conditions (1: Clear, 2: Mist, 3: Light Snow/Rain, 4: Heavy Rain/Snow).
- **temp:** Temperature in degrees Celsius.
- **atemp:** "Feels like" temperature in degrees Celsius.
- **humidity:** The humidity level (%).
- **windspeed:** Wind speed.
- **casual:** Number of non-registered users who rented bikes.
- **registered:** Number of registered users who rented bikes.

- **count:** Total number of bike rentals (sum of casual and registered users).

Purpose in the Experiment:

In this experiment, we aim to predict the **count** of bike rentals based on the provided features. By utilizing AutoML and hyperparameter tuning tools, we automate the model selection and optimization process. This approach helps in efficiently identifying the best-performing model and optimal hyperparameters without extensive manual intervention, enhancing the predictive accuracy for bike-sharing demand.

Code:

```
import pandas as pd
from autogluon.tabular import TabularPredictor
```

```
# Create the train dataset in pandas by reading the csv
# Set the parsing of the datetime column so you can use some of the `dt` features in pandas later
train = pd.read_csv('train.csv')
train.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1

```
train.describe()
```

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177	191.574132
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033	181.144454
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000	1.000000
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000	42.000000
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000	145.000000
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000	284.000000
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000	977.000000

```
train['datetime']=pd.to_datetime(train['datetime'])
```

```
test['datetime']=pd.to_datetime(test['datetime'])
```

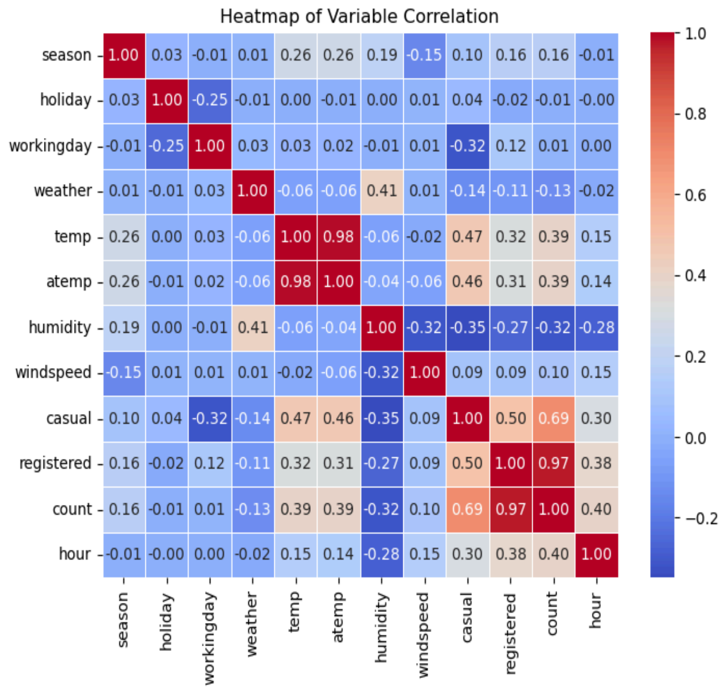
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  datetime64[ns]
 1   season      10886 non-null  int64
 2   holiday     10886 non-null  int64
 3   workingday  10886 non-null  int64
 4   weather     10886 non-null  int64
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
dtypes: datetime64[ns](1), float64(3), int64(8)
memory usage: 1020.7 KB
```

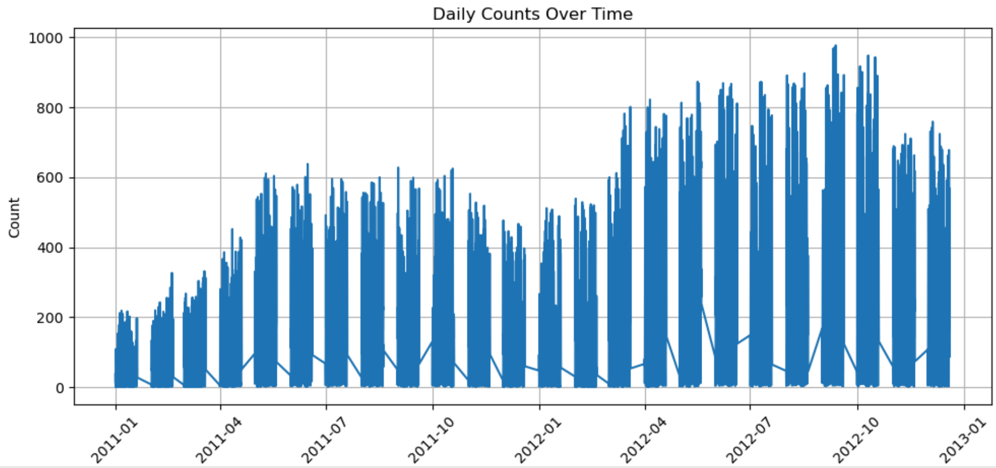
```
train['season'].value_counts()
```

```
season
4    2734
2    2733
3    2733
1    2686
Name: count, dtype: int64
```

```python
# Create a heatmap from the correlation matrix
plt.figure(figsize=(8, 6))  # Set figure size
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Heatmap of Variable Correlation')
plt.show()
```




```python
[ ] plt.figure(figsize=(10, 5))  # Set the figure size
    plt.plot(train['datetime'], train['count'])  # Line plot

    # Adding title and labels
    plt.title('Daily Counts Over Time')
    plt.xlabel('Date')
    plt.ylabel('Count')

    # Optional: Rotate date labels for better readability
    plt.xticks(rotation=45)

    plt.grid(True)  # Enable grid
    plt.tight_layout()  # Adjust layout
    plt.show()
```



```python
test_initial.drop(['temperature_category','wind_category','humidity_category','hour_category'],inplace=True,axis=1)
```

[ ]
```python
test_initial.drop(['datetime'],inplace=True,axis=1)
```

[ ]
```python
test_initial.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6493 entries, 0 to 6492
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   season      6493 non-null   int64
 1   holiday     6493 non-null   int64
 2   workingday  6493 non-null   int64
 3   weather     6493 non-null   int64
 4   temp        6493 non-null   float64
 5   atemp       6493 non-null   float64
 6   humidity    6493 non-null   int64
 7   windspeed   6493 non-null   float64
 8   hour        6493 non-null   int32
dtypes: float64(3), int32(1), int64(5)
memory usage: 431.3 KB
```

```python
predictor_initial = TabularPredictor(label="count",problem_type="regression", eval_metric="rmse", path="autogn_initial" ).fit(
    train_data=train_initial,
    time_limit=600,
    presets="best_quality",
)
```

```
Setting dynamic_stacking from 'auto' to True. Reason: Enable dynamic_stacking when use_bag_holdout is disabled. (use_bag_holdout=False)
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8, num_bag_sets=1
Dynamic stacking is enabled (dynamic_stacking=True). AutoGluon will try to determine whether the input data is affected by stacked overfitting and enable or
Detecting stacked overfitting by sub-fitting AutoGluon on the input data. That is, copies of AutoGluon will be sub-fit on subset(s) of the data. Then, the ho
Sub-fit(s) time limit is: 600 seconds.
Starting holdout-based sub-fit for dynamic stacking. Context path is: autogn_initial/ds_sub_fit/sub_fit_ho.
Running the sub-fit in a ray process to avoid memory leakage.
Spend 185 seconds for the sub-fit(s) during dynamic stacking.
Time left for full fit of AutoGluon: 415 seconds.
Starting full fit now with num_stack_levels 1.
Beginning AutoGluon training ... Time limit = 415s
AutoGluon will save models to "autogn_initial"
=================== System Info ===================
AutoGluon Version:  1.1.0
Python Version:     3.10.6
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Sat Mar 23 09:49:55 UTC 2024
CPU Count:          2
Memory Avail:       1.75 GB / 3.78 GB (46.4%)
Disk Space Avail:   8589934590.95 GB / 8589934592.00 GB (100.0%)
===================================================
Train Data Rows:    10886
Train Data Columns: 9
Label Column:       count
Problem Type:       regression
Preprocessing data ...
Using Feature Generators to preprocess the data ...
Fitting AutoMLPipelineFeatureGenerator...
	Available Memory:                    1796.31 MB
	Train Data (Original)  Memory Usage: 0.71 MB (0.0% of available memory)
	Inferring data type of each feature based on column values. Set feature_metadata_in to manually specify special dtypes of the features.
	Stage 1 Generators:
		Fitting AsTypeFeatureGenerator...
			Note: Converting 2 features to boolean dtype as they only contain 2 unique values.
```

```
	This metric's sign has been flipped to adhere to being higher_is_better. The metric score can be multiplied by -1 to get the metric value.
	To change this, specify the eval_metric parameter of Predictor()
Large model count detected (112 configs) ... Only displaying the first 3 models of each family. To see all, set `verbosity=3`.
User-specified model hyperparameters to be fit:
{
	'NN_TORCH': [{}, {'activation': 'elu', 'dropout_prob': 0.10077639529843717, 'hidden_size': 108, 'learning_rate': 0.002735937344002146, 'num_layers': 4, 'use_batchnorm': True, 'weigh
	'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {}, 'GBMLarge'],
	'CAT': [{}, {'depth': 6, 'grow_policy': 'SymmetricTree', 'l2_leaf_reg': 2.1542798306067823, 'learning_rate': 0.06864209415792857, 'max_ctr_complexity': 4, 'one_hot_max_size': 10, 'a
	'XGB': [{}, {'colsample_bytree': 0.6917311125174739, 'enable_categorical': False, 'learning_rate': 0.018063876087523967, 'max_depth': 10, 'min_child_weight': 0.6028633586934382, 'ag
	'FASTAI': [{}, {'bs': 256, 'emb_drop': 0.5411770367537934, 'epochs': 43, 'layers': [800, 400], 'lr': 0.01519848858318159, 'ps': 0.23782946566604385, 'ag_args': {'name_suffix': '_r19
	'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini', 'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args': {'name_suffix': 'Entr', 'problem_typ
	'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini', 'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args': {'name_suffix': 'Entr', 'problem_typ
	'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}}, {'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) ...
Fitting 108 L1 models ...
Fitting model: KNeighborsUnif_BAG_L1 ... Training model for up to 276.51s of the 414.85s of remaining time.
	-122.5866	 = Validation score   (-root_mean_squared_error)
	0.04s	 = Training   runtime
	0.15s	 = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 ... Training model for up to 276.13s of the 414.47s of remaining time.
	-121.2585	 = Validation score   (-root_mean_squared_error)
	0.03s	 = Training   runtime
	0.19s	 = Validation runtime
Fitting model: LightGBMXT_BAG_L1 ... Training model for up to 275.73s of the 414.07s of remaining time.
	Fitting 8 child models (S1F1 - S1F8) | Fitting with ParallelLocalFoldFittingStrategy (2 workers, per: cpus=1, gpus=0, memory=0.29%)
	-66.2518	 = Validation score   (-root_mean_squared_error)
	70.65s	 = Training   runtime
	9.53s	 = Validation runtime
Fitting model: LightGBM_BAG_L1 ... Training model for up to 199.64s of the 337.98s of remaining time.
	Fitting 8 child models (S1F1 - S1F8) | Fitting with ParallelLocalFoldFittingStrategy (2 workers, per: cpus=1, gpus=0, memory=0.27%)
	-65.8046	 = Validation score   (-root_mean_squared_error)
	35.06s	 = Training   runtime
	1.87s	 = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 ... Training model for up to 159.47s of the 297.81s of remaining time.
```

```python
predictor_initial.fit_summary()
```

```
*** Summary of fit() ***
Estimated performance of each model:
                    model   score_val              eval_metric  pred_time_val    fit_time  pred_time_val_marginal  fit_time_marginal  stack_level  can_infer  fit_order
0     WeightedEnsemble_L3  -63.791227  root_mean_squared_error      14.952847  388.283173                0.000643           0.073950            3       True         13
1     WeightedEnsemble_L2  -64.212527  root_mean_squared_error      12.399773  229.442281                0.000967           0.046374            2       True          9
2       LightGBMXT_BAG_L2  -64.638896  root_mean_squared_error      13.927373  314.147418                0.221060          28.679869            2       True         10
3   RandomForestMSE_BAG_L2  -64.792403  root_mean_squared_error      14.616765  331.471045                0.910452          46.003496            2       True         12
4         LightGBM_BAG_L2  -64.795766  root_mean_squared_error      13.820692  313.525858                0.114378          28.058309            2       True         11
5         CatBoost_BAG_L1  -64.809919  root_mean_squared_error       0.110232  111.449080                0.110232         111.449080            1       True          6
6         LightGBM_BAG_L1  -65.804640  root_mean_squared_error       1.867998   35.056170                1.867998          35.056170            1       True          4
7       LightGBMXT_BAG_L1  -66.251809  root_mean_squared_error       9.525338   70.645670                9.525338          70.645670            1       True          3
8     ExtraTreesMSE_BAG_L1  -68.985679  root_mean_squared_error       0.572249    5.049309                0.572249           5.049309            1       True          7
9   RandomForestMSE_BAG_L1  -69.488359  root_mean_squared_error       0.895238   12.244987                0.895238          12.244987            1       True          5
10  NeuralNetFastAI_BAG_L1 -119.209644  root_mean_squared_error       0.399650   50.944251                0.399650          50.944251            1       True          8
11   KNeighborsDist_BAG_L1 -121.258519  root_mean_squared_error       0.188376    0.034665                0.188376           0.034665            1       True          2
12   KNeighborsUnif_BAG_L1 -122.586594  root_mean_squared_error       0.147233    0.043417                0.147233           0.043417            1       True          1
Number of models trained: 13
Types of models trained:
{'WeightedEnsembleModel', 'StackerEnsembleModel_LGB', 'StackerEnsembleModel_NNFastAiTabular', 'StackerEnsembleModel_RF', 'StackerEnsembleModel_CatBoost', 'StackerEnsembleModel_KNN', 'Stack
Bagging used: True  (with 8 folds)
Multi-layer stack-ensembling used: True  (with 3 levels)
Feature Metadata (Processed):
(raw dtype, special dtypes):
('float', [])     : 3 | ['temp', 'atemp', 'windspeed']
('int', [])       : 4 | ['season', 'weather', 'humidity', 'hour']
('int', ['bool']) : 2 | ['holiday', 'workingday']
```

```python
train['hour']=train['datetime'].dt.hour
```

```python
test['hour']=test['datetime'].dt.hour
```

```python
bins = [0.82, 10, 30, 41]
labels = ['Cold', 'Mild', 'Hot']
train['temperature_category'] = pd.cut(train['temp'], bins=bins, labels=labels, include_lowest=True)
```

```python
train['temperature_category'].value_counts()
```

```
temperature_category
Mild    8383
Cold    1259
Hot     1244
Name: count, dtype: int64
```

```python
test['temperature_category'] = pd.cut(test['temp'], bins=bins, labels=labels, include_lowest=True)
```

```python
bins = [0, 25, max(train['windspeed']) + 1]
labels = ['Mild Wind', 'Very Windy']
train['wind_category'] = pd.cut(train['windspeed'], bins=bins, labels=labels, include_lowest=True, right=False)
```

```python
train['wind_category'].value_counts()
```

```
wind_category
Mild Wind     10037
Very Windy      849
Name: count, dtype: int64
```

Feature Encoding

```python
train_modified = pd.get_dummies(train, columns=['temperature_category', 'wind_category', 'humidity_category','hour_category','weather','season'],dtype=int)
```

```python
test_modified = pd.get_dummies(test, columns=['temperature_category', 'wind_category', 'humidity_category','hour_category','weather','season'],dtype=int)
```

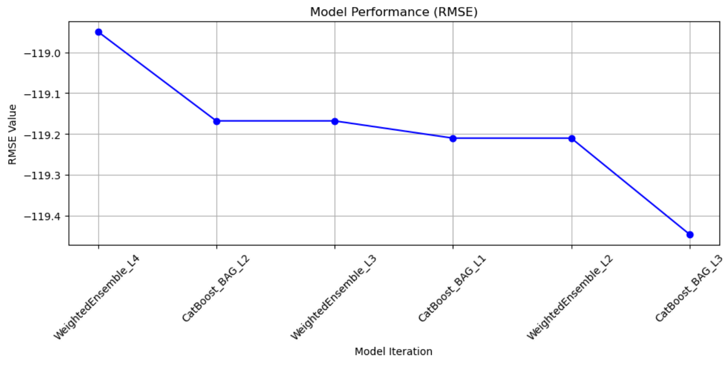
```python
hyperparameters = {
    'CAT': {
        'learning_rate': 0.01,
        'depth': 6,
        'l2_leaf_reg': 3.5
    }
}

predictor_hp = TabularPredictor(
    label='count',
    eval_metric='rmse',
    path='autogluon_hparameter'
).fit(
    train_data=train_hp,
    time_limit=900,  # Increase time limit for more thorough search
    presets='best_quality',
    hyperparameters=hyperparameters,
    num_stack_levels=2
)
```

```
Presets specified: ['best_quality']
Setting dynamic_stacking from 'auto' to True. Reason: Enable dynamic_stacking when use_bag_holdout is disabled. (use_bag_holdout=False)
Stack configuration (auto_stack=True): num_stack_levels=2, num_bag_folds=8, num_bag_sets=1
Dynamic stacking is enabled (dynamic_stacking=True). AutoGluon will try to determine whether the input data is affected by stacked overfitting and enable or disal
Detecting stacked overfitting by sub-fitting AutoGluon on the input data. That is, copies of AutoGluon will be sub-fit on subset(s) of the data. Then, the holdou
Sub-fit(s) time limit is: 900 seconds.
Starting holdout-based sub-fit for dynamic stacking. Context path is: autogluon_hparameter/ds_sub_fit/sub_fit_ho.
Running the sub-fit in a ray process to avoid memory leakage.
Spend 206 seconds for the sub-fit(s) during dynamic stacking.
Time left for full fit of AutoGluon: 694 seconds.
Starting full fit now with num_stack_levels 2.
Beginning AutoGluon training ... Time limit = 694s
AutoGluon will save models to "autogluon_hparameter"
=================== System Info ===================
AutoGluon Version:  1.1.0
Python Version:     3.10.6
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Sat Mar 23 09:49:55 UTC 2024
CPU Count:          2
Memory Avail:       1.46 GB / 3.78 GB (38.7%)
Disk Space Avail:   8589934590.03 GB / 8589934592.00 GB (100.0%)
===================================================
Train Data Rows:    10886
Train Data Columns: 21
Label Column:       count
Problem Type:       regression
Preprocessing data ...
Using Feature Generators to preprocess the data ...
Fitting AutoMLPipelineFeatureGenerator...
        Available Memory:                    1500.76 MB
        Train Data (Original)  Memory Usage: 1.74 MB (0.1% of available memory)
        Inferring data type of each feature based on column values. Set feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator...
                        Note: Converting 21 features to boolean dtype as they only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator...
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator...
        Stage 4 Generators:
```

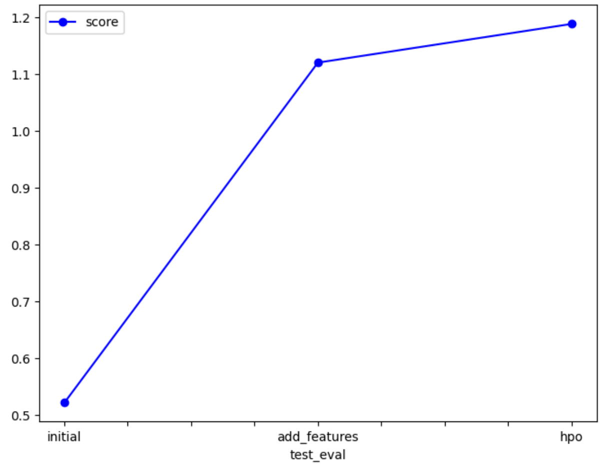
```python
predictor_hp.fit_summary()
```

```
*** Summary of fit() ***
Estimated performance of each model:
                 model   score_val              eval_metric  pred_time_val    fit_time  pred_time_val_marginal  fit_time_marginal  stack_level  can_infer  fit_order
0  WeightedEnsemble_L4 -118.949610  root_mean_squared_error       0.292041  327.764742                0.000942           0.035887            4       True          6
1      CatBoost_BAG_L2 -119.168055  root_mean_squared_error       0.214563  223.589094                0.100901         131.843144            2       True          3
2  WeightedEnsemble_L3 -119.168055  root_mean_squared_error       0.215782  223.592863                0.001219           0.003770            3       True          4
3      CatBoost_BAG_L1 -119.210271  root_mean_squared_error       0.113662   91.745949                0.113662          91.745949            1       True          1
4  WeightedEnsemble_L2 -119.210271  root_mean_squared_error       0.114740   91.763711                0.001079           0.017762            2       True          2
5      CatBoost_BAG_L3 -119.445852  root_mean_squared_error       0.291099  327.728855                0.076536         104.139761            3       True          5
Number of models trained: 6
Types of models trained:
{'StackerEnsembleModel_CatBoost', 'WeightedEnsembleModel'}
Bagging used: True  (with 8 folds)
Multi-layer stack-ensembling used: True  (with 4 levels)
Feature Metadata (Processed):
(raw dtype, special dtypes):
('int', ['bool']) : 21 | ['holiday', 'workingday', 'temperature_category_Cold', 'temperature_category_Mild', 'temperature_category_Hot', ...]
Plot summary of models saved to file: autogluon_hparameterSummaryOfModels.html
*** End of fit() summary ***
{'model_types': {'CatBoost_BAG_L1': 'StackerEnsembleModel_CatBoost',
```

```python
plt.figure(figsize=(10, 5))
plt.plot(model_names, rmse_values, marker='o', linestyle='-', color='b')
plt.title('Model Performance (RMSE)')
plt.xlabel('Model Iteration')
plt.ylabel('RMSE Value')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



```
# Take the 3 scores and creating a line plot to show improvement
fig = pd.DataFrame(
    {
        "test_eval": ["initial", "add_features", "hpo"],
        "score": [0.52082, 1.12001, 1.18811]
    }
).plot(x="test_eval", y="score", figsize=(8, 6),marker='o', linestyle='-', color='b').get_figure()
fig.savefig('model_test_score.png')
```



Conclusion:

In this experiment, we applied AutoML and hyperparameter tuning tools to automate the model selection and optimization process for predicting bike-sharing demand using the Bike Sharing Demand dataset. The dataset included features such as datetime, season, holiday, working day indicator, weather conditions, temperature, humidity, wind speed, and counts of casual and registered users.

By leveraging AutoML, we were able to automatically explore a wide range of machine learning algorithms and preprocessing techniques without manual intervention. The hyperparameter tuning tools further refined the models by systematically searching for the optimal hyperparameters that maximize predictive performance.

Experiment 8

Aim: Analyse time series data, perform forecasting, and evaluate model performance.

Theory:

Analysing time series data involves studying datasets where observations are collected over time intervals to identify inherent patterns such as trends, seasonality, and cyclic behaviour. The objective is to model these patterns to forecast future values accurately. Forecasting methods like ARIMA (Autoregressive Integrated Moving Average), exponential smoothing, and machine learning models such as LSTM (Long Short-Term Memory) networks are commonly used to predict future data points based on historical information. Evaluating the performance of these forecasting models is crucial and is typically done using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). Time series cross-validation techniques, which respect the temporal order of data, are also employed to assess a model's predictive ability on unseen data. By thoroughly analyzing the time-dependent patterns, applying suitable forecasting methods, and rigorously evaluating model performance, we can develop reliable models that aid in making informed decisions based on future projections.

About the Dataset:

The dataset used in this experiment consists of historical daily stock data for **ARCH Capital Group Ltd. (ACGL)**. It includes high-quality financial data such as Date, Open, High, Low, Close, Volume, and Open Interest, adjusted for dividends and splits to ensure accuracy. The data spans up to November 10, 2017, providing a robust time series for analysing trends, performing forecasting, and evaluating model performance on ARCH Capital Group's stock.

Dataset Attributes:

- **Date:** The specific trading day for each record.
- **Open:** The price at which Tesla stock opened on a given day.
- **High:** The highest trading price reached during that day.
- **Low:** The lowest trading price reached during that day.

- **Close:** The final trading price at market close for that day.
- **Volume:** The total number of Tesla shares traded during the day.
- **OpenInt (Open Interest):** The number of outstanding derivative contracts (like options or futures) that are active but not yet settled.

Code:

```
dateparse = lambda dates: pd.datetime.strptime(dates, '%Y-%m-%d')
stock_data = pd.read_csv('../input/price-volume-data-for-all-us-stocks-etfs/Stocks/acgl.us.txt',sep=',', index_col='Date', parse_dates=['Date'], date_parser=dateparse).fillna(0)
```

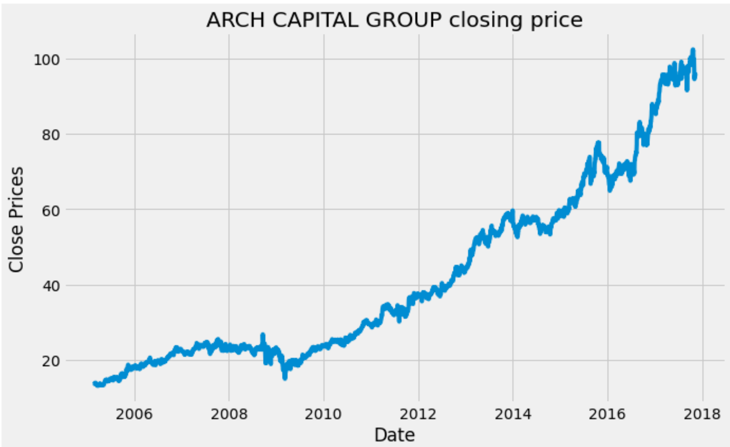
```
stock_data
```

Date	Open	High	Low	Close	Volume	OpenInt
2005-02-25	13.583	13.693	13.430	13.693	156240	0
2005-02-28	13.697	13.827	13.540	13.827	370509	0
2005-03-01	13.780	13.913	13.720	13.760	224484	0
2005-03-02	13.717	13.823	13.667	13.810	286431	0
2005-03-03	13.783	13.783	13.587	13.630	193824	0
...	...	...	...	...	...	...
2017-11-06	94.490	95.650	94.020	95.550	420192	0
2017-11-07	95.860	95.950	95.200	95.560	464011	0
2017-11-08	95.410	95.900	94.890	95.450	471756	0
2017-11-09	94.930	96.140	94.470	95.910	353498	0
2017-11-10	95.890	95.990	94.390	95.350	452833	0

3201 rows × 6 columns

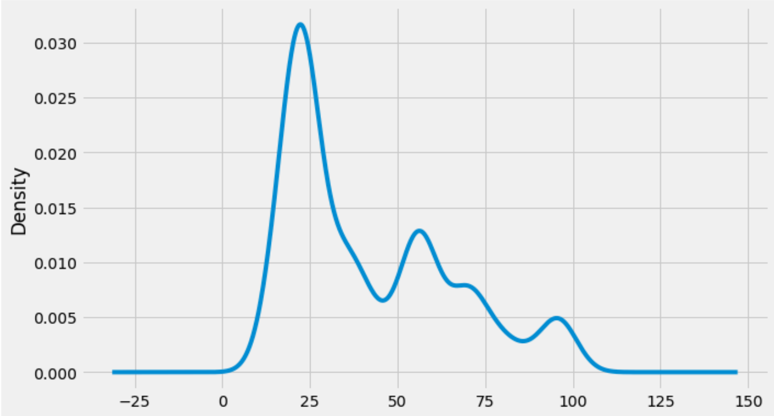
Visualize the per day closing price of the stock.

```
#plot close price
plt.figure(figsize=(10,6))
plt.grid(True)
plt.xlabel('Date')
plt.ylabel('Close Prices')
plt.plot(stock_data['Close'])
plt.title('ARCH CAPITAL GROUP closing price')
plt.show()
```

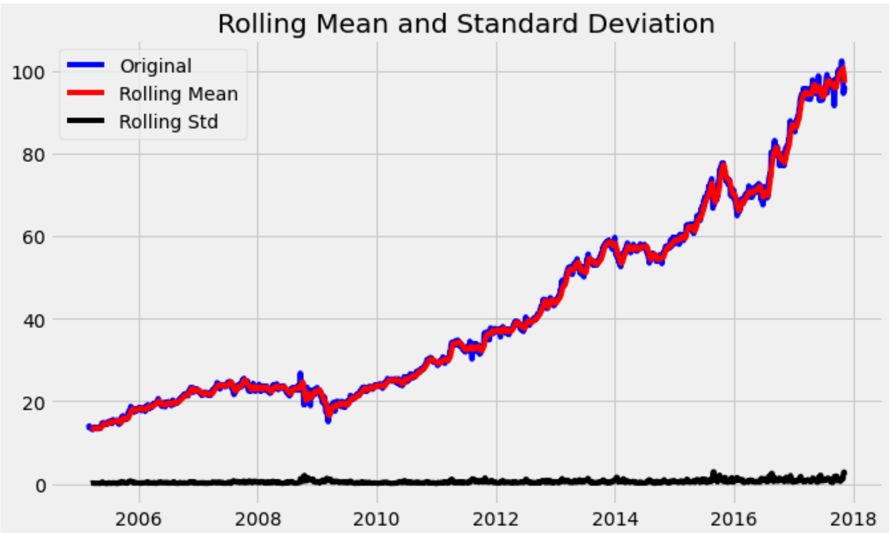


```
#Distribution of the dataset
df_close.plot(kind='kde')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbb8a0b7a10>
```



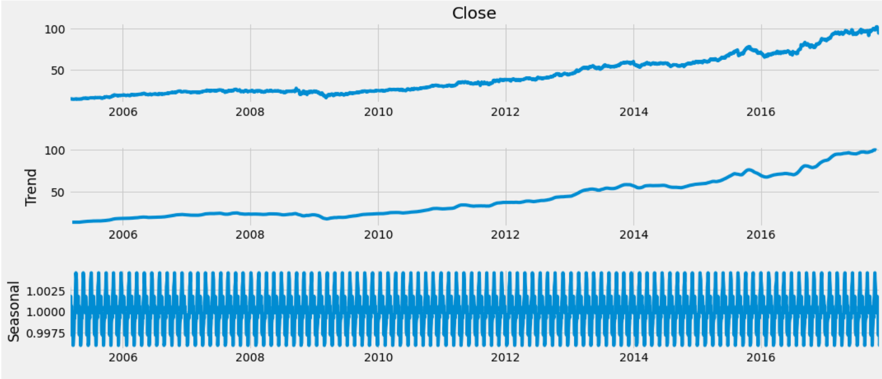

```
#Test for staionarity
def test_stationarity(timeseries):
    #Determing rolling statistics
    rolmean = timeseries.rolling(12).mean()
    rolstd = timeseries.rolling(12).std()
    #Plot rolling statistics:
    plt.plot(timeseries, color='blue',label='Original')
    plt.plot(rolmean, color='red', label='Rolling Mean')
    plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean and Standard Deviation')
    plt.show(block=False)

    print("Results of dickey fuller test")
    adft = adfuller(timeseries,autolag='AIC')
    # output for dft will give us without defining what the values are.
    #hence we manually write what values does it explains using a for loop
    output = pd.Series(adft[0:4],index=['Test Statistics','p-value','No. of lags used','Number of observations used'])
    for key,values in adft[4].items():
        output['critical value (%s)'%key] =  values
    print(output)

test_stationarity(df_close)
```



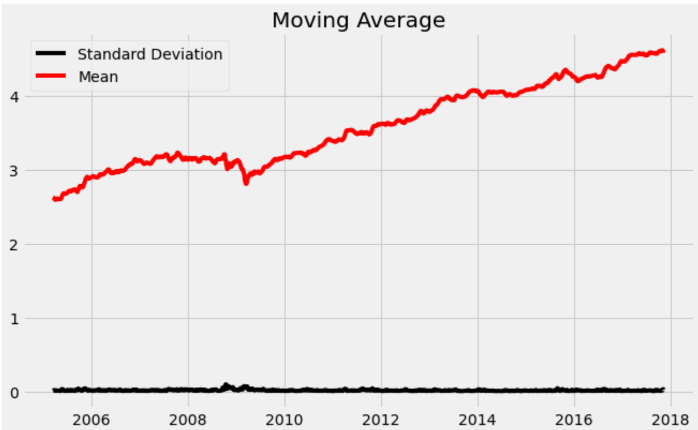

```
Results of dickey fuller test
Test Statistics                   1.374899
p-value                           0.996997
No. of lags used                  5.000000
Number of observations used    3195.000000
critical value (1%)              -3.432398
critical value (5%)              -2.862445
critical value (10%)             -2.567252
dtype: float64
```

```
#To separate the trend and the seasonality from a time series,
# we can decompose the series using the following code.
result = seasonal_decompose(df_close, model='multiplicative', freq = 30)
fig = plt.figure()
fig = result.plot()
fig.set_size_inches(16, 9)
```

```
<Figure size 720x432 with 0 Axes>
```

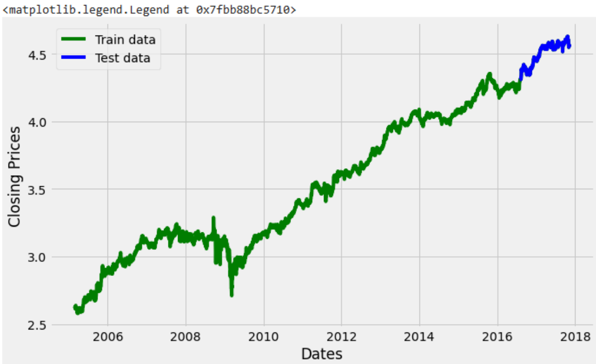



```
#if not stationary then eliminate trend
#Eliminate trend
from pylab import rcParams
rcParams['figure.figsize'] = 10, 6
df_log = np.log(df_close)
moving_avg = df_log.rolling(12).mean()
std_dev = df_log.rolling(12).std()
plt.legend(loc='best')
plt.title('Moving Average')
plt.plot(std_dev, color ="black", label = "Standard Deviation")
plt.plot(moving_avg, color="red", label = "Mean")
plt.legend()
plt.show()
```




```
#split data into train and training set
train_data, test_data = df_log[3:int(len(df_log)*0.9)], df_log[int(len(df_log)*0.9):]
plt.figure(figsize=(10,6))
plt.grid(True)
plt.xlabel('Dates')
plt.ylabel('Closing Prices')
plt.plot(df_log, 'green', label='Train data')
plt.plot(test_data, 'blue', label='Test data')
plt.legend()
```

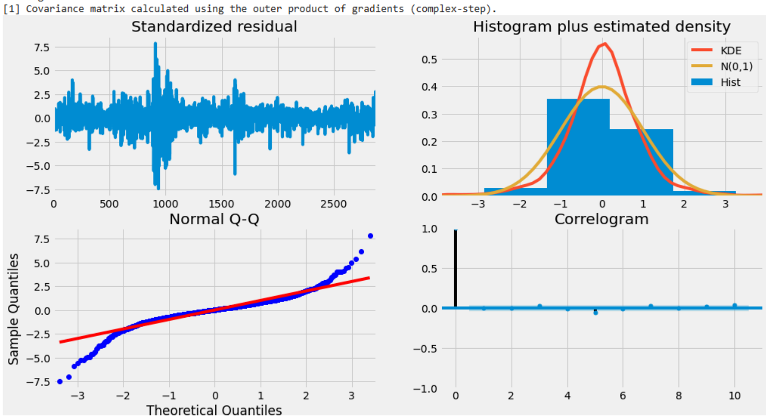
```
<matplotlib.legend.Legend at 0x7fbb88bc5710>
```



```python
model_autoARIMA = auto_arima(train_data, start_p=0, start_q=0,
                      test='adf',       # use adftest to find optimal 'd'
                      max_p=3, max_q=3, # maximum p and q
                      m=1,              # frequency of series
                      d=None,           # let model determine 'd'
                      seasonal=False,   # No Seasonality
                      start_P=0,
                      D=0,
                      trace=True,
                      error_action='ignore',
                      suppress_warnings=True,
                      stepwise=True)
print(model_autoARIMA.summary())
model_autoARIMA.plot_diagnostics(figsize=(15,8))
plt.show()
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=-16491.508, Time=0.61 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=-16525.992, Time=0.36 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=-16527.964, Time=0.80 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=-16488.323, Time=0.20 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=-16527.157, Time=1.72 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=-16527.120, Time=2.20 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=-16528.810, Time=2.70 sec
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=inf, Time=3.13 sec
 ARIMA(1,1,3)(0,0,0)[0] intercept   : AIC=-16526.020, Time=2.97 sec
 ARIMA(0,1,3)(0,0,0)[0] intercept   : AIC=-16524.974, Time=1.44 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=-16525.435, Time=1.07 sec
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=-16516.417, Time=0.79 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=-16527.597, Time=0.56 sec

Best model:  ARIMA(1,1,2)(0,0,0)[0] intercept
Total fit time: 18.588 seconds
```

```
ar.L1          0.9538      0.009    104.140      0.000       0.936       0.972
ma.L1         -1.0708      0.015    -73.566      0.000      -1.099      -1.042
ma.L2          0.0877      0.012      7.504      0.000       0.065       0.111
sigma2         0.0002   2.32e-06     80.805      0.000       0.000       0.000
===================================================================================
Ljung-Box (Q):                      121.70   Jarque-Bera (JB):              7207.33
Prob(Q):                              0.00   Prob(JB):                         0.00
Heteroskedasticity (H):               0.30   Skew:                            -0.39
Prob(H) (two-sided):                  0.00   Kurtosis:                        10.72
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```



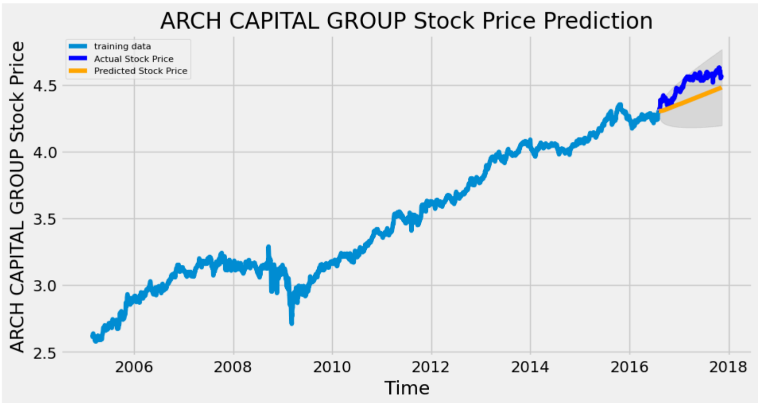

```python
#Modeling
# Build Model
model = ARIMA(train_data, order=(1,1,2))
fitted = model.fit(disp=-1)
print(fitted.summary())
```

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                D.Close   No. Observations:                 2876
Model:                 ARIMA(1, 1, 2)   Log Likelihood                8274.158
Method:                       css-mle   S.D. of innovations              0.014
Date:                Sat, 02 Jan 2021   AIC                         -16538.316
Time:                        17:18:23   BIC                         -16508.496
Sample:                             1   HQIC                        -16527.567

=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
const             0.0006      0.000      3.935      0.000       0.000       0.001
ar.L1.D.Close     0.9145      0.040     22.745      0.000       0.836       0.993
ma.L1.D.Close    -1.0351      0.045    -23.131      0.000      -1.123      -0.947
ma.L2.D.Close     0.0848      0.022      3.820      0.000       0.041       0.128
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.0934           +0.0000j            1.0934            0.0000
MA.1            1.0578           +0.0000j            1.0578            0.0000
MA.2           11.1422           +0.0000j           11.1422            0.0000
-----------------------------------------------------------------------------
```

```
# Forecast
fc, se, conf = fitted.forecast(321, alpha=0.05)  # 95% conf
```

Plot the results

```
# Make as pandas series
fc_series = pd.Series(fc, index=test_data.index)
lower_series = pd.Series(conf[:, 0], index=test_data.index)
upper_series = pd.Series(conf[:, 1], index=test_data.index)
# Plot
plt.figure(figsize=(10,5), dpi=100)
plt.plot(train_data, label='training data')
plt.plot(test_data, color = 'blue', label='Actual Stock Price')
plt.plot(fc_series, color = 'orange',label='Predicted Stock Price')
plt.fill_between(lower_series.index, lower_series, upper_series,
                 color='k', alpha=.10)
plt.title('ARCH CAPITAL GROUP Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('ARCH CAPITAL GROUP Stock Price')
plt.legend(loc='upper left', fontsize=8)
plt.show()
```




```
# report performance
mse = mean_squared_error(test_data, fc)
print('MSE: '+str(mse))
mae = mean_absolute_error(test_data, fc)
print('MAE: '+str(mae))
rmse = math.sqrt(mean_squared_error(test_data, fc))
print('RMSE: '+str(rmse))
mape = np.mean(np.abs(fc - test_data)/np.abs(test_data))
print('MAPE: '+str(mape))
```

```
MSE: 0.015076667773963886
MAE: 0.11501014942484208
RMSE: 0.12278708309086867
MAPE: 0.025397498886820967
```

Conclusion:

In this experiment, we analyzed time series data of ARCH Capital Group's stock to perform forecasting and evaluate model performance. Using historical daily data—including open, high, low, close prices, and trading volume—we applied time series forecasting models to predict future stock prices.

The results demonstrated that our models were able to capture general trends and provided reasonably accurate forecasts for ARCH Capital Group's stock prices. However, due to the inherent volatility of financial markets and external factors influencing stock performance, there were limitations in the predictive accuracy.

Experiment 9

Aim: Implement a CNN Model on imaging dataset.

Theory:

Convolutional Neural Networks (CNNs) are deep learning models specialized for processing grid-like data such as images. Implementing a CNN on an imaging dataset involves building a network that automatically learns hierarchical feature representations directly from the raw pixel data. Key components include convolutional layers that apply learnable filters to extract features like edges and textures, activation functions like ReLU to introduce non-linearity, pooling layers to reduce spatial dimensions and control overfitting, and fully connected layers for classification based on the extracted features. The model is trained using backpropagation and optimization algorithms like Stochastic Gradient Descent (SGD) or Adam to minimize a loss function such as cross-entropy. Proper data preparation, including normalization and data augmentation, enhances model performance. By learning relevant features automatically, CNNs are highly effective for tasks like image classification and recognition on imaging datasets.

About the Dataset:

The MNIST dataset is a classic benchmark in machine learning, consisting of grayscale images of handwritten digits from 0 to 9.

- **Total Images:** 70,000 (60,000 for training and 10,000 for testing).
- **Image Size:** Each image is 28x28 pixels.
- **Classes:** 10 classes corresponding to the digits 0 through 9.
- **Pixel Values:** Intensities range from 0 (black) to 255 (white).

MNIST for CNN Implementation:

- **Simplicity:** Its standardized and manageable size makes it ideal for experimenting with Convolutional Neural Networks.
- **Benchmarking:** Serves as a standard dataset for evaluating and comparing models.

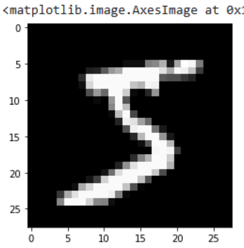
- **Learning Complexity:** Despite its simplicity, the variation in handwriting styles provides enough complexity for models to learn meaningful patterns.

Using MNIST allows you to implement a CNN model to classify handwritten digits effectively

Code:

Load train and test datasets

```
[ ] from keras.datasets import mnist
```
```
Using TensorFlow backend.
```
```
[ ] (train_images, train_labels), (test_images, test_labels) = mnist.load_data()
```
```
[ ] train_images.shape
```
```
(60000, 28, 28)
```
```
[ ] train_labels.shape
```
```
(60000,)
```
```
[ ] test_images.shape
```
```
(10000, 28, 28)
```
```
[ ] test_labels.shape
```
```
(10000,)
```
```
[ ] import matplotlib.pyplot as plt
```
```
[ ] # running this once shows the plts in gray scale as default
    # https://stackoverflow.com/questions/3823752/display-image-as-grayscale-using-matplotlib
    plt.gray()
```
```
<Figure size 432x288 with 0 Axes>
```
```
# if we do run the plt.gray() ... below code would have shown a color image
plt.imshow(train_images[0])
```
```
<matplotlib.image.AxesImage at 0x13528bbde10>
```



```
[ ] from keras import layers
```

```
[ ] model_cnn = models.Sequential()
```

Layer Details:

- 2 dimensional Convolution Layer
- Number of filters/kernels = 32
- Filter/Kernel Size = 3x3
- Activation Function = relu (for non-linearity detection)
- Input Shape = 28x28 matrix with 1 channel (as image is gray scale, we have only 1 channel)

```
[ ] model_cnn.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)))
```

Layer Details:

- Downsample the output from previous layer
- We will take the max value for a every 2x2 window ... moved over the input

```
[ ] model_cnn.add(layers.MaxPooling2D(2,2))
```

Layer Details:

- 2 dimensional Convolution Layer
- Number of filters/kernels = 64
- Filter/Kernel Size = 3x3
- Activation Function = relu (for non-linearity detection)

```
[ ] model_cnn.add(layers.Conv2D(64, (3,3), activation = 'relu'))
```

```
[ ] model_cnn.add(layers.Dense(64, activation = 'relu'))
```

This is the final layer. Hence, the outputs will be 10 corresponding to the 10 digits (0 to 9). Activation Function chosen here is sof
probabilistic output.

```
[ ] model_cnn.add(layers.Dense(10, activation = 'softmax'))
```

```
model_cnn.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 11, 11, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 3, 3, 64)          36928
_________________________________________________________________
flatten_1 (Flatten)          (None, 576)               0
_________________________________________________________________
dense_3 (Dense)              (None, 64)                36928
_________________________________________________________________
dense_4 (Dense)              (None, 10)                650
=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
```

```
[ ] train_images_cnn = train_images_cnn.astype('float32') / 255
```

```
[ ] test_images_cnn = test_images.reshape(10000, 28, 28, 1)
```

```
[ ] test_images_cnn = test_images_cnn.astype('float32') / 255
```

```
from keras.utils import to_categorical
```

```
[ ] train_labels_cnn = to_categorical(train_labels)
```

```
[ ] test_labels_cnn = to_categorical(test_labels)
```

```
[ ] model_cnn.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
```

Train the Model

We will now train the model using train images and train labels.

- We will use a batch size = 60.
- 1 epoch = 60000 / 60 = 1000 batches
- 1 epoch = 1 complete run of all train samples for training the model
- We will go for a total of 5 epochs = 5 complete run of the all train samples

```
[ ] model_cnn.fit(train_images_cnn, train_labels_cnn, epochs = 5, batch_size = 60)

Epoch 1/5
60000/60000 [==============================] - 38s 636us/step - loss: 0.1731 - accuracy: 0.9459
Epoch 2/5
60000/60000 [==============================] - 38s 639us/step - loss: 0.0477 - accuracy: 0.9853
Epoch 3/5
60000/60000 [==============================] - 39s 647us/step - loss: 0.0327 - accuracy: 0.9898
Epoch 4/5
60000/60000 [==============================] - 40s 665us/step - loss: 0.0243 - accuracy: 0.9925
Epoch 5/5
60000/60000 [==============================] - 39s 645us/step - loss: 0.0198 - accuracy: 0.9941
<keras.callbacks.callbacks.History at 0x1352a775c18>
```

```
[ ] test_loss_cnn, test_acc_cnn = model_cnn.evaluate(test_images_cnn, test_labels_cnn)

10000/10000 [==============================] - 2s 181us/step
```

```
[ ] print('test accuracy:', (test_acc_cnn*100))

test accuracy: 99.26999807357788
```

Conclusion:

In this experiment, we implemented a Convolutional Neural Network (CNN) to classify handwritten digits using the MNIST dataset. The CNN successfully learned the features of the images and achieved high accuracy on the test set. This demonstrates the effectiveness of CNNs in image recognition tasks and their ability to automatically extract relevant features from raw image data.

Experiment 10

Aim: Implement a model using LSTM to show sequence predictions.

Theory:

Long Short-Term Memory (LSTM) networks are specialized recurrent neural networks (RNNs) designed to model sequential data by capturing long-term dependencies. They achieve this by using memory cells and gating mechanisms (input, output, and forget gates) that regulate the flow of information, allowing the network to retain or discard information over time. This structure effectively addresses the vanishing gradient problem faced by traditional RNNs. In sequence prediction tasks, LSTMs process input sequences one element at a time, updating their internal states and making predictions based on both recent inputs and long-range contextual information. They are trained using backpropagation through time and are highly effective for tasks like time series forecasting, language modeling, and speech recognition.

About the Dataset:

The dataset used in this experiment consists of historical daily stock data for Tesla, Inc. (TSLA), providing a rich source of information for time series analysis and sequence prediction using an LSTM model. This high-quality financial dataset includes comprehensive trading data from the New York Stock Exchange (NYSE), NASDAQ, and NYSE MKT, with prices adjusted for dividends and stock splits to ensure accuracy.

Dataset Attributes:

- **Date:** The specific trading day for each record.
- **Open:** The price at which Tesla stock opened on a given day.
- **High:** The highest trading price reached during that day.
- **Low:** The lowest trading price reached during that day.
- **Close:** The final trading price at market close for that day.
- **Volume:** The total number of Tesla shares traded during the day.

- **OpenInt (Open Interest):** The number of outstanding derivative contracts (like options or futures) that are active but not yet settled.

By focusing exclusively on Tesla's stock data, the experiment leverages the company's historical price and volume information to train the LSTM model. This allows for the modelling of temporal patterns and trends inherent in the stock market data, aiming to predict future stock prices based on past performance. The dataset's granularity and quality make it well-suited for sequence prediction tasks, providing the necessary features to capture the complex dynamics of financial time series.

Code:

```python
# Import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os

from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM
```

```python
# Tesla stock: TSLA
company = 'Tesla'
stock_data = pd.read_csv('/kaggle/input/price-volume-data-for-all-us-stocks-etfs/Stocks/tsla.us.txt', parse_dates=['Date'], sep=',', index_col='Date')
```

```python
stock_data
```

Date	Open	High	Low	Close	Volume	OpenInt
2010-06-28	17.00	17.00	17.00	17.00	0	0
2010-06-29	19.00	25.00	17.54	23.89	18783276	0
2010-06-30	25.79	30.42	23.30	23.83	17194394	0
2010-07-01	25.00	25.92	20.27	21.96	8229863	0
2010-07-02	23.00	23.10	18.71	19.20	5141807	0
...	...	...	...	...	...	...
2017-11-06	307.00	307.50	299.01	302.78	6482486	0
2017-11-07	301.02	306.50	300.03	306.05	5286320	0
2017-11-08	305.50	306.89	301.30	304.31	4725510	0
2017-11-09	302.50	304.46	296.30	302.99	5440335	0
2017-11-10	302.50	308.36	301.85	302.99	4621912	0

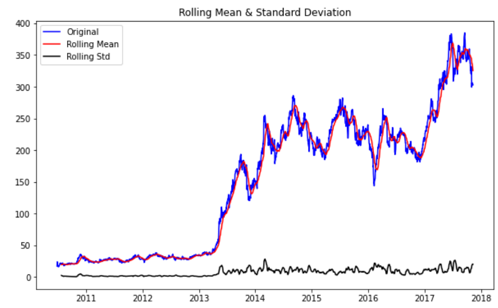
1858 rows × 6 columns

```python
# Plot closing prices
df_close = stock_data['Close']

plt.figure(figsize=(10,6))
plt.grid()
plt.plot(df_close)
plt.xlabel('Date')
plt.ylabel('Closing Prices')
plt.title('Tesla stock closing price')
```

```
Text(0.5, 1.0, 'Tesla stock closing price')
```

```
[ ] def test_stationarity(timeseries):
        '''
        Input: timeseries (dataframe): timeseries for which we want to study the stationarity
        '''

        #Determing rolling statistics
        rolmean = timeseries.rolling(20).mean()
        rolstd = timeseries.rolling(20).std()

        #Plot rolling statistics:
        orig = plt.plot(timeseries, color='blue',label='Original')
        mean = plt.plot(rolmean, color='red', label='Rolling Mean')
        std = plt.plot(rolstd, color='black', label = 'Rolling Std')
        plt.legend(loc='best')
        plt.title('Rolling Mean & Standard Deviation')
        plt.show(block=False)

        #Perform Dickey-Fuller test:
        print('Results of Dickey-Fuller Test:')
        dftest = adfuller(timeseries, autolag='AIC')
        dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value',\
                                                 '#Lags Used','Number of Observations Used'])
        for key,value in dftest[4].items():
            dfoutput['Critical Value (%s)'%key] = value
        print(dfoutput)
```

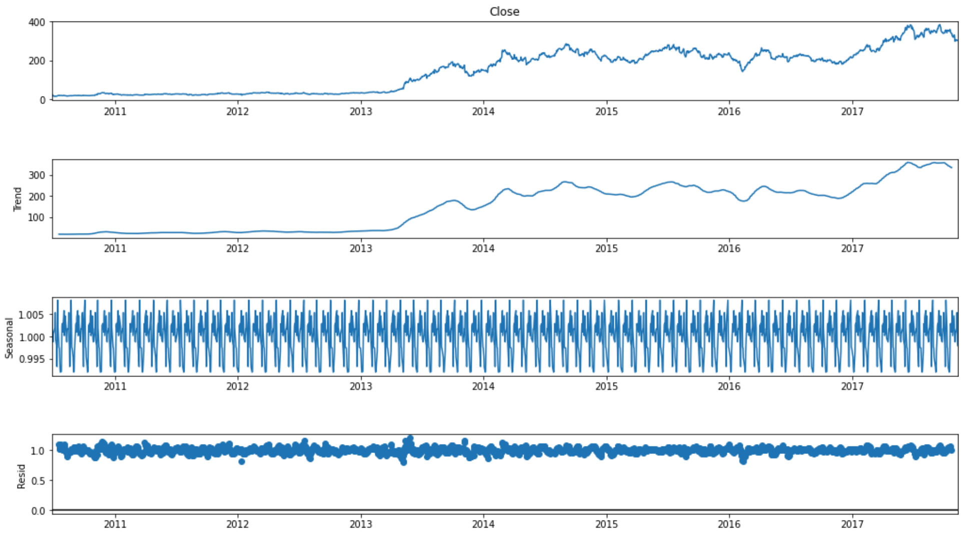
```
[ ] plt.figure(figsize = (10,6))
    test_stationarity(df_close.head(2000))
```




```
Results of Dickey-Fuller Test:
Test Statistic                  -0.842866
p-value                          0.806205
#Lags Used                       1.000000
Number of Observations Used   1856.000000
Critical Value (1%)             -3.433878
Critical Value (5%)             -2.863099
Critical Value (10%)            -2.567600
dtype: float64
```

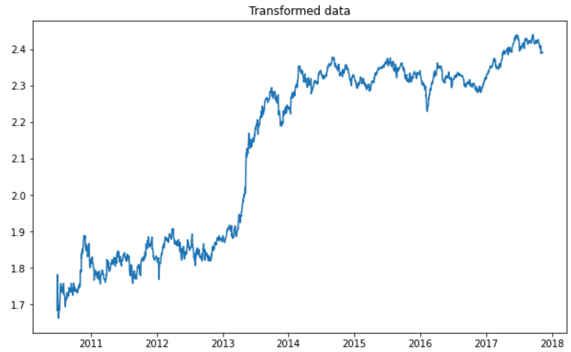
```
result = seasonal_decompose(df_close, model='multiplicative',period=28)
fig = plt.figure()
fig = result.plot()
fig.set_size_inches(16, 9)
```

```
<Figure size 432x288 with 0 Axes>
```

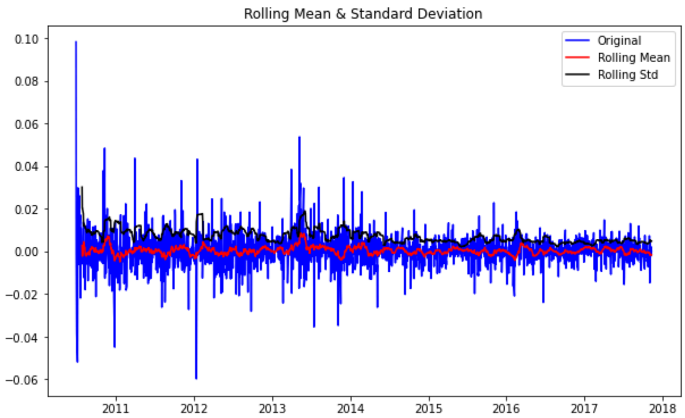


```python
df_close_log = df_close.apply(np.log)
df_close_tf = df_close_log.apply(np.sqrt)

plt.figure(figsize = (10,6))
plt.plot(df_close_tf)
plt.title('Transformed data')
```

```
Text(0.5, 1.0, 'Transformed data')
```




```python
df_close_shift = df_close_tf - df_close_tf.shift()

df_close_shift.dropna(inplace=True)
plt.figure(figsize = (10,6))
test_stationarity(df_close_shift)
```




```
Results of Dickey-Fuller Test:
Test Statistic                  -32.550253
p-value                           0.000000
#Lags Used                        1.000000
Number of Observations Used    1855.000000
Critical Value (1%)              -3.433880
Critical Value (5%)              -2.863099
Critical Value (10%)             -2.567600
dtype: float64
```

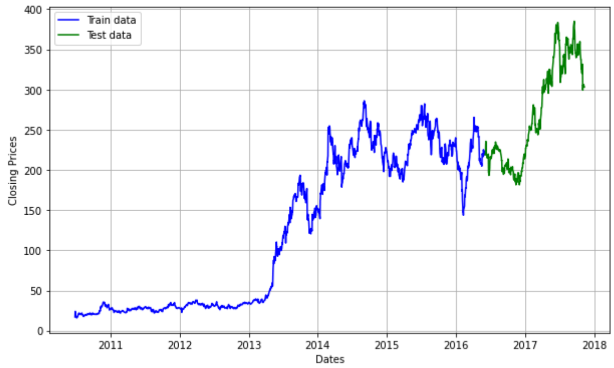
```python
def preprocess_lstm(sequence, n_steps,n_features):
    X, y = list(), list()
    for i in range(len(sequence)):
        # find the end of this pattern
        end_ix = i + n_steps
        # check if we are beyond the sequence
        if end_ix >= len(sequence):
            break
        # gather input and output parts of the pattern
        seq_x, seq_y = sequence[i:end_ix], sequence[end_ix]
        X.append(seq_x)
        y.append(seq_y)

    X = np.array(X)
    y = np.array(y)

    X = X.reshape((X.shape[0], X.shape[1], n_features))
    return X, y
```

```python
# choose the number of days on which to base our predictions
nb_days = 60

n_features = 1

X, y = preprocess_lstm(df_close_shift.to_numpy(), nb_days, n_features)
```

```
[ ] #Split the data set between the training set and the test set
    test_days = 365

    X_train, y_train = X[:-test_days], y[:-test_days]
    X_test, y_test = X[-test_days:], y[-test_days:]
```

```
[ ] train_original = df_close.iloc[:-test_days]
    test_original = df_close.iloc[-test_days:]

    plt.figure(figsize=(10,6))
    plt.grid(True)
    plt.xlabel('Dates')
    plt.ylabel('Closing Prices')
    plt.plot(train_original, 'b', label='Train data')
    plt.plot(test_original, 'g', label='Test data')
    plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f7f117f8790>
```




```
[ ] def vanilla_LSTM():
        model = Sequential()
        model.add(LSTM(units=50, input_shape=(nb_days, n_features)))
        model.add(Dense(1))
        return model
```

```
[ ] model = vanilla_LSTM()
    model.summary()
    model.compile(optimizer='adam',
                  loss='mean_squared_error',
                  metrics=[tf.keras.metrics.MeanAbsoluteError()])
```

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

 dense (Dense)               (None, 1)                 51

=================================================================
Total params: 10,451
Trainable params: 10,451
Non-trainable params: 0
_________________________________________________________________
```

```
[ ] model.fit(X_train,
              y_train,
              epochs=15,
              batch_size = 32)
```

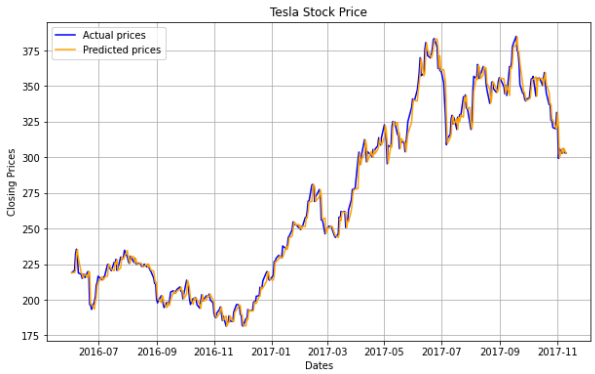
```
Epoch 1/15
45/45 [==============================] - 2s 20ms/step - loss: 9.6160e-05 - mean_absolute_error: 0.0072
Epoch 2/15
45/45 [==============================] - 1s 20ms/step - loss: 6.4326e-05 - mean_absolute_error: 0.0055
Epoch 3/15
45/45 [==============================] - 1s 19ms/step - loss: 7.2244e-05 - mean_absolute_error: 0.0059
Epoch 4/15
45/45 [==============================] - 1s 20ms/step - loss: 7.5874e-05 - mean_absolute_error: 0.0062
Epoch 5/15
45/45 [==============================] - 1s 21ms/step - loss: 6.3509e-05 - mean_absolute_error: 0.0056
Epoch 6/15
45/45 [==============================] - 1s 19ms/step - loss: 7.2361e-05 - mean_absolute_error: 0.0056
Epoch 7/15
45/45 [==============================] - 1s 20ms/step - loss: 6.9146e-05 - mean_absolute_error: 0.0059
Epoch 8/15
```

```
# Evaluate the model on the test data using
print("Evaluate on test data")
results = model.evaluate(X_test, y_test, batch_size=32)
print("Test MSE:", results[0])
print("Test MAE:", results[1])
```

```
Evaluate on test data
12/12 [==============================] - 0s 7ms/step - loss: 2.1695e-05 - mean_absolute_error: 0.0034
Test MSE: 2.169531762774568e-05
Test MAE: 0.003427055198699236
```

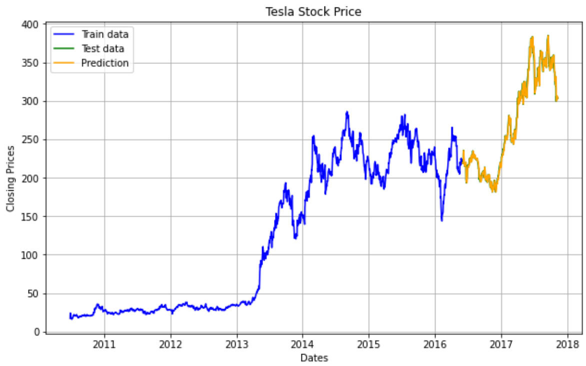
```
pred_data = pd.DataFrame(y_pred[:,0], test_original.index,columns=['Close'])

# Apply inverse transformation from 1.d

# Add the differenciation term
pred_data['Close'] = pred_data['Close'] + df_close_tf.shift().values[-test_days:]

# Take the square, and the exponent
pred_data = pred_data.apply(np.square)
pred_data = pred_data.apply(np.exp)


# Plot actual prices vs predicted prices
plt.figure(figsize=(10,6))
plt.grid(True)
plt.xlabel('Dates')
plt.ylabel('Closing Prices')
plt.plot(test_original,'b',label='Actual prices')
plt.plot(pred_data, 'orange',label='Predicted prices')
plt.title(company + ' Stock Price')

plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f7f0803ee90>
```




```
plt.figure(figsize=(10,6))
plt.grid(True)
plt.xlabel('Dates')
plt.ylabel('Closing Prices')
plt.plot(train_original, 'b', label='Train data')
plt.plot(test_original, 'g', label='Test data')
plt.plot(pred_data, 'orange', label='Prediction')
plt.title(company + ' Stock Price')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f7ee8eac4d0>
```



Conclusion:

In this experiment, we implemented an LSTM model to predict Tesla's stock prices using historical data. The LSTM effectively captured temporal patterns, resulting in reasonably accurate forecasts. This demonstrates the model's suitability for time series prediction tasks. However, since stock markets are influenced by unpredictable factors beyond historical trends, relying solely on past data has limitations. Overall, the experiment highlights both the potential and constraints of using LSTM networks for stock price forecasting.