Ensemble Machine Learning For NIFTY-50 Price Forecasting And Trend Classification: A Flask-Deployed Decision Support System

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Abstract- *Stock market forecasting poses a significant challenge due to the non-linear, high-volatility nature of financial time series. This paper presents an end-to-end machine learning pipeline for predicting NIFTY-50 closing prices and next-day directional trends. The system trains Random Forest (RF) and Decision Tree (DT) regressors on historical OHLCV data augmented with engineered technical features (MA10, MA50, daily returns). A fusion mechanism averages RF and DT outputs to produce a stabilized price estimate. A separate RF classifier outputs categorical trend labels (UP/DOWN/NEUTRAL), avoiding the pitfall of inferring direction from regression residuals. Experimental results show that the RF+DT fusion achieves an R^2 of 0.9451, outperforming standalone RF (0.9312) and DT (0.8841) regressors. The trend classifier achieves 82.4% accuracy and an F1-score of 0.81. The complete pipeline is deployed as a Flask web application supporting user authentication, interactive prediction, candlestick visualization, CSV upload, live data fetch via Yahoo Finance, PDF report export, and an administrative panel. The system provides a practical, interpretable, and deployable solution for short-term NIFTY-50 decision support.*

Keywords: stock market prediction, NIFTY-50, Random Forest, Decision Tree, ensemble fusion, trend classification, Flask, machine learning.

I. INTRODUCTION

Stock market indices encode a complex superposition of macroeconomic signals, institutional activity, and investor sentiment. Standard linear forecasting methods — ARIMA, exponential smoothing — capture autocorrelation in stationary series but fail on the non-stationary, fat-tailed distributions characteristic of equity indices [1].

Tree-based ensemble methods offer a non-parametric alternative that is robust to outliers, handles non-linearity without explicit feature transformation, and provides feature importances for interpretability. The NIFTY-50 index, comprising the fifty most liquid large-cap equities listed on the National Stock Exchange of India, is a widely tracked benchmark.

Short-term price forecasting on NIFTY-50 has direct utility for risk management, algorithmic trading, and portfolio rebalancing. Despite a substantial body of work on ML-based forecasting, most published prototypes do not progress beyond offline script-based evaluation. This paper fills that gap by presenting a production-ready, web-deployed pipeline with full administrative controls and reporting features.

The contributions of this work are: (i) a reproducible feature-engineering pipeline on OHLCV data; (ii) a comparative evaluation of RF and DT regressors; (iii) an average-fusion mechanism that reduces prediction variance; (iv) a dedicated trend classifier that avoids directional inference from regression residuals; and (v) a Flask-based application with live data integration and multi-user support.

II. RELATED WORK

Sang et al. [1] demonstrated that ensemble-based representations significantly improve robustness against noise in structured prediction tasks — a principle directly applicable to financial time series where noisy OHLCV data is the primary input. Zhang et al. [2] showed that global matching across multiple weak signal sources improves prediction accuracy beyond single-source models, motivating the use of technical indicators alongside raw prices.

Everingham et al. [3] established foundational methodology for weakly supervised classification using contextual cues, analogous to using lagged market features as supervisory signals for trend labels. Liang et al. [4] and Hong et al. [6] reinforced the value of structured, multi-modal pipelines for classification, which informs the separation of regression and classification tasks in our architecture.

Recent surveys on equity prediction [5] confirm the dominance of tree-based ensembles over single models for tabular financial data in low-data regimes, particularly when interpretability is required. LSTM-based approaches [7] achieve competitive accuracy but introduce higher computational cost and require significantly more historical data for convergence.

III. METHODOLOGY

A. Data Acquisition and Preprocessing

Historical daily OHLCV data for the NIFTY-50 index (^NSEI) was sourced from Yahoo Finance via the yfinance Python library. The dataset spans approximately five years of trading days. Columns retained are: Open, High, Low, Close, Volume. Missing values are forward-filled; rows with no valid close are dropped.

Feature engineering adds four derived columns: (1) MA10 — 10-day simple moving average of Close; (2) MA50 — 50-day simple moving average; (3) Daily Return — percentage change in Close; (4) Lag-1 Close — previous day closing price. The target for regression is the next-day Close. The target for classification is a ternary label: UP if next-day return > +0.2%, DOWN if < −0.2%, NEUTRAL otherwise.

B. Model Architecture

Two regression models are trained independently on an 80/20 chronological train-test split to prevent look-ahead bias:

- Random Forest Regressor (n_estimators=100, max_features=‘sqrt’, random_state=42)
- Decision Tree Regressor (criterion=‘squared_error’, random_state=42)

Fusion is computed as: $\hat{Y}_{fusion} = (\hat{Y}_{RF} + \hat{Y}_{DT}) / 2$. The trend classifier is a separate Random Forest Classifier (n_estimators=100) trained on the same feature matrix with the ternary label. Separating regression and classification tasks prevents directional leakage from regression residuals.

C. Evaluation Metrics

Regression performance is measured by Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). Classification performance is measured by accuracy and weighted F1-score, averaged over the three classes.

IV. EXPERIMENTAL RESULTS

A. Regression Performance

Table I summarizes model performance on the 20% hold-out test set. The RF+DT fusion consistently outperforms both individual regressors across all metrics, confirming that variance reduction via averaging improves generalization.

TABLE I
Model Performance Comparison on NIFTY-50 Test Set

Model	RMSE	MAE	R^2	Train (s)
Random Forest	142.37	98.12	0.9312	4.21
Decision Tree	198.54	131.76	0.8841	0.43
RF+DT Fusion	128.94	87.63	0.9451	4.64
Trend (RF)	—	—	—	Acc:82.4%

B. Trend Classification

The RF trend classifier achieves 82.4% overall accuracy on next-day direction prediction. Precision and recall are highest for the UP class (0.85, 0.83) and lowest for NEUTRAL (0.78, 0.76), reflecting the expected difficulty of predicting flat sessions. The F1-score of 0.81 indicates reliable signal quality for trading decision support.

C. Fusion Gain

The fusion model reduces RMSE by 9.4% relative to standalone RF and 35.1% relative to standalone DT. R^2 improvement of 1.5 percentage points over RF suggests that DT captures complementary variance components that RF averages out. This is consistent with the bias-variance decomposition framework for ensemble methods.

V. SYSTEM ARCHITECTURE

The Flask application implements a three-tier architecture: (1) a data layer comprising a MySQL database for user accounts and prediction history; (2) a model layer housing the trained RF, DT, and trend classifier; and (3) a presentation layer serving Jinja2-rendered HTML templates.

Key application routes include /predict (POST: accepts OHLCV + feature inputs, returns RF price, DT price, fusion price, trend label, and model R^2), /candlestick (renders 50-day candlestick chart via Chart.js), /upload (admin CSV ingestion triggering model retraining), /fetch_latest (live ^NSEI price via yfinance), and /export_pdf (generates downloadable prediction report via ReportLab).

Role-based access control segregates admin endpoints (/admin, /manage_users, /all_history, /delete_user) from standard user endpoints. Sessions are managed with Flask-Session; passwords are stored as bcrypt hashes.

VI. CONCLUSION

This paper presents a complete, deployable ML pipeline for NIFTY-50 short-term forecasting. The RF+DT fusion achieves $R^2 = 0.9451$ on hold-out data, outperforming single-model baselines. The dedicated trend classifier provides 82.4% directional accuracy. The Flask deployment with live data integration, multi-user management, and PDF reporting demonstrates the feasibility of bridging research prototypes to operational tools.

Future work will incorporate additional features — options chain data, macroeconomic releases, and news sentiment scores — and evaluate LSTM and Transformer architectures on the same chronological splits to provide a fair comparison baseline. Automated daily retraining triggered by the CSV upload endpoint will also be investigated.

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