```
In [1]: # Importing necessary libraries
        import numpy as np
        import pandas as pd
        import yfinance as yf
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.model_selection import train_test_split
        from sklearn.preprocessing import StandardScaler
        from sklearn.decomposition import PCA
        from sklearn.metrics import r2_score
        from pyts.image import GramianAngularField
        import tensorflow as tf
        from keras import Sequential
        from keras.callbacks import EarlyStopping
        from keras.layers import Dense, LSTM, Dropout, Conv2D, MaxPool2D, Flatten
        sns.set(style="whitegrid")
```

Step 1

a. Gather information on time series of the prices

```
In [2]: # Define stock information
        ticker = 'AMZN'
        start = '2015-01-01'
        end = '2023-01-01'
        # Download stock data using yfinance
        stock_data = yf.download(ticker, start=start, end=end)
        # Calculate daily returns and drop missing values
        stock_data['returns'] = stock_data['Close'].pct_change()
        stock_data.dropna(inplace=True)
        # Display the first few rows of the stock data
        stock_data.head()
       [********* 100%********** 1 of 1 completed
Out[2]:
                             High
                                            Close Adj Close
                                                             Volume
                     Open
                                     Low
                                                                       returns
```

 Date

 2015-01-05
 15.3505
 15.4190
 15.0425
 15.1095
 15.1095
 55484000
 -0.020517

 2015-01-06
 15.1120
 15.1500
 14.6190
 14.7645
 14.7645
 70380000
 -0.022833

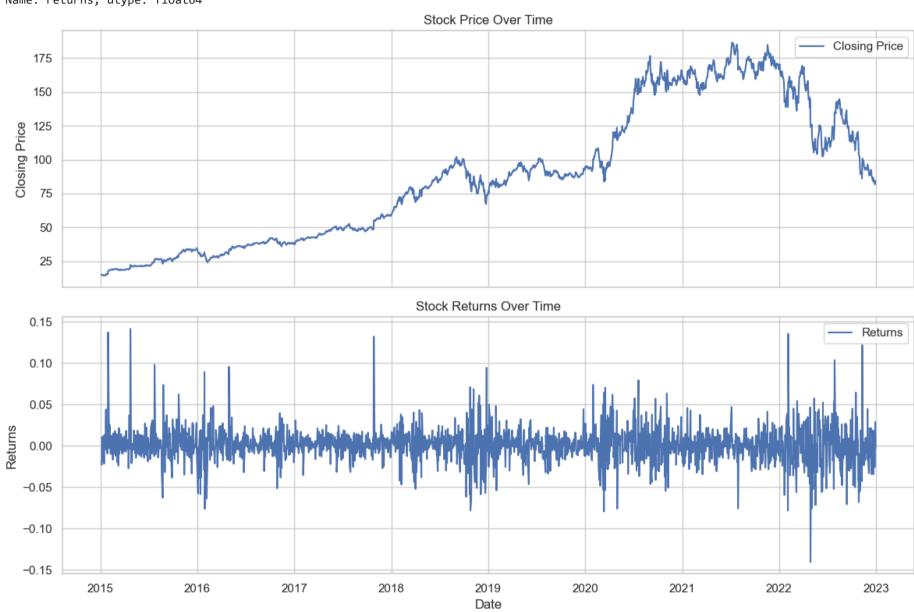
 2015-01-07
 14.8750
 15.0640
 14.7665
 14.9210
 14.9210
 52806000
 0.010600

 2015-01-08
 15.0160
 15.1570
 14.8055
 15.0230
 15.0230
 61768000
 0.006836

 2015-01-09
 15.0740
 15.1435
 14.8340
 14.8465
 14.8465
 51848000
 -0.011749

```
In [3]: # Create a 2x1 subplot grid
        fig, axs = plt.subplots(2, 1, figsize=(12, 8), sharex=True)
        # First subplot for Closing Price
        axs[0].plot(stock_data['Close'], label='Closing Price')
        axs[0].set_ylabel('Closing Price')
        axs[0].set_title('Stock Price Over Time')
        axs[0].legend()
        # Second subplot for Stock Returns
        axs[1].plot(stock_data['returns'], label='Returns')
        axs[1].set_xlabel('Date')
        axs[1].set_ylabel('Returns')
        axs[1].set_title('Stock Returns Over Time')
        axs[1].legend()
        # Adjust Layout for better appearance
        plt.tight_layout()
        # Descriptive statistics for Closing Price
        print("Descriptive Statistics for Closing Price:")
        print(stock_data['Close'].describe())
        # Descriptive statistics for Returns
        print("\nDescriptive Statistics for Returns:")
        print(stock_data['returns'].describe())
        # Show the plot
        plt.show()
```

```
Descriptive Statistics for Closing Price:
         2013.000000
count
           88.334524
mean
std
           49.948132
           14.347500
min
           40.949501
25%
           86.982498
50%
          127.898003
75%
          186.570496
max
Name: Close, dtype: float64
Descriptive Statistics for Returns:
         2013.000000
            0.001061
mean
            0.020975
std
min
           -0.140494
           -0.008544
25%
            0.001168
50%
            0.010892
75%
            0.141311
Name: returns, dtype: float64
```



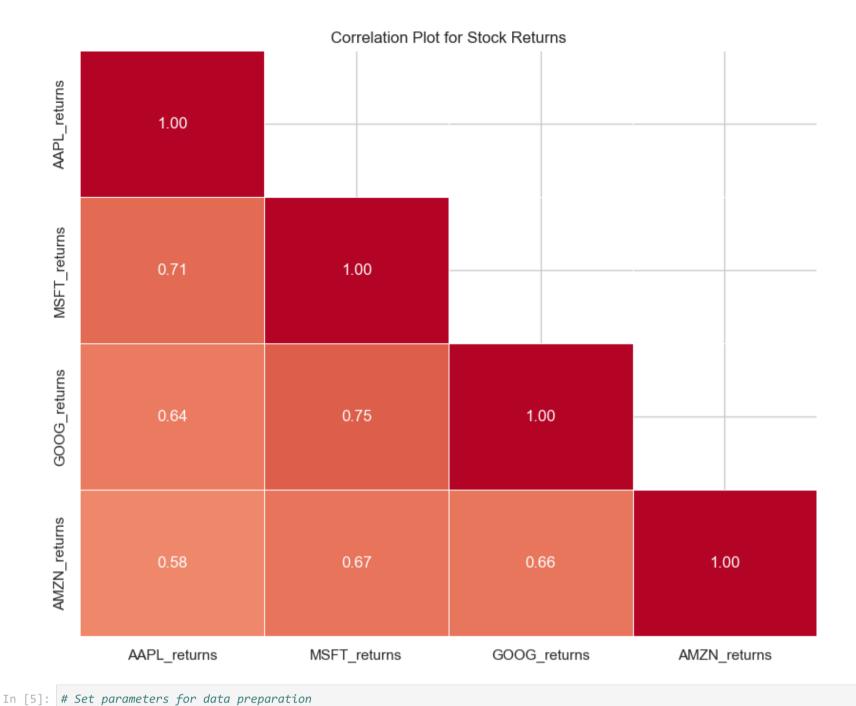
b. Build labels with leakage of information

```
In [4]: # Function to fetch stock data
        def fetch_stock_data(tickers, start, end):
            stock_data = pd.DataFrame()
            # Fetch stock data for each ticker and calculate returns and log volume
            for tick in tickers:
                df = yf.download(tick, start=start, end=end)
                stock_data[f'{tick}_returns'] = df['Close'].pct_change()[1:]
                stock_data[f'{tick}_volume'] = np.log(df['Volume'][1:])
            stock_data.dropna(inplace=True)
            return stock_data
        # Define a list of stock tickers
        tickers = ['AAPL', 'MSFT', 'GOOG', 'AMZN']
        # Fetch stock data using the defined function
        stock_data = fetch_stock_data(tickers, start, end)
        # Create a 2x2 subplot grid
        fig, axs = plt.subplots(2, 2, figsize=(15, 12))
        # Plot individual stock closing prices and returns
        for i, tick in enumerate(tickers):
            row, col = divmod(i, 2)
            axs[row, col].plot(stock_data.index, stock_data[f'{tick}_returns'], label=f'{tick} Returns')
            axs[row, col].set_title(f'{tick} Stock Returns Over Time')
            axs[row, col].set_xlabel('Date')
```

```
axs[row, col].set_ylabel('Returns')
     axs[row, col].legend(loc='upper left')
 plt.tight_layout()
 # Descriptive statistics for returns
 print("Descriptive Statistics for Returns:")
 print(stock_data.filter(like='_returns').describe())
 # Correlation plot for stock returns
 correlation_matrix = stock_data.filter(like='_returns').corr()
 plt.figure(figsize=(10, 8))
 sns.heatmap(correlation_matrix,
              mask=np.triu(correlation_matrix, 1),
              annot=True,
              cmap='coolwarm',
              vmin=-1,
              vmax=1,
              fmt=".2f",
              linewidths=0.5,
              cbar=False)
 plt.title('Correlation Plot for Stock Returns')
 plt.show()
1 of 1 completed
                                                     1 of 1 completed
[********** 100%********** 1 of 1 completed
Descriptive Statistics for Returns:
       AAPL_returns MSFT_returns GOOG_returns AMZN_returns
                      2013.000000
        2013.000000
                                     2013.000000
                                                   2013.000000
count
                         0.000970
           0.000953
                                        0.000765
                                                       0.001061
mean
std
           0.018875
                         0.017747
                                        0.017852
                                                      0.020975
                         -0.147390
                                                      -0.140494
min
          -0.128647
                                       -0.111008
25%
          -0.007630
                         -0.006849
                                       -0.006885
                                                      -0.008544
                                        0.000866
50%
           0.000749
                         0.000827
                                                      0.001168
75%
           0.010345
                          0.009845
                                        0.009048
                                                      0.010892
           0.119808
                                                      0.141311
max
                          0.142169
                                        0.160524
                          AAPL Stock Returns Over Time
                                                                                                 MSFT Stock Returns Over Time
                                                                         0.15
                                                                                 - MSFT Returns
            AAPL Returns
  0.10
                                                                         0.10
  0.05
                                                                         0.05
                                                                      Returns
  0.00
                                                                         0.00
                                                                        -0.05
  -0.05
                                                                        -0.10
  -0.10
                                                                        -0.15
        2015
               2016
                      2017
                                    2019
                                           2020
                                                  2021
                                                         2022
                                                                2023
                                                                              2015
                                                                                     2016
                                                                                            2017
                                                                                                          2019
                                                                                                                        2021
                                                                                                                                      2023
                            2018
                                                                                                   2018
                                                                                                                 2020
                                                                                                                               2022
                                    Date
                                                                                                          Date
                          GOOG Stock Returns Over Time
                                                                                                 AMZN Stock Returns Over Time
                                                                         0.15

    GOOG Returns

                                                                                  AMZN Returns
  0.15
                                                                         0.10
  0.10
                                                                         0.05
  0.05
                                                                      Retu
  0.00
  -0.05
                                                                        -0.10
  -0.10
                                                                        -0.15
        2015
               2016
                      2017
                             2018
                                    2019
                                           2020
                                                  2021
                                                         2022
                                                                2023
                                                                              2015
                                                                                     2016
                                                                                            2017
                                                                                                   2018
                                                                                                          2019
                                                                                                                 2020
                                                                                                                        2021
                                                                                                                               2022
                                                                                                                                      2023
                                    Date
                                                                                                          Date
```



```
window_size = 20
         window_hp = 10
         # Data preparation with leakage (deliberately ignoring the past signals from the rolling mean)
         stock_data['target'] = (1 + stock_data[f'{ticker}_returns']).rolling(window=window_hp).apply(np.prod, raw=True) - 1
         stock_data.dropna(inplace=True)
         # Split data into features (X) and target variable (y)
        X, y = stock_data.drop(columns=[f'{ticker}_returns', 'target']), stock_data['target']
         # Split data into training and testing sets
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, shuffle=False)
         # Standardize the features using StandardScaler
         scaler = StandardScaler()
         X_train_scaled = scaler.fit_transform(X_train)
        X_test_scaled = scaler.transform(X_test)
In [6]: # Convert data to numpy arrays for MLP model
        X_train_mlp = np.array(X_train_scaled)
        X_test_mlp = np.array(X_test_scaled)
        y_train_mlp = np.array(y_train)
        y_test_mlp = np.array(y_test)
         # Data preparation for LSTM model
         X_train_lstm = []
         y_train_lstm = []
        X_{\text{test_lstm}} = []
         y_test_lstm = []
         # Create sequences for training data
         for i in range(window_size, y_train.shape[0]):
            X_train_lstm.append(X_train_scaled[i - window_size: i, :])
             y_train_lstm.append(y_train.iloc[i])
        X_{\text{train\_lstm}}, y_{\text{train\_lstm}} = np.array(X_{\text{train\_lstm}}), np.array(y_{\text{train\_lstm}})
         # Create sequences for testing data
         for i in range(window_size, y_test.shape[0]):
             X_test_lstm.append(X_test_scaled[i - window_size: i, :])
             y_test_lstm.append(y_test.iloc[i])
        X_test_lstm, y_test_lstm = np.array(X_test_lstm), np.array(y_test_lstm)
         # Data preparation for CNN model
        X_train_cnn = []
        y_train_cnn = y_train_lstm.copy()
         # Create Gramian Angular Field images for training data
```

```
for c in range(X_train_scaled.shape[1]):
     slice train = []
     for i in range(window_size, y_train.shape[0]):
          transformer = GramianAngularField()
          slice_train.append(X_train_scaled[:, c][i - window_size: i])
     X_train_cnn.append(((transformer.transform(slice_train) + 1) / 2) * 255)
 X_train_cnn = np.array(X_train_cnn).transpose(1, 2, 0, 3)
 X_train_cnn = X_train_cnn.reshape(X_train_scaled.shape[0] - window_size, X_train_scaled.shape[1] * window_size, window_size)
 # Data preparation for testing data
 X_{test_cnn} = []
 y_test_cnn = y_test_lstm.copy()
 for c in range(X_test_scaled.shape[1]):
     slice_test = []
     for i in range(window_size, y_test.shape[0]):
         transformer = GramianAngularField()
          slice_test.append(X_test_scaled[:, c][i - window_size: i])
     X_{\text{test\_cnn.append}}(((\text{transformer.transform}(\text{slice\_test}) + 1) / 2) * 255)
 X_test_cnn = np.array(X_test_cnn).transpose(1, 2, 0, 3)
 X_test_cnn = X_test_cnn.reshape(X_test_scaled.shape[0] - window_size, X_test_scaled.shape[1] * window_size, window_size)
 # Print shapes of the prepared data
 print("X_train_mlp shape:", X_train_mlp.shape)
 print("X_test_mlp shape:", X_test_mlp.shape)
 print("y_train_mlp shape:", y_train_mlp.shape)
 print("y_test_mlp shape:", y_test_mlp.shape)
 print("X_train_lstm shape:", X_train_lstm.shape)
 print("y_train_lstm shape:", y_train_lstm.shape)
 print("X_test_lstm shape:", X_test_lstm.shape)
 print("y_test_lstm shape:", y_test_lstm.shape)
 print("X_train_cnn shape:", X_train_cnn.shape)
 print("y_train_cnn shape:", y_train_cnn.shape)
 print("X_test_cnn shape:", X_test_cnn.shape)
 print("y_test_cnn shape:", y_test_cnn.shape)
X_train_mlp shape: (1202, 7)
X_test_mlp shape: (802, 7)
y_train_mlp shape: (1202,)
y_test_mlp shape: (802,)
X_train_lstm shape: (1182, 20, 7)
y_train_lstm shape: (1182,)
X_test_lstm shape: (782, 20, 7)
y_test_lstm shape: (782,)
X_train_cnn shape: (1182, 140, 20)
y_train_cnn shape: (1182,)
X_test_cnn shape: (782, 140, 20)
y_test_cnn shape: (782,)
 c. Deep learning models
```

```
In [7]: # Set random seed for reproducibility
        seed = 42
        np.random.seed(seed)
        tf.random.set_seed(seed)
        initializer = tf.keras.initializers.GlorotUniform(seed)
```

MLP model

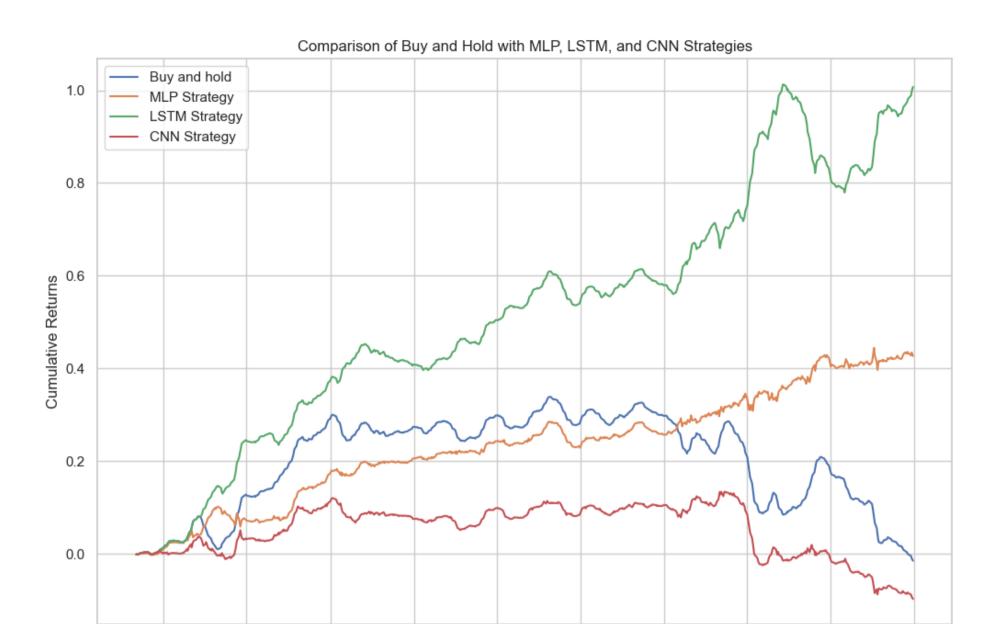
```
In [8]: # MLP Model
        print("Training MLP model")
        model_mlp = Sequential([
            Dense(units=64, activation='relu', kernel_initializer=initializer, bias_initializer='zeros', input_shape=(X_train_mlp.shape[1],))
            Dense(units=128, activation='relu', kernel_initializer=initializer, bias_initializer='zeros'),
            Dense(units=64, activation='relu', kernel_initializer=initializer, bias_initializer='zeros'),
            Dense(units=32, activation='relu', kernel_initializer=initializer, bias_initializer='zeros'),
            Dense(units=1, activation='linear')
        ])
        model_mlp.compile(optimizer='adam', loss='mean_absolute_error')
        es = EarlyStopping(monitor='val_loss', mode='min', verbose=0, patience=5, restore_best_weights=True)
        # MLP Model Training
        model_mlp.fit(X_train_mlp, y_train_mlp, validation_split=0.3, epochs=30, batch_size=32, verbose=1, callbacks=[es])
        # MLP Model Prediction
        y_pred_mlp = model_mlp.predict(X_test_mlp)
        # Calculate R2 score for MLP
        r2_mlp = r2_score(y_test, y_pred_mlp.flatten())
        print("R2 Score (MLP):", r2_mlp)
```

```
Training MLP model
     Epoch 1/30
    Epoch 2/30
    Epoch 3/30
    Epoch 4/30
    Epoch 5/30
    Epoch 6/30
    Epoch 7/30
    Epoch 8/30
    Epoch 9/30
    26/26 [========== ] - 0s 800us/step
    R2 Score (MLP): -0.1053166058982018
      LSTM model
In [9]: # LSTM Model
      print("Training LSTM model")
      model_lstm = Sequential([
        LSTM(units=64, return_sequences=True, activation='tanh', input_shape=(window_size, X_train_lstm.shape[2]), kernel_initializer=init
        LSTM(units=128, return_sequences=True, activation='tanh', kernel_initializer=initializer, bias_initializer='zeros'),
        LSTM(units=32, return_sequences=False, activation='tanh', kernel_initializer=initializer, bias_initializer='zeros'),
        Dense(units=64, activation='relu', kernel initializer=initializer, bias initializer='zeros'),
        Dense(units=128, activation='relu', kernel_initializer=initializer, bias_initializer='zeros'),
        Dense(units=64, activation='relu', kernel_initializer=initializer, bias_initializer='zeros'),
        Dense(units=32, activation='relu', kernel_initializer=initializer, bias_initializer='zeros'),
        Dense(units=1, activation='linear')
     ])
      model_lstm.compile(optimizer='adam', loss='mean_absolute_error')
      # LSTM Model Training
      model_lstm.fit(X_train_lstm, y_train_lstm, validation_split=0.3, epochs=30, batch_size=32, verbose=1, callbacks=[es])
      # LSTM Model Prediction
      y_pred_lstm = model_lstm.predict(X_test_lstm)
      # Calculate R2 score for LSTM
      r2_lstm = r2_score(y_test[window_size:], y_pred_lstm.flatten())
      print("R2 Score (LSTM):", r2_lstm)
    Training LSTM model
    Epoch 1/30
    Epoch 2/30
    Epoch 3/30
    Epoch 4/30
    Epoch 5/30
    Epoch 6/30
    Epoch 7/30
    25/25 [========= ] - 1s 4ms/step
    R2 Score (LSTM): 0.21429252349232386
      CNN model
In [10]: # CNN Model
      print("Training CNN model")
      model cnn = Sequential([
        Conv2D(filters=32, kernel_size=3, activation='relu', input_shape=(X_train_scaled.shape[1] * window_size, window_size, 1), kernel_:
        MaxPool2D(pool_size=2),
        Conv2D(filters=64, kernel size=3, activation='relu', kernel initializer=initializer, bias initializer='zeros'),
        MaxPool2D(pool_size=2),
        Flatten(),
        Dense(units=128, activation='relu', kernel initializer=initializer, bias initializer='zeros'),
        Dense(units=32, activation='relu', kernel_initializer=initializer, bias_initializer='zeros'),
        Dense(units=1, activation='linear')
     ])
      model_cnn.compile(optimizer='adam', loss='mean_absolute_error')
      # CNN Model Training
      model_cnn.fit(X_train_cnn, y_train_cnn, validation_split=0.3, epochs=30, batch_size=32, verbose=1, callbacks=[es])
      # CNN Model Prediction
      y_pred_cnn = model_cnn.predict(X_test_cnn)
```

Calculate R2 score for CNN

```
r2_cnn = r2_score(y_test[window_size:], y_pred_cnn.flatten())
      print("R2 Score (CNN):", r2_cnn)
     Training CNN model
     Epoch 1/30
     Epoch 2/30
     Epoch 3/30
     Epoch 4/30
     Epoch 5/30
     Epoch 6/30
     Epoch 7/30
     26/26 [============] - 0s 5ms/step - loss: 0.0257 - val_loss: 0.0595
     Epoch 8/30
     26/26 [============] - 0s 5ms/step - loss: 0.0231 - val_loss: 0.0600
     Epoch 9/30
     25/25 [=========== ] - 0s 4ms/step
     R2 Score (CNN): -0.29289432516301694
In [11]: # Create a DataFrame with predictions and strategy returns
      df_pred = pd.DataFrame({
         'y_test': y_test[window_size:],
         'pred_mlp': y_pred_mlp.flatten()[window_size:],
         'pred_lstm': y_pred_lstm.flatten(),
         'pred_cnn': y_pred_cnn.flatten()
      })
      # Calculate buy and hold cumulative return
      # MLP Strategy
      df_pred['positions_mlp'] = df_pred['pred_mlp'].apply(np.sign)
      df_pred['strat_ret_mlp'] = df_pred['positions_mlp'] * df_pred['y_test']
       df\_pred['cum\_ret\_mlp'] = df\_pred['strat\_ret\_mlp'].expanding().apply(lambda \ x: \ np.prod(1 + x)**(window\_hp/252) - 1) 
      # LSTM Strategy
      df_pred['positions_lstm'] = df_pred['pred_lstm'].apply(np.sign)
      df_pred['strat_ret_lstm'] = df_pred['positions_lstm'] * df_pred['y_test']
      # CNN Strategy
      df_pred['positions_cnn'] = df_pred['pred_cnn'].apply(np.sign)
      df_pred['strat_ret_cnn'] = df_pred['positions_cnn'] * df_pred['y_test']
      # Calculate final returns
      buy_return = np.prod(1 + df_pred['y_test']) ** (window_hp/252) - 1
      strat_return_mlp = np.prod(1 + df_pred['strat_ret_mlp']) ** (window_hp/252) - 1
      strat_return_lstm = np.prod(1 + df_pred['strat_ret_lstm']) ** (window_hp/252) - 1
      strat_return_cnn = np.prod(1 + df_pred['strat_ret_cnn']) ** (window_hp/252) - 1
      # Print returns
      print("Buy and Hold Return: {:.4%}".format(buy_return))
      print("MLP Strategy Return: {:.4%}".format(strat_return_mlp))
      print("LSTM Strategy Return: {:.4%}".format(strat_return_lstm))
      print("CNN Strategy Return: {:.4%}".format(strat_return_cnn))
      # Combined Plot
      plt.figure(figsize=(12, 8))
      # Plot cumulative returns with labels and legend
      plt.plot(df_pred['cum_ret_bh'], label='Buy and hold')
      plt.plot(df_pred['cum_ret_mlp'], label='MLP Strategy')
      plt.plot(df_pred['cum_ret_lstm'], label='LSTM Strategy')
      plt.plot(df_pred['cum_ret_cnn'], label='CNN Strategy')
      # Add labels and title
      plt.xlabel('Time')
      plt.ylabel('Cumulative Returns')
      plt.title('Comparison of Buy and Hold with MLP, LSTM, and CNN Strategies')
      plt.legend()
      # Display the plot
      plt.show()
     Buy and Hold Return: -1.4490%
     MLP Strategy Return: 42.6781%
```

LSTM Strategy Return: 100.7310% CNN Strategy Return: -9.6984%



2021-05

Time

2021-09

2022-01

2022-05

2022-09

2023-01

Step 2

2020-01

Perform walk-forward backtest for MLP

2020-05

2020-09

pred_mlp = walk_forward_backtest(model_mlp, X_mlp, y_mlp, train_size=500, test_size=500)

a. Non achored walk forward method with train/test split with 500 observations in each set.

2021-01

```
In [12]: def walk_forward_backtest(model, X, y, train_size, test_size):
             predictions = []
             # Calculate the number of steps for the walk-forward backtest
             num_steps = len(range(train_size, len(X), test_size))
             # Iterate through the data for walk-forward backtesting
             for step, i in enumerate(range(train_size, len(X), test_size)):
                 X_train = X[i - train_size:i]
                 X_test = X[i:i + test_size]
                 y_train = y[i - train_size:i]
                 y_test = y[i:i + test_size]
                 # Print information about the current step
                 print(f"Step {step + 1}/{num_steps}, Index: {i} \n")
                 print(f"X_train shape: {X_train.shape}, X_test shape: {X_test.shape}, y_train shape: {y_train.shape}, y_test shape: {y_test.shape}
                 # Train the model on the current training set
                 model.fit(X_train, y_train, validation_split=0.3, epochs=30, batch_size=32, verbose=1, callbacks=[es])
                 # Extend the predictions with the model's predictions on the current test set
                 predictions.extend(model.predict(X_test).flatten())
             r2 = r2_score(y[-len(predictions):], predictions)
             print("R2 Score:", r2)
             return np.array(predictions)
In [13]: # Combine training and test sets for MLP
         X_mlp = np.vstack((X_train_mlp, X_test_mlp))
         y_mlp = np.hstack((y_train_mlp, y_test_mlp))
```

```
X_train shape: (500, 7), X_test shape: (500, 7), y_train shape: (500,), y_test shape: (500,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
16/16 [============ ] - 0s 800us/step
Step 2/4, Index: 1000
X_train shape: (500, 7), X_test shape: (500, 7), y_train shape: (500,), y_test shape: (500,)
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
16/16 [=======] - 0s 800us/step
Step 3/4, Index: 1500
X_train shape: (500, 7), X_test shape: (500, 7), y_train shape: (500,), y_test shape: (500,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
16/16 [=======] - 0s 800us/step
Step 4/4, Index: 2000
X_train shape: (500, 7), X_test shape: (4, 7), y_train shape: (500,), y_test shape: (4,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
11/11 [============= - 0s 4ms/step - loss: 0.0405 - val loss: 0.0698
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Epoch 12/30
Epoch 13/30
R2 Score: -0.04258133444236645
X_lstm = np.vstack((X_train_lstm, X_test_lstm))
y_lstm = np.hstack((y_train_lstm, y_test_lstm))
```

In [14]: # Combine training and test sets for LSTM

```
R2 Score: 0.2725306559477475

In [15]: # Combine training and test sets for CNN

X_cnn = np.vstack((X_train_cnn, X_test_cnn))

y_cnn = np.hstack((y_train_cnn, y_test_cnn))

# Perform walk-forward backtest for CNN

pred_cnn = walk_forward_backtest(model_cnn, X_cnn, y_cnn, train_size=500, test_size=500)
```

15/15 [======] - 0s 4ms/step

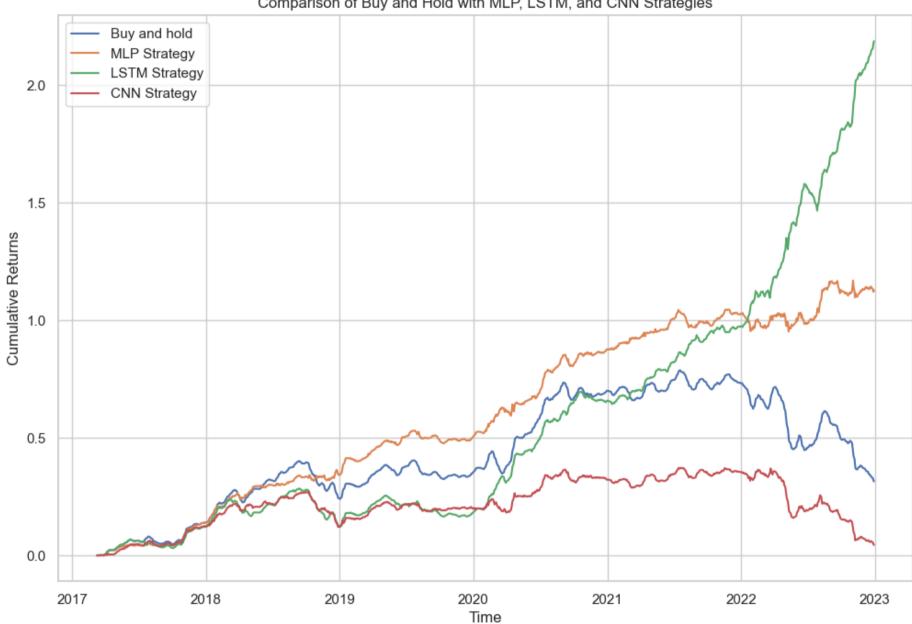
Epoch 9/30

```
X_train shape: (500, 140, 20), X_test shape: (500, 140, 20), y_train shape: (500,), y_test shape: (500,)
    Epoch 1/30
    Epoch 2/30
    Epoch 3/30
    Epoch 4/30
    Epoch 5/30
    Epoch 6/30
    16/16 [=========== ] - 0s 6ms/step
    Step 2/3, Index: 1000
    X_train shape: (500, 140, 20), X_test shape: (500, 140, 20), y_train shape: (500,), y_test shape: (500,)
    Epoch 2/30
    Epoch 3/30
    Epoch 4/30
    Epoch 5/30
    Epoch 6/30
    16/16 [======] - 0s 1ms/step
    Step 3/3, Index: 1500
    X_train shape: (500, 140, 20), X_test shape: (464, 140, 20), y_train shape: (500,), y_test shape: (464,)
    Epoch 1/30
    Epoch 2/30
    Epoch 3/30
    Epoch 4/30
    Epoch 6/30
    Epoch 7/30
    11/11 [============] - 0s 7ms/step - loss: 0.0289 - val_loss: 0.0503
    R2 Score: -0.28222179667747116
In [16]: # Create a DataFrame for walk-forward backtest results
     df_pred_wf = pd.DataFrame(index=y.iloc[-len(pred_lstm):].index)
     # Populate DataFrame with actual and predicted values
     df_pred_wf['y_test'] = y.iloc[-len(pred_lstm):]
     df_pred_wf['pred_mlp'] = pred_mlp[-len(pred_lstm):]
     df_pred_wf['pred_lstm'] = pred_lstm
     df_pred_wf['pred_cnn'] = pred_cnn
     # Calculate buy and hold cumulative return
     # MLP Strategy
     df_pred_wf['positions_mlp'] = df_pred_wf['pred_mlp'].apply(np.sign)
     df_pred_wf['strat_ret_mlp'] = df_pred_wf['positions_mlp'] * df_pred_wf['y_test']
     df_pred_wf['cum_ret_mlp'] = df_pred_wf['strat_ret_mlp'].expanding().apply(lambda x: np.prod(1 + x)**(window_hp/252) - 1)
     # LSTM Strategy
     df_pred_wf['positions_lstm'] = df_pred_wf['pred_lstm'].apply(np.sign)
     df_pred_wf['strat_ret_lstm'] = df_pred_wf['positions_lstm'] * df_pred_wf['y_test']
     # CNN Strategy
     df_pred_wf['positions_cnn'] = df_pred_wf['pred_cnn'].apply(np.sign)
     df_pred_wf['strat_ret_cnn'] = df_pred_wf['positions_cnn'] * df_pred_wf['y_test']
     df pred wf['cum ret cnn'] = df pred wf['strat ret cnn'].expanding().apply(lambda x: np.prod(1 + x)**(window hp/252) - 1)
     # Calculate final returns
     buy return = np.prod(1 + df pred wf['y test'])**(window hp/252) - 1
     strat_return_mlp = np.prod(1 + df_pred_wf['strat_ret_mlp'])**(window_hp/252) - 1
     strat_return_lstm = np.prod(1 + df_pred_wf['strat_ret_lstm'])**(window_hp/252) - 1
     strat_return_cnn = np.prod(1 + df_pred_wf['strat_ret_cnn'])**(window_hp/252) - 1
     # Print returns
     print("Buy and Hold Return: {:.4%}".format(buy_return))
     print("MLP Strategy Return: {:.4%}".format(strat_return_mlp))
     print("LSTM Strategy Return: {:.4%}".format(strat_return_lstm))
     print("CNN Strategy Return: {:.4%}".format(strat_return_cnn))
     # Combined Plot
```

```
plt.figure(figsize=(12, 8))
# Plot cumulative returns with labels and legend
plt.plot(df_pred_wf['cum_ret_bh'], label='Buy and hold')
plt.plot(df_pred_wf['cum_ret_mlp'], label='MLP Strategy')
plt.plot(df_pred_wf['cum_ret_lstm'], label='LSTM Strategy')
plt.plot(df_pred_wf['cum_ret_cnn'], label='CNN Strategy')
# Add labels and title
plt.xlabel('Time')
plt.ylabel('Cumulative Returns')
plt.title('Comparison of Buy and Hold with MLP, LSTM, and CNN Strategies')
plt.legend()
# Display the plot
plt.show()
```

Buy and Hold Return: 31.5357% MLP Strategy Return: 112.4213% LSTM Strategy Return: 218.7272% CNN Strategy Return: 4.4786%

Comparison of Buy and Hold with MLP, LSTM, and CNN Strategies



b. Non achored walk forward method with train/test split with 500 observations in training set and 100 observations in test set.

```
In [17]: # Perform walk-forward backtest for MLP
         pred_mlp = walk_forward_backtest(model_mlp, X_mlp, y_mlp, train_size=500, test_size=100)
```

```
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [========] - 0s 1ms/step
Step 2/16, Index: 600
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
4/4 [======== ] - 0s 1ms/step
Step 3/16, Index: 700
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Step 4/16, Index: 800
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [======= ] - Os 1ms/step
Step 5/16, Index: 900
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
```

```
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Epoch 12/30
Epoch 13/30
4/4 [=======] - 0s 1ms/step
Step 6/16, Index: 1000
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [=======] - 0s 1ms/step
Step 7/16, Index: 1100
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [=======] - 0s 1ms/step
Step 8/16, Index: 1200
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
11/11 [============== ] - 0s 5ms/step - loss: 0.0340 - val loss: 0.0381
4/4 [========] - 0s 1ms/step
Step 9/16, Index: 1300
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
```

```
Epoch 11/30
Epoch 12/30
Epoch 13/30
Epoch 14/30
4/4 [======== ] - 0s 1ms/step
Step 10/16, Index: 1400
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [=======] - 0s 1ms/step
Step 11/16, Index: 1500
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Epoch 12/30
Epoch 13/30
4/4 [======== ] - 0s 1ms/step
Step 12/16, Index: 1600
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
11/11 [========================= ] - 0s 5ms/step - loss: 0.0320 - val_loss: 0.0401
Epoch 7/30
Epoch 8/30
Step 13/16, Index: 1700
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
```

```
Epoch 9/30
  Epoch 10/30
  Epoch 11/30
  Epoch 12/30
  Epoch 13/30
  Epoch 14/30
  Epoch 15/30
  4/4 [=======] - 0s 1ms/step
  Step 14/16, Index: 1800
  X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
  Epoch 1/30
  11/11 [============] - 0s 7ms/step - loss: 0.0324 - val_loss: 0.0509
  Epoch 2/30
  Epoch 3/30
  11/11 [============] - 0s 5ms/step - loss: 0.0301 - val_loss: 0.0512
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  4/4 [=======] - 0s 1ms/step
  Step 15/16, Index: 1900
  X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
  Epoch 1/30
  Epoch 2/30
  Epoch 3/30
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  Epoch 7/30
  Epoch 8/30
  Epoch 9/30
  Epoch 10/30
  Epoch 11/30
  Epoch 12/30
  Step 16/16, Index: 2000
  X_train shape: (500, 7), X_test shape: (4, 7), y_train shape: (500,), y_test shape: (4,)
  Epoch 1/30
  Epoch 2/30
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  Epoch 7/30
  Epoch 8/30
  1/1 [=======] - 0s 17ms/step
  R2 Score: -0.08242593962143041
In [18]: # Perform walk-forward backtest for LSTM
  pred_lstm = walk_forward_backtest(model_lstm, X_lstm, y_lstm, train_size=500, test_size=100)
```

Epoch 8/30

```
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [======== ] - 0s 4ms/step
Step 2/15, Index: 600
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [======== ] - 0s 4ms/step
Step 3/15, Index: 700
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Step 4/15, Index: 800
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 5/30
Epoch 7/30
4/4 [========] - 0s 5ms/step
Step 5/15, Index: 900
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
```

```
Epoch 9/30
4/4 [======== ] - 0s 4ms/step
Step 6/15, Index: 1000
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Step 7/15, Index: 1100
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Step 8/15, Index: 1200
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [========= ] - 0s 4ms/step
Step 9/15, Index: 1300
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
```

```
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Epoch 12/30
Epoch 13/30
4/4 [======== ] - 0s 4ms/step
Step 11/15, Index: 1500
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
4/4 [======== ] - 0s 4ms/step
Step 12/15, Index: 1600
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 9/30
Epoch 10/30
Step 13/15, Index: 1700
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
```

```
Epoch 8/30
  Epoch 9/30
  Epoch 10/30
  Epoch 11/30
  4/4 [======== ] - 0s 4ms/step
  Step 14/15, Index: 1800
  X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
  Epoch 1/30
  Epoch 2/30
  Epoch 3/30
  Epoch 5/30
  Epoch 6/30
  Epoch 7/30
  4/4 [======== ] - 0s 4ms/step
  Step 15/15, Index: 1900
  X_train shape: (500, 20, 7), X_test shape: (64, 20, 7), y_train shape: (500,), y_test shape: (64,)
  Epoch 1/30
  Epoch 2/30
  Epoch 3/30
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  2/2 [=======] - 0s 4ms/step
  R2 Score: 0.2836281185037809
In [19]: # Perform walk-forward backtest for CNN
  pred_cnn = walk_forward_backtest(model_cnn, X_cnn, y_cnn, train_size=500, test_size=100)
```

```
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
4/4 [======== ] - 0s 20ms/step
Step 2/15, Index: 600
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Step 3/15, Index: 700
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [======== ] - 0s 1ms/step
Step 4/15, Index: 800
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
11/11 [============= ] - 0s 7ms/step - loss: 0.0156 - val loss: 0.0407
4/4 [========] - 0s 1ms/step
Step 5/15, Index: 900
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [======== ] - 0s 1ms/step
Step 6/15, Index: 1000
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
```

```
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
4/4 [=======] - 0s 1ms/step
Step 7/15, Index: 1100
X train shape: (500, 140, 20), X test shape: (100, 140, 20), y train shape: (500,), y test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [=======] - 0s 1ms/step
Step 8/15, Index: 1200
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Step 9/15, Index: 1300
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [======== ] - 0s 1ms/step
Step 10/15, Index: 1400
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [======== ] - 0s 1ms/step
Step 11/15, Index: 1500
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
```

```
Epoch 2/30
Epoch 3/30
11/11 [============] - 0s 7ms/step - loss: 0.0287 - val_loss: 0.0500
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Step 12/15, Index: 1600
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [=======] - 0s 1ms/step
Step 13/15, Index: 1700
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Epoch 12/30
Epoch 13/30
Epoch 14/30
Epoch 15/30
4/4 [=======] - 0s 1ms/step
Step 14/15, Index: 1800
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [======== ] - 0s 1ms/step
Step 15/15, Index: 1900
X_train shape: (500, 140, 20), X_test shape: (64, 140, 20), y_train shape: (500,), y_test shape: (64,)
```

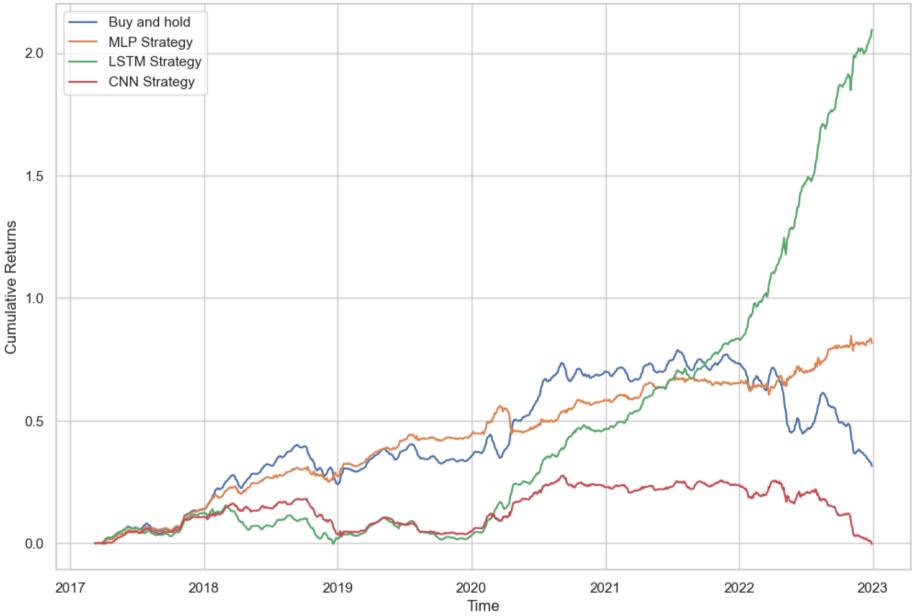
Epoch 1/30

```
Epoch 2/30
  Epoch 3/30
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  Epoch 7/30
  Epoch 8/30
  Epoch 9/30
  Epoch 11/30
  Epoch 12/30
  Epoch 13/30
  Epoch 14/30
  Epoch 15/30
  Epoch 16/30
  Epoch 17/30
  Epoch 18/30
  Epoch 19/30
  Epoch 20/30
  Epoch 21/30
  Epoch 22/30
  Epoch 23/30
  Epoch 24/30
  Epoch 25/30
  Epoch 26/30
  Epoch 27/30
  Epoch 28/30
  Epoch 29/30
  Epoch 30/30
  2/2 [=======] - 0s 2ms/step
  R2 Score: -0.1733671050747274
In [20]: # Create a DataFrame for walk-forward backtest results
   df_pred_wf = pd.DataFrame(index=y.iloc[-len(pred_lstm):].index)
   # Populate DataFrame with actual and predicted values
   df_pred_wf['y_test'] = y.iloc[-len(pred_lstm):]
   df_pred_wf['pred_mlp'] = pred_mlp[-len(pred_lstm):]
   df_pred_wf['pred_lstm'] = pred_lstm
   df_pred_wf['pred_cnn'] = pred_cnn
   # Calculate buy and hold cumulative return
   df_pred_wf['cum_ret_bh'] = df_pred_wf['y_test'].expanding().apply(lambda x: np.prod(1 + x)**(window_hp/252) - 1)
   # MLP Strategy
   df_pred_wf['positions_mlp'] = df_pred_wf['pred_mlp'].apply(np.sign)
   df_pred_wf['strat_ret_mlp'] = df_pred_wf['positions_mlp'] * df_pred_wf['y_test']
   # LSTM Strategy
   df_pred_wf['positions_lstm'] = df_pred_wf['pred_lstm'].apply(np.sign)
   df_pred_wf['strat_ret_lstm'] = df_pred_wf['positions_lstm'] * df_pred_wf['y_test']
   df_pred_wf['cum_ret_lstm'] = df_pred_wf['strat_ret_lstm'].expanding().apply(lambda x: np.prod(1 + x)**(window_hp/252) - 1)
   # CNN Strategy
   df_pred_wf['positions_cnn'] = df_pred_wf['pred_cnn'].apply(np.sign)
   df_pred_wf['strat_ret_cnn'] = df_pred_wf['positions_cnn'] * df_pred_wf['y_test']
   # Calculate final returns
   buy_return = np.prod(1 + df_pred_wf['y_test'])**(window_hp/252) - 1
   strat_return_mlp = np.prod(1 + df_pred_wf['strat_ret_mlp'])**(window_hp/252) - 1
```

```
strat_return_lstm = np.prod(1 + df_pred_wf['strat_ret_lstm'])**(window_hp/252) - 1
strat_return_cnn = np.prod(1 + df_pred_wf['strat_ret_cnn'])**(window_hp/252) - 1
# Print returns
print("Buy and Hold Return: {:.4%}".format(buy_return))
print("MLP Strategy Return: {:.4%}".format(strat_return_mlp))
print("LSTM Strategy Return: {:.4%}".format(strat_return_lstm))
print("CNN Strategy Return: {:.4%}".format(strat_return_cnn))
# Combined Plot
plt.figure(figsize=(12, 8))
# Plot cumulative returns with labels and legend
plt.plot(df_pred_wf['cum_ret_bh'], label='Buy and hold')
plt.plot(df_pred_wf['cum_ret_mlp'], label='MLP Strategy')
plt.plot(df_pred_wf['cum_ret_lstm'], label='LSTM Strategy')
plt.plot(df_pred_wf['cum_ret_cnn'], label='CNN Strategy')
# Add labels and title
plt.xlabel('Time')
plt.ylabel('Cumulative Returns')
plt.title('Comparison of Buy and Hold with MLP, LSTM, and CNN Strategies')
plt.legend()
# Display the plot
plt.show()
```

Buy and Hold Return: 31.5357% MLP Strategy Return: 81.7002% LSTM Strategy Return: 209.4659% CNN Strategy Return: -0.2701%





Step 3

a. Set up and describe a method to reduce the extent of leakage between training and test samples

```
In [21]: # Alleviate leakage by shifting the labels which carry the information
    shifted_X_mlp = X_mlp[window_hp:]
    shifted_y_mlp = y_mlp[:-window_hp]

    shifted_X_cnn = X_cnn[window_hp:]
    shifted_y_cnn = y_cnn[:-window_hp]

    shifted_X_lstm = X_lstm[window_hp:]
    shifted_y_lstm = y_lstm[:-window_hp]
```

b. Non achored walk forward method with train/test split with 500 observations in each set.

```
X_train shape: (500, 7), X_test shape: (494, 7), y_train shape: (500,), y_test shape: (494,)
Epoch 1/30
Epoch 2/30
11/11 [============] - 0s 5ms/step - loss: 0.0423 - val_loss: 0.0493
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
16/16 [=========== ] - 0s 733us/step
R2 Score: -0.17727516257561438
```

pred_lstm = walk_forward_backtest(model_lstm, shifted_X_lstm, shifted_y_lstm, train_size=500, test_size=500)

In [23]: # Perform walk-forward backtest for LSTM

```
X_train shape: (500, 20, 7), X_test shape: (500, 20, 7), y_train shape: (500,), y_test shape: (500,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Epoch 12/30
Epoch 13/30
Epoch 14/30
Epoch 15/30
Epoch 16/30
16/16 [=======] - 0s 4ms/step
Step 2/3, Index: 1000
X_train shape: (500, 20, 7), X_test shape: (500, 20, 7), y_train shape: (500,), y_test shape: (500,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
16/16 [========== ] - 0s 4ms/step
Step 3/3, Index: 1500
X_train shape: (500, 20, 7), X_test shape: (454, 20, 7), y_train shape: (500,), y_test shape: (454,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
15/15 [============ ] - 0s 4ms/step
R2 Score: 0.2610945087871973
pred_cnn = walk_forward_backtest(model_cnn, shifted_X_cnn, shifted_y_cnn, train_size=500, test_size=500)
```

```
X_train shape: (500, 140, 20), X_test shape: (500, 140, 20), y_train shape: (500,), y_test shape: (500,)
    Epoch 1/30
    Epoch 2/30
    Epoch 3/30
    Epoch 4/30
    Epoch 5/30
    Epoch 6/30
    Epoch 7/30
    Step 2/3, Index: 1000
    X_train shape: (500, 140, 20), X_test shape: (500, 140, 20), y_train shape: (500,), y_test shape: (500,)
    Epoch 2/30
    Epoch 3/30
    Epoch 4/30
    Epoch 5/30
    11/11 [===========] - 0s 6ms/step - loss: 0.0259 - val_loss: 0.0599
    Epoch 6/30
    Epoch 7/30
    11/11 [===========] - 0s 7ms/step - loss: 0.0236 - val_loss: 0.0606
    16/16 [============ ] - 0s 1ms/step
    Step 3/3, Index: 1500
    X_train shape: (500, 140, 20), X_test shape: (454, 140, 20), y_train shape: (500,), y_test shape: (454,)
    Epoch 1/30
    Epoch 2/30
    Epoch 4/30
    Epoch 5/30
    Epoch 6/30
    R2 Score: -0.11343733139140966
In [25]: # Create a DataFrame for walk-forward backtest results
     df_pred_wf = pd.DataFrame(index=y.iloc[-len(pred_lstm):].index)
     # Populate DataFrame with actual and predicted values
     df_pred_wf['y_test'] = y.iloc[-len(pred_lstm):]
     df_pred_wf['pred_mlp'] = pred_mlp[-len(pred_lstm):]
     df_pred_wf['pred_lstm'] = pred_lstm
     df_pred_wf['pred_cnn'] = pred_cnn
     # Calculate buy and hold cumulative return
     # MLP Strategy
     df_pred_wf['positions_mlp'] = df_pred_wf['pred_mlp'].apply(np.sign)
     df_pred_wf['strat_ret_mlp'] = df_pred_wf['positions_mlp'] * df_pred_wf['y_test']
     # LSTM Strategy
     df_pred_wf['positions_lstm'] = df_pred_wf['pred_lstm'].apply(np.sign)
     df_pred_wf['strat_ret_lstm'] = df_pred_wf['positions_lstm'] * df_pred_wf['y_test']
     # CNN Strategy
     df_pred_wf['positions_cnn'] = df_pred_wf['pred_cnn'].apply(np.sign)
     df_pred_wf['strat_ret_cnn'] = df_pred_wf['positions_cnn'] * df_pred_wf['y_test']
      df\_pred\_wf['cum\_ret\_cnn'] = df\_pred\_wf['strat\_ret\_cnn']. expanding().apply(lambda \ x: \ np.prod(1 + x)**(window\_hp/252) - 1) 
     # Calculate final returns
     buy_return = np.prod(1 + df_pred_wf['y_test'])**(window_hp/252) - 1
     strat_return_mlp = np.prod(1 + df_pred_wf['strat_ret_mlp'])**(window_hp/252) - 1
     strat_return_lstm = np.prod(1 + df_pred_wf['strat_ret_lstm'])**(window_hp/252) - 1
     strat_return_cnn = np.prod(1 + df_pred_wf['strat_ret_cnn'])**(window_hp/252) - 1
     # Print returns
     print("Buy and Hold Return: {:.4%}".format(buy_return))
     print("MLP Strategy Return: {:.4%}".format(strat_return_mlp))
     print("LSTM Strategy Return: {:.4%}".format(strat_return_lstm))
     print("CNN Strategy Return: {:.4%}".format(strat_return_cnn))
```

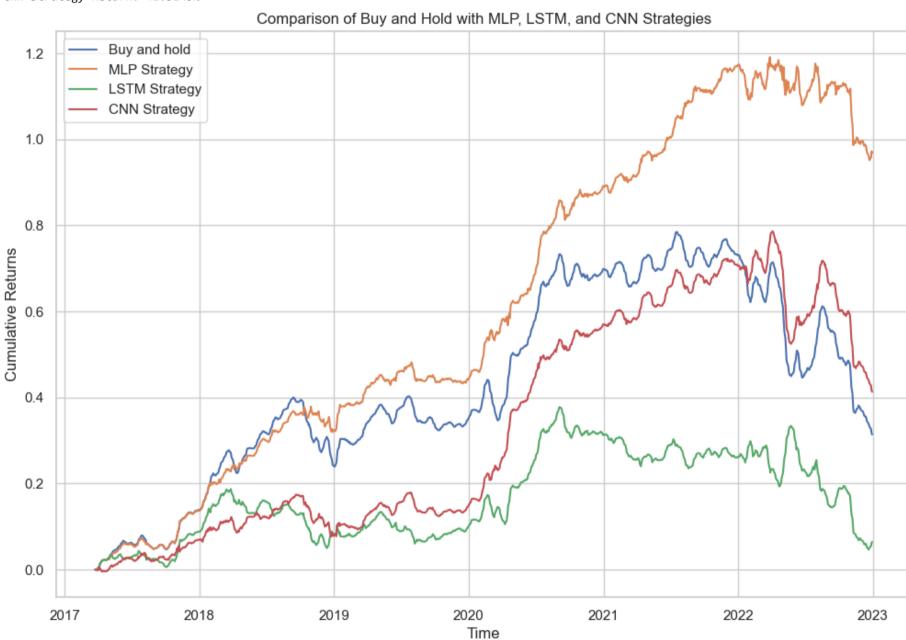
```
# Combined Plot
plt.figure(figsize=(12, 8))

# Plot cumulative returns with labels and legend
plt.plot(df_pred_wf['cum_ret_bh'], label='Buy and hold')
plt.plot(df_pred_wf['cum_ret_mlp'], label='MLP Strategy')
plt.plot(df_pred_wf['cum_ret_lstm'], label='LSTM Strategy')
plt.plot(df_pred_wf['cum_ret_cnn'], label='CNN Strategy')

# Add Labels and title
plt.xlabel('Time')
plt.ylabel('Cumulative Returns')
plt.title('Comparison of Buy and Hold with MLP, LSTM, and CNN Strategies')
plt.legend()

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

Buy and Hold Return: 31.3705% MLP Strategy Return: 96.8299% LSTM Strategy Return: 6.4004% CNN Strategy Return: 41.3245%



c. Non achored walk forward method with train/test split with 500 observations in training set and 100 observations in test set.

```
In [26]: # Perform walk-forward backtest for MLP
pred_mlp = walk_forward_backtest(model_mlp, shifted_X_mlp, shifted_y_mlp, train_size=500, test_size=100)
```

Epoch 19/30

```
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Step 2/15, Index: 600
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
11/11 [===========] - 0s 5ms/step - loss: 0.0308 - val_loss: 0.0305
Epoch 7/30
4/4 [======== ] - 0s 1ms/step
Step 3/15, Index: 700
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Step 4/15, Index: 800
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Epoch 12/30
Epoch 13/30
Epoch 14/30
Epoch 15/30
Epoch 16/30
Epoch 17/30
Epoch 18/30
```

```
4/4 [========] - 0s 1ms/step
Step 5/15, Index: 900
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 8/30
Epoch 9/30
Step 6/15, Index: 1000
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [======== ] - 0s 1ms/step
Step 7/15, Index: 1100
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
11/11 [============] - 0s 5ms/step - loss: 0.0247 - val_loss: 0.0573
Epoch 8/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
4/4 [=======] - 0s 1ms/step
Step 8/15, Index: 1200
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
11/11 [============= ] - 0s 8ms/step - loss: 0.0403 - val loss: 0.0409
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
4/4 [=======] - 0s 1ms/step
Step 9/15, Index: 1300
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
```

Epoch 1/30

```
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [======== ] - 0s 1ms/step
Step 10/15, Index: 1400
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [=======] - 0s 1ms/step
Step 11/15, Index: 1500
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
4/4 [=======] - 0s 1ms/step
Step 12/15, Index: 1600
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [======== ] - 0s 1ms/step
Step 13/15, Index: 1700
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
11/11 [============== - 0s 5ms/step - loss: 0.0418 - val loss: 0.0405
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
4/4 [=======] - 0s 1ms/step
Step 14/15, Index: 1800
X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100,)
```

X_train shape: (500, 7), X_test shape: (100, 7), y_train shape: (500,), y_test shape: (100, 5)
Epoch 1/30

```
Epoch 2/30
 Epoch 3/30
 Epoch 4/30
 Epoch 5/30
 Epoch 6/30
 4/4 [=========] - 0s 1ms/step
 Step 15/15, Index: 1900
 X_train shape: (500, 7), X_test shape: (94, 7), y_train shape: (500,), y_test shape: (94,)
 Epoch 1/30
 Epoch 2/30
 Epoch 5/30
 Epoch 6/30
 Epoch 7/30
 Epoch 8/30
 Epoch 9/30
 3/3 [=======] - 0s 1ms/step
 R2 Score: -0.23800973403602144
In [27]: # Perform walk-forward backtest for LSTM
```

pred_lstm = walk_forward_backtest(model_lstm, shifted_X_lstm, shifted_y_lstm, train_size=500, test_size=100)

```
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [=======] - 0s 4ms/step
Step 2/15, Index: 600
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
4/4 [======== ] - 0s 5ms/step
Step 3/15, Index: 700
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Step 4/15, Index: 800
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Step 5/15, Index: 900
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
```

```
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
4/4 [=======] - 0s 4ms/step
Step 6/15, Index: 1000
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
4/4 [======== ] - 0s 4ms/step
Step 7/15, Index: 1100
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Step 8/15, Index: 1200
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Step 9/15, Index: 1300
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
```

```
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
4/4 [======== ] - 0s 4ms/step
Step 10/15, Index: 1400
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [=======] - 0s 4ms/step
Step 11/15, Index: 1500
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Step 12/15, Index: 1600
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 9/30
Epoch 10/30
4/4 [======== ] - 0s 5ms/step
Step 13/15, Index: 1700
X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [======== ] - 0s 5ms/step
```

Epoch 1/30

Epoch 2/30

Epoch 3/30

```
Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  4/4 [======== ] - 0s 4ms/step
  Step 15/15, Index: 1900
  X_train shape: (500, 20, 7), X_test shape: (54, 20, 7), y_train shape: (500,), y_test shape: (54,)
  Epoch 2/30
  Epoch 3/30
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  Epoch 7/30
  Epoch 8/30
  Epoch 9/30
  Epoch 10/30
  2/2 [======] - 0s 5ms/step
  R2 Score: 0.3308382308098812
In [28]: # Perform walk-forward backtest for CNN
  pred_cnn = walk_forward_backtest(model_cnn, shifted_X_cnn, shifted_y_cnn, train_size=500, test_size=100)
```

X_train shape: (500, 20, 7), X_test shape: (100, 20, 7), y_train shape: (500,), y_test shape: (100,)

```
X train shape: (500, 140, 20), X test shape: (100, 140, 20), y train shape: (500,), y test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [=======] - 0s 2ms/step
Step 2/15, Index: 600
X train shape: (500, 140, 20), X test shape: (100, 140, 20), y train shape: (500,), y test shape: (100,)
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [======== ] - 0s 2ms/step
Step 3/15, Index: 700
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Step 4/15, Index: 800
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 5/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Step 5/15, Index: 900
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
```

```
Step 6/15, Index: 1000
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
4/4 [=======] - 0s 1ms/step
Step 7/15, Index: 1100
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [=======] - 0s 1ms/step
Step 8/15, Index: 1200
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
4/4 [======== ] - 0s 2ms/step
Step 9/15, Index: 1300
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 8/30
11/11 [============= - 0s 6ms/step - loss: 0.0208 - val loss: 0.0541
Epoch 9/30
Epoch 10/30
Step 10/15, Index: 1400
X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
```

```
Step 11/15, Index: 1500
  X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
  Epoch 1/30
  Epoch 2/30
  Epoch 3/30
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  4/4 [=======] - 0s 1ms/step
  Step 12/15, Index: 1600
  X train shape: (500, 140, 20), X test shape: (100, 140, 20), y train shape: (500,), y test shape: (100,)
  Epoch 2/30
  Epoch 3/30
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  4/4 [=======] - 0s 1ms/step
  Step 13/15, Index: 1700
  X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
  Epoch 1/30
  Epoch 2/30
  Epoch 3/30
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  Epoch 7/30
  Step 14/15, Index: 1800
  X_train shape: (500, 140, 20), X_test shape: (100, 140, 20), y_train shape: (500,), y_test shape: (100,)
  Epoch 1/30
  Epoch 2/30
  Epoch 3/30
  Epoch 4/30
  Epoch 5/30
  4/4 [========] - 0s 1ms/step
  Step 15/15, Index: 1900
  X_train shape: (500, 140, 20), X_test shape: (54, 140, 20), y_train shape: (500,), y_test shape: (54,)
  Epoch 1/30
  11/11 [===========] - 0s 9ms/step - loss: 0.0404 - val_loss: 0.0892
  Epoch 2/30
  Epoch 3/30
  Epoch 4/30
  Epoch 5/30
  Epoch 6/30
  Epoch 7/30
  2/2 [========] - 0s 2ms/step
  R2 Score: -0.0976623232553473
In [29]: # Create a DataFrame for walk-forward backtest results
  df_pred_wf = pd.DataFrame(index=y.iloc[-len(pred_lstm):].index)
  # Populate DataFrame with actual and predicted values
```

```
df_pred_wf['y_test'] = y.iloc[-len(pred_lstm):]
df_pred_wf['pred_mlp'] = pred_mlp[-len(pred_lstm):]
df_pred_wf['pred_lstm'] = pred_lstm
df_pred_wf['pred_cnn'] = pred_cnn
# Calculate buy and hold cumulative return
df_pred_wf['cum_ret_bh'] = df_pred_wf['y_test'].expanding().apply(lambda x: np.prod(1 + x)**(window_hp/252) - 1)
# MLP Strategy
df_pred_wf['positions_mlp'] = df_pred_wf['pred_mlp'].apply(np.sign)
df_pred_wf['strat_ret_mlp'] = df_pred_wf['positions_mlp'] * df_pred_wf['y_test']
# LSTM Strategy
df_pred_wf['positions_lstm'] = df_pred_wf['pred_lstm'].apply(np.sign)
df_pred_wf['strat_ret_lstm'] = df_pred_wf['positions_lstm'] * df_pred_wf['y_test']
df_pred_wf['cum_ret_lstm'] = df_pred_wf['strat_ret_lstm'].expanding().apply(lambda x: np.prod(1 + x)**(window_hp/252) - 1)
# CNN Strategy
df_pred_wf['positions_cnn'] = df_pred_wf['pred_cnn'].apply(np.sign)
df_pred_wf['strat_ret_cnn'] = df_pred_wf['positions_cnn'] * df_pred_wf['y_test']
# Calculate final returns
buy_return = np.prod(1 + df_pred_wf['y_test'])**(window_hp/252) - 1
strat_return_mlp = np.prod(1 + df_pred_wf['strat_ret_mlp'])**(window_hp/252) - 1
strat_return_lstm = np.prod(1 + df_pred_wf['strat_ret_lstm'])**(window_hp/252) - 1
strat_return_cnn = np.prod(1 + df_pred_wf['strat_ret_cnn'])**(window_hp/252) - 1
# Print returns
print("Buy and Hold Return: {:.4%}".format(buy_return))
print("MLP Strategy Return: {:.4%}".format(strat_return_mlp))
print("LSTM Strategy Return: {:.4%}".format(strat_return_lstm))
print("CNN Strategy Return: {:.4%}".format(strat_return_cnn))
# Combined Plot
plt.figure(figsize=(12, 8))
# Plot cumulative returns with labels and legend
plt.plot(df_pred_wf['cum_ret_bh'], label='Buy and hold')
plt.plot(df_pred_wf['cum_ret_mlp'], label='MLP Strategy')
plt.plot(df_pred_wf['cum_ret_lstm'], label='LSTM Strategy')
plt.plot(df_pred_wf['cum_ret_cnn'], label='CNN Strategy')
# Add labels and title
plt.xlabel('Time')
plt.ylabel('Cumulative Returns')
plt.title('Comparison of Buy and Hold with MLP, LSTM, and CNN Strategies')
plt.legend()
# Display the plot
plt.show()
```

Buy and Hold Return: 31.3705% MLP Strategy Return: 40.0560% LSTM Strategy Return: -1.3837% CNN Strategy Return: 32.1789%

