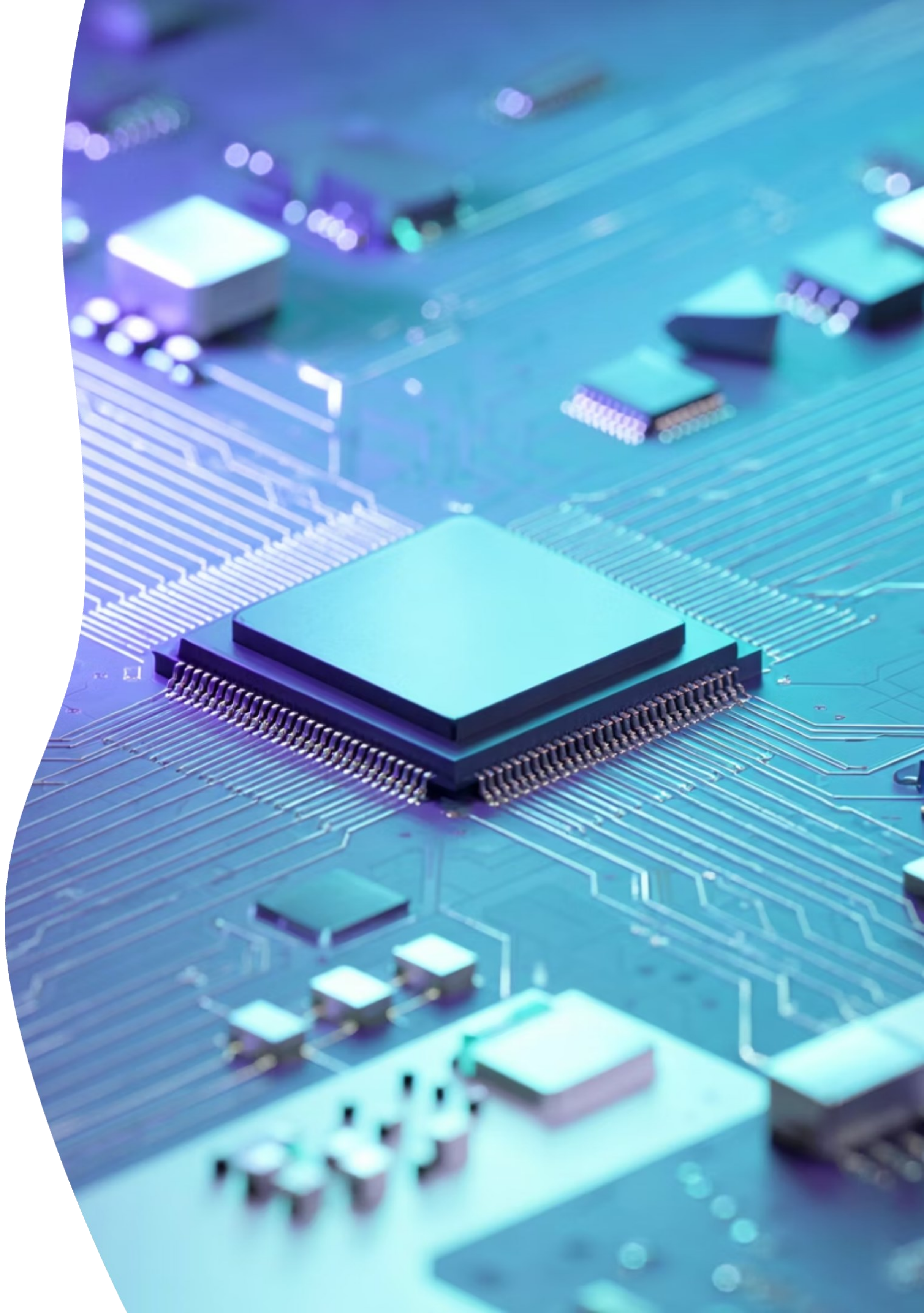
Week 6: Tree Ensembles Assignment – Random Forest & XGBoost for Portfolio Optimization

A comprehensive analysis of tree ensemble models for semiconductor portfolio optimization, focusing on maximizing risk-adjusted returns through Sharpe and Sortino ratios across ten major **semiconductor** stocks.



The Challenge

Portfolio Composition

Ten semiconductor stocks: INTC, NVDA, AMD, QCOM, TXN, MU, AVGO, AMAT, ASML, TSM

Prediction Horizon

10-day returns to balance noise reduction with tactical rebalancing practicality

Objective

Maximize risk-adjusted performance through Sharpe and Sortino ratios, with emphasis on downside risk management

Data Scope

2,444 observations spanning a decade: 1,955 training samples, 489 test samples

Three Models Compared

Random Forest

150 trees with max depth 6, minimum 30 samples for splitting. Bagging approach for robust generalization against financial noise.

Gradient Boosting

150 iterations, learning rate 0.05, max depth 4. Sequential boosting with 0.8 subsample ratio for gradual pattern learning.

XGBoost

L1 (0.5) and L2 (1.0) regularization, 0.8 column/row subsampling. Advanced regularization to combat overfitting.

Comprehensive Feature Engineering

01

Market Microstructure (Week 5 core - 21 features)

HMact indicators for all 10 stocks, VRSpike volatility regime metrics, and Herd_t behavioral index

02

Momentum Signals (3 features)

Multi-horizon momentum at 5, 10, and 20 days capturing tactical and strategic trends

03

Volatility Measures (3 features)

20-day and 60-day standard deviations plus critical 20-day downside volatility for Sortino optimization

04

Cross-Sectional Features (3 features)

Return dispersion, max-min spread, and 20-day average pairwise correlations

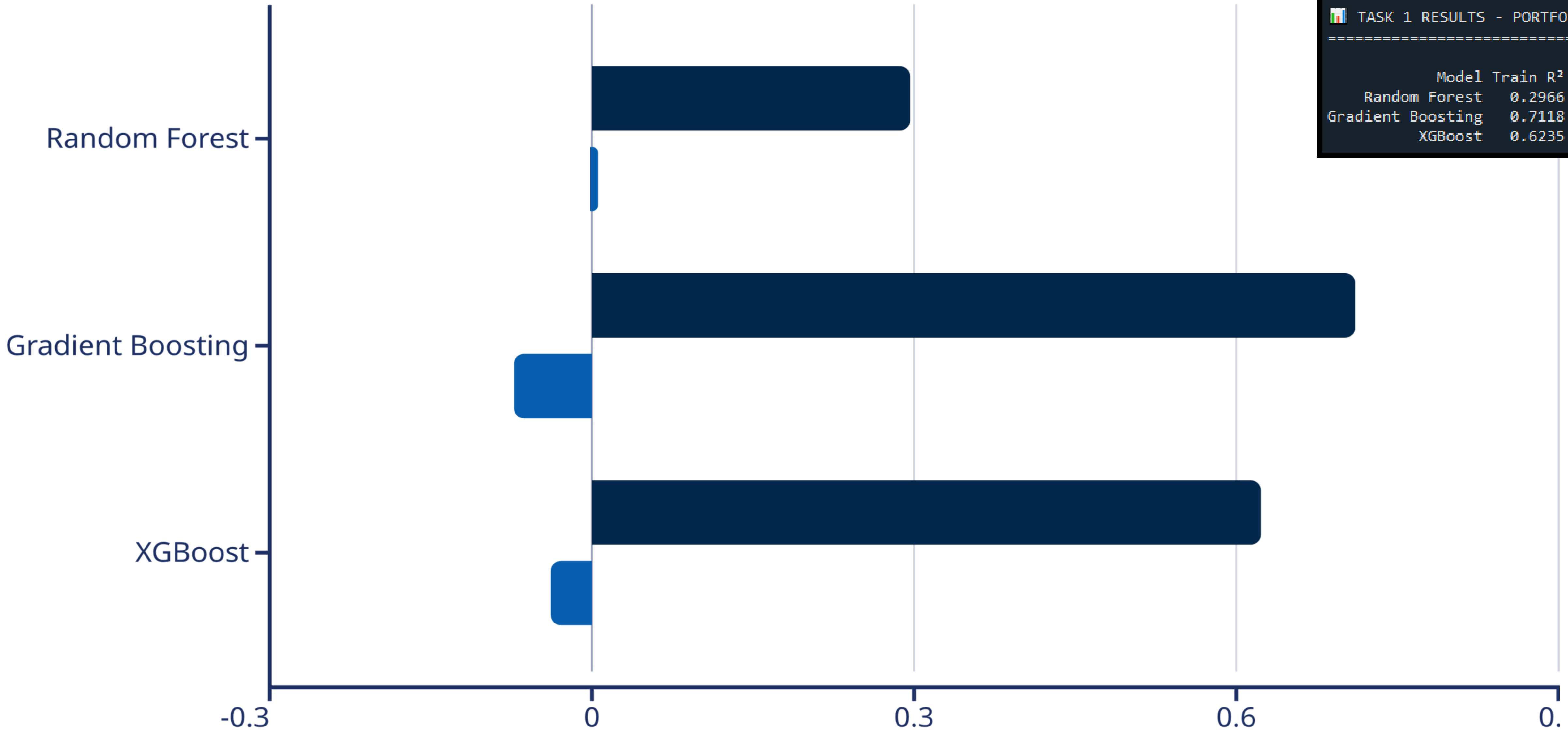
05

Stock Aggregates (4 features)

Average momentum and volatility across all stocks for bottom-up portfolio perspective

Total: 34 engineered features across five categories, substantially exceeding the 15-feature minimum requirement.

Model Performance Results

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📊 TASK 1 RESULTS - PORTFOLIO OPTIMIZATION
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Model	Train R²	Test R²	Test MSE	Test MAE	p-value vs RF
Random Forest	0.2966	0.0053	0.004162	0.050798	–
Gradient Boosting	0.7118	-0.0727	0.004488	0.051641	0.0889
XGBoost	0.6235	-0.0380	0.004343	0.051320	0.0519

Random Forest: Best Generalization

Only positive Test R^2 (0.0053), lowest train-test gap (0.29), MSE: 0.004162, MAE: 0.050798

G. Boosting: Severe Overfitting

Train-test gap of 0.78 indicates memorization without generalization, MSE: 0.004488

XGBoost: Moderate Overfitting

Despite regularization, train-test gap of 0.66 persists, MSE: 0.004343

Why Random Forest Wins

Only Positive Test R^2

Achieves genuine out-of-sample predictive power with $R^2 = 0.0053$, a result comparable to or exceeding standard benchmarks for financial return prediction models in the academic literature (where even R^2 values as low as 0.002–0.01 are considered statistically and economically significant).

Superior Generalization

Lowest train-test performance gap and smallest variance across 5-fold cross-validation, indicating stability across market regimes

Inherent Robustness

Bagging architecture naturally resistant to financial time series noise compared to sequential boosting methods

Feature Importance (Built-in): The Power Players

8.1%

NVDA_HMact

Dominant predictor capturing Nvidia's sector leadership and institutional order flow

6.2%

Avg Correlation

20-day rolling correlation measuring portfolio diversification dynamics

5.8%

ASML_HMact

Upstream supply chain indicator from lithography equipment monopolist

5.4%

Downside Vol

20-day downside volatility critical for Sortino ratio optimization

4.4%

MU_HMact

Trading activity from Micron, a key indicator for global memory demand cycles and supply chain turning points

Top 5 features account for ~30% of total predictive power despite representing only ~15% of feature set, demonstrating strong concentration in market leaders and risk measures.

SHAP Analysis: True Causal Impact

Top 5 SHAP Features

1. **NVDA_HMact** (0.00236)
2. **ASML_HMact** (0.00185)
3. **AVGO_HMact** (0.00185)
4. **TSM_VRSpike** (0.00178)
5. **MU_VRSpike** (0.00172)

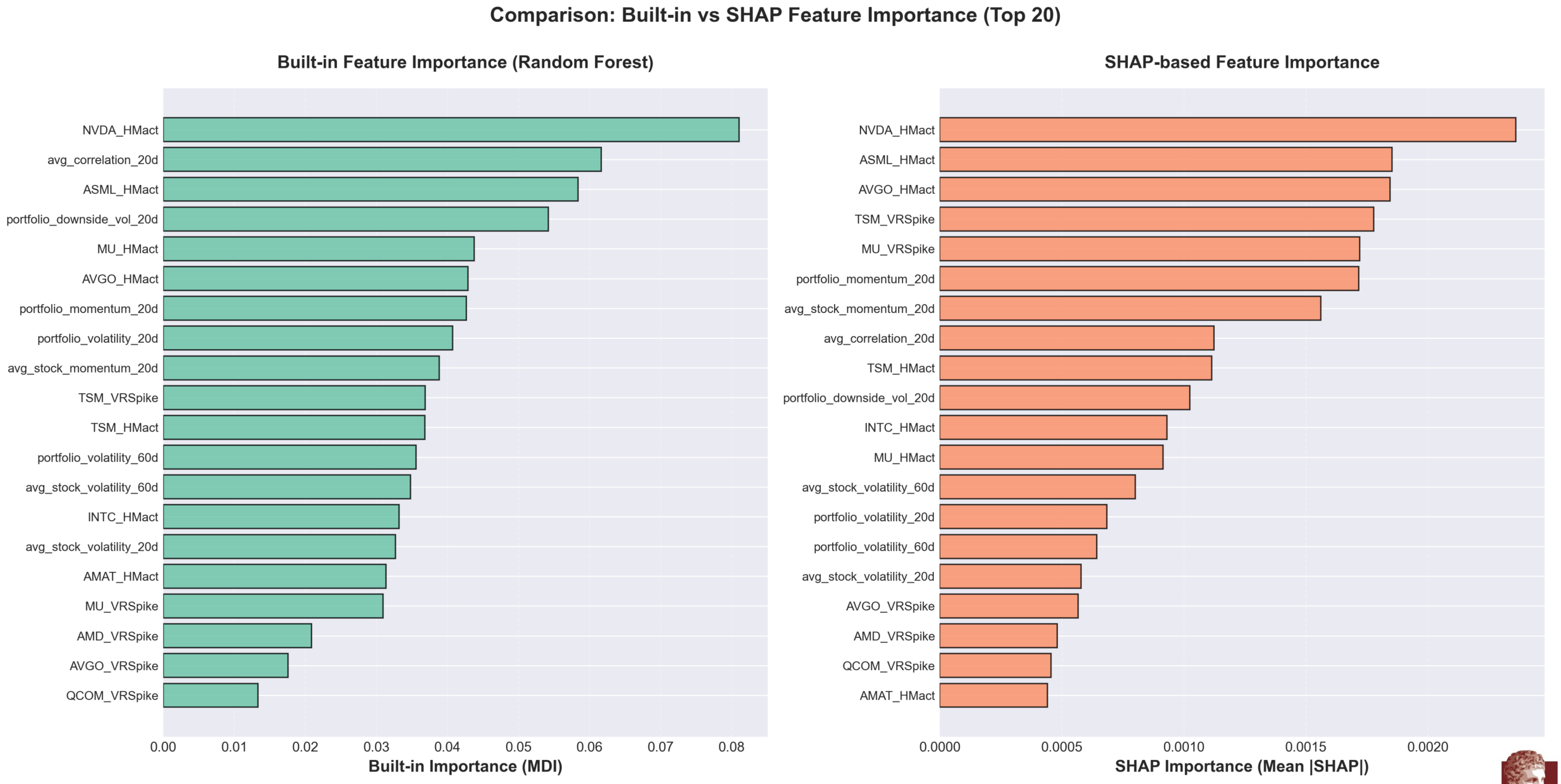
Collectively account for **36.48%** of total SHAP importance

Key Insights

Volatility regime features (VRSpike) rank higher in SHAP than built-in importance, revealing strong causal impact through complex interactions.

High correlation (r=0.827) between built-in and SHAP methods validates genuine predictive patterns, not algorithmic artifacts.

Market microstructure dominates: trading activity in sector leaders supersedes traditional momentum metrics.



Comparison: Built-in vs SHAP Feature Importance (Top 20)
Built-in Feature Importance (Random Forest)
NVDA_HMact
avg_correlation_20d
ASML_HMact
portfolio_downside_vol_20d
MU_HMact
AVGO_HMact
portfolio_momentum_20d
portfolio_volatility_20d
avg_stock_momentum_20d
TSM_VRSpike
TSM_HMact
portfolio_volatility_60d
avg_stock_volatility_60d
INTC_HMact
avg_stock_volatility_20d
AMAT_HMact
MU_VRSpike
AMD_VRSpike
AVGO_VRSpike
QCOM_VRSpike
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
Built-in Importance (MDI)
SHAP-based Feature Importance
NVDA_HMact
ASML_HMact
AVGO_HMact
TSM_VRSpike
MU_VRSpike
portfolio_momentum_20d
avg_stock_momentum_20d
avg_correlation_20d
TSM_HMact
portfolio_downside_vol_20d
INTC_HMact
MU_HMact
avg_stock_volatility_60d
portfolio_volatility_20d
portfolio_volatility_60d
avg_stock_volatility_20d
AVGO_VRSpike
AMD_VRSpike
QCOM_VRSpike
AMAT_HMact
0.0000
0.0005
0.0010
0.0015
0.0020
SHAP Importance (Mean |SHAP|)

Non-Linear Patterns Discovered

NVDA_HMact: Inverted U-Shape

Moderate activity (0.25-0.35) yields maximum positive returns. Extreme activity (>0.4) signals speculative froth with diminishing effects.

TSM_VRSpike: J-Curve Dynamics

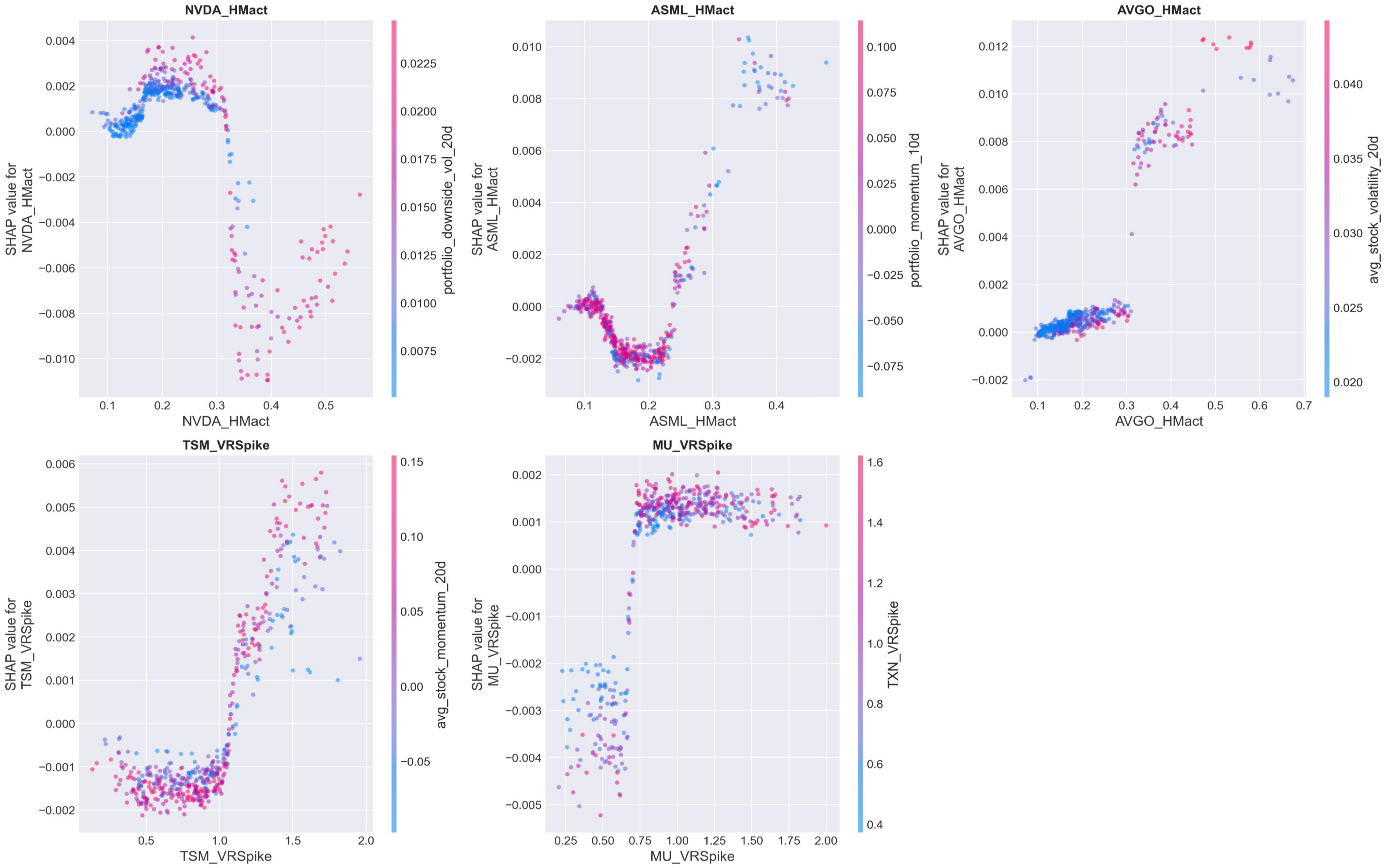
Low ratios (<1.0) predict negative returns. High ratios (>1.5) generate exponentially positive returns, capturing mean reversion after panic selling.

ASML_HMact: Threshold Effects

Binary-like behavior: values below 0.25 yield negative contributions, above triggers strongly positive effects reflecting lumpy equipment orders.

These non-monotonic relationships cannot be captured by linear models, justifying the tree-based ensemble approach.

SHAP Dependence Plots - Top 5 Features (Non-linear Relationships)



Financial Validation & Implementation

Theoretical Alignment

Results align with market microstructure theory (order flow information), regime-switching models, and behavioral finance predictions of panic-driven overshooting.

Supply Chain Economics

ASML upstream signals propagate through TSM foundry to NVDA downstream, embedding input-output production network dynamics.

Practical Application

10-day horizon aligns with institutional rebalancing frequencies. Test R^2 of 0.53% is commercially exploitable for portfolio construction.

Recommended Strategy

Deploy Random Forest predictions as expected return estimates in portfolio optimization framework, targeting Sortino ratio maximization through downside volatility features. Combine with conservative position sizing for risk-adjusted performance in semiconductor sector portfolios.

Thank You