```
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime, timedelta


plt.style.use('seaborn-v0_8-whitegrid')
plt.rcParams['figure.figsize'] = (12, 6)
sns.set_palette('viridis')



stocks = ['AAPL', 'MSFT', 'AMZN', 'GOOGL', 'TSLA', 'NVDA', 'META', 'BRK-B', 'JPM', 'JNJ']
end_date = datetime.today().strftime('%Y-%m-%d')
start_date = (datetime.today() - timedelta(days=5*365)).strftime('%Y-%m-%d')  # 5 years of data



stock_data = yf.download(stocks, start=start_date, end=end_date)['Close']

# Display data
print(f"Collected data for {len(stocks)} stocks from {start_date} to {end_date}")
print(f"Data shape: {stock_data.shape}")
stock_data.head()
```

```
/tmp/ipython-input-6-1910386598.py:1: FutureWarning: YF.download() has changed argument auto_adjust default to True
  stock_data = yf.download(stocks, start=start_date, end=end_date)['Close']
[*********************100%***********************]  10 of 10 completed
Collected data for 10 stocks from 2020-07-06 to 2025-07-05
Data shape: (1256, 10)
```

Ticker	AAPL	AMZN	BRK-B	GOOGL	JNJ	JPM	META	MSFT	NVDA	TSLA
Date										
2020-07-06	90.852028	152.852005	182.720001	74.535492	124.058273	83.070816	238.969009	201.868637	9.806925	91.438667
2020-07-07	90.570099	150.005997	181.149994	74.051880	123.945488	80.727341	239.545837	199.521332	9.839319	92.657333
2020-07-08	92.679497	154.055496	181.199997	74.731812	124.309921	81.584312	242.250992	203.909363	10.182438	91.058670
2020-07-09	93.078033	159.131500	178.800003	75.480316	123.633118	79.817940	243.165985	205.336914	10.474476	92.952003
2020-07-10	93.240868	160.000000	182.899994	76.491753	123.528992	84.181343	243.732864	204.714142	10.444823	102.976669

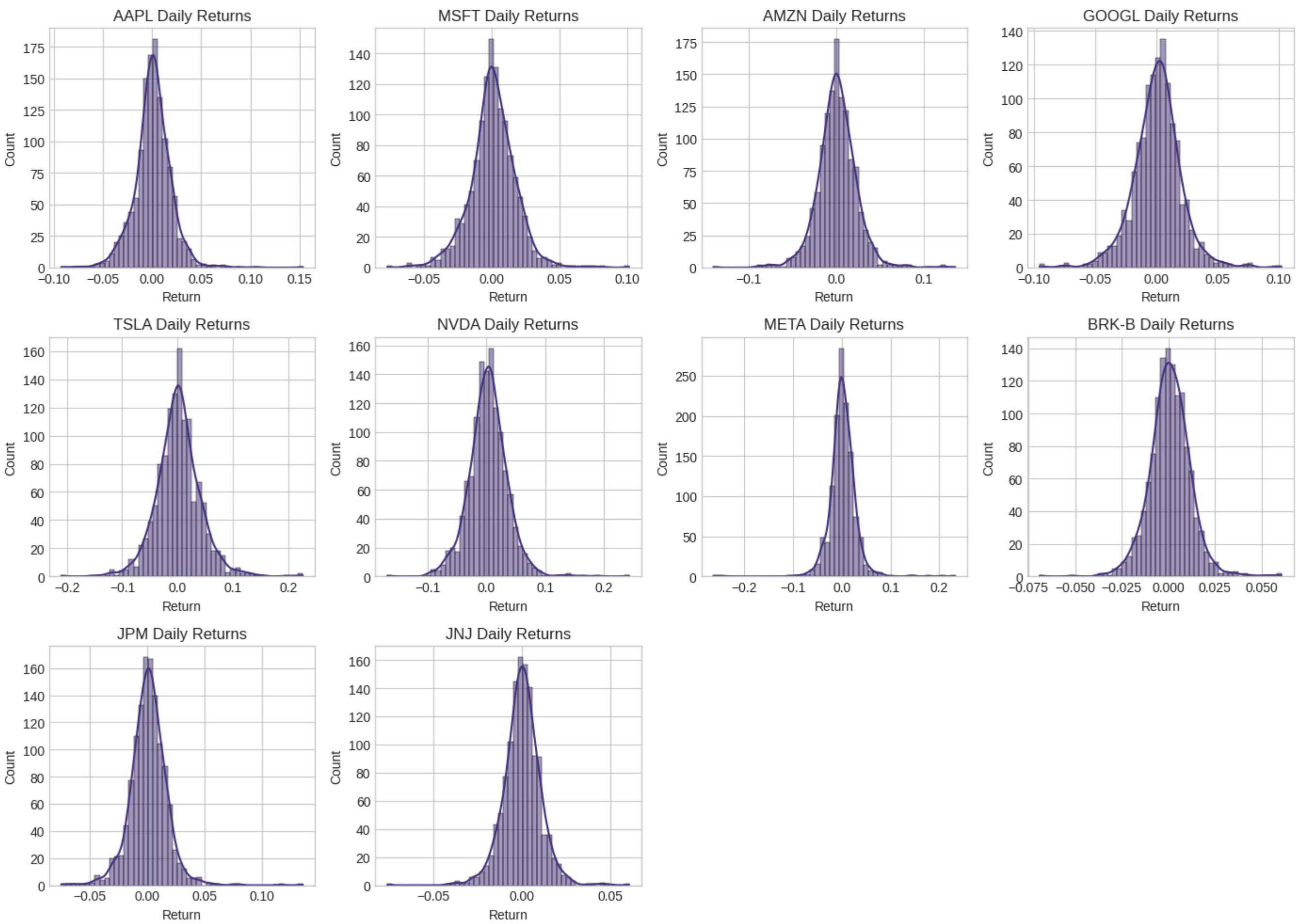
```
# Calculate daily returns
returns = stock_data.pct_change().dropna()

# Calculate actual 5-day forward returns for each stock individually
for stock in stocks:
    returns[f'{stock}_Actual_5d_Return'] = stock_data[stock].pct_change(5).shift(-5)

# Calculate overall actual return (average across all stocks)
returns['Actual_5d_Return'] = returns[[f'{stock}_Actual_5d_Return' for stock in stocks]].mean(axis=1)

# Display returns data
print("\nDaily returns data:")
returns.head()
```

```
Daily returns data:
```

Ticker	AAPL	AMZN	BRK-B	GOOGL	JNJ	JPM	META	MSFT	NVDA	TSLA	...	MSFT_Actual_5d_Return	AM
Date													
2020-07-07	-0.003103	-0.018619	-0.008592	-0.006488	-0.000909	-0.028211	0.002414	-0.011628	0.003303	0.013328	...	0.000480	
2020-07-08	0.023290	0.026996	0.000276	0.009182	0.002940	0.010616	0.011293	0.021993	0.034872	-0.017254	...	-0.022506	
2020-07-09	0.004300	0.032949	-0.013245	0.010016	-0.005444	-0.021651	0.003777	0.007001	0.028681	0.020792	...	-0.048526	
2020-07-10	0.001749	0.005458	0.022931	0.013400	-0.000842	0.054667	0.002331	-0.003033	-0.002831	0.107848	...	-0.050498	
2020-07-13	-0.004613	-0.030000	0.006725	-0.017401	0.019948	0.014335	-0.024768	-0.030888	-0.040747	-0.030810	...	0.021876	

5 rows × 21 columns

```
plt.figure(figsize=(14, 10))
for i, stock in enumerate(stocks, 1):
    plt.subplot(3, 4, i)
    sns.histplot(returns[stock], bins=50, kde=True)
    plt.title(f"{stock} Daily Returns")
    plt.xlabel('Return')
plt.tight_layout()
plt.show()
```




```
# Technical indicators
def calculate_technical_indicators(data):
    # Moving averages
    data['MA_5'] = data.rolling(window=5).mean()
    data['MA_20'] = data.rolling(window=20).mean()

    # Bollinger Bands
    data['BB_upper'] = data['MA_20'] + 2 * data.rolling(window=20).std()
    data['BB_lower'] = data['MA_20'] - 2 * data.rolling(window=20).std()

    # Relative Strength Index (RSI)
    delta = data.diff()
    gain = delta.where(delta > 0, 0)
    loss = -delta.where(delta < 0, 0)
    avg_gain = gain.rolling(window=14).mean()
    avg_loss = loss.rolling(window=14).mean()
    rs = avg_gain / avg_loss
    data['RSI'] = 100 - (100 / (1 + rs))

    # MACD
```

```
        ema12 = data.ewm(span=12, adjust=False).mean()
        ema26 = data.ewm(span=26, adjust=False).mean()
        data['MACD'] = ema12 - ema26
        data['Signal_Line'] = data['MACD'].ewm(span=9, adjust=False).mean()

        # Price Rate of Change
        data['ROC'] = data.pct_change(periods=5)

        return data



    # First, ensure all our price data is numeric
    stock_data = stock_data.apply(pd.to_numeric, errors='coerce')

    # Calculate daily returns properly
    returns = pd.DataFrame()
    for stock in stocks:
        returns[stock] = stock_data[stock].pct_change()

    # Calculate 5-day forward returns for each stock
    forward_returns = pd.DataFrame()
    for stock in stocks:
        forward_returns[f'{stock}_Actual_5d_Return'] = stock_data[stock].pct_change(5).shift(-5)

    # Combine into single returns DataFrame
    returns = pd.concat([returns, forward_returns], axis=1).dropna()

    # Technical Indicators Calculation (fixed version)
    def calculate_technical_indicators(price_series):
        """
        Calculate technical indicators for a single stock price series
        Returns a DataFrame with all indicators
        """
        indicators = pd.DataFrame(index=price_series.index)
        price_values = price_series.values

        # Simple Moving Averages
        indicators['MA_5'] = price_series.rolling(window=5).mean()
        indicators['MA_20'] = price_series.rolling(window=20).mean()

        # Bollinger Bands
        rolling_std = price_series.rolling(window=20).std()
        indicators['BB_upper'] = indicators['MA_20'] + (2 * rolling_std)
        indicators['BB_lower'] = indicators['MA_20'] - (2 * rolling_std)

        # RSI
        delta = price_series.diff()
        gain = delta.where(delta > 0, 0)
        loss = -delta.where(delta < 0, 0)

        avg_gain = gain.rolling(window=14).mean()
        avg_loss = loss.rolling(window=14).mean()

        rs = avg_gain / avg_loss
        indicators['RSI'] = 100 - (100 / (1 + rs))

        # MACD
        ema12 = price_series.ewm(span=12, adjust=False).mean()
        ema26 = price_series.ewm(span=26, adjust=False).mean()
        indicators['MACD'] = ema12 - ema26
        indicators['Signal_Line'] = indicators['MACD'].ewm(span=9, adjust=False).mean()

        # Rate of Change
        indicators['ROC'] = price_series.pct_change(periods=5)

        return indicators

    # Calculate indicators for each stock
    all_indicators = {}
    for stock in stocks:
        all_indicators[stock] = calculate_technical_indicators(stock_data[stock])

    # Combine indicators into main returns DataFrame
    for stock in stocks:
        indicators = all_indicators[stock]
        for col in indicators.columns:
            returns[f'{stock}_{col}'] = indicators[col]

    # Add market return (S&P 500)
    sp500 = yf.download('^GSPC', start=start_date, end=end_date)['Close']
    returns['Market_Return'] = sp500.pct_change()
```

```
    # Add volatility measure
    returns['Volatility'] = returns[stocks].std(axis=1)

    # Create lag features
    for stock in stocks:
        for lag in [1, 2, 3, 5]:
            returns[f'{stock}_lag{lag}'] = returns[stock].shift(lag)

    # Calculate overall actual return (average across all stocks)
    returns['Actual_5d_Return'] = returns[[f'{stock}_Actual_5d_Return' for stock in stocks]].mean(axis=1)

    # Clean up - drop any remaining NA values
    returns.dropna(inplace=True)

    # Display the final prepared data
    print("\nFinal prepared dataset:")
    print(f"Shape: {returns.shape}")
    returns.head()
```

```
/tmp/ipython-input-14-2800685593.py:69: FutureWarning: YF.download() has changed argument auto_adjust default to True
  sp500 = yf.download('^GSPC', start=start_date, end=end_date)['Close']
[*********************100%***********************]  1 of 1 completed
Final prepared dataset:
Shape: (1232, 143)

/tmp/ipython-input-14-2800685593.py:78: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of cal
  returns[f'{stock}_lag{lag}'] = returns[stock].shift(lag)
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/tmp/ipython-input-14-2800685593.py:78: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of cal
  returns[f'{stock}_lag{lag}'] = returns[stock].shift(lag)
/tmp/ipython-input-14-2800685593.py:81: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of cal
  returns['Actual_5d_Return'] = returns[[f'{stock}_Actual_5d_Return' for stock in stocks]].mean(axis=1)
```
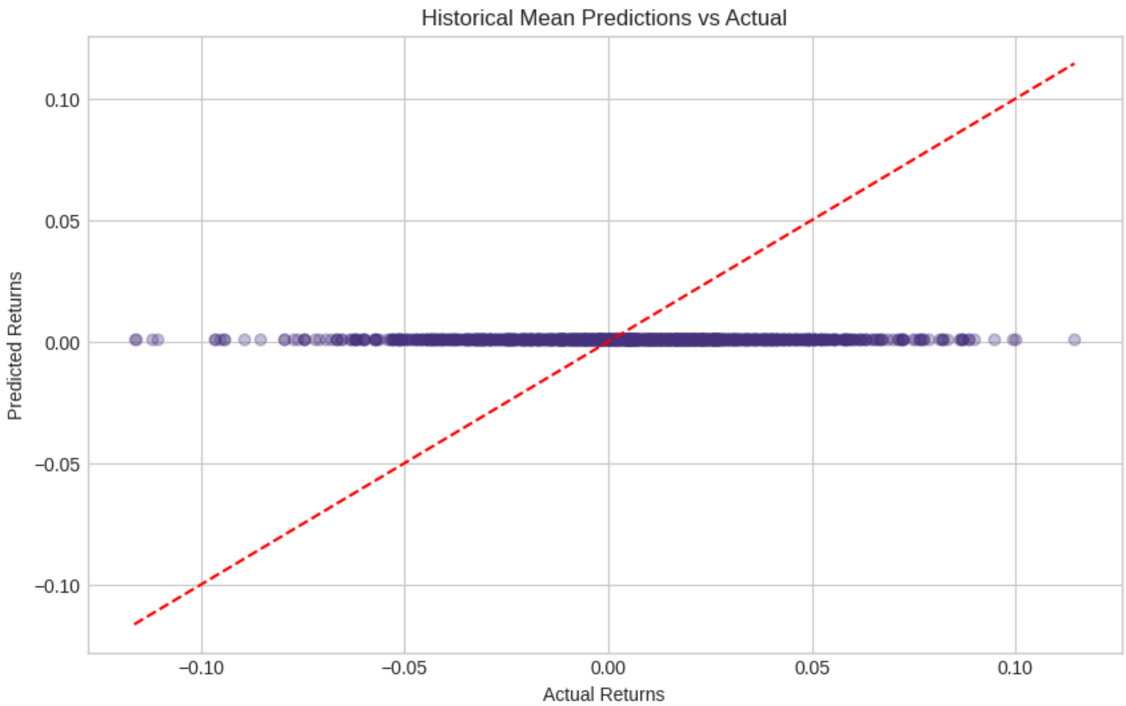

Date	AAPL	MSFT	AMZN	GOOGL	TSLA	NVDA	META	BRK-B	JPM	JNJ	...	BRK-B_lag5	JPM_lag1	JPM_lag2
2020-07-31	0.104689	0.005444	0.036961	-0.032775	-0.038138	0.000071	0.081748	0.007617	-0.003917	-0.007355	...	0.006572	-0.026685	0.024250
2020-08-03	0.025198	0.056241	-0.016681	-0.003488	0.037910	0.037260	-0.006741	0.017775	-0.005588	0.010908	...	-0.012235	-0.003917	-0.026685
2020-08-04	0.006678	-0.015009	0.008657	-0.006380	0.001347	0.019754	-0.008454	0.004918	-0.005723	-0.000882	...	0.010305	-0.005588	-0.003917
2020-08-05	0.003624	-0.001641	0.021091	0.003930	-0.001332	0.005255	-0.002842	0.016880	0.017373	0.008015	...	0.011797	-0.005723	-0.005588
2020-08-06	0.034889	0.016014	0.006231	0.017484	0.003071	0.004319	0.064869	0.006876	0.000309	-0.005728	...	-0.010743	0.017373	-0.005723

5 rows × 143 columns

```
def evaluate_model(y_true, y_pred, model_name):
    """Enhanced evaluation function with NaN handling"""
    # Align and drop NA values
    df = pd.DataFrame({'true': y_true, 'pred': y_pred}).dropna()
    if len(df) == 0:
        raise ValueError("No valid data points after NA removal")

    y_true = df['true']
    y_pred = df['pred']
```

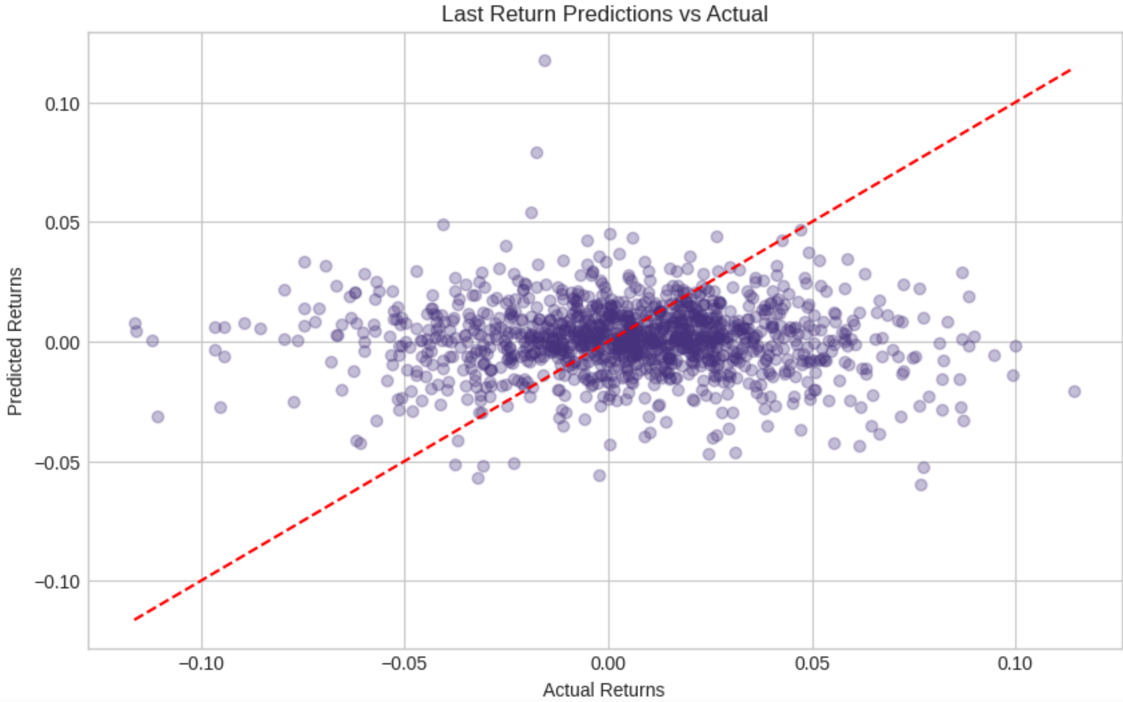
```
    # Rest of your evaluation code...
    mse = mean_squared_error(y_true, y_pred)
    mae = mean_absolute_error(y_true, y_pred)
    r2 = r2_score(y_true, y_pred)

    print(f"{model_name} Performance:")
    print(f"  MSE: {mse:.6f}")
    print(f"  MAE: {mae:.6f}")
    print(f"  R²: {r2:.4f}")

    # Plotting code...
    plt.figure(figsize=(10, 6))
    plt.scatter(y_true, y_pred, alpha=0.3)
    plt.plot([y_true.min(), y_true.max()], [y_true.min(), y_true.max()], 'r--')
    plt.xlabel('Actual Returns')
    plt.ylabel('Predicted Returns')
    plt.title(f'{model_name} Predictions vs Actual')
    plt.show()

    return mse, mae, r2

print("## Baseline Model 1: Historical Mean ##")
historical_mean = returns[stocks].mean().mean()
mean_predictions = [historical_mean] * len(returns)
mean_perf = evaluate_model(returns['Actual_5d_Return'], mean_predictions, "Historical Mean")
```

```
## Baseline Model 1: Historical Mean ##
Historical Mean Performance:
  MSE: 0.001063
  MAE: 0.025106
  R²: -0.0174
```



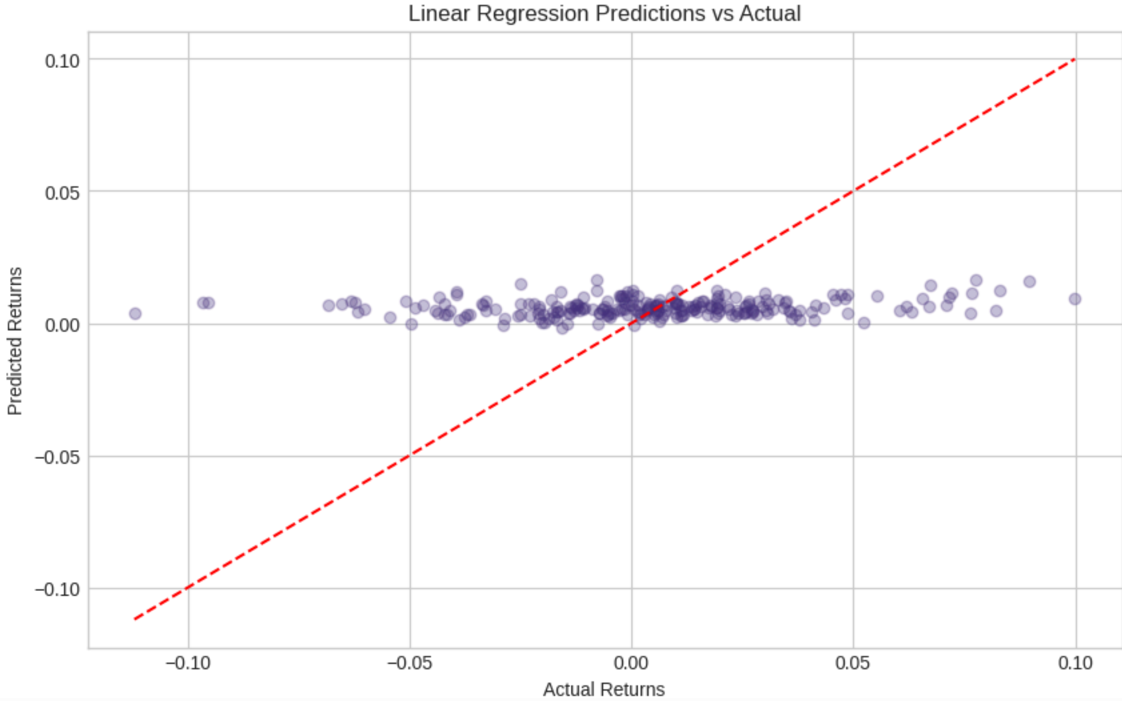

```
# Model 2: Last Return (Naive Forecast)
print("\n## Baseline Model 2: Last Return ##")
last_return_predictions = returns[stocks].shift(1).mean(axis=1)
last_return_perf = evaluate_model(returns['Actual_5d_Return'], last_return_predictions, "Last Return")
```

```
## Baseline Model 2: Last Return ##
Last Return Performance:
  MSE: 0.001335
  MAE: 0.027539
  R²: -0.2778
```



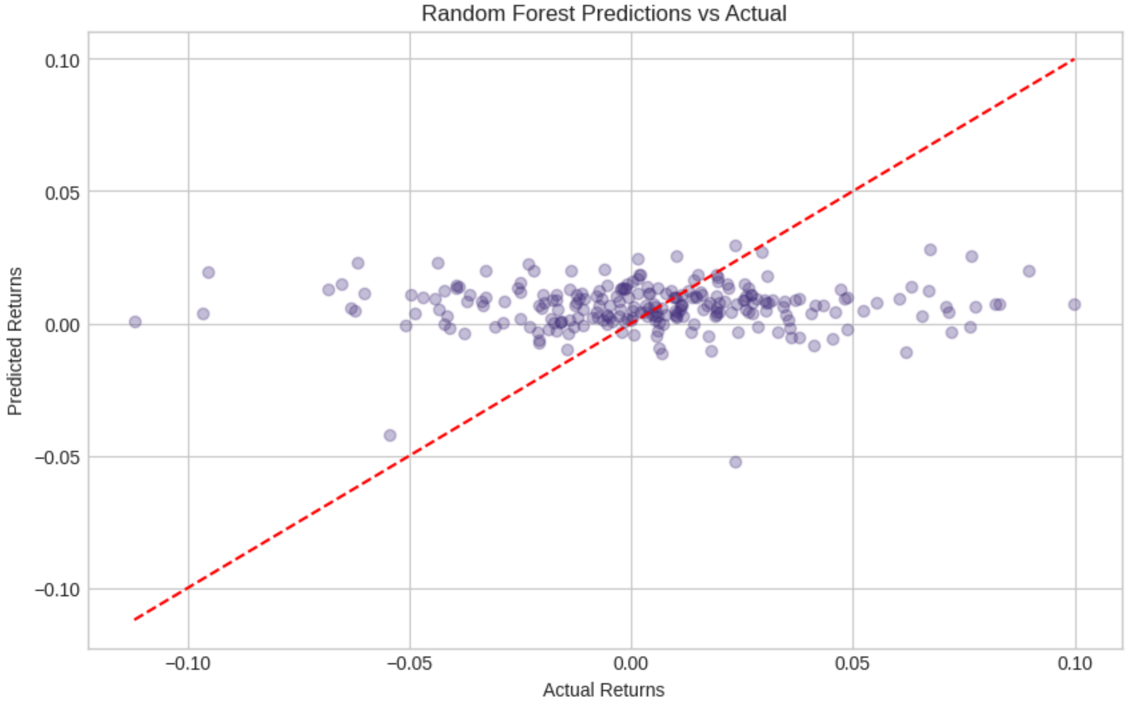

```
# Model 3: Linear Regression
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

print("\n## Model 3: Linear Regression ##")

# Prepare features and target
features = [f'{stock}_lag1' for stock in stocks] + ['Market_Return', 'Volatility']
X = returns[features]
y = returns['Actual_5d_Return']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, shuffle=False, random_state=42
)

# Train model
lr = LinearRegression()
lr.fit(X_train, y_train)

# Predict and evaluate
lr_predictions = lr.predict(X_test)
lr_perf = evaluate_model(y_test, lr_predictions, "Linear Regression")
```

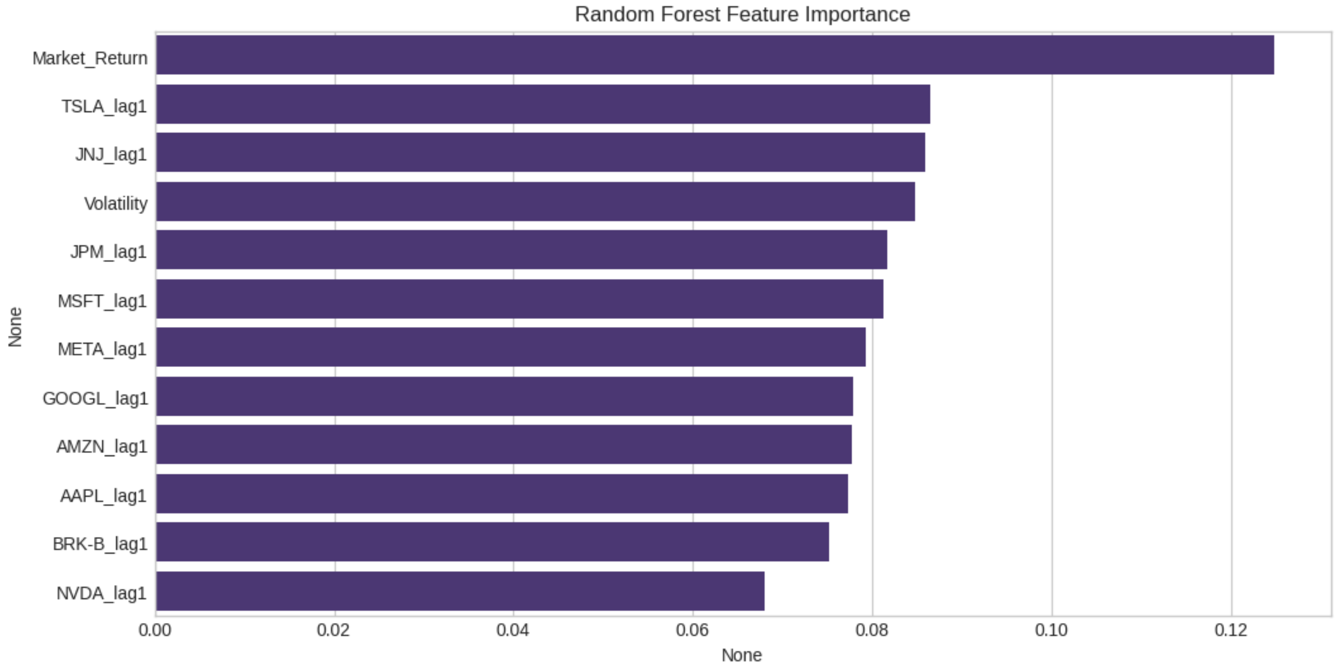
```
## Model 3: Linear Regression ##
Linear Regression Performance:
  MSE: 0.001032
  MAE: 0.023991
  R²: 0.0305
```




```
# Model 4: Random Forest
from sklearn.ensemble import RandomForestRegressor

print("\n## Model 4: Random Forest ##")

rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

rf_predictions = rf.predict(X_test)
rf_perf = evaluate_model(y_test, rf_predictions, "Random Forest")

# Feature importance
feature_imp = pd.Series(rf.feature_importances_, index=X.columns).sort_values(ascending=False)
plt.figure(figsize=(12, 6))
sns.barplot(x=feature_imp, y=feature_imp.index)
plt.title("Random Forest Feature Importance")
plt.show()
```

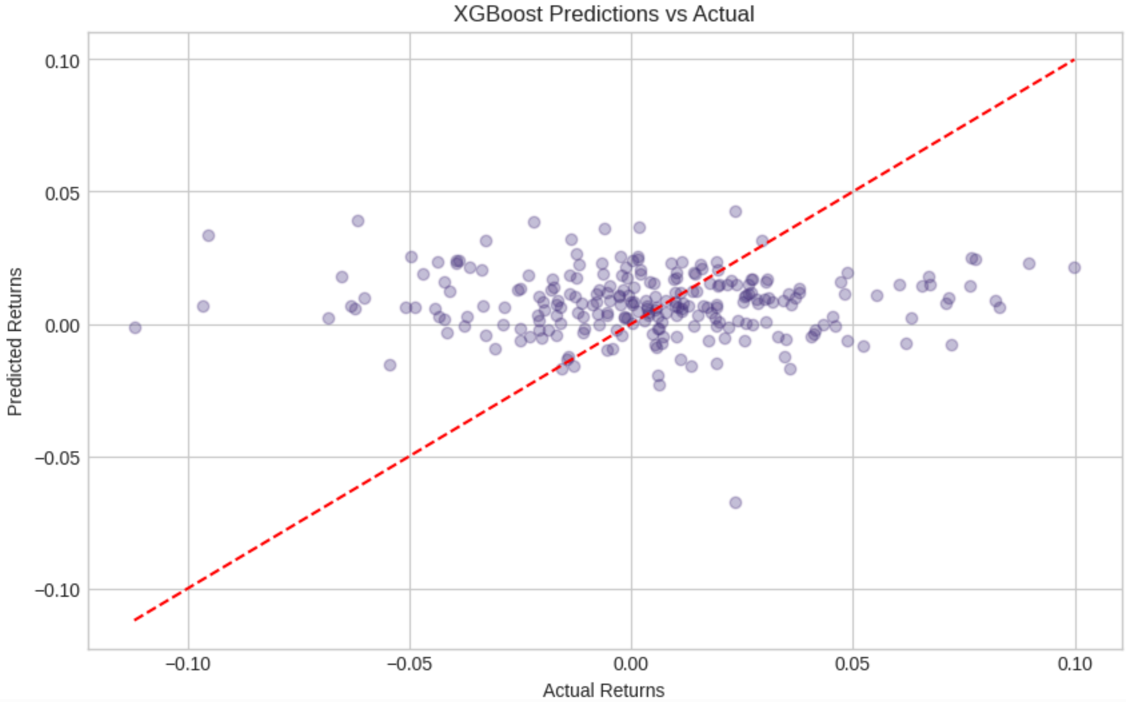
```
## Model 4: Random Forest ##
Random Forest Performance:
  MSE: 0.001140
  MAE: 0.024999
  R²: -0.0708
```





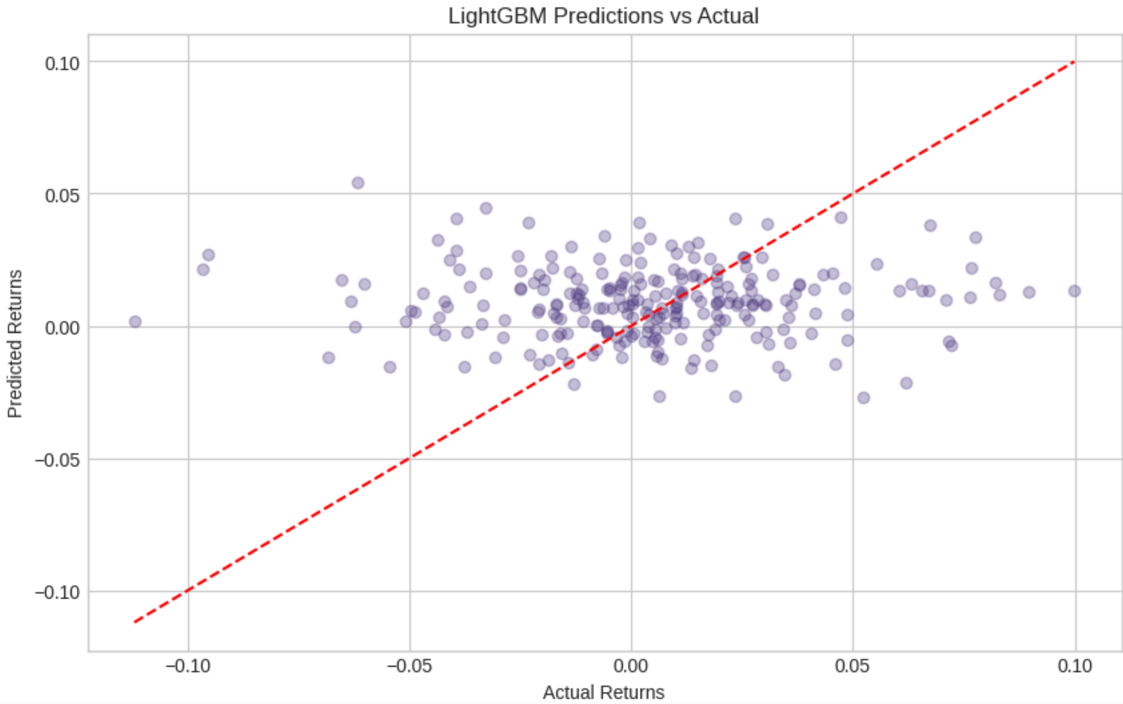

```
# Model 5: XGBoost
from xgboost import XGBRegressor

print("\n## Model 5: XGBoost ##")

xgb = XGBRegressor(n_estimators=200, learning_rate=0.05, random_state=42)
xgb.fit(X_train, y_train)

xgb_predictions = xgb.predict(X_test)
xgb_perf = evaluate_model(y_test, xgb_predictions, "XGBoost")
```

```
## Model 5: XGBoost ##
XGBoost Performance:
  MSE: 0.001257
  MAE: 0.026750
  R²: -0.1810
```




```
from lightgbm import LGBMRegressor

print("\n## Model 6: LightGBM ##")

lgbm = LGBMRegressor(n_estimators=200, learning_rate=0.05, random_state=42)
lgbm.fit(X_train, y_train)

lgbm_predictions = lgbm.predict(X_test)
lgbm_perf = evaluate_model(y_test, lgbm_predictions, "LightGBM")
```

```
## Model 6: LightGBM ##
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000429 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 3060
[LightGBM] [Info] Number of data points in the train set: 985, number of used features: 12
[LightGBM] [Info] Start training from score 0.005616
LightGBM Performance:
  MSE: 0.001278
  MAE: 0.026567
  R²: -0.2003
```

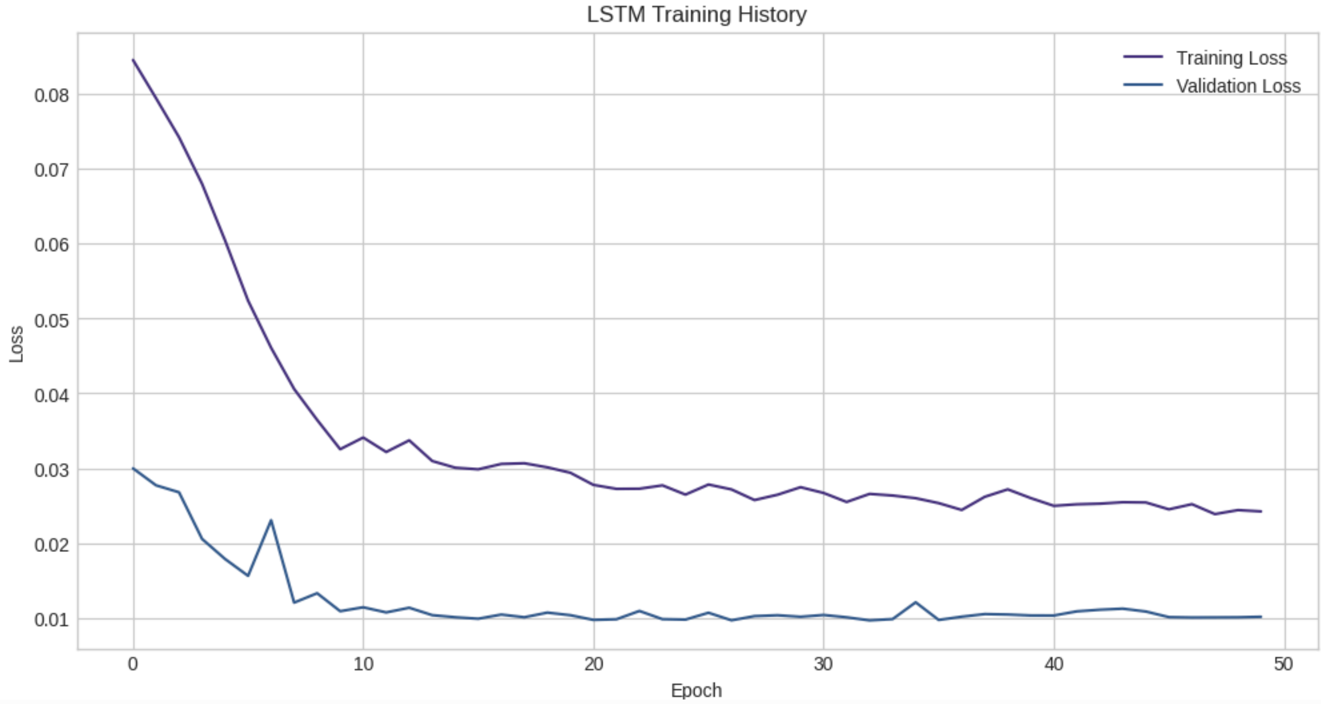



```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from sklearn.preprocessing import MinMaxScaler

# Prepare data for LSTM
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length, -1])  # Last column is target
    return np.array(X), np.array(y)


scaler = MinMaxScaler(feature_range=(-1, 1))
scaled_data = scaler.fit_transform(returns[features + ['Actual_5d_Return']])

# Create sequences
seq_length = 10
X_seq, y_seq = create_sequences(scaled_data, seq_length)

# Train-test split
split = int(0.8 * len(X_seq))
X_train_seq, X_test_seq = X_seq[:split], X_seq[split:]
y_train_seq, y_test_seq = y_seq[:split], y_seq[split:]


model = Sequential([
    LSTM(64, return_sequences=True, input_shape=(seq_length, len(features)+1)),
    Dropout(0.2),
    LSTM(32),
    Dropout(0.2),
    Dense(16, activation='relu'),
    Dense(1)
])

model.compile(optimizer='adam', loss='mse')
# Train model
print("\n## Training LSTM Model ##")
history = model.fit(
    X_train_seq, y_train_seq,
    epochs=50,
```

```
    batch_size=32,
    validation_split=0.1,
    verbose=1
)
```

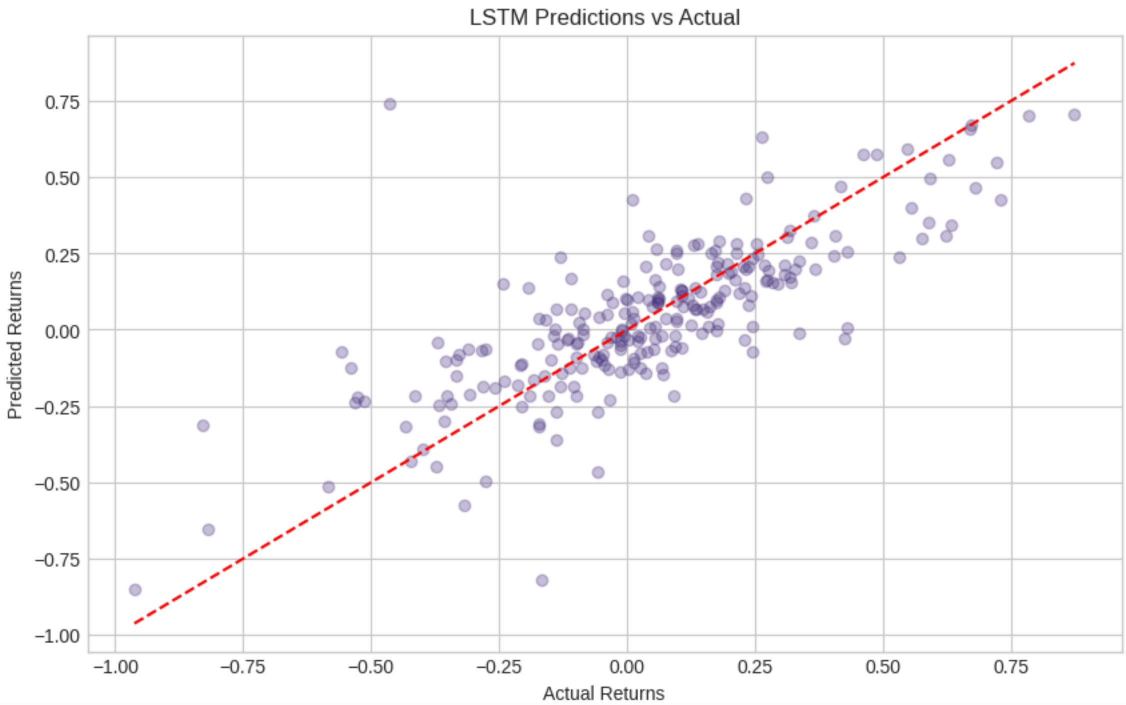
```
## Training LSTM Model ##
Epoch 1/50
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim
  super().__init__(**kwargs)
28/28 ━━━━━━━━━━━━━━━━━━━━ 5s 42ms/step - loss: 0.0931 - val_loss: 0.0300
Epoch 2/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 2s 15ms/step - loss: 0.0840 - val_loss: 0.0277
Epoch 3/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 19ms/step - loss: 0.0763 - val_loss: 0.0268
Epoch 4/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - loss: 0.0649 - val_loss: 0.0205
Epoch 5/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - loss: 0.0591 - val_loss: 0.0179
Epoch 6/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 24ms/step - loss: 0.0554 - val_loss: 0.0156
Epoch 7/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 30ms/step - loss: 0.0446 - val_loss: 0.0230
Epoch 8/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 29ms/step - loss: 0.0437 - val_loss: 0.0120
Epoch 9/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 28ms/step - loss: 0.0355 - val_loss: 0.0133
Epoch 10/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0377 - val_loss: 0.0109
Epoch 11/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step - loss: 0.0319 - val_loss: 0.0114
Epoch 12/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0343 - val_loss: 0.0107
Epoch 13/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step - loss: 0.0332 - val_loss: 0.0114
Epoch 14/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0313 - val_loss: 0.0104
Epoch 15/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step - loss: 0.0294 - val_loss: 0.0101
Epoch 16/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0301 - val_loss: 0.0099
Epoch 17/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - loss: 0.0302 - val_loss: 0.0104
Epoch 18/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0294 - val_loss: 0.0101
Epoch 19/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - loss: 0.0306 - val_loss: 0.0107
Epoch 20/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - loss: 0.0294 - val_loss: 0.0104
Epoch 21/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - loss: 0.0279 - val_loss: 0.0097
Epoch 22/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - loss: 0.0265 - val_loss: 0.0098
Epoch 23/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0261 - val_loss: 0.0109
Epoch 24/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - loss: 0.0296 - val_loss: 0.0098
Epoch 25/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0262 - val_loss: 0.0098
Epoch 26/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 0.0261 - val_loss: 0.0107
Epoch 27/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - loss: 0.0282 - val_loss: 0.0097
```

```
# Plot training history
plt.figure(figsize=(12, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('LSTM Training History')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```




```
lstm_predictions = model.predict(X_test_seq).flatten()
lstm_perf = evaluate_model(y_test_seq, lstm_predictions, "LSTM")
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 136ms/step
LSTM Performance:
  MSE: 0.032627
  MAE: 0.127754
  R²: 0.5928
```




```
# Compile performance metrics
model_names = [
    "Historical Mean", "Last Return", "Linear Regression",
    "Random Forest", "XGBoost", "LightGBM", "LSTM"
]
performance = [
    mean_perf, last_return_perf, lr_perf,
    rf_perf, xgb_perf, lgbm_perf, lstm_perf
]


# Create comparison DataFrame
results = pd.DataFrame({
    'Model': model_names,
```

```
    'MSE': [p[0] for p in performance],
    'MAE': [p[1] for p in performance],
    'R²': [p[2] for p in performance]
})

# Sort by R² (descending)
results = results.sort_values('R²', ascending=False)

# Display results
print("\n## Model Performance Comparison ##")
display(results)
```

```
## Model Performance Comparison ##
```

	Model	MSE	MAE	R^2
6	LSTM	0.032627	0.127754	0.592836
2	Linear Regression	0.001032	0.023991	0.030516
0	Historical Mean	0.001063	0.025106	-0.017361
3	Random Forest	0.001140	0.024999	-0.070814
4	XGBoost	0.001257	0.026750	-0.181008
5	LightGBM	0.001278	0.026567	-0.200266
1	Last Return	0.001335	0.027539	-0.277838

Next steps: Generate code with results | View recommended plots | New interactive sheet

```
test_dates = returns.index[-len(X_test_seq):]
returns.loc[test_dates, 'LSTM_Pred'] = lstm_predictions  # New column for predictions
```

```
/tmp/ipython-input-63-1771422314.py:2: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of call:
  returns.loc[test_dates, 'LSTM_Pred'] = lstm_predictions  # New column for predictions
```

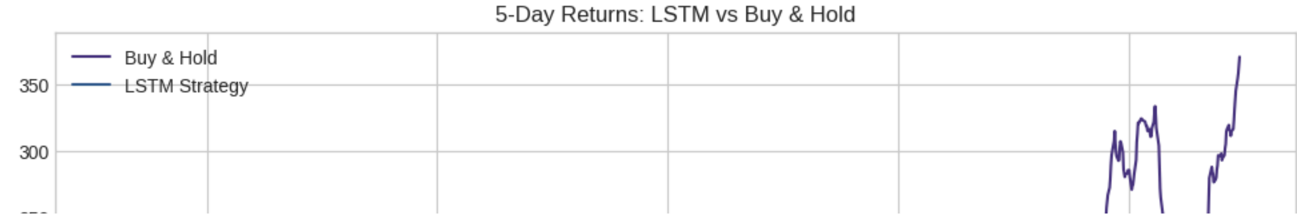
```
returns['Signal'] = 0
returns.loc[returns['LSTM_Pred'] > 0.005, 'Signal'] = 1    # Buy if prediction > 0.5%
returns.loc[returns['LSTM_Pred'] < -0.005, 'Signal'] = -1  # Sell if prediction < -0.5%
```

```
/tmp/ipython-input-65-4044107946.py:1: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of call:
  returns['Signal'] = 0
```

```
# Avoid lookahead bias by executing next day
returns['Strategy_Return'] = returns['Signal'].shift(1) * returns['Actual_5d_Return']
returns.dropna(subset=['Strategy_Return'], inplace=True)  # Clean NaN from shift
```

```
/tmp/ipython-input-66-1116317196.py:2: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of call:
  returns['Strategy_Return'] = returns['Signal'].shift(1) * returns['Actual_5d_Return']
```

```
# Cumulative returns
plt.figure(figsize=(12, 6))
(1 + returns['Actual_5d_Return']).cumprod().plot(label='Buy & Hold')
(1 + returns['Strategy_Return']).cumprod().plot(label='LSTM Strategy')
plt.title('5-Day Returns: LSTM vs Buy & Hold')
plt.legend()
plt.show()
```




```
# Win rate
win_rate = (returns['Strategy_Return'] > 0).mean()

# Sharpe ratio (annualized)
sharpe = np.sqrt(252/5) * returns['Strategy_Return'].mean() / returns['Strategy_Return'].std()

print(f"Win Rate: {win_rate:.2%}")
print(f"Sharpe Ratio: {sharpe:.2f}")
```

```
Win Rate: 14.70%
Sharpe Ratio: 1.54
```

```
# Analyze trades
positive_trades = returns[returns['Strategy_Return'] > 0]
negative_trades = returns[returns['Strategy_Return'] < 0]

print(f"Avg. Winning Trade: {positive_trades['Strategy_Return'].mean():.2%}")
print(f"Avg. Losing Trade: {negative_trades['Strategy_Return'].mean():.2%}")
```

```
Avg. Winning Trade: 2.71%
Avg. Losing Trade: -1.85%
```

```
from scipy.optimize import minimize_scalar

def objective(threshold):
    # Generate signals as a Pandas Series
    signals = pd.Series(
        np.where(
            returns['LSTM_Pred'] > threshold, 1,
            np.where(returns['LSTM_Pred'] < -threshold, -1, 0)
        ),
        index=returns.index  # very important for alignment
```