Adaptive ML-Driven Equity Strategy

Techfest Algorithmic Trading – Final Round

Team: Pushkar Byadgi, Abhikalp Shekhar, Visharad Srivastava

The Problem We're Solving

Why Most ML Trading Strategies Fail

- Pure ML overfits noisy price data
- Ignores execution costs & liquidity
- Weak or absent risk control
- Performs well in backtests, fails live

Core Idea

Trade **only the strongest stocks,**
only when probability supports it,
and **size every trade by risk.**
Pure ML overfits noisy price data

- Stage 1 filters opportunity
- Stage 2 gates execution
- Risk management dominates returns

Strategy Architecture

- Universe Selection
- Feature Engineering
- Calculating ML Probability
- Execution

Why ML Comes *After* Selection

Why Use ML Only After Filtering	ML does **not predict prices**
	ML estimates **probability of favorable move**
	Used as a **trade permission system**
Signal logic:	BUY → probability > threshold
	SELL / EXIT → probability collapse or stop hit

Selection Process

- ***Filtering for Tradeable Reality***
  - Start with broad NSE equity universe
  - Price filter: **₹10 minimum**
  - Liquidity filter: **Top 60 by dollar volume**
  - Synthetic market index for benchmarking
  - Model learns only to interact with "useful" stocks, also run time of the model is cut significantly since it is dealing with much fewer stocks(60 compared to 500)

Model & Features

Following features are calculated

- Momentum: RSI, ROC
- Trend efficiency
- Volatility: ATR%, ATR slope
- Relative strength vs market
- Volume shock & money flow

Entry and Exit Conditions

What the Model Learns

- Entry targets: 1.5% move over 5 days
- Exit targets:1.25% move in opposite direction over 4 days
- Separate models for entry & exit

ML model

Robust, Interpretable, Regularized

- LightGBM binary classifiers
- Heavy regularization
- Class imbalance correction

Objective & Learning

- Binary log-loss (cross-entropy)
- Learns **probability of favorable vs adverse outcome**, not returns
- Naturally handles **non-linear feature interactions**

ML model

Regularization & Stability

- Leaf-wise tree growth with depth & leaf caps
- L1/L2 regularization on leaf weights
- Minimum data per leaf leads to noise suppression
- Early stopping via validation loss

Why LightGBM (over XGBoost)

- Faster training results in frequent retraining possible
- Better handling of **continuous features**
- Leaf-wise splits capture **rare but important regimes**
- Lower variance under heavy regularization

Position Sizing

Risk is diversified as follows:

- Risk per trade: **0.5% equity**
- Stop distance: **2 × ATR**
- Max allocation per stock: **25%**
- Max concurrent positions: **30**

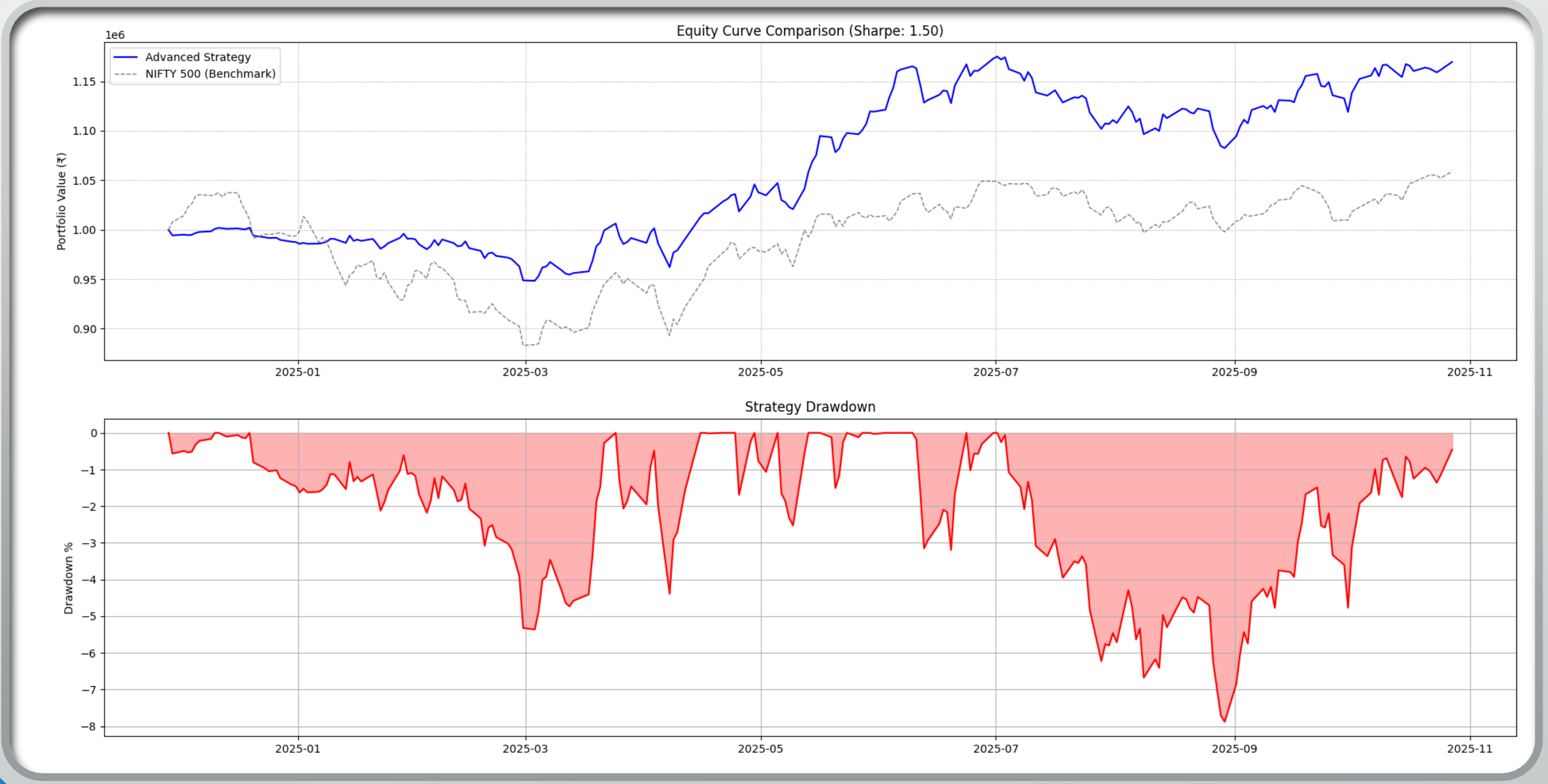
Backtesting Framework

Strict No-Lookahead Simulation

- Walk-forward training split
- Daily rebalancing
- Cash & position accounting
- Realistic costs modeled

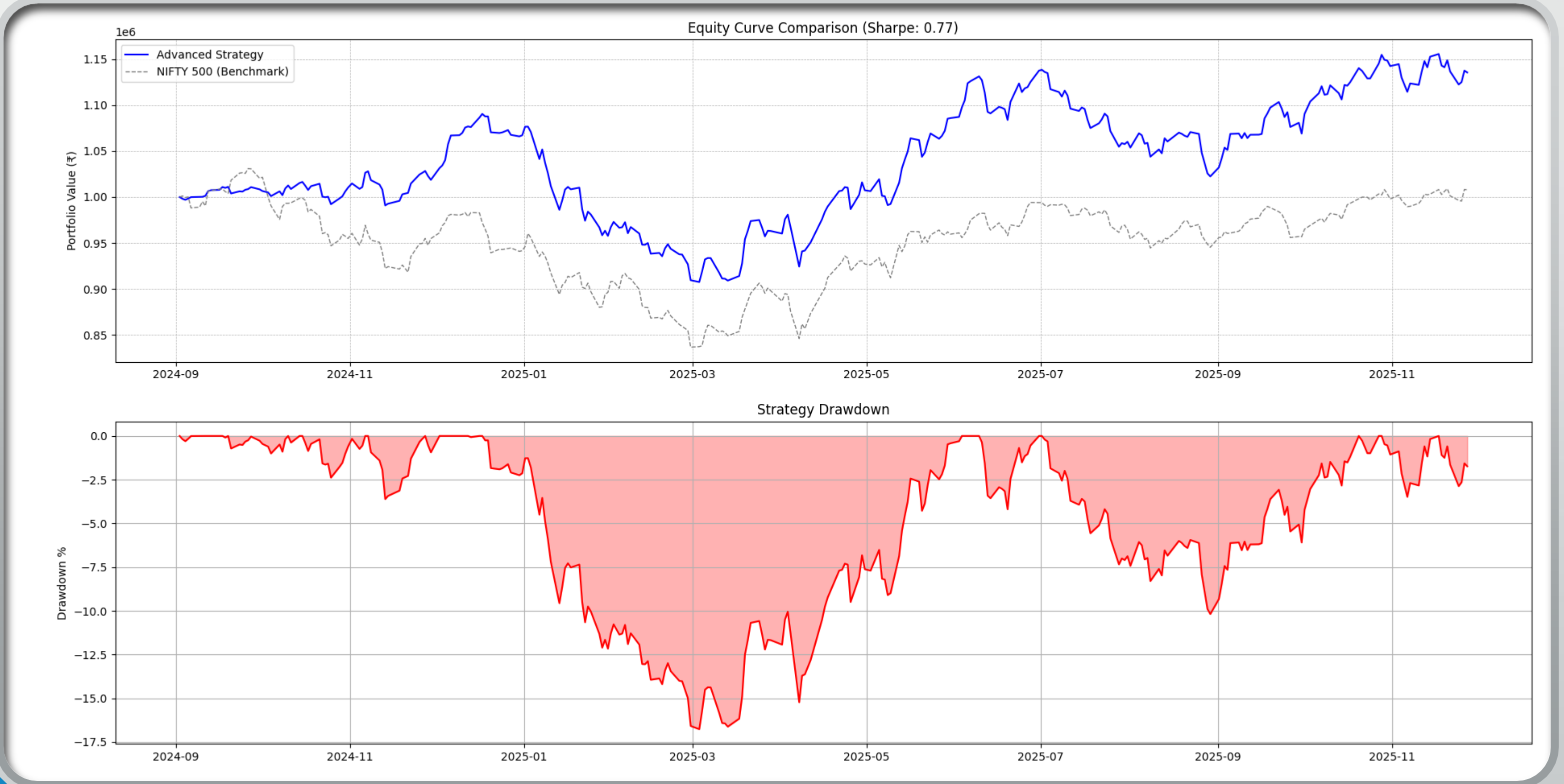
Performance Metrics(28/11/24-28/11/25)

- Sharpe Ratio :1.5
- Max Drawdown -7.88%
- Equity Curve vs Benchmark (+16.97% VS 5.89%)



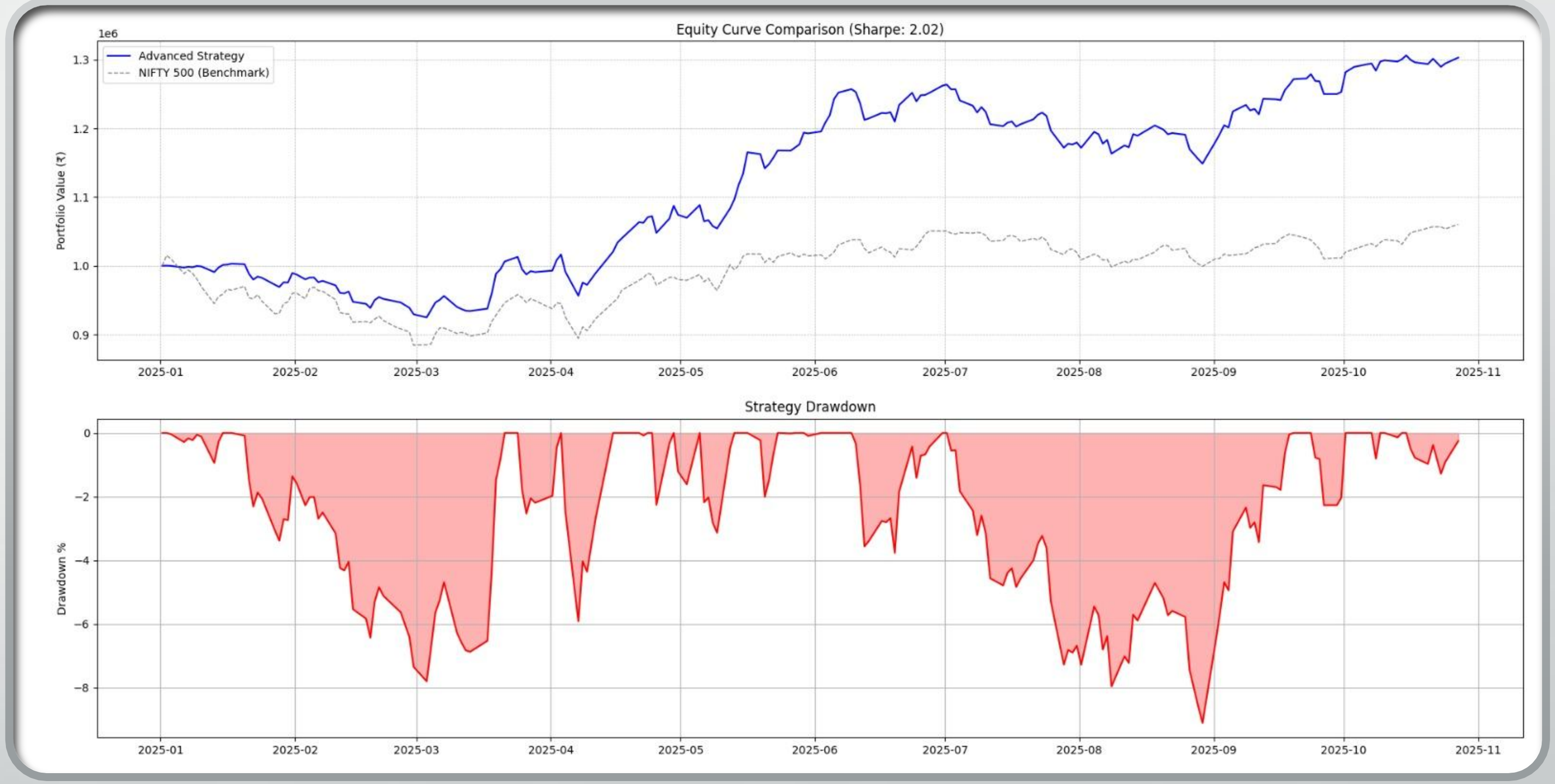
Performance Metrics(01/09/24-28/11/25)

- Sharpe Ratio :0.77
- Max Drawdown -16.76%%
- Equity Curve vs Benchmark (+13.54% VS 0.79%)



Performance Metrics(01/01/25-28/11/25)

- Sharpe Ratio :2.02
- Max Drawdown -9.10%
- Equity Curve vs Benchmark (+30.30% VS 6.05%)



Inferences

Where the Strategy Works Best

- Moderate, sustained trends
- Liquid, institutionally traded stocks
- Volatility expansion after compression
- Stock-specific alpha environments

Where the Strategy Underperforms

- Sideways, mean-reverting markets
- Sudden regime shocks / overnight events
- Ultra-low volatility periods
- Strong index-driven moves

THANK YOU