

```
In [1]: # --- Setup Project Path ---
import sys
import os

# Add the project root to the Python path to allow imports from 'src'
project_root = os.path.abspath(os.path.join(os.getcwd(), '..'))
if project_root not in sys.path:
    sys.path.append(project_root)

# --- General Imports ---
import yaml
import pandas as pd

# --- Custom Project Imports ---
from src.training_pipeline import TrainingPipeline
from src.backtester import VectorizedBacktester

# --- Load Configuration ---
config_path = os.path.join(project_root, 'configs', 'config.yaml')
print(f"Loading configuration from: {config_path}")
with open(config_path, 'r') as file:
    config = yaml.safe_load(file)
print("Configuration loaded successfully.")
```

Loading configuration from: C:\Projetos\_Python\gld\_lstm\_strategy\configs\config.yaml  
Configuration loaded successfully.

```
In [2]: # --- 1. Run Pipeline with LSTM Model ---

# Instantiate the main pipeline
pipeline = TrainingPipeline(config=config, project_root=project_root)

print("="*50)
print("RUNNING PIPELINE FOR LSTM MODEL")
print("="*50)

# Run the static test specifically for the 'lstm' model type
lstm_results = pipeline.run_static_test(model_type='lstm')
```

```
print("\n\n✅ --- LSTM Pipeline Finished! --- ✅")
```

Random seeds set to 2025 for reproducibility.

=====

RUNNING PIPELINE FOR LSTM MODEL

=====

===== Starting STATIC Test Run for model\_type='lstm' =====

===== Step 1: Loading and Preparing Full Dataset =====

--- Loading Main Asset Data ---

File not found for SPY. Downloading data...

YF.download() has changed argument auto\_adjust default to True

Data for SPY saved to C:\Projetos\_Python\gld\_lstm\_strategy\data\spy\_data.csv

--- Loading Macroeconomic Data ---

Loading DX-Y.NYB data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\dx-y.nyb\_data.csv

Loading ^TNX data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\^tnx\_data.csv

Loading ^VIX data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\^vix\_data.csv

Loading CL=F data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\cl=f\_data.csv

Loading SI=F data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\si=f\_data.csv

Loading TIP data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\tip\_data.csv

Loading HG=F data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\hg=f\_data.csv

===== Starting Feature Engineering Pipeline =====

Step 1: Creating custom OHLCV features...

Step 2: Applying 'All' technical indicator strategy from pandas\_ta...

130it [00:11, 11.66it/s]

```
-> Dropped 2 redundant TA columns.
Step 3: Creating custom interaction and ratio features...
Step 4: Creating lagged and momentum features...
Step 5: Merging macroeconomic features...
    -> Macro features merged and forward-filled.
Step 6: Defining target variable...
```

```
Pipeline complete. Dropped 77 rows with NaN values.  
Final dataset shape: (2438, 247)
```

=====





















```
--- Splitting data chronologically ---
Train set size: 1761, Validation set size: 311, Test set size: 366
```






















```
--- Running Feature Selection ---
Selected 25 features via BorutaPy.
```

```
--- Scaling data ---
```

```
--- Preparing data and training LSTM Model ---
```

Epoch 1/100	<div><div></div></div>	18s	276ms/step	- accuracy: 0.5639	- loss: 0.6850	- val_accuracy: 0.6639	- val_loss: 0.6379
Epoch 2/100	<div><div></div></div>	13s	266ms/step	- accuracy: 0.6347	- loss: 0.6575	- val_accuracy: 0.6639	- val_loss: 0.6386
Epoch 3/100	<div><div></div></div>	13s	250ms/step	- accuracy: 0.6386	- loss: 0.6599	- val_accuracy: 0.6639	- val_loss: 0.6370
Epoch 4/100	<div><div></div></div>	13s	252ms/step	- accuracy: 0.6415	- loss: 0.6589	- val_accuracy: 0.6639	- val_loss: 0.6364
Epoch 5/100	<div><div></div></div>	13s	258ms/step	- accuracy: 0.6382	- loss: 0.6522	- val_accuracy: 0.6639	- val_loss: 0.6366
Epoch 6/100	<div><div></div></div>	13s	253ms/step	- accuracy: 0.6396	- loss: 0.6543	- val_accuracy: 0.6639	- val_loss: 0.6354
Epoch 7/100	<div><div></div></div>	14s	272ms/step	- accuracy: 0.6375	- loss: 0.6565	- val_accuracy: 0.6639	- val_loss: 0.6348
Epoch 8/100	<div><div></div></div>	13s	267ms/step	- accuracy: 0.6382	- loss: 0.6501	- val_accuracy: 0.6639	- val_loss: 0.6345
Epoch 9/100	<div><div></div></div>	13s	256ms/step	- accuracy: 0.6387	- loss: 0.6494	- val_accuracy: 0.6639	- val_loss: 0.6345
Epoch 10/100	<div><div></div></div>	13s	263ms/step	- accuracy: 0.6397	- loss: 0.6519	- val accuracy: 0.6639	- val loss: 0.6316

Epoch 11/100									
<b>50/50</b>		<b>13s</b>	269ms/step	-	accuracy: 0.6389	-	loss: 0.6475	-	val_accuracy: 0.6639 - val_loss: 0.6297
Epoch 12/100									
<b>50/50</b>		<b>14s</b>	278ms/step	-	accuracy: 0.6421	-	loss: 0.6417	-	val_accuracy: 0.6639 - val_loss: 0.6269
Epoch 13/100									
<b>50/50</b>		<b>13s</b>	261ms/step	-	accuracy: 0.6370	-	loss: 0.6405	-	val_accuracy: 0.6639 - val_loss: 0.6307
Epoch 14/100									
<b>50/50</b>		<b>14s</b>	286ms/step	-	accuracy: 0.6466	-	loss: 0.6400	-	val_accuracy: 0.6639 - val_loss: 0.6316
Epoch 15/100									
<b>50/50</b>		<b>13s</b>	264ms/step	-	accuracy: 0.6568	-	loss: 0.6312	-	val_accuracy: 0.6885 - val_loss: 0.6389
Epoch 16/100									
<b>50/50</b>		<b>16s</b>	329ms/step	-	accuracy: 0.6561	-	loss: 0.6237	-	val_accuracy: 0.6639 - val_loss: 0.6362
Epoch 17/100									
<b>50/50</b>		<b>22s</b>	358ms/step	-	accuracy: 0.6721	-	loss: 0.6261	-	val_accuracy: 0.6393 - val_loss: 0.6675
Epoch 18/100									
<b>50/50</b>		<b>13s</b>	262ms/step	-	accuracy: 0.6515	-	loss: 0.6213	-	val_accuracy: 0.6803 - val_loss: 0.6206
Epoch 19/100									
<b>50/50</b>		<b>13s</b>	254ms/step	-	accuracy: 0.6797	-	loss: 0.5959	-	val_accuracy: 0.6148 - val_loss: 0.6715
Epoch 20/100									
<b>50/50</b>		<b>13s</b>	264ms/step	-	accuracy: 0.6853	-	loss: 0.6062	-	val_accuracy: 0.7049 - val_loss: 0.6124
Epoch 21/100									
<b>50/50</b>		<b>13s</b>	253ms/step	-	accuracy: 0.7023	-	loss: 0.5763	-	val_accuracy: 0.6639 - val_loss: 0.6162
Epoch 22/100									
<b>50/50</b>		<b>13s</b>	252ms/step	-	accuracy: 0.7105	-	loss: 0.5803	-	val_accuracy: 0.6475 - val_loss: 0.6418
Epoch 23/100									
<b>50/50</b>		<b>13s</b>	257ms/step	-	accuracy: 0.7186	-	loss: 0.5753	-	val_accuracy: 0.6557 - val_loss: 0.6045
Epoch 24/100									
<b>50/50</b>		<b>13s</b>	257ms/step	-	accuracy: 0.7174	-	loss: 0.5590	-	val_accuracy: 0.6639 - val_loss: 0.6014
Epoch 25/100									
<b>50/50</b>		<b>13s</b>	254ms/step	-	accuracy: 0.7301	-	loss: 0.5409	-	val_accuracy: 0.6803 - val_loss: 0.6178
Epoch 26/100									
<b>50/50</b>		<b>12s</b>	247ms/step	-	accuracy: 0.7298	-	loss: 0.5368	-	val_accuracy: 0.6393 - val_loss: 0.6278
Epoch 27/100									
<b>50/50</b>		<b>13s</b>	254ms/step	-	accuracy: 0.7436	-	loss: 0.5328	-	val_accuracy: 0.6721 - val_loss: 0.6223
Epoch 28/100									
<b>50/50</b>		<b>13s</b>	259ms/step	-	accuracy: 0.7297	-	loss: 0.5325	-	val_accuracy: 0.6803 - val_loss: 0.6355
Epoch 29/100									
<b>50/50</b>		<b>13s</b>	251ms/step	-	accuracy: 0.7342	-	loss: 0.5310	-	val_accuracy: 0.6885 - val_loss: 0.6277
Epoch 30/100									
<b>50/50</b>		<b>12s</b>	248ms/step	-	accuracy: 0.7544	-	loss: 0.5127	-	val_accuracy: 0.6721 - val_loss: 0.6119
Epoch 31/100									

<b>50/50</b>		<b>12s</b>	249ms/step	- accuracy: 0.7621	- loss: 0.5110	- val_accuracy: 0.6721	- val_loss: 0.6063
Epoch 32/100							
<b>50/50</b>		<b>12s</b>	246ms/step	- accuracy: 0.7480	- loss: 0.5161	- val_accuracy: 0.6721	- val_loss: 0.6247
Epoch 33/100							
<b>50/50</b>		<b>12s</b>	246ms/step	- accuracy: 0.7548	- loss: 0.5072	- val_accuracy: 0.6721	- val_loss: 0.6205
Epoch 34/100							
<b>50/50</b>		<b>12s</b>	247ms/step	- accuracy: 0.7572	- loss: 0.5047	- val_accuracy: 0.6803	- val_loss: 0.5881
Epoch 35/100							
<b>50/50</b>		<b>13s</b>	260ms/step	- accuracy: 0.7708	- loss: 0.4931	- val_accuracy: 0.6885	- val_loss: 0.5889
Epoch 36/100							
<b>50/50</b>		<b>13s</b>	253ms/step	- accuracy: 0.7766	- loss: 0.4822	- val_accuracy: 0.6885	- val_loss: 0.5727
Epoch 37/100							
<b>50/50</b>		<b>12s</b>	246ms/step	- accuracy: 0.7875	- loss: 0.4718	- val_accuracy: 0.6803	- val_loss: 0.6367
Epoch 38/100							
<b>50/50</b>		<b>12s</b>	246ms/step	- accuracy: 0.7685	- loss: 0.4720	- val_accuracy: 0.6885	- val_loss: 0.5900
Epoch 39/100							
<b>50/50</b>		<b>13s</b>	259ms/step	- accuracy: 0.7867	- loss: 0.4490	- val_accuracy: 0.6639	- val_loss: 0.6281
Epoch 40/100							
<b>50/50</b>		<b>13s</b>	254ms/step	- accuracy: 0.7833	- loss: 0.4720	- val_accuracy: 0.6557	- val_loss: 0.6164
Epoch 41/100							
<b>50/50</b>		<b>13s</b>	252ms/step	- accuracy: 0.7663	- loss: 0.4718	- val_accuracy: 0.6885	- val_loss: 0.6234
Epoch 42/100							
<b>50/50</b>		<b>12s</b>	247ms/step	- accuracy: 0.7703	- loss: 0.4666	- val_accuracy: 0.6967	- val_loss: 0.5892
Epoch 43/100							
<b>50/50</b>		<b>13s</b>	253ms/step	- accuracy: 0.7749	- loss: 0.4687	- val_accuracy: 0.6721	- val_loss: 0.6437
Epoch 44/100							
<b>50/50</b>		<b>13s</b>	263ms/step	- accuracy: 0.7817	- loss: 0.4506	- val_accuracy: 0.6967	- val_loss: 0.6298
Epoch 45/100							
<b>50/50</b>		<b>12s</b>	248ms/step	- accuracy: 0.7785	- loss: 0.4352	- val_accuracy: 0.6885	- val_loss: 0.6529
Epoch 46/100							
<b>50/50</b>		<b>13s</b>	258ms/step	- accuracy: 0.7796	- loss: 0.4342	- val_accuracy: 0.6311	- val_loss: 0.6399
Epoch 47/100							
<b>50/50</b>		<b>13s</b>	251ms/step	- accuracy: 0.7832	- loss: 0.4497	- val_accuracy: 0.6885	- val_loss: 0.6456
Epoch 48/100							
<b>50/50</b>		<b>12s</b>	247ms/step	- accuracy: 0.7947	- loss: 0.4348	- val_accuracy: 0.6639	- val_loss: 0.6748
Epoch 49/100							
<b>50/50</b>		<b>12s</b>	247ms/step	- accuracy: 0.8120	- loss: 0.4335	- val_accuracy: 0.6639	- val_loss: 0.6750
Epoch 50/100							
<b>50/50</b>		<b>13s</b>	254ms/step	- accuracy: 0.8097	- loss: 0.4165	- val_accuracy: 0.6639	- val_loss: 0.6776
Epoch 51/100							
<b>50/50</b>		<b>13s</b>	251ms/step	- accuracy: 0.7947	- loss: 0.4244	- val_accuracy: 0.6721	- val_loss: 0.6832

6/6  2s 181ms/step

--- Evaluating Model on Unseen Test Data ---

✅ --- LSTM Pipeline Finished! --- ✅

In [3]: # --- 2. Run Pipeline with XGBoost Model ---

```
# We can reuse the same pipeline instance
print("="*50)
print("RUNNING PIPELINE FOR XGBOOST MODEL")
print("="*50)

# Run the static test specifically for the 'xgboost' model type
xgboost_results = pipeline.run_static_test(model_type='xgboost')

print("\n\n✅ --- XGBoost Pipeline Finished! --- ✅")
```

```
=====
RUNNING PIPELINE FOR XGBOOST MODEL
=====
```

===== Starting STATIC Test Run for model\_type='xgboost' =====

===== Step 1: Loading and Preparing Full Dataset =====

--- Loading Main Asset Data ---

Loading SPY data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\spy\_data.csv

--- Loading Macroeconomic Data ---

Loading DX-Y.NYB data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\dx-y.nyb\_data.csv

Loading ^TNX data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\^tnx\_data.csv

Loading ^VIX data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\^vix\_data.csv

Loading CL=F data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\cl=f\_data.csv

Loading SI=F data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\si=f\_data.csv

Loading TIP data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\tip\_data.csv

Loading HG=F data from local cache: C:\Projetos\_Python\gld\_lstm\_strategy\data\hg=f\_data.csv

===== Starting Feature Engineering Pipeline =====

Step 1: Creating custom OHLCV features...

Step 2: Applying 'All' technical indicator strategy from pandas\_ta...

```
130it [00:09, 14.08it/s]
```

```
-> Dropped 2 redundant TA columns.
Step 3: Creating custom interaction and ratio features...
Step 4: Creating lagged and momentum features...
Step 5: Merging macroeconomic features...
-> Macro features merged and forward-filled.
Step 6: Defining target variable...
```

```
Pipeline complete. Dropped 77 rows with NaN values.
```

```
Final dataset shape: (2438, 247)
```

```
=====
```

```
--- Splitting data chronologically ---
```

```
Train set size: 1761, Validation set size: 311, Test set size: 366
```

```
--- Running Feature Selection ---
```

```
Selected 25 features via BorutaPy.
```

```
--- Scaling data ---
```

```
--- Preparing data and training XGBoost Model ---
```

```
C:\Users\rbert\.venv\lib\site-packages\xgboost\callback.py:386: UserWarning:
```

```
[15:47:40] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\learner.cc:738:
Parameters: { "use_label_encoder" } are not used.
```

```
--- Evaluating Model on Unseen Test Data ---
```

```
✅ --- XGBoost Pipeline Finished! --- ✅
```

```
In [4]: # --- 3. Run Backtests for Both Models ---
```

```
def run_backtest_for_results(results_dict, config, model_name):
    """
    Helper function to run the backtest for a given results dictionary.
    """
    print("\n" + "="*50)
```

```
print(f"RUNNING BACKTEST FOR {model_name.upper()} MODEL")
print("="*50)

# Extract necessary data from the results dictionary
processed_data = results_dict['processed_data_for_backtest']
y_pred_proba = results_dict['pred_probas']

# Recreate X_test to get the prices and the correct date index
X = processed_data.drop(columns=[config['TARGET_NAME']])
train_val_size = int(len(X) * (1 - config['TEST_SIZE']))
X_test = X.iloc[train_val_size:]

# Convert probabilities to binary signals
test_predictions = (y_pred_proba > 0.5).astype(int)

# Create a pandas Series for the signals with the correct date index
if model_name.lower() == 'lstm':
    signal_dates = X_test.index[config['TIME_STEPS']:]
else: # XGBoost uses 2D data, so no offset is needed for the index
    signal_dates = X_test.index

signals_series = pd.Series(test_predictions, index=signal_dates, name="signal")

# Get the price data for the same period
price_data_for_backtest = X_test.loc[signal_dates]

# Instantiate and run the backtester
backtester = VectorizedBacktester(
    price_data=price_data_for_backtest,
    signals=signals_series,
    config=config
)

portfolio = backtester.run(commission=0.001, slippage=0.001)
return portfolio

# Run the backtest for each model's results
lstm_portfolio = run_backtest_for_results(lstm_results, config, "LSTM")
xgboost_portfolio = run_backtest_for_results(xgboost_results, config, "XGBoost")
```



```
=====
RUNNING BACKTEST FOR LSTM MODEL
=====
```

```
===== Starting Vectorized Backtest with vectorbt =====
```

```
--- Backtest Performance Stats ---
```

Start	2024-04-18 00:00:00
End	2024-12-30 00:00:00
Period	177 days 00:00:00
Start Value	100.0
End Value	128.792376
Total Return [%]	28.792376
Benchmark Return [%]	18.898143
Max Gross Exposure [%]	100.0
Total Fees Paid	1.858152
Max Drawdown [%]	2.29424
Max Drawdown Duration	22 days 00:00:00
Total Trades	8
Total Closed Trades	8
Total Open Trades	0
Open Trade PnL	0.0
Win Rate [%]	100.0
Best Trade [%]	6.57933
Worst Trade [%]	1.864559
Avg Winning Trade [%]	3.231731
Avg Losing Trade [%]	NaN
Avg Winning Trade Duration	12 days 00:00:00
Avg Losing Trade Duration	NaT
Profit Factor	inf
Expectancy	3.599047
Sharpe Ratio	5.049487
Calmar Ratio	29.859026
Omega Ratio	2.685281
Sortino Ratio	9.870426

dtype: object

```
--- Plotting Equity Curve and Drawdowns ---
```





===== Backtest Finished =====

=====

RUNNING BACKTEST FOR XGBOOST MODEL

=====

===== Starting Vectorized Backtest with vectorbt =====

--- Backtest Performance Stats ---

Start	2023-07-19 00:00:00
End	2024-12-30 00:00:00
Period	366 days 00:00:00
Start Value	100.0
End Value	155.118712
Total Return [%]	55.118712
Benchmark Return [%]	31.874076
Max Gross Exposure [%]	100.0
Total Fees Paid	7.263764
Max Drawdown [%]	3.106266
Max Drawdown Duration	19 days 00:00:00
Total Trades	29
Total Closed Trades	29
Total Open Trades	0
Open Trade PnL	0.0
Win Rate [%]	86.206897
Best Trade [%]	6.11943
Worst Trade [%]	-0.619491
Avg Winning Trade [%]	1.825389
Avg Losing Trade [%]	-0.242082
Avg Winning Trade Duration	8 days 01:55:12
Avg Losing Trade Duration	1 days 18:00:00
Profit Factor	41.918888
Expectancy	1.900645
Sharpe Ratio	4.032945
Calmar Ratio	17.684501
Omega Ratio	2.065181
Sortino Ratio	7.020935

dtype: object

--- Plotting Equity Curve and Drawdowns ---



===== Backtest Finished =====

```
In [5]: # --- 4. Final Results Comparison ---

# Extract the statistics from both portfolio objects
lstm_stats = lstm_portfolio.stats()
xgboost_stats = xgboost_portfolio.stats()

# Define the key metrics we want to compare
metrics_to_compare = [
    'Total Return [%]',
    'Benchmark Return [%]',
    'Sharpe Ratio',
    'Sortino Ratio',
    'Max Drawdown [%]',
    'Win Rate [%]',
    'Profit Factor',
    'Total Trades'
]

# Create a comparison DataFrame
comparison_df = pd.DataFrame({
    'LSTM': lstm_stats[metrics_to_compare],
    'XGBoost': xgboost_stats[metrics_to_compare]
})
```

```
print("\n\n" + "="*50)
print("MODEL BENCHMARK COMPARISON")
print("="*50)
display(comparison_df.round(4))
```

=====
MODEL BENCHMARK COMPARISON
=====

	LSTM	XGBoost
Total Return [%]	28.792376	55.118712
Benchmark Return [%]	18.898143	31.874076
Sharpe Ratio	5.049487	4.032945
Sortino Ratio	9.870426	7.020935
Max Drawdown [%]	2.29424	3.106266
Win Rate [%]	100.0	86.206897
Profit Factor	inf	41.918888
Total Trades	8	29