Introduction

This is part 2 of a two part 'end-of-phase' project with Flatiron School. In the previous notebook I conducted an descriptive and inferential analysis of the dataset that I will be using in this model creation.

Recap

In the first notebook I answered many questions both descriptive and inferential about the data within my dataset here. I think the question that will be most apparent in this notebook is 'Which Companies Account for the highest amount of Market Capitalization?' I will later use that question first to create a failled model and then to use as the outputs for my working model

Table of Contents


```
import nbformat

def generate_toc(notebook_path):
    with open(notebook_path) as f:
        nb = nbformat.read(f, as_version=4)

    toc = []
    for cell in nb.cells:
        if cell.cell_type == 'markdown':
            lines = cell.source.split('\n')
            for line in lines:
                if line.startswith('#'):
                    header_level = line.count('#')
                    header_text = line.replace('#', '').strip()
                    toc.append((header_level, header_text))

    toc_md = ['## Table of Contents']
    for level, text in toc:
        toc_md.append(f"{'    ' * (level - 1)}- [{text}](#{text.replace(' ', '-')})")

    return '\n'.join(toc_md)

notebook_path = 'stock model.ipynb'
toc_md = generate_toc(notebook_path)

# Print the generated TOC
# print(toc_md)
```

Data Cleaning and Preprocessing

Lets begin!

Imports

```
import pandas as pd
import os
import tensorflow as tf
import matplotlib.pyplot as plt
```

```
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from keras.models import Sequential, load_model
from keras.layers import LSTM, Dense, Dropout, BatchNormalization, Bidirectional
from keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
from keras.regularizers import l2
from keras.optimizers import Adam
from keras.utils import plot_model
from sklearn.preprocessing import MinMaxScaler, LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error, explained_variance_score, mean_absolute_error, root_mean_squared_error, mean_absolu
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
import yfinance as yf
from datetime import datetime, timedelta
import warnings
from math import pi
import io
warnings.filterwarnings('ignore')
```

```
df_stocks = pd.read_csv('data/sp500_stocks.csv')
```

Im going to use the data from the S&P 500 dataset simply to get the tickers my model

```
sp500_tickers = df_stocks['Symbol'].unique()
tickers = []
for x in sp500_tickers:
    tickers.append(x)
```

Now im using yfinance (yahoo finance api) to collect the data I want to use for shotgun method model prediction

```
# Keys you're interested in from the 'info' function
keys = ['country', 'sector', 'previousClose', 'overallRisk', 'beta', 'trailingPE', 'forwardPE', 'volume', 'marketCap',
    'enterpriseValue', 'profitMargins', 'sharesOutstanding', 'bookValue',
    'priceToBook', 'trailingEps', 'forwardEps', 'pegRatio', 'enterpriseToRevenue',
    'enterpriseToEbitda', 'totalCash', 'totalCashPerShare', 'ebitda', 'totalDebt',
    'quickRatio', 'currentRatio', 'totalRevenue', 'debtToEquity', 'revenuePerShare',
    'returnOnAssets', 'returnOnEquity', 'freeCashflow', 'operatingCashflow',
    'earningsGrowth', 'revenueGrowth', 'grossMargins', 'ebitdaMargins',
    'operatingMargins', 'trailingPegRatio'
]
```

```
# Empty list to store results
data = []

# Loop through tickers and get the specific info
for ticker in tickers:
    stock = yf.Ticker(ticker)
    info = stock.info
    # Extract the values of the keys you're interested in
    row = {key: info.get(key, None) for key in keys}
    data.append(row)

# Convert the list of dictionaries into a pandas DataFrame
df = pd.DataFrame(data)
```

```
# Initialize the LabelEncoder
label_encoder = LabelEncoder()

# Apply label encoding to both columns and replace the original ones
df['country'] = label_encoder.fit_transform(df['country'])
df['sector'] = label_encoder.fit_transform(df['sector'])
```

```
# Initialize the MinMaxScaler
scaler = StandardScaler()

# Columns to scale
```

```
columns_to_scale = ['previousClose', 'overallRisk', 'beta', 'trailingPE', 'forwardPE', 'volume', 'marketCap',
    'enterpriseValue', 'profitMargins', 'sharesOutstanding', 'bookValue',
    'priceToBook', 'trailingEps', 'forwardEps', 'pegRatio', 'enterpriseToRevenue',
    'enterpriseToEbitda', 'totalCash', 'totalCashPerShare', 'ebitda', 'totalDebt',
    'quickRatio', 'currentRatio', 'totalRevenue', 'debtToEquity', 'revenuePerShare',
    'returnOnAssets', 'returnOnEquity', 'freeCashflow', 'operatingCashflow',
    'earningsGrowth', 'revenueGrowth', 'grossMargins', 'ebitdaMargins',
    'operatingMargins', 'trailingPegRatio'
]

# Apply MinMaxScaler to the selected columns
df[columns_to_scale] = scaler.fit_transform(df[columns_to_scale])
```

```
df.dropna(inplace=True)
```

```
features = df.drop(columns=['previousClose'])
```

Shotgun Method

This method is used to create a baseline accuracy from a number of models all at once

```
X = features
y = df['previousClose']
```

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.25,random_state=42)
```

```
def train_and_evaluate_models(models):
    metrics = {
        'R-squared': r2_score,
        'Mean Squared Error': mean_squared_error,
        'Mean Absolute Error': mean_absolute_error,
        'Explained Variance': explained_variance_score,
        'Root Mean Squared Error': root_mean_squared_error,
        'Mean Absolute Percentage Error': mean_absolute_percentage_error
    }

    results = {}

    for metric_name, metric_function in metrics.items():
        model_scores = {}
        for model in models:
            model.fit(X_train, y_train)
            y_pred = model.predict(X_test)
            score = metric_function(y_test, y_pred)
            model_scores[str(model)] = score
        results[metric_name] = model_scores

    return results
```

```
models = [RandomForestRegressor(), LinearRegression(), KNeighborsRegressor()]
model_metrics = train_and_evaluate_models(models=models)
```

```
fig, axes = plt.subplots(6, 1, figsize=(20, 15))

# List of metric names for easier iteration
metric_names = ['R-squared', 'Explained Variance', 'Mean Squared Error', 'Mean Absolute Error', 'Root Mean Squared Error', 'Mean Absolute Pe

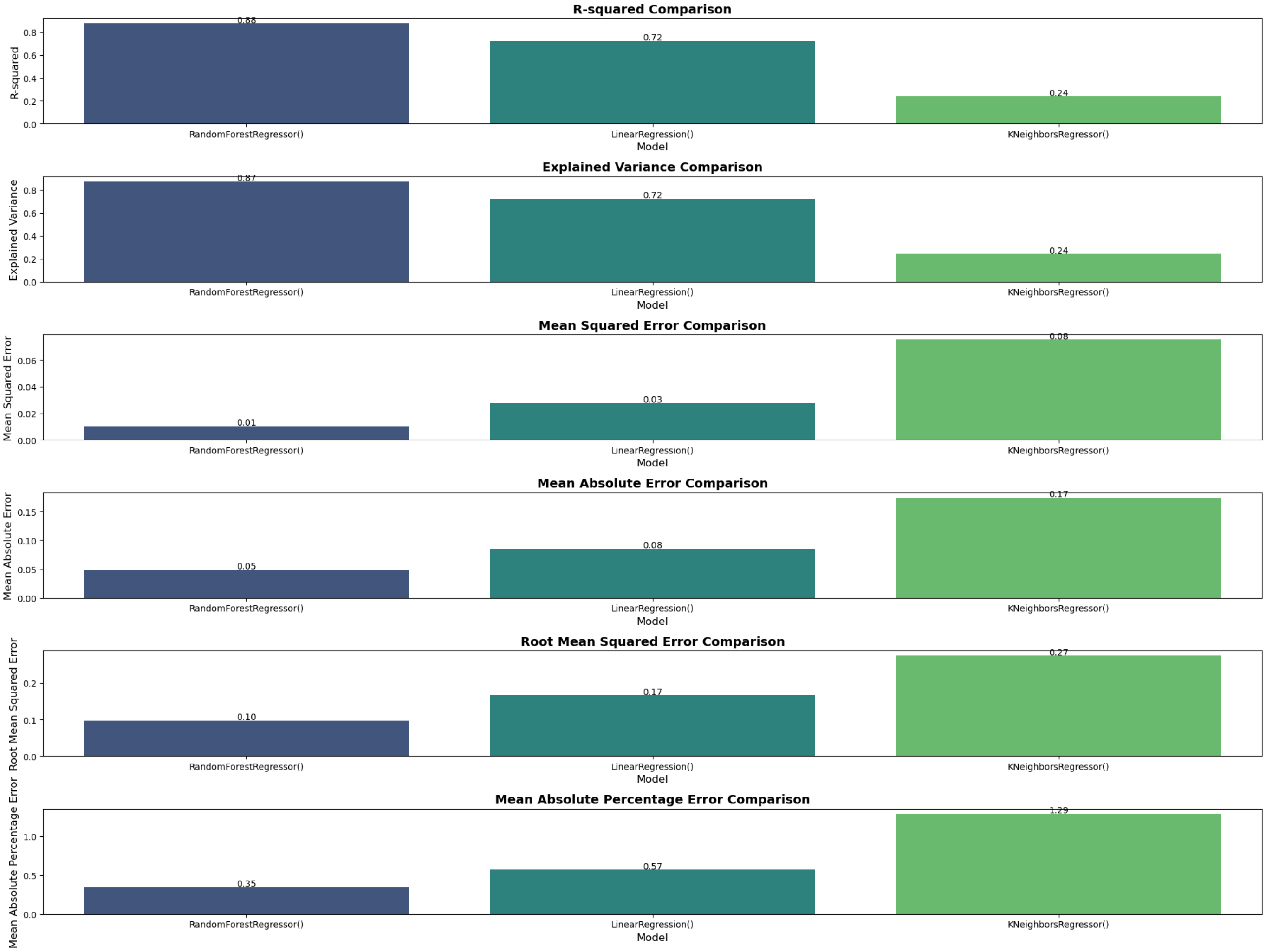
for i, metric_name in enumerate(metric_names):
    ax = axes[i]
    model_scores = model_metrics[metric_name]

    sns.barplot(x=list(model_scores.keys()), y=list(model_scores.values()), palette="viridis", ax=ax)

    # Add labels to the bars
    for j, score in enumerate(model_scores.values()):
        if metric_name == 'R-squared':
            ax.text(j, score + 0.01 *max(model_scores.values()), f'{score:.2f}', ha='center')
        else:
            ax.text(j, score + 0.01 * max(model_scores.values()), f'{score:.2f}', ha='center')
```

```
        # Adding labels and title
        ax.set_xlabel('Model', fontsize=12)
        ax.set_ylabel(metric_name, fontsize=12)
        ax.set_title(f'{metric_name} Comparison', fontsize=14, weight='bold')

    # Adjust layout to prevent overlapping
    plt.tight_layout()
    # plt.savefig('savefig/RegressionModels.png')
    plt.show()
```


R-squared Comparison
R-squared
0.88
0.72
0.24
Explained Variance Comparison
Explained Variance
0.87
0.72
0.24
Mean Squared Error Comparison
Mean Squared Error
0.01
0.03
0.08
Mean Absolute Error Comparison
Mean Absolute Error
0.05
0.08
0.17
Root Mean Squared Error Comparison
Root Mean Squared Error
0.10
0.17
0.27
Mean Absolute Percentage Error Comparison
Mean Absolute Percentage Error
0.35
0.57
1.29
RandomForestRegressor()
LinearRegression()
KNeighborsRegressor()
Model

```
# Reorder the list of metric names so that 'R-squared' and 'Explained Variance' are next to each other
metric_names = ['R-squared', 'Explained Variance', 'Mean Squared Error', 'Mean Absolute Error', 'Root Mean Squared Error', 'Mean Absolute Pe

# Prepare the data for radar chart
model_names = list(next(iter(model_metrics.values())).keys())  # Get the list of model names
num_metrics = len(metric_names)

# Initialize a dictionary to hold the scaled values
scaled_model_metrics = {metric: {} for metric in metric_names}

# Apply MinMax scaling for each metric individually across models
scaler = MinMaxScaler()

for metric in metric_names:
    # Extract the scores for this metric across all models
    scores = np.array([model_metrics[metric][model] for model in model_names]).reshape(-1, 1)

    # Scale the scores for this metric
    scaled_scores = scaler.fit_transform(scores).flatten()

    # Store the scaled scores back into the dictionary
    for i, model in enumerate(model_names):
        scaled_model_metrics[metric][model] = scaled_scores[i]

# Create angles for the radar plot to form a hexagon (6 sides)
angles = [n / float(num_metrics) * 2 * pi for n in range(num_metrics)]
angles += angles[:1]  # Complete the loop

# Define the color mapping for each model with exact colors
color_mapping = {
    'RandomForestRegressor()': '#4CAF50',  # Green used previously
    'KNeighborsRegressor()': 'yellow',
    'LinearRegression()': '#F44336'  # Red used previously
}

# Create the radar plot with hexagonal grid
fig, ax = plt.subplots(figsize=(10, 10), subplot_kw=dict(polar=True))

# Customize the hexagonal appearance by manually setting the radial ticks and limits
ax.set_theta_offset(pi / 6)  # Start the first axis at the top of the hexagon
ax.set_theta_direction(-1)   # Ensure the axes go clockwise

# Plot each model's scaled metrics with their assigned colors
for model in model_names:
    scores = [scaled_model_metrics[metric][model] for metric in metric_names]
    scores += scores[:1]  # Complete the loop for radar chart

    ax.plot(angles, scores, linewidth=2, linestyle='solid', label=model, color=color_mapping.get(str(model), 'blue'))
    ax.fill(angles, scores, alpha=0.25, color=color_mapping.get(str(model), 'blue'))

# Add labels for each metric at the corresponding angles
plt.xticks(angles[:-1], metric_names, color='black', size=14, weight='bold')

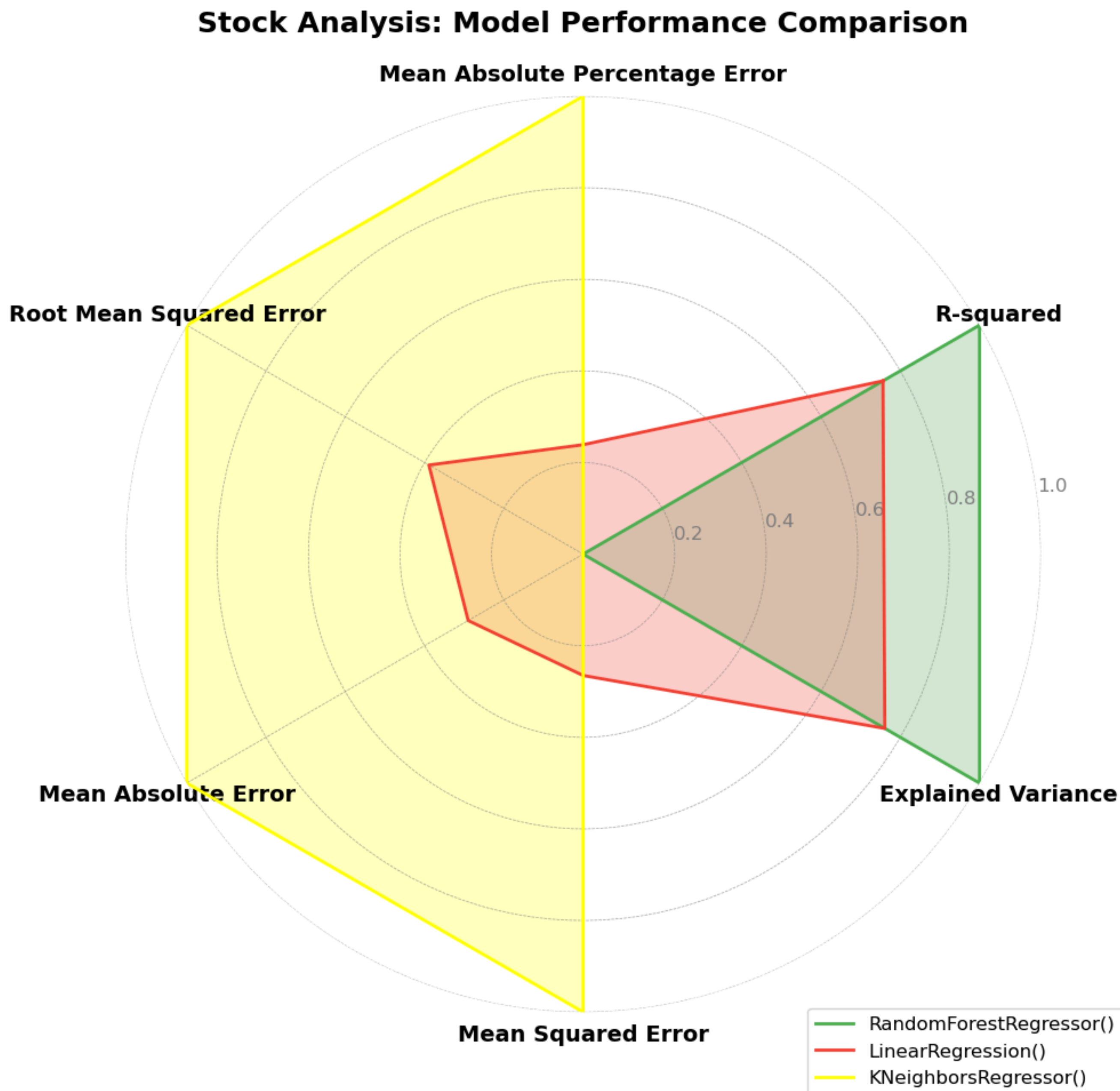
# Set y-ticks and y-limits for better readability (since everything is now scaled between 0 and 1)
plt.yticks([0.2, 0.4, 0.6, 0.8, 1.0], ['0.2', '0.4', '0.6', '0.8', '1.0'], color="grey", size=12)
plt.ylim(0, 1)

# Customize the grid to have a hexagonal shape
ax.grid(color='grey', linestyle='--', linewidth=0.5, alpha=0.7)
ax.spines['polar'].set_visible(False)

# Title and legend
plt.title('Stock Analysis: Model Performance Comparison', size=18, color='black', weight='bold', pad=20)

# Move the legend to the lower-right corner
plt.legend(loc='lower right', bbox_to_anchor=(1.1, -0.1), fontsize=12)

# Display the plot
plt.tight_layout()
plt.savefig('shotgun.png', transparent=True)
plt.show()
```



Advanced Machine Learning: 35 Stocks

This was the original concept I concieved, the plan was to train the model on 35 different stocks at once and then use that model to predict new data for a stock that wasn't in the original 35, it went just about as well as it sounds

```
# List of 35 stocks with the highest market cap in respective sector
tickers = ['AAPL', 'MSFT', 'NVDA', 'AVGO', 'ORCL', 'ADBE', 'CRM', 'AMD', 'ACN', # 9 Stocks from the Technology Sector
           'BRK-B', 'JPM', 'V', 'MA', 'BAC', 'WFC', # 6 Stocks from the Financial Services Sector
           'LLY', 'UNH', 'JNJ', 'ABBV', # 4 Stocks from the Healthcare Sector
           'GE', 'CAT', 'RTX', 'UNP', # 4 Stocks from the Industrials Sector
           'AMZN', 'TSLA', 'HD', # 3 Stocks from the Consumer Cyclical Sector
           'GOOGL', 'META', 'NFLX', # 3 Stocks from the Communication Services Sector
           'WMT', 'PG', # 2 Stocks from the Consumer Defensive Sector
           'XOM', # 1 Stock from the Energy Sector
           'PLD', # 1 Stock from the Real Estate Sector
           'NEE', # 1 Stock from the Utilities Sector
           'LIN' # 1 Stock from the Basic Materials Sector
]
```

```
# Define the end date as yesterday
end_date = datetime.now() - timedelta(1)
end_date_str = end_date.strftime('%Y-%m-%d')


stock_data = pd.DataFrame()
for ticker in tickers:
    df = yf.download(ticker, start="2014-01-01", end=end_date_str)
    df['Ticker'] = ticker
    stock_data = pd.concat([stock_data, df])
```

```
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
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[*********************100%***********************]  1 of 1 completed
```

```
# Select and pivot the data
stock_data = stock_data[['Ticker', 'Adj Close']]
stock_data = stock_data.pivot_table(index=stock_data.index, columns='Ticker', values='Adj Close')


# Scaling my data
scaler = MinMaxScaler()
scaled_data = pd.DataFrame(scaler.fit_transform(stock_data), columns=stock_data.columns, index=stock_data.index)


# Define time step
time_step = 60

# Create sequences
X_train, y_train = [], []
for i in range(len(scaled_data) - time_step):
    X_train.append(scaled_data.iloc[i:i+time_step].values)
    y_train.append(scaled_data.iloc[i + time_step].values)

X_train = np.array(X_train)
y_train = np.array(y_train)

# Display the shapes of X_train and y_train
X_train.shape, y_train.shape
```

```
((2631, 60, 35), (2631, 35))
```

```
num_samples, time_steps, num_stocks = X_train.shape

# Reshape the training data to (num_samples * num_stocks, 1, time_steps, num_features)
X_train_reshaped = X_train.reshape(-1, 1, time_steps)
y_train_reshaped = y_train.reshape(-1)  # Adjust labels accordingly
```

```
X_train_reshaped.shape, y_train_reshaped.shape
```

```
((92085, 1, 60), (92085,))
```

```
model = Sequential()
model.add(LSTM(100, return_sequences=True, input_shape=(1, time_steps)))
model.add(Dropout(0.2))
model.add(Bidirectional(LSTM(100, return_sequences=True)))
model.add(Dropout(0.2))
model.add(Bidirectional(LSTM(100, return_sequences=True)))
model.add(Dropout(0.2))
model.add(LSTM(100))
model.add(Dropout(0.2))
model.add(Dense(1))

optimizer = Adam(learning_rate=0.0000001)
model.compile(optimizer=optimizer, loss='mean_squared_error')

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 1, 100)            64400

 dropout (Dropout)           (None, 1, 100)            0

 bidirectional (Bidirectiona  (None, 1, 200)           160800
 l)

 dropout_1 (Dropout)         (None, 1, 200)            0

 bidirectional_1 (Bidirectio  (None, 1, 200)           240800
 nal)

 dropout_2 (Dropout)         (None, 1, 200)            0

 lstm_3 (LSTM)               (None, 100)               120400

 dropout_3 (Dropout)         (None, 100)               0

 dense (Dense)               (None, 1)                 101

=================================================================
Total params: 586,501
Trainable params: 586,501
Non-trainable params: 0
_________________________________________________________________
```

i commented the fitting of my model as the best model has been saved and I wont accidentally spend the time retraining it

```
# # Early stopping callback
# early_stop = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

# # Train the model with the checkpoint
# history = model.fit(X_train_reshaped, y_train_reshaped, epochs=50, batch_size=10, validation_split=0.2, shuffle=False, callbacks=[early_st
```

```
# model.save('best_model.h5')
```

```
model= load_model('best_model.h5')
```

```
def stock_prediction(test_ticker):
    # Load test stock data
    test_stock = pd.DataFrame()
    df = yf.download(test_ticker, start="2014-01-01", end=end_date_str)
    df['Ticker'] = test_ticker
    test_stock = pd.concat([test_stock, df])

    # Select and pivot the test data
    test_stock = test_stock[['Ticker', 'Adj Close']]
    test_stock = test_stock.pivot_table(index=test_stock.index, columns='Ticker', values='Adj Close')

    # Scaling the test data
    scaler = MinMaxScaler()
```

```
    scaled_test_data = pd.DataFrame(scaler.fit_transform(test_stock), columns=test_stock.columns, index=test_stock.index)

    # Create sequences
    X_test, y_test = [], []
    for i in range(len(scaled_test_data) - time_step):
        X_test.append(scaled_test_data.iloc[i:i + time_step].values)
        y_test.append(scaled_test_data.iloc[i + time_step].values)

    X_test = np.array(X_test)
    y_test = np.array(y_test)

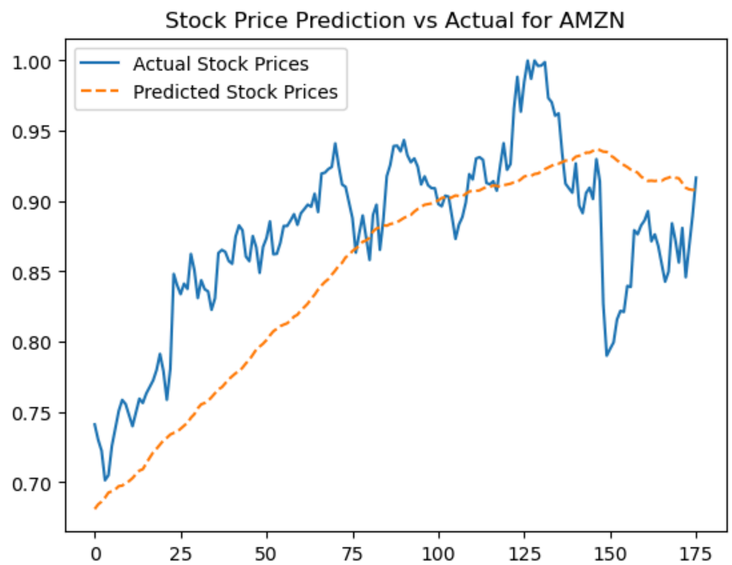
    # Reshape the test data
    X_test_reshaped = X_test.reshape(-1, 1, time_step)
    y_test_reshaped = y_test.reshape(-1)

    # Make predictions
    predictions = model.predict(X_test_reshaped)

    # Plot the predictions vs actual stock prices starting from the 2000th sample
    plt.plot(y_test_reshaped[2455:], label='Actual Stock Prices')
    plt.plot(predictions[2455:], label='Predicted Stock Prices', linestyle='--')
    plt.legend()
    plt.title(f'Stock Price Prediction vs Actual for {test_ticker}')
    plt.show()
```

```
stock_prediction('AMZN')
```

```
[*********************100%***********************]  1 of 1 completed
83/83 [==============================] - 4s 2ms/step
```



as you can see, the results were not good

Advanced Machine Learning: Single Stock Futures

```
# Define the end date as yesterday
end_date = datetime.now() - timedelta(1)
end_date_str = end_date.strftime('%Y-%m-%d')


# Define the start date as a year before yesterday
start_date = end_date - timedelta(1825)
start_date_str = start_date.strftime('%Y-%m-%d')


# Download stock data
stock_data = yf.download('WM', start=start_date_str, end=end_date_str)
```

```
# Scaling
scaler = MinMaxScaler(feature_range=(-1, 1))
scaled_data = scaler.fit_transform(stock_data['Close'].values.reshape(-1,1))
```

```
[*********************100%***********************]  1 of 1 completed
```

```
time_step = 7
```

```
# Define the model
model = Sequential()
model.add(LSTM(units=64, return_sequences=True, input_shape=(time_step, 1)))
model.add(Bidirectional(LSTM(units=64)))
model.add(Dense(units=64))
model.add(Dropout(0.5))
model.add(Dense(units=1))

# Compile the model
optimizer = Adam(learning_rate=0.001)
model.compile(optimizer=optimizer, loss='mean_squared_error')

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 lstm_4 (LSTM)               (None, 7, 64)             16896     
                                                                 
 bidirectional_2 (Bidirectio  (None, 128)              66048     
 nal)                                                            
                                                                 
 dense_1 (Dense)             (None, 64)                8256      
                                                                 
 dropout_4 (Dropout)         (None, 64)                0         
                                                                 
 dense_2 (Dense)             (None, 1)                 65        
                                                                 
=================================================================
Total params: 91,265
Trainable params: 91,265
Non-trainable params: 0
_________________________________________________________________
```

```
# Step 1: Predict today’s data
todays_data = scaled_data[-time_step:].reshape(1, time_step, 1)
todays_prediction = model.predict(todays_data)
todays_prediction_inversed = scaler.inverse_transform(todays_prediction)
todays_prediction_inversed
```

```
1/1 [==============================] - 1s 1s/step
array([[148.81094]], dtype=float32)
```

```
# Step 2: Append today’s prediction to the dataset
new_data_point = np.append(stock_data['Close'].values, todays_prediction_inversed)

# Recreate scaled_data based on the updated dataset
updated_scaled_data = scaler.fit_transform(new_data_point.reshape(-1, 1))
```

```
# Recreate X and y with the updated dataset
X_new, y_new = [], []
for i in range(len(updated_scaled_data) - time_step - 1):
    X_new.append(updated_scaled_data[i:(i + time_step), 0])  # Add time_step-length sequences to X
    y_new.append(updated_scaled_data[i + time_step, 0])      # Add the next value to y

X_new = np.array(X_new)
y_new = np.array(y_new)
X_new = np.reshape(X_new, (X_new.shape[0], X_new.shape[1], 1))
```

```
# Early stopping callback
early_stop = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

# Learning rate reducer callback
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=5, min_lr=1e-10, verbose=1)
```

```
# Train the model with the checkpoint
history = model.fit(X_new, y_new, epochs=100, batch_size=10, validation_split=0.2, shuffle=False, callbacks=[early_stop, reduce_lr])
```

```
Epoch 1/100
100/100 [==============================] - 9s 20ms/step - loss: 0.0288 - val_loss: 0.0999 - lr: 0.0010
Epoch 2/100
100/100 [==============================] - 1s 7ms/step - loss: 0.0184 - val_loss: 0.0484 - lr: 0.0010
Epoch 3/100
100/100 [==============================] - 1s 7ms/step - loss: 0.0137 - val_loss: 0.0105 - lr: 0.0010
Epoch 4/100
100/100 [==============================] - 1s 6ms/step - loss: 0.0094 - val_loss: 0.0041 - lr: 0.0010
Epoch 5/100
100/100 [==============================] - 1s 6ms/step - loss: 0.0078 - val_loss: 0.0047 - lr: 0.0010
Epoch 6/100
100/100 [==============================] - 1s 7ms/step - loss: 0.0068 - val_loss: 0.0048 - lr: 0.0010
Epoch 7/100
100/100 [==============================] - 1s 8ms/step - loss: 0.0069 - val_loss: 0.0055 - lr: 0.0010
Epoch 8/100
100/100 [==============================] - 1s 7ms/step - loss: 0.0071 - val_loss: 0.0053 - lr: 0.0010
Epoch 9/100
 99/100 [============================>.] - ETA: 0s - loss: 0.0072
Epoch 9: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
100/100 [==============================] - 1s 7ms/step - loss: 0.0072 - val_loss: 0.0048 - lr: 0.0010
Epoch 10/100
100/100 [==============================] - 1s 7ms/step - loss: 0.0131 - val_loss: 0.0316 - lr: 1.0000e-04
Epoch 11/100
100/100 [==============================] - 1s 7ms/step - loss: 0.0059 - val_loss: 0.0175 - lr: 1.0000e-04
Epoch 12/100
100/100 [==============================] - 1s 7ms/step - loss: 0.0053 - val_loss: 0.0140 - lr: 1.0000e-04
Epoch 13/100
100/100 [==============================] - 1s 7ms/step - loss: 0.0055 - val_loss: 0.0116 - lr: 1.0000e-04
Epoch 14/100
 99/100 [============================>.] - ETA: 0s - loss: 0.0053
Epoch 14: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
100/100 [==============================] - 1s 7ms/step - loss: 0.0053 - val_loss: 0.0110 - lr: 1.0000e-04
```

```
# Plot the training loss and validation loss with stock analysis theme
plt.figure(figsize=(10, 6))

# Plot training loss in green (typically for "positive" improvement)
plt.plot(history.history['loss'], label='Training Loss', color='#4CAF50', linewidth=2)

# Plot validation loss in red (for validation, possibly showing "issues")
plt.plot(history.history['val_loss'], label='Validation Loss', color='#F44336', linewidth=2)

# Set title and labels
plt.title('Training and Validation Loss (Stock Analysis Theme)', fontsize=18, weight='bold', pad=20)
plt.xlabel('Epochs', fontsize=14, weight='bold')
plt.ylabel('Loss', fontsize=14, weight='bold')

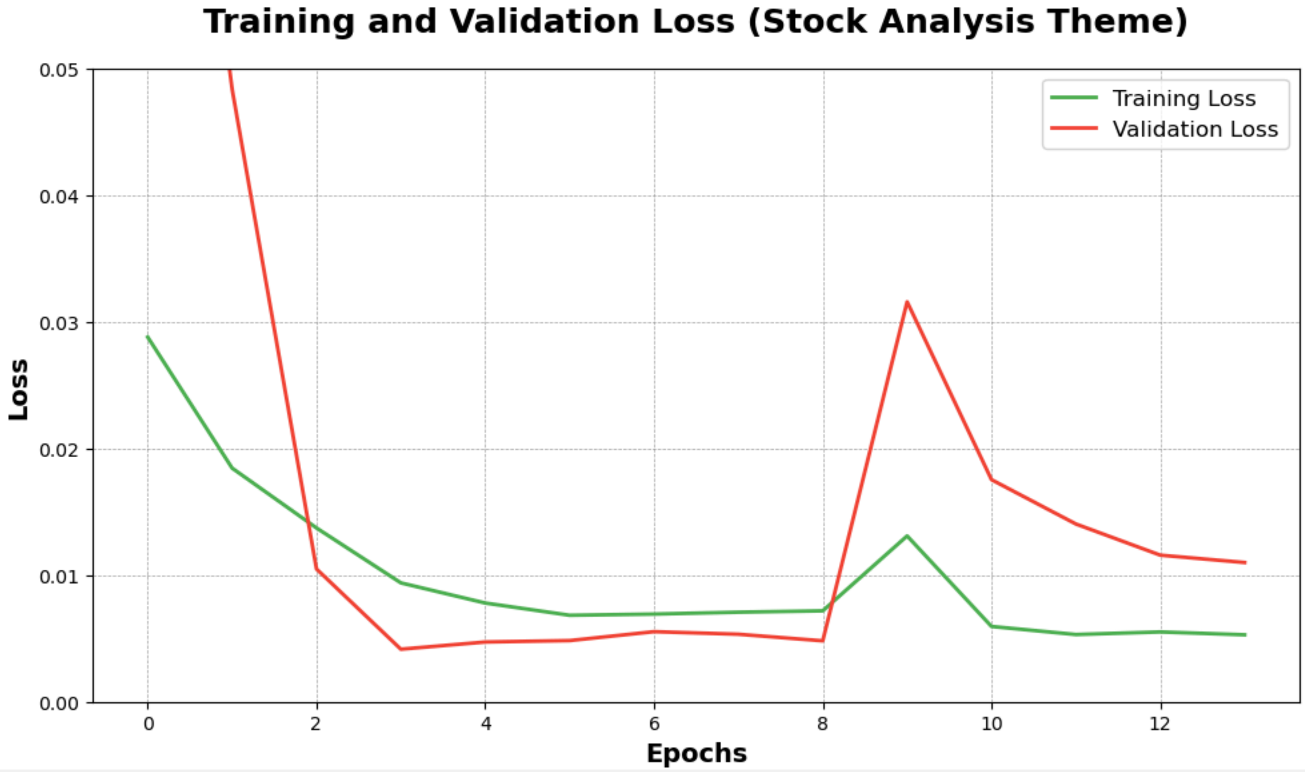
# Set y-axis limits from 0 to 0.05 as requested
plt.ylim(0, 0.05)

# Add grid lines for better readability
plt.grid(color='grey', linestyle='--', linewidth=0.5, alpha=0.7)

# Customize the legend and display it in the lower right corner
plt.legend(loc='upper right', fontsize=12)

# Clean and polished layout
plt.tight_layout()

# Show the plot
plt.savefig('Loss.png', transparent= True)
plt.show()
```



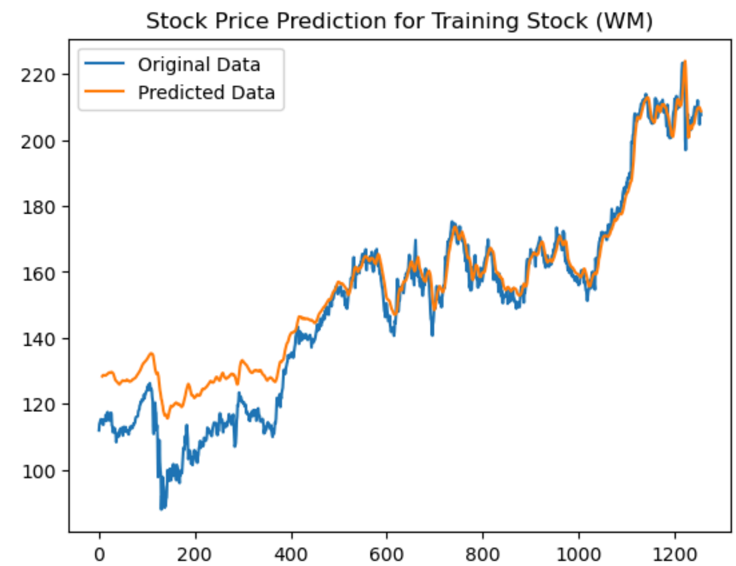

```
# Make new predictions after retraining
predictions = model.predict(X_new)
predictions = scaler.inverse_transform(predictions)
print(f'Predicted Close: {predictions[-1:]}')
print(f"Actual Close: {stock_data['Close'][-1:].values}")
```

```
40/40 [==============================] - 0s 2ms/step
Predicted Close: [[208.76282]]
Actual Close: [207.63999939]
```

```
# Collect data for the plot
original_data = stock_data['Close'].values
predicted_data = np.empty_like(original_data)
predicted_data[:] = np.nan
predicted_data[-len(predictions):] = predictions.reshape(-1)

# Create the plot
fig, ax = plt.subplots()
ax.plot(original_data, label='Original Data')
ax.plot(predicted_data, label='Predicted Data')
ax.legend()

plt.title(f"Stock Price Prediction for Training Stock (WM)")
plt.show()
```




```
# Initialize the data with the last `time_step` days from the initial_data
initial_data = scaled_data[-7:]
current_window = initial_data[-time_step:].copy()  # Assuming `initial_data` is already defined
all_predictions = []

for i in range(30):
    # Reshape current_window to match the model input shape (assuming a 3D input for LSTM)
    X_input = current_window.reshape((1, time_step, current_window.shape[1]))

    # Generate multiple predictions (ensemble) for the current day
    ensemble_predictions = []
    for _ in range(15):
        predicted_value = model.predict(X_input)[0][0]  # Assuming a single output per prediction
        ensemble_predictions.append(predicted_value)

    # Calculate the mean of the ensemble predictions
    predicted_value = np.mean(ensemble_predictions)

    # Append the prediction to the list of predictions
    all_predictions.append(predicted_value)

    # Update the current window with the new predicted value
    # We assume here that we're predicting a single feature, like the "Close" price
    predicted_value_as_array = np.array([[predicted_value]])
    current_window = np.vstack([current_window[1:], predicted_value_as_array])
```

```
1/1 [==============================] - 0s 16ms/step
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1/1 [==============================] - 0s 16ms/step
1/1 [==============================] - 0s 21ms/step
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```
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```

```python
# Convert predictions back to original scale (if using a scaler)
predicted_prices = scaler.inverse_transform(np.array(all_predictions).reshape(-1, 1))

# Optionally: Plot or use these predictions as needed
print("Predicted Prices for the next 14 days (using ensemble averaging):", predicted_prices)
```

```
Predicted Prices for the next 14 days (using ensemble averaging): [[207.97527]
 [207.69579]
 [207.42749]
 [207.29591]
 [207.7851 ]
 [207.62437]
 [207.5071 ]
 [207.4927 ]
 [207.41284]
 [207.37335]
 [207.3719 ]
 [207.38762]
 [207.31448]
 [207.26453]
 [207.22813]
 [207.18695]
 [207.1525 ]
 [207.11801]
 [207.07718]
 [207.0268 ]
 [206.98174]
 [206.93758]
 [206.89188]
 [206.8454 ]
 [206.79678]
 [206.74591]
 [206.69359]
 [206.64117]
 [206.58757]
 [206.53241]]
```

```python
# # Number of days to zoom in on
# zoom_days = 730

# # Create a timeline for the final `zoom_days` of the actual data and original predictions
# days = np.arange(len(original_data))[-zoom_days:]  # Last `zoom_days` days for the actual data
# predicted_days = np.arange(len(original_data))[-zoom_days:]  # Adjust for the predicted data's timeline
# future_days = np.arange(len(original_data), len(original_data) + len(predicted_prices))  # Future timeline

# plt.figure(figsize=(10, 6))

# # Plot last `zoom_days` of actual data in blue
# plt.plot(days, original_data[-zoom_days:], label='Actual Data', color='blue')

# # Plot last `zoom_days` of original predictions in orange
```

```
# plt.plot(predicted_days, predicted_data[-zoom_days:], label='Predicted Data', color='orange')

# # Plot future predictions in green after the dotted line
# plt.plot(future_days, predicted_prices, label='Future Predicted Data', color='green')

# # Add a vertical dotted line at the point where the future predictions start
# plt.axvline(x=len(original_data) - 1, color='black', linestyle='--', label='Prediction Boundary')

# # Add labels and title
# plt.xlabel('Days')
# plt.ylabel('Stock Price')
# plt.title('Stock Price Prediction for Stock')

# # Show legend
# plt.legend()

# # Show plot
# plt.show()


noise_factor = 0.02
initial_data = scaled_data[-7:]
current_window = initial_data[-time_step:].copy()  # Assuming `initial_data` is already defined
noisy_predictions = []

for i in range(30):
    X_input = current_window.reshape((1, time_step, current_window.shape[1]))

    ensemble_predictions = []
    for _ in range(15):
        predicted_value = model.predict(X_input)[0][0]
        ensemble_predictions.append(predicted_value)

    # Calculate the mean of the ensemble predictions
    predicted_value = np.mean(ensemble_predictions)

    # Add random noise to introduce variance
    predicted_value += noise_factor * np.random.randn()

    noisy_predictions.append(predicted_value)

    predicted_value_as_array = np.array([[predicted_value]])
    current_window = np.vstack([current_window[1:], predicted_value_as_array])
```

```
1/1 [==============================] - 0s 17ms/step
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```
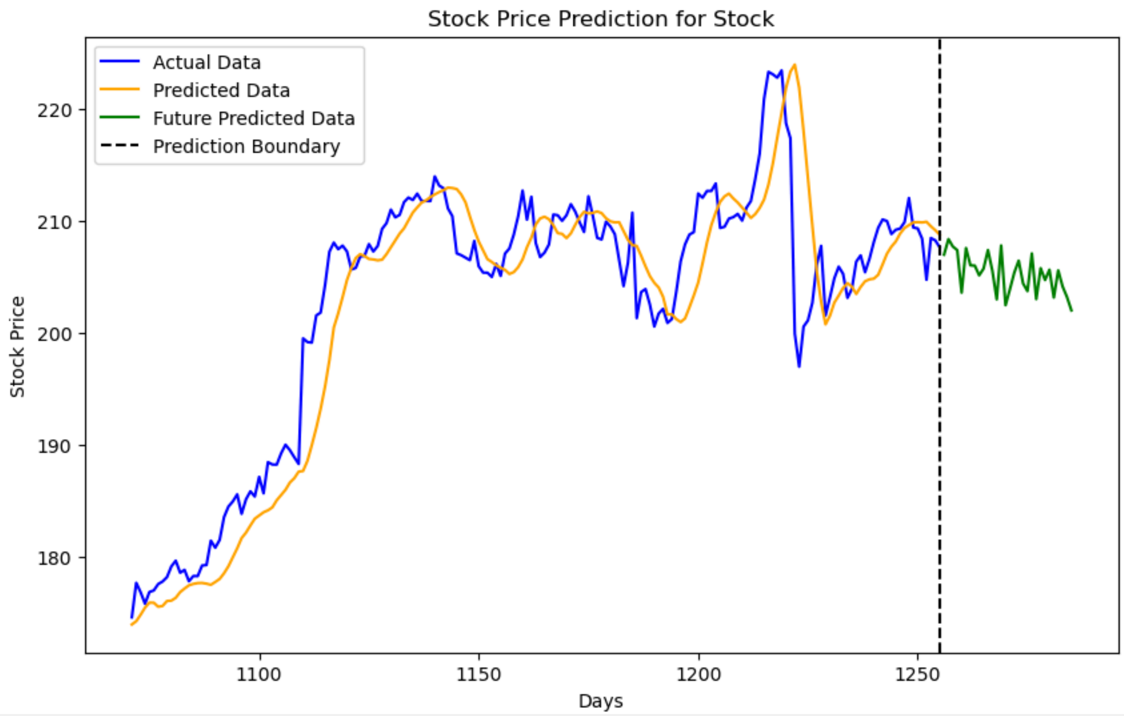

```
# Convert predictions back to original scale (if using a scaler)
predicted_prices = scaler.inverse_transform(np.array(noisy_predictions).reshape(-1, 1))

# Optionally: Plot or use these predictions as needed
print("Predicted Prices for the next 14 days (using ensemble averaging):", predicted_prices)
```

```
Predicted Prices for the next 14 days (using ensemble averaging): [[206.9749627 ]
 [208.364777  ]
 [207.69948994]
 [207.37926336]
 [203.57838716]
 [207.56803575]
 [206.02246478]
 [205.99270564]
 [205.12475882]
 [205.72914817]
 [207.39012355]
 [205.54218722]
 [202.97661714]
 [207.79488951]
 [202.45196959]
 [203.87972648]
 [205.37233854]
 [206.43699131]
 [204.39886884]
 [203.71280882]
 [207.08200002]
 [202.99952227]
 [205.76681022]
 [204.70464947]
 [205.62861474]
 [203.14258957]
 [205.56741431]
 [204.1310381 ]
 [203.18284465]
 [201.99510227]]
```

```
# Number of days to zoom in on
zoom_days = 185

# Create a timeline for the final `zoom_days` of the actual data and original predictions
days = np.arange(len(original_data))[-zoom_days:]  # Last `zoom_days` days for the actual data
predicted_days = np.arange(len(original_data))[-zoom_days:]  # Adjust for the predicted data's timeline
future_days = np.arange(len(original_data), len(original_data) + len(predicted_prices))  # Future timeline

plt.figure(figsize=(10, 6))

# Plot last `zoom_days` of actual data in blue
plt.plot(days, original_data[-zoom_days:], label='Actual Data', color='blue')

# Plot last `zoom_days` of original predictions in orange
plt.plot(predicted_days, predicted_data[-zoom_days:], label='Predicted Data', color='orange')

# Plot future predictions in green after the dotted line
plt.plot(future_days, predicted_prices, label='Future Predicted Data', color='green')

# Add a vertical dotted line at the point where the future predictions start
plt.axvline(x=len(original_data) - 1, color='black', linestyle='--', label='Prediction Boundary')
```

```
# Add labels and title
plt.xlabel('Days')
plt.ylabel('Stock Price')
plt.title('Stock Price Prediction for Stock')

# Show legend
plt.legend()

# Show plot
plt.show()
```



This process on the otherhand came out REALLY WELL!!

Creating The Pipeline

now that I know my model works and it is performing successfully, i combined all the steps into 1 function

```
def pipeline(ticker):
    # Define the end date as yesterday
    end_date = datetime.now() - timedelta(1)
    end_date_str = end_date.strftime('%Y-%m-%d')

    # Define the start date as 5 years before yesterday
    start_date = end_date - timedelta(1825)
    start_date_str = start_date.strftime('%Y-%m-%d')

    # Define the directory path
    directory = f'Stock Graphs/{ticker}'

    # Check if the directory exists, and create it if it doesn't
    if not os.path.exists(directory):
        os.makedirs(directory)

    # Download stock data
    stock_data = yf.download(ticker, start=start_date_str, end=end_date_str)

    # Scaling
    scaler = MinMaxScaler(feature_range=(-1, 1))
    scaled_data = scaler.fit_transform(stock_data['Close'].values.reshape(-1,1))
```

```
time_step = 7

# Define the model
model = Sequential()
model.add(LSTM(units=64, return_sequences=True, input_shape=(time_step, 1)))
model.add(Bidirectional(LSTM(units=64)))
model.add(Dense(units=64))
model.add(Dropout(0.5))
model.add(Dense(units=1))

# Compile the model
optimizer = Adam(learning_rate=0.001)
model.compile(optimizer=optimizer, loss='mean_squared_error')

# Step 1: Predict today’s data
todays_data = scaled_data[-time_step:].reshape(1, time_step, 1)
todays_prediction = model.predict(todays_data)
todays_prediction_inversed = scaler.inverse_transform(todays_prediction)
todays_prediction_inversed

# Step 2: Append today’s prediction to the dataset
new_data_point = np.append(stock_data['Close'].values, todays_prediction_inversed)

# Recreate scaled_data based on the updated dataset
updated_scaled_data = scaler.fit_transform(new_data_point.reshape(-1, 1))

# Recreate X and y with the updated dataset
X_new, y_new = [], []
for i in range(len(updated_scaled_data) - time_step - 1):
    X_new.append(updated_scaled_data[i:(i + time_step), 0])  # Add time_step-length sequences to X
    y_new.append(updated_scaled_data[i + time_step, 0])      # Add the next value to y

X_new = np.array(X_new)
y_new = np.array(y_new)
X_new = np.reshape(X_new, (X_new.shape[0], X_new.shape[1], 1))

# Early stopping callback
early_stop = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

# Learning rate reducer callback
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=5, min_lr=1e-10, verbose=1)

# Train the model with the checkpoint
model.fit(X_new, y_new, epochs=100, batch_size=10, validation_split=0.2, shuffle=False, callbacks=[early_stop, reduce_lr])

# Make new predictions after retraining
predictions = model.predict(X_new)
predictions = scaler.inverse_transform(predictions)
print(f'Predicted Close: {predictions[-1:]}')
print(f"Actual Close: {stock_data['Close'][-1:].values}")

# Collect data for the plot
original_data = stock_data['Close'].values
predicted_data = np.empty_like(original_data)
predicted_data[:] = np.nan
predicted_data[-len(predictions):] = predictions.reshape(-1)

# Historical data plot with prediction
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot(original_data, label='Original Data', color='blue', linewidth=2)
ax.plot(predicted_data, label='Predicted Data', color='orange', linewidth=2)

# Add labels and title with bold, larger fonts
ax.set_title(f'Stock Price Prediction for {ticker}', fontsize=18, weight='bold', pad=20)
ax.set_xlabel('Days', fontsize=14, weight='bold')
ax.set_ylabel('Stock Price', fontsize=14, weight='bold')

# Add a grid and legend
ax.grid(color='grey', linestyle='--', linewidth=0.5, alpha=0.7)
ax.legend(loc='lower right', fontsize=12)

plt.savefig(f'{directory}/historical.png')
plt.close()

# Initialize the data with the last `time_step` days from the initial_data
initial_data = scaled_data[-7:]
```

```
current_window = initial_data[-time_step:].copy()  # Assuming `initial_data` is already defined
all_predictions = []

for i in range(30):
    # Reshape current_window to match the model input shape (assuming a 3D input for LSTM)
    X_input = current_window.reshape((1, time_step, current_window.shape[1]))

    # Generate multiple predictions (ensemble) for the current day
    ensemble_predictions = []
    for _ in range(15):
        predicted_value = model.predict(X_input)[0][0]  # Assuming a single output per prediction
        ensemble_predictions.append(predicted_value)

    # Calculate the mean of the ensemble predictions
    predicted_value = np.mean(ensemble_predictions)

    # Append the prediction to the list of predictions
    all_predictions.append(predicted_value)

    # Update the current window with the new predicted value
    # We assume here that we're predicting a single feature, like the "Close" price
    predicted_value_as_array = np.array([[predicted_value]])
    current_window = np.vstack([current_window[1:], predicted_value_as_array])

# Convert predictions back to original scale (if using a scaler)
predicted_prices = scaler.inverse_transform(np.array(all_predictions).reshape(-1, 1))

# Number of days to zoom in on
zoom_days = 730

# Create a timeline for the final `zoom_days` of the actual data and original predictions
days = np.arange(len(original_data))[-zoom_days:]  # Last `zoom_days` days for the actual data
predicted_days = np.arange(len(original_data))[-zoom_days:]  # Adjust for the predicted data's timeline
future_days = np.arange(len(original_data), len(original_data) + len(predicted_prices))  # Future timeline


# Future predictions plot
plt.figure(figsize=(10, 6))
plt.plot(days, original_data[-zoom_days:], label='Actual Data', color='blue', linewidth=2)
plt.plot(predicted_days, predicted_data[-zoom_days:], label='Predicted Data', color='orange', linewidth=2)
plt.plot(future_days, predicted_prices, label='Future Predicted Data', color='#4CAF50', linewidth=2)  # Green color for future predictic

# Add a vertical dotted line at the point where the future predictions start
plt.axvline(x=len(original_data) - 1, color='black', linestyle='--', label='Prediction Boundary')

# Add labels and title with bold fonts
plt.title(f'Stock Price Prediction for {ticker}', fontsize=18, weight='bold', pad=20)
plt.xlabel('Days', fontsize=14, weight='bold')
plt.ylabel('Stock Price', fontsize=14, weight='bold')

# Add grid and legend
plt.grid(color='grey', linestyle='--', linewidth=0.5, alpha=0.7)
plt.legend(loc='lower right', fontsize=12)

plt.savefig(f'{directory}/future.png')
plt.close()

noise_factor = 0.02  # Adjust this factor to control the level of noise
initial_data = scaled_data[-7:]
current_window = initial_data[-time_step:].copy()  # Assuming `initial_data` is already defined
noisy_predictions = []

for i in range(30):
    X_input = current_window.reshape((1, time_step, current_window.shape[1]))

    ensemble_predictions = []
    for _ in range(15):
        predicted_value = model.predict(X_input)[0][0]
        ensemble_predictions.append(predicted_value)

    # Calculate the mean of the ensemble predictions
    predicted_value = np.mean(ensemble_predictions)

    # Add random noise to introduce variance
    predicted_value += noise_factor * np.random.randn()

    noisy_predictions.append(predicted_value)
```

```
        predicted_value_as_array = np.array([[predicted_value]])
        current_window = np.vstack([current_window[1:], predicted_value_as_array])

    # Convert predictions back to original scale (if using a scaler)
    predicted_prices = scaler.inverse_transform(np.array(noisy_predictions).reshape(-1, 1))

    # Number of days to zoom in on
    zoom_days = 185

    # Create a timeline for the final `zoom_days` of the actual data and original predictions
    days = np.arange(len(original_data))[-zoom_days:]  # Last `zoom_days` days for the actual data
    predicted_days = np.arange(len(original_data))[-zoom_days:]  # Adjust for the predicted data's timeline
    future_days = np.arange(len(original_data), len(original_data) + len(predicted_prices))  # Future timeline

    # Noisy future predictions plot
    plt.figure(figsize=(10, 6))
    plt.plot(days, original_data[-zoom_days:], label='Actual Data', color='blue', linewidth=2)
    plt.plot(predicted_days, predicted_data[-zoom_days:], label='Predicted Data', color='orange', linewidth=2)
    plt.plot(future_days, predicted_prices, label='Future Predicted Data', color='#4CAF50', linewidth=2)  # Green color for future predictic

    # Add a vertical dotted line at the point where the future predictions start
    plt.axvline(x=len(original_data) - 1, color='black', linestyle='--', label='Prediction Boundary')

    # Add labels and title with bold fonts
    plt.title(f'Future Stock Price Prediction for {ticker}', fontsize=18, weight='bold', pad=20)
    plt.xlabel('Days', fontsize=14, weight='bold')
    plt.ylabel('Stock Price', fontsize=14, weight='bold')

    # Add grid and legend
    plt.grid(color='grey', linestyle='--', linewidth=0.5, alpha=0.7)
    plt.legend(loc='lower right', fontsize=12)

    plt.savefig(f'{directory}/noisy_future.png')
    plt.close()
```

testing the function

```
# #test
# pipeline('WM')
```

IT WORKS!!!

The Final Result

```
# List of 35 stocks with the highest market cap in respective sector
tickers = ['AAPL', 'MSFT', 'NVDA', 'AVGO', 'ORCL', 'ADBE', 'CRM', 'AMD', 'ACN', # 9 Stocks from the Technology Sector
           'BRK-B', 'JPM', 'V', 'MA', 'BAC', 'WFC', # 6 Stocks from the Financial Services Sector
           'LLY', 'UNH', 'JNJ', 'ABBV', # 4 Stocks from the Healthcare Sector
           'GE', 'CAT', 'RTX', 'UNP', # 4 Stocks from the Industrials Sector
           'AMZN', 'TSLA', 'HD', # 3 Stocks from the Consumer Cyclical Sector
           'GOOGL', 'META', 'NFLX', # 3 Stocks from the Communication Services Sector
           'WMT', 'PG', # 2 Stocks from the Consumer Defensive Sector
           'XOM', # 1 Stock from the Energy Sector
           'PLD', # 1 Stock from the Real Estate Sector
           'NEE', # 1 Stock from the Utilities Sector
           'LIN' # 1 Stock from the Basic Materials Sector
]
```

```
# for ticker in tickers:
#     pipeline(ticker)
```

Summary

This is a summary of my entire modeling notebook from start to finish.