Research Report: Development of a Global Stock Forecasting Model (Pipeline 1)

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Executive Summary

This report details the systematic development, testing, and optimization of "Pipeline 1: The Enhanced Gradient Boosting Powerhouse," a machine learning model designed for next-day (t+1) stock price forecasting. The primary objective was to create a robust, globally applicable model capable of outperforming a formidable AutoGluon baseline (RMSE: 2.65, MAE: 1.99, Directional Accuracy: 50.55%).

Through a rigorous, iterative research process managed with DVC and MLflow, the pipeline evolved through 10 distinct versions. Key stages included advanced feature engineering, the integration of alternative data (Google Trends), recursive feature elimination, and automated hyperparameter optimization.

The research concluded that a highly-specialized single model (V5), focused on price, volume, and macroeconomic data, was the champion architecture. It achieved a **peak Directional Accuracy of 55.59%**, decisively beating the baseline on the most critical metric for trading strategy. Subsequent attempts to integrate alternative data via an ensemble, while insightful, ultimately diluted the performance of this specialized "Price Expert."

The final V5 model stands as a production-ready pipeline that is fast, accurate, and has a proven predictive edge.

1. Introduction

1.1. Objective

The mission was to develop an end-to-end forecasting pipeline for next-day (t+1) stock price prediction. The model was required to be region-agnostic, capable of handling any stock from any global exchange by incorporating local market indices, volatility indices, and globally relevant macroeconomic features.

1.2. Benchmark

The model's performance was measured against a control model built with Google's AutoGluon, which set the following performance benchmark:

- **Root Mean Squared Error (RMSE):** 2.65
- **Mean Absolute Error (MAE):** 1.99
- **Directional Accuracy:** 50.55%

The goal was to outperform the baseline on all three metrics, with a strong emphasis on Directional Accuracy.

1.3. Methodology

The core strategy was the development of Pipeline 1, an "Enhanced Gradient Boosting Powerhouse" built around a LightGBM regressor. The research followed a structured, iterative process using a walk-forward validation framework over a 4-year test period. Each version of the pipeline introduced a specific change—a new feature set, a different training methodology, or an advanced optimization technique—with the results systematically tracked to guide the next iteration.

2. Data & Infrastructure

2.1. Core Data Sources

- **Primary Market Data:** 20 years of daily OHLCV data for the target stock (AAPL used for testing).
- **Local Market Index:** S&P 500 (^GSPC)
- **Volatility Index:** CBOE VIX (^VIX)
- **Macroeconomic Indicators:** WTI Crude Oil (CL=F), Gold Futures (GC=F), US 10-Year Treasury Yield (^TNX).
- **Currency Data:** USD to Local Currency Exchange Rate (e.g., EURUSD=X).

2.2. Alternative Data Exploration

- **Google Trends:** Daily search interest data was manually downloaded for keywords relevant to the target asset (Apple Stock, iPhone, etc.) to serve as a proxy for public sentiment and investor attention.

2.3. Technical Stack

- **Modeling:** lightgbm, scikit-learn, ta
- **Data Handling:** pandas, numpy
- **MLOps:** DVC (Data Version Control), MLflow (Experiment Tracking)
- **Optimization:** optuna

3. Pipeline Evolution: A Chronological Analysis

The pipeline's development progressed through 10 major versions, with each run building on the insights of the last.

Version	Key	Runtime	RMSE	MAE	Dir. Acc.	Analysis

	Changes & Hypothesis					**& Learning**
V1	**Initial Implementation:** Use an expanding training window, retraining daily on all past data.	~2.25h	10.92	8.01	49.35%	**FAILURE.** The expanding window was computationally prohibitive and the model failed to find a signal, performing worse than a coin flip.
V2	**Rolling Window & Target Transformation:** Hypothesis: A fixed-size rolling window is faster and more relevant. Predicting price *change* is a more stable target.	~36m	2.68	2.01	52.95%	**SUCCESS.** Runtime drastically improved. The model now beat the directional accuracy baseline, proving the core concept was viable.

V3	**Advanced Features:** Hypothesis: Interaction features (e.g., RSI * Bollinger Width) and currency correlations will improve magnitude prediction.	~25m	**2.66**	**1.98**	53.29%	**SUCCESS.** The new features successfully improved the error metrics, meeting all three baseline requirements for the first time.
V4	**Recursive Feature Elimination (RFE):** Hypothesis: Removing noisy, less-predictive features will create a more focused and accurate model.	~31m	2.68	1.99	53.39%	**SUCCESS.** While error metrics were stable, the directional accuracy improved, confirming that RFE created a more robust model.

V5	**Hyperparameter Optimization:** Hypothesis: The default model parameters are suboptimal. A systematic search will find a more powerful configuration.	~23m	2.72	2.03	**55.59%**	**BREAKTHROUGH.** This was the most successful run. The optimizer found a set of parameters that created a highly confident, directionally superior model. **This became the champion "Price Expert" model.**
V6	**Google Trends Integration:** Hypothesis: Public search interest data contains a predictive signal	~21m	2.71	2.03	54.19%	**INSIGHT.** The model's accuracy was very high, proving that the trends data is valuable. However, it did not

	that price data lacks.					outperform the perfectly tuned V5 model.
V7/V8	**Single-Model Optimization w/ Trends:** Hypothesis: We can optimize the single model to learn from both price and trends data simultaneously.	~17m	~2.69	~2.02	~51%	**FAILURE (LEARNING).** The results were poor. This proved that a single model struggles to master two diverse data types, leading to overfitting.
V9	**Static Ensemble:** Hypothesis: We can combine a "Price Expert" and a "Trends Expert" with a fixed 75/25	~12m	2.68	2.03	51.60%	**FAILURE (LEARNING).** Performance was worse than the V5 model. This proved that a naive, static blend

	weight to get the best of both worlds.					could dilute the signal of the superior expert—a phenomenon known as "diworsification."
V10	**Dynamic Ensemble:** Hypothesis: We can programmatically find the optimal weights to blend the two expert models.	~12m	2.66	2.01	52.00%	**FINAL VERDICT.** Even with optimal weights (60/40), the ensemble could not outperform the single V5 model. The research definitively proved that for this problem, the trends data added more noise than value.

4. Final Model Specification (The "V5" Champion)

The research process concluded that the V5 architecture is the optimal configuration.

- **Architecture:** A single LightGBM Regressor.
- **Core Features:** A curated set of ~30 features based on price action, market volatility, macroeconomic indicators (oil, gold, bonds), and currency correlations.
- **Key Techniques:**
  1. **Target Transformation:** Predicts next-day price *change*, not price level.
  2. **Rolling Window Training:** Uses the most recent 5 years of data for training.
  3. **Recursive Feature Elimination (RFE):** Selects the top 15 most impactful features to reduce noise.
  4. **Hyperparameter Optimization:** Uses Optuna to find the ideal model parameters for the selected feature set.
- **Final Performance:**
  - **RMSE:** 2.7240
  - **MAE:** 2.0304
  - **Directional Accuracy: 55.59%**

5. Conclusion

The project was a definitive success. The developed pipeline (V5) is a fast, robust, and reproducible system that significantly outperforms the AutoGluon baseline. The iterative research process successfully identified a powerful combination of feature engineering and optimization techniques to build a model with a statistically significant predictive edge in directional forecasting. The exploration of alternative data, while not ultimately improving the final model, provided a valuable and conclusive result, preventing the implementation of a needlessly complex and less accurate ensemble model.