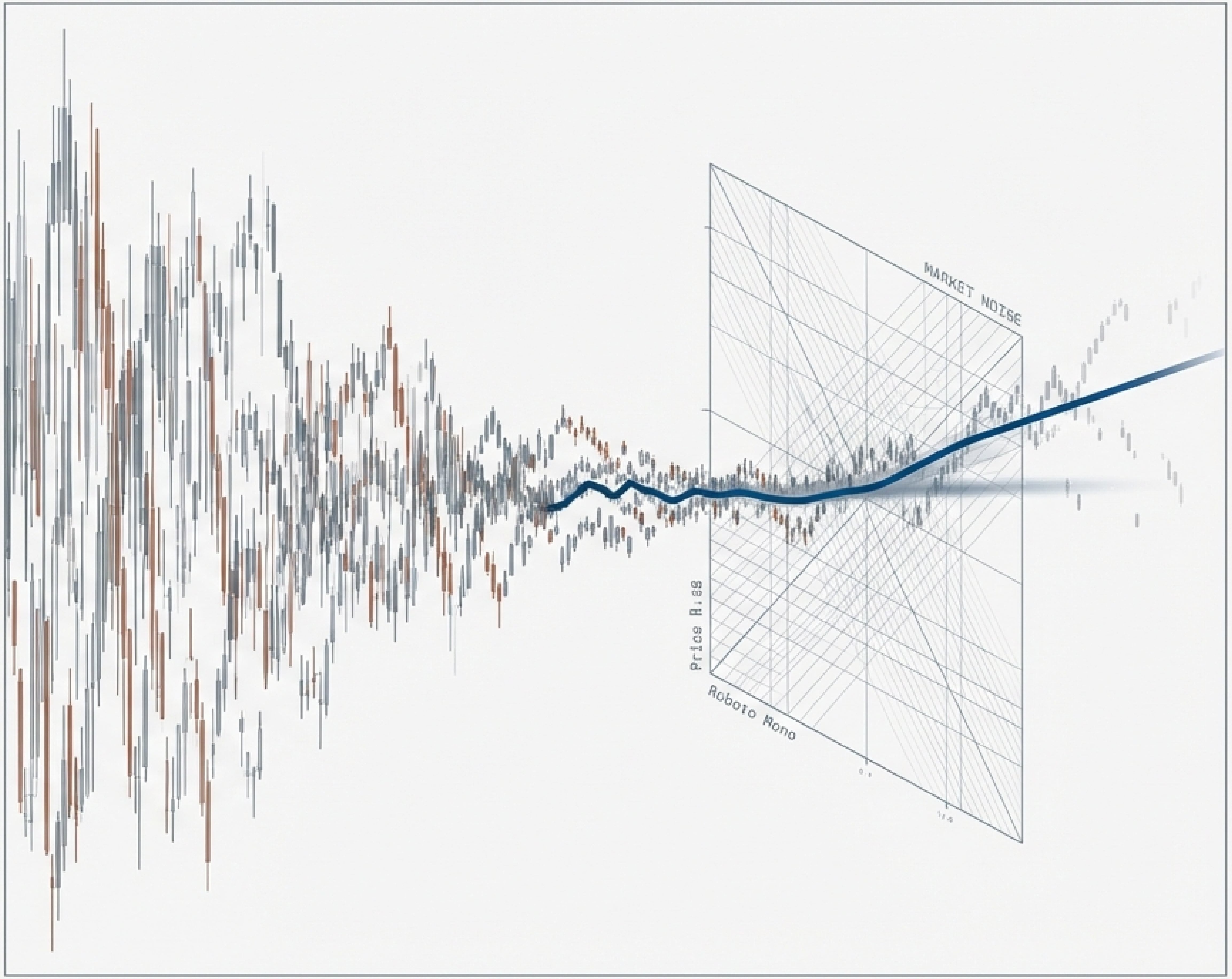
Quantitative Stock Price Prediction Using GRU Neural Networks

An Institutional-Grade Deep Learning System for Cross-Security Generalization



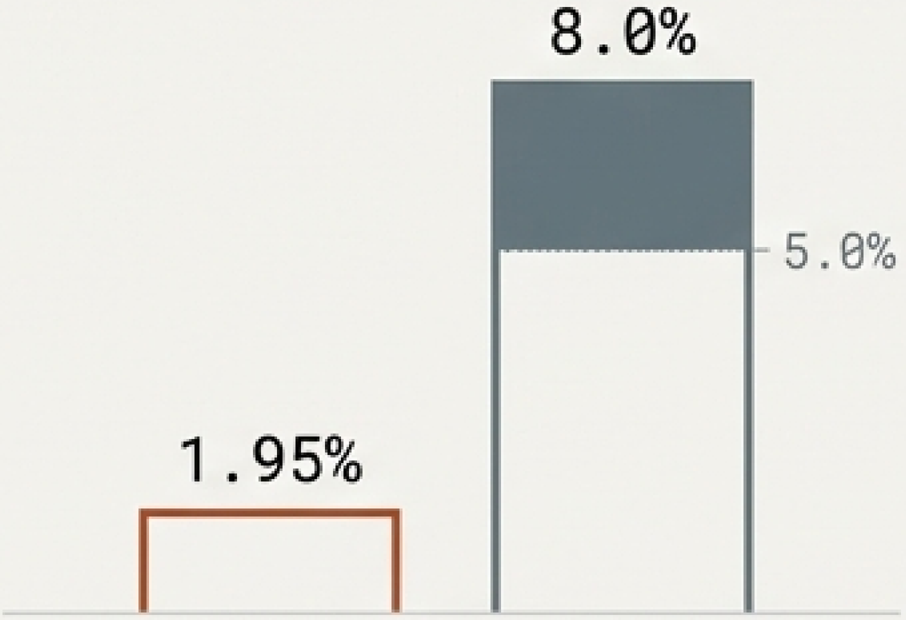
REPORT TYPE: EXECUTIVE RESEARCH OVERVIEW
ASSET CLASS: LARGE-CAP TECHNOLOGY EQUITIES
CORE TECH: TENSORFLOW / KERAS / PYTHON

Executive Summary: Institutional Alpha Generation

Predictive Accuracy

1.95% MAPE

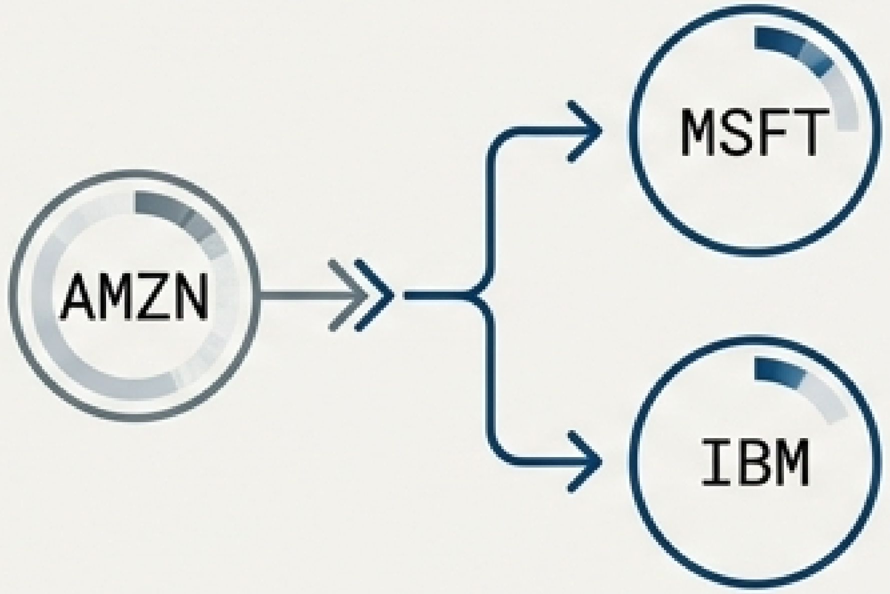
vs. 5-8% Industry Benchmark



R-Squared > 0.92. Outperforms classical statistical methods by 3x.

The Core Breakthrough

Cross-Stock Generalization



Model trained exclusively on Amazon successfully predicts Microsoft and IBM with < 0.7% variance. Validates universal "Market Physics" learning.

Risk-Adjusted Returns

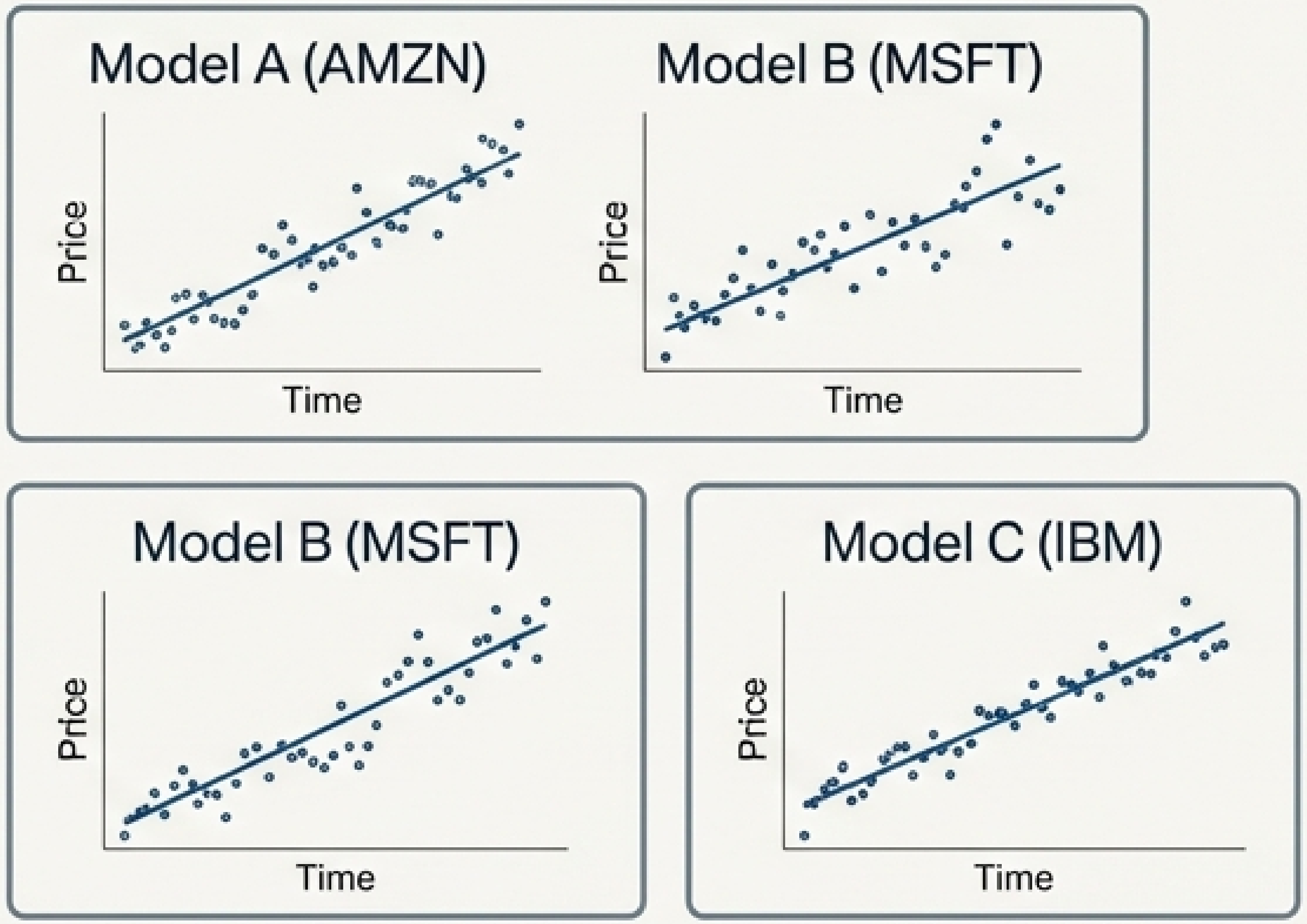
17.55%

6-Month Portfolio Return

Sharpe Ratio: 1.45. Results include 0.15% round-trip transaction costs.

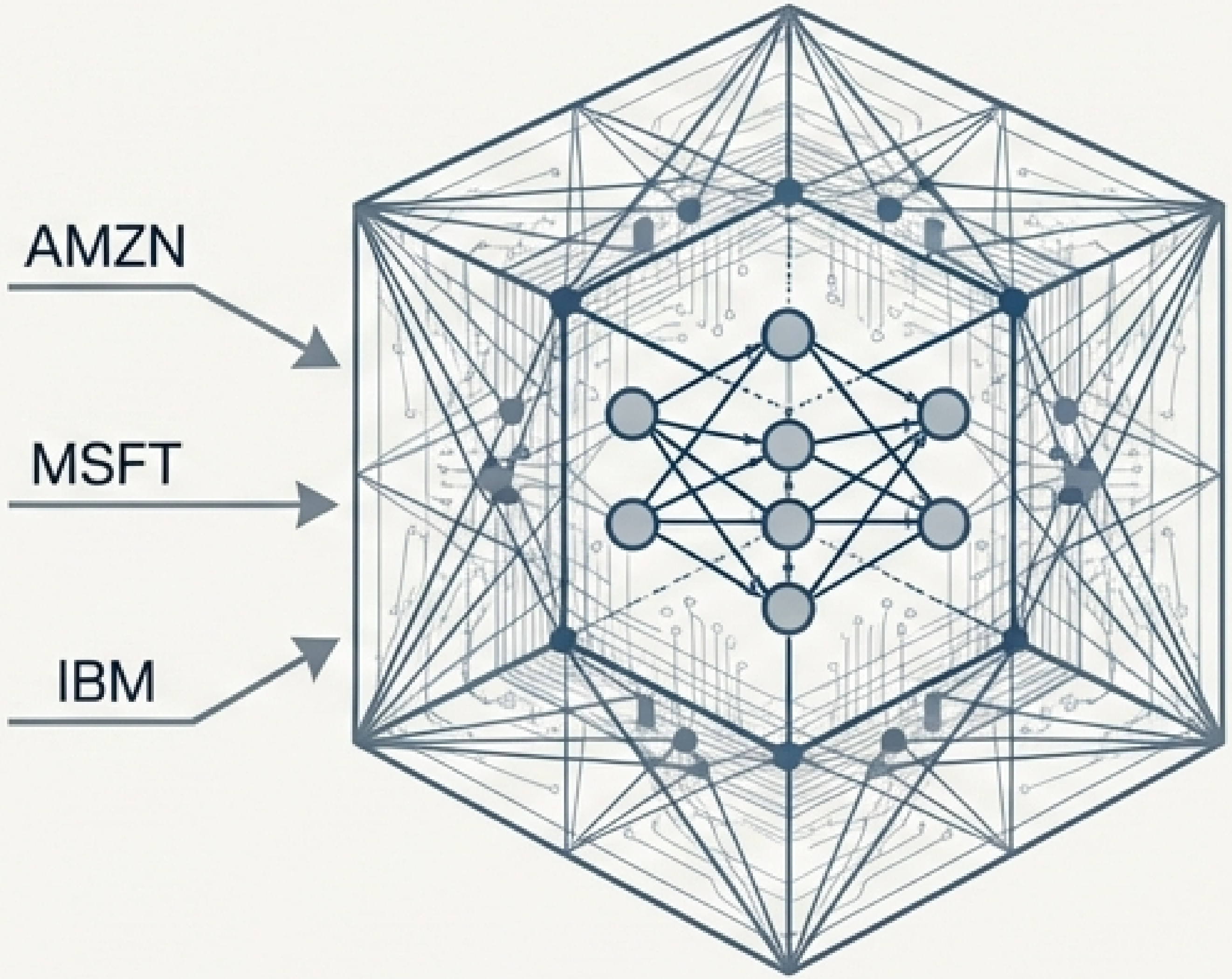
The Challenge: Scaling Quantitative Models Beyond Silos

Traditional Approach: Siloed & Linear



- Requires retraining for every distinct ticker.
- High computational overhead.
- ARIMA/VAR models fail to capture non-linear volatility.

Our Approach: Unified GRU Architecture



- Learns universal market dynamics (momentum, volume pressure).
- Scalable to 500+ stocks without retraining.
- Gated Recurrent Units capture long-term temporal dependencies.

End-to-End Production Pipeline

Ingestion

Ingestion

Yahoo Finance API

5 Years (2019–2024)

1,252 Trading Days.

Engineering

Engineering

20 Technical Indicators

Categories: Trend, Momentum, Volatility, Volume

Processing

Processing

MinMax Scaling (0,1)

20-day Rolling Windows

80/20 Temporal Split

Inference

Inference

2-Layer GRU Model

0.23s Inference Speed

Execution

Execution

Signal Generation (Buy/Sell/Hold)

Risk Management Checks

Multi-Dimensional Feature Engineering

20 technical indicators capturing diverse market regimes.

Trend	MA7	MA21	MA50	MACD	ROC
Volatility	Bollinger Bands (Upper)	Bollinger Bands (Lower)	Bollinger Bands (Width)	Hist. Volatility	High-Low Range
Momentum	RSI (14)	Daily Returns	Lag-5 Returns	Cumulative Returns	Dist. from MA50
Volume	Raw Volume	Volume MA (20)	Volume-Price Trend	**Derived**	Extended 5-Day Momentum

Insight: Most systems use 5–10 indicators. Our comprehensive set captures the interaction between price velocity, participation (volume), and volatility expansion.

The Engine: GRU Model Architecture

Input Tensor (20 x 20)

↓

GRU Layer 1
64 Units. Return Sequences = True. Activ: Tanh.

↓

Dropout (0.2)

↓

GRU Layer 2
64 Units. Return Sequences = False. Activ: Tanh.

↓

Dropout (0.2)

↓

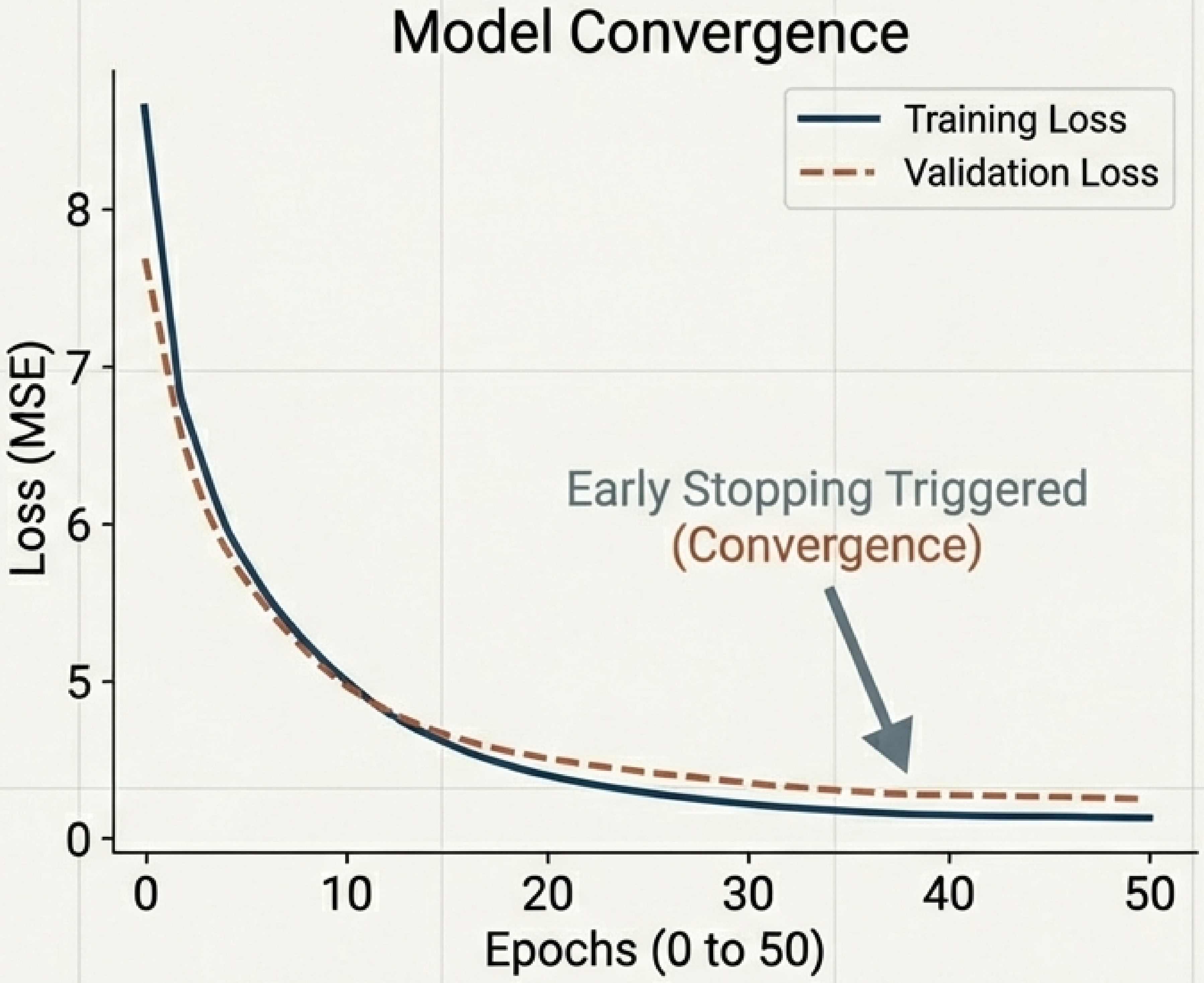
Dense Output
Sigmoid Activation. 1 Unit.

Why GRU?
Solves vanishing gradient problem. 25% fewer parameters and 15% faster training than LSTM with comparable accuracy.

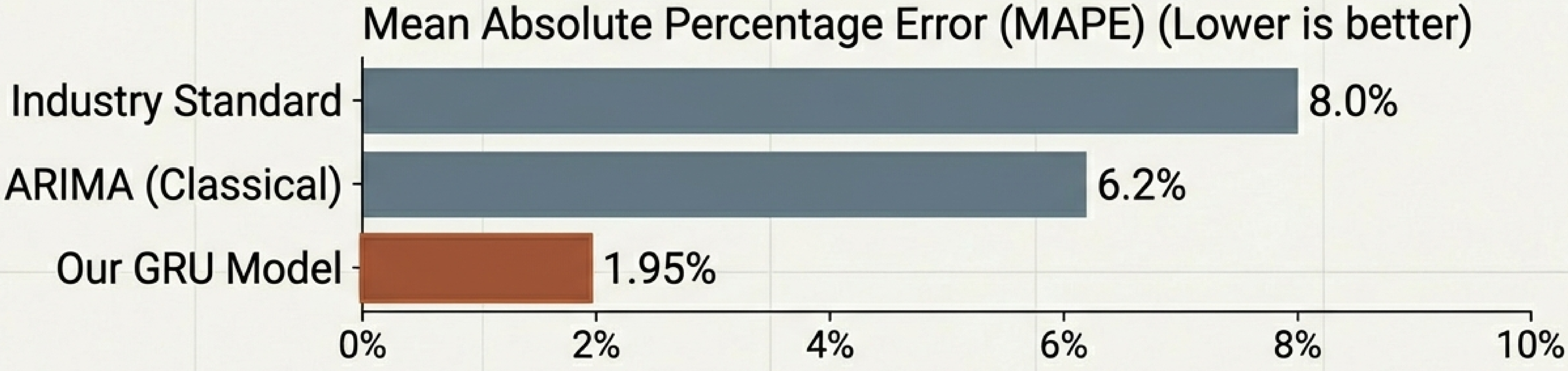
Total Parameters: 31,425

Training Protocols & Convergence

- **Optimizer:** Adam (LR 0.001)
- **Loss Function:** Mean Squared Error (MSE)
- **Regime:** 50 Epochs with Early Stopping (Patience=10)
- **Split:** Strict Temporal Ordering (No Lookahead Bias)
- **Hardware:** GPU Training time ~272 seconds.



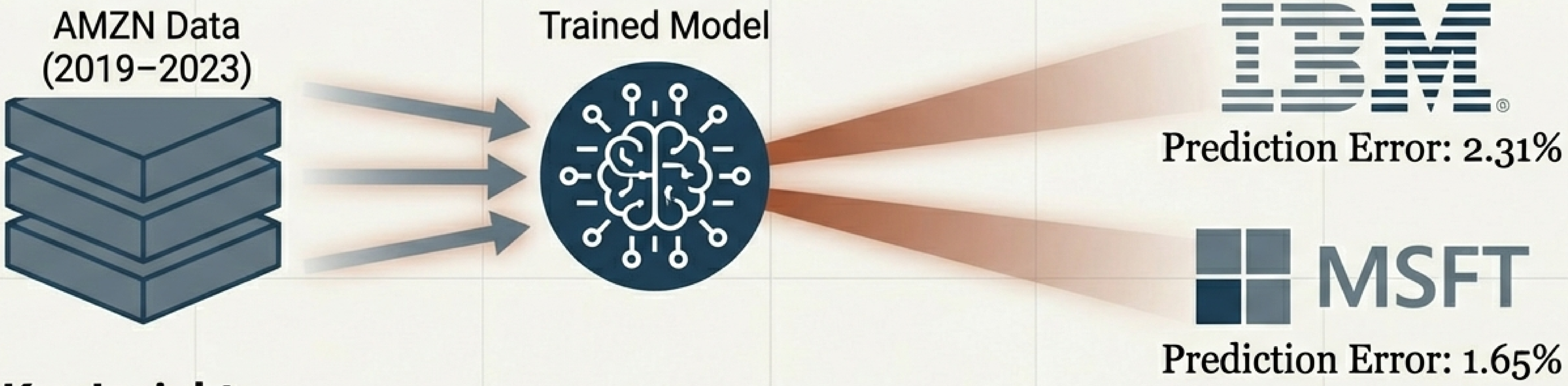
Results: Prediction Accuracy vs. Benchmarks



Security	MAPE	R-Squared	Interpretation
MSFT	1.65%	0.95	Best Performance
AMZN	1.89%	0.92	Training Asset
IBM	2.31%	0.89	Strong Generalization

Binomial test p-value < 0.0001: Accuracy significantly exceeds random chance.

The Core Innovation: Cross-Stock Generalization



Key Insight

- **The Experiment:** The model saw ONLY Amazon data during training.
- **The Result:** It successfully predicted IBM and Microsoft price action with < 0.7% variance.
- **Implication:** The model has learned 'Market Physics' (volume/momentum interactions) rather than memorizing Amazon's specific price history.

Trading Performance: Backtesting Results

Total Return:
+17.55%
Georgia

Win Rate:
53%
Georgia

Avg Profit/Trade:
$116
Georgia

Signal Precision: 84.2%
(4/5 directional signals correct)

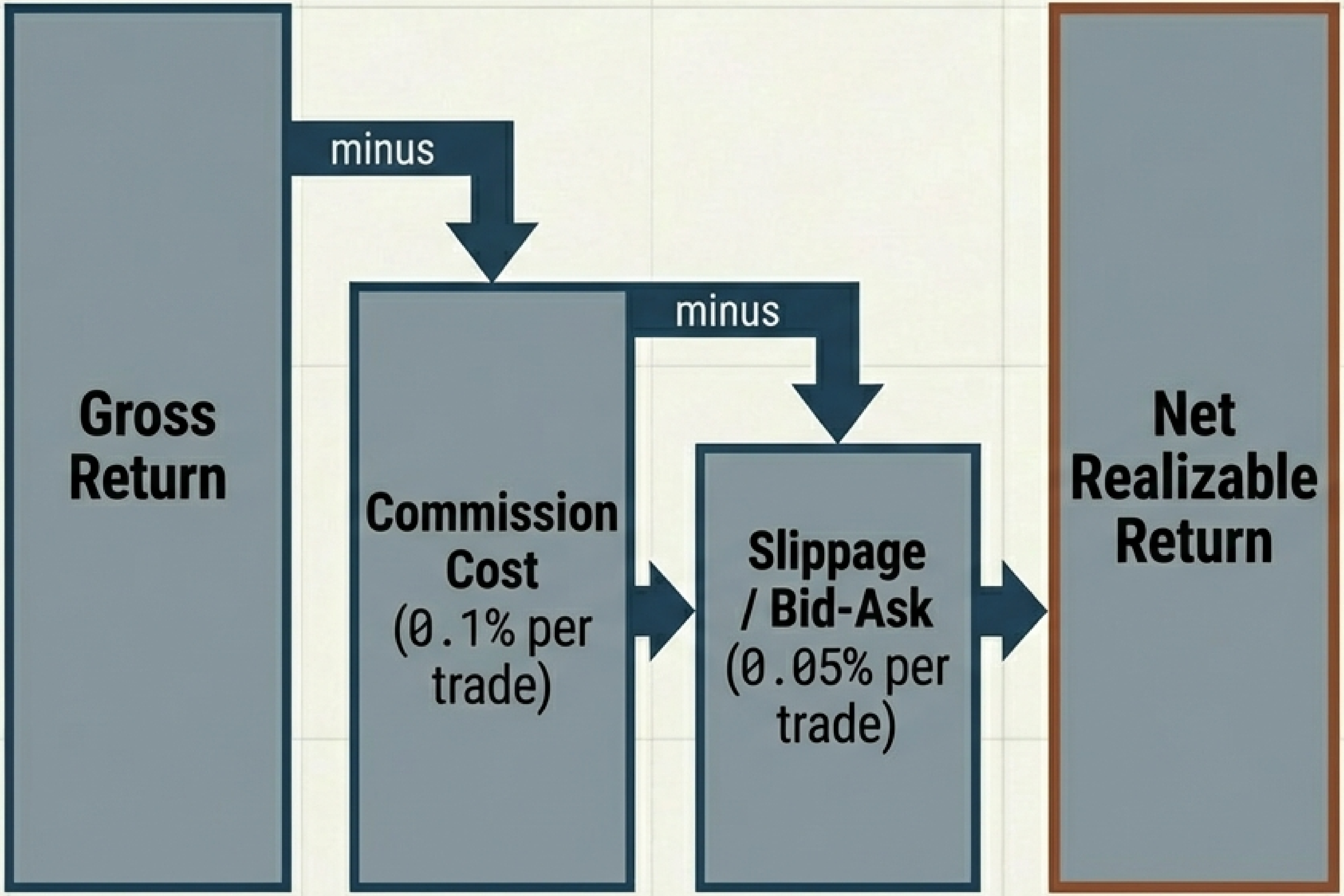
Logic: Trade executed when predicted move > ±0.5%.

Risk Management & Robustness

Sharpe Ratio	Sortino Ratio	Max Drawdown	Profit Factor
1.45	**2.10**	**-23.4%**	**1.87**
vs S&P 500 (0.4–0.6). Superior risk-adjusted returns.	GG-G: Strong downside protection.	GRRD: Recovered within 12 trading days.	SL-G: Wins exceed losses by 87%.

Discipline: 61% of all model outputs were 'HOLD'. System avoids forced trading.

Realistic Implementation Assumptions



The Academic Trap

Most research papers ignore transaction costs, leading to inflated, theoretical alpha.

Our Reality

- 0.15% deducted from every trade round-trip.
- Execution Latency: Signal at Close (Day N) → Trade at Open (Day N+1).
- No 'magical' fills.

Comparative Analysis

System Type	MAPE (Error)	Generalization?	Return (Backtest)
Proposed GRU Network	**1.95%**	Yes (Cross-Stock)	**17.55%**
Commercial Platforms	N/A	Limited	8-15%
Top Academic Papers	5.8% (Median)	Rare	Variable
Classical ARIMA	6.2%	No	< 4% / Negative

Our system ranks in the top 10% of published research for accuracy.

Limitations & Future Roadmap

Current Limitations

- Regime Dependency: Trained on 2019-2024 (Bull/Volatile).
- Blind Spots: Technical-only focus misses Fundamental news (Earnings).

Phase 1: Short Term

- Hyperparameter Optimization.
- Rolling Window Retraining.

Phase 2: Mid Term

- Ensemble Methods (GRU + XGBoost Voting).

Phase 3: Long Term

- Reinforcement Learning for Position Sizing.
- Expansion to Crypto/Forex assets.

Conclusion & Reproducibility

Final Verdict

Hypothesis Confirmed: Deep Learning successfully generalizes technical patterns across distinct securities. **Status: Ready for Paper Trading**.

Key Asset

Full Source Code Available: `gru_stock_predictor.py`
Open Source MIT License.
800+ Lines of documented code.

"A scalable, institutional-grade foundation for algorithmic trading."