In [ ]:
```
import pandas as pd
import numpy as np
from scipy.stats import zscore
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

In [ ]:
```
# Read the dataset
data = pd.read_parquet('data.parquet')

# Handle missing values by interpolating
data = data.interpolate(method='linear')
data = data.between_time('09:15', '15:30')

print(data.head())
```

```
                     banknifty     nifty  tte
time
2021-01-01 09:15:00   0.286058  0.199729   27
2021-01-01 09:16:00   0.285381  0.200433   27
2021-01-01 09:17:00   0.284233  0.200004   27
2021-01-01 09:18:00   0.286104  0.199860   27
2021-01-01 09:19:00   0.285539  0.198951   27
```

In [ ]:
```
# Calculate spread
data['Spread'] = data['banknifty'] - data['nifty']

data['P/L'] = data['Spread'] * (data['tte'] ** 0.7)

print(data[['Spread', 'P/L']].head())
```

```
                       Spread       P/L
time
2021-01-01 09:15:00  0.086329  0.867184
2021-01-01 09:16:00  0.084948  0.853317
2021-01-01 09:17:00  0.084229  0.846089
2021-01-01 09:18:00  0.086244  0.866325
2021-01-01 09:19:00  0.086588  0.869786
```

In [ ]:
```
# Calculate z-scores
data['Spread_Zscore'] = zscore(data['Spread'])

# Define entry and exit thresholds
entry_threshold = 1

# Generate signals
data['Signal'] = np.where(data['Spread_Zscore'] > entry_threshold, -1, np

data.head()
```

Out[ ]:

	banknifty	nifty	tte	Spread	P/L	Spread_Zscore	Signal
time							
2021-01-01 09:15:00	0.286058	0.199729	27	0.086329	0.867184	0.543776	0
2021-01-01 09:16:00	0.285381	0.200433	27	0.084948	0.853317	0.491764	0
2021-01-01 09:17:00	0.284233	0.200004	27	0.084229	0.846089	0.464655	0
2021-01-01 09:18:00	0.286104	0.199860	27	0.086244	0.866325	0.540555	0
2021-01-01 09:19:00	0.285539	0.198951	27	0.086588	0.869786	0.553535	0

In [ ]:

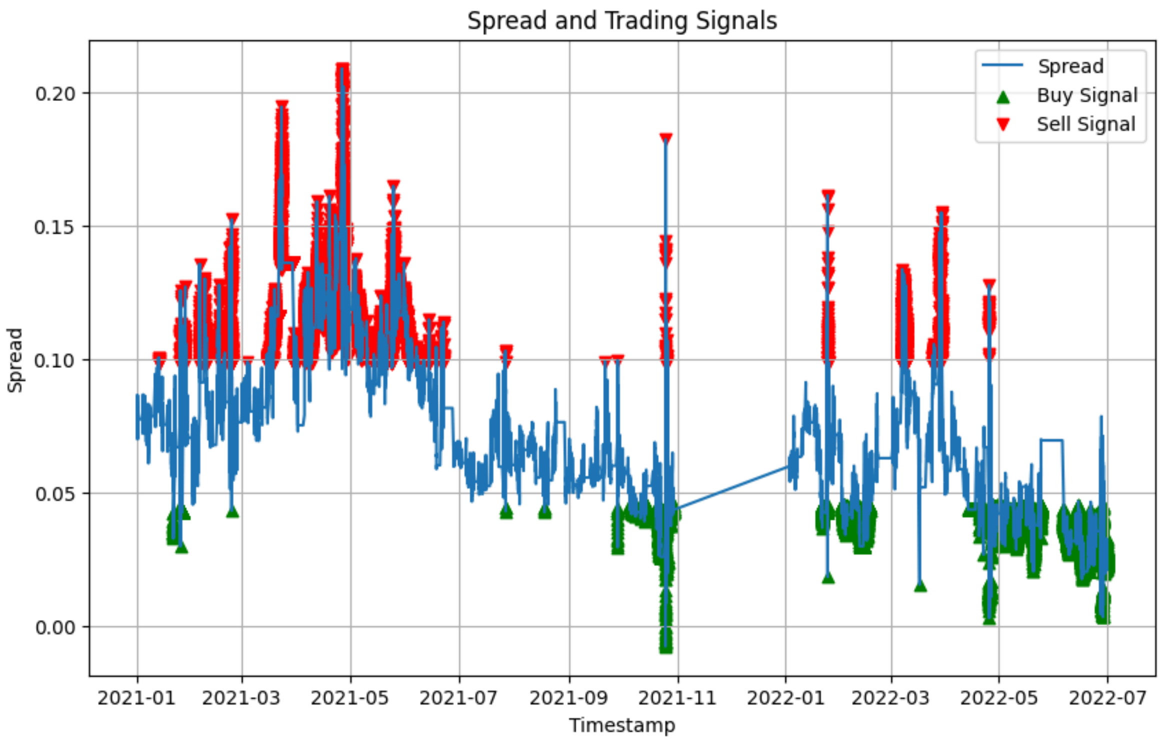
```
def calculate_pl(data):
    return data['P/L'].sum()

def calculate_sharpe_ratio(data):
    mean_return = data['P/L'].mean()
    std_dev = data['P/L'].std()
    sharpe_ratio = (mean_return / std_dev) * (252 ** 0.5)  # Assuming 252
    return sharpe_ratio

def calculate_drawdown(data):
    cum_pnl = data['P/L'].cumsum()
    max_drawdown = (cum_pnl - cum_pnl.expanding().max()).min()
    return max_drawdown

base_model_pl = calculate_pl(data)
base_model_sharpe_ratio = calculate_sharpe_ratio(data)
base_model_drawdown = calculate_drawdown(data)
base_model_pl, base_model_sharpe_ratio, base_model_drawdown
print("Predicted Model Performance:")
print("Total Profit:", base_model_pl)
print("Sharpe Ratio:", base_model_sharpe_ratio)
print("Maximum Drawdown:", base_model_drawdown)
```

```
Predicted Model Performance:
Total Profit: 86321.02160308613
Sharpe Ratio: 27.393970439725493
Maximum Drawdown: -0.07677310948929517
```

In [ ]:

```
plt.figure(figsize=(10, 6))
plt.plot(data.index, data['Spread'], label='Spread')
plt.scatter(data[data['Signal'] == 1].index, data[data['Signal'] == 1]['S
plt.scatter(data[data['Signal'] == -1].index, data[data['Signal'] == -1][
plt.legend()
plt.title('Spread and Trading Signals')
plt.xlabel('Timestamp')
plt.ylabel('Spread')
```

```
plt.grid(True)
plt.show()
```



LSTM model

In [ ]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense
from keras.optimizers import Adam
from sklearn.metrics import mean_squared_error


# Assuming 'Bank Nifty IV' and 'Nifty IV' are columns in the dataset
X = data[['banknifty', 'nifty', 'tte']]
y = data['Spread'] # Assuming 'Spread' is the target variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

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

# Reshape input data to fit LSTM model
X_train_reshaped = np.reshape(X_train_scaled, (X_train_scaled.shape[0], X
X_test_reshaped = np.reshape(X_test_scaled, (X_test_scaled.shape[0], X_te

# Build LSTM model
model = Sequential()
model.add(LSTM(50, input_shape=(X_train_reshaped.shape[1], X_train_reshap
model.add(Dense(1))
```

```
model.compile(optimizer= Adam(learning_rate=0.001), loss='mean_squared_er

# Train the model
model.fit(X_train_reshaped, y_train, epochs=25, batch_size=32, verbose=1)

# Predict the spread for test data
pred = model.predict(X_test_reshaped)
pred = pred.flatten()

# Generate trading signals based on predicted spread values
Signal_Predicted = np.where(pred > 0, 1, -1)

# Calculate P/L using predicted spread values
P_L_Predicted = pred * (X_test['tte'] ** 0.7)
# Evaluate model performance
predicted_model_profit = P_L_Predicted.sum()
predicted_model_sharpe_ratio = P_L_Predicted.mean() / P_L_Predicted.std()
predicted_model_drawdown = P_L_Predicted.cumsum().min()# Display predicte
print("Predicted Model Performance:")
print("Total Profit:", predicted_model_profit)
print("Sharpe Ratio:", predicted_model_sharpe_ratio)
print("Maximum Drawdown:", predicted_model_drawdown)
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam`
runs slowly on M1/M2 Macs, please use the legacy Keras optimizer instead,
located at `tf.keras.optimizers.legacy.Adam`.
```

```
Epoch 1/25
4522/4522 [==============================] - 6s 1ms/step - loss: 3.6426e-0
5
Epoch 2/25
4522/4522 [==============================] - 4s 965us/step - loss: 6.6181e
-07
Epoch 3/25
4522/4522 [==============================] - 4s 995us/step - loss: 4.2079e
-07
Epoch 4/25
4522/4522 [==============================] - 4s 981us/step - loss: 3.4171e
-07
Epoch 5/25
4522/4522 [==============================] - 5s 1ms/step - loss: 2.8402e-0
7
Epoch 6/25
4522/4522 [==============================] - 5s 1ms/step - loss: 1.7093e-0
7
Epoch 7/25
4522/4522 [==============================] - 5s 1ms/step - loss: 1.4883e-0
7
Epoch 8/25
4522/4522 [==============================] - 5s 998us/step - loss: 1.4471e
-07
Epoch 9/25
4522/4522 [==============================] - 5s 1ms/step - loss: 1.1221e-0
7
Epoch 10/25
4522/4522 [==============================] - 4s 982us/step - loss: 9.3790e
-08
Epoch 11/25
4522/4522 [==============================] - 5s 997us/step - loss: 9.7583e
-08
Epoch 12/25
4522/4522 [==============================] - 5s 996us/step - loss: 7.9390e
-08
Epoch 13/25
4522/4522 [==============================] - 4s 984us/step - loss: 8.1655e
-08
Epoch 14/25
4522/4522 [==============================] - 5s 996us/step - loss: 6.5523e
-08
Epoch 15/25
4522/4522 [==============================] - 4s 985us/step - loss: 5.6303e
-08
Epoch 16/25
4522/4522 [==============================] - 5s 1000us/step - loss: 5.1621
e-08
Epoch 17/25
4522/4522 [==============================] - 5s 999us/step - loss: 5.0022e
-08
Epoch 18/25
4522/4522 [==============================] - 4s 989us/step - loss: 4.6757e
-08
Epoch 19/25
4522/4522 [==============================] - 5s 999us/step - loss: 4.2960e
-08
Epoch 20/25
4522/4522 [==============================] - 4s 992us/step - loss: 4.8639e
-08
```

```
Epoch 21/25
4522/4522 [==============================] - 5s 999us/step - loss: 4.2126e
-08
Epoch 22/25
4522/4522 [==============================] - 5s 999us/step - loss: 4.4523e
-08
Epoch 23/25
4522/4522 [==============================] - 4s 988us/step - loss: 3.6407e
-08
Epoch 24/25
4522/4522 [==============================] - 5s 1ms/step - loss: 3.7480e-0
8
Epoch 25/25
4522/4522 [==============================] - 4s 990us/step - loss: 4.2349e
-08
1131/1131 [==============================] - 1s 520us/step
Predicted Model Performance:
Total Profit: 17217.311214744874
Sharpe Ratio: 1.732090261630026
Maximum Drawdown: 0.7348807642505046
```

Performance on entire dataset

In [ ]:

```
pred = model.predict(X)
pred = pred.flatten()

# Generate trading signals based on predicted spread values
Signal_Predicted = np.where(pred > 0, 1, -1)

# Calculate P/L using predicted spread values
P_L_Predicted = pred * (X['tte'] ** 0.7)
# Evaluate model performance
lstm_model_profit = P_L_Predicted.sum()
lstm_model_sharpe_ratio = P_L_Predicted.mean() / P_L_Predicted.std()
lstm_model_drawdown = P_L_Predicted.cumsum().min()# Display predicted moo
print("Predicted Model Performance:")
print("Total Profit:", lstm_model_profit)
print("Sharpe Ratio:", lstm_model_sharpe_ratio)
print("Maximum Drawdown:", lstm_model_drawdown)
```

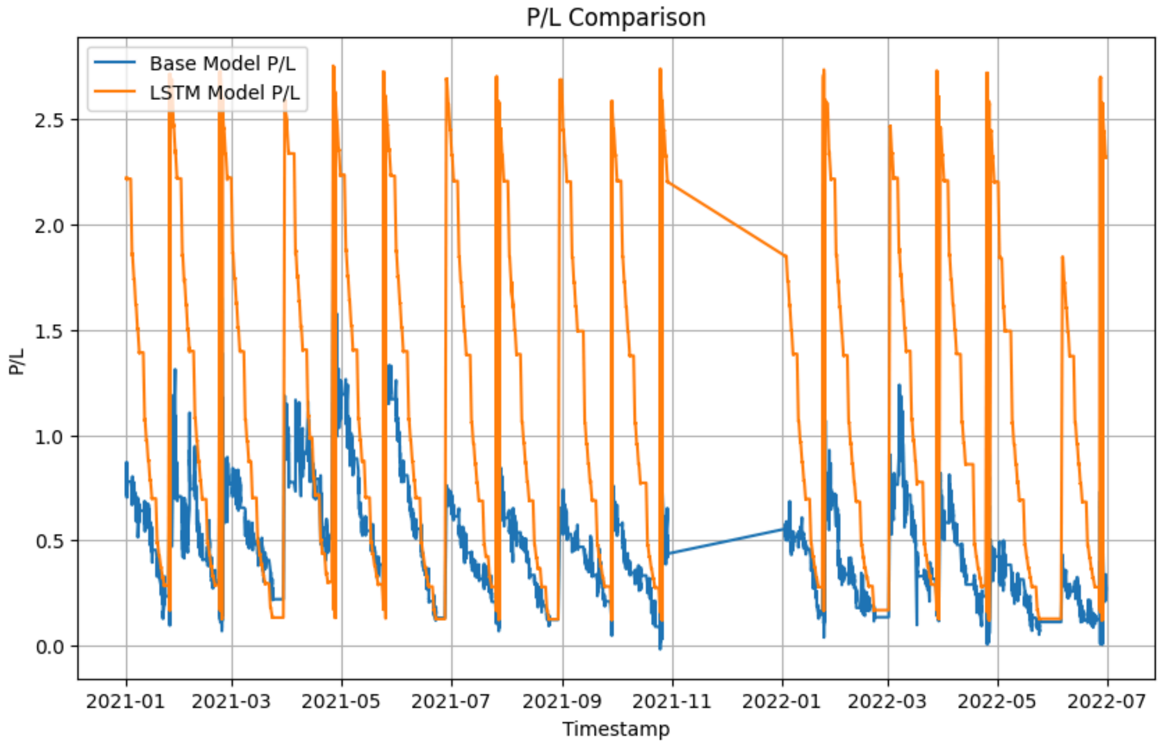
```
5652/5652 [==============================] - 3s 469us/step
Predicted Model Performance:
Total Profit: 202730.33858176225
Sharpe Ratio: 1.416262458317246
Maximum Drawdown: 2.220305191310001
```

In [ ]:

```
# Base model evaluation
print("Base Model Performance:")
print("Total Profit:", base_model_pl)
print("Sharpe Ratio:", base_model_sharpe_ratio)
print("Maximum Drawdown:", base_model_drawdown)

# LSTM model evaluation
print("\nLSTM Model Performance:")
print("Total Profit:", lstm_model_profit)
print("Sharpe Ratio:", lstm_model_sharpe_ratio)
print("Maximum Drawdown:", lstm_model_drawdown)
```

```
# Comparison
print("\nModel Comparison:")
print("Base Model vs. LSTM Model")
print("Absolute P/L Improvement:", lstm_model_profit - base_model_pl)
print("Sharpe Ratio Improvement:", lstm_model_sharpe_ratio - base_model_s
print("Drawdown Difference:", lstm_model_drawdown - base_model_drawdown)

# Additional insights
plt.figure(figsize=(10, 6))
plt.plot(data.index, data['P/L'], label='Base Model P/L')
plt.plot(data.index, P_L_Predicted, label='LSTM Model P/L')
plt.legend()
plt.title('P/L Comparison')
plt.xlabel('Timestamp')
plt.ylabel('P/L')
plt.grid(True)
plt.show()
```

```
Base Model Performance:
Total Profit: 86321.02160308613
Sharpe Ratio: 27.393970439725493
Maximum Drawdown: -0.07677310948929517

LSTM Model Performance:
Total Profit: 202730.33858176225
Sharpe Ratio: 1.416262458317246
Maximum Drawdown: 2.220305191310001

Model Comparison:
Base Model vs. LSTM Model
Absolute P/L Improvement: 116409.31697867611
Sharpe Ratio Improvement: -25.977707981408248
Drawdown Difference: 2.297078300799296
```



Conclusion:

While the LSTM Model generates higher total profits, it comes with increased risk and lower risk-adjusted returns compared to the Base Model. Depending on the investor's risk tolerance and investment objectives, they may prefer one model over the other. The Base Model may be suitable for risk-averse investors looking for stable returns, while the LSTM Model may appeal to investors willing to tolerate higher risk for potentially higher rewards