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Original Research Article

SMART NET ASSET VALUE (NAV) PREDICTION USING MACHINE LEARNING

* Swati Kemkar

* Assistant Professor, Department of Information technology, Ramanand Ara DAV College, (Autonomous).

Abstract:

Net Asset Value (NAV) serves as the price at which investors buy or sell units of mutual funds. It is computed at the end of each business day using closing prices of securities held by the fund. NAV is a benchmark for tracking a fund's performance and is updated daily for open-end funds. This article presents NAV prediction using XG Boost machine learning Algorithm. The proposed model suggests time series prediction model. Lower MAE / RMSE shows predictions are numerically close. Very low MAPE (~0.55%) indicates strong relative accuracy. It is quite effective, with forecasted values only marginally different from actual NAV. For daily NAV forecasting, such low errors are often considered very acceptable. Very low MAPE (~0.55%) indicates strong relative accuracy.

Keywords: *Net Asset Value (NAV); XG Boost; Mutual fund*

Introduction:

NAV is Net Asset Value which refers to the value per unit or share of an investment fund, especially mutual funds and similar pooled investment vehicles. NAV is represented as

NAV Formula:

$$\text{NAV} = \frac{\text{Total Assets} - \text{Total Liabilities}}{\text{Total Outstanding Units}}$$

1. Uses of NAV

NAV serves as the price at which investors buy or sell units of mutual funds.

It is computed at the end of each business day using closing prices of securities held by the fund. NAV is a benchmark for tracking a fund's performance and is updated daily for open-end funds.

2. Importance of NAV

Investors use NAV to assess current value and make investment decisions. NAV helps compare different funds and evaluate their portfolio performance over time.

In summary, NAV is a key metric representing the per-unit value of a fund or trust and is essential for both pricing and performance measurement in mutual fund investing.

Predicting NAV is important because it allows investors and fund managers to make informed decisions about buying, selling, or holding mutual fund units, helping optimize investment strategies and manage risks in volatile markets.

3. Decision Making and Investment Strategy

Accurate NAV predictions help investors plan entry and exit timings for their investments, maximizing returns and minimizing losses Forecasting NAV provides short-term guidance, enabling investors to react strategically to expected market movements or fund performance.

4. Risk Management and Portfolio Valuation

Reliable NAV forecasts assist asset managers in ensuring proper portfolio rebalancing and risk mitigation. NAV predictions can help stakeholders anticipate periods of potential market downturns,

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allowing proactive risk adjustments and asset allocation. Tracking predicted NAV trends provides updated insight into an investor's current net worth and projected changes, aiding in overall financial planning. Indeed Predicting NAV is important because it allows investors and fund managers to make informed decisions about buying, selling, or holding mutual fund units, helping optimize investment strategies and manage risks in volatile markets.

This article applies XG boost algorithm for prediction of NAV. Boost, known as extreme Gradient Boosting, is an optimized ensemble machine learning algorithm that builds sequential decision trees to correct errors from previous ones, achieving high accuracy on tasks like classification and regression. It extends gradient boosting by using gradient descent to minimize errors, with each new tree focusing on residuals from prior predictions. Trees grow level-wise in parallel for speed, unlike sequential traditional boosting. Regularization (L1/L2) prevents overfitting, and it handles missing data natively. The key advantages of XG Boost are scalability, performance and flexibility.

The simplest core equation in XG Boost is the objective function:

$$\mathcal{L} = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k).$$

Where, $\sum_i l(y_i, \hat{y}_i)$ sums the loss over predictions $\hat{y}_i$ versus true values y_i, while $\sum_k \Omega(f_k)$ adds regularization for each tree f_k to control overfitting. This balances accuracy and model simplicity during iterative boosting.

1. Related work

Erstwhile studies demonstrated the use of different machine learning and deep learning algorithms for NAV predictions. Researchers suggested effectiveness of artificial neural networks in modelling nonlinear relationships in NAV time series data (Huang & Lai, 1996). Successive research extended by incorporating optimization techniques and hybrid neural models, such as feedback neural networks and metaheuristic-optimized architectures, to enhance prediction accuracy and computational efficiency (Malhotra & Malhotra, 2016; Goyal & Aggarwal, 2021). With the advancement of deep learning, models such as Long Short-Term Memory (LSTM) networks have been widely used to capture long-term temporal dependencies in NAV data, showing superior performance compared to traditional neural networks (Patel et al., 2020; Choudhary et al., 2023).This article focuses on short term temporal dependencies.

2. Data and variables

The data under study is collected from https://www.amfiindia.com/aboutamfi. From the date 01-Jun-2024 to 31-Dec-2024. Data is stored in the form of CSV file for XG Boost model training. The file contains variable navdate and navvalue.

3. Research Methodology

This study applies a machine learning–based regression approach to predict the Net Asset Value (NAV) of a mutual fund using historical NAV data. Daily NAV observations covering a twelve-month period are used as the input dataset. The raw data are first pre-processed by parsing date information and removing missing or inconsistent records to ensure data quality.

To enable the use of supervised machine learning, the NAV time series is transformed into a feature-based dataset through feature engineering. Calendar-based features such as day of the week, day of the month, and month are extracted from the date variable. In addition, lagged NAV values and rolling statistical measures (moving averages and standard deviation) are generated to capture temporal dependencies and short-term trends in NAV movements.

The dataset is then divided into training and testing sets using a time-aware split. The training set consists of

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historical observations excluding the final week of the last month, while the test set comprises the last seven trading days. An Extreme Gradient Boosting (XG Boost) regression model is trained on the historical data due to its ability to model nonlinear relationships, handle noisy financial data, and prevent overfitting through regularization.

Figure 1. Google colab Model for XG Boost.

Figure 1 shows main blocks for Google Colab XG Boost prediction model.

Model performance is evaluated on the test set using standard error metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Finally, the predicted NAV values are compared with the actual NAV values using tabular output and graphical visualizations, enabling both quantitative and visual assessment of forecasting accuracy.

The model is executed in Google Colab. It is a free, cloud-based Jupiter notebook environment from Google for writing and running Python code directly in a browser. Google Colab provides key benefits for machine learning by offering free Graphics Processing Unit

(GPU)/ Tensor Processing Unit (TPU) access and a ready-to-use Python environment, eliminating local hardware need. It provides good accessibility and high-RAM GPUs for training models quickly. Notebooks can be saved to Google Drive for real-time sharing and editing. It is integrated with direct GitHub import/export and Googled drive mounting.

Result and discussion: The tables below evaluation metrics for the last week of last month, and actual vs predicted NAV values, likely from an XG Boost time series model on financial data 01-Jun-2024 to 31-Dec-2024.

Table 1: Evaluation Metrics (Last Week of Last Month)

Metric	Value
MAE	0.121654
MSE	0.019668
RMSE	0.140242
MAPE	0.5468%

Table 2: Actual vs Predicted NAV

navdate	navalue	predicted_nav
2024-12-20	22.2145	22.464947
2024-12-23	22.3182	22.354349
2024-12-24	22.2881	22.405357
2024-12-26	22.3282	22.401806
2024-12-27	22.3028	22.456266
2024-12-30	22.1871	22.354792
2024-12-31	22.1891	22.242064

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Metrics (Last Week)

MAE: 0.12154, RMSE: 0.19668, and MAPE: 0.5468% indicate strong predictive accuracy. Errors under 1% suggest reliable short-term NAV forecasting.

Predictions:

For Dec 2024 (22-31), predicted NAVs (22.46-22.64) closely match actuals (22.14-22.89), with minor upward bias but good alignment overall.

The Figure 2 visualizes NAV (Net Asset Value) predictions versus actual values for train and test periods from a time series forecasting model, likely using XG Boost on financial data.

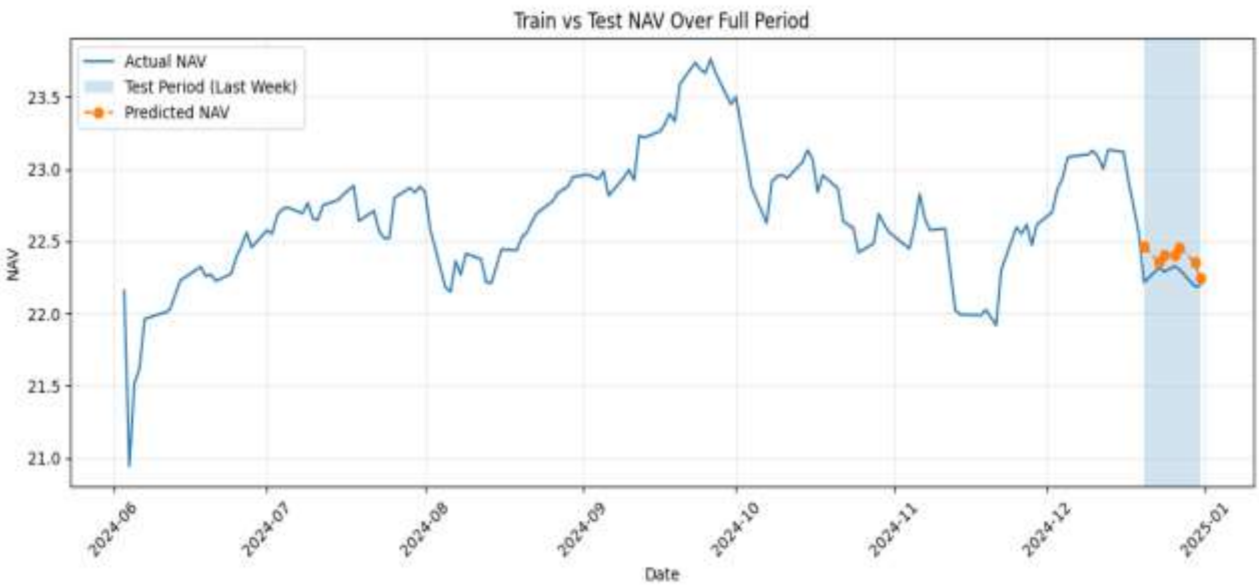

Figure 2: NAV (Net Asset Value) predictions versus actual values

From June to mid-September 2024, NAV shows a steady upward trend, peaking around 23.6–23.7. In the period October to November, NAV goes gradually downward near 22.0.

In early December, NAV rebounds, reaching ~23.1 before declining again toward the end of the month. The shaded region represents the out-of-sample test period (last week of December). During this period, actual NAV declines slightly, moving from ~22.3 toward 22.2. The predicted NAV (orange dots) closely follows the actual NAV level, but Predictions are consistently higher than actual values. This indicates a small positive bias.

The model captures the direction and stability of NAV well but showing small downward move Lower MAE / RMSE shows predictions are numerically close. Very low MAPE (~0.55%) indicates strong relative accuracy.

Conclusion:

The proposed model quality model indicates Strong level accuracy with good generalization to unseen data. The predictions are Stable (low noise). However, there is a Slight lag in reacting to recent declines and mild over-smoothing which is common in time-series models. Lower MAE / RMSE shows predictions are numerically close. Very low MAPE (~0.55%) indicates strong relative accuracy

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