Capstone Project: Machine Learning-Driven Long/Short Pair Trading Strategies in Cryptocurrencies

Members

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1. Environment Setup

```
pip install keras-tuner
```

```
Collecting keras-tuner
  Downloading keras_tuner-1.4.8-py3-none-any.whl.metadata (5.6 kB)
Requirement already satisfied: keras in /usr/local/lib/python3.12/dist-packag
Requirement already satisfied: packaging in /usr/local/lib/python3.12/dist-pa
Requirement already satisfied: requests in /usr/local/lib/python3.12/dist-pac
Collecting kt-legacy (from keras-tuner)
  Downloading kt_legacy-1.0.5-py3-none-any.whl.metadata (221 bytes)
Requirement already satisfied: grpcio in /usr/local/lib/python3.12/dist-packa
Requirement already satisfied: protobuf in /usr/local/lib/python3.12/dist-pac
Requirement already satisfied: typing-extensions~=4.12 in /usr/local/lib/pyth
Requirement already satisfied: absl-py in /usr/local/lib/python3.12/dist-pack
Requirement already satisfied: numpy in /usr/local/lib/python3.12/dist-packag
Requirement already satisfied: rich in /usr/local/lib/python3.12/dist-package
Requirement already satisfied: namex in /usr/local/lib/python3.12/dist-packag
Requirement already satisfied: h5py in /usr/local/lib/python3.12/dist-package
Requirement already satisfied: optree in /usr/local/lib/python3.12/dist-packa
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.12/dist-pa
Requirement already satisfied: charset_normalizer<4,>=2 in /usr/local/lib/pyt
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.12/dist
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.1
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.1
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/pyth
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.12/dist-p
Downloading keras_tuner-1.4.8-py3-none-any.whl (129 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 129.4/129.4 kB 4.0 MB/s eta 0:00:
Downloading kt_legacy-1.0.5-py3-none-any.whl (9.6 kB)
Installing collected packages: kt-legacy, keras-tuner
Successfully installed keras-tuner-1.4.8 kt-legacy-1.0.5
```

```
# Required imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
import seaborn as sns
import statsmodels.api as sm
from statsmodels.tsa.stattools import coint
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.model_selection import train_test_split, TimeSeriesSplit
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout
from datetime import datetime
import yfinance as yf
from statsmodels.tsa.stattools import coint
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, Input
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegresso
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from scipy import stats
import time
import platform
import keras_tuner as kt

import warnings
warnings.filterwarnings("ignore")
```

2. Data Collection & Preprocessing

2.Cryptocurrency Data (Yahoo Finance)

```
# ==========================
# CONFIGURATION
# ==========================

tickers = [
    "BTC-USD",  # Bitcoin
```

```
    "ETH-USD",  # Ethereum
    "XRP-USD",  # Ripple
    "LTC-USD",  # Litecoin
    "ADA-USD",  # Cardano
    "DOT-USD",  # Polkadot
    "SOL-USD",  # Solana
    "AVAX-USD", # Avalanche
    "BNB-USD"   # Binance Coin
]

start_date = "2016-09-30"
end_date = "2025-09-29"

# ==========================
# DOWNLOAD & COMBINE DATA
# ==========================

print("📥 Downloading daily closing prices (including weekends)...")

# Create an empty DataFrame for aligned daily data
all_prices = pd.DataFrame()

# Generate continuous daily date index including weekends
full_dates = pd.date_range(start=start_date, end=end_date, freq='D')

for ticker in tickers:
    print(f"Fetching {ticker}...")
    df = yf.download(ticker, start=start_date, end=end_date, interval='1d')

    if not df.empty:
        df = df[['Close']].rename(columns={'Close': ticker})
        df = df.reindex(full_dates)  # ensure all dates including weekends
        df[ticker] = df[ticker].ffill()  # forward-fill weekends
        all_prices = pd.concat([all_prices, df[ticker]], axis=1)
    else:
        print(f"⚠️ Warning: No data found for {ticker}")

# Set Date as column
all_prices.index.name = "Date"
all_prices.reset_index(inplace=True)

# ==========================
# SAVE TO EXCEL
# ==========================

output_file = "crypto_prices_9yrs_full.xlsx"
sheet_name = "Closing_Prices"

all_prices.to_excel(output_file, sheet_name=sheet_name, index=False)

print(f"✅ Completed! Saved all daily (incl. weekend) closing prices to '{ou
```

```
print(f"✅ Completed! Saved all daily (incl. weekend) closing prices to '{o
```

```
📥 Downloading daily closing prices (including weekends)...
Fetching BTC-USD...
[*********************100%***********************]  1 of 1 completed
Fetching ETH-USD...
[*********************100%***********************]  1 of 1 completed
Fetching XRP-USD...
[*********************100%***********************]  1 of 1 completed
Fetching LTC-USD...
[*********************100%***********************]  1 of 1 completed
Fetching ADA-USD...
[*********************100%***********************]  1 of 1 completed
Fetching DOT-USD...
[*********************100%***********************]  1 of 1 completed
Fetching SOL-USD...
[*********************100%***********************]  1 of 1 completed
Fetching AVAX-USD...
[*********************100%***********************]  1 of 1 completed
Fetching BNB-USD...
[*********************100%***********************]  1 of 1 completed
✅ Completed! Saved all daily (incl. weekend) closing prices to 'crypto_price
```

3. Exploratory Data Analysis (EDA)

```
# ==========================
# STEP 3: EDA on Prices, Returns, and COVID-19 Regime Analysis
# ==========================

# Use the DataFrame created earlier
price_df = all_prices.copy()

# Set Date as index
price_df['Date'] = pd.to_datetime(price_df['Date'])
price_df.set_index('Date', inplace=True)

# Drop rows with any missing values (optional)
price_df.dropna(inplace=True)

print("✅ Combined price data shape:", price_df.shape)
display(price_df.head())

# ==========================
# Summary Statistics
# ==========================
print("\n📊 Price Summary Statistics:")
display(price_df.describe().round(2))

# ==========================
# Price Trend Visualization
```

```
# ==========================
plt.figure(figsize=(14, 6))
for col in price_df.columns:
    plt.plot(price_df.index, price_df[col], label=col)
plt.title("Daily Closing Prices (Last 9 Years)")
plt.xlabel("Date")
plt.ylabel("Price (USD)")
plt.legend(loc="upper left", ncol=2)
plt.grid(True)
plt.show()

# ==========================
# Daily Returns
# ==========================
returns_df = price_df.pct_change().dropna() * 100  # percentage returns

print("\n📈 Daily Returns Sample:")
display(returns_df.head())

print("\n📊 Returns Summary Statistics:")
display(returns_df.describe().round(2))

# ==========================
# Time Series of Daily Returns
# ==========================
plt.figure(figsize=(14, 6))
for col in returns_df.columns:
    plt.plot(returns_df.index, returns_df[col], label=col, alpha=0.7)
plt.title("Time Series of Daily Returns for Cryptocurrencies")
plt.xlabel("Date")
plt.ylabel("Daily Return (%)")
plt.legend(loc="upper left", ncol=2)
plt.grid(True)
plt.show()

# ==========================
# Plot Returns Distribution (for BTC if present)
# ==========================
if 'BTC-USD' in returns_df.columns:
    plt.figure(figsize=(14, 6))
    sns.histplot(returns_df['BTC-USD'], bins=100, kde=True, color='gold')
    plt.title("Distribution of Daily Returns - BTC")
    plt.xlabel("Daily Return (%)")
    plt.ylabel("Frequency")
    plt.grid(True)
    plt.show()

# ==========================
# Correlation Matrix (Returns)
# ==========================
```

```
corr = returns_df.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, fmt=".2f", cmap="coolwarm", center=0)
plt.title("Correlation Matrix of Daily Returns")
plt.show()

# ==========================
# Rolling Volatility (30-day)
# ==========================
rolling_vol = returns_df.rolling(window=30).std()

plt.figure(figsize=(14, 6))
for col in rolling_vol.columns:
    plt.plot(rolling_vol.index, rolling_vol[col], label=col)
plt.title("30-Day Rolling Volatility (%)")
plt.xlabel("Date")
plt.ylabel("Volatility (%)")
plt.legend(loc="upper left", ncol=2)
plt.grid(True)
plt.show()

# ==========================
# REGIME ANALYSIS: During COVID vs Post-COVID
# ==========================

# Define COVID-19 and post-COVID periods
during_covid = ('2020-01-01', '2021-12-31')
post_covid = ('2022-01-01', price_df.index.max().strftime('%Y-%m-%d'))

# Segment returns by regime
returns_covid = returns_df.loc[during_covid[0]:during_covid[1]]
returns_post = returns_df.loc[post_covid[0]:post_covid[1]]

print("\n📊 Regime Periods:")
print(f"During COVID: {during_covid[0]} → {during_covid[1]} ({len(returns_co
print(f"Post-COVID:  {post_covid[0]} → {post_covid[1]} ({len(returns_post)}

# Summary stats per regime
print("\n📈 Mean Returns by Regime (%):")
mean_returns = pd.DataFrame({
    "During COVID": returns_covid.mean(),
    "Post-COVID": returns_post.mean()
}).round(3)
display(mean_returns)

print("\n📉 Volatility (Std Dev) by Regime (%):")
volatility = pd.DataFrame({
    "During COVID": returns_covid.std(),
    "Post-COVID": returns_post.std()
}).round(3)
```

```
display(volatility)

# ==========================
# Plot BTC Returns with Regime Shading
# ==========================
if 'BTC-USD' in returns_df.columns:
    plt.figure(figsize=(14, 6))
    plt.plot(returns_df.index, returns_df['BTC-USD'], label='BTC-USD Returns
    plt.axvspan(during_covid[0], during_covid[1], color='red', alpha=0.15, l
    plt.axvspan(post_covid[0], post_covid[1], color='blue', alpha=0.1, label
    plt.title("BTC Daily Returns – During vs Post COVID-19")
    plt.xlabel("Date")
    plt.ylabel("Daily Return (%)")
    plt.legend(loc="upper left")
    plt.grid(True)
    plt.show()

# ==========================
# Correlation Comparison: During vs Post COVID
# ==========================
corr_covid = returns_covid.corr()
corr_post = returns_post.corr()

fig, axes = plt.subplots(1, 2, figsize=(16, 6))
sns.heatmap(corr_covid, annot=False, cmap="coolwarm", center=0, ax=axes[0])
axes[0].set_title("During COVID Correlations")

sns.heatmap(corr_post, annot=False, cmap="coolwarm", center=0, ax=axes[1])
axes[1].set_title("Post-COVID Correlations")

plt.tight_layout()
plt.show()
```

✅ Combined price data shape: (1867, 9)

Ticker	BTC-USD	ETH-USD	XRP-USD	LTC-USD	ADA-USD	DOT-USD	S
Date							
2020-08-20	11878.372070	416.439789	0.292573	62.966755	0.133642	2.900080	3.
2020-08-21	11592.489258	389.126343	0.280682	59.379021	0.123760	2.875028	2.
2020-08-22	11681.825195	395.835144	0.286546	60.311157	0.125276	4.484690	3.
2020-08-23	11664.847656	391.384491	0.285386	60.623260	0.121595	3.967066	3.
2020-08-24	11774.595703	408.144196	0.289215	62.199425	0.124488	4.602614	3.

📊 Price Summary Statistics:

Ticker	BTC-USD	ETH-	XRP-	LTC-	ADA-	DOT-	SOL-	AVAX-

Ticker	BTC-USD	USD	USD	USD	USD	USD	USD	USD
count	1867.00	1867.00	1867.00	1867.00	1867.00	1867.00	1867.00	1867.00
mean	49326.75	2339.94	0.91	102.94	0.71	11.29	88.59	29.88
std	28735.44	1014.16	0.78	50.17	0.53	10.65	72.96	23.52
min	10131.52	321.12	0.21	43.06	0.08	2.88	1.21	2.91
25%	26826.09	1640.44	0.46	68.81	0.35	4.67	22.18	14.86
50%	42270.53	2241.98	0.58	87.83	0.51	6.40	62.43	22.92
75%	64078.28	3117.95	0.99	119.65	0.92	13.79	150.86	35.97
max	123344.06	4831.35	3.56	386.45	2.97	53.88	261.87	134.53

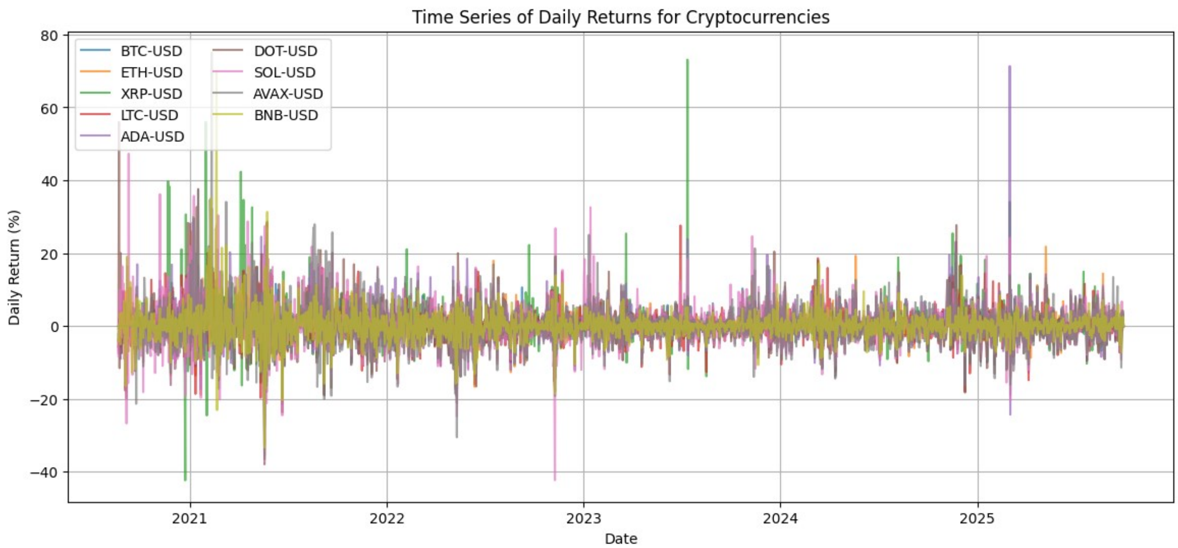
📈 Daily Returns Sample:

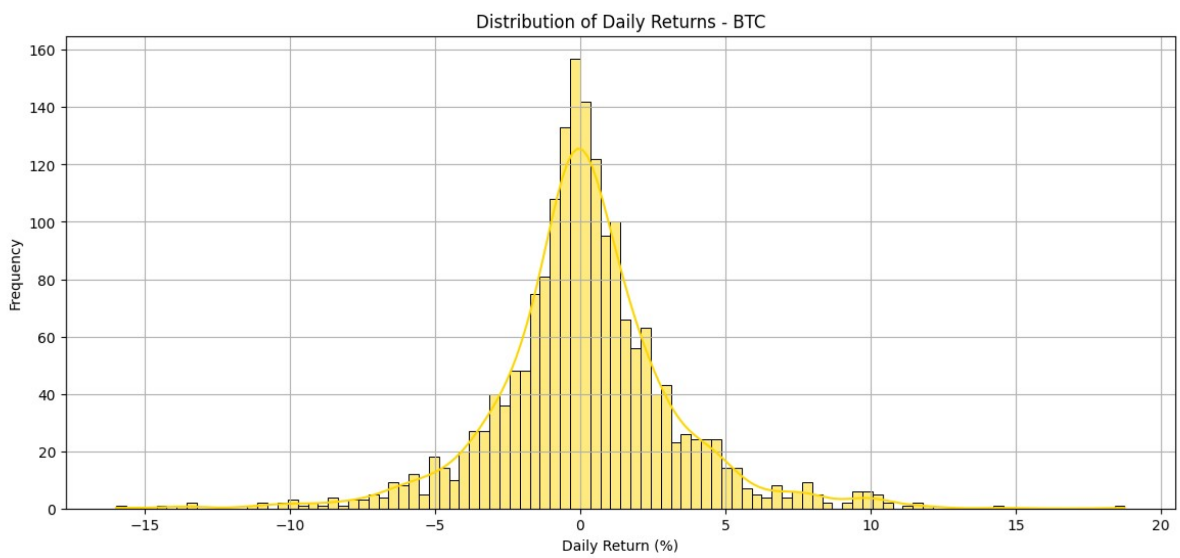
Ticker	BTC-USD	ETH-USD	XRP-USD	LTC-USD	ADA-USD	DOT-USD	SOL
Date							
2020-08-21	-2.406751	-6.558798	-4.064287	-5.697823	-7.394384	-0.863841	-8.24
2020-08-22	0.770636	1.724068	2.089195	1.569808	1.224951	55.987710	2.62
2020-08-23	-0.145333	-1.124370	-0.404820	0.517488	-2.938310	-11.542027	9.98
2020-08-24	0.940844	4.282159	1.341692	2.599933	2.379210	16.020602	0.67
2020-08-25	-3.469002	-5.915350	-3.902974	-5.817995	-8.993640	20.005572	-2.39

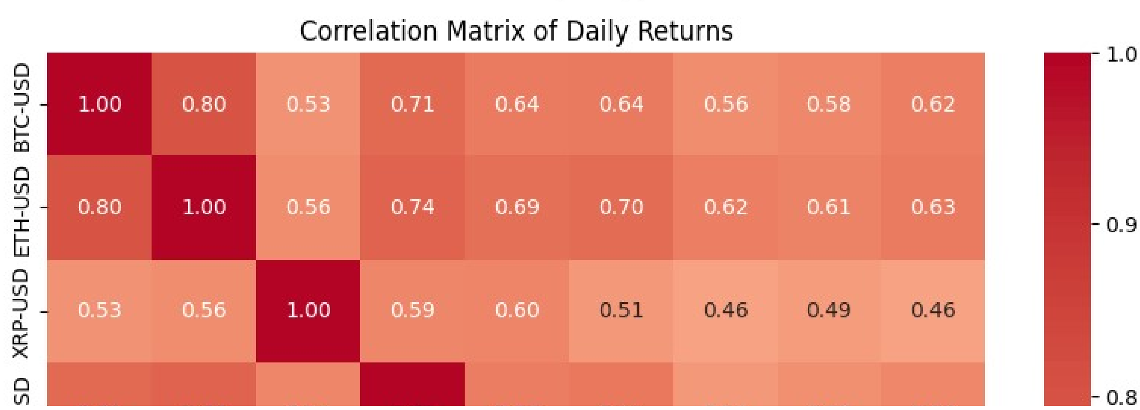
📊 Returns Summary Statistics:

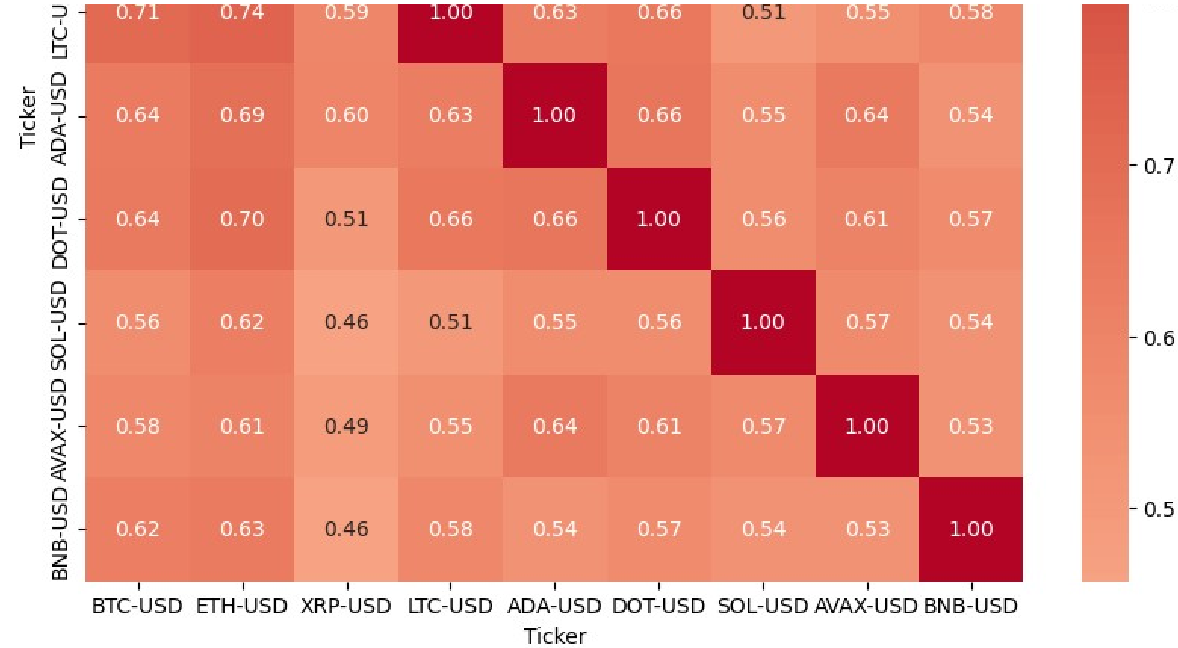
Ticker	BTC-USD	ETH-USD	XRP-USD	LTC-USD	ADA-USD	DOT-USD	SOL-USD	AVAX-USD	
count	1866.00	1866.00	1866.00	1866.00	1866.00	1866.00	1866.00	1866.00	1
mean	0.17	0.21	0.28	0.13	0.23	0.16	0.42	0.28	

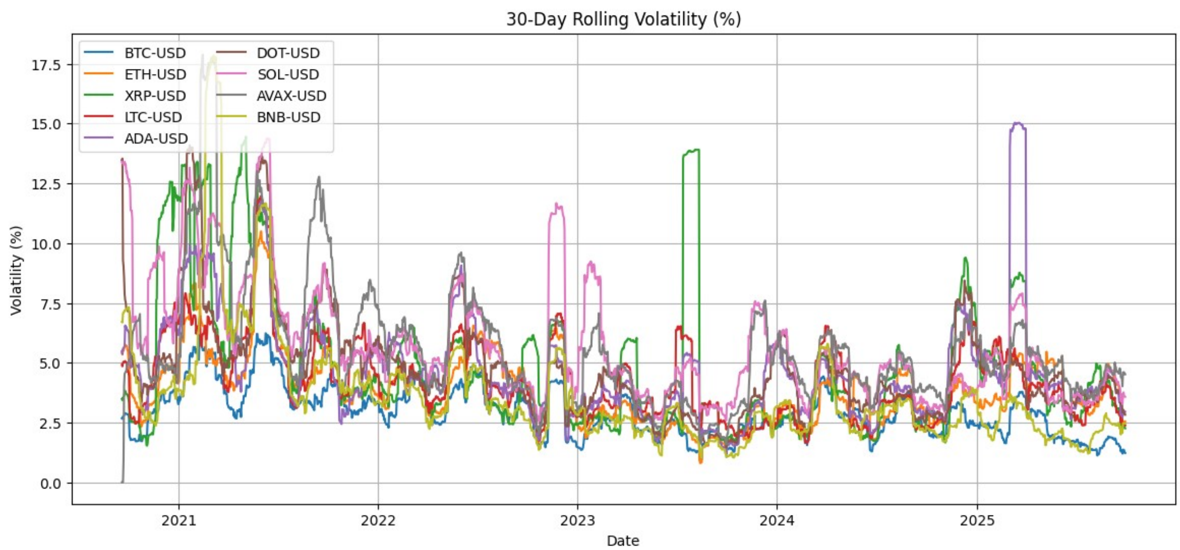
mean	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
std	3.09	4.16	5.73	4.57	5.27	5.45	6.33	6.25
min	-15.97	-27.20	-42.33	-35.67	-26.01	-37.93	-42.28	-36.50
25%	-1.27	-1.78	-1.98	-2.09	-2.41	-2.70	-3.01	-2.96
50%	0.04	0.10	0.05	0.14	0.02	-0.05	-0.02	0.00
75%	1.52	2.14	2.03	2.23	2.32	2.53	3.32	3.04
max	18.75	25.95	73.08	28.20	71.33	55.99	47.28	75.00











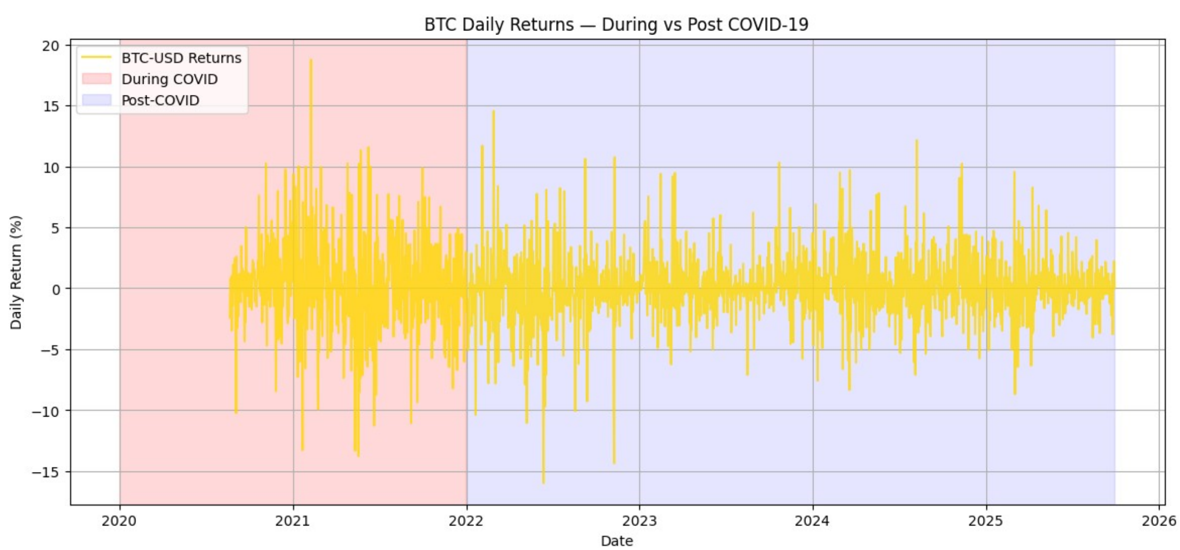

```
📊 Regime Periods:
During COVID: 2020-01-01 → 2021-12-31 (498 days)
Post-COVID:  2022-01-01 → 2025-09-29 (1368 days)

📈 Mean Returns by Regime (%):
```

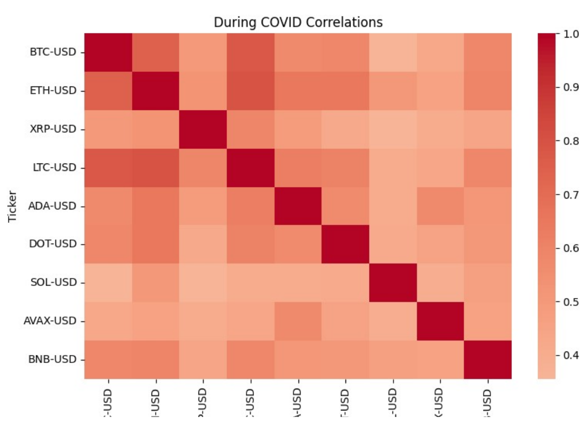
Ticker	During COVID	Post-COVID
BTC-USD	0.350	0.102
ETH-USD	0.578	0.076
XRP-USD	0.522	0.188
LTC-USD	0.348	0.056
ADA-USD	0.668	0.069
DOT-USD	0.745	-0.051

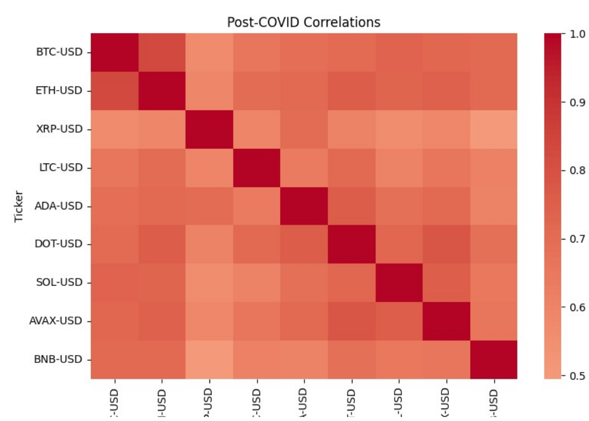
SOL-USD	1.171	0.150
AVAX-USD	0.980	0.031
BNB-USD	0.854	0.093

📉 Volatility (Std Dev) by Regime (%):

Ticker	During COVID	Post-COVID
BTC-USD	3.918	2.728
ETH-USD	5.279	3.666
XRP-USD	8.072	4.592
LTC-USD	5.896	3.977
ADA-USD	6.560	4.707
DOT-USD	7.895	4.198
SOL-USD	8.734	5.162
AVAX-USD	8.777	5.004
BNB-USD	7.033	2.987








BTC
ETH
LTC
BNB
Ticker
BTC
ETH
LTC
BNB
Ticker

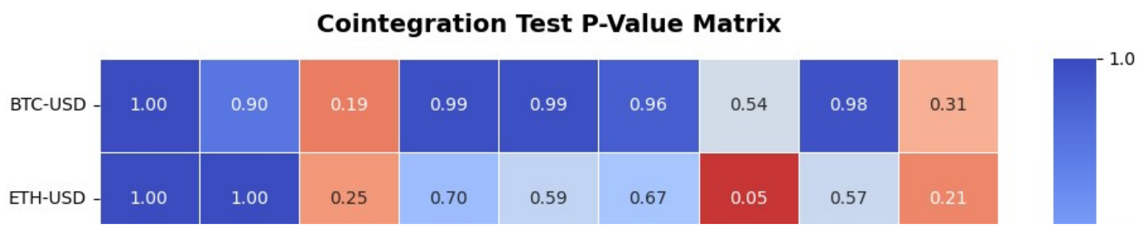
Next steps: Generate code with `mean_returns` New interactive sheet Generate code with

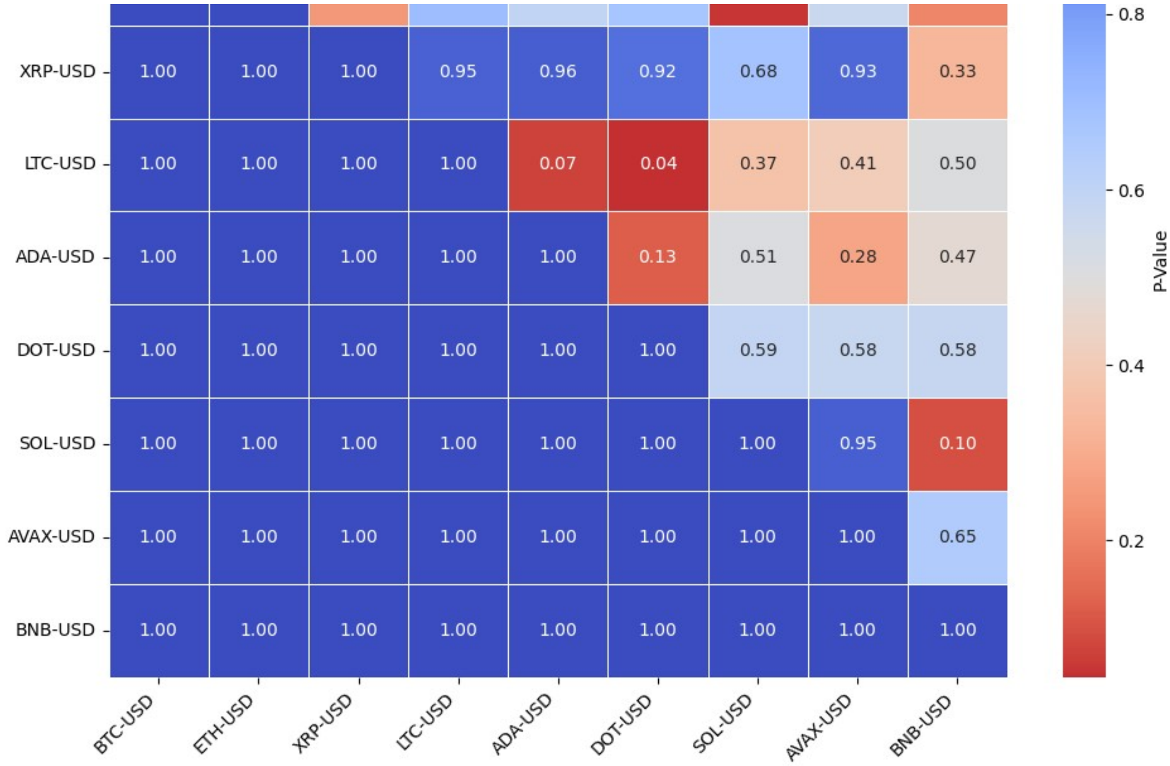
4. Co-integration Test (Pairs Selection)

```
# ======================================
# 4. COINTEGRATION TEST (PAIRS SELECTION)
# ======================================

# ==========================
# FUNCTION: Find Co-integrated Pairs
# ==========================

def find_cointegrated_pairs(data: pd.DataFrame, pvalue_threshold: float = 0.
    """
    Runs Engle-Granger cointegration tests on all column pairs in `data`.

    Parameters:
        data (pd.DataFrame): Price data (columns = asset symbols, rows = tim
        pvalue_threshold (float): Significance threshold for cointegration

    Returns:
        pvalue_matrix (ndarray): matrix of p-values
        pairs (list): list of tuples (asset1, asset2, p-value)
    """
    n = data.shape[1]
    keys = data.columns
    pvalue_matrix = np.ones((n, n))
    pairs = []

    for i in range(n):
        for j in range(i + 1, n):
            series_i = data[keys[i]].dropna()
            series_j = data[keys[j]].dropna()

            # Align both series by date
            combined = pd.concat([series_i, series_j], axis=1).dropna()
            if combined.shape[0] < 100:  # Skip if overlap is too short
                continue

            try:
                score, pvalue, _ = coint(combined.iloc[:, 0], combined.iloc[
                pvalue_matrix[i, j] = pvalue
                if pvalue < pvalue_threshold:
                    pairs.append((keys[i], keys[j], round(pvalue, 4)))
            except Exception as e:
                print(f"⚠️ Error testing {keys[i]} and {keys[j]}: {e}")
                continue

    return pvalue_matrix, pairs
```

```
# ==========================
# RUN CO-INTEGRATION TEST
# ==========================

#Replace with your DataFrame (from crypto_prices_9yrs_full.xlsx)
# Example:
# price_df = pd.read_excel("crypto_prices_9yrs_full.xlsx", sheet_name="Closi

print("Running Engle-Granger Cointegration Tests...")
p_matrix, coint_pairs = find_cointegrated_pairs(price_df, pvalue_threshold=0

# Display Results
print(f"\nFound {len(coint_pairs)} co-integrated pairs (p < 0.05):")
for a, b, p in coint_pairs:
    print(f"  • {a} & {b} → p = {p}")

# ==========================
# VISUALIZE P-VALUE HEATMAP
# ==========================

plt.figure(figsize=(10, 8))

sns.heatmap(
    p_matrix,
    xticklabels=price_df.columns,
    yticklabels=price_df.columns,
    cmap="coolwarm_r",
    center=0.5,
    annot=True,        # show p-values
    fmt=".2f",         # 2 decimal places
    linewidths=0.5,
    cbar_kws={"label": "P-Value"}
)

plt.title("Cointegration Test P-Value Matrix", fontsize=14, fontweight="bold
plt.xticks(rotation=45, ha="right")
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```

```
Running Engle-Granger Cointegration Tests...

Found 1 co-integrated pairs (p < 0.05):
  • LTC-USD & DOT-USD → p = 0.0441
```





5. Feature Engineering

```
# ==========================
# STEP 5: FEATURE ENGINEERING
# ==========================

# ✅ 1. Calculate log returns
log_returns = np.log(price_df / price_df.shift(1)).dropna()

print("✅ Log returns calculated:")
display(log_returns.head())
```

```
# ✅ 2. Select first cointegrated pair
if len(coint_pairs) == 0:
    raise ValueError("No cointegrated pairs found. Please run Step 4 first."

pair = coint_pairs[0]  # (asset1, asset2, p-value)
asset1, asset2 = pair[0], pair[1]
print(f"\n📈 Selected Co-integrated Pair: {asset1} / {asset2} (p={pair[2]})'

# ✅ 3. Create spread
spread = price_df[asset1] - price_df[asset2]
spread_mean = spread.mean()
spread_std = spread.std()
z_score = (spread - spread_mean) / spread_std

# ✅ 4. Combine into feature dataframe
features_df = pd.DataFrame({
    "Spread": spread,
    "Z_Score": z_score,
    f"{asset1}_Return": log_returns[asset1],
    f"{asset2}_Return": log_returns[asset2]
})

# ✅ 5. Add optional technical indicators
features_df["Spread_MA_5"] = features_df["Spread"].rolling(5).mean()
features_df["Spread_MA_20"] = features_df["Spread"].rolling(20).mean()
features_df["Spread_Volatility_20"] = features_df["Spread"].rolling(20).std(
features_df["Z_Score_Lag1"] = features_df["Z_Score"].shift(1)

features_df.dropna(inplace=True)

print("\n✅ Engineered Features:")
display(features_df.head())

# ==========================
# OPTIONAL: SAVE TO FILE
# ==========================
output_file = f"features_{asset1}_{asset2}.xlsx"
features_df.to_excel(output_file, index=True)
print(f"\n✅ Feature dataset saved to '{output_file}'")
```

✅ Log returns calculated:

Ticker	BTC-USD	ETH-USD	XRP-USD	LTC-USD	ADA-USD	DOT-USD	SOL-
Date							
2020-08-21	-0.024362	-0.067838	-0.041492	-0.058666	-0.076820	-0.008676	-0.086
2020-08-22	0.007677	0.017094	0.020677	0.015576	0.012175	0.444607	0.025

2020-08-23	-0.001454	-0.011307	-0.004056	0.005162	-0.029823	-0.122643	0.095
2020-08-24	0.009364	0.041930	0.013328	0.025667	0.023513	0.148598	0.006
2020-08-25	-0.035306	-0.060975	-0.039812	-0.059941	-0.094241	0.182368	-0.024

📈 Selected Co-integrated Pair: LTC-USD / DOT-USD (p=0.0441)

✅ Engineered Features:

Date	Spread	Z_Score	LTC-USD_Return	DOT-USD_Return	Spread_MA_5	Spread_M
2020-09-08	43.109477	-1.176044	-0.028837	-0.072271	43.894396	51.32
2020-09-09	43.188758	-1.174123	0.010787	0.096837	43.438960	50.47
2020-09-10	44.135270	-1.151191	0.016958	-0.027418	43.572610	49.85
2020-09-11	44.444185	-1.143707	0.007625	0.013869	43.810626	49.29
2020-09-12	45.680117	-1.113764	0.034584	0.100563	44.111561	48.74

6. ML/DL Modeling

6.Random Forest Regressor (ML baseline)

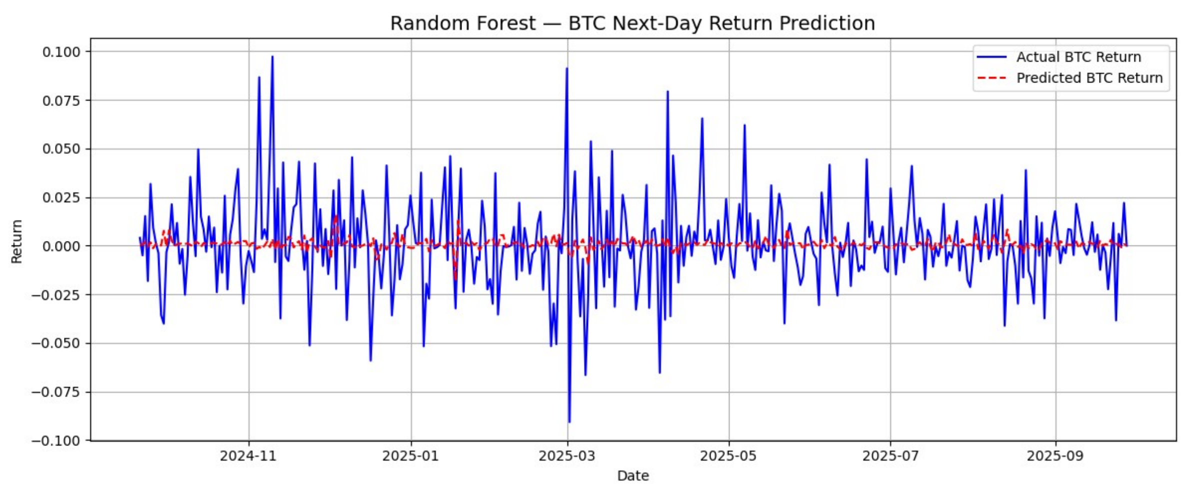
```
# ============================================================
# Random Forest Regressor — Based on Log Returns (9 Years)
# ============================================================

# ============================================================
# 1. Load Data
# ============================================================
file_path = "crypto_prices_9yrs_full.xlsx"
sheet_name = "Closing_Prices"

# Read prices
prices_df = pd.read_excel(file_path, sheet_name=sheet_name, parse_dates=["Da
prices_df.set_index("Date", inplace=True)

print("✅ Data Loaded:", prices_df.shape)
print("Columns:", list(prices_df.columns))

# ============================================================
# 2. Convert Prices → Log Returns
# ============================================================
returns_df = np.log(prices_df / prices_df.shift(1)).dropna()
```

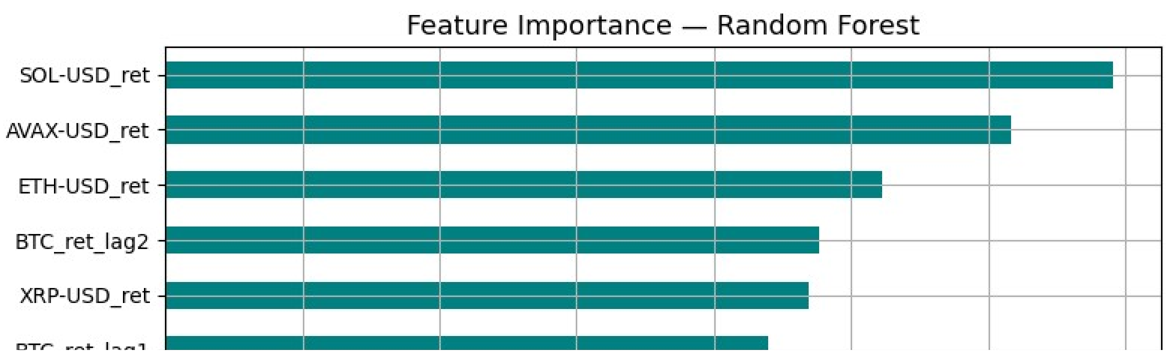
```
returns_df = returns_df.replace([np.inf, -np.inf], np.nan).dropna()

print("✅ Log Returns Calculated:", returns_df.shape)

# ============================================================
# 3. Choose Reference Crypto (BTC)
# ============================================================
target_crypto = "BTC-USD"
assert target_crypto in returns_df.columns, f"{target_crypto} not found in d

# ============================================================
# 4. Feature Engineering
# ============================================================
features = pd.DataFrame(index=returns_df.index)

# Include BTC's lagged returns as autoregressive features
features["BTC_ret"] = returns_df[target_crypto]
features["BTC_ret_lag1"] = returns_df[target_crypto].shift(1)
features["BTC_ret_lag2"] = returns_df[target_crypto].shift(2)

# Include other cryptos' returns as explanatory features
for col in returns_df.columns:
    if col != target_crypto:
        features[f"{col}_ret"] = returns_df[col]

# Target: next-day BTC return
features["target"] = returns_df[target_crypto].shift(-1)

# Drop NaN caused by shifting
features = features.dropna()

print("✅ Features Ready:", features.shape)
print(features.head())

# ============================================================
# 5. Train/Test Split (80/20, no shuffle — time-series order)
# ============================================================
X = features.drop(columns="target")
y = features["target"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, shuffle=False
)

print(f"🧠 Training Samples: {len(X_train)} | 🧪 Testing Samples: {len(X_te

# ============================================================
# 6. Train Random Forest Regressor
# ============================================================
rf = RandomForestRegressor(
    n_estimators=300,
```

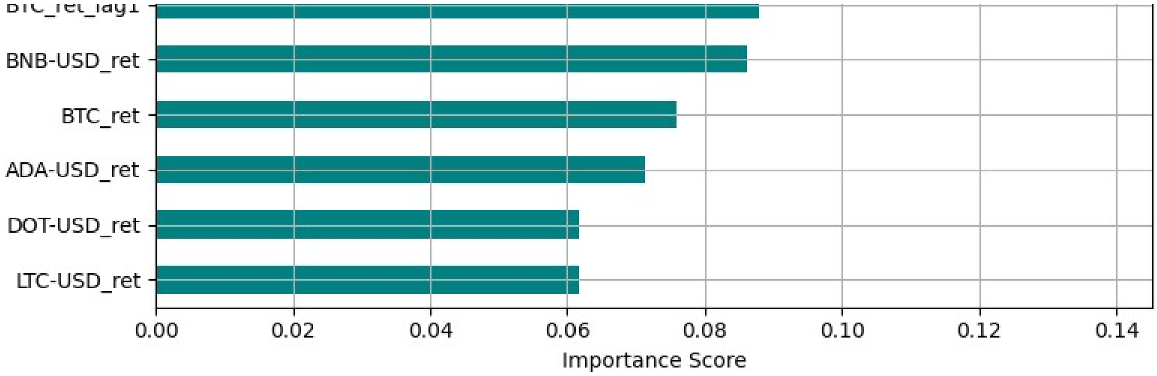
```
    max_depth=8,
    random_state=42
)

rf.fit(X_train, y_train)
print("✅ Random Forest Model Trained")

# ============================================================
# 7. Evaluate Model
# ============================================================
y_pred = rf.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("\n🔹 Model Performance:")
print(f"Mean Squared Error (MSE): {mse:.8f}")
print(f"R² Score: {r2:.4f}")

# ============================================================
# 8. Plot Actual vs Predicted BTC Returns
# ============================================================
plt.figure(figsize=(12, 5))
plt.plot(y_test.index, y_test, label="Actual BTC Return", color="blue")
plt.plot(y_test.index, y_pred, label="Predicted BTC Return", color="red", li
plt.title("Random Forest — BTC Next-Day Return Prediction", fontsize=14)
plt.xlabel("Date")
plt.ylabel("Return")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# ============================================================
# 9. Feature Importance
# ============================================================
importances = pd.Series(rf.feature_importances_, index=X.columns)
plt.figure(figsize=(8, 5))
importances.sort_values(ascending=True).plot(kind="barh", color="teal")
plt.title("Feature Importance — Random Forest", fontsize=13)
plt.xlabel("Importance Score")
plt.grid(True)
plt.tight_layout()
plt.show()

print("\n📊 Top 10 Features by Importance:")
print(importances.sort_values(ascending=False).head(10))
```

```
✅ Data Loaded: (3287, 9)
Columns: ['BTC-USD', 'ETH-USD', 'XRP-USD', 'LTC-USD', 'ADA-USD', 'DOT-USD', '
```

```
✅ Log Returns Calculated: (1866, 9)
✅ Features Ready: (1863, 12)
             BTC_ret  BTC_ret_lag1  BTC_ret_lag2  ETH-USD_ret  XRP-USD_ret  \
Date
2020-08-23 -0.001454      0.007677     -0.024362    -0.011307    -0.004056
2020-08-24  0.009364     -0.001454      0.007677     0.041930     0.013328
2020-08-25 -0.035306      0.009364     -0.001454    -0.060975    -0.039812
2020-08-26  0.010696     -0.035306      0.009364     0.006399    -0.001570
2020-08-27 -0.014463      0.010696     -0.035306    -0.009969    -0.047906

            LTC-USD_ret  ADA-USD_ret  DOT-USD_ret  SOL-USD_ret  AVAX-USD_ret
Date
2020-08-23     0.005162    -0.029823    -0.122643     0.095147           0.0
2020-08-24     0.025667     0.023513     0.148598     0.006766           0.0
2020-08-25    -0.059941    -0.094241     0.182368    -0.024249           0.0
2020-08-26    -0.003805     0.017439     0.096295     0.086090           0.0
2020-08-27    -0.040516    -0.076225    -0.077473    -0.032363           0.0

            BNB-USD_ret    target
Date
2020-08-23    -0.016730  0.009364
2020-08-24     0.033054 -0.035306
2020-08-25    -0.051302  0.010696
2020-08-26     0.036662 -0.014463
2020-08-27     0.035431  0.019165
🧠 Training Samples: 1490 | 🧪 Testing Samples: 373
✅ Random Forest Model Trained

🔹 Model Performance:
Mean Squared Error (MSE): 0.00052058
R² Score: 0.0003
```





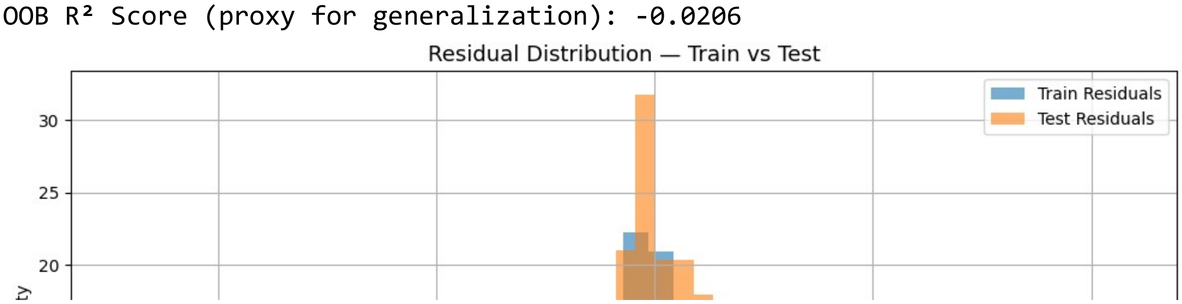


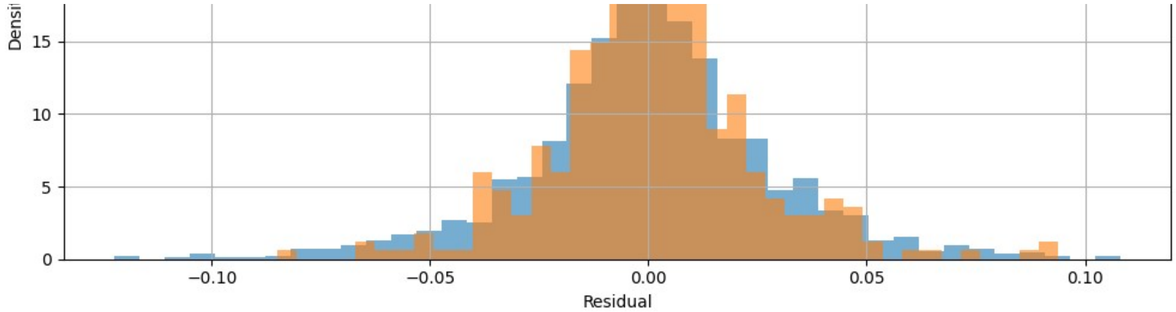

```
📊 Top 10 Features by Importance:
SOL-USD_ret     0.138333
AVAX-USD_ret    0.123460
ETH-USD_ret     0.104643
BTC_ret_lag2    0.095290
XRP-USD_ret     0.093787
BTC_ret_lag1    0.087877
BNB-USD_ret     0.086120
BTC_ret         0.075944
ADA-USD_ret     0.071199
DOT-USD_ret     0.061726
dtype: float64
```

```
# ============================================================
# 7.1 Overfitting Inspection (Beyond Train/Test Comparison)
# ============================================================

# Refit model with out-of-bag score enabled
rf_oob = RandomForestRegressor(
```

```
    n_estimators=300,
    max_depth=8,
    random_state=42,
    oob_score=True
)
rf_oob.fit(X_train, y_train)

print("\n🔍 Overfitting Inspection:")
print(f"OOB R² Score (proxy for generalization): {rf_oob.oob_score_:.4f}")

# Compare in-sample vs. out-of-sample residual distributions
train_pred = rf.predict(X_train)
test_pred = rf.predict(X_test)

train_resid = y_train - train_pred
test_resid = y_test - test_pred

plt.figure(figsize=(10, 5))
plt.hist(train_resid, bins=40, alpha=0.6, label="Train Residuals", density=T
plt.hist(test_resid, bins=40, alpha=0.6, label="Test Residuals", density=Tru
plt.title("Residual Distribution — Train vs Test", fontsize=13)
plt.xlabel("Residual")
plt.ylabel("Density")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# Residual variance comparison
train_var = np.var(train_resid)
test_var = np.var(test_resid)

print(f"Train Residual Variance: {train_var:.6f}")
print(f"Test Residual Variance: {test_var:.6f}")

if test_var > train_var * 1.5:
    print("⚠️ Possible overfitting: test residuals show higher variance thar
else:
    print("✅ Residuals consistent across train/test — overfitting not sever
```

```
🔍 Overfitting Inspection:
OOB R² Score (proxy for generalization): -0.0206
```






```
Train Residual Variance: 0.000771
Test Residual Variance: 0.000520
✅ Residuals consistent across train/test — overfitting not severe.
```

7.LSTM Deep Learning Model

```
#============================================================
# LSTM Deep Learning Model with Hyperparameter Tuning & Runtime Reporting
# ============================================================

# ============================================================
# 1. LOAD DATA (Ensure price_df exists)
# ============================================================

# Compute log returns
returns_df = np.log(price_df / price_df.shift(1)).dropna()

# ============================================================
# 2. AUTO TARGET SELECTION
# ============================================================

target = "BTC-USD" if "BTC-USD" in returns_df.columns else returns_df.column
print(f"✅ Target selected for prediction: {target}")

features = returns_df.columns.tolist()

X = returns_df[features].values
y = returns_df[target].values
```

```
# ============================================================
# 3. SCALE DATA
# ============================================================

scaler_X = MinMaxScaler(feature_range=(0, 1))
X_scaled = scaler_X.fit_transform(X)

scaler_y = MinMaxScaler(feature_range=(0, 1))
y_scaled = scaler_y.fit_transform(y.reshape(-1, 1))

# ============================================================
# 4. CREATE SUPERVISED SEQUENCES
# ============================================================

def create_sequences(X, y, lookback=30):
    Xs, ys = [], []
    for i in range(lookback, len(X)):
        Xs.append(X[i - lookback:i])
        ys.append(y[i])
    return np.array(Xs), np.array(ys)

lookback = 30
X_seq, y_seq = create_sequences(X_scaled, y_scaled, lookback=lookback)

split = int(0.8 * len(X_seq))
X_train, X_test = X_seq[:split], X_seq[split:]
y_train, y_test = y_seq[:split], y_seq[split:]

print(f"Training samples: {len(X_train)} | Testing samples: {len(X_test)}")

# ============================================================
# 5. SYSTEM INFO (Computational Environment)
# ============================================================

print("\n💻 System Information:")
print(f"Platform: {platform.system()} {platform.release()}")
print(f"Python version: {platform.python_version()}")
print(f"TensorFlow version: {tf.__version__}")
print(f"GPU available: {tf.config.list_physical_devices('GPU') != []}")
if tf.config.list_physical_devices('GPU'):
    print(f"GPU devices: {tf.config.list_physical_devices('GPU')}")

# ============================================================
# 6. HYPERPARAMETER TUNING FUNCTION
# ============================================================

def build_model(hp):
    model = Sequential()
    model.add(
        LSTM(
            units=hp.Int('units1', min_value=32, max_value=128, step=32),
```

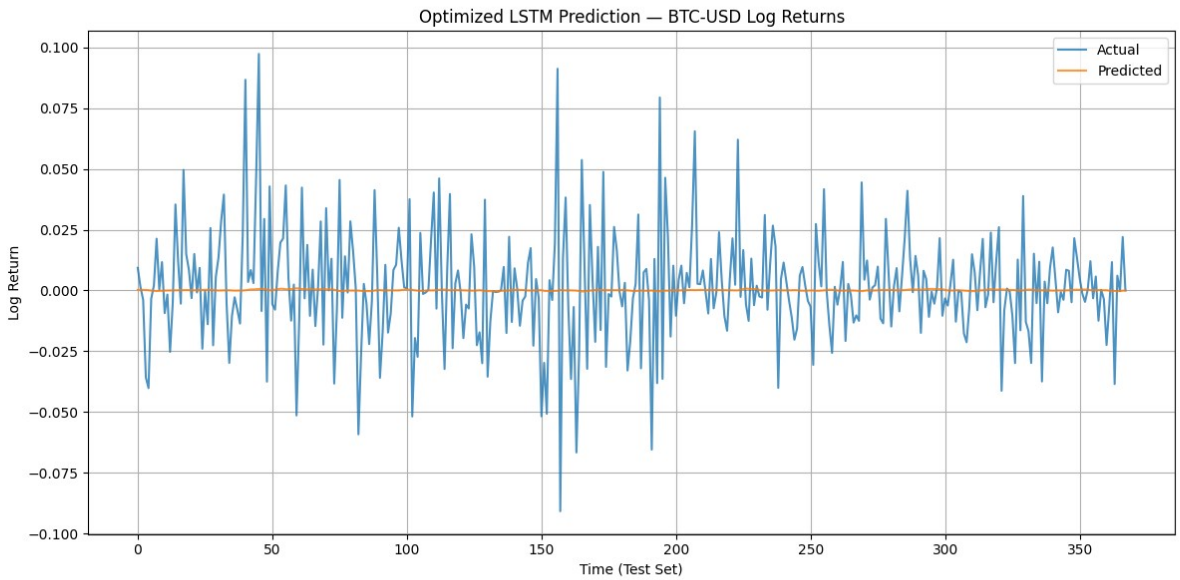
```
                return_sequences=True,
                input_shape=(X_train.shape[1], X_train.shape[2])
            )
        )
        model.add(Dropout(rate=hp.Float('dropout1', 0.1, 0.5, step=0.1)))
        model.add(
            LSTM(
                units=hp.Int('units2', min_value=16, max_value=64, step=16),
                return_sequences=False
            )
        )
        model.add(Dropout(rate=hp.Float('dropout2', 0.1, 0.5, step=0.1)))
        model.add(Dense(hp.Int('dense_units', 8, 32, step=8), activation='relu')
        model.add(Dense(1))

        lr = hp.Choice('learning_rate', [1e-2, 1e-3, 1e-4])
        model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=lr), loss
        return model

    # ============================================================
    # 7. RUN HYPERPARAMETER SEARCH (with timing)
    # ============================================================

    tuner = kt.RandomSearch(
        build_model,
        objective='val_loss',
        max_trials=10,
        executions_per_trial=1,
        directory='lstm_tuning',
        project_name='lstm_returns'
    )

    early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_best_weig

    print("\n⏳ Starting hyperparameter search...")
    start_tuning = time.time()

    tuner.search(
        X_train, y_train,
        validation_split=0.1,
        epochs=30,
        batch_size=32,
        callbacks=[early_stop],
        verbose=1
    )

    end_tuning = time.time()
    tuning_time = end_tuning - start_tuning
    print(f"\n⏱ Hyperparameter tuning completed in {tuning_time:.2f} seconds (·

    #
```

```
# ============================================================
# 8. TRAIN FINAL MODEL WITH BEST HYPERPARAMETERS (timed)
# ============================================================

best_hp = tuner.get_best_hyperparameters(1)[0]
print("\n✅ Best Hyperparameters Found:")
for key, value in best_hp.values.items():
    print(f" - {key}: {value}")

print("\n⏳ Training final LSTM model with optimal parameters...")
start_training = time.time()

best_model = tuner.hypermodel.build(best_hp)
history = best_model.fit(
    X_train, y_train,
    validation_split=0.1,
    epochs=50,
    batch_size=32,
    callbacks=[early_stop],
    verbose=1
)

end_training = time.time()
training_time = end_training - start_training
print(f"\n⏱️ Final model training time: {training_time:.2f} seconds ({train:

# ============================================================
# 9. EVALUATE MODEL
# ============================================================

y_pred_scaled = best_model.predict(X_test)
y_pred = scaler_y.inverse_transform(y_pred_scaled)
y_true = scaler_y.inverse_transform(y_test)

mse = mean_squared_error(y_true, y_pred)
r2 = r2_score(y_true, y_pred)

print(f"\n📊 Optimized LSTM Model Performance on Test Set:")
print(f"MSE: {mse:.6f}")
print(f"R²:  {r2:.4f}")

# ============================================================
# 10. VISUALIZE RESULTS
# ============================================================

plt.figure(figsize=(12, 6))
plt.plot(y_true, label='Actual', alpha=0.8)
plt.plot(y_pred, label='Predicted', alpha=0.8)
plt.title(f"Optimized LSTM Prediction — {target} Log Returns")
plt.xlabel("Time (Test Set)")
plt.ylabel("Log Return")
```

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

# ============================================================
# 11. REPORT COMPUTATIONAL REQUIREMENTS
# ============================================================

total_time = tuning_time + training_time
print("\n🧾 Computational Summary:")
print(f" - Hyperparameter tuning time: {tuning_time:.2f} sec ({tuning_time/6
print(f" - Final training time: {training_time:.2f} sec ({training_time/60:.
print(f" - Total LSTM runtime: {total_time:.2f} sec ({total_time/60:.2f} min
print(f" - Environment: {platform.system()} {platform.release()} | Python {p
if tf.config.list_physical_devices('GPU'):
    print(f" - GPU used: {tf.config.list_physical_devices('GPU')[0]}")
else:
    print(" - GPU not detected; computation done on CPU.")
```

```
Trial 10 Complete [00h 00m 28s]
val_loss: 0.0070311082527041435

Best val_loss So Far: 0.005845590494573116
Total elapsed time: 00h 04m 42s

⏱ Hyperparameter tuning completed in 281.69 seconds (4.69 minutes).

✅ Best Hyperparameters Found:
 - units1: 32
 - dropout1: 0.30000000000000004
 - units2: 64
 - dropout2: 0.5
 - dense_units: 32
 - learning_rate: 0.01

⏳ Training final LSTM model with optimal parameters...
Epoch 1/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 6s 53ms/step - loss: 0.1069 - mse: 0.1069 - val_lo
Epoch 2/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 2s 54ms/step - loss: 0.0109 - mse: 0.0109 - val_lo
Epoch 3/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - loss: 0.0105 - mse: 0.0105 - val_lo
Epoch 4/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 1s 31ms/step - loss: 0.0108 - mse: 0.0108 - val_lo
Epoch 5/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 1s 31ms/step - loss: 0.0096 - mse: 0.0096 - val_lo
Epoch 6/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 1s 31ms/step - loss: 0.0088 - mse: 0.0088 - val_lo
Epoch 7/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 1s 32ms/step - loss: 0.0085 - mse: 0.0085 - val_lo
Epoch 8/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - loss: 0.0106 - mse: 0.0106 - val_lo
```

```
Epoch 9/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 1s 31ms/step - loss: 0.0091 - mse: 0.0091 - val_lo
Epoch 10/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 3s 49ms/step - loss: 0.0087 - mse: 0.0087 - val_lo
Epoch 11/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - loss: 0.0090 - mse: 0.0090 - val_lo
Epoch 12/50
42/42 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - loss: 0.0098 - mse: 0.0098 - val_lo

⏱️ Final model training time: 25.73 seconds (0.43 minutes).
12/12 ━━━━━━━━━━━━━━━━━━━━ 1s 36ms/step

📊 Optimized LSTM Model Performance on Test Set:
MSE: 0.000526
R²:  -0.0039
```




```
🧮 Computational Summary:
 - Hyperparameter tuning time: 281.69 sec (4.69 min)
 - Final training time: 25.73 sec (0.43 min)
 - Total LSTM runtime: 307.42 sec (5.12 min)
 - Environment: Linux 6.6.105+ | Python 3.12.12
 - GPU not detected; computation done on CPU.
```

```
best_model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 30, 32)	5,376
dropout_2 (Dropout)	(None, 30, 32)	0
lstm_3 (LSTM)	(None, 64)	24,832
dropout_3 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 32)	2,080
dense_3 (Dense)	(None, 1)	33

Total params: 96,965 (378.77 KB)
Trainable params: 32,321 (126.25 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 64,644 (252.52 KB)

8.Ensemble for risk-adjusted portfolio allocation

```
# ============================================================
# ENSEMBLE MODEL + RISK-ADJUSTED PORTFOLIO ALLOCATION
# ============================================================


# ============================================================
# 1. LOAD DATA (Closing Prices)
# ============================================================

# Replace with your saved Excel file
file_path = "crypto_prices_9yrs_full.xlsx"

price_df = pd.read_excel(
    file_path,
    sheet_name="Closing_Prices",
    index_col="Date",
    parse_dates=True
)

print("Price data loaded:", price_df.shape)
print("Columns:", list(price_df.columns))
```

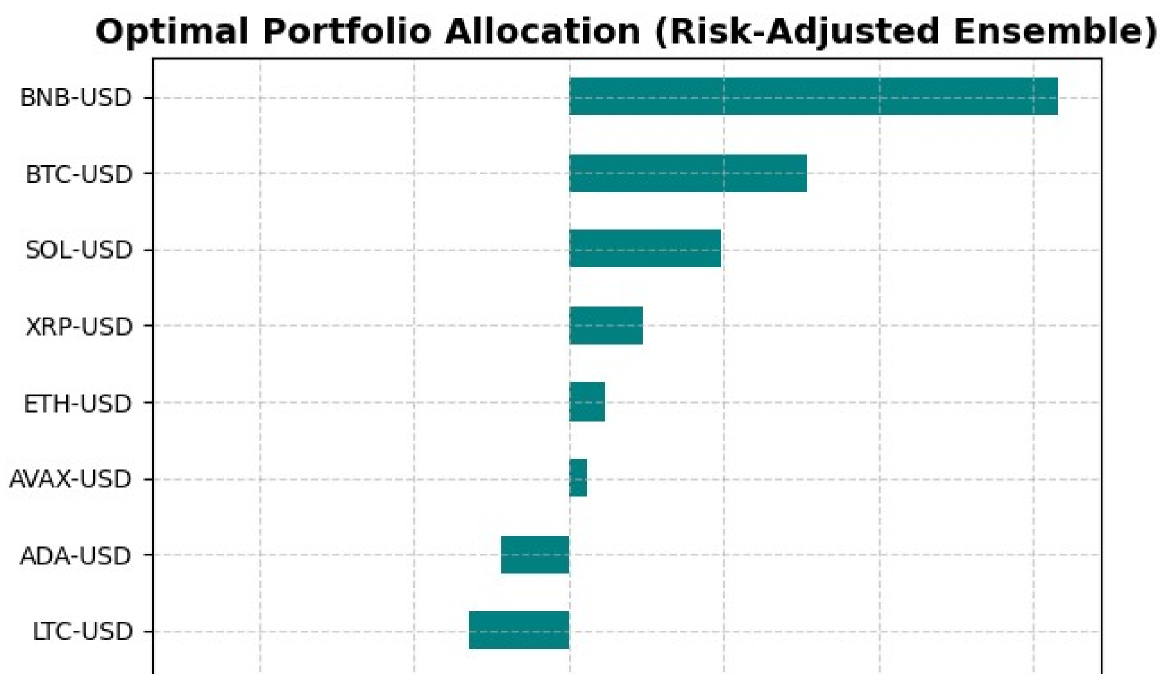
```
# ============================================================
# 2. COMPUTE LOG RETURNS
# ============================================================

returns_df = np.log(price_df / price_df.shift(1)).dropna()
print("Returns data created:", returns_df.shape)

# ============================================================
# 3. DEFINE ENSEMBLE MODELS
# ============================================================

models = {
    "RandomForest": RandomForestRegressor(n_estimators=200, max_depth=6, ran
    "GradientBoost": GradientBoostingRegressor(n_estimators=200, learning_ra
    "Linear": LinearRegression()
}

N_LAGS = 3  # use 3-day lags for prediction
ensemble_preds = pd.DataFrame(index=returns_df.index)

# ============================================================
# 4. TRAIN ENSEMBLE MODEL FOR EACH CRYPTO
# ============================================================

print("\n Training ensemble models for each crypto...\n")
metrics = {}

for crypto in returns_df.columns:
    print(f"Training on {crypto}...")
    data = returns_df.copy()

    # Create lag features
    for lag in range(1, N_LAGS + 1):
        data[f"{crypto}_lag{lag}"] = data[crypto].shift(lag)

    # Drop NaN
    data = data.dropna()

    # Features = lagged returns
    X = data[[f"{crypto}_lag{i}" for i in range(1, N_LAGS + 1)]]
    y = data[crypto]

    # Split (80/20)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

    # Scale features
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)
```

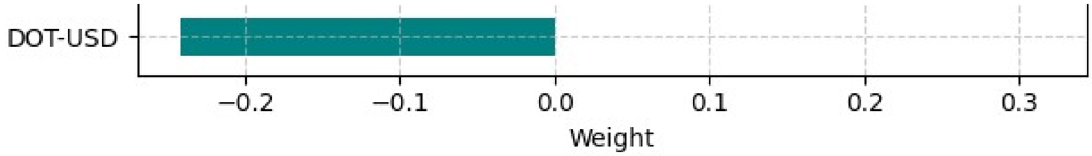
```
    # Ensemble predictions
    preds = []
    for name, model in models.items():
        model.fit(X_train_scaled, y_train)
        pred = model.predict(X_test_scaled)
        preds.append(pred)

    # Average predictions (ensemble)
    ensemble_pred = np.mean(np.column_stack(preds), axis=1)

    # Store predictions
    ensemble_preds[crypto] = np.nan
    ensemble_preds.loc[y_test.index, crypto] = ensemble_pred

    # Evaluate R²
    r2 = r2_score(y_test, ensemble_pred)
    metrics[crypto] = r2
    print(f"{crypto}: R² = {r2:.4f}")

ensemble_preds = ensemble_preds.dropna()
print("\nEnsemble predictions shape:", ensemble_preds.shape)

# ============================================================
# 5. ESTIMATE MEAN & COVARIANCE
# ============================================================

mu = ensemble_preds.mean()                # expected returns
historical_cov = returns_df.loc[ensemble_preds.index].cov()  # covariance ma

print("\nMean predicted returns (mu):")
print(mu.round(6))
print("\nCovariance matrix (shape):", historical_cov.shape)

# ============================================================
# 6. RISK-ADJUSTED PORTFOLIO OPTIMIZATION
# ============================================================

# Mean-variance optimization (inverse covariance weighting)
inv_cov = np.linalg.inv(historical_cov.values)
raw_weights = inv_cov @ mu.values

# Normalize (sum = 1)
weights = raw_weights / np.sum(np.abs(raw_weights))
weights_df = pd.DataFrame({"Weight": weights}, index=returns_df.columns)

print("\nOptimal Risk-Adjusted Weights:")
print(weights_df.sort_values("Weight", ascending=False).round(4))

# Portfolio statistics
portfolio_return = np.dot(weights, mu.values)
portfolio_vol = np.sqrt(weights.T @ historical_cov.values @ weights)
```

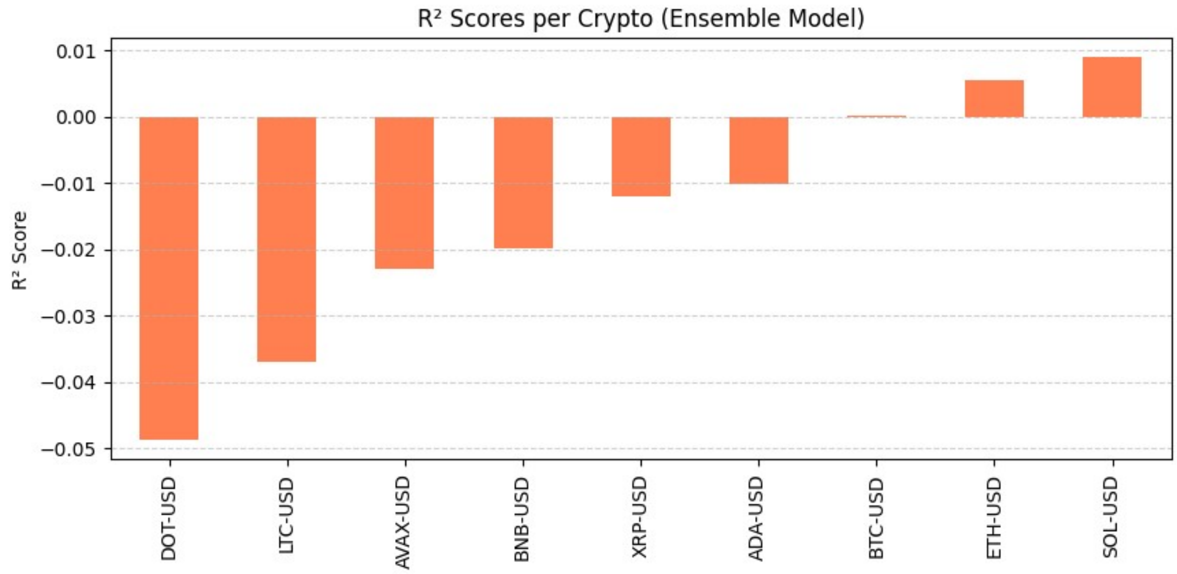
```
sharpe_ratio = portfolio_return / portfolio_vol

print(f"\nPortfolio Expected Return: {portfolio_return:.6f}")
print(f"Portfolio Volatility: {portfolio_vol:.6f}")
print(f"Sharpe Ratio: {sharpe_ratio:.4f}")

# ============================================================
# 7. VISUALIZE PORTFOLIO ALLOCATION
# ============================================================

plt.figure(figsize=(10, 6))
weights_df.sort_values("Weight", ascending=True).plot.barh(legend=False, col
plt.title("Optimal Portfolio Allocation (Risk-Adjusted Ensemble)", fontsize=
plt.xlabel("Weight")
plt.grid(True, linestyle="--", alpha=0.6)
plt.tight_layout()
plt.show()

# ============================================================
# 8. VISUALIZE ENSEMBLE MODEL PERFORMANCE
# ============================================================

plt.figure(figsize=(10, 4))
pd.Series(metrics).sort_values().plot(kind="bar", color="coral")
plt.title("R² Scores per Crypto (Ensemble Model)")
plt.ylabel("R² Score")
plt.grid(axis="y", linestyle="--", alpha=0.6)
plt.show()
```

```
Price data loaded: (3287, 9)
Columns: ['BTC-USD', 'ETH-USD', 'XRP-USD', 'LTC-USD', 'ADA-USD', 'DOT-USD', '
Returns data created: (1866, 9)

 Training ensemble models for each crypto...

Training on BTC-USD...
BTC-USD: R² = 0.0000
Training on ETH-USD...
ETH-USD: R² = 0.0054
Training on XRP-USD...
XRP-USD: R² = -0.0120
Training on LTC-USD...
LTC-USD: R² = -0.0369
Training on ADA-USD...
ADA-USD: R² = -0.0101
Training on DOT-USD...
DOT-USD: R² = -0.0487
Training on SOL-USD...
SOL-USD: R² = 0.0089
Training on AVAX-USD...
AVAX-USD: R² = -0.0230
```

```
Training on BNB-USD...
BNB-USD: R² = -0.0200

Ensemble predictions shape: (373, 9)

Mean predicted returns (mu):
BTC-USD     0.001039
ETH-USD     0.001174
XRP-USD     0.000678
LTC-USD    -0.000445
ADA-USD     0.000462
DOT-USD    -0.000971
SOL-USD     0.002232
AVAX-USD    0.000600
BNB-USD     0.001430
dtype: float64

Covariance matrix (shape): (9, 9)

Optimal Risk-Adjusted Weights:
          Weight
BNB-USD   0.3158
BTC-USD   0.1535
SOL-USD   0.0985
XRP-USD   0.0472
ETH-USD   0.0236
AVAX-USD  0.0112
ADA-USD  -0.0435
LTC-USD  -0.0648
DOT-USD  -0.2418

Portfolio Expected Return: 0.001141
Portfolio Volatility: 0.009704
Sharpe Ratio: 0.1176
<Figure size 1000x600 with 0 Axes>
```







9. Backtesting Long/Short Pairs Strategy

```
# @title
# ============================================================
# FULL BACKTEST: LSTM vs Random Forest vs Ensemble (stacking)
# ============================================================
# ---------------------------
# CONFIG
# ---------------------------
file_path = "crypto_prices_9yrs_full.xlsx"   # <-- set your file
sheet_name = "Closing_Prices"                # <-- set if needed
target_lookback = 5        # lookback days for LSTM sequences
rf_lags = 1                # number of lag days used by RF (using 1 day here
test_size_ratio = 0.2
rf_trees = 200
lstm_epochs = 20           # reduce for quick testing
```

```
random_state = 42

# ---------------------------
# 1) LOAD PRICES -> LOG RETURNS
# ---------------------------
# read Excel (assumes Date column or index)
try:
    prices = pd.read_excel(file_path, sheet_name=sheet_name, index_col="Date
except Exception:
    # fallback: read first sheet and assume index in first col
    prices = pd.read_excel(file_path, index_col=0, parse_dates=True)

prices = prices.sort_index()
returns = np.log(prices / prices.shift(1)).dropna()
tickers = returns.columns.tolist()
print("Loaded returns:", returns.shape, "tickers:", tickers)

# ---------------------------
# 2) TRAIN/TEST SPLIT (time-based)
# ---------------------------
split_idx = int(len(returns) * (1 - test_size_ratio))
train_returns = returns.iloc[:split_idx]
test_returns = returns.iloc[split_idx:]

# We'll create models that predict next-day return:
# For RF: features = lagged returns (1 lag)
# For LSTM: sequences of past `target_lookback` days for all assets (multiva

# ---------------------------
# 3) RANDOM FOREST PREDICTIONS (per asset)
# ---------------------------
rf_preds = pd.DataFrame(index=test_returns.index, columns=tickers)

print("\nTraining Random Forests per asset...")
for asset in tickers:
    # prepare lagged feature DataFrame for whole sample
    df = returns[[asset]].copy()
    for lag in range(1, rf_lags + 1):
        df[f"lag{lag}"] = df[asset].shift(lag)
    df = df.dropna()

    # align train/test split on df
    train_df = df.iloc[:split_idx - (rf_lags)]   # -rf_lags because lagging
    test_df = df.iloc[split_idx - (rf_lags):]    # same indexing

    X_train = train_df[[f"lag{l}" for l in range(1, rf_lags + 1)]].values
    y_train = train_df[asset].values
    X_test = test_df[[f"lag{l}" for l in range(1, rf_lags + 1)]].values
    y_test = test_df[asset].values
    idx_test = test_df.index
```

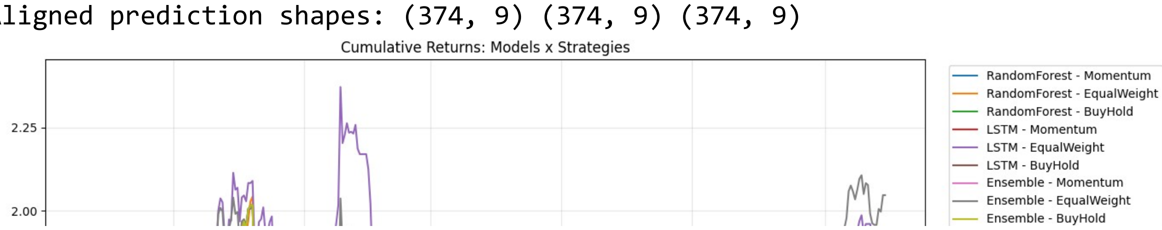
```
    # scale features
    scaler = StandardScaler().fit(X_train)
    X_train_s = scaler.transform(X_train)
    X_test_s = scaler.transform(X_test)

    # train RF
    rf = RandomForestRegressor(n_estimators=rf_trees, random_state=random_st
    rf.fit(X_train_s, y_train)

    # predict
    pred = rf.predict(X_test_s)
    rf_preds.loc[idx_test, asset] = pred

print("RF predictions done. Shape:", rf_preds.shape)

# ---------------------------
# 4) LSTM PREDICTIONS (per asset, multivariate input)
# ---------------------------
# We'll build LSTM using multivariate inputs (all assets' returns) and predi
def create_sequences_mv(X_array, y_array, lookback):
    Xs, ys = [], []
    for i in range(lookback, len(X_array)):
        Xs.append(X_array[i - lookback:i])
        ys.append(y_array[i])
    return np.array(Xs), np.array(ys)

lstm_preds = pd.DataFrame(index=test_returns.index, columns=tickers)
print("\nTraining LSTM per asset (multivariate inputs)...")

# scale full returns using a scaler fitted on train_returns
scaler_all = StandardScaler().fit(train_returns.values)
train_scaled = pd.DataFrame(scaler_all.transform(train_returns.values), inde
test_scaled = pd.DataFrame(scaler_all.transform(test_returns.values), index=

# build full arrays for sequence creation (concatenate train + test scaled t
combined_scaled = pd.concat([train_scaled, test_scaled])
combined_index = combined_scaled.index

for asset in tickers:
    # prepare X (multivariate) and y (single asset)
    X_array = combined_scaled.values
    y_array = combined_scaled[asset].values

    # create sequences
    Xs, ys = create_sequences_mv(X_array, y_array, target_lookback)

    # determine train/test split index in sequence space
    # sequences start at combined index position = target_lookback
    seq_start_idx = target_lookback
    seq_train_end = split_idx - seq_start_idx  # number of training sequence
```

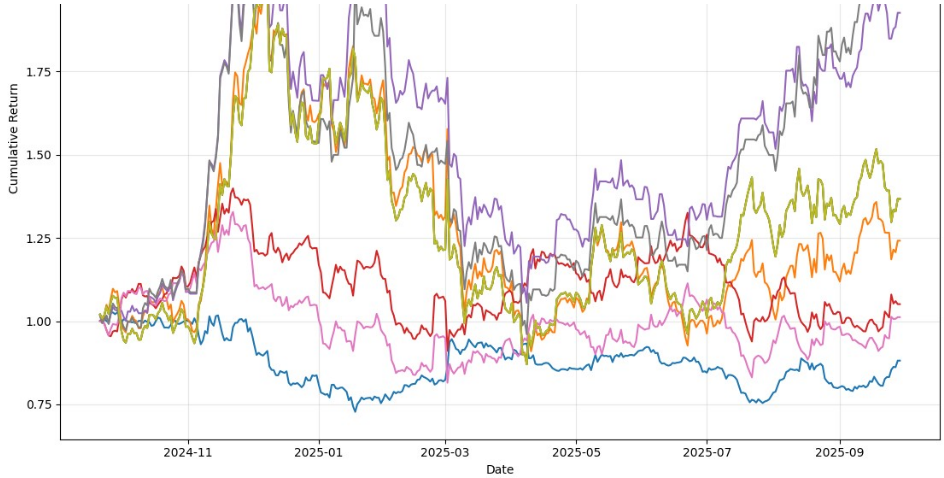
```
    if seq_train_end <= 0:
        raise RuntimeError("Not enough data for chosen lookback and test_siz

    Xs_train, Xs_test = Xs[:seq_train_end], Xs[seq_train_end:]
    ys_train, ys_test = ys[:seq_train_end], ys[seq_train_end:]

    # build model (small to speed up)
    model = Sequential([
        Input(shape=(target_lookback, len(tickers))),
        LSTM(32, return_sequences=False),
        Dropout(0.2),
        Dense(16, activation="relu"),
        Dense(1)
    ])
    model.compile(optimizer="adam", loss="mse")

    # train
    model.fit(Xs_train, ys_train, epochs=lstm_epochs, batch_size=32, verbose

    # predict on Xs_test
    preds_scaled = model.predict(Xs_test, verbose=0).flatten()

    # map sequence-test indices to actual dates in combined_index
    # Xs_test corresponds to combined_index positions from seq_start_idx + s
    seq_test_start_pos = seq_start_idx + seq_train_end
    seq_test_positions = np.arange(seq_test_start_pos, seq_test_start_pos +
    # the date for a sequence ending at position p corresponds to combined_i
    pred_dates = combined_index[seq_test_positions]
    # but our test_returns index starts at split_idx; ensure alignment:
    # select preds mapped to dates that appear in test_returns.index
    mapped = pd.Series(preds_scaled, index=pred_dates)
    mapped = mapped.reindex(test_returns.index)  # only keep test dates; NaN
    lstm_preds[asset] = mapped.values

print("LSTM predictions done. Shape:", lstm_preds.shape)

# ---------------------------
# 5) ENSEMBLE PREDICTIONS (average RF & LSTM where both available)
# ---------------------------
rf_preds = rf_preds.astype(float)
lstm_preds = lstm_preds.astype(float)

# Align indices and drop rows with all-NaN
common_index = rf_preds.index.intersection(lstm_preds.index)
rf_preds = rf_preds.loc[common_index]
lstm_preds = lstm_preds.loc[common_index]
test_returns_aligned = test_returns.loc[common_index]

ensemble_preds = (rf_preds + lstm_preds) / 2.0
```

```
# Drop any rows that are fully NaN in ensemble
valid_mask = ~ensemble_preds.isna().all(axis=1)
ensemble_preds = ensemble_preds.loc[valid_mask]
rf_preds = rf_preds.loc[valid_mask]
lstm_preds = lstm_preds.loc[valid_mask]
test_returns_aligned = test_returns_aligned.loc[valid_mask]

print("\nAligned prediction shapes:", rf_preds.shape, lstm_preds.shape, ense

# --------------------------
# 6) STRATEGIES (Momentum, Equal-weight long-only, Buy & Hold)
# --------------------------
def compute_portfolio_returns(preds_df, actual_returns_df, mode="momentum"):
    """
    preds_df, actual_returns_df must have same index & columns (tickers).
    mode in {'momentum', 'equal-weight', 'buy-hold'}:
      - momentum: long if pred>0 else short (-1)
      - equal-weight: long-only equal weight across predicted-positive asset
      - buy-hold: equal-weight long-only across all assets (benchmark)
    Returns series of cumulative returns.
    """
    preds = preds_df.copy()
    actual = actual_returns_df.copy()

    if mode == "momentum":
        # signals: 1 for long, -1 for short
        signals = preds.applymap(lambda x: 1 if x > 0 else -1)
        # daily portfolio return = average across assets of (signal * actual
        daily = (signals * actual).mean(axis=1)
    elif mode == "equal-weight":
        # long-only: allocate equally among positively predicted assets
        pos = preds > 0
        # compute count of positives each day
        counts = pos.sum(axis=1).replace(0, np.nan)
        weights = pos.div(counts, axis=0).fillna(0)
        daily = (weights * actual).sum(axis=1)
    elif mode == "buy-hold":
        # equal-weight long-only across all assets
        n = actual.shape[1]
        daily = actual.mean(axis=1)
    else:
        raise ValueError("Unknown mode")

    cum = (1 + daily).cumprod().fillna(method="ffill")
    return daily, cum

# compute for models
models_preds = {"RandomForest": rf_preds, "LSTM": lstm_preds, "Ensemble": en
results = {}
for name, preds in models_preds.items():
    results[(name, "Momentum")] = compute_portfolio_returns(preds, test_retu
```

```
    results[(name, "EqualWeight")] = compute_portfolio_returns(preds, test_r
    results[(name, "BuyHold")] = compute_portfolio_returns(preds, test_retur

# ---------------------------
# 7) PLOT CUMULATIVE RETURNS
# ---------------------------
plt.figure(figsize=(14, 8))
for (name, strat), (daily, cum) in results.items():
    plt.plot(cum.index, cum.values, label=f"{name} - {strat}")
plt.title("Cumulative Returns: Models x Strategies")
plt.xlabel("Date")
plt.ylabel("Cumulative Return")
plt.legend(loc="upper left", bbox_to_anchor=(1.02, 1))
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

# ---------------------------
# 8) SUMMARY METRICS (Total Return, Annualized Vol, Sharpe)
# ---------------------------
summary = []
trading_days_per_year = 365  # using daily including weekends; adjust if usi

for (name, strat), (daily, cum) in results.items():
    total_return = cum.iloc[-1] - 1
    # compute daily returns series for volatility and Sharpe (use daily, not
    daily_ret = daily.dropna()
    ann_vol = daily_ret.std() * np.sqrt(trading_days_per_year)
    ann_ret = daily_ret.mean() * trading_days_per_year
    sharpe = ann_ret / ann_vol if ann_vol != 0 else np.nan
    summary.append([name, strat, float(total_return), float(ann_ret), float(

summary_df = pd.DataFrame(summary, columns=["Model", "Strategy", "TotalRetur
print("\nPerformance Summary:")
print(summary_df.sort_values(["Sharpe"], ascending=False).reset_index(drop=T
```

```
Loaded returns: (1866, 9) tickers: ['BTC-USD', 'ETH-USD', 'XRP-USD', 'LTC-USD

Training Random Forests per asset...
RF predictions done. Shape: (374, 9)

Training LSTM per asset (multivariate inputs)...
LSTM predictions done. Shape: (374, 9)

Aligned prediction shapes: (374, 9) (374, 9) (374, 9)
```





Performance Summary:

	Model	Strategy	TotalReturn	AnnReturn	AnnVol	Sharpe
0	Ensemble	EqualWeight	1.046683	0.890279	0.619112	1.437993
1	LSTM	EqualWeight	0.926766	0.826061	0.610839	1.352337
2	Ensemble	BuyHold	0.367580	0.530204	0.668474	0.793157
3	LSTM	BuyHold	0.367580	0.530204	0.668474	0.793157
4	RandomForest	BuyHold	0.367580	0.530204	0.668474	0.793157
5	RandomForest	EqualWeight	0.241849	0.453071	0.693615	0.653201
6	LSTM	Momentum	0.051136	0.141176	0.430097	0.328244
7	Ensemble	Momentum	0.012000	0.099040	0.417939	0.236972
8	RandomForest	Momentum	-0.118618	-0.083592	0.282445	-0.295958

More Performance summaries

More Performance summaries

```
####
# ---------------------------
# 6) STRATEGIES + Transaction costs + Metric helpers
# ---------------------------
trading_days_per_year = 252  # adjust if you want 365
tc_per_unit = 0.0005         # transaction cost per unit of turnover (e.g. 0

def compute_weights_and_daily_returns(preds_df, actual_returns_df, mode="mom
    """
    Returns:
      daily_returns: pd.Series (raw, before transaction costs)
      cum_returns: pd.Series (cumulative, before tc)
      weights: pd.DataFrame (daily weights used in portfolio: rows=index, co
    """
    preds = preds_df.copy()
    actual = actual_returns_df.copy()
    dates = preds.index
    tickers = preds.columns.tolist()
    n_assets = len(tickers)

    if mode == "momentum":
        # signals: 1 for long, -1 for short
        signals = preds.applymap(lambda x: 1 if x > 0 else -1)
        # weights: equal weight per asset with sign (so sum of absolute weig
        # Using 1/n per asset (signed)
        weights = signals.div(n_assets)
        daily = (weights * actual).sum(axis=1)
    elif mode == "equal-weight":
        pos = preds > 0
        counts = pos.sum(axis=1).replace(0, np.nan)
        weights = pos.div(counts, axis=0).fillna(0)  # long-only equal among
        daily = (weights * actual).sum(axis=1)
    elif mode == "buy-hold":
        n = actual.shape[1]
        weights = pd.DataFrame(1.0 / n, index=preds.index, columns=preds.col
        daily = (weights * actual).sum(axis=1)
    else:
        raise ValueError("Unknown mode")

    cum = (1 + daily).cumprod().fillna(method="ffill")
    return daily, cum, weights

def compute_turnover(weights):
    """
    Compute daily turnover series from weights DataFrame.
    turnover_t = 0.5 * sum(|w_t - w_{t-1}|)  (0.5 for round-trip convention)
    returns a pd.Series indexed like weights.index, first day turnover = 0
    """
    w_prev = weights.shift(1).fillna(0)
```

```
    w_prev = weights.shift(1).fillna(0)
    delta = weights.subtract(w_prev).abs().sum(axis=1)
    turnover = 0.5 * delta
    turnover.iloc[0] = 0.0
    return turnover

def max_drawdown(cum_series):
    """
    Returns drawdown series and max drawdown value
    """
    running_max = cum_series.cummax()
    drawdown = (cum_series - running_max) / running_max
    max_dd = drawdown.min()
    return drawdown, max_dd

def annualized_return(daily_ret, trading_days=trading_days_per_year):
    # CAGR approximate from mean daily: (1+mean_daily)^(T) -1 is approximate
    total_periods = len(daily_ret.dropna())
    if total_periods == 0:
        return np.nan
    cumulative = (1 + daily_ret.dropna()).cumprod().iloc[-1]
    yrs = total_periods / trading_days
    if yrs == 0:
        return np.nan
    cagr = cumulative ** (1.0 / yrs) - 1.0
    return cagr

def annualized_vol(daily_ret, trading_days=trading_days_per_year):
    return daily_ret.std() * np.sqrt(trading_days)

def sortino_ratio(daily_ret, trading_days=trading_days_per_year, mar=0.0):
    # downside deviation
    downside = daily_ret.copy()
    downside = downside[downside < mar]
    if downside.empty:
        return np.nan
    downside_std = np.sqrt((downside ** 2).mean())  # daily downside deviati
    downside_annual = downside_std * np.sqrt(trading_days)
    ann_ret = annualized_return(daily_ret, trading_days)
    if downside_annual == 0:
        return np.nan
    return ann_ret / downside_annual

def hit_ratio(daily_ret):
    dr = daily_ret.dropna()
    if len(dr) == 0:
        return np.nan
    return float((dr > 0).sum()) / len(dr)

def performance_metrics_from_daily(daily_ret, weights_df, tc_per_unit=tc_per
    """
```

```
    Given raw daily returns and weights, compute:
      - turnover, transaction costs, net daily returns
      - cumulative returns (gross & net)
      - TotalReturn, AnnReturn (CAGR), AnnVol, Sharpe, Sortino, Hit ratio, M
    """
    # turnover
    turnover = compute_turnover(weights_df)
    # transaction cost series (cost applied to portfolio turnover each day)
    tc_series = turnover * tc_per_unit

    # net daily return after tc
    net_daily = daily_ret.fillna(0) - tc_series.reindex(daily_ret.index).fil

    # cumulative
    cum_gross = (1 + daily_ret.fillna(0)).cumprod()
    cum_net = (1 + net_daily).cumprod()

    # metrics
    total_return_gross = cum_gross.iloc[-1] - 1.0
    total_return_net = cum_net.iloc[-1] - 1.0
    ann_ret_gross = annualized_return(daily_ret, trading_days)
    ann_ret_net = annualized_return(net_daily, trading_days)
    ann_vol_gross = annualized_vol(daily_ret, trading_days)
    ann_vol_net = annualized_vol(net_daily, trading_days)
    sharpe_gross = ann_ret_gross / ann_vol_gross if ann_vol_gross != 0 else
    sharpe_net = ann_ret_net / ann_vol_net if ann_vol_net != 0 else np.nan
    sortino_gross = sortino_ratio(daily_ret, trading_days)
    sortino_net = sortino_ratio(net_daily, trading_days)
    hit = hit_ratio(daily_ret)
    avg_turnover = turnover.mean()
    cumulative_tc = tc_series.sum()

    # drawdowns
    dd_series_gross, max_dd_gross = max_drawdown(cum_gross)
    dd_series_net, max_dd_net = max_drawdown(cum_net)
    # simple average drawdown (mean of negative drawdown values)
    avg_dd_gross = dd_series_gross[dd_series_gross < 0].mean()
    avg_dd_net = dd_series_net[dd_series_net < 0].mean()

    metrics = {
        "TotalReturn_Gross": float(total_return_gross),
        "TotalReturn_Net": float(total_return_net),
        "AnnReturn_Gross": float(ann_ret_gross) if not pd.isna(ann_ret_gross
        "AnnReturn_Net": float(ann_ret_net) if not pd.isna(ann_ret_net) else
        "AnnVol_Gross": float(ann_vol_gross) if not pd.isna(ann_vol_gross) e
        "AnnVol_Net": float(ann_vol_net) if not pd.isna(ann_vol_net) else np
        "Sharpe_Gross": float(sharpe_gross) if not pd.isna(sharpe_gross) els
        "Sharpe_Net": float(sharpe_net) if not pd.isna(sharpe_net) else np.n
        "Sortino_Gross": float(sortino_gross) if not pd.isna(sortino_gross)
        "Sortino_Net": float(sortino_net) if not pd.isna(sortino_net) else n
        "HitRatio": float(hit) if not pd.isna(hit) else np.nan
```

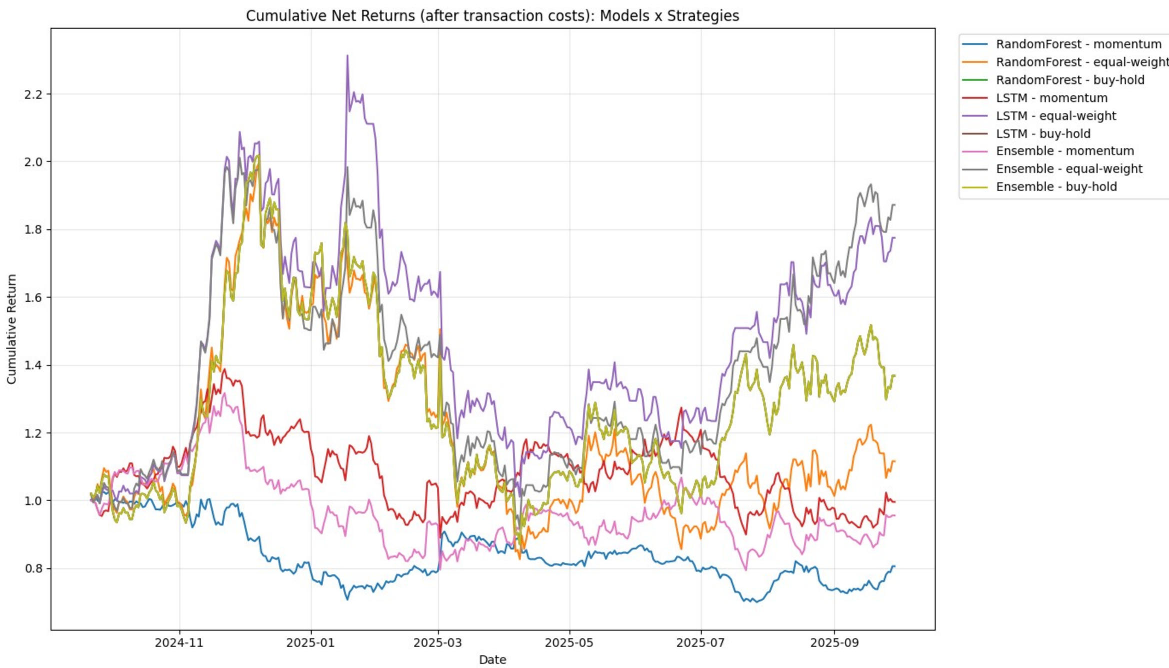
```
            "HitRatio": float(hit) if not pd.isna(hit) else np.nan,
            "AvgTurnover": float(avg_turnover),
            "CumulativeTC": float(cumulative_tc),
            "MaxDrawdown_Gross": float(max_dd_gross),
            "MaxDrawdown_Net": float(max_dd_net),
            "AvgDrawdown_Gross": float(avg_dd_gross) if not pd.isna(avg_dd_gross
            "AvgDrawdown_Net": float(avg_dd_net) if not pd.isna(avg_dd_net) else
            "CumGrossSeries": cum_gross,
            "CumNetSeries": cum_net,
            "TurnoverSeries": turnover,
            "TC_Series": tc_series,
            "DailyNet": net_daily,
        }
        return metrics

    # ---------------------------
    # 7) Compute results for all models & strategies (with metrics)
    # ---------------------------
    models_preds = {"RandomForest": rf_preds, "LSTM": lstm_preds, "Ensemble": en
    all_metrics = []

    results_time_series = {}  # store cumulative series for plotting if needed

    for name, preds in models_preds.items():
        for strat in ["momentum", "equal-weight", "buy-hold"]:
            daily, cum, weights = compute_weights_and_daily_returns(preds, test_
            metrics = performance_metrics_from_daily(daily, weights, tc_per_unit
            metrics.update({"Model": name, "Strategy": strat})
            all_metrics.append(metrics)

            # store for plotting
            results_time_series[(name, strat)] = {
                "cum_gross": metrics["CumGrossSeries"],
                "cum_net": metrics["CumNetSeries"],
                "daily_net": metrics["DailyNet"],
                "turnover": metrics["TurnoverSeries"],
                "tc": metrics["TC_Series"]
            }

    # ---------------------------
    # 8) SUMMARY METRICS TABLE (pretty)
    # ---------------------------
    summary_rows = []
    for m in all_metrics:
        summary_rows.append([
            m["Model"],
            m["Strategy"],
            m["TotalReturn_Gross"],
            m["TotalReturn_Net"],
            m["AnnReturn_Net"],
            m["AnnVol_Net"],
```

```
        m["Sharpe_Net"],
        m["Sortino_Net"],
        m["HitRatio"],
        m["AvgTurnover"],
        m["CumulativeTC"],
        m["MaxDrawdown_Net"]
    ])

summary_df = pd.DataFrame(summary_rows, columns=[
    "Model", "Strategy",
    "TotalReturn_Gross", "TotalReturn_Net",
    "AnnReturn_Net", "AnnVol_Net",
    "Sharpe_Net", "Sortino_Net", "HitRatio",
    "AvgTurnover", "CumulativeTC", "MaxDrawdown_Net"
])
# nicer ordering
summary_df = summary_df.sort_values(["Sharpe_Net"], ascending=False).reset_i
print("\nPerformance Summary (with transaction costs & more metrics):")
print(summary_df)

# ---------------------------
# 9) PLOT CUMULATIVE RETURNS (gross and net) - example plot
# ---------------------------
plt.figure(figsize=(14, 8))
for (name, strat), ts in results_time_series.items():
    # plot net cumulative for clarity
    cum_net = ts["cum_net"]
    plt.plot(cum_net.index, cum_net.values, label=f"{name} - {strat}")
plt.title("Cumulative Net Returns (after transaction costs): Models x Strate
plt.xlabel("Date")
plt.ylabel("Cumulative Return")
plt.legend(loc="upper left", bbox_to_anchor=(1.02, 1))
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```

```
Performance Summary (with transaction costs & more metrics):
          Model      Strategy  TotalReturn_Gross  TotalReturn_Net  \
0      Ensemble  equal-weight           1.046683         0.871649
1          LSTM  equal-weight           0.926766         0.774634
2      Ensemble      buy-hold           0.367580         0.367580
3          LSTM      buy-hold           0.367580         0.367580
4  RandomForest      buy-hold           0.367580         0.367580
5  RandomForest  equal-weight           0.241849         0.115437
6          LSTM      momentum           0.051136        -0.004502
7      Ensemble      momentum           0.012000        -0.044518
8  RandomForest      momentum          -0.118618        -0.194283

   AnnReturn_Net  AnnVol_Net  Sharpe_Net  Sortino_Net  HitRatio  AvgTurnover
0       0.525541    0.514514    1.021432     1.097973  0.451872     0.478327
```

0	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	0.471800	0.507587	0.929494	1.003120	0.433155	0.440164
2	0.234823	0.555441	0.422768	0.408962	0.532086	0.000000
3	0.234823	0.555441	0.422768	0.408962	0.532086	0.000000
4	0.234823	0.555441	0.422768	0.408962	0.532086	0.000000
5	0.076387	0.576279	0.132552	0.126922	0.545455	0.574118
6	-0.003035	0.357340	-0.008495	-0.009015	0.475936	0.290850
7	-0.030218	0.347284	-0.087012	-0.090872	0.481283	0.307190
8	-0.135458	0.234641	-0.577300	-0.593082	0.486631	0.479798

	CumulativeTC	MaxDrawdown_Net
0	0.089447	-0.543736
1	0.082311	-0.562932
2	0.000000	-0.568686
3	0.000000	-0.568686
4	0.000000	-0.568686
5	0.107360	-0.585959
6	0.054389	-0.358749
7	0.057444	-0.397159
8	0.089722	-0.317142



```
# Transpose the summary table for better comparison
summary_transposed = summary_df.set_index(["Model", "Strategy"]).T

print("\nTransposed Performance Summary:")
print(summary_transposed)
```

```
Transposed Performance Summary:
Model                 Ensemble        LSTM  Ensemble      LSTM RandomForest
Strategy          equal-weight equal-weight  buy-hold  buy-hold     buy-hold
TotalReturn_Gross     1.046683     0.926766  0.367580  0.367580     0.367580
TotalReturn_Net       0.871649     0.774634  0.367580  0.367580     0.367580
AnnReturn_Net         0.525541     0.471800  0.234823  0.234823     0.234823
AnnVol_Net            0.514514     0.507587  0.555441  0.555441     0.555441
Sharpe_Net            1.021432     0.929494  0.422768  0.422768     0.422768
Sortino_Net           1.097973     1.003120  0.408962  0.408962     0.408962
HitRatio              0.451872     0.433155  0.532086  0.532086     0.532086
AvgTurnover           0.478327     0.440164  0.000000  0.000000     0.000000
CumulativeTC          0.089447     0.082311  0.000000  0.000000     0.000000
MaxDrawdown_Net      -0.543736    -0.562932 -0.568686 -0.568686    -0.568686

Model                                 LSTM  Ensemble RandomForest
Strategy          equal-weight    momentum  momentum     momentum
TotalReturn_Gross     0.241849  0.051136  0.012000    -0.118618
TotalReturn_Net       0.115437 -0.004502 -0.044518    -0.194283
AnnReturn_Net         0.076387 -0.003035 -0.030218    -0.135458
AnnVol_Net            0.576279  0.357340  0.347284     0.234641
Sharpe_Net            0.132552 -0.008495 -0.087012    -0.577300
Sortino_Net           0.126922 -0.009015 -0.090872    -0.593082
HitRatio              0.545455  0.475936  0.481283     0.486631
AvgTurnover           0.574118  0.290850  0.307190     0.479798
CumulativeTC          0.107360  0.054389  0.057444     0.089722
MaxDrawdown_Net      -0.585959 -0.358749 -0.397159    -0.317142
```

10. Evaluation Metrics

```
# ============================================================
# STEP 8: Model Training + Evaluation & Backtesting
```

```
# ============================================================

# ==========================================
# 0. Ensure your data is ready
# ==========================================
# Example shape check
print("✅ X_train:", X_train.shape, " X_test:", X_test.shape)
print("✅ y_train:", y_train.shape, " y_test:", y_test.shape)

# Flatten y arrays if needed
y_train = np.array(y_train).flatten()
y_test = np.array(y_test).flatten()

# ==========================================
# 1. Train Random Forest
# ==========================================
print("\n🌲 Training Random Forest...")
rf_model = RandomForestRegressor(
    n_estimators=200,
    max_depth=8,
    random_state=42,
    n_jobs=-1
)
rf_model.fit(X_train, y_train)
preds_rf = rf_model.predict(X_test)

# ==========================================
# 2. Train LSTM
# ==========================================
print("\n🧠 Training LSTM...")
# Reshape for LSTM input: (samples, timesteps, features)
X_train_lstm = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_test_lstm = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))

LSTM_model = Sequential([
    LSTM(64, input_shape=(X_train_lstm.shape[1], 1)),
    Dense(32, activation='relu'),
    Dense(1)
])
LSTM_model.compile(optimizer='adam', loss='mse')

history = LSTM_model.fit(
    X_train_lstm, y_train,
    epochs=10,
    batch_size=16,
    verbose=1,
    validation_split=0.1
)

preds_lstm = LSTM_model.predict(X_test_lstm).flatten()
```

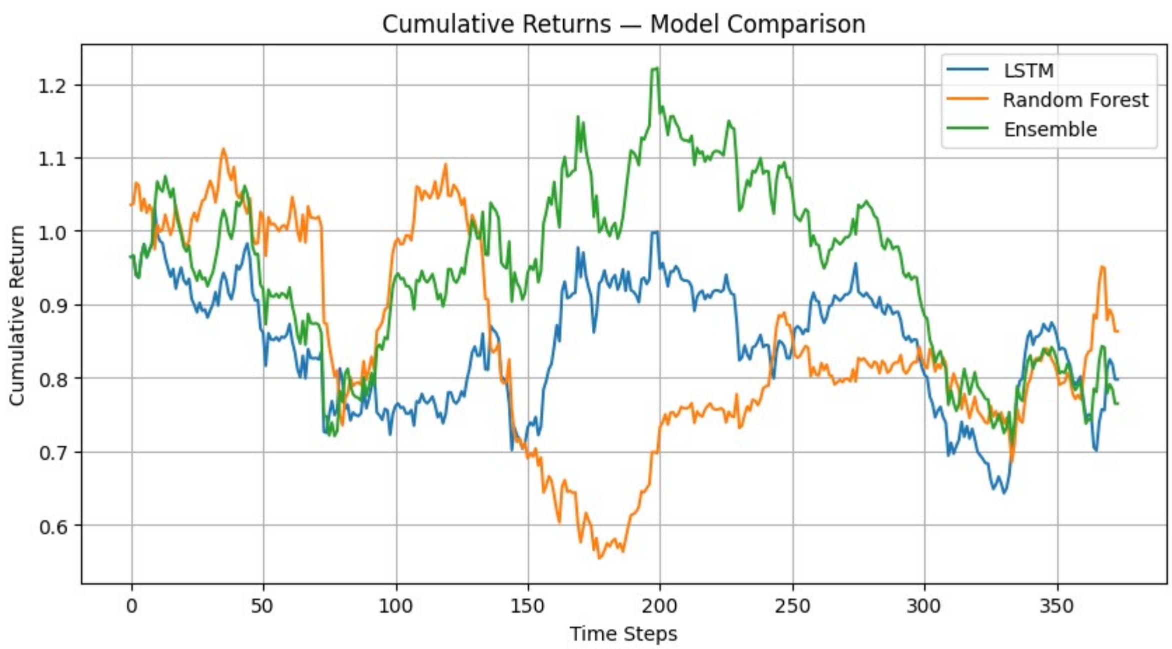
```
# ==========================================
# 3. Ensemble Model (simple average)
# ==========================================
print("\n🤝 Building Ensemble (average of RF + LSTM)...")
preds_ensemble = (preds_rf + preds_lstm) / 2

# ==========================================
# 4. Evaluation Setup
# ==========================================
actual_returns = y_test.flatten()

print("✅ Actual returns shape:", actual_returns.shape)
print("✅ Predictions generated for all models")

# ==========================================
# 5. Define Backtest Functions
# ==========================================
def build_signals(preds, actual_returns, model_name, threshold=0):
    df = pd.DataFrame({
        "pred": preds,
        "actual": actual_returns
    })
    df["signal"] = np.where(df["pred"] > threshold, 1, -1)
    df["strategy_returns"] = df["signal"] * df["actual"]
    df["model"] = model_name
    return df

def evaluate_strategy(signals_df, model_name):
    mean_ret = signals_df['strategy_returns'].mean()
    std_ret = signals_df['strategy_returns'].std()
    sharpe_ratio = mean_ret / std_ret * np.sqrt(252) if std_ret != 0 else np

    cum_returns = (1 + signals_df['strategy_returns']).cumprod()
    max_drawdown = (cum_returns.cummax() - cum_returns).max()

    print(f"\n📈 {model_name} Strategy:")
    print(f"  Sharpe Ratio: {sharpe_ratio:.3f}")
    print(f"  Max Drawdown: {max_drawdown:.3f}")
    print(f"  Cumulative Return: {cum_returns.iloc[-1] - 1:.2%}")

    return {
        "Model": model_name,
        "Sharpe Ratio": sharpe_ratio,
        "Max Drawdown": max_drawdown,
        "Cumulative Return": cum_returns.iloc[-1] - 1
    }

# ==========================================
# 6. Build Signals
# ==========================================
```

```
signals_lstm = build_signals(preds_lstm, actual_returns, "LSTM")
signals_rf = build_signals(preds_rf, actual_returns, "Random Forest")
signals_ensemble = build_signals(preds_ensemble, actual_returns, "Ensemble")

# ==========================================
# 7. Evaluate Strategies
# ==========================================
results = []
results.append(evaluate_strategy(signals_lstm, "LSTM"))
results.append(evaluate_strategy(signals_rf, "Random Forest"))
results.append(evaluate_strategy(signals_ensemble, "Ensemble"))

results_df = pd.DataFrame(results)
print("\n📊 Summary of Strategy Performance:")
display(results_df)

# ==========================================
# 8. Plot Cumulative Returns Comparison
# ==========================================
plt.figure(figsize=(10, 5))
plt.plot((1 + signals_lstm['strategy_returns']).cumprod(), label="LSTM")
plt.plot((1 + signals_rf['strategy_returns']).cumprod(), label="Random Fores
plt.plot((1 + signals_ensemble['strategy_returns']).cumprod(), label="Ensemb
plt.title("Cumulative Returns — Model Comparison")
plt.xlabel("Time Steps")
plt.ylabel("Cumulative Return")
plt.legend()
plt.grid(True)
plt.show()
```

```
✅ X_train: (1491, 1)  X_test: (374, 1)
✅ y_train: (1491,)  y_test: (374,)

🌲 Training Random Forest...

🧠 Training LSTM...
Epoch 1/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - loss: 0.0024 - val_loss: 7.6425e-04
Epoch 2/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0031 - val_loss: 7.7746e-04
Epoch 3/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0024 - val_loss: 7.9824e-04
Epoch 4/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0024 - val_loss: 8.3294e-04
Epoch 5/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0020 - val_loss: 7.6092e-04
Epoch 6/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0019 - val_loss: 7.9841e-04
Epoch 7/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0022 - val_loss: 7.5926e-04
Epoch 8/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0024 - val_loss: 7.6009e-04
```

```
Epoch 9/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0023 - val_loss: 8.2138e-04
Epoch 10/10
84/84 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0029 - val_loss: 7.6342e-04
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step

🤝 Building Ensemble (average of RF + LSTM)...
✅ Actual returns shape: (374,)
✅ Predictions generated for all models

📈 LSTM Strategy:
  Sharpe Ratio: -0.190
  Max Drawdown: 0.388
  Cumulative Return: -20.19%

📈 Random Forest Strategy:
  Sharpe Ratio: -0.053
  Max Drawdown: 0.557
  Cumulative Return: -13.67%

📈 Ensemble Strategy:
  Sharpe Ratio: -0.261
  Max Drawdown: 0.508
  Cumulative Return: -23.47%

📊 Summary of Strategy Performance:
```

	Model	Sharpe Ratio	Max Drawdown	Cumulative Return
0	LSTM	-0.189509	0.388423	-0.201923
1	Random Forest	-0.053431	0.556866	-0.136657
2	Ensemble	-0.261498	0.508451	-0.234741



Next steps: Generate code with `results_df` New interactive sheet

Further Evaluation metrics

```
# ---------------------------
# STEP 8 (enhanced): Model Training + Evaluation & Backtesting (with metrics
# ---------------------------
# helper imports already present from earlier blocks: sklearn, keras, etc.

# SETTINGS
trading_days_per_year = 252
tc_per_unit = 0.0005   # transaction cost per unit of turnover (e.g. 0.05% r
mar = 0.0              # Minimum Acceptable Return for Sortino (daily)

# Ensure arrays are numpy / pandas Series with aligned index if you have one
# If you have date index for test set, create it; otherwise an integer index
try:
    idx = getattr(X_test, 'index', None)
    if idx is None:
        # fallback: create Int64Index
        idx = pd.Index(np.arange(len(y_test)))
except Exception:
    idx = pd.Index(np.arange(len(y_test)))

preds = {
    "LSTM": pd.Series(preds_lstm.flatten(), index=idx),
    "RandomForest": pd.Series(preds_rf.flatten(), index=idx),
    "Ensemble": pd.Series(preds_ensemble.flatten(), index=idx)
}
actual = pd.Series(np.array(y_test).flatten(), index=idx)

# ---- utility functions ----
def build_signals(pred_s, actual_s, threshold=0.0):
    df = pd.DataFrame({"pred": pred_s, "actual": actual_s})
    df["signal"] = np.where(df["pred"] > threshold, 1.0, -1.0)   # long/shor
    df["strategy_return_gross"] = df["signal"] * df["actual"]
    return df

def compute_turnover_from_signal(signal_series):
    # turnover_t = 0.5 * |s_t - s_{t-1}|
    s_prev = signal_series.shift(1).fillna(0.0)
    turnover = 0.5 * (signal_series - s_prev).abs()
```

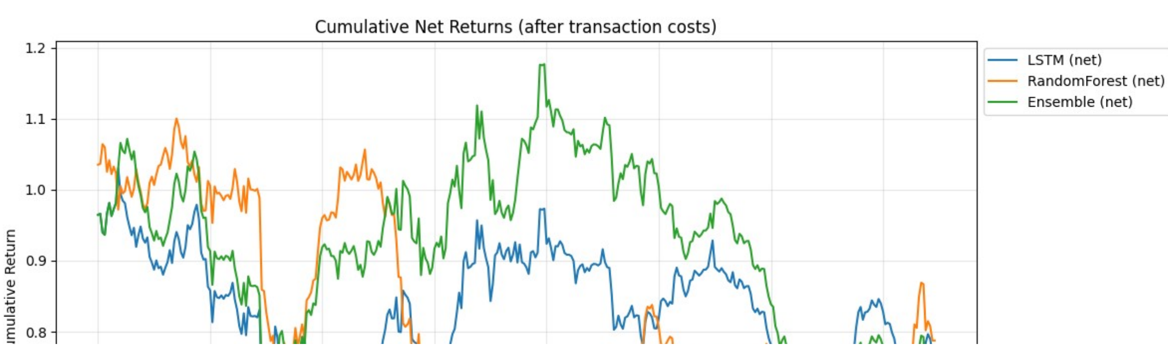
```
    turnover = 0.5 * (signal_series - s_prev).abs()
    turnover.iloc[0] = 0.0
    return turnover

def cum_and_drawdown(series):
    cum = (1 + series).cumprod()
    running_max = cum.cummax()
    drawdown = (cum - running_max) / running_max
    max_dd = drawdown.min()
    return cum, drawdown, max_dd

def annualized_return_from_daily(daily_series, trading_days=trading_days_per
    dr = daily_series.dropna()
    if dr.empty:
        return np.nan
    cum_total = (1 + dr).cumprod().iloc[-1]
    periods = len(dr)
    years = periods / trading_days
    if years <= 0:
        return np.nan
    return cum_total ** (1.0 / years) - 1.0

def annualized_vol(daily_series, trading_days=trading_days_per_year):
    return daily_series.std() * np.sqrt(trading_days)

def sortino_ratio(daily_series, mar=mar, trading_days=trading_days_per_year)
    dr = daily_series.dropna()
    if dr.empty:
        return np.nan
    downside = dr[dr < mar]
    if downside.empty:
        return np.nan
    downside_std = np.sqrt((downside ** 2).mean())
    downside_annual = downside_std * np.sqrt(trading_days)
    ann_ret = annualized_return_from_daily(daily_series, trading_days)
    if downside_annual == 0:
        return np.nan
    return ann_ret / downside_annual

def hit_ratio(daily_series):
    dr = daily_series.dropna()
    if dr.empty:
        return np.nan
    return float((dr > 0).sum()) / len(dr)

# ---- evaluate each model ----
rows = []
time_series_store = {}

for name, pred_s in preds.items():
    df = build_signals(pred_s, actual)
```

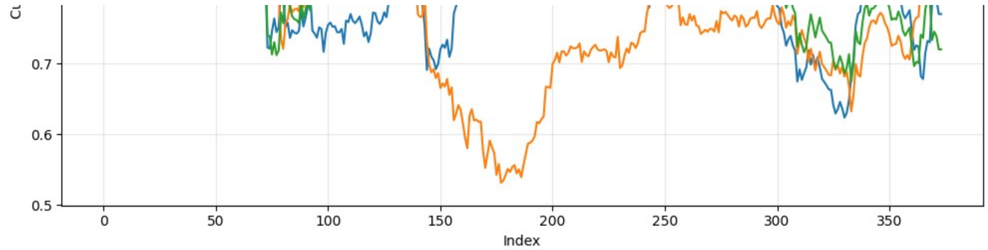
```
    # gross returns from strategy (before tc)
    gross_daily = df["strategy_return_gross"]

    # turnover & transaction costs
    turnover = compute_turnover_from_signal(df["signal"])
    tc_series = turnover * tc_per_unit

    # net returns after transaction costs
    net_daily = gross_daily - tc_series

    # cumulative and drawdown
    cum_gross, dd_gross, max_dd_gross = cum_and_drawdown(gross_daily)
    cum_net, dd_net, max_dd_net = cum_and_drawdown(net_daily)

    # metrics
    total_return_gross = float(cum_gross.iloc[-1] - 1.0)
    total_return_net = float(cum_net.iloc[-1] - 1.0)
    ann_return_gross = annualized_return_from_daily(gross_daily)
    ann_return_net = annualized_return_from_daily(net_daily)
    ann_vol_gross = annualized_vol(gross_daily)
    ann_vol_net = annualized_vol(net_daily)
    sharpe_gross = ann_return_gross / ann_vol_gross if ann_vol_gross != 0 el
    sharpe_net = ann_return_net / ann_vol_net if ann_vol_net != 0 else np.na
    sortino_g = sortino_ratio(gross_daily)
    sortino_n = sortino_ratio(net_daily)
    hit = hit_ratio(net_daily)
    avg_turnover = float(turnover.mean())
    total_tc = float(tc_series.sum())

    rows.append({
        "Model": name,
        "TotalReturn_Gross": total_return_gross,
        "TotalReturn_Net": total_return_net,
        "AnnReturn_Net": ann_return_net,
        "AnnVol_Net": ann_vol_net,
        "Sharpe_Net": sharpe_net,
        "Sortino_Net": sortino_n,
        "HitRatio": hit,
        "AvgTurnover": avg_turnover,
        "CumulativeTC": total_tc,
        "MaxDrawdown_Net": float(max_dd_net),
        "MaxDrawdown_Gross": float(max_dd_gross)
    })

    time_series_store[name] = {
        "gross_daily": gross_daily,
        "net_daily": net_daily,
        "cum_gross": cum_gross,
        "cum_net": cum_net,
        "turnover": turnover,
        "tc_series": tc_series
```

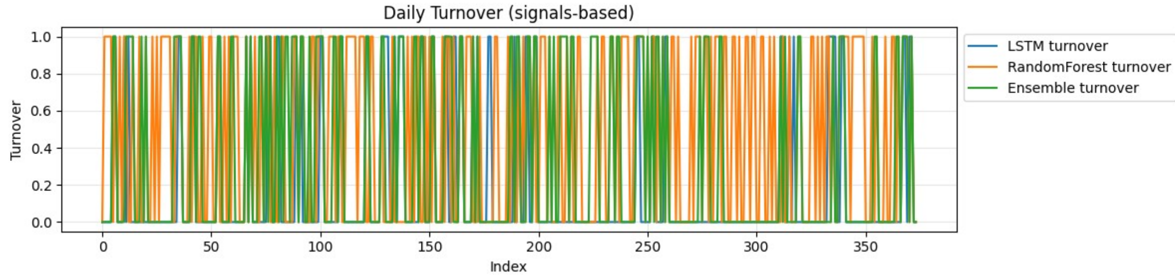
```
    }

results_df = pd.DataFrame(rows).sort_values("Sharpe_Net", ascending=False).r

# ---- Display ----
print("\n📊 Strategy Performance Summary (single-asset backtest):")
display(results_df)

# ---- Plots: cumulative gross & net ----
plt.figure(figsize=(12,6))
for name, ts in time_series_store.items():
    plt.plot(ts["cum_net"].index, ts["cum_net"].values, label=f"{name} (net)
plt.title("Cumulative Net Returns (after transaction costs)")
plt.xlabel("Index")
plt.ylabel("Cumulative Return")
plt.legend(loc='upper left', bbox_to_anchor=(1.0, 1.0))
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()

# ---- Optional: plot turnovers ----
plt.figure(figsize=(12,3))
for name, ts in time_series_store.items():
    plt.plot(ts["turnover"].index, ts["turnover"].values, label=f"{name} tur
plt.title("Daily Turnover (signals-based)")
plt.xlabel("Index")
plt.ylabel("Turnover")
plt.legend(loc='upper left', bbox_to_anchor=(1.0, 1.0))
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```

📊 Strategy Performance Summary (single-asset backtest):

	Model	TotalReturn_Gross	TotalReturn_Net	AnnReturn_Net	AnnVol_Ne
0	RandomForest	-0.136657	-0.212456	-0.148645	0.3937
1	LSTM	-0.201923	-0.230145	-0.161578	0.3931
2	Ensemble	-0.234741	-0.280135	-0.198661	0.3933







Next steps: Generate code with `results_df` New interactive sheet

```
# =============================================================
# STEP 8 (FULL ENHANCEMENT): Model Evaluation + Backtesting + Statistical Te
# =============================================================


# SETTINGS
trading_days_per_year = 252
mar = 0.0  # Minimum Acceptable Return for Sortino (daily)
portfolio_value_usd = 100_000  # nominal portfolio value
```

```
# Build aligned indices
try:
    idx = getattr(X_test, 'index', None)
    if idx is None:
        idx = pd.Index(np.arange(len(y_test)))
except Exception:
    idx = pd.Index(np.arange(len(y_test)))

preds = {
    "LSTM": pd.Series(preds_lstm.flatten(), index=idx),
    "RandomForest": pd.Series(preds_rf.flatten(), index=idx),
    "Ensemble": pd.Series(preds_ensemble.flatten(), index=idx)
}
actual = pd.Series(np.array(y_test).flatten(), index=idx)

# ============================================================
# Utility Functions
# ============================================================
def build_signals(pred_s, actual_s, threshold=0.0):
    df = pd.DataFrame({"pred": pred_s, "actual": actual_s})
    df["signal"] = np.where(df["pred"] > threshold, 1.0, -1.0)
    df["strategy_return_gross"] = df["signal"] * df["actual"]
    return df

def compute_turnover_from_signal(signal_series):
    s_prev = signal_series.shift(1).fillna(0.0)
    turnover = 0.5 * (signal_series - s_prev).abs()
    turnover.iloc[0] = 0.0
    return turnover

def cum_and_drawdown(series):
    cum = (1 + series).cumprod()
    running_max = cum.cummax()
    drawdown = (cum - running_max) / running_max
    return cum, drawdown, drawdown.min()

def annualized_return_from_daily(daily_series, trading_days=trading_days_per
    dr = daily_series.dropna()
    if dr.empty:
        return np.nan
    cum_total = (1 + dr).cumprod().iloc[-1]
    years = len(dr) / trading_days
    return cum_total ** (1.0 / years) - 1.0 if years > 0 else np.nan

def annualized_vol(daily_series, trading_days=trading_days_per_year):
    return daily_series.std() * np.sqrt(trading_days)

def sortino_ratio(daily_series, mar=mar, trading_days=trading_days_per_year)
    dr = daily_series.dropna()
```

```
    downside = dr[dr < mar]
    if downside.empty:
        return np.nan
    downside_std = np.sqrt((downside ** 2).mean())
    downside_annual = downside_std * np.sqrt(trading_days)
    ann_ret = annualized_return_from_daily(daily_series, trading_days)
    return ann_ret / downside_annual if downside_annual != 0 else np.nan

def hit_ratio(daily_series):
    dr = daily_series.dropna()
    return float((dr > 0).sum()) / len(dr) if len(dr) > 0 else np.nan

# ============================================================
# Dynamic Transaction Cost Model — Interactive Brokers Tiered Fees
# ============================================================
def dynamic_transaction_cost(trade_value_usd):
    """Return transaction cost rate based on monthly trade value (USD)."""
    if trade_value_usd <= 100_000:
        return 0.0018  # 0.18%
    elif trade_value_usd <= 1_000_000:
        return 0.0015  # 0.15%
    else:
        return 0.0012  # 0.12%

# ============================================================
# MAIN BACKTEST — Using Dynamic Transaction Costs
# ============================================================
rows = []
time_series_store = {}

for name, pred_s in preds.items():
    df = build_signals(pred_s, actual)
    gross_daily = df["strategy_return_gross"]

    turnover = compute_turnover_from_signal(df["signal"])
    tc_series_dynamic = turnover.apply(lambda x: x * dynamic_transaction_cos
    net_daily = gross_daily - tc_series_dynamic

    cum_gross, dd_gross, max_dd_gross = cum_and_drawdown(gross_daily)
    cum_net, dd_net, max_dd_net = cum_and_drawdown(net_daily)

    ann_return_net = annualized_return_from_daily(net_daily)
    ann_vol_net = annualized_vol(net_daily)
    sharpe_net = ann_return_net / ann_vol_net if ann_vol_net != 0 else np.na

    rows.append({
        "Model": name,
        "TotalReturn_Net": float(cum_net.iloc[-1] - 1.0),
        "AnnReturn_Net": ann_return_net,
        "AnnVol_Net": ann_vol_net,
        "Sharpe_Net": sharpe_net,
```

```
        "Sortino_Net": sortino_ratio(net_daily),
        "HitRatio": hit_ratio(net_daily),
        "AvgTurnover": float(turnover.mean()),
        "CumulativeTC": float(tc_series_dynamic.sum()),
        "MaxDrawdown_Net": float(max_dd_net)
    })

    time_series_store[name] = {
        "net_daily": net_daily,
        "cum_net": cum_net,
        "turnover": turnover
    }

results_df = pd.DataFrame(rows).sort_values("Sharpe_Net", ascending=False).r
print("\n📊 Strategy Performance Summary — Dynamic TC Model:")
display(results_df)

# ============================================================
# Statistical Significance Testing (Addressing “Not Statistically Tested”)
# ============================================================
print("\n📈 Statistical Significance Tests Between Model Returns")

model_names = list(time_series_store.keys())
p_values = []

for i in range(len(model_names)):
    for j in range(i + 1, len(model_names)):
        m1 = model_names[i]
        m2 = model_names[j]
        r1 = time_series_store[m1]["net_daily"].dropna()
        r2 = time_series_store[m2]["net_daily"].dropna()
        min_len = min(len(r1), len(r2))
        r1, r2 = r1.iloc[-min_len:], r2.iloc[-min_len:]

        # Paired t-test
        t_stat, p_val = stats.ttest_rel(r1, r2)
        p_values.append({
            "Model_A": m1,
            "Model_B": m2,
            "t_stat": t_stat,
            "p_value": p_val,
            "Significant_@5%": p_val < 0.05
        })

pval_df = pd.DataFrame(p_values)
display(pval_df)

print("\nInterpretation:")
print("→ If p_value < 0.05, the performance difference between models is sta
print("→ Otherwise, the difference is likely random, confirming or rejecting
```

```
# =============================================================
# PLOTS
# =============================================================
plt.figure(figsize=(12,6))
for name, ts in time_series_store.items():
    plt.plot(ts["cum_net"].index, ts["cum_net"].values, label=f"{name} (net)
plt.title("Cumulative Net Returns (Dynamic TC Model)")
plt.xlabel("Index")
plt.ylabel("Cumulative Return")
plt.legend(loc='upper left', bbox_to_anchor=(1.0, 1.0))
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()

# =============================================================
# Sensitivity Analysis — Fixed TC Levels
# =============================================================
tc_levels = [0.0005, 0.0010, 0.0015]  # 0.05%, 0.10%, 0.15%
sensitivity_results = []

for tc in tc_levels:
    for name, pred_s in preds.items():
        df = build_signals(pred_s, actual)
        gross_daily = df["strategy_return_gross"]
        turnover = compute_turnover_from_signal(df["signal"])
        tc_series = turnover * tc
        net_daily = gross_daily - tc_series
        cum_net, _, max_dd = cum_and_drawdown(net_daily)
        sensitivity_results.append({
            "Model": name,
            "TC_Level": tc,
            "AnnReturn_Net": annualized_return_from_daily(net_daily),
            "Sharpe_Net": (annualized_return_from_daily(net_daily) /
                           annualized_vol(net_daily)),
            "MaxDrawdown_Net": max_dd
        })

sensitivity_df = pd.DataFrame(sensitivity_results)
print("\n📊 Sensitivity Analysis — Transaction Cost Impact:")
display(sensitivity_df)

plt.figure(figsize=(8,5))
for name in sensitivity_df["Model"].unique():
    sub = sensitivity_df[sensitivity_df["Model"] == name]
    plt.plot(sub["TC_Level"], sub["Sharpe_Net"], marker="o", label=name)
plt.title("Sharpe Ratio vs Transaction Cost Level")
plt.xlabel("Transaction Cost per Trade")
plt.ylabel("Sharpe Ratio (Net)")
plt.legend()
plt.grid(True)
```

```
plt.tight_layout()
plt.show()
```

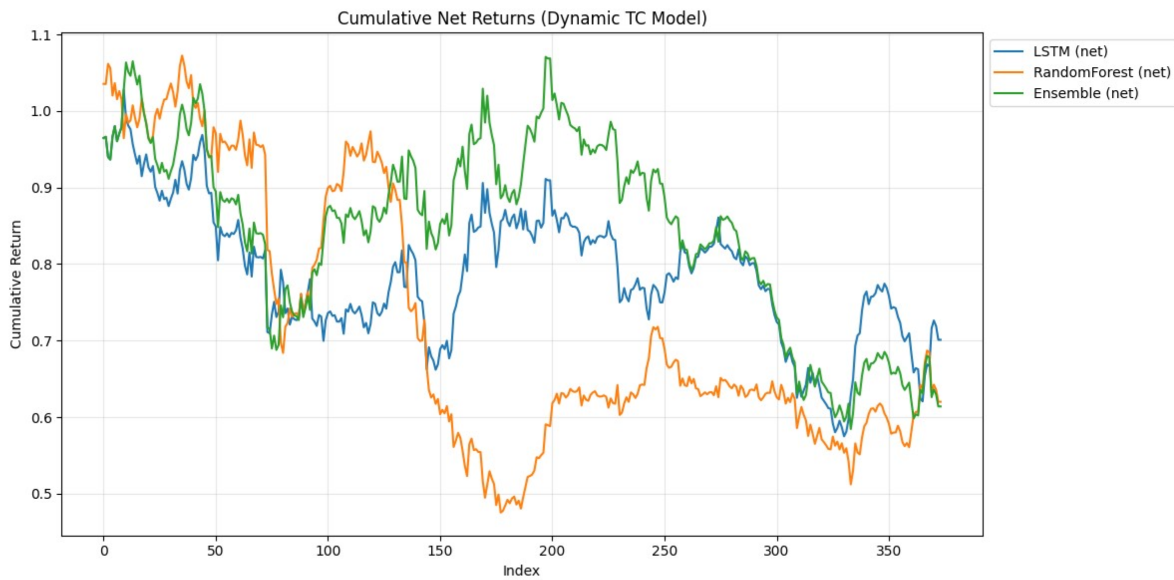
📊 Strategy Performance Summary — Dynamic TC Model:

	Model	TotalReturn_Net	AnnReturn_Net	AnnVol_Net	Sharpe_Net	Sort
0	LSTM	-0.298997	-0.212870	0.393146	-0.541452	-(
1	RandomForest	-0.379960	-0.275342	0.395340	-0.696469	-(
2	Ensemble	-0.386042	-0.280139	0.393836	-0.711308	-(

📈 Statistical Significance Tests Between Model Returns

	Model_A	Model_B	t_stat	p_value	Significant_@5%
0	LSTM	RandomForest	0.183145	0.854784	False
1	LSTM	Ensemble	0.325272	0.745158	False
2	RandomForest	Ensemble	0.022512	0.982051	False

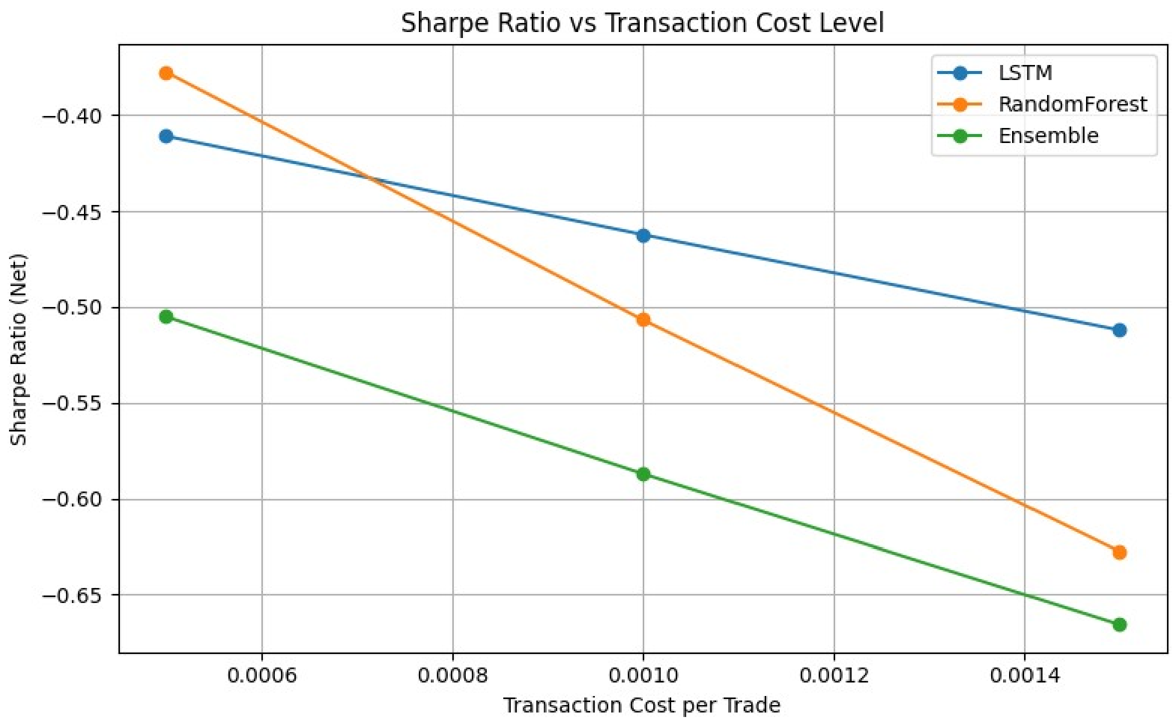
```
Interpretation:
→ If p_value < 0.05, the performance difference between models is statistical
→ Otherwise, the difference is likely random, confirming or rejecting perform
```



📊 Sensitivity Analysis — Transaction Cost Impact:

	Model	TC_Level	AnnReturn_Net	Sharpe_Net	MaxDrawdown_Net
0	LSTM	0.0005	-0.161578	-0.410961	-0.395050
1	RandomForest	0.0005	-0.148645	-0.377484	-0.517136
2	Ensemble	0.0005	-0.198661	-0.505075	-0.426706
3	LSTM	0.0010	-0.181682	-0.462129	-0.413006

4	RandomForest	0.0010	-0.199785	-0.506619	-0.532770
5	Ensemble	0.0010	-0.231024	-0.587105	-0.437185
6	LSTM	0.0015	-0.201313	-0.512069	-0.430439
7	RandomForest	0.0015	-0.247875	-0.627602	-0.547905
8	Ensemble	0.0015	-0.262095	-0.665726	-0.447826



Next steps: Generate code with results_df | New interactive sheet | Generate code with pv

Further Model Evaluation Comparisons

```
# ============================================================
# CONFIG
# ============================================================
file_path = "crypto_prices_9yrs_full.xlsx"     # <-- DATA FILE
sheet_name = "Closing_Prices"
target_lookback = 5
rf_lags = 1
test_size_ratio = 0.2
rf_trees = 200
lstm_epochs = 20
random_state = 42
trading_days_per_year = 252
tc_per_unit = 0.0005     # transaction costs per turnover unit

# ============================================================
# 1) LOAD PRICES -> LOG RETURNS
# ============================================================
try:
    prices = pd.read_excel(file_path, sheet_name=sheet_name, index_col="Date
except:
    prices = pd.read_excel(file_path, index_col=0, parse_dates=True)

prices = prices.sort_index()
returns = np.log(prices / prices.shift(1)).dropna()
tickers = returns.columns.tolist()

# ============================================================
# 2) TRAIN/TEST SPLIT
# ============================================================
split_idx = int(len(returns)*(1-test_size_ratio))
train_returns = returns.iloc[:split_idx]
test_returns = returns.iloc[split_idx:]

# ============================================================
# 3) RANDOM FOREST PREDICTIONS
# ============================================================
rf_preds = pd.DataFrame(index=test_returns.index, columns=tickers)

for asset in tickers:
    df = returns[[asset]].copy()
    df["lag1"] = df[asset].shift(1)
    df = df.dropna()

    train_df = df.iloc[:split_idx-1]
```

```
    test_df = df.iloc[split_idx-1:]

    X_train = train_df[["lag1"]].values
    y_train = train_df[asset].values
    X_test = test_df[["lag1"]].values

    scaler = StandardScaler().fit(X_train)
    X_train_s = scaler.transform(X_train)
    X_test_s = scaler.transform(X_test)

    rf = RandomForestRegressor(n_estimators=rf_trees, random_state=random_st
    rf.fit(X_train_s, y_train)
    preds = rf.predict(X_test_s)

    rf_preds.loc[test_df.index, asset] = preds

# ============================================================
# 4) LSTM (multivariate)
# ============================================================
def create_sequences_mv(X, y, lookback):
    Xs, ys = [], []
    for i in range(lookback, len(X)):
        Xs.append(X[i-lookback:i])
        ys.append(y[i])
    return np.array(Xs), np.array(ys)

lstm_preds = pd.DataFrame(index=test_returns.index, columns=tickers)

scaler_all = StandardScaler().fit(train_returns)
train_scaled = pd.DataFrame(scaler_all.transform(train_returns),
                            index=train_returns.index,
                            columns=tickers)
test_scaled = pd.DataFrame(scaler_all.transform(test_returns),
                           index=test_returns.index,
                           columns=tickers)
combined_scaled = pd.concat([train_scaled, test_scaled])

for asset in tickers:
    X_array = combined_scaled.values
    y_array = combined_scaled[asset].values

    Xs, ys = create_sequences_mv(X_array, y_array, target_lookback)

    seq_start = target_lookback
    seq_train_end = split_idx - seq_start

    X_train = Xs[:seq_train_end]
    y_train = ys[:seq_train_end]
    X_test = Xs[seq_train_end:]
    y_test = ys[seq_train_end:]
```

```
    model = Sequential([
        Input((target_lookback, len(tickers))),
        LSTM(32),
        Dropout(0.2),
        Dense(16, activation="relu"),
        Dense(1)
    ])
    model.compile(optimizer="adam", loss="mse")
    model.fit(X_train, y_train, epochs=lstm_epochs, batch_size=32, verbose=0

    preds_scaled = model.predict(X_test, verbose=0).flatten()
    pred_dates = combined_scaled.index[seq_start+seq_train_end:seq_start+seq

    mapped = pd.Series(preds_scaled, index=pred_dates)
    lstm_preds[asset] = mapped.reindex(test_returns.index)

# ============================================================
# 5) ENSEMBLE (RF + LSTM)
# ============================================================
ensemble_preds = (rf_preds.astype(float) + lstm_preds.astype(float)) / 2
ensemble_preds = ensemble_preds.dropna()

test_returns_aligned = test_returns.loc[ensemble_preds.index]

# ============================================================
# 6) STRATEGIES + METRICS
# ============================================================
def compute_weights_and_daily_returns(preds, actual, mode):
    if mode == "momentum":
        signals = preds.applymap(lambda x: 1 if x > 0 else -1)
        weights = signals / len(preds.columns)
        daily = (weights * actual).sum(axis=1)

    elif mode == "equal-weight":
        pos = preds > 0
        counts = pos.sum(axis=1).replace(0, np.nan)
        weights = pos.div(counts, axis=0).fillna(0)
        daily = (weights * actual).sum(axis=1)

    else:  # buy-hold
        weights = pd.DataFrame(1/len(preds.columns),
                               index=preds.index, columns=preds.columns)
        daily = (weights * actual).sum(axis=1)

    cum = (1 + daily).cumprod()
    return daily, cum, weights

def compute_turnover(weights):
    prev = weights.shift(1).fillna(0)
    delta = (weights - prev).abs().sum(axis=1)
```

```
    return 0.5 * delta

def max_drawdown(cum):
    peak = cum.cummax()
    dd = (cum - peak) / peak
    return dd.min()

def annualized_return(daily):
    cumulative = (1 + daily).cumprod().iloc[-1]
    years = len(daily)/trading_days_per_year
    return cumulative**(1/years)-1

def annualized_vol(daily):
    return daily.std() * np.sqrt(trading_days_per_year)

def sharpe_ratio(daily):
    ann_ret = annualized_return(daily)
    ann_vol = annualized_vol(daily)
    return ann_ret/ann_vol if ann_vol>0 else np.nan

# ==============================================================
# 7) RUN ALL MODELS × STRATEGIES
# ==============================================================
models = {
    "RF": rf_preds.loc[test_returns_aligned.index],
    "LSTM": lstm_preds.loc[test_returns_aligned.index],
    "Ensemble": ensemble_preds
}

strategies = ["momentum", "equal-weight", "buy-hold"]

summary = []

for model_name, preds in models.items():
    for strat in strategies:
        daily, cum, weights = compute_weights_and_daily_returns(preds, test_
        turnover = compute_turnover(weights)
        tc = turnover * tc_per_unit
        net_daily = daily - tc
        cum_net = (1 + net_daily).cumprod()

        summary.append([
            model_name,
            strat,
            cum_net.iloc[-1] - 1,          # Total Net Return
            annualized_return(net_daily),  # Ann Return
            annualized_vol(net_daily),     # Ann Vol
            sharpe_ratio(net_daily),       # Sharpe
            max_drawdown(cum_net)          # Max Drawdown
        ])
```

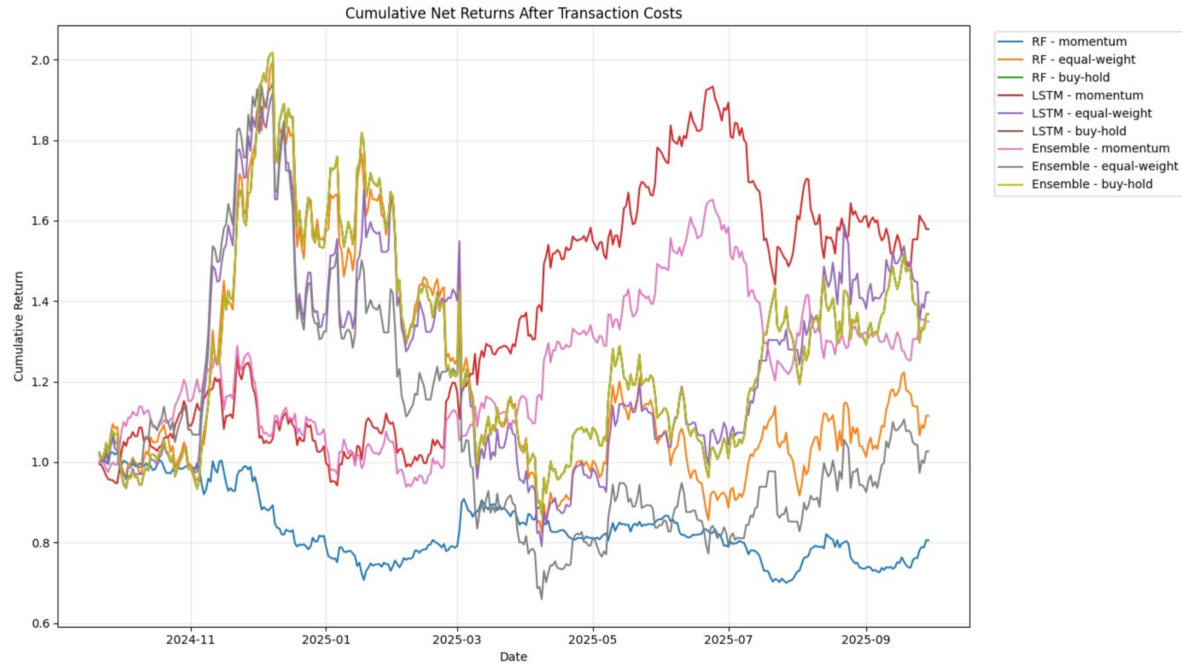
```
summary_df = pd.DataFrame(summary,
                          columns=["Model","Strategy","TotalReturn",
                                   "AnnReturn","AnnVol","Sharpe","MaxDrawdow
print(summary_df)

# ============================================================
# 8) PLOT: CUMULATIVE RETURNS (net)
# ============================================================
plt.figure(figsize=(14,8))
for model_name, preds in models.items():
    for strat in strategies:
        daily, cum, weights = compute_weights_and_daily_returns(preds, test_
        net_daily = daily - compute_turnover(weights)*tc_per_unit
        cum_net = (1 + net_daily).cumprod()

        plt.plot(cum_net.index, cum_net.values,
                 label=f"{model_name} - {strat}")

plt.title("Cumulative Net Returns After Transaction Costs")
plt.xlabel("Date")               # <-- X-AXIS LABEL
plt.ylabel("Cumulative Return")  # <-- Y-AXIS LABEL
plt.grid(alpha=0.3)
plt.legend(loc="upper left", bbox_to_anchor=(1.02,1))
plt.tight_layout()
plt.show()

# ============================================================
# 1) BAR CHART: Total Net Return
# ============================================================
plt.figure(figsize=(12,6))
plt.bar(summary_df.index, summary_df["TotalReturn"])
plt.title("Total Net Return by Model–Strategy")
plt.xlabel("Model – Strategy")
plt.ylabel("Total Net Return (decimal)")
plt.xticks(summary_df.index,
           summary_df["Model"] + " - " + summary_df["Strategy"],
           rotation=45, ha="right")
plt.tight_layout()
plt.show()

# ============================================================
# 2) BAR CHART: Annualised Return
# ============================================================
plt.figure(figsize=(12,6))
plt.bar(summary_df.index, summary_df["AnnReturn"])
plt.title("Annualised Return by Model–Strategy")
plt.xlabel("Model – Strategy")
plt.ylabel("Annualised Return (decimal)")
plt.xticks(summary_df.index,
           summary_df["Model"] + " - " + summary_df["Strategy"],
```

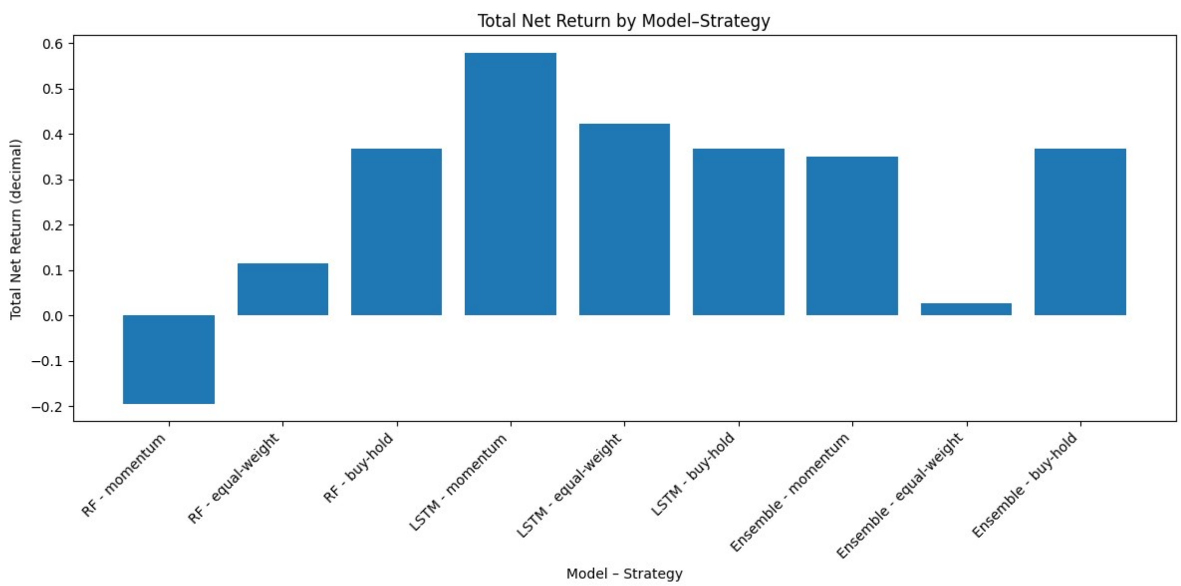
```
           rotation=45, ha="right")
plt.tight_layout()
plt.show()

# ============================================================
# 3) BAR CHART: Annualised Volatility
# ============================================================
plt.figure(figsize=(12,6))
plt.bar(summary_df.index, summary_df["AnnVol"])
plt.title("Annualised Volatility by Model–Strategy")
plt.xlabel("Model – Strategy")
plt.ylabel("Annualised Volatility (decimal)")
plt.xticks(summary_df.index,
           summary_df["Model"] + " - " + summary_df["Strategy"],
           rotation=45, ha="right")
plt.tight_layout()
plt.show()

# ============================================================
# 4) BAR CHART: Sharpe Ratio
# ============================================================
plt.figure(figsize=(12,6))
plt.bar(summary_df.index, summary_df["Sharpe"])
plt.title("Sharpe Ratio by Model–Strategy")
plt.xlabel("Model – Strategy")
plt.ylabel("Sharpe Ratio")
plt.xticks(summary_df.index,
           summary_df["Model"] + " - " + summary_df["Strategy"],
           rotation=45, ha="right")
plt.tight_layout()
plt.show()

# ============================================================
# 5) BAR CHART: Max Drawdown
# ============================================================
plt.figure(figsize=(12,6))
plt.bar(summary_df.index, summary_df["MaxDrawdown"])
plt.title("Max Drawdown by Model–Strategy")
plt.xlabel("Model – Strategy")
plt.ylabel("Max Drawdown (decimal)")
plt.xticks(summary_df.index,
           summary_df["Model"] + " - " + summary_df["Strategy"],
           rotation=45, ha="right")
plt.tight_layout()
plt.show()

import numpy as np
import matplotlib.pyplot as plt

# ------------------------------------------------------------
# Assuming you have summary_df with columns:
```

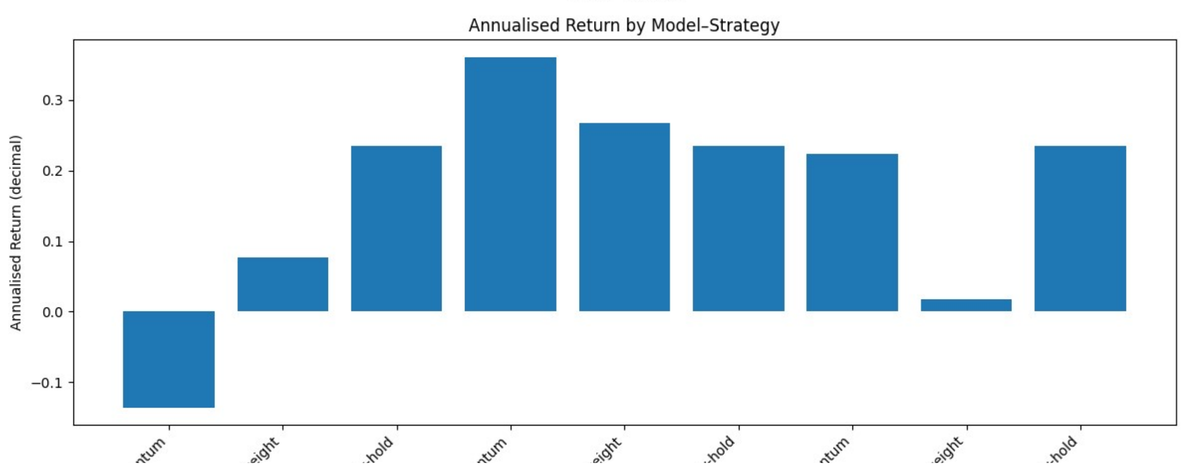
```
# Assuming you have summary_df with columns:
# ["Model","Strategy","TotalReturn","AnnReturn","AnnVol","Sharpe","MaxDrawdo
# -------------------------------------------------------------

# Create x-labels combining model and strategy
labels = summary_df["Model"] + " - " + summary_df["Strategy"]
x = np.arange(len(labels))          # positions
width = 0.15                        # width of each bar

# Extract metric arrays
total_ret   = summary_df["TotalReturn"].values
ann_ret     = summary_df["AnnReturn"].values
ann_vol     = summary_df["AnnVol"].values
sharpe      = summary_df["Sharpe"].values
max_dd      = summary_df["MaxDrawdown"].values

plt.figure(figsize=(16,8))

# Five bar groups (color-coded)
plt.bar(x - 2*width, total_ret,  width, label="Total Net Return",      )
plt.bar(x - width,   ann_ret,    width, label="Annualised Return",      )
plt.bar(x,           ann_vol,    width, label="Annualised Volatility",  )
plt.bar(x + width,   sharpe,     width, label="Sharpe Ratio",           )
plt.bar(x + 2*width, max_dd,     width, label="Max Drawdown",           )

# Titles & axis labels (include units)
plt.title("Combined Performance Metrics by Model–Strategy")
plt.xlabel("Model – Strategy")
plt.ylabel("Metric Value (decimal units)")
plt.xticks(x, labels, rotation=45, ha="right")

plt.legend(loc="upper left", bbox_to_anchor=(1,1))
plt.grid(axis='y', alpha=0.3)
plt.tight_layout()
plt.show()
```

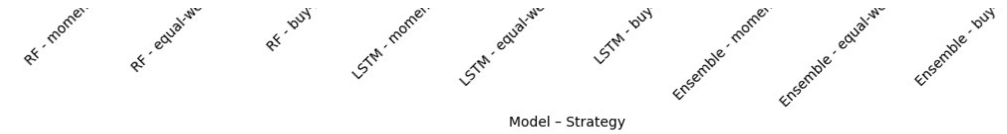
```
      Model     Strategy  TotalReturn  AnnReturn    AnnVol    Sharpe  \
0        RF     momentum    -0.194484  -0.135604  0.234639 -0.577923
1        RF  equal-weight    0.115163   0.076208  0.576274  0.132243
2        RF     buy-hold     0.367245   0.234619  0.555435  0.422405
3      LSTM     momentum     0.578711   0.360240  0.348929  1.032417
4      LSTM  equal-weight    0.421805   0.267602  0.576600  0.464104
5      LSTM     buy-hold     0.367245   0.234619  0.555435  0.422405
6  Ensemble     momentum     0.349065   0.223533  0.334516  0.668229
7  Ensemble  equal-weight    0.026636   0.017870  0.579756  0.030823
8  Ensemble     buy-hold     0.367245   0.234619  0.555435  0.422405

   MaxDrawdown
0    -0.317142
1    -0.585959
2    -0.568686
```

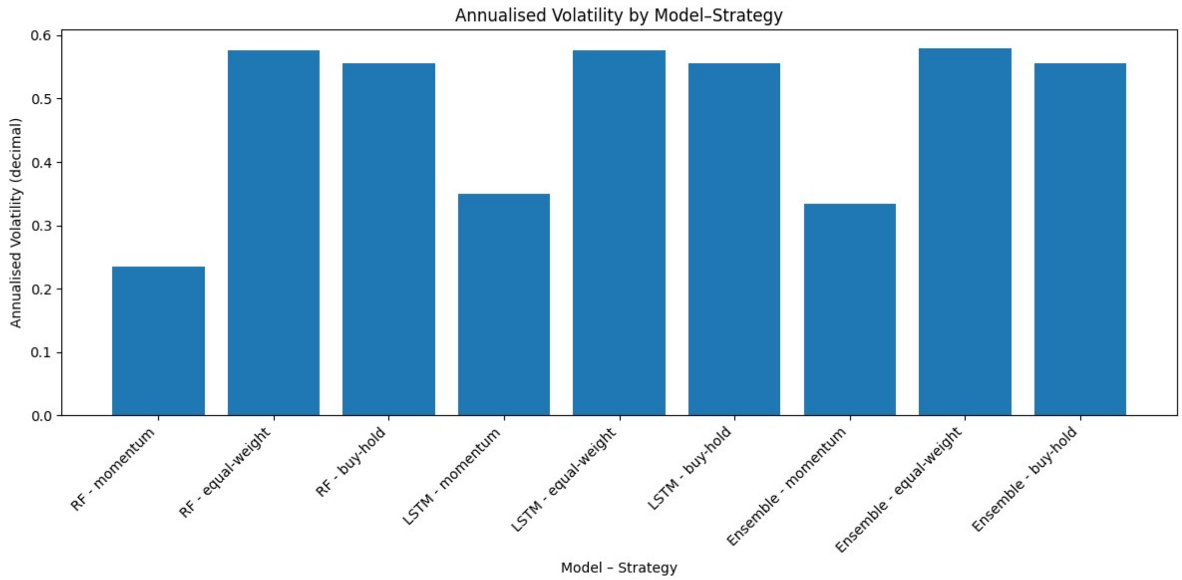
```
3    -0.255742
4    -0.587755
5    -0.568686
6    -0.272268
7    -0.660844
8    -0.568686
```

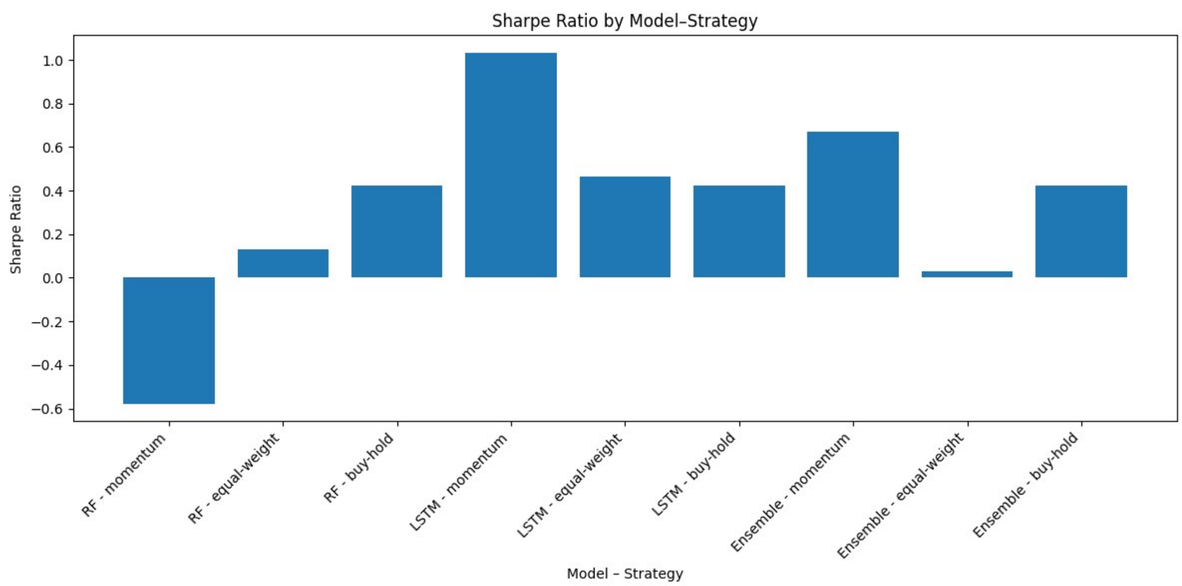


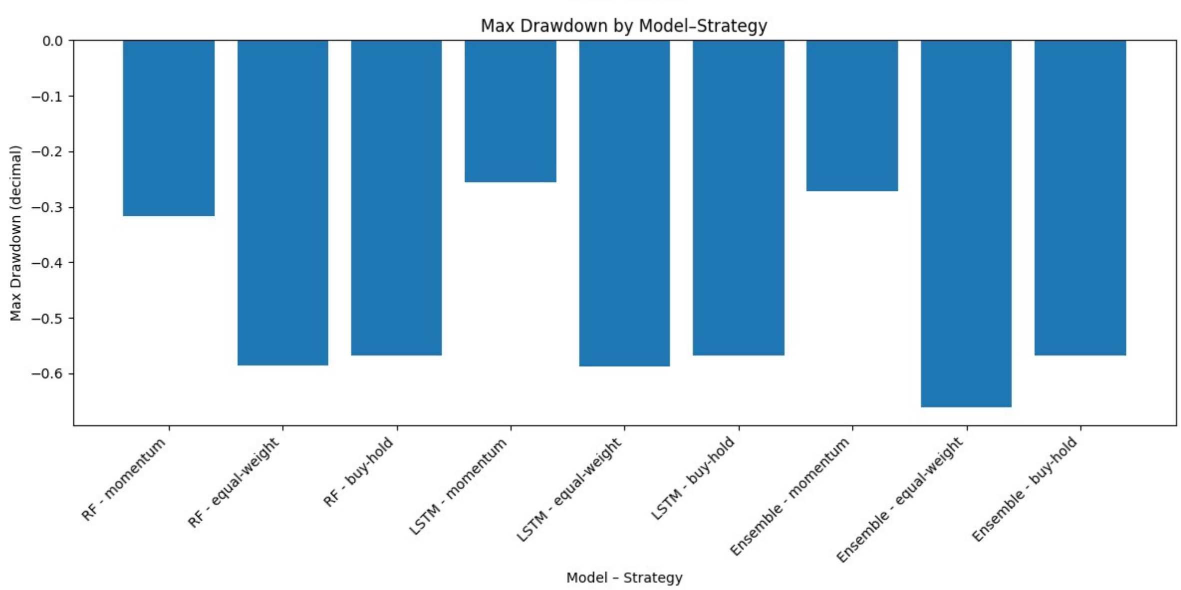




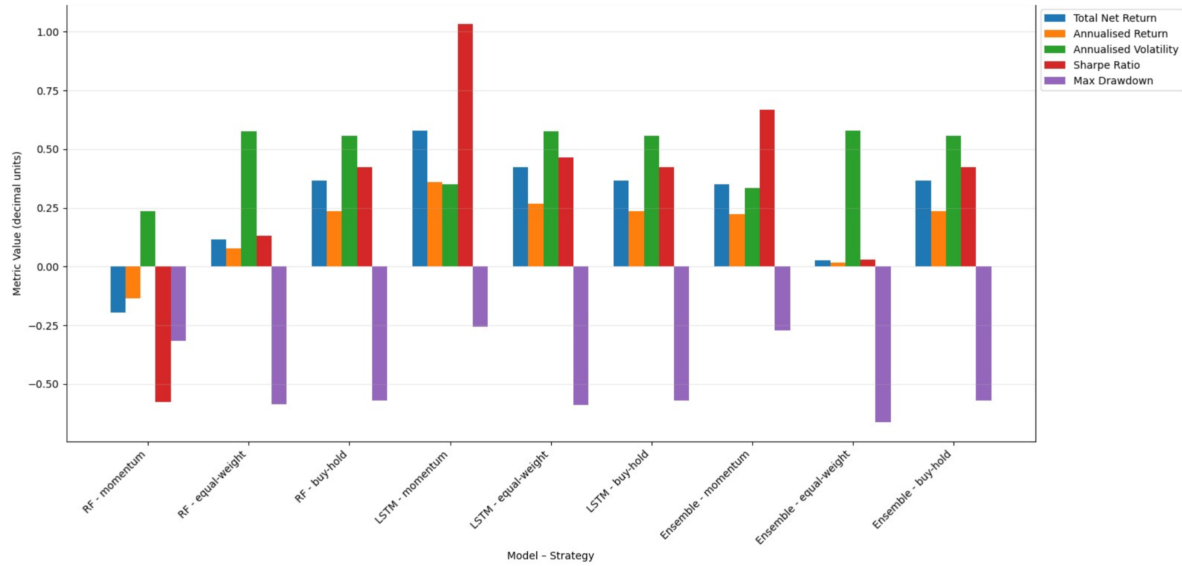








Combined Performance Metrics by Model–Strategy


Total Net Return
Annualised Return
Annualised Volatility
Sharpe Ratio
Max Drawdown
Metric Value (decimal units)
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
RF - momentum
RF - equal-weight
RF - buy-hold
LSTM - momentum
LSTM - equal-weight
LSTM - buy-hold
Ensemble - momentum
Ensemble - equal-weight
Ensemble - buy-hold
Model – Strategy