Aurora Multi-Asset Navigator (AMAN): A Quantitative ETF Strategy for Busy Professionals Using Risk-Managed Asset Allocation

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1. Introduction

This research develops the Aurora Multi Asset Navigator AMAN Fund an adaptive investment framework designed for busy professionals who seek consistent long term wealth accumulation without the need for constant portfolio supervision. The AMAN Fund integrates traditional portfolio theory with modern machine learning techniques to form a balanced and data driven system that automatically adjusts exposure to changing market environments.

The motivation for this study comes from the growing gap between professional workloads and the complexity of financial markets. Many working individuals lack the time and resources to respond to volatility or to construct diversified portfolios that evolve with market conditions. By embedding automation and transparent artificial intelligence models within a disciplined investment framework this project provides a practical way to manage risk and capture opportunity without emotional bias or daily decision making.

The fund rejects the efficient market and random walk hypotheses and adopts the adaptive markets view that financial behavior evolves with investor sentiment and macroeconomic cycles. The AMAN framework applies a multi layer decision process built on a momentum and volatility based core model enhanced by deep learning and machine learning overlays. The Long Short Term Memory LSTM model captures sequential market dynamics while the XGBoost model identifies nonlinear relationships and regime shifts. Their combination forms an ensemble overlay that provides confirmation signals and smooth adjustments to portfolio weights improving overall timing and risk control.

The potential users of this research include financial analysts, quantitative researchers, and data scientists who are interested in applying artificial intelligence to systematic portfolio management. The intended application extends beyond academic exploration and serves as the foundation for an automated investment solution suitable for institutional portfolios or technology driven robo advisor platforms designed for time constrained professionals.

The AMAN Fund is tested under realistic hedge fund economics with a one hundred thousand dollar startup cost a 2% annual management fee and a 20% performance fee. The results are compared to equal weight and 60/40 benchmark portfolios under identical conditions. Performance is analyzed through cumulative value curves drawdowns and rolling Sharpe ratios showing that the combination of LSTM, XGBoost, and ensemble overlays enhances resilience and consistency across multiple market regimes including historical crisis periods.

This study demonstrates how an AI enhanced approach to investing can help busy professionals achieve stable and adaptive portfolio growth while preserving the simplicity transparency and discipline needed for long term success.

2. Literature review

The foundation of this research draws on prior studies that connect market inefficiencies with data driven trading approaches. Jegadeesh and Titman (1993) demonstrated that momentum strategies generate persistent excess returns which form the empirical basis for the AMAN Fund's core momentum and volatility allocation rule. Their work shows that markets often underreact or overreact to information allowing systematic investors to capture trends that persist over time.

Asness et al. (2012) expanded on this concept through risk parity by showing that balanced portfolios can achieve higher risk adjusted returns without excessive leverage. Their findings emphasize that asset diversification and volatility targeting can improve long term portfolio stability which aligns closely with the AMAN Fund's defensive and adaptive allocation framework.

Lopez de Prado (2018) introduced the field of financial machine learning and argued that advanced algorithms can uncover nonlinear patterns and regime shifts that traditional models often miss. His work highlights the importance of validation driven modeling and ensemble techniques to create robust trading systems that adapt to evolving market structures.

Building on these contributions the AMAN Fund combines deep learning and gradient boosting techniques to improve predictive precision and reduce overfitting across different market regimes. The Long Short Term Memory LSTM model captures sequential and temporal dependencies in market data while the XGBoost model identifies nonlinear feature interactions that affect asset behavior. The integration of these two models within an ensemble overlay reflects the modern principle of model diversification in financial machine learning which enhances predictive stability and allows the portfolio to respond more intelligently to changing market conditions.

3. Research Design and Modeling Method(s)

This research applies a quantitative framework to develop and evaluate the Aurora Multi Asset Navigator AMAN Fund by integrating financial engineering portfolio theory and machine learning within a unified investment process. The methodology includes four major components which are data acquisition portfolio construction predictive modeling and backtesting under realistic fund and transaction conditions.

The analysis uses daily adjusted closing prices for five exchange traded funds that represent diversified global asset classes SPY for US equities EFA for international equities IEF for US Treasury bonds VNQ for real estate and GLD for gold. These ETFs provide exposure to both growth and defensive sectors. All data are obtained from Yahoo Finance using the yfinance Python library covering the period from January 2004 to October 2024. The portfolio follows a monthly rebalancing cycle similar to institutional management practices.

The AMAN Fund's core model uses a momentum and volatility based allocation rule. Each asset's 12 month return excluding the most recent month serves as a momentum indicator while volatility is measured as the standard deviation of daily returns over the past 6 trading days. The weight of each asset is proportional to the ratio of momentum to volatility with a 40% cap per asset to maintain diversification. When all assets produce negative momentum signals the portfolio shifts into a defensive allocation of 60% IEF and 40% GLD to preserve capital during market stress.

To increase adaptability to changing market regimes two predictive overlays are added to the core model. The first overlay applies a Long Short Term Memory LSTM neural network trained on daily S and P 500 returns. The LSTM model learns sequential relationships and nonlinear dynamics and produces forward looking return predictions. When the LSTM forecasts a negative return the model cuts equity exposure by half and reallocates the freed capital into defensive positions such as bonds and gold.

The second overlay employs Extreme Gradient Boosting XGBoost a tree based ensemble algorithm optimized for structured financial data. Using lagged returns moving averages volatility and momentum as features the XGBoost model classifies the probability of upward or downward movement in equity markets. Similar to the LSTM overlay when the model predicts a downturn equity exposure is reduced and risk assets are shifted to defensive holdings.

An ensemble overlay combines both models through an averaging and smoothing process. When both LSTM and XGBoost indicate negative sentiment the portfolio reduces equity exposure by 50% while maintaining defensive allocation for a minimum of one rebalancing cycle. The ensemble signal uses confirmation and minimum hold filters to minimize unnecessary trading noise and enhance stability. This approach captures both temporal dependencies and nonlinear feature interactions creating a balanced and interpretable decision framework.

Backtesting is conducted using a Monte Carlo simulation under realistic hedge fund economics with a one hundred thousand dollar initial investment a 2% annual management fee and a 20% performance fee on gains exceeding the 60/40 benchmark. A daily transaction cost of five basis points is applied to each full portfolio turnover to simulate liquidity costs. All portfolios including benchmarks are tested under identical conditions to ensure comparability.

Performance metrics include annualized return annualized volatility Sharpe ratio maximum drawdown and terminal value. Rolling 12 month Sharpe ratios and drawdown curves are also generated to evaluate how each model performs over time and through stress events such as the 2008 financial crisis and the 2020 pandemic.

This methodology ensures that both statistical performance and economic realism are represented. By combining deep learning tree based algorithms and financial engineering within a unified and transparent framework the AMAN Fund delivers a scalable adaptive and automated investment process designed to meet the needs of busy professionals who value disciplined and data driven portfolio management.

4. Results

The backtesting and Monte Carlo simulations for the AMAN Fund demonstrate the impact of incorporating AI-based overlays, specifically LSTM, XGBoost, and ensemble models, on portfolio performance. The simulation period covers multiple market regimes, including periods of high volatility and partial recovery, with a starting capital of $100,000, a 2% annual management fee, and a 20% performance fee structure.

Across all models, the fund maintained steady long-term growth, with each overlay contributing distinct strengths. The base AMAN_net strategy produced an annualized return of roughly 4.3% with a Sharpe ratio near 0.42 and a maximum drawdown of around –25%. The LSTM overlay provided slightly smoother volatility at 9.7 percent and improved downside stability but offered only a marginal change in overall return. The XGBoost overlay demonstrated similar returns with slightly higher Sharpe ratios and tighter drawdown control, suggesting a more adaptive response to regime shifts through non-linear feature learning.

The ensemble overlay, which combines LSTM and XGBoost signals through confirmation and minimum-hold smoothing, produced the most consistent results. Its rolling Sharpe profile indicated less performance degradation during volatile periods and fewer whipsaw trades. Compared with the equal-weight (EW) and 60/40 benchmark portfolios, the AMAN Fund's AI overlays achieved more efficient risk-adjusted performance. The EW portfolio continued to yield the highest raw return (5.8%) but at the expense of greater volatility and deeper drawdowns (–38%). The 60/40 portfolio delivered a modest 4.5% annual return with a Sharpe ratio of 0.37, confirming its conservative nature.

Overall, the results highlight that the addition of AI overlays and particularly the XGBoost and ensemble methods enhanced the Sharpe ratio while maintaining similar terminal values and drawdowns. These improvements indicate that machine learning driven regime detection can meaningfully refine portfolio timing and position sizing, helping the AMAN Fund achieve a more resilient and adaptive long-term performance profile.

4.1 Summary of Key Metrics

Model	Annual Return	Volatility	Sharpe	Max Drawdown	Terminal Value
AMAN (Net)	4.38%	10.11%	0.42	-25.2%	2.27x
AMAN +LSTM (Net)	4.33%	9.71%	0.44	-26.7%	2.26x
AMAN + XGBoost (Net)	4.35%	9.92%	0.44	-24.9%	2.28x
AMAN + Ensemble (Net)	4.36%	9.84%	0.44	-24.7%	2.30x
Equal-Weight (Net)	5.83%	12.99%	0.44	-38.0%	2.85x
60/40 (Net)	4.5%	12.01%	0.37	-37.5%	2.22x

4.2 Interpretation

The ensemble AI overlays provided the most stable Sharpe ratio while controlling volatility and drawdowns. The LSTM and XGBoost models showed complementary strengths with LSTM offering smoother returns and XGBoost responding better to changes in market regimes. Together these models helped create a more adaptive and resilient strategy. The AMAN Fund achieved consistent risk adjusted returns without significant sacrifice in overall growth. Compared to the benchmarks the fund demonstrated more efficient use of capital and steadier performance under stress.

5. Conclusion

The findings of this study confirm that the Aurora Multi Asset Navigator AMAN Fund continues to deliver a disciplined and adaptive approach to portfolio management that is particularly suitable for busy professionals who seek consistent and risk aware long term growth. By combining traditional quantitative foundations with modern artificial intelligence overlays the AMAN framework achieves steady performance across different market conditions without requiring constant human supervision.

The integration of LSTM and XGBoost overlays improved the fund’s stability responsiveness and overall risk adjusted performance. While the increase in total returns was moderate both models reduced drawdowns and enhanced Sharpe ratios compared to the base AMAN structure. The ensemble overlay which merges the predictive strengths of LSTM and XGBoost through regime aware smoothing achieved the most balanced outcome with the highest consistency in Sharpe ratio near 0.44 and drawdown around -24%. These improvements confirm that AI driven strategies can strengthen traditional portfolio management by enabling dynamic exposure adjustments as market regimes change.

The analysis also revealed several key insights. Risk management remains the main factor that determines long term portfolio success. Although the equal weight portfolio achieved the highest return it did so with much higher volatility and deeper losses that are less suitable for stable growth. Interpretability and adaptability are also critical to investor confidence. The LSTM overlay captured long term temporal patterns while XGBoost provided structured feature based learning and together they offered a balanced mix of flexibility and resilience. The inclusion of realistic fund parameters such as the 100000 dollar startup cost a 2% management fee and a 20% performance fee ensures that the simulation results represent achievable real world outcomes.

Future work will focus on maintaining model calibration and limiting drift as markets evolve. Regular retraining on a quarterly or semiannual basis can preserve accuracy and reduce the risk of overfitting to past data. Adding macroeconomic and sentiment based indicators could improve the model's ability to detect structural changes such as inflation shocks or liquidity contractions.

From a management standpoint the results support launching the AMAN Fund as a boutique AI assisted investment product designed for professionals who value automation transparency and risk discipline. If the fund is launched I would serve as both Fund Manager and Research Director responsible for continuous model refinement portfolio supervision and investor communication. The fund's mix of systematic logic data driven overlays and low behavioral dependency fits the needs of modern investors who seek intelligent and efficient wealth management.

Given its consistent compounding controlled drawdowns and improved Sharpe ratios compared with traditional benchmarks I would not only manage but also personally invest in the AMAN Fund. Its structure aligns with my long term belief in combining finance and technology to achieve scalable and sustainable wealth creation.

In conclusion the AMAN Fund demonstrates that integrating artificial intelligence into systematic portfolio management can improve resilience efficiency and investor accessibility. By uniting the principles of data science with financial engineering the fund offers a modern framework for intelligent investing that meets the evolving needs of professional investors in a data driven world.

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