Problem Statement

To estimate the delivery time of Porter using Neural Networks

Importing libraries

In [1]:

```
# Importing necessary libraries for data manipulation and analysis
import pandas as pd
import numpy as np

# Importing libraries for data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Importing libraries for handling datetime operations
from datetime import datetime

# Importing libraries for preprocessing and encoding
from sklearn.preprocessing import StandardScaler, OneHotEncoder


# Importing libraries for splitting data
from sklearn.model_selection import train_test_split

# Importing libraries for neural network
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping

# Importing libraries for evaluation metrics
from sklearn.metrics import mean_squared_error, mean_absolute_error

# Setting up visualization styles
sns.set(style='whitegrid')
plt.rcParams['figure.figsize'] = (10, 6)

# Ignoring warnings
import warnings
warnings.filterwarnings('ignore')
```

Importing Porter data

In [2]:

```
df=pd.read_csv('porter_data.csv')
df.head()
```

Out[2]:

	market_id	created_at	actual_delivery_time	store_id	store_primary_c
0	1.0	2015-02-06 22:24:17	2015-02-06 23:27:16	df263d996281d984952c07998dc54358	a
1	2.0	2015-02-10 21:49:25	2015-02-10 22:56:29	f0ade77b43923b38237db569b016ba25	
2	3.0	2015-01-22 20:39:28	2015-01-22 21:09:09	f0ade77b43923b38237db569b016ba25	
3	3.0	2015-02-03 21:21:45	2015-02-03 22:13:00	f0ade77b43923b38237db569b016ba25	
4	3.0	2015-02-15 02:40:36	2015-02-15 03:20:26	f0ade77b43923b38237db569b016ba25	

Printing basic info of the features

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 197428 entries, 0 to 197427
Data columns (total 14 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   market_id                 196441 non-null  float64
 1   created_at                197428 non-null  object
 2   actual_delivery_time      197421 non-null  object
 3   store_id                  197428 non-null  object
 4   store_primary_category    192668 non-null  object
 5   order_protocol            196433 non-null  float64
 6   total_items               197428 non-null  int64
 7   subtotal                  197428 non-null  int64
 8   num_distinct_items        197428 non-null  int64
 9   min_item_price            197428 non-null  int64
 10  max_item_price            197428 non-null  int64
 11  total_onshift_partners    181166 non-null  float64
 12  total_busy_partners       181166 non-null  float64
 13  total_outstanding_orders  181166 non-null  float64
dtypes: float64(5), int64(5), object(4)
memory usage: 21.1+ MB
```

Converting relevant columns to pandas Datetime

In [4]:
```
# Converting 'created_at' and 'actual_delivery_time' to datetime format
df['created_at'] = pd.to_datetime(df['created_at'])
df['actual_delivery_time'] = pd.to_datetime(df['actual_delivery_time'])
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 197428 entries, 0 to 197427
Data columns (total 14 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   market_id                 196441 non-null  float64
 1   created_at                197428 non-null  datetime64[ns]
 2   actual_delivery_time      197421 non-null  datetime64[ns]
 3   store_id                  197428 non-null  object
 4   store_primary_category    192668 non-null  object
 5   order_protocol            196433 non-null  float64
 6   total_items               197428 non-null  int64
 7   subtotal                  197428 non-null  int64
 8   num_distinct_items        197428 non-null  int64
 9   min_item_price            197428 non-null  int64
 10  max_item_price            197428 non-null  int64
 11  total_onshift_partners    181166 non-null  float64
 12  total_busy_partners       181166 non-null  float64
 13  total_outstanding_orders  181166 non-null  float64
dtypes: datetime64[ns](2), float64(5), int64(5), object(2)
memory usage: 21.1+ MB
```

Creating target column(Time taken)

In [13]:
```python
# Create a new column named 'time_taken' to store the difference in minutes
df['time_taken'] = (df['actual_delivery_time'] - df['created_at'])
```

In [14]:
```python
df.head()
```

Out[14]:

	market_id	created_at	actual_delivery_time	store_id	store_primary_c
0	1.0	2015-02-06 22:24:17	2015-02-06 23:27:16	df263d996281d984952c07998dc54358	a
1	2.0	2015-02-10 21:49:25	2015-02-10 22:56:29	f0ade77b43923b38237db569b016ba25	
2	3.0	2015-01-22 20:39:28	2015-01-22 21:09:09	f0ade77b43923b38237db569b016ba25	
3	3.0	2015-02-03 21:21:45	2015-02-03 22:13:00	f0ade77b43923b38237db569b016ba25	
4	3.0	2015-02-15 02:40:36	2015-02-15 03:20:26	f0ade77b43923b38237db569b016ba25	

In [15]:
```python
# Extracting the total minutes from the 'time_taken' column
df['time_taken_minutes'] = df['time_taken'].dt.total_seconds() // 60
```

In [16]:
```python
df.head()
```

Out[16]:

	market_id	created_at	actual_delivery_time	store_id	store_primary_c
0	1.0	2015-02-06 22:24:17	2015-02-06 23:27:16	df263d996281d984952c07998dc54358	a
1	2.0	2015-02-10 21:49:25	2015-02-10 22:56:29	f0ade77b43923b38237db569b016ba25	
2	3.0	2015-01-22 20:39:28	2015-01-22 21:09:09	f0ade77b43923b38237db569b016ba25	
3	3.0	2015-02-03 21:21:45	2015-02-03 22:13:00	f0ade77b43923b38237db569b016ba25	
4	3.0	2015-02-15 02:40:36	2015-02-15 03:20:26	f0ade77b43923b38237db569b016ba25	

Feature Engineering and Data Preprocessing

Creating hour and day of week column

In [17]:

```
# Extracting hour and day of the week from 'created_at'
df['order_hour'] = df['created_at'].dt.hour
df['order_day_of_week'] = df['created_at'].dt.dayofweek  # Monday=0, Sunday=6
```

In [18]:

```
df.head()
```

Out[18]:

	market_id	created_at	actual_delivery_time	store_id	store_primary_c
0	1.0	2015-02-06 22:24:17	2015-02-06 23:27:16	df263d996281d984952c07998dc54358	a
1	2.0	2015-02-10 21:49:25	2015-02-10 22:56:29	f0ade77b43923b38237db569b016ba25	
2	3.0	2015-01-22 20:39:28	2015-01-22 21:09:09	f0ade77b43923b38237db569b016ba25	
3	3.0	2015-02-03 21:21:45	2015-02-03 22:13:00	f0ade77b43923b38237db569b016ba25	
4	3.0	2015-02-15 02:40:36	2015-02-15 03:20:26	f0ade77b43923b38237db569b016ba25	

Dropping columns that arent useful anymore

In [19]:

```
df.drop(['time_taken','created_at','actual_delivery_time'],axis=1,inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 197428 entries, 0 to 197427
Data columns (total 15 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   market_id                 196441 non-null  float64
 1   store_id                  197428 non-null  object 
 2   store_primary_category    192668 non-null  object 
 3   order_protocol            196433 non-null  float64
 4   total_items               197428 non-null  int64  
 5   subtotal                  197428 non-null  int64  
 6   num_distinct_items        197428 non-null  int64  
 7   min_item_price            197428 non-null  int64  
 8   max_item_price            197428 non-null  int64  
 9   total_onshift_partners    181166 non-null  float64
 10  total_busy_partners       181166 non-null  float64
 11  total_outstanding_orders  181166 non-null  float64
 12  time_taken_minutes        197421 non-null  float64
 13  order_hour                197428 non-null  int32  
 14  order_day_of_week         197428 non-null  int32  
dtypes: float64(6), int32(2), int64(5), object(2)
memory usage: 21.1+ MB
```

In [ ]:

Handling Null values

In [20]:
```
df.isna().sum()
```

Out[20]:
```
market_id                     987
store_id                        0
store_primary_category       4760
order_protocol                995
total_items                     0
subtotal                        0
num_distinct_items              0
min_item_price                  0
max_item_price                  0
total_onshift_partners      16262
total_busy_partners         16262
total_outstanding_orders    16262
time_taken_minutes              7
order_hour                      0
order_day_of_week               0
dtype: int64
```

In [25]:
```
# Finding the number of unique values in each column
unique_values = {column: df[column].nunique() for column in df.columns}

# Displaying the unique values count for each column
for column, unique_count in unique_values.items():
    print(f"{column}: {unique_count}")
```

```
market_id: 6
store_id: 6743
store_primary_category: 74
order_protocol: 7
total_items: 57
subtotal: 8368
num_distinct_items: 20
min_item_price: 2312
max_item_price: 2652
total_onshift_partners: 172
total_busy_partners: 159
total_outstanding_orders: 281
time_taken_minutes: 274
order_hour: 19
order_day_of_week: 7
```

In [71]:
```
df1=df.dropna()
```

In [93]:
```
df[df["store_id"]=="252a3dbaeb32e7690242ad3b556e626b"]
```

Out[93]:

	market_id	store_id	store_primary_category	order_protocol	tot
52018	6.0	252a3dbaeb32e7690242ad3b556e626b	american	5.0	
52019	6.0	252a3dbaeb32e7690242ad3b556e626b	american	5.0	
52020	2.0	252a3dbaeb32e7690242ad3b556e626b	burger	3.0	
52021	6.0	252a3dbaeb32e7690242ad3b556e626b	american	5.0	
52022	6.0	252a3dbaeb32e7690242ad3b556e626b	american	5.0	
...	...	...	...	...	
63432	6.0	252a3dbaeb32e7690242ad3b556e626b	american	5.0	
63433	6.0	252a3dbaeb32e7690242ad3b556e626b	american	5.0	
63434	6.0	252a3dbaeb32e7690242ad3b556e626b	american	5.0	
63435	6.0	252a3dbaeb32e7690242ad3b556e626b	american	5.0	
63436	6.0	252a3dbaeb32e7690242ad3b556e626b	american	5.0	

350 rows × 15 columns

Checking whether mean or median is the right choice for Null imputation

In [100…
```
df.groupby("market_id")["total_onshift_partners"].mean()
```

Out[100]:
```
market_id
1.0    24.208854
2.0    62.590695
3.0    18.847580
4.0    60.464482
5.0    23.911045
6.0    44.929771
Name: total_onshift_partners, dtype: float64
```

In [101…
```
df.groupby("market_id")["total_onshift_partners"].median()
```

Out[101]:
```
market_id
1.0    19.0
2.0    55.0
3.0    15.0
4.0    60.0
5.0    20.0
6.0    36.0
Name: total_onshift_partners, dtype: float64
```

In [103…
```
df.groupby("order_hour")["total_onshift_partners"].mean()
```

Out[103]:
```
order_hour
0     27.933751
1     54.325601
2     67.995169
3     64.205588
4     44.996112
5     23.589613
6     13.421094
7     10.777778
8      0.000000
14     0.550000
15     2.141473
16     4.965949
17     7.757729
18    15.092275
19    32.199487
20    37.353387
21    30.325540
22    22.749043
23    20.274580
Name: total_onshift_partners, dtype: float64
```

In [105…
```
df.groupby("order_day_of_week")["total_onshift_partners"].mean()
```

Out[105]:
```
order_day_of_week
0    42.084044
1    37.333062
2    40.067352
3    43.746503
4    48.602855
5    52.111917
6    45.943654
Name: total_onshift_partners, dtype: float64
```

In [112…
```
df.groupby(["market_id","order_hour"])["total_onshift_partners"].mean()
```

Out[112]:
```
market_id  order_hour
1.0        0             14.437811
           1             26.014145
           2             36.809734
           3             37.072227
           4             27.385254
                           ...
6.0        19            30.744186
           20            40.627907
           21            31.200000
           22            23.806452
           23            18.000000
Name: total_onshift_partners, Length: 106, dtype: float64
```

Mean Imputation

In [113…
```python
# List of columns to impute
columns_to_impute = ['total_outstanding_orders', 'total_busy_partners', 'total_onsh

# Group by 'market_id' and 'order_hour'
grouped = df.groupby(['market_id', 'order_hour'])

# Impute missing values
for column in columns_to_impute:
    # Calculate the mean for each group and transform to align with the original Da
    df[column] = grouped[column].transform(lambda x: x.fillna(x.mean()))
```

In [114…
```python
df
```

Out[114]:

	market_id	store_id	store_primary_category	order_protocol	tc
0	1.0	df263d996281d984952c07998dc54358	american	1.0	
1	2.0	f0ade77b43923b38237db569b016ba25	mexican	2.0	
2	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
3	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
4	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
...	...	...	...	...	
197423	1.0	a914ecef9c12ffdb9bede64bb703d877	fast	4.0	
197424	1.0	a914ecef9c12ffdb9bede64bb703d877	fast	4.0	
197425	1.0	a914ecef9c12ffdb9bede64bb703d877	fast	4.0	
197426	1.0	c81e155d85dae5430a8cee6f2242e82c	sandwich	1.0	
197427	1.0	c81e155d85dae5430a8cee6f2242e82c	sandwich	1.0	

197428 rows × 15 columns

In [115…
```python
df.isna().sum()
```

Out[115]:
```
market_id                    987
store_id                       0
store_primary_category      4760
order_protocol               995
total_items                    0
subtotal                       0
num_distinct_items             0
min_item_price                 0
max_item_price                 0
total_onshift_partners       989
total_busy_partners          989
total_outstanding_orders     989
time_taken_minutes             7
order_hour                     0
order_day_of_week              0
dtype: int64
```

Dropping null rows

In [117…
```python
df[df["total_onshift_partners"].isnull()].dropna(inplace=True)
```

In [118…

```
df.isna().sum()
```

Out[118]:

```
market_id                    987
store_id                       0
store_primary_category      4760
order_protocol               995
total_items                    0
subtotal                       0
num_distinct_items             0
min_item_price                 0
max_item_price                 0
total_onshift_partners       989
total_busy_partners          989
total_outstanding_orders     989
time_taken_minutes             7
order_hour                     0
order_day_of_week              0
dtype: int64
```

In [119…

```
df= df[~df['total_onshift_partners'].isnull()]
```

In [121…

```
df.isna().sum()
```

Out[121]:

```
market_id                      0
store_id                       0
store_primary_category      4268
order_protocol               508
total_items                    0
subtotal                       0
num_distinct_items             0
min_item_price                 0
max_item_price                 0
total_onshift_partners         0
total_busy_partners            0
total_outstanding_orders       0
time_taken_minutes             7
order_hour                     0
order_day_of_week              0
dtype: int64
```

In [122…

```
df= df[~df['order_protocol'].isnull()]
```

In [123…

```
df.isna().sum()
```

Out[123]:

```
market_id                      0
store_id                       0
store_primary_category      4005
order_protocol                 0
total_items                    0
subtotal                       0
num_distinct_items             0
min_item_price                 0
max_item_price                 0
total_onshift_partners         0
total_busy_partners            0
total_outstanding_orders       0
time_taken_minutes             7
order_hour                     0
order_day_of_week              0
dtype: int64
```

In [124…

```
df= df[~df['time_taken_minutes'].isnull()]
```

In [125…

```
df.isna().sum()
```

Out[125]:

```
market_id                       0
store_id                        0
store_primary_category       4005
order_protocol                  0
total_items                     0
subtotal                        0
num_distinct_items              0
min_item_price                  0
max_item_price                  0
total_onshift_partners          0
total_busy_partners             0
total_outstanding_orders        0
time_taken_minutes              0
order_hour                      0
order_day_of_week               0
dtype: int64
```

In [126…

```
df[df["store_primary_category"].isna()]
```

Out[126]:

	market_id	store_id	store_primary_category	order_protocol	tc
2	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
3	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
4	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
5	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
6	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
...	...	...	...	...	
197208	1.0	77c493ec14246d748db3ee8fce0092db	NaN	1.0	
197209	1.0	77c493ec14246d748db3ee8fce0092db	NaN	1.0	
197210	1.0	77c493ec14246d748db3ee8fce0092db	NaN	1.0	
197211	1.0	77c493ec14246d748db3ee8fce0092db	NaN	1.0	
197212	1.0	77c493ec14246d748db3ee8fce0092db	NaN	1.0	

4005 rows × 15 columns

In [128…

```
df[df["store_id"]=='f0ade77b43923b38237db569b016ba25']
```

Out[128]:

	market_id	store_id	store_primary_category	order_protocol	total_it
1	2.0	f0ade77b43923b38237db569b016ba25	mexican	2.0	
2	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
3	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
4	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
5	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
6	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
7	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
8	2.0	f0ade77b43923b38237db569b016ba25	indian	3.0	
9	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
10	3.0	f0ade77b43923b38237db569b016ba25	NaN	4.0	
11	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
12	3.0	f0ade77b43923b38237db569b016ba25	NaN	1.0	
13	3.0	f0ade77b43923b38237db569b016ba25	NaN	4.0	

In [129…

```
df[df["store_primary_category"].isna()]["store_id"].nunique()
```

Out[129]: 632

In [131…

```
df2=df[df["store_primary_category"].isna()]["store_id"].unique()
```

Imputing store_primary_category by mode

In [138…

```
# Function to impute missing values by mode, handling ties randomly
def impute_by_mode(df, column):
    # Get the mode(s)
    modes = df[column].mode()

    if len(modes) > 1:
        # If there are ties, choose one randomly with equal probability
        chosen_mode = np.random.choice(modes)
    else:
        # If no tie, use the single mode
        chosen_mode = modes[0]

    # Impute missing values with the chosen mode
    df[column].fillna(chosen_mode, inplace=True)

# List of columns to impute
columns_to_impute = ['store_primary_category']

# Apply the function to each column
for column in columns_to_impute:
    impute_by_mode(df, column)
```

In [139…

```
df.isna().sum()
```

Out[139]:
```
market_id                   0
store_id                    0
store_primary_category      0
order_protocol              0
total_items                 0
subtotal                    0
num_distinct_items          0
min_item_price              0
max_item_price              0
total_onshift_partners      0
total_busy_partners         0
total_outstanding_orders    0
time_taken_minutes          0
order_hour                  0
order_day_of_week           0
dtype: int64
```

In [140…
```
df.shape
```

Out[140]:
```
(195924, 15)
```

In [142…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 195924 entries, 0 to 197427
Data columns (total 15 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   market_id                 195924 non-null  float64
 1   store_id                  195924 non-null  object 
 2   store_primary_category    195924 non-null  object 
 3   order_protocol            195924 non-null  float64
 4   total_items               195924 non-null  int64  
 5   subtotal                  195924 non-null  int64  
 6   num_distinct_items        195924 non-null  int64  
 7   min_item_price            195924 non-null  int64  
 8   max_item_price            195924 non-null  int64  
 9   total_onshift_partners    195924 non-null  float64
 10  total_busy_partners       195924 non-null  float64
 11  total_outstanding_orders  195924 non-null  float64
 12  time_taken_minutes        195924 non-null  float64
 13  order_hour                195924 non-null  int32  
 14  order_day_of_week         195924 non-null  int32  
dtypes: float64(6), int32(2), int64(5), object(2)
memory usage: 22.4+ MB
```

In [143…
```
store_name_counts = df['store_id'].value_counts()
df['store_name_enc'] = df['store_id'].map(store_name_counts)
```

In [148…
```
df = df.drop('store_name_enc', axis=1)
```

In [149…
```
df
```

Out[149]:

	market_id	store_id	store_primary_category	order_protocol	tc
0	1.0	df263d996281d984952c07998dc54358	american	1.0	
1	2.0	f0ade77b43923b38237db569b016ba25	mexican	2.0	
2	3.0	f0ade77b43923b38237db569b016ba25	american	1.0	
3	3.0	f0ade77b43923b38237db569b016ba25	american	1.0	
4	3.0	f0ade77b43923b38237db569b016ba25	american	1.0	
...	...	...	...	...	
197423	1.0	a914ecef9c12ffdb9bede64bb703d877	fast	4.0	
197424	1.0	a914ecef9c12ffdb9bede64bb703d877	fast	4.0	
197425	1.0	a914ecef9c12ffdb9bede64bb703d877	fast	4.0	
197426	1.0	c81e155d85dae5430a8cee6f2242e82c	sandwich	1.0	
197427	1.0	c81e155d85dae5430a8cee6f2242e82c	sandwich	1.0	

195924 rows × 15 columns

Using Label Encoding for store name

In [150…

```
from sklearn.preprocessing import LabelEncoder
```

In [152…

```
label_encoder = LabelEncoder()
df['store_name_encoded'] = label_encoder.fit_transform(df['store_id'])
```

In [153…

```
df
```

Out[153]:

	market_id	store_id	store_primary_category	order_protocol	tc
0	1.0	df263d996281d984952c07998dc54358	american	1.0	
1	2.0	f0ade77b43923b38237db569b016ba25	mexican	2.0	
2	3.0	f0ade77b43923b38237db569b016ba25	american	1.0	
3	3.0	f0ade77b43923b38237db569b016ba25	american	1.0	
4	3.0	f0ade77b43923b38237db569b016ba25	american	1.0	
...	...	...	...	...	
197423	1.0	a914ecef9c12ffdb9bede64bb703d877	fast	4.0	
197424	1.0	a914ecef9c12ffdb9bede64bb703d877	fast	4.0	
197425	1.0	a914ecef9c12ffdb9bede64bb703d877	fast	4.0	
197426	1.0	c81e155d85dae5430a8cee6f2242e82c	sandwich	1.0	
197427	1.0	c81e155d85dae5430a8cee6f2242e82c	sandwich	1.0	

195924 rows × 16 columns

In [154…

```
df=df.drop("store_id",axis=1)
```

In [155...

```
df
```

Out[155]:

	market_id	store_primary_category	order_protocol	total_items	subtotal	num_distinct_iter
0	1.0	american	1.0	4	3441	
1	2.0	mexican	2.0	1	1900	
2	3.0	american	1.0	1	1900	
3	3.0	american	1.0	6	6900	
4	3.0	american	1.0	3	3900	
...	...	...	...	...	...	
197423	1.0	fast	4.0	3	1389	
197424	1.0	fast	4.0	6	3010	
197425	1.0	fast	4.0	5	1836	
197426	1.0	sandwich	1.0	1	1175	
197427	1.0	sandwich	1.0	4	2605	

195924 rows × 15 columns

In [156...

```
duplicates = df.duplicated()

# Print the original DataFrame with a marker for duplicates
print(df.loc[duplicates])
```

```
        market_id store_primary_category  order_protocol  total_items  \
139263        6.0                 indian             3.0            2
166281        6.0                   cafe             4.0            1

        subtotal  num_distinct_items  min_item_price  max_item_price  \
139263      1650                   1             825             825
166281       350                   1             350             350

        total_onshift_partners  total_busy_partners  total_outstanding_orders  \
139263               39.813559             40.40678                 51.135593
166281               39.813559             40.40678                 51.135593

        time_taken_minutes  order_hour  order_day_of_week  store_name_encoded
139263                24.0           4                  1                2637
166281                39.0           4                  4                1501
```

In [159...

```
df=df.drop_duplicates()
```

In [160...

```
df
```

Out[160]:

	market_id	store_primary_category	order_protocol	total_items	subtotal	num_distinct_iter
0	1.0	american	1.0	4	3441	
1	2.0	mexican	2.0	1	1900	
2	3.0	american	1.0	1	1900	
3	3.0	american	1.0	6	6900	
4	3.0	american	1.0	3	3900	
...	...	...	...	...	...	
197423	1.0	fast	4.0	3	1389	
197424	1.0	fast	4.0	6	3010	
197425	1.0	fast	4.0	5	1836	
197426	1.0	sandwich	1.0	1	1175	
197427	1.0	sandwich	1.0	4	2605	

195922 rows × 15 columns

In [161…

```
df.isna().sum()
```

Out[161]:

```
market_id                    0
store_primary_category       0
order_protocol               0
total_items                  0
subtotal                     0
num_distinct_items           0
min_item_price               0
max_item_price               0
total_onshift_partners       0
total_busy_partners          0
total_outstanding_orders     0
time_taken_minutes           0
order_hour                   0
order_day_of_week            0
store_name_encoded           0
dtype: int64
```

In [163…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 195922 entries, 0 to 197427
Data columns (total 15 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   market_id                 195922 non-null  float64
 1   store_primary_category    195922 non-null  object 
 2   order_protocol            195922 non-null  float64
 3   total_items               195922 non-null  int64  
 4   subtotal                  195922 non-null  int64  
 5   num_distinct_items        195922 non-null  int64  
 6   min_item_price            195922 non-null  int64  
 7   max_item_price            195922 non-null  int64  
 8   total_onshift_partners    195922 non-null  float64
 9   total_busy_partners       195922 non-null  float64
 10  total_outstanding_orders  195922 non-null  float64
 11  time_taken_minutes        195922 non-null  float64
 12  order_hour                195922 non-null  int32  
 13  order_day_of_week         195922 non-null  int32  
 14  store_name_encoded        195922 non-null  int32  
dtypes: float64(6), int32(3), int64(5), object(1)
memory usage: 21.7+ MB
```

label Encoding store_primary_category

In [164…
```
label_encoder = LabelEncoder()
df['store_primary_category_enc'] = label_encoder.fit_transform(df['store_primary_ca
```

In [166…
```
df=df.drop("store_primary_category",axis=1)
```

In [ ]:
```
```

In [167…
```
df
```

Out[167]:

	market_id	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max
0	1.0	1.0	4	3441	4	557	
1	2.0	2.0	1	1900	1	1400	
2	3.0	1.0	1	1900	1	1900	
3	3.0	1.0	6	6900	5	600	
4	3.0	1.0	3	3900	3	1100	
...	...	...	...	...	...	...	
197423	1.0	4.0	3	1389	3	345	
197424	1.0	4.0	6	3010	4	405	
197425	1.0	4.0	5	1836	3	300	
197426	1.0	1.0	1	1175	1	535	
197427	1.0	1.0	4	2605	4	425	

195922 rows × 15 columns

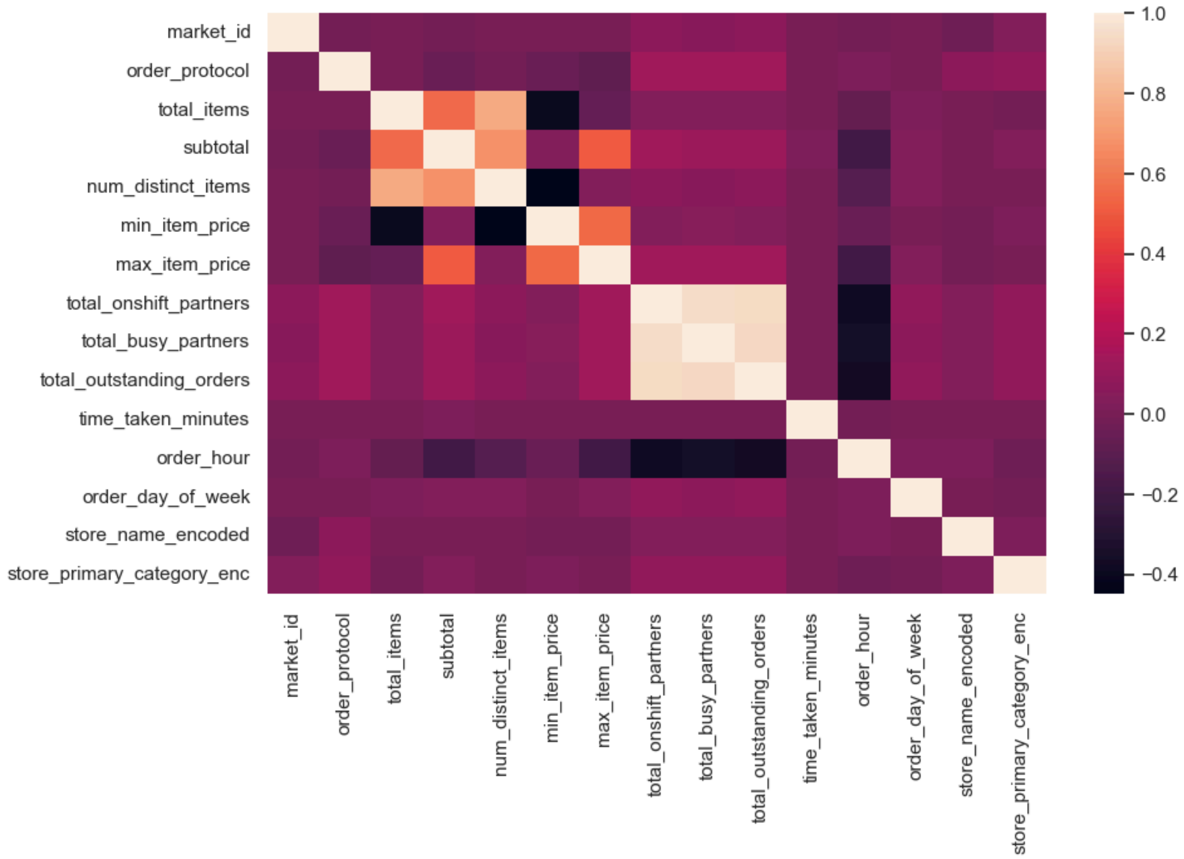
Data Vizualisation

In [168…

```python
sns.heatmap(df.corr())
```

Out[168]:

```
<Axes: >
```



In [169…

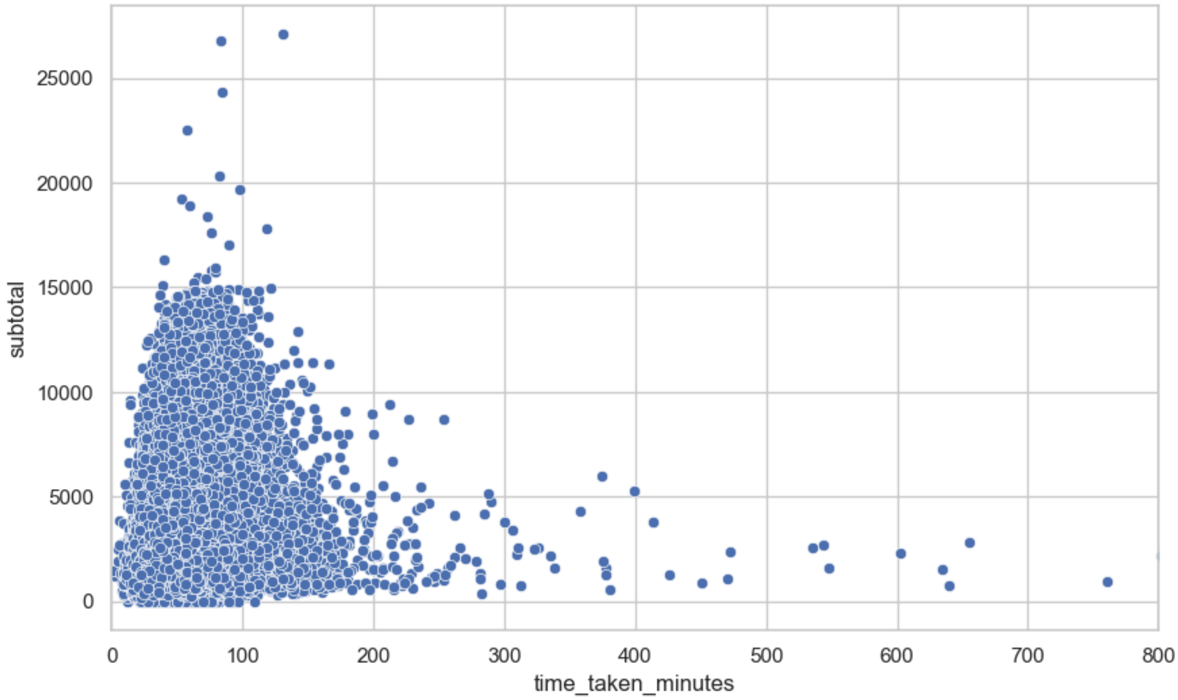
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 195922 entries, 0 to 197427
Data columns (total 15 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   market_id                   195922 non-null  float64
 1   order_protocol              195922 non-null  float64
 2   total_items                 195922 non-null  int64  
 3   subtotal                    195922 non-null  int64  
 4   num_distinct_items          195922 non-null  int64  
 5   min_item_price              195922 non-null  int64  
 6   max_item_price              195922 non-null  int64  
 7   total_onshift_partners      195922 non-null  float64
 8   total_busy_partners         195922 non-null  float64
 9   total_outstanding_orders    195922 non-null  float64
 10  time_taken_minutes          195922 non-null  float64
 11  order_hour                  195922 non-null  int32  
 12  order_day_of_week           195922 non-null  int32  
 13  store_name_encoded          195922 non-null  int32  
 14  store_primary_category_enc  195922 non-null  int32  
dtypes: float64(6), int32(4), int64(5)
memory usage: 20.9 MB
```

In [178…

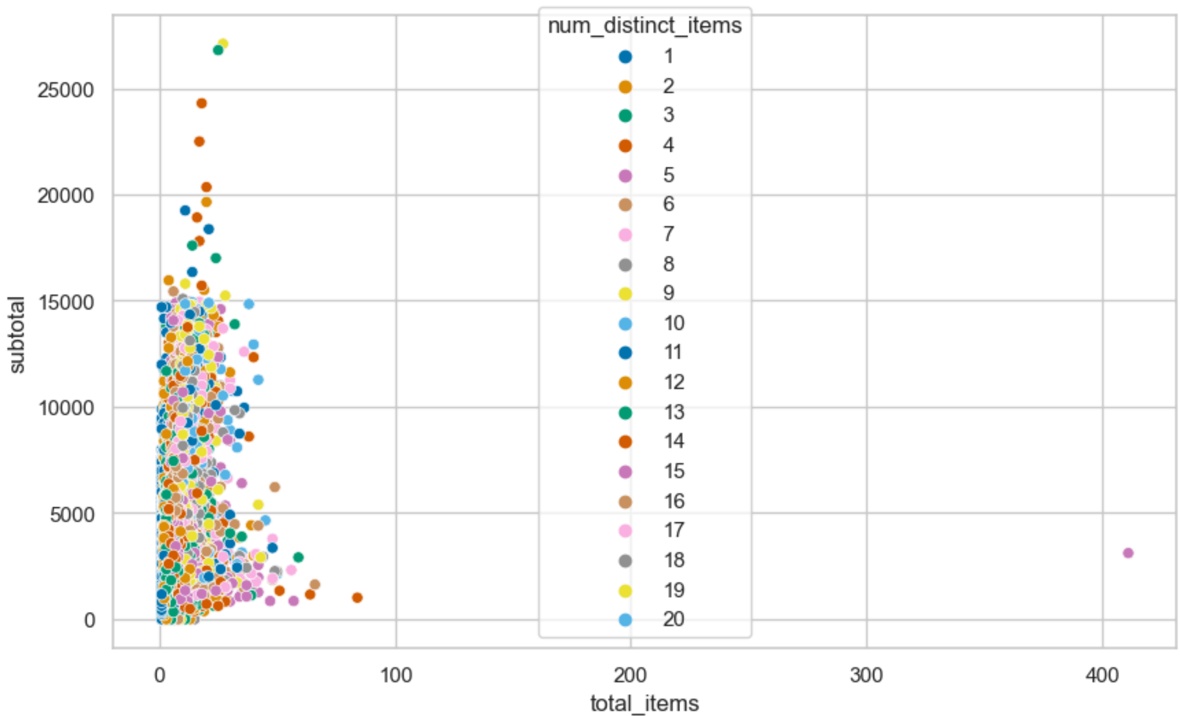
```python
# Create the scatter plot
sns.scatterplot(x='time_taken_minutes', y='subtotal', data=df)

# Set the x-axis limit
plt.xlim(0, 800)
```

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



In [173…
```
sns.scatterplot(x='total_items', y='subtotal', hue='num_distinct_items',palette='co
```

Out[173]:
```
<Axes: xlabel='total_items', ylabel='subtotal'>
```



In [222…
```
df3=df.copy()
```

In [223…
```
df3.shape
```

Out[223]:
```
(195922, 15)
```

In [225…
```
df3=df3.drop("store_name_encoded",axis=1)
```

Removing outliers using LOF

In [228…

```
from sklearn.neighbors import LocalOutlierFactor
import matplotlib.pyplot as plt
model1 = LocalOutlierFactor(contamination=0.05)
df3['lof_anomaly_score'] = model1.fit_predict(df3)
```

In [229…

```
print("number of outliers : ",(len(df3.loc[(df3['lof_anomaly_score'] == -1)])))
df3=df3.loc[(df3['lof_anomaly_score'] == 1)]
```

```
number of outliers :  8817
```

In [230…

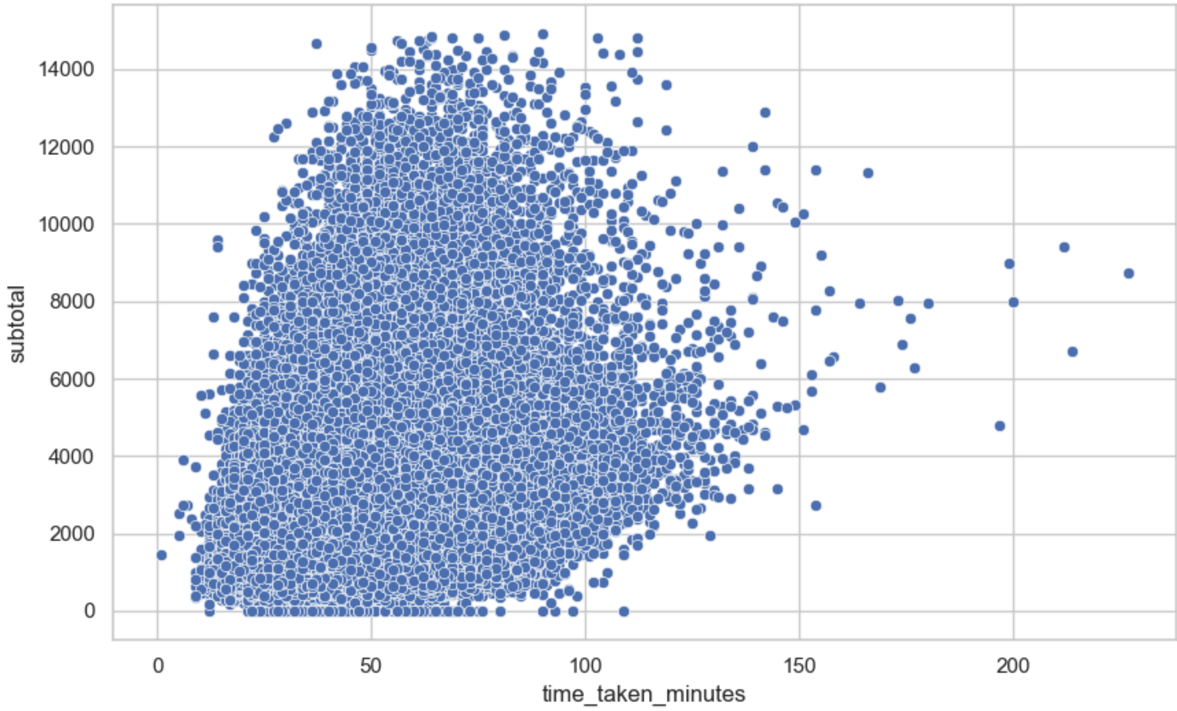
```
df3.drop(['lof_anomaly_score'],axis=1,inplace=True)
```

In [231…

```
# Create the scatter plot
sns.scatterplot(x='time_taken_minutes', y='subtotal', data=df3)
```

Out[231]:

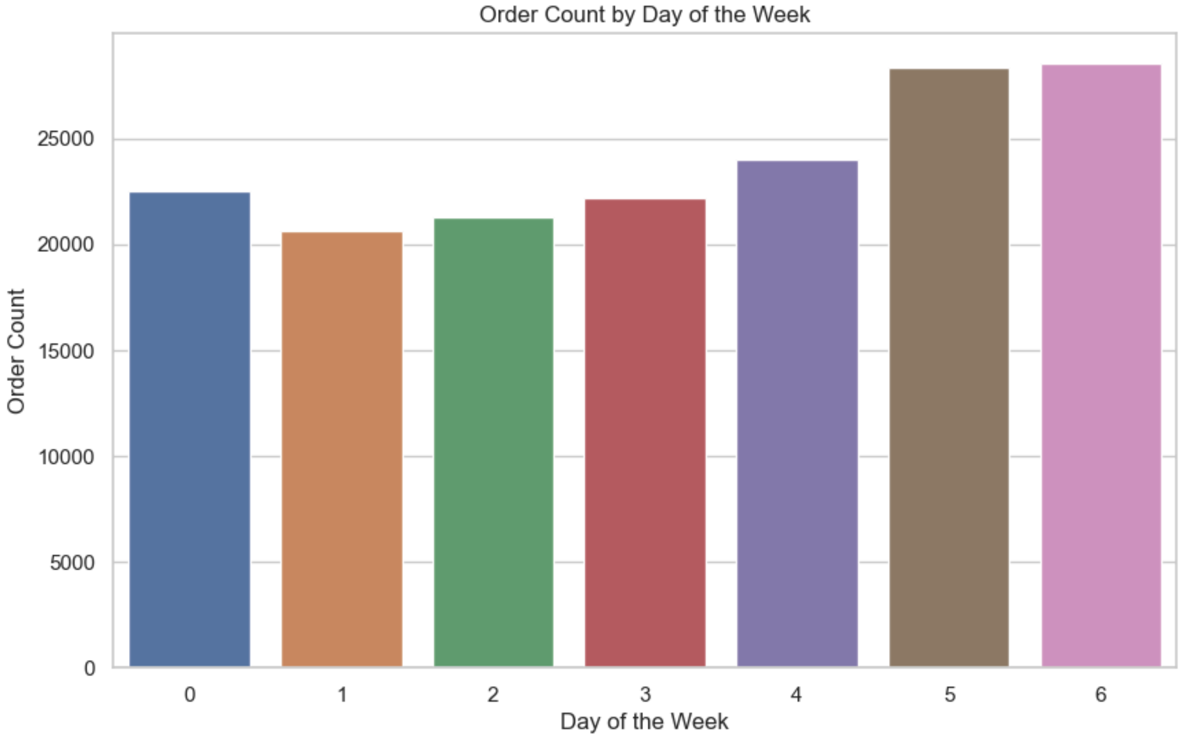
```
<Axes: xlabel='time_taken_minutes', ylabel='subtotal'>
```



Making various plots from features

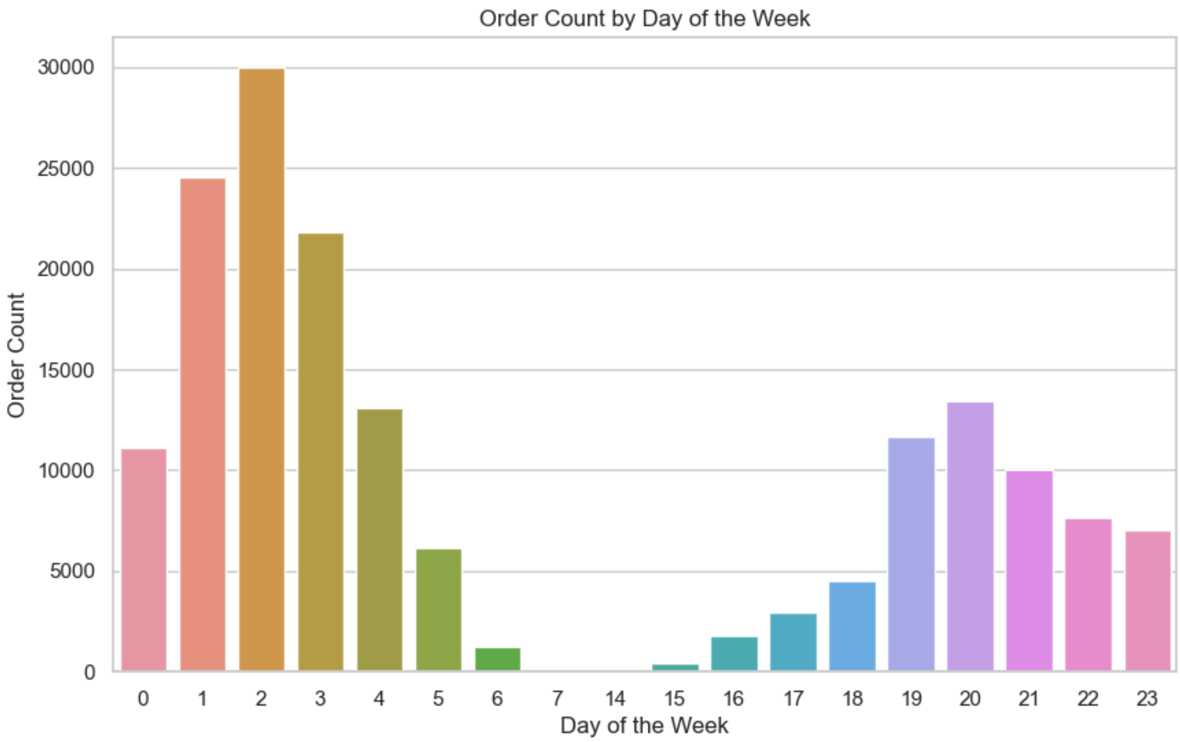
In [232…

```
# Create a countplot for the 'order_day_of_week' column
sns.countplot(x='order_day_of_week', data=df3)

# Set the title and labels
plt.title('Order Count by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Order Count')

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



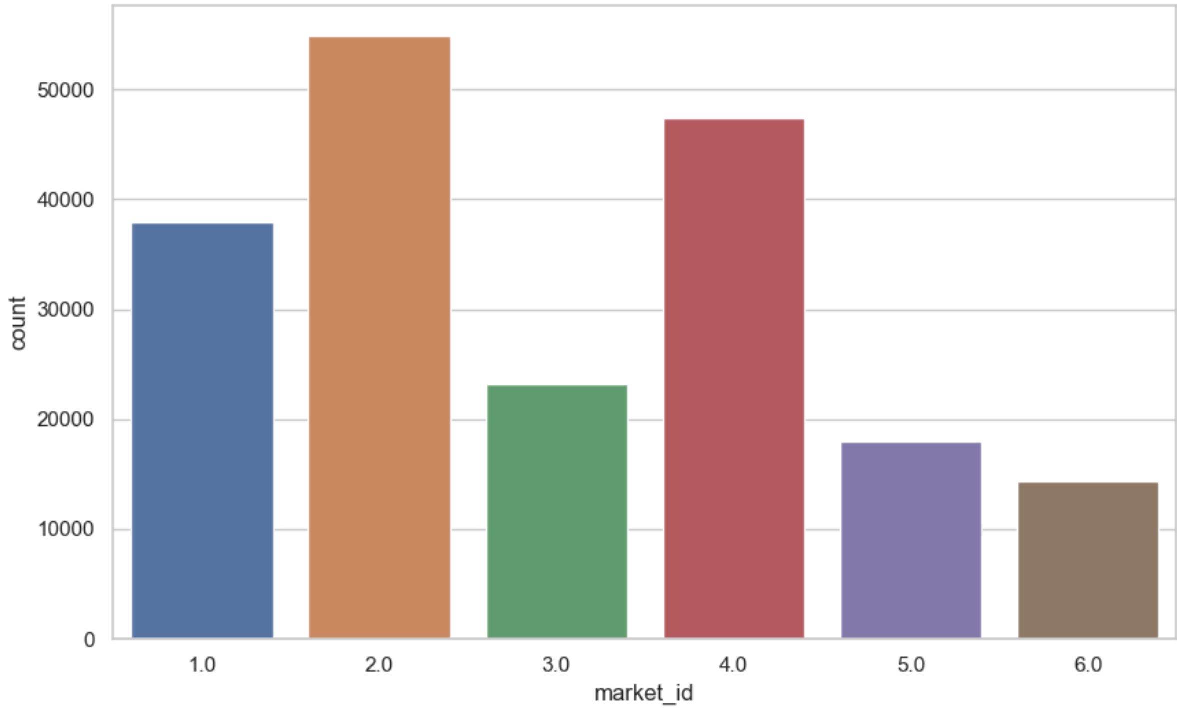
In [233...

```
# Create a countplot for the 'order_day_of_week' column
sns.countplot(x='order_hour', data=df3)

# Set the title and labels
plt.title('Order Count by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Order Count')

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



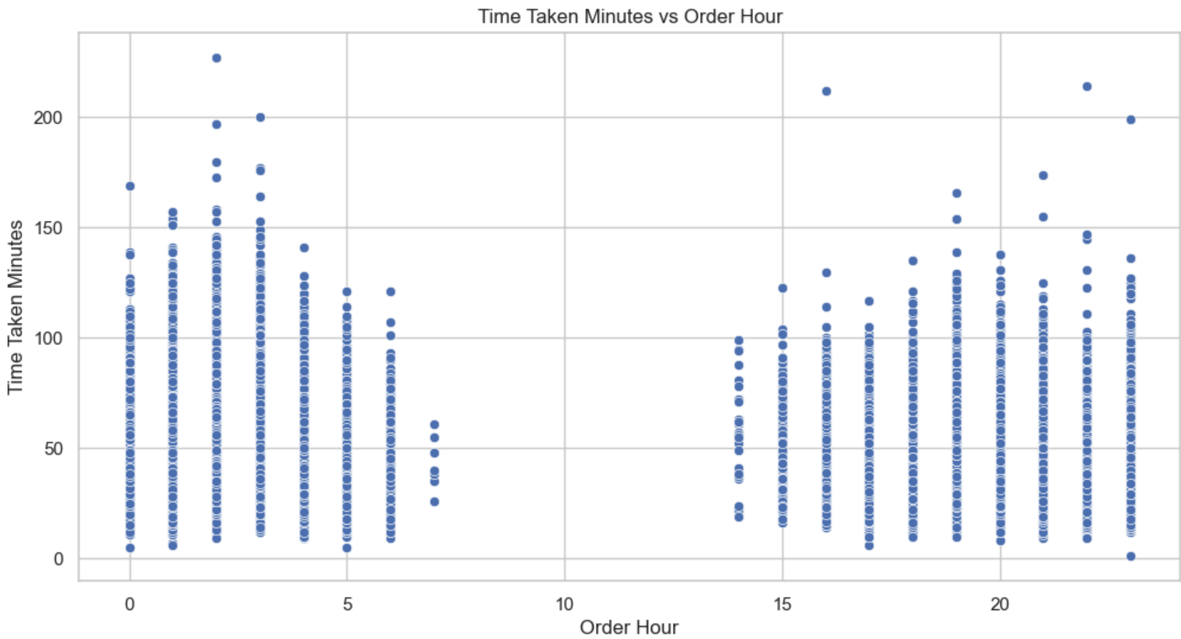
In [276...

```
sns.countplot(x=df.market_id)
plt.show()
```



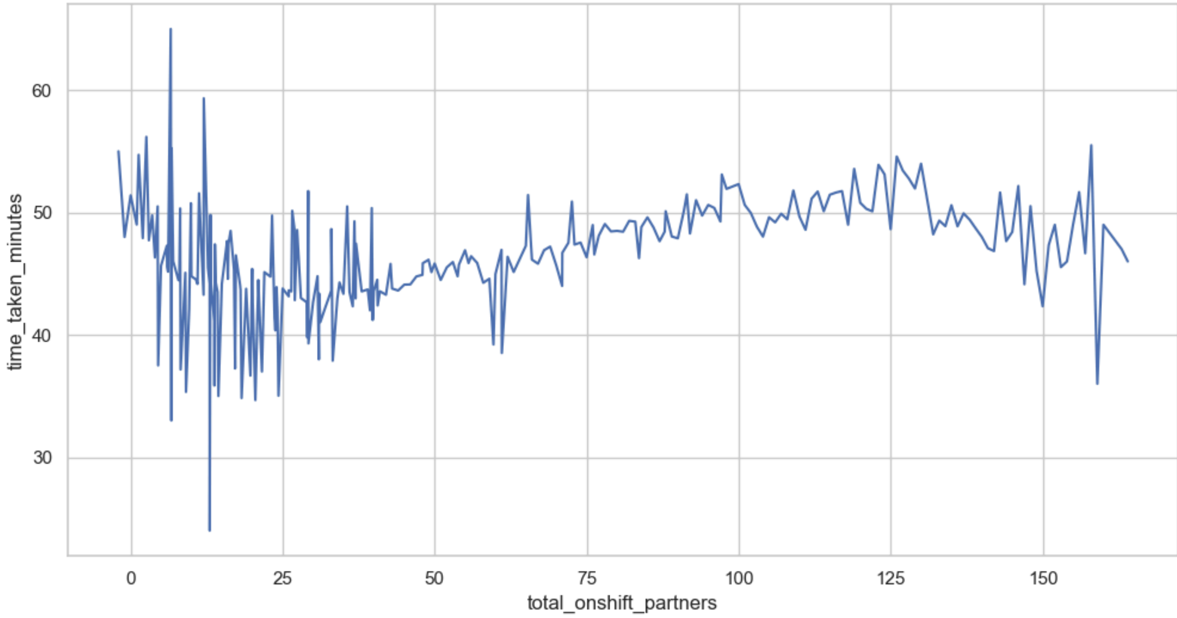
In [234…

```
# Create a scatter plot for 'order_hour' vs 'time_taken_minutes'
plt.figure(figsize=(12, 6))
sns.scatterplot(x='order_hour', y='time_taken_minutes', data=df3)

# Set the title and labels
plt.title('Time Taken Minutes vs Order Hour')
plt.xlabel('Order Hour')
plt.ylabel('Time Taken Minutes')

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



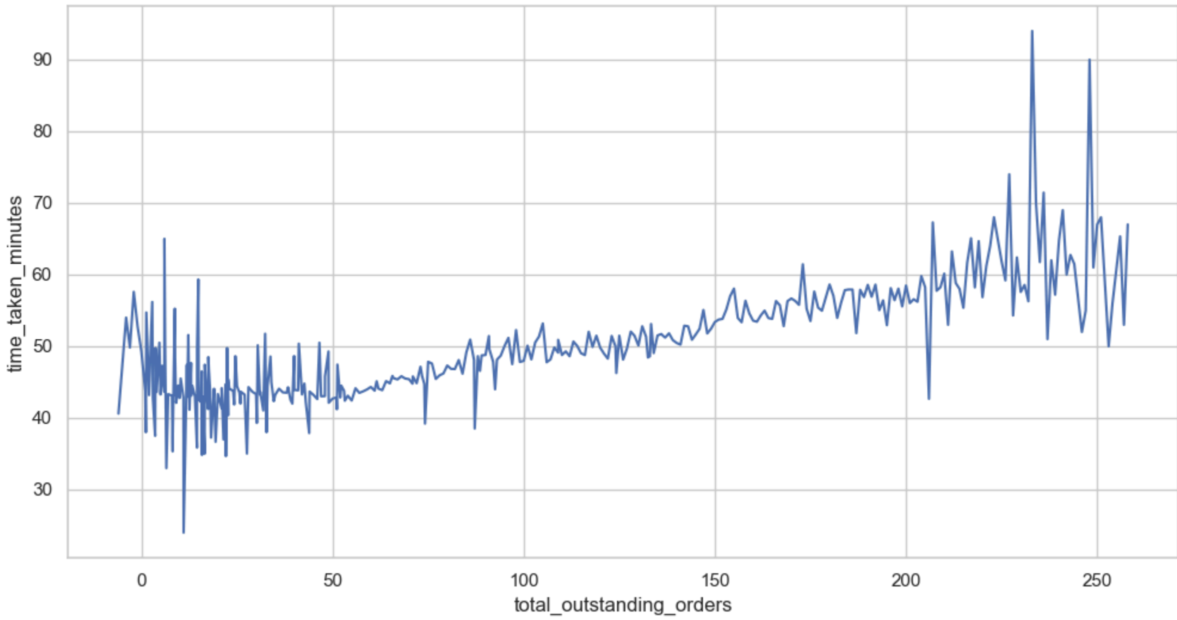
In [277…

```
plt.figure(figsize=(12, 6))
sns.lineplot(x='total_onshift_partners', y='time_taken_minutes', data=df3, ci=None)
plt.show()
```



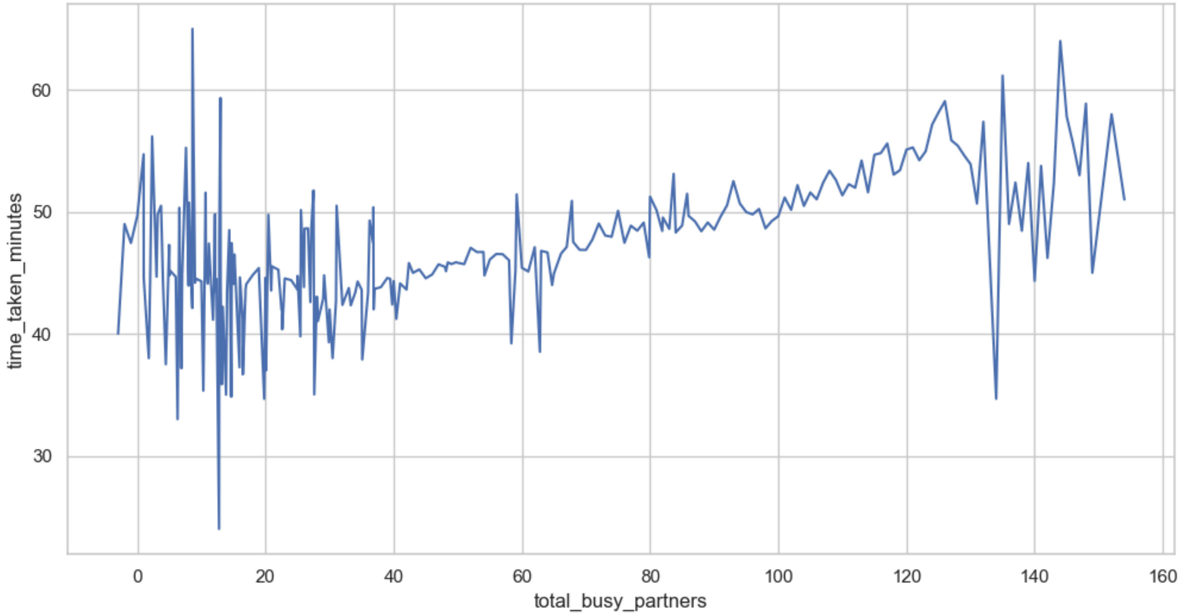
In [278…

```
plt.figure(figsize=(12, 6))
sns.lineplot(x='total_outstanding_orders', y='time_taken_minutes', data=df3, ci=Nor
plt.show()
```



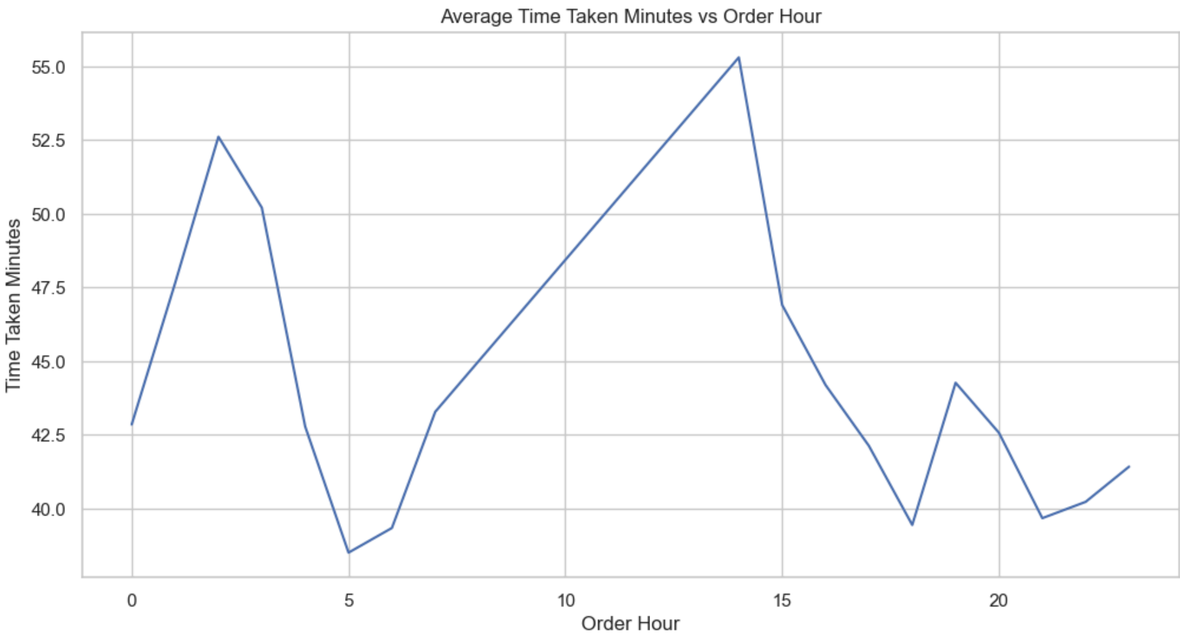
In [279…

```
plt.figure(figsize=(12, 6))
sns.lineplot(x='total_busy_partners', y='time_taken_minutes', data=df3, ci=None)
plt.show()
```



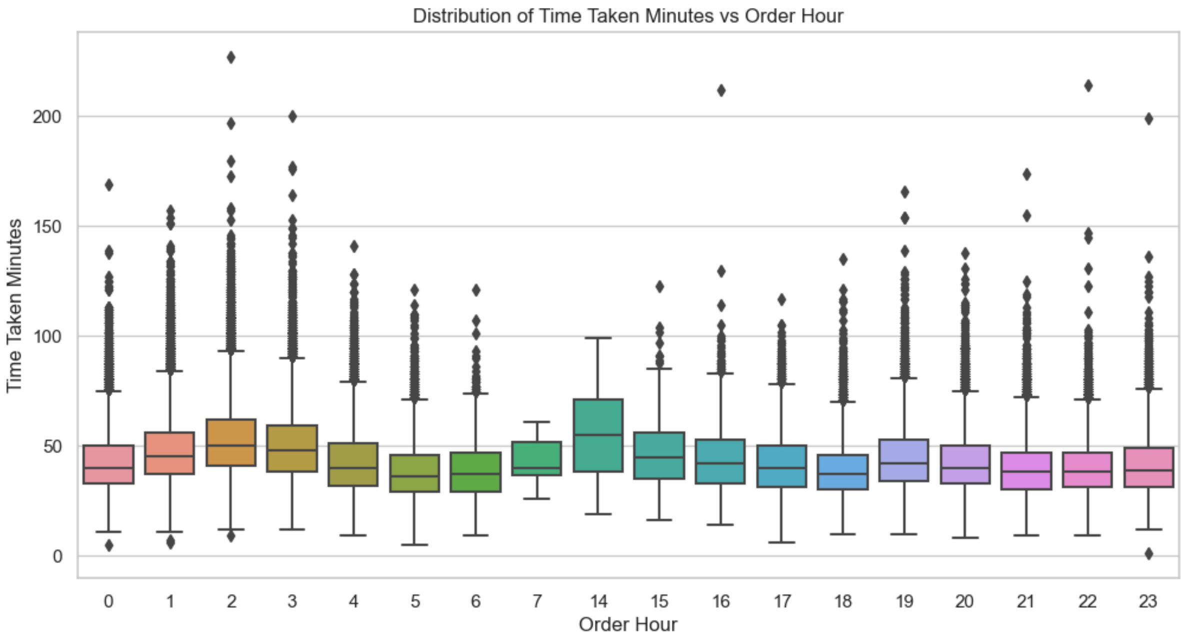
In [235…

```
plt.figure(figsize=(12, 6))
sns.lineplot(x='order_hour', y='time_taken_minutes', data=df3, ci=None)

# Set the title and labels
plt.title('Average Time Taken Minutes vs Order Hour')
plt.xlabel('Order Hour')
plt.ylabel('Time Taken Minutes')

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



In [236…

```
# Create a box plot for 'order_hour' vs 'time_taken_minutes'
plt.figure(figsize=(12, 6))
sns.boxplot(x='order_hour', y='time_taken_minutes', data=df3)

# Set the title and labels
plt.title('Distribution of Time Taken Minutes vs Order Hour')
plt.xlabel('Order Hour')
plt.ylabel('Time Taken Minutes')

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



In [237…

```
y=df3['time_taken_minutes']
x = df3.drop(['time_taken_minutes'], axis=1)

X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2,  random_st
```

In [267…

```
x
```

Out[267]:

	market_id	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max
0	1.0	1.0	4	3441	4	557	
1	2.0	2.0	1	1900	1	1400	
2	3.0	1.0	1	1900	1	1900	
3	3.0	1.0	6	6900	5	600	
4	3.0	1.0	3	3900	3	1100	
...	...	...	...	...	...	...	
197422	1.0	4.0	7	2445	3	145	
197423	1.0	4.0	3	1389	3	345	
197424	1.0	4.0	6	3010	4	405	
197425	1.0	4.0	5	1836	3	300	
197427	1.0	1.0	4	2605	4	425	

167512 rows × 13 columns

In [239…

```
y
```

Out[239]:
```
0         62.0
1         67.0
2         29.0
3         51.0
4         39.0
          ...
197422    39.0
197423    65.0
197424    56.0
197425    50.0
197427    37.0
Name: time_taken_minutes, Length: 167512, dtype: float64
```

In [240…
```
#random forest model training
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn.metrics import mean_absolute_error
from sklearn.ensemble import RandomForestRegressor
```

Creating baseline model RF to compare with Neural Networks

In [241…
```
regressor = RandomForestRegressor()

regressor.fit(X_train, y_train)
```

Out[241]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [242…
```
prediction = regressor.predict(X_test)
mse = mean_squared_error(y_test, prediction)
rmse = mse**.5
print("mse : ", mse)
print("rmse : ",rmse)
mae = mean_absolute_error(y_test, prediction)
print('mae:' ,mae)
```

```
mse :  189.7520443763879
rmse :  13.775051519917735
mae: 10.596033335678541
```

In [243…
```
r2_score(y_test, prediction)
```

Out[243]:
```
0.2674632758036619
```

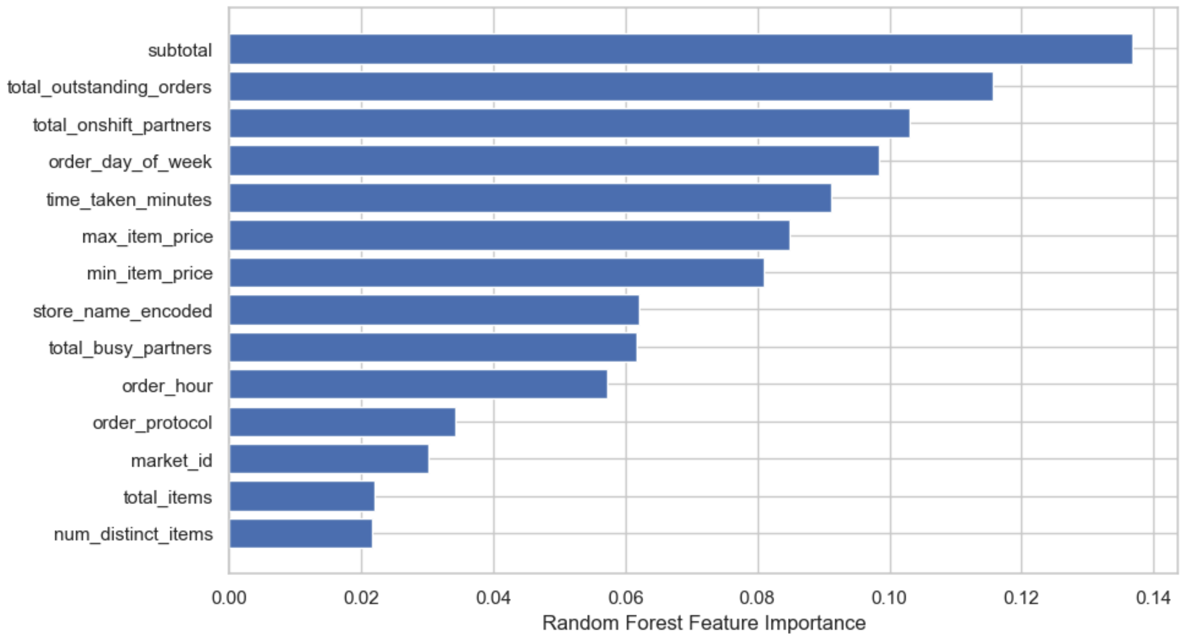
In [210…
```
def MAPE(Y_actual,Y_Predicted):
    mape = np.mean(np.abs((Y_actual - Y_Predicted)/Y_actual))*100
    return mape
```

In [211…
```
print("mape : ",MAPE(y_test, prediction))
```

```
mape :  26.785473813844728
```

In [212…
```
sorted_idx = regressor.feature_importances_.argsort()
plt.barh(df3.columns[sorted_idx], regressor.feature_importances_[sorted_idx])
plt.xlabel("Random Forest Feature Importance")
```

Out[212]:
```
Text(0.5, 0, 'Random Forest Feature Importance')
```



Train-Test Splitting Standard Scaling

In [268…

```
from sklearn import preprocessing
scaler = preprocessing.MinMaxScaler()
x_scaled = scaler.fit_transform(x)
X_train, X_test, y_train, y_test = train_test_split(x_scaled, y, test_size=0.2,  ra
```

Creating Neural Network Architecture

In [269…

```
model = Sequential()
model.add(Dense(11,  kernel_initializer='normal'))
model.add(Dense(256, activation='relu'))
model.add(Dense(512, activation='relu'))
model.add(Dense(256, activation='relu'))
model.add(Dense(1, activation='linear'))
```

Model Training

In [270…

```
from tensorflow.keras.optimizers import Adam
adam=Adam(learning_rate=0.01)
model.compile(loss='mse', optimizer=adam, metrics=['mse','mae'])
history=model.fit(X_train, y_train, epochs=30, batch_size=512, verbose=1, validatic
```

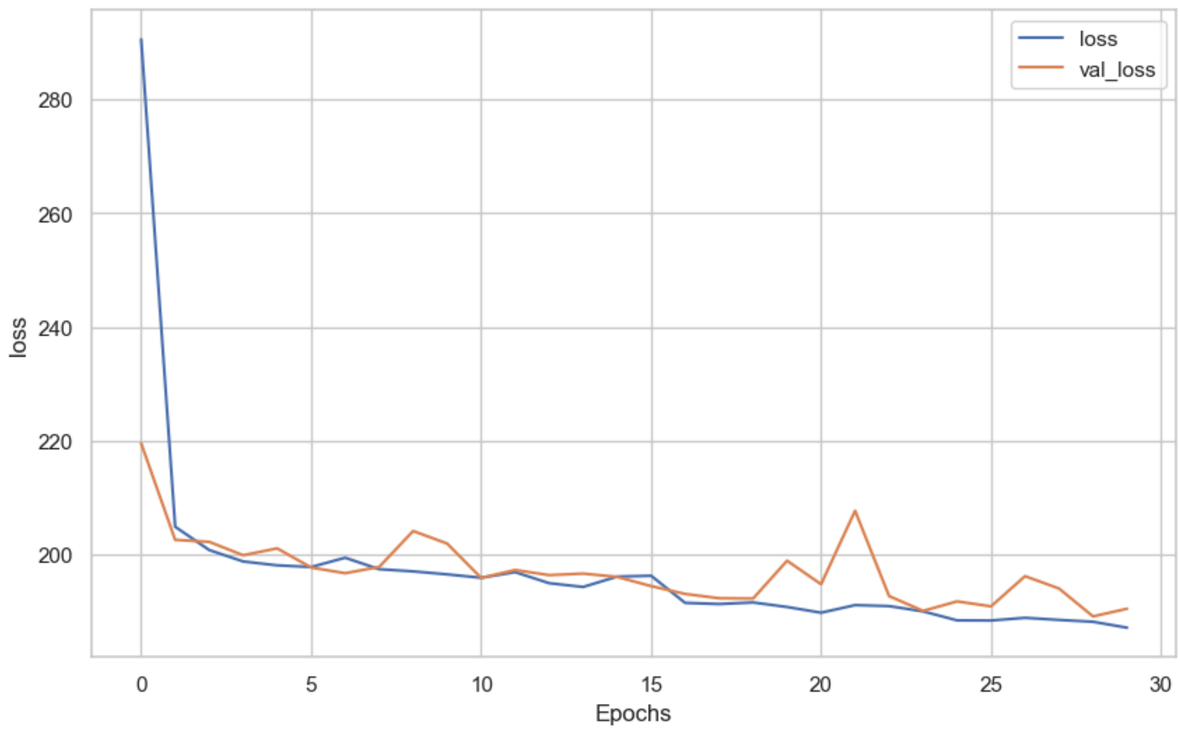
```
Epoch 1/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 5s 16ms/step - loss: 494.4725 - mae: 16.5599 - mse: 4
94.4740 - val_loss: 219.5136 - val_mae: 11.8986 - val_mse: 219.2648
Epoch 2/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 208.4257 - mae: 11.1222 - mse: 2
08.4255 - val_loss: 202.5453 - val_mae: 11.0873 - val_mse: 202.2113
Epoch 3/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 202.7528 - mae: 10.9684 - mse: 2
02.7528 - val_loss: 202.1935 - val_mae: 11.1603 - val_mse: 201.9666
Epoch 4/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 200.8208 - mae: 10.8961 - mse: 2
00.8214 - val_loss: 199.8381 - val_mae: 10.7330 - val_mse: 199.5218
Epoch 5/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 197.0804 - mae: 10.7782 - mse: 1
97.0802 - val_loss: 201.0477 - val_mae: 10.6818 - val_mse: 200.7270
Epoch 6/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 12ms/step - loss: 198.9585 - mae: 10.8274 - mse: 1
98.9591 - val_loss: 197.6735 - val_mae: 10.6539 - val_mse: 197.4005
Epoch 7/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 12ms/step - loss: 198.5806 - mae: 10.7971 - mse: 1
98.5815 - val_loss: 196.6758 - val_mae: 10.8178 - val_mse: 196.4910
Epoch 8/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 194.5566 - mae: 10.7437 - mse: 1
94.5569 - val_loss: 197.7736 - val_mae: 10.7849 - val_mse: 197.4755
Epoch 9/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 196.7931 - mae: 10.7770 - mse: 1
96.7944 - val_loss: 204.1001 - val_mae: 10.6567 - val_mse: 203.7290
Epoch 10/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 198.3773 - mae: 10.8183 - mse: 1
98.3757 - val_loss: 201.8943 - val_mae: 11.2187 - val_mse: 201.7478
Epoch 11/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 196.2389 - mae: 10.7865 - mse: 1
96.2393 - val_loss: 195.8507 - val_mae: 10.8117 - val_mse: 195.6897
Epoch 12/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 196.2606 - mae: 10.7662 - mse: 1
96.2606 - val_loss: 197.2385 - val_mae: 10.8333 - val_mse: 197.0347
Epoch 13/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 194.5317 - mae: 10.7362 - mse: 1
94.5317 - val_loss: 196.3446 - val_mae: 10.9340 - val_mse: 196.2122
Epoch 14/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 191.7983 - mae: 10.6656 - mse: 1
91.7988 - val_loss: 196.6102 - val_mae: 10.6663 - val_mse: 196.4121
Epoch 15/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 12ms/step - loss: 196.8160 - mae: 10.7610 - mse: 1
96.8164 - val_loss: 196.0317 - val_mae: 10.8560 - val_mse: 195.7986
Epoch 16/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 12ms/step - loss: 197.4550 - mae: 10.7620 - mse: 1
97.4549 - val_loss: 194.4084 - val_mae: 10.6706 - val_mse: 194.1733
Epoch 17/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 192.2394 - mae: 10.6451 - mse: 1
92.2399 - val_loss: 193.0311 - val_mae: 10.8362 - val_mse: 192.9578
Epoch 18/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 190.3562 - mae: 10.5848 - mse: 1
90.3559 - val_loss: 192.2704 - val_mae: 10.5375 - val_mse: 192.2027
Epoch 19/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 191.5047 - mae: 10.6351 - mse: 1
91.5045 - val_loss: 192.2225 - val_mae: 10.5080 - val_mse: 192.1069
Epoch 20/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 192.4837 - mae: 10.6682 - mse: 1
92.4836 - val_loss: 198.8735 - val_mae: 10.5644 - val_mse: 198.6196
Epoch 21/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 190.0445 - mae: 10.5599 - mse: 1
90.0448 - val_loss: 194.7332 - val_mae: 10.4838 - val_mse: 194.6393
Epoch 22/30
```

```
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 191.4072 - mae: 10.6043 - mse: 191.4075 - val_loss: 207.6593 - val_mae: 10.7024 - val_mse: 207.4223
Epoch 23/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 195.8305 - mae: 10.6910 - mse: 195.8312 - val_loss: 192.6539 - val_mae: 10.8769 - val_mse: 192.7865
Epoch 24/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 15ms/step - loss: 187.9753 - mae: 10.5507 - mse: 187.9752 - val_loss: 190.0480 - val_mae: 10.6299 - val_mse: 190.0943
Epoch 25/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - loss: 187.6799 - mae: 10.5330 - mse: 187.6788 - val_loss: 191.7179 - val_mae: 10.4794 - val_mse: 191.6578
Epoch 26/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 189.6170 - mae: 10.5656 - mse: 189.6173 - val_loss: 190.8470 - val_mae: 10.6809 - val_mse: 190.8350
Epoch 27/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 15ms/step - loss: 189.3345 - mae: 10.5635 - mse: 189.3333 - val_loss: 196.1583 - val_mae: 10.9565 - val_mse: 196.2539
Epoch 28/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 15ms/step - loss: 190.7337 - mae: 10.6078 - mse: 190.7346 - val_loss: 193.9751 - val_mae: 10.4601 - val_mse: 193.8635
Epoch 29/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 4s 18ms/step - loss: 186.8568 - mae: 10.4933 - mse: 186.8566 - val_loss: 189.0742 - val_mae: 10.5091 - val_mse: 189.0633
Epoch 30/30
210/210 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - loss: 187.7057 - mae: 10.5109 - mse: 187.7060 - val_loss: 190.4315 - val_mae: 10.7709 - val_mse: 190.5894
```

Comparing losses with epochs

In [271…

```
def plot_history(history, key):
  plt.plot(history.history[key])
  plt.plot(history.history['val_'+key])
  plt.xlabel("Epochs")
  plt.ylabel(key)
  plt.legend([key, 'val_'+key])
  plt.show()
# Plot the history
plot_history(history, 'loss')
```



In [272…

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

```
1047/1047 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step
```

In [273…

```
r2_score(y_test, z)
```

Out[273]:

```
0.25638306639426456
```

MAE RMSE MSE values for Neural Networks

In [275…

```
mse = mean_squared_error(y_test, z)
rmse = mse**.5
print("mse : ",mse)
print("rmse : ",rmse)
mae = mean_absolute_error(y_test, z)
print("mae : ",mae)
```

```
mse :  192.6221972548777
rmse :  13.878839910269075
mae :  10.842252765538582
```

In [ ]: