AI IN FINANCE: NAVIGATING THE FUTURE

AIIF Conference at St Edward's University in Austin, TX

Title: *"AI-based Trading Strategies: Advanced Deep Learning Approaches"*

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https://github.com/FranQuant/AI-based-Trading-Strategies

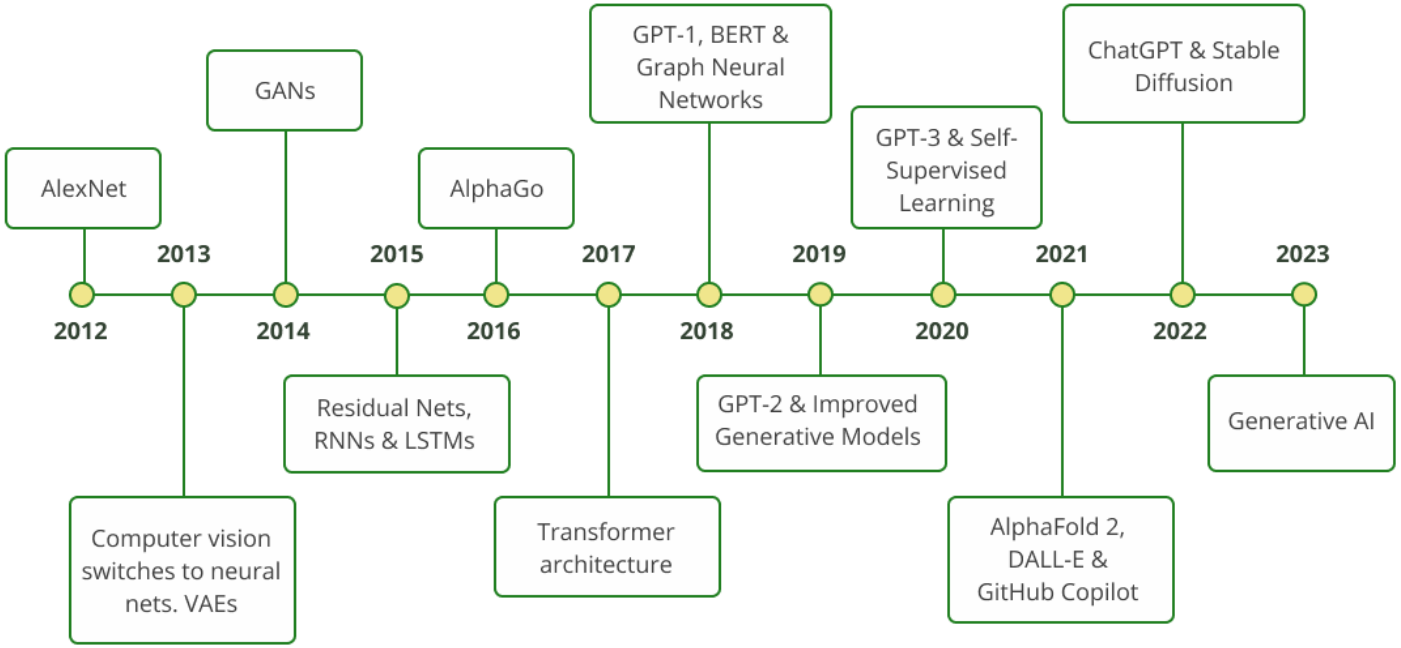
April 4, 2025

Why Deep Learning in Trading?

Market Complexity and AI Advantage

- **Why Deep Learning?**
- DL captures **complex, nonlinear relationships** in financial markets better than traditional linear models.
- Superior performance in **high-dimensional data** (e.g., price, volume, sentiment).
- Increasingly proven effective in **return forecasting** and **algorithmic trading strategies**.
- **Motivation for Exploring DL in Trading**
- Recent advancements in **LSTM** and **Attention mechanisms** offer promising tools to model financial time series dynamics.
- Growing emphasis on **Explainable AI (XAI)** aligns with practical needs for interpretability and regulatory compliance.
- Potential to leverage **alternative and high-frequency data** for enhanced predictive accuracy and robust trading decisions.

Transition from Traditional Machine Learning to Neural Networks and Deep Learning

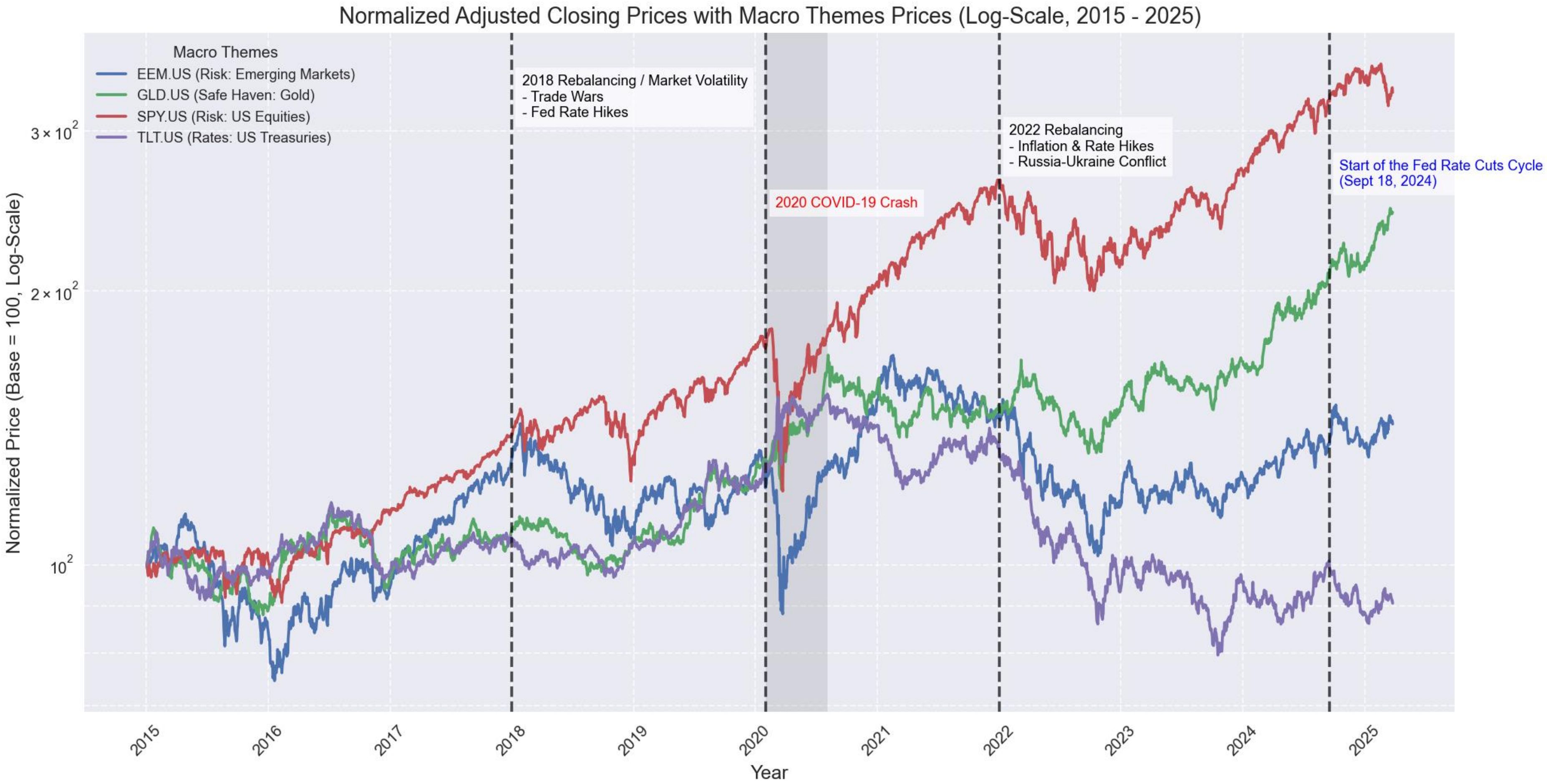


LinkedIn Pulse

Research Objectives in the Context of Recent Market Developments

Research Objectives Framed by Real-World Market Complexity

- Evaluate deep learning models (LSTM, Attention) for financial forecasting.
- Generate trading signals robust to volatility and structural shifts.
- Implement a realistic backtesting engine with risk controls.
- Compare model-driven strategies to benchmarks (SPY, gold, bonds).
- Explore interpretability (Attention weights, regimes).
- Bridge AI insights with human expertise (AI + HI synergy).



Deep Learning Strategy Pipeline: From Market Data to Model Evaluation

Structured Approach to Model-Driven Strategy

Data Pipeline

- **Data source**: EODHD API (2014–2025, SPY)
- Daily OHLCV + volume
- Adjusted log returns & volatility metrics

Feature Engineering

- **Momentum:** RSI, MACD, OBV
- **Trend:** EMA(50,200), ADX, Parabolic SAR
- **Volatility:** ATR, log-returns, slope
- Regime detection via HMM (3 states smoothed)

Modeling

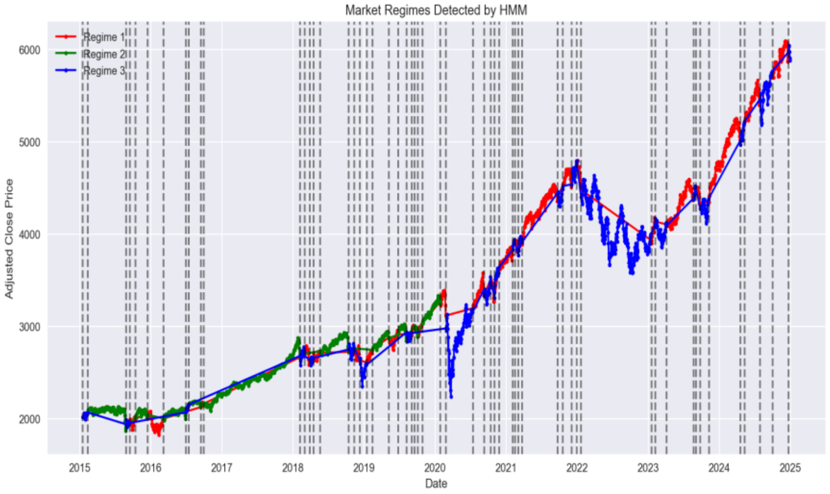
- LSTM 2-layer stacked
  GRU
  CNN
  Att-LSTM
  Transformer
- Binary classifier (next-day return sign)
- Dropout + early stopping
- Rolling TimeSeries CV (6 folds)

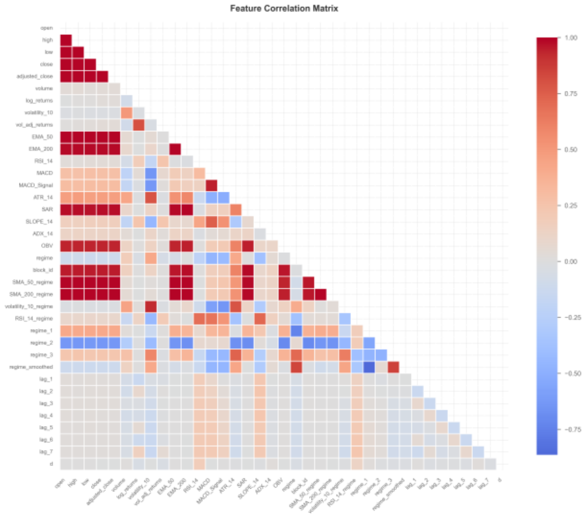
Signal & Strategy

- Threshold-based signal generation
- Adaptive holding
- Stop-loss + volatility-based position sizing

Backtesting & Evaluation

- Strategy vs. SPY (Sharpe, Drawdown)
- Transaction cost simulation
- QuantStats reports & visualizations





Performance Metrics

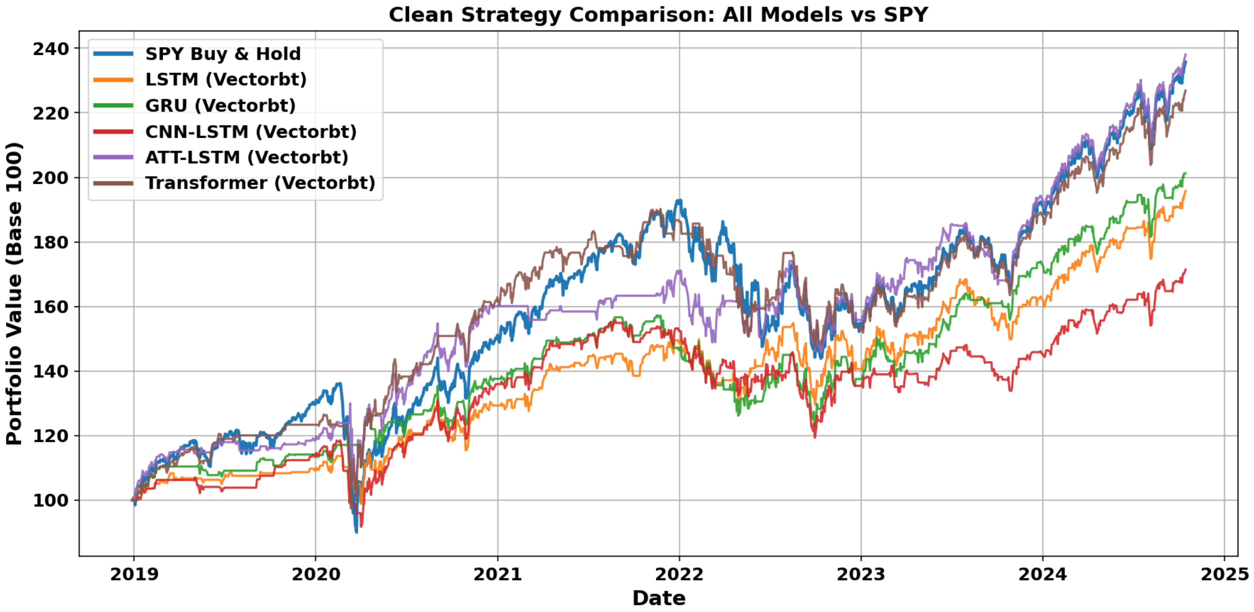
	Benchmark	Strategy
Start Period	2018-12-28	2018-12-28
End Period	2024-12-31	2024-12-31
Risk-Free Rate	0.0%	0.0%
Time in Market	100.0%	92.0%
Cumulative Return	136.32%	133.19%
CAGR﹪	10.38%	10.21%
Sharpe	0.81	1.07
Prob. Sharpe Ratio	97.48%	99.59%
Sortino	1.14	1.65
Sortino/√2	0.81	1.16
Omega	1.2	1.2
Max Drawdown	-33.92%	-20.9%
Longest DD Days	745	605
Gain/Pain Ratio	0.17	0.2
Gain/Pain (1M)	0.95	1.18
Payoff Ratio	1.15	1.2
Profit Factor	1.17	1.2
Common Sense Ratio	1.1	1.3
CPC Index	0.74	0.72
Tail Ratio	0.94	1.08
Outlier Win Ratio	3.37	4.25
Outlier Loss Ratio	3.28	4.32
MTD	-2.5%	1.53%
3M	2.5%	0.84%
6M	7.71%	3.23%
YTD	23.31%	4.57%
1Y	23.31%	4.57%
3Y (ann.)	6.93%	16.24%
5Y (ann.)	8.52%	14.8%
10Y (ann.)	10.38%	10.21%
All-time (ann.)	10.38%	10.21%
Avg. Drawdown	-1.76%	-2.03%
Avg. Drawdown Days	16	27
Recovery Factor	2.9	4.34
Ulcer Index	0.09	0.06
Serenity Index	0.78	1.05

Data → Feature Engineering → Deep Learning → Trading Signal → Backtesting → Trading Decisions

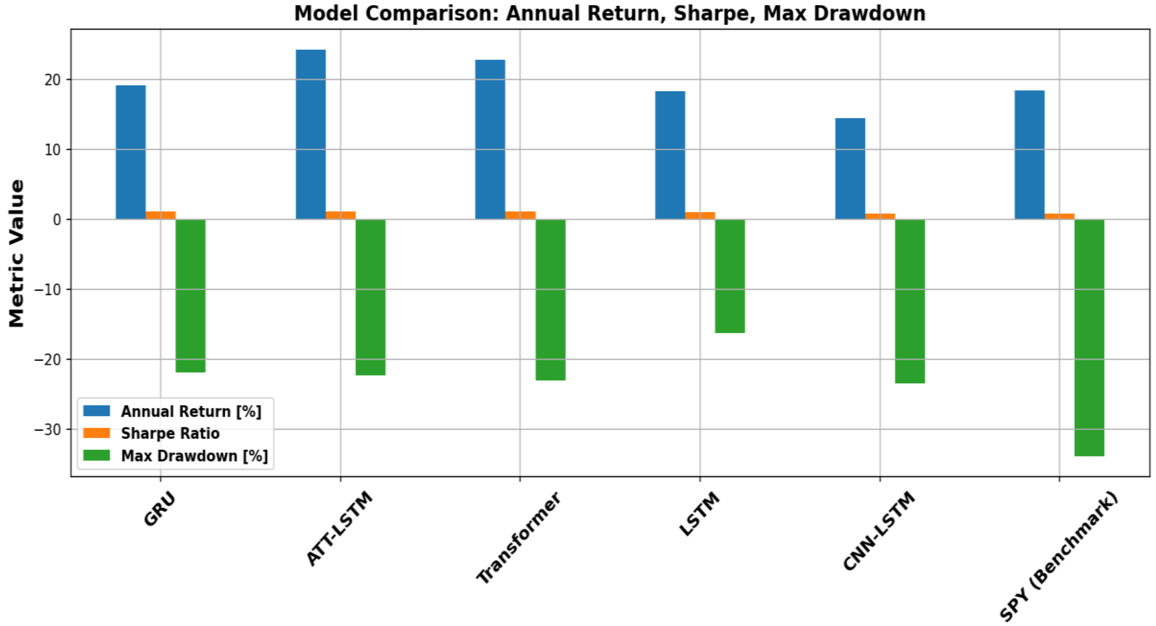
Performance Evaluation Dashboard

Performance Evaluation

Cumulative Returns



Key Metrics Visualization

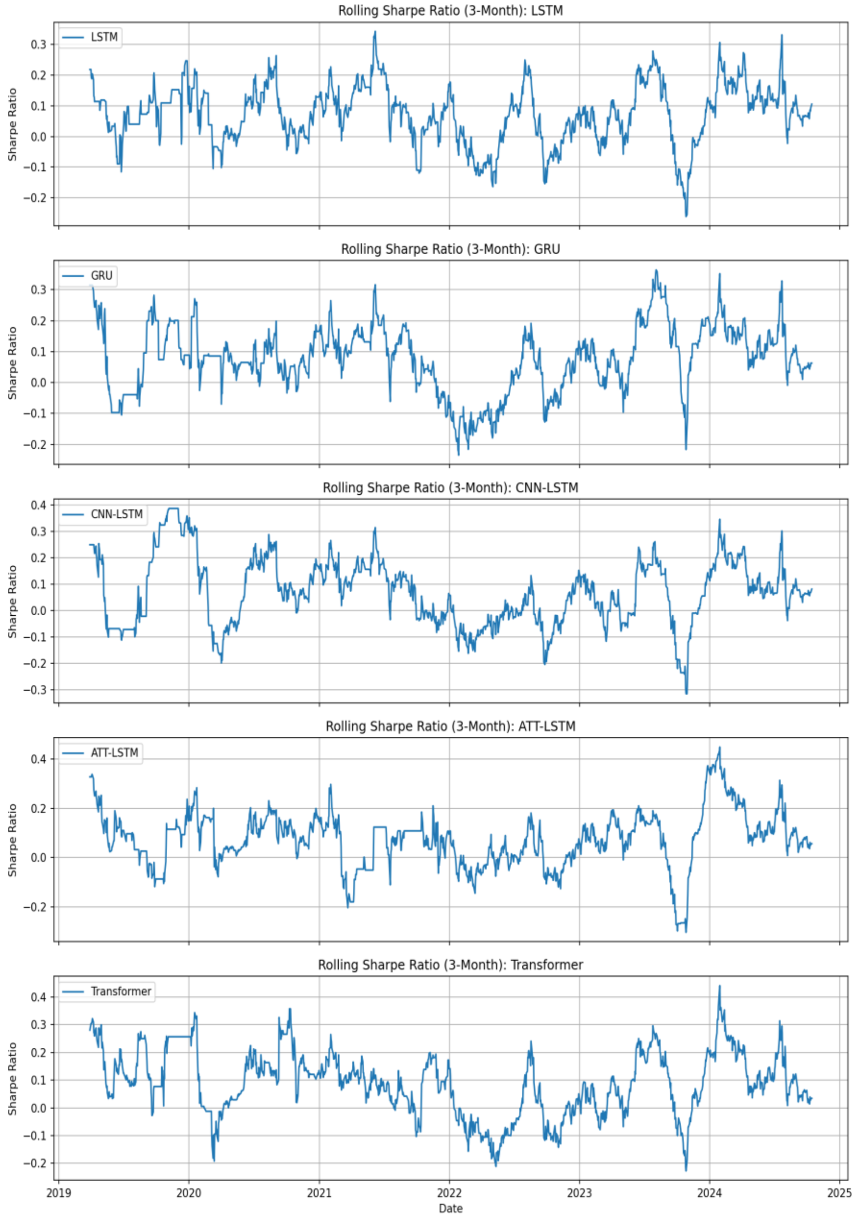


Performance Metrics

	Final Value	Total Return [%]	Annual Return [%]	Volatility [%]	Sharpe Ratio	Max Drawdown [%]
GRU	201.22	101.22	19.13	16.41	1.15	-21.91
ATT-LSTM	238.07	138.07	24.25	21.52	1.12	-22.37
Transformer	226.93	126.93	22.77	20.94	1.08	-23.02
LSTM	195.81	95.81	18.32	17.34	1.06	-16.30
CNN-LSTM	171.44	71.44	14.45	17.73	0.85	-23.42
SPY (Benchmark)	235.74	133.75	18.42	20.35	0.83	-33.92

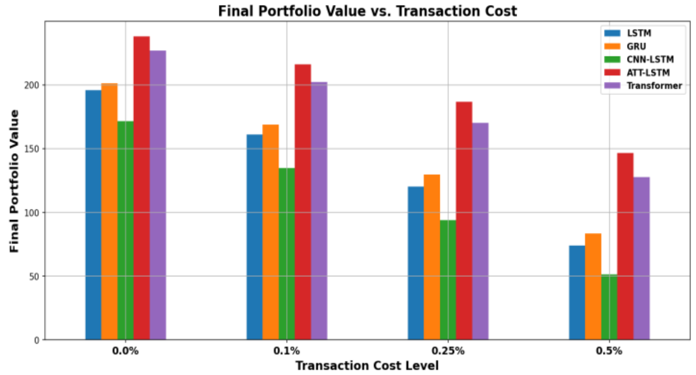
Strategy Diagnostics & Deep Dive

Rolling Sharpe Ratio Analysis

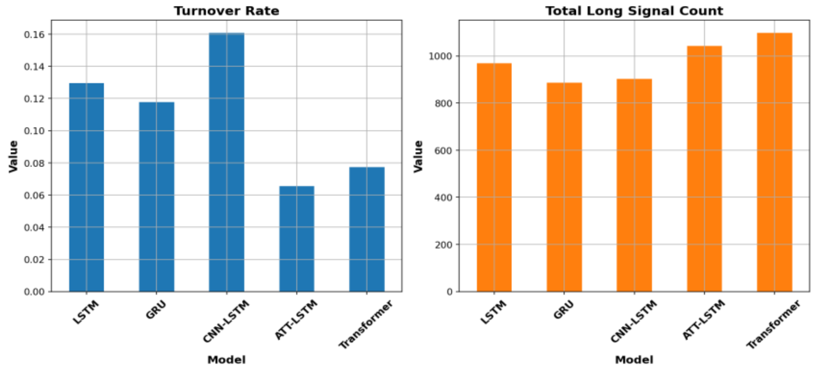


Strategy Behavior Diagnostics

Transaction Cost Sensitivity

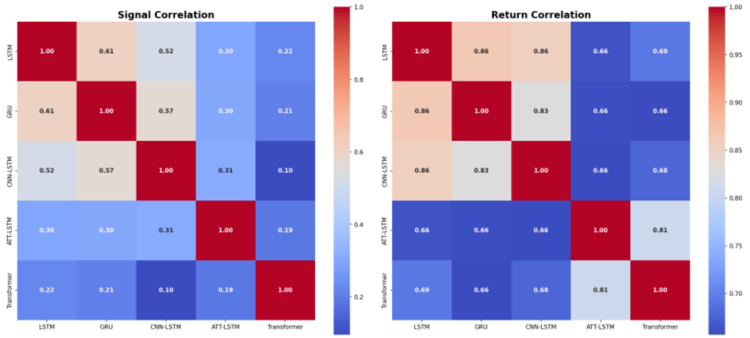


Turnover & Signal Activity

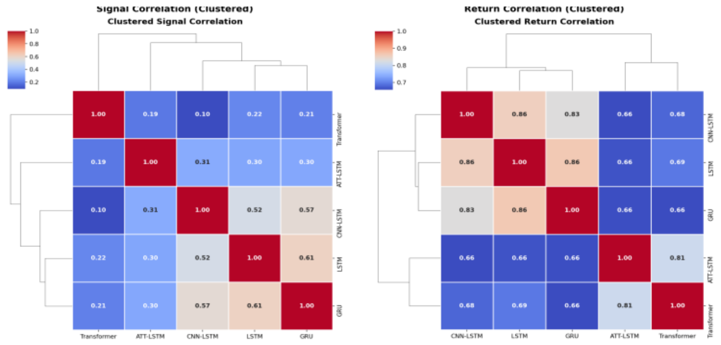


Cross-Model Strategy Correlation

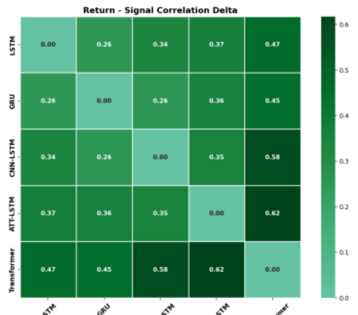
Signal & Return Correlation Heatmaps



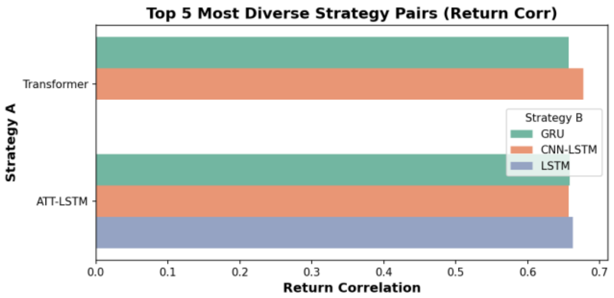
Clustered Strategy Correlation (Signal & Return)



Return vs. Signal Delta Analysis



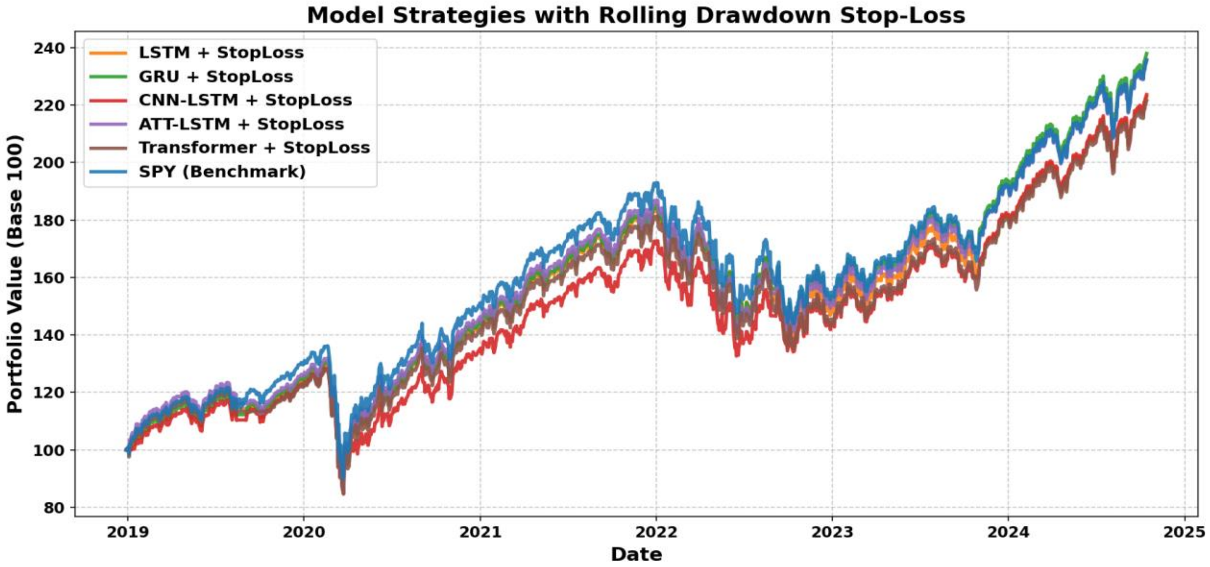
Low-Correlation Model Pairs for Diversified Allocation

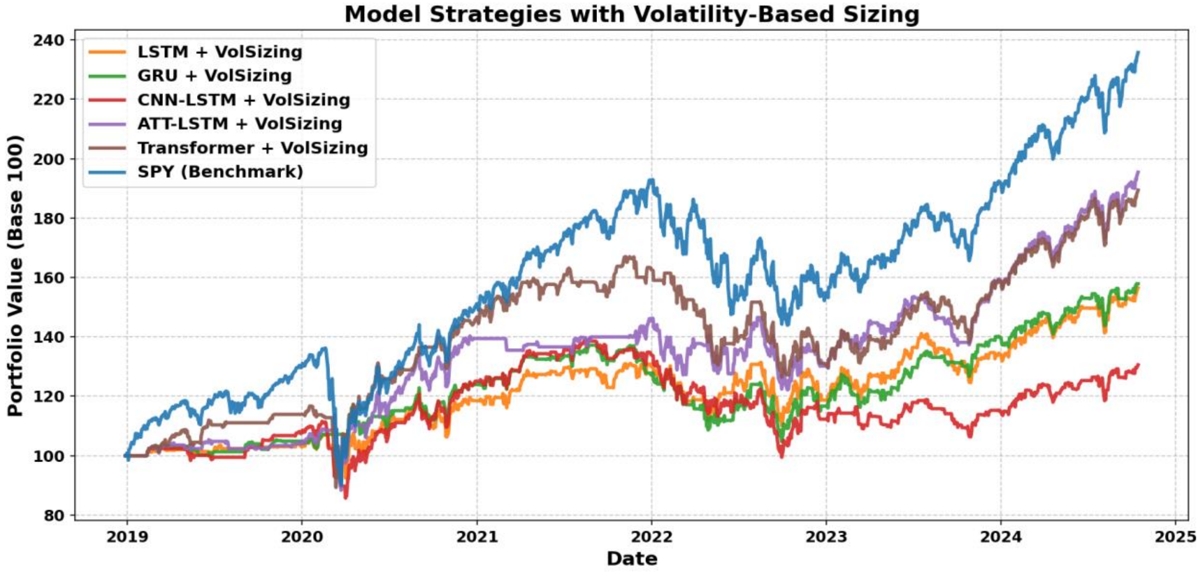


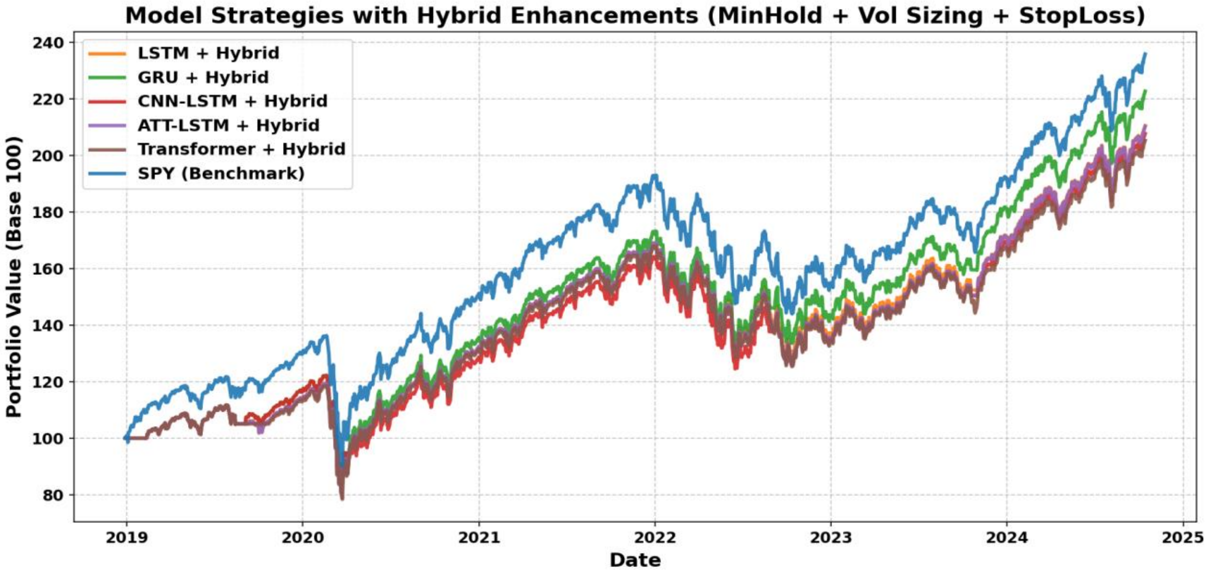
Strategy Enhancements & Realism Constraints: “From Signal to Deployable Strategy”

Strategy Enhancements (Overlays) — Cumulative Performance

How do constraint-based enhancements affect model returns over time?



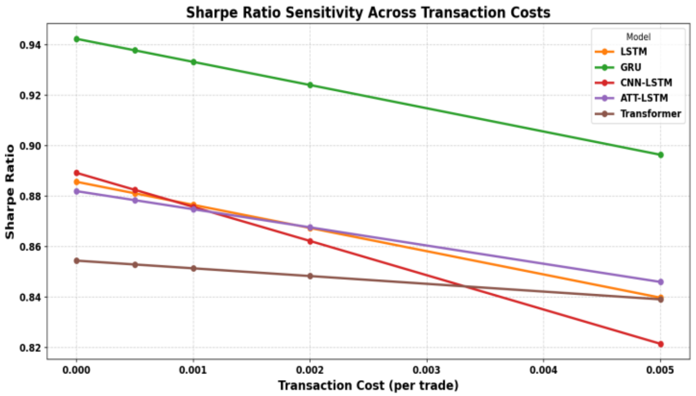


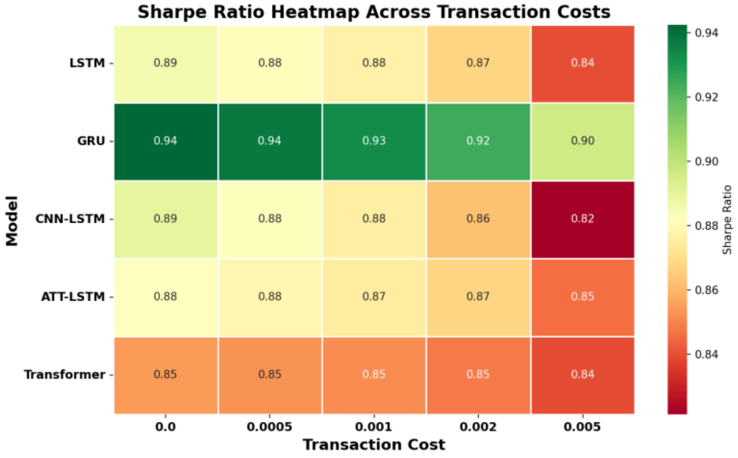


Strategy Enhancements & Realism Constraints: “From Signal to Deployable Strategy”

Sharpe Ratio Sensitivity (Robustness to Costs)

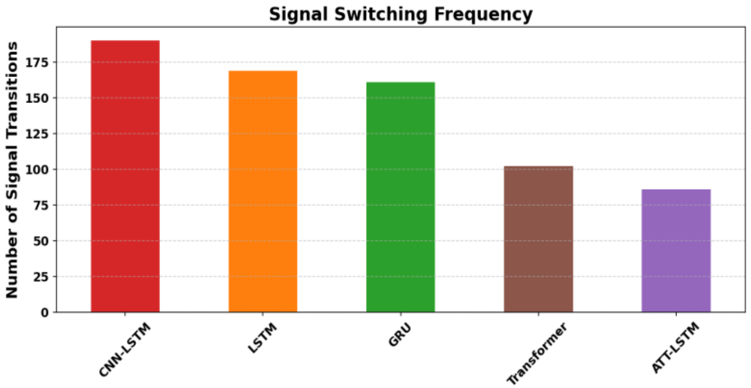
Are models still viable when frictional costs increase?

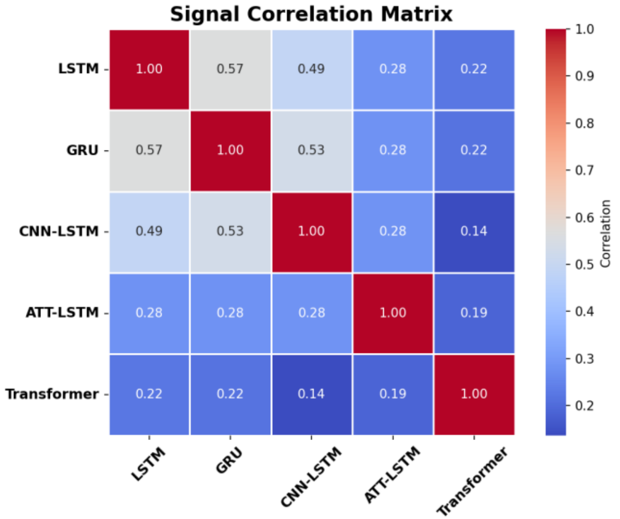




Signal Behavior Diagnostics

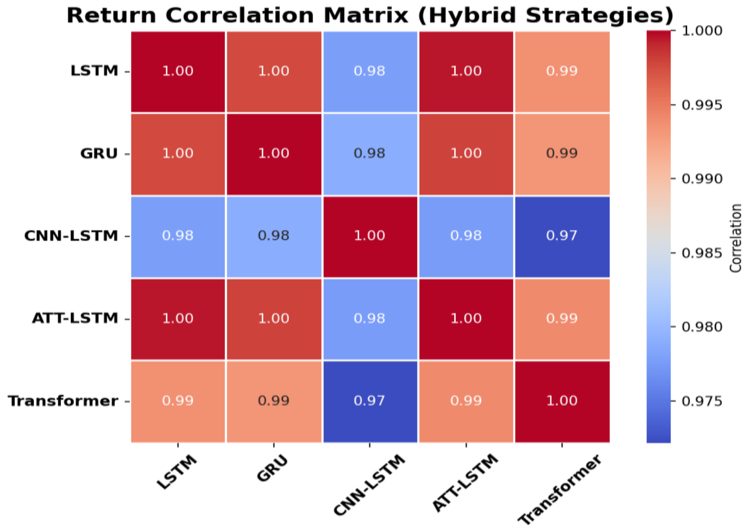
Which models trade more frequently or behave similarly?

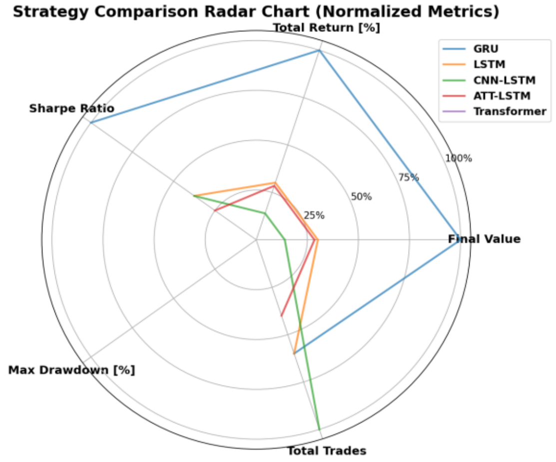




Return Correlation & Multi-Dimensional Profile

Are strategies offering complementary return paths and balanced tradeoffs across risk, return, and execution?

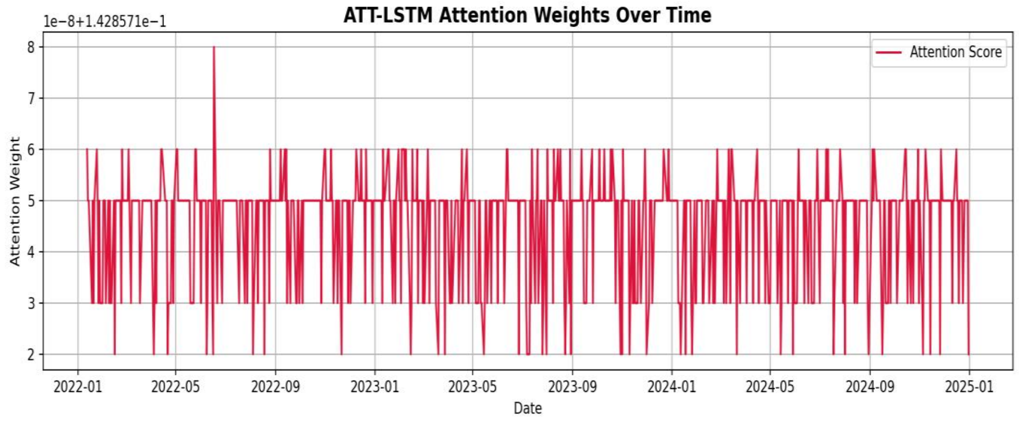


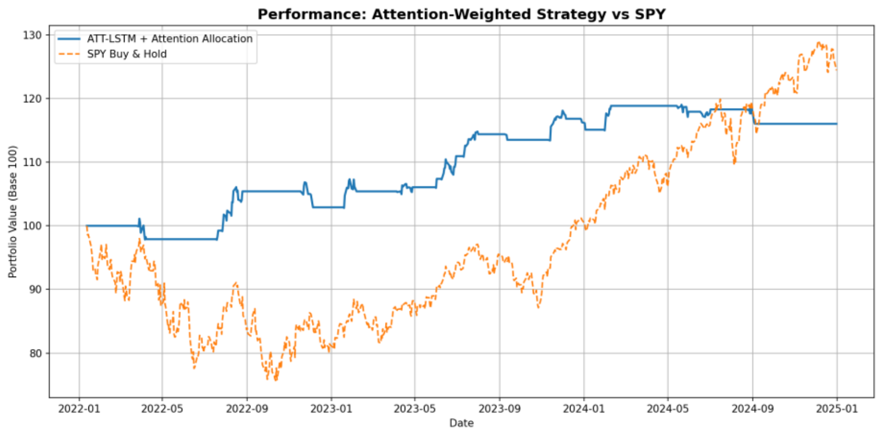


Attention-Based Strategy: From Interpretability to Allocation Precision

Section A: Interpretable Learning:

"Model-derived attention weights over time"





Stats Summary

Start	2022-01-12 00:00:00
End	2024-12-31 00:00:00
Period	746 days 00:00:00
Start Value	100.0
End Value	116.030009
Total Return [%]	16.030009
Benchmark Return [%]	24.443382
Max Gross Exposure [%]	100.0
Total Fees Paid	5.713962
Max Drawdown [%]	3.78842
Max Drawdown Duration	154 days 00:00:00
Total Trades	26
Total Closed Trades	26
Total Open Trades	0
Open Trade PnL	0.0
Win Rate [%]	57.692308
Best Trade [%]	4.886602
Worst Trade [%]	-2.104766
Avg Winning Trade [%]	1.847684
Avg Losing Trade [%]	-1.124925
Avg Winning Trade Duration	6 days 14:24:00
Avg Losing Trade Duration	3 days 08:43:38.181818181
Profit Factor	2.178734
Expectancy	0.616539
Sharpe Ratio	1.165968
Calmar Ratio	1.991759
Omega Ratio	1.443848
Sortino Ratio	1.932117
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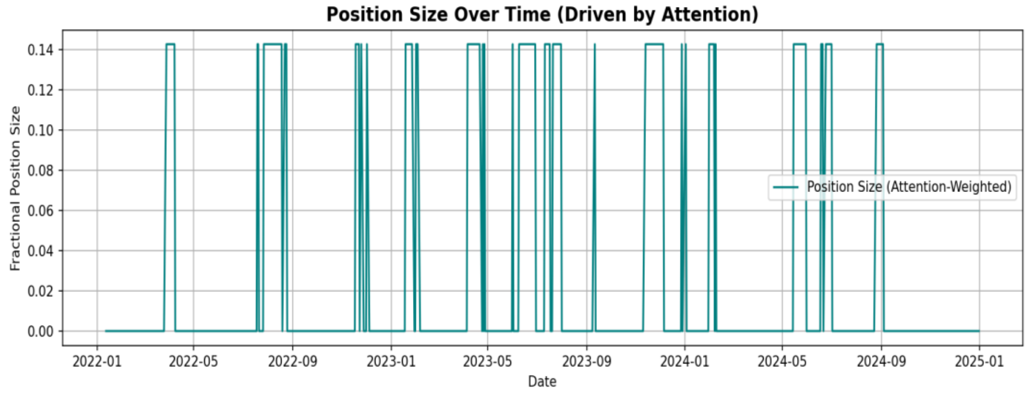
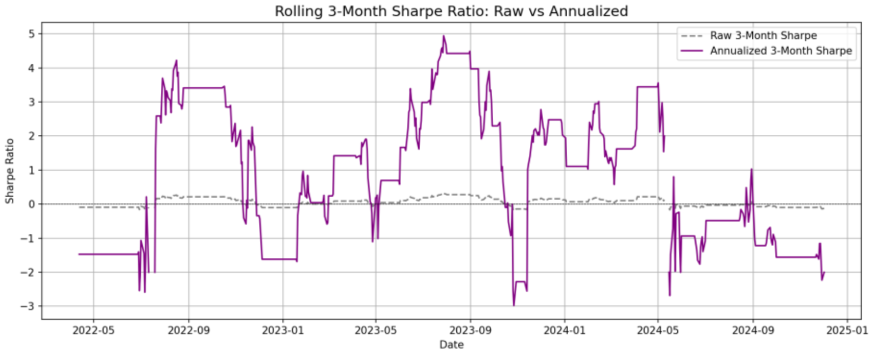
Section B: Strategy Deployment Logic:

"Position sizing and performance are governed by attention weights"



Section C: Risk-Adjusted Evaluation

"Evaluating consistency of performance with rolling Sharpe metrics"



Total Trades	26
Total Return [%]	16.030009
Max Drawdown [%]	3.78842
Sharpe Ratio	1.165968
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Next Steps: Forward-Looking Enhancements

The analysis provides a strong foundation for more advanced development. Recommended next steps include:

- **Model Ensembling**
  Combine models via voting, stacking, or weighted strategies to enhance robustness and exploit complementary signals.
- **Walk-Forward & Live Simulation**
  Introduce walk-forward testing to validate adaptability in changing market regimes.
- **Feature Expansion**
  Incorporate volatility, macro factors, and alternative data to enrich model inputs.
- **Risk-Aware Allocation**
  Move beyond binary signals toward dynamic position sizing and regime-based allocation.
- **Reinforcement Learning**
  Use RL agents for adaptive signal generation, cost-sensitive execution, and portfolio-level optimization.
- **LLM Integration: LLM-Augmented Signal Extraction**
  Use LLMs to extract structured sentiment and event signals from financial news and commentary. Enhance interpretability and predictive accuracy of deep learning signals. Incorporate LLM-derived insights as features in future Attention-based models for e.g.
- **Deployment Readiness**
  Prepare for live deployment using vectorbt-pro, API endpoints, and broker integration.

Bibliography

📚 **Literature Support Core Foundations:**

- Hochreiter & Schmidhuber (1997) — Long Short-Term Memory. (Introduced the LSTM architecture to solve vanishing gradient issues in sequence learning.)
- Goodfellow et al. (2016) — Deep Learning (Book). Chapter 7 discusses regularization (dropout, early stopping) and bias–variance in DL

📚 **Literature Support for Regime Detection:**

- López de Prado (2018), *"Advances in Financial Machine Learning"* (chapter on feature importance).

📚 **Literature Support for Regime Detection:**

- Hamilton (1989), "A new approach to the economic analysis of nonstationary time series."
- Nystrup, Hansen, & Madsen (2017), "Regime-Based Asset Allocation."

📚 **Literature Support for LSTM for Financial Forecasting:**

- Fischer & Krauss (2018), "Deep learning with long short-term memory networks for financial market predictions."
- Bao et al. (2017), "A deep learning framework for financial time series using stacked autoencoders and LSTM."

📚 **Literature for Grounding Backtesting & Evaluation**:

- Lopez de Prado (2018), *"Advances in Financial Machine Learning"*, particularly chapters on backtesting and strategy evaluation.
- Hilpisch (2020), *"Python for Algorithmic Trading"*, practical examples for backtesting.
- Bailey, Borwein, Prado, Zhu (2014), "Pseudo-Mathematics and Financial Charlatanism", to ensure rigorous evaluation avoiding biases.

📚 **Literature Support for Attention Mechanism:**

- Vaswani et al. (2017). "Attention Is All You Need" (Transformer architecture that replaced recurrence entirely.)
- Bahdanau et al. (2014). "Neural Machine Translation by Jointly Learning to Align and Translate" (First to apply attention to align input-output sequences dynamically)
- Zhang et al. (2022). "Attention Mechanisms in Time-Series Forecasting"

📚 **Literature Support (LLMs in Financial Forecasting):**

- Cao et al. (2023). "ChatGPT for Stock Market Prediction: Leveraging Language Models for Financial Forecasting"
- Xing, F.Z., et al. (2023). "Financial Sentiment Analysis Using Large Language Models"