Import Libraries & Load Data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers
from sklearn.compose import ColumnTransformer
from tensorflow.keras.layers import Dense

# Load the data
df = pd.read_csv('dataset.csv')
df.head()
```

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

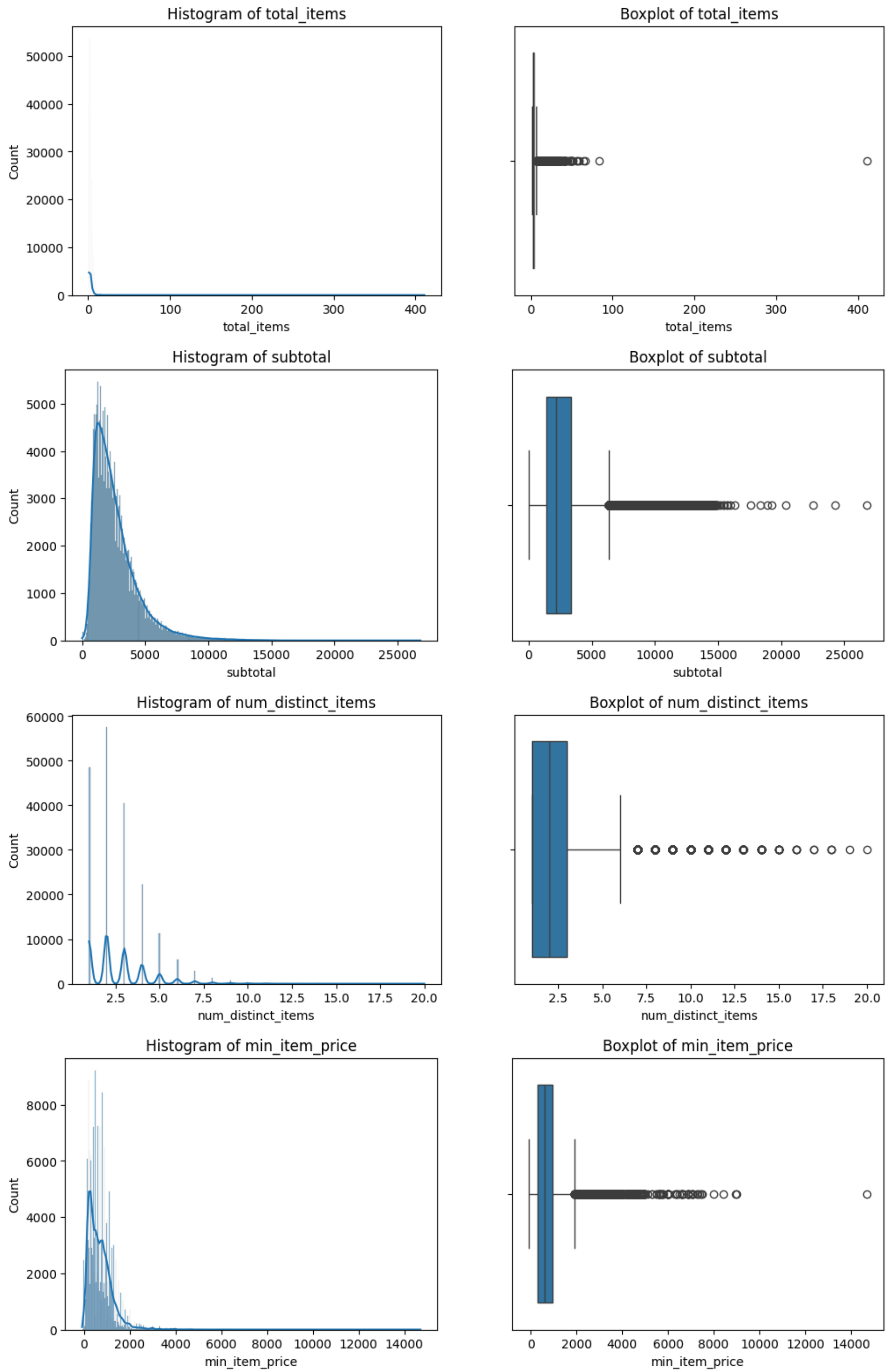
Exploratory Data Analysis (EDA)

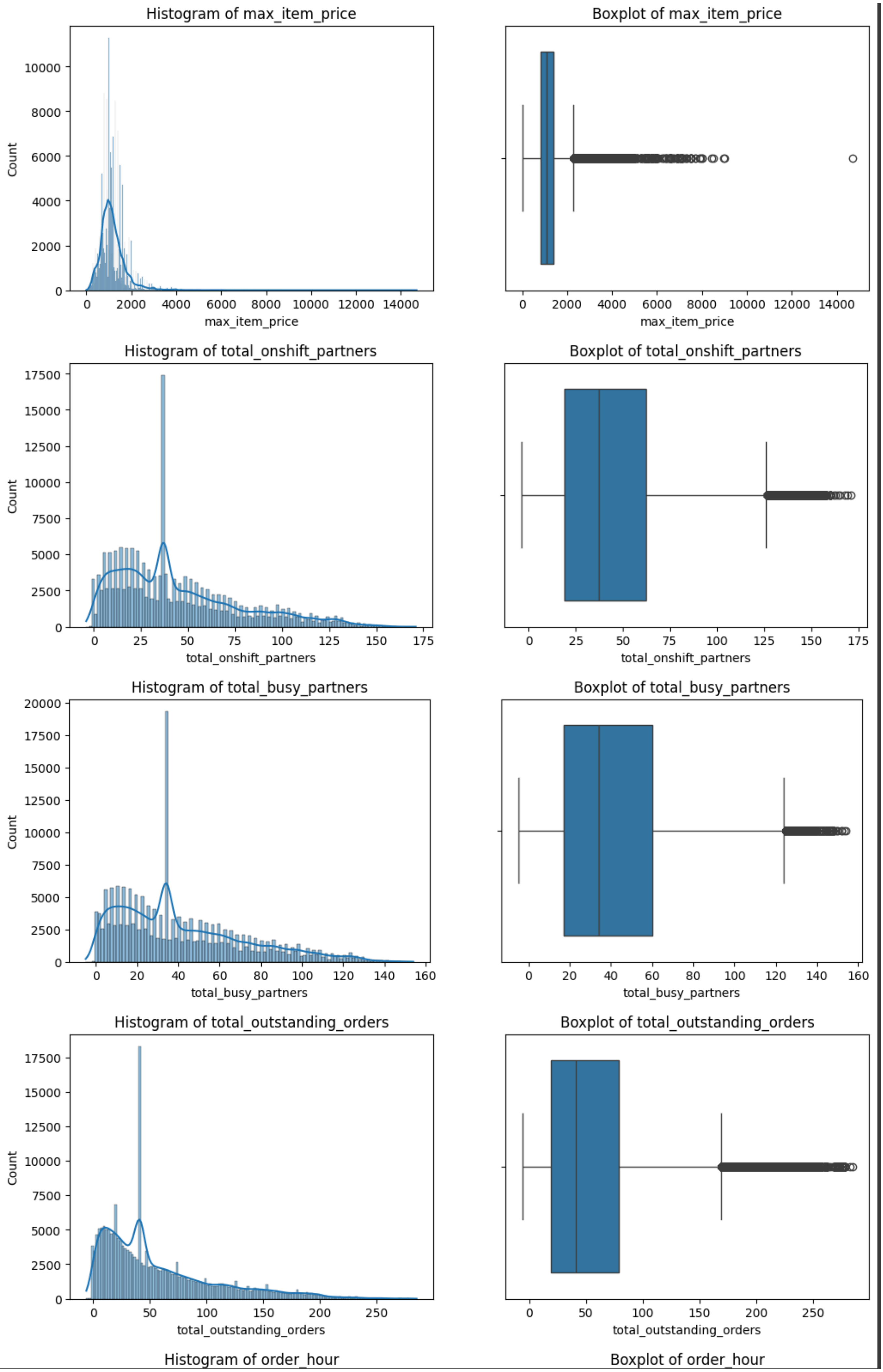
```
# Check data structure
print(df.info())

# Summary statistics
print(df.describe())

# Check missing values
print("Missing values:\n", df.isnull().sum())

# Unique categories in categorical columns
print("Unique store categories:", df['store_primary_category'].unique())
```

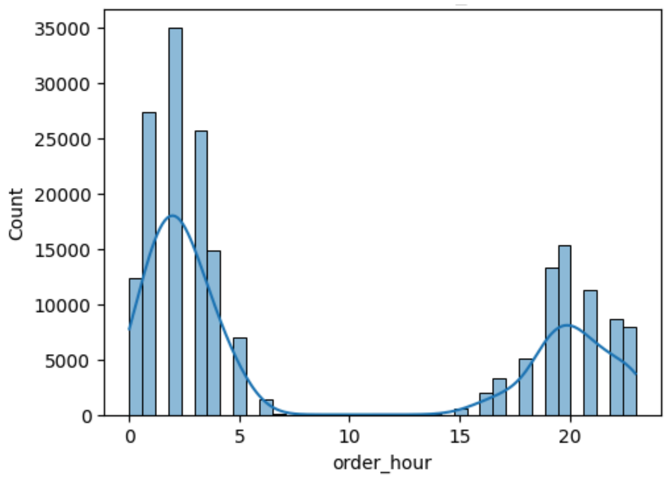
```
None
           market_id  order_protocol    total_items       subtotal  \
count  196441.000000   196433.000000  197428.000000  197428.000000
mean        2.978706        2.882352       3.196391    2682.331402
std         1.524867        1.503771       2.666546    1823.093688
min         1.000000        1.000000       1.000000       0.000000
25%         2.000000        1.000000       2.000000    1400.000000
50%         3.000000        3.000000       3.000000    2200.000000
```

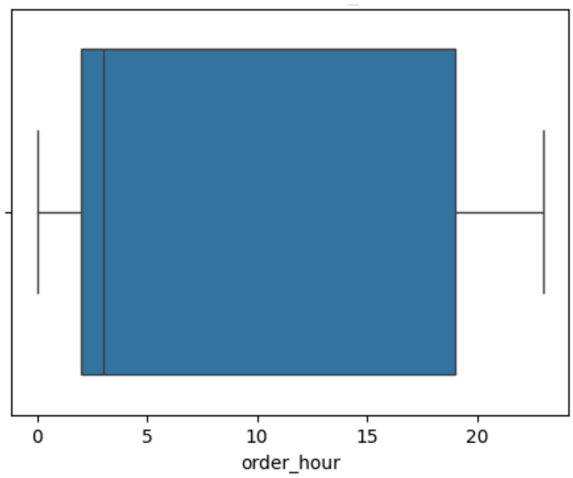
```
max               171.000000          154.000000                285.000000
Missing values:
 market_id                     987
created_at                      0
actual_delivery_time            7
store_id                        0
store_primary_category       4760
order_protocol                995
total_items                     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
dtype: int64
Unique store categories: ['american' 'mexican' nan 'indian' 'italian' 'sandwich' 'thai' 'cafe'
 'salad' 'pizza' 'chinese' 'singaporean' 'burger' 'breakfast'
 'mediterranean' 'japanese' 'greek' 'catering' 'filipino'
 'convenience-store' 'other' 'korean' 'vegan' 'asian' 'barbecue' 'fast'
 'dessert' 'smoothie' 'seafood' 'vietnamese' 'cajun' 'steak'
 'middle-eastern' 'soup' 'vegetarian' 'persian' 'nepalese' 'sushi'
 'latin-american' 'hawaiian' 'chocolate' 'burmese' 'british' 'pasta'
 'alcohol' 'dim-sum' 'peruvian' 'turkish' 'malaysian' 'ethiopian' 'afghan'
 'bubble-tea' 'german' 'french' 'caribbean' 'gluten-free' 'comfort-food'
 'gastropub' 'pakistani' 'moroccan' 'spanish' 'southern' 'tapas' 'russian'
 'brazilian' 'european' 'cheese' 'african' 'argentine' 'kosher' 'irish'
 'lebanese' 'belgian' 'indonesian' 'alcohol-plus-food']
```

```
import matplotlib.pyplot as plt
import seaborn as sns

# Define numerical and categorical features
numerical_features = ['total_items', 'subtotal', 'num_distinct_items',
                      'min_item_price', 'max_item_price', 'total_onshift_partners',
                      'total_busy_partners', 'total_outstanding_orders',
                      'order_hour', 'order_day', 'delivery_time']
categorical_features = ['market_id', 'store_primary_category', 'order_protocol']

# Plot numerical features
for feature in numerical_features:
    plt.figure(figsize=(12, 4))
    plt.subplot(1, 2, 1)
    sns.histplot(df[feature], kde=True)
    plt.title(f'Histogram of {feature}')

    plt.subplot(1, 2, 2)
    sns.boxplot(x=df[feature])
    plt.title(f'Boxplot of {feature}')
    plt.show()

# Plot categorical features
for feature in categorical_features:
    plt.figure(figsize=(10, 4))
    if feature == 'market_id':
        # Show top 10 markets
        top_markets = df[feature].value_counts().nlargest(10).index
        df_top = df[df[feature].isin(top_markets)]
        sns.countplot(x=feature, data=df_top)
    else:
        sns.countplot(x=feature, data=df)
    plt.title(f'Countplot of {feature}')
    plt.xticks(rotation=45)
    plt.show()
```

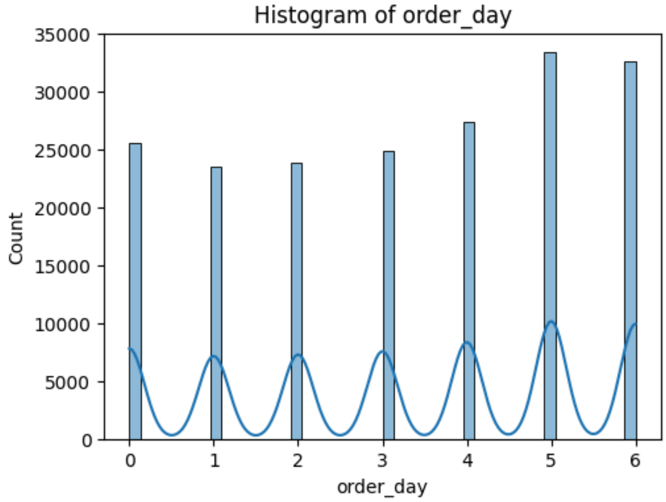

Histogram of total_items
Count
total_items
Boxplot of total_items
total_items
Histogram of subtotal
Count
subtotal
Boxplot of subtotal
subtotal
Histogram of num_distinct_items
Count
num_distinct_items
Boxplot of num_distinct_items
num_distinct_items
Histogram of min_item_price
Count
min_item_price
Boxplot of min_item_price
min_item_price


Histogram of max_item_price
Count
max_item_price
Boxplot of max_item_price
max_item_price
Histogram of total_onshift_partners
Count
total_onshift_partners
Boxplot of total_onshift_partners
total_onshift_partners
Histogram of total_busy_partners
Count
total_busy_partners
Boxplot of total_busy_partners
total_busy_partners
Histogram of total_outstanding_orders
Count
total_outstanding_orders
Boxplot of total_outstanding_orders
total_outstanding_orders
Histogram of order_hour
Boxplot of order_hour

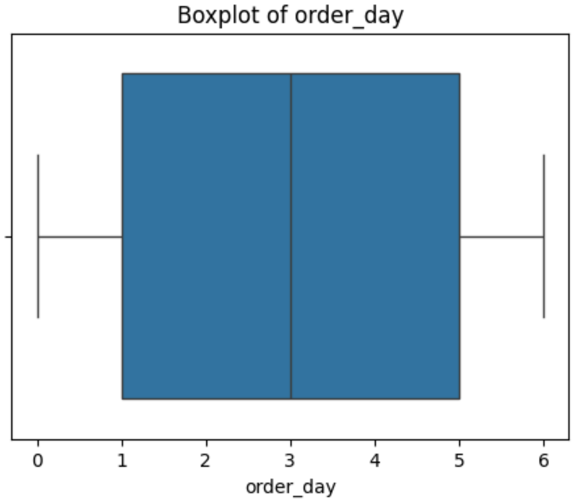




Histogram of order_day

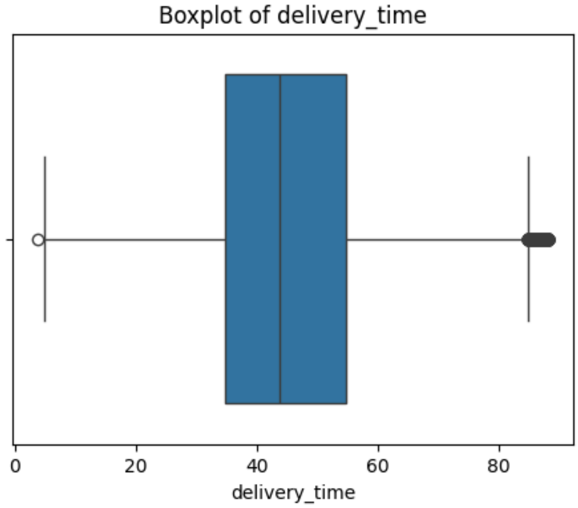


Boxplot of order_day

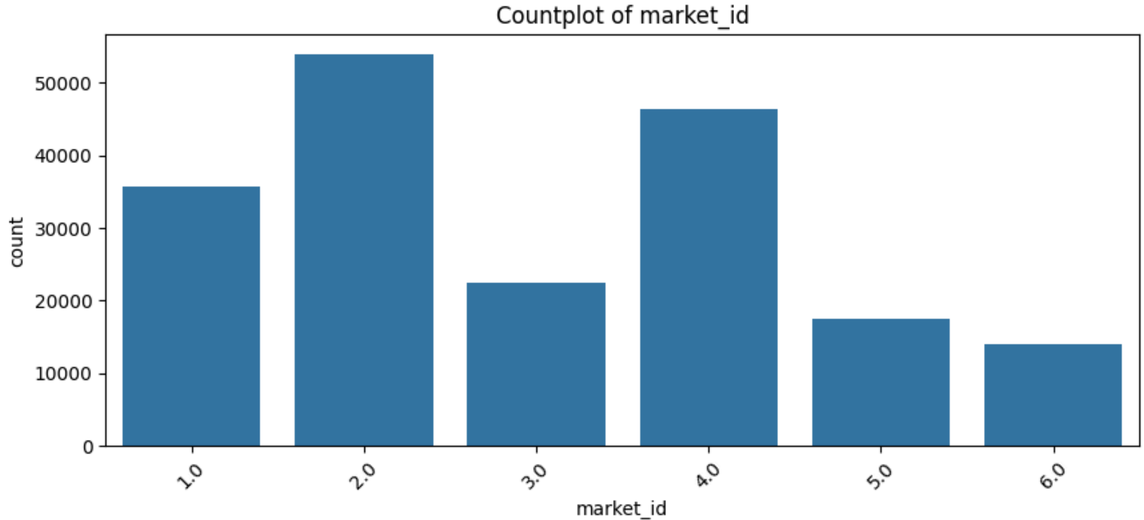


Histogram of delivery_time

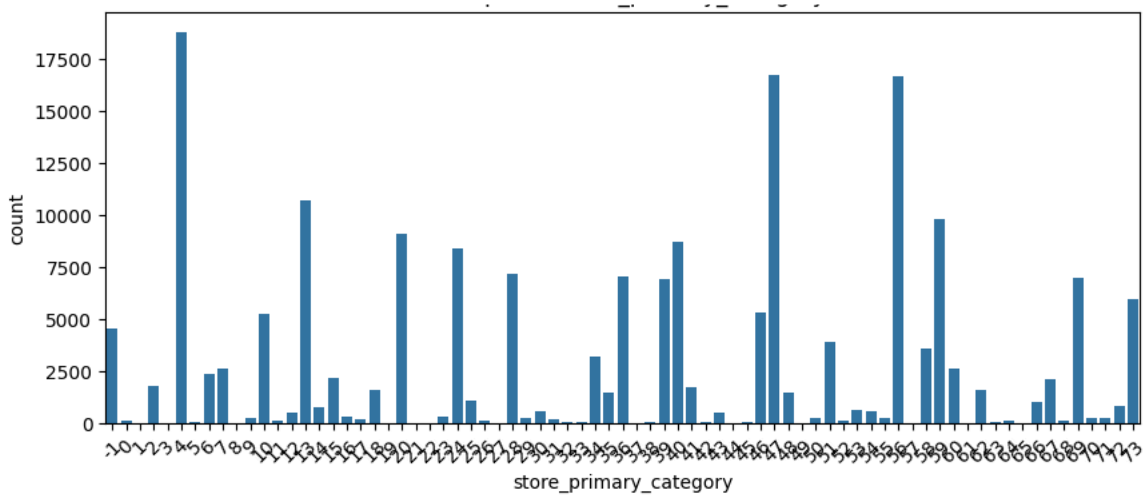
Boxplot of delivery_time



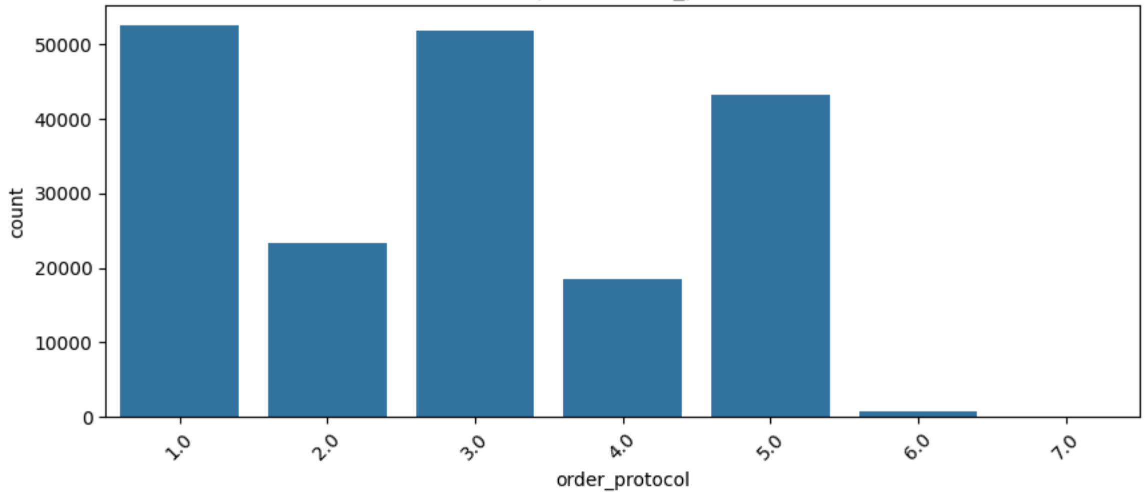
Countplot of market_id



Countplot of store_primary_category



Countplot of order_protocol



Feature Engineering

```
# Convert timestamp columns to datetime
df['created_at'] = pd.to_datetime(df['created_at'])
df['actual_delivery_time'] = pd.to_datetime(df['actual_delivery_time'])

# Create target variable (delivery time in minutes)
df['delivery_time'] = (df['actual_delivery_time'] - df['created_at']).dt.total_seconds() / 60

# Extract hour and day of week
df['order_hour'] = df['created_at'].dt.hour
df['order_day'] = df['created_at'].dt.dayofweek

# Handle categorical variables
df['store_primary_category'] = pd.Categorical(df['store_primary_category']).codes

# Check for null values
print(df.isnull().sum())
```

```
market_id                     987
created_at                      0
actual_delivery_time            7
store_id                        0
store_primary_category          0
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
delivery_time                   7
order_hour                      0
order_day                       0
dtype: int64
```

Handle Missing Values

```
# Impute numerical columns with median
num_cols = ['total_onshift_partners', 'total_busy_partners', 'total_outstanding_orders']
for col in num_cols:
    df[col] = df[col].fillna(df[col].median())

# Fill categorical columns with 'Unknown'
cat_cols = ['store_primary_category']
df[cat_cols] = df[cat_cols].fillna('Unknown')
```

Encode Categorical Features

```
# Import necessary libraries
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
# Define categorical and numerical features
categorical_features = ['market_id', 'store_primary_category', 'order_protocol']
numerical_features = ['total_items', 'subtotal', 'num_distinct_items',
                      'min_item_price', 'max_item_price', 'total_onshift_partners',
                      'total_busy_partners', 'total_outstanding_orders',
                      'order_hour', 'order_day']

# Use ColumnTransformer for encoding
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features),
        ('num', StandardScaler(), numerical_features)
    ])

# Apply transformations
X = df.drop('delivery_time', axis=1)
y = df['delivery_time']
X_processed = preprocessor.fit_transform(X)
```

Outlier Detection & Removal

```
# Plot boxplot for delivery time
plt.figure(figsize=(10, 4))
sns.boxplot(x=df['delivery_time'])
plt.title("Delivery Time Outliers")
plt.show()

# Remove outliers using IQR
Q1 = df['delivery_time'].quantile(0.25)
Q3 = df['delivery_time'].quantile(0.75)
IQR = Q3 - Q1
df = df[(df['delivery_time'] >= Q1 - 1.5*IQR) &
        (df['delivery_time'] <= Q3 + 1.5*IQR)]
```

Split Data into Train/Test Sets

```
# Split data
X_train, X_test, y_train, y_test = train_test_split(
    X_processed, y, test_size=0.2, random_state=42
)
print("Training shape:", X_train.shape)
print("Testing shape:", X_test.shape)
```

```
Training shape: (157942, 100)
Testing shape: (39486, 100)
```

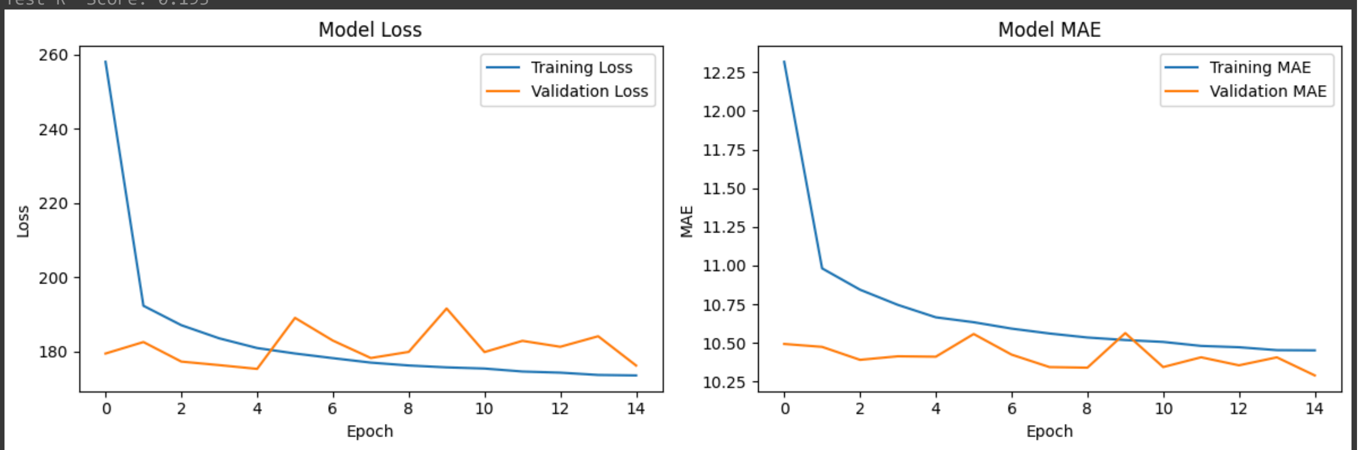
Build & Train Neural Network

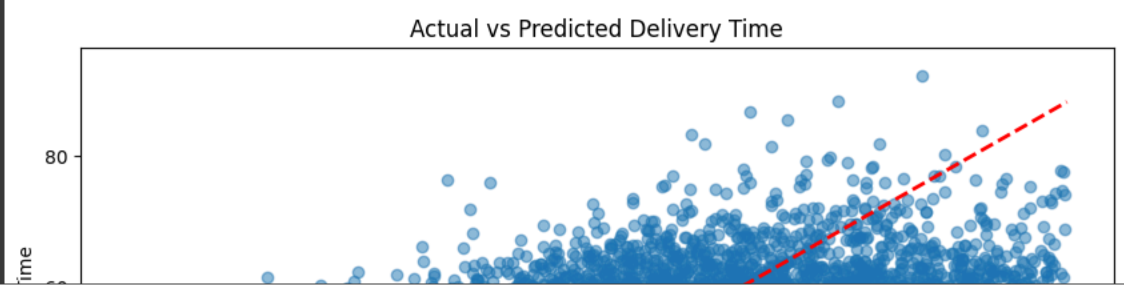
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping

# 1. First, let's check where the NaN values are coming from
print("Checking NaN values in features:")
print(X.isna().sum())
print("\nChecking NaN values in target:")
print(y.isna().sum())

# 2. Clean the data by removing rows with NaN values
df_clean = df.dropna()

# 3. Prepare the clean data
features = ['market_id', 'store_primary_category', 'order_protocol',
           'total_items', 'subtotal', 'num_distinct_items',
           'min_item_price', 'max_item_price', 'total_onshift_partners',
           'total_busy_partners', 'total_outstanding_orders',
           'order_hour', 'order_day']

X = df_clean[features]
y = df_clean['delivery_time']
```

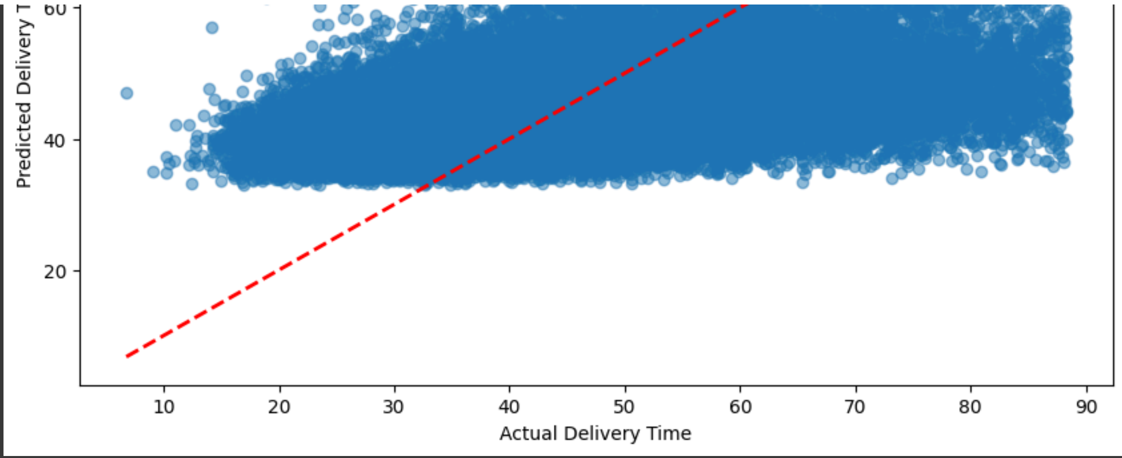
```
# 4. Split the clean data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# 5. Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# 6. Create and train the neural network
model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=(len(features),)),
    layers.Dropout(0.2),
    layers.Dense(32, activation='relu'),
    layers.Dropout(0.1),
    layers.Dense(16, activation='relu'),
    layers.Dense(1)
])

model.compile(optimizer='adam', loss='mse', metrics=['mae'])

# Add early stopping
early_stopping = keras.callbacks.EarlyStopping(
    patience=10,
    min_delta=0.001,
    restore_best_weights=True
)

# Train the model
history = model.fit(
    X_train_scaled, y_train,
    validation_split=0.2,
    epochs=100,
    batch_size=32,
    callbacks=[early_stopping],
    verbose=1
)

from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# 7. Make predictions
train_predictions = model.predict(X_train_scaled)
test_predictions = model.predict(X_test_scaled)

# 8. Calculate metrics
train_mse = mean_squared_error(y_train, train_predictions)
test_mse = mean_squared_error(y_test, test_predictions)
train_rmse = np.sqrt(train_mse)
test_rmse = np.sqrt(test_mse)
train_mae = mean_absolute_error(y_train, train_predictions)
test_mae = mean_absolute_error(y_test, test_predictions)
test_r2 = r2_score(y_test, test_predictions)

print("\nModel Performance Metrics:")
print(f"Train RMSE: {train_rmse:.2f} minutes")
print(f"Test RMSE: {test_rmse:.2f} minutes")
print(f"Train MAE: {train_mae:.2f} minutes")
print(f"Test MAE: {test_mae:.2f} minutes")
print(f"Test R² Score: {test_r2:.3f}")

# 9. Plot training history
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['mae'], label='Training MAE')
plt.plot(history.history['val_mae'], label='Validation MAE')
plt.title('Model MAE')
plt.xlabel('Epoch')
plt.ylabel('MAE')
plt.legend()

plt.tight_layout()
plt.show()

# 10. Visualize predictions vs actual values
```

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, test_predictions, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.xlabel('Actual Delivery Time')
plt.ylabel('Predicted Delivery Time')
plt.title('Actual vs Predicted Delivery Time')
plt.show()
```

```
Checking NaN values in features:
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
order_hour                  0
order_day                   0
dtype: int64

Checking NaN values in target:
0
Epoch 1/100
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` arg
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - loss: 440.0865 - mae: 15.5926 - val_loss: 179.4315 - val_mae: 10.4932
Epoch 2/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 18s 3ms/step - loss: 195.0731 - mae: 11.0530 - val_loss: 182.5258 - val_mae: 10.4744
Epoch 3/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 22s 3ms/step - loss: 187.7186 - mae: 10.8732 - val_loss: 177.2603 - val_mae: 10.3906
Epoch 4/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 13s 3ms/step - loss: 184.6445 - mae: 10.7735 - val_loss: 176.3089 - val_mae: 10.4135
Epoch 5/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step - loss: 182.6427 - mae: 10.7165 - val_loss: 175.2968 - val_mae: 10.4108
Epoch 6/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - loss: 178.6758 - mae: 10.6013 - val_loss: 189.0352 - val_mae: 10.5575
Epoch 7/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step - loss: 178.8369 - mae: 10.6078 - val_loss: 182.9107 - val_mae: 10.4243
Epoch 8/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step - loss: 177.1358 - mae: 10.5647 - val_loss: 178.2231 - val_mae: 10.3438
Epoch 9/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step - loss: 176.7563 - mae: 10.5510 - val_loss: 179.8740 - val_mae: 10.3399
Epoch 10/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step - loss: 175.4659 - mae: 10.5064 - val_loss: 191.5581 - val_mae: 10.5635
Epoch 11/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - loss: 174.8971 - mae: 10.4910 - val_loss: 179.8246 - val_mae: 10.3439
Epoch 12/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step - loss: 174.1083 - mae: 10.4620 - val_loss: 182.8482 - val_mae: 10.4070
Epoch 13/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step - loss: 173.9432 - mae: 10.4633 - val_loss: 181.2471 - val_mae: 10.3552
Epoch 14/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step - loss: 175.3021 - mae: 10.4991 - val_loss: 184.0875 - val_mae: 10.4067
Epoch 15/100
3794/3794 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - loss: 173.9874 - mae: 10.4744 - val_loss: 176.2024 - val_mae: 10.2898
4743/4743 ━━━━━━━━━━━━━━━━━━━━ 7s 1ms/step
1186/1186 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step

Model Performance Metrics:
Train RMSE: 13.23 minutes
Test RMSE: 13.22 minutes
Train MAE: 10.43 minutes
Test MAE: 10.42 minutes
Test R² Score: 0.193
```







Hyperparameter Tuning

```
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

def build_model(hidden_units=64, learning_rate=0.001, dropout_rate=0.2):
    model = keras.Sequential([
        Dense(hidden_units, activation='relu', input_shape=(X_train.shape[1],)),
        Dropout(dropout_rate),
        Dense(hidden_units//2, activation='relu'),
        Dense(1)
    ])
    optimizer = Adam(learning_rate=learning_rate)
    model.compile(optimizer=optimizer, loss='mse', metrics=['mae'])
    return model

# Try different hyperparameters
params = [
    {'hidden_units': 32, 'learning_rate': 0.01, 'dropout_rate': 0.1},
    {'hidden_units': 64, 'learning_rate': 0.001, 'dropout_rate': 0.3},
    {'hidden_units': 128, 'learning_rate': 0.0001, 'dropout_rate': 0.5}
]
```