Advanced Price Prediction: A Multi-Scenario Forecasting Tool Using Machine Learning

In the world of financial markets, accurate forecasting is a significant challenge. While standard methods like Monte Carlo simulations are widely used, I observed that they often fall short. My analysis of Monte Carlo simulations showed that they can produce overly simplified results, with optimistic scenarios reaching unrealistic highs and median predictions that often fail to capture the nuances of market sentiment. This realization became the catalyst for a personal project I undertook: to build a more sophisticated and reliable price prediction tool that moves beyond pure statistical randomness and incorporates a deep understanding of market dynamics through machine learning.

A Data-Driven Approach to Financial Forecasting

This project involved a complete development cycle, from foundational research and method selection to building, backtesting, and implementing a new predictive model. My approach was centered on creating a multi-scenario forecasting engine that leverages advanced feature engineering and a powerful machine learning algorithm to generate a more realistic and actionable range of potential future prices.

I. Preliminary Research & Method Selection

The foundation of this project was a preliminary research phase to identify influential parameters and robust analytical methods from the fields of quantitative finance and digital signal processing. The goal was to select a combination of tools that could effectively model both trend/momentum and cyclical market behaviors.

- **Core Machine Learning Engine:** My research into predictive algorithms for non-linear, noisy data like financial prices led me to ensemble methods. I selected the **Random Forest Regressor** for its robustness, its ability to capture complex relationships without overfitting, and its stability, which comes from averaging the results of hundreds of individual decision trees.
- **Foundational Indicators:** I identified a baseline set of industry-standard technical indicators known for their proven effectiveness in measuring market state. This included the **Relative Strength Index (RSI)** for momentum, **Simple Moving Averages (SMA)** for long-term trend, and **Moving Average Convergence Divergence (MACD)** for trend changes.

- **Advanced Cyclical Analysis:** To address the core limitation of simpler models, my research focused on methods to objectively identify and analyze market cycles. This led me to select a two-part approach from digital signal processing:
    1. **Fast Fourier Transform (FFT):** To decompose historical price data and quantitatively identify the dominant, most influential cycle period.
    2. **Hilbert Transform:** To analyze the current price action *within* the context of the dominant cycle identified by the FFT, determining its instantaneous phase (e.g., uptrend, downtrend) and amplitude.

This research phase provided the essential building blocks for the system architecture.

II. Model Validation & Backtesting

With the core methods selected, the next critical step was to validate the model's logic. Before using it for forecasting, I conducted a rigorous backtesting process against historical data. This involved training the model and then testing its ability to predict prices in a subsequent period it had not seen before. The results were highly successful and validated the model's effectiveness:

- **Average Monthly Absolute Error:** The model demonstrated an exceptionally low average error rate of just **0.91%** per month.
- **Model Confidence Level:** This translates to a monthly accuracy or confidence level of **99.09%**.

The close alignment between the model's predictions and the actual historical prices confirmed that the chosen architecture was sound.

Backtesting Results: A graph showing the model's predicted price (red line) closely tracking the actual historical price (blue line) for Asset X, demonstrating the model's high accuracy.

III. Multi-Scenario System Architecture

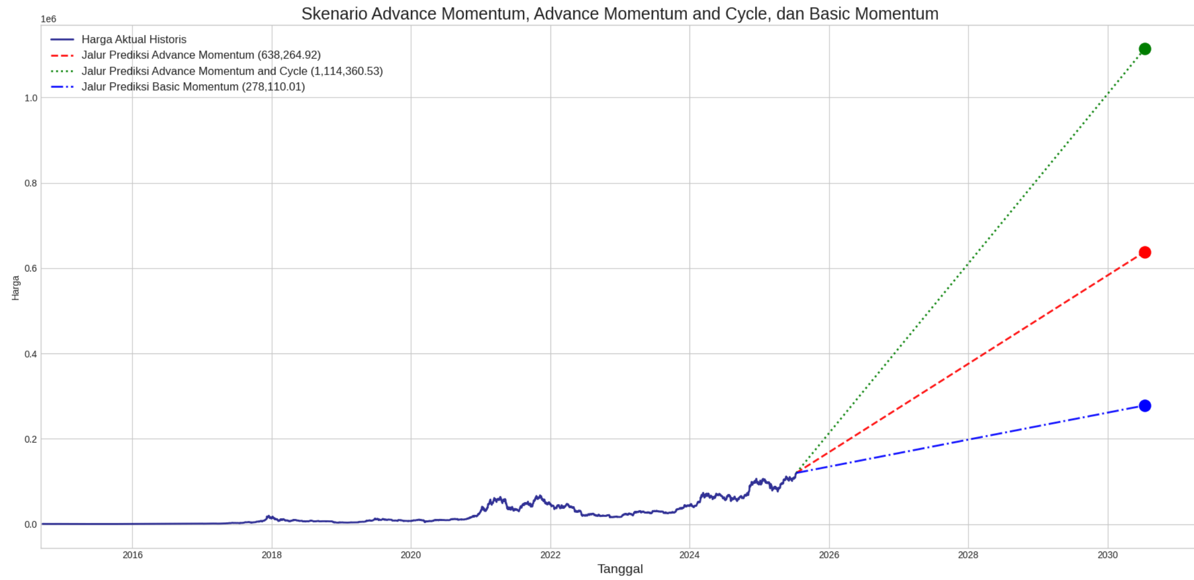
The validated components from my research were then assembled into a sophisticated, multi-scenario architecture. This system generates three distinct forecasts by feeding different layers of analytical features into the Random Forest engine, thereby modeling different levels of market conviction:

- **Basic Momentum:** This model is trained using only the **foundational technical indicators** (RSI, SMA, MACD). Its deliberately limited worldview results in a more cautious and conservative forecast.
- **Advance Momentum:** This model uses a comprehensive set of advanced technical features, including volatility and multiple return lags, providing a well-informed and balanced perspective without the influence of the more aggressive cyclical analysis.
- **Advance Momentum and Cycle:** This is the most advanced model, utilizing all available features, including the powerful **cyclical data from the Hilbert-FFT method**. By understanding the market's current position within its dominant cycle, this scenario can identify and project stronger potential upside moves.

IV. Forecasting Results: A BTC-USD Case Study

I implemented the entire system in Python. To demonstrate the tool's capability, I ran a 5-year (1825-day) forecast for **Asset X** from 16 July 2025, which yielded the following results:

- **Basic Momentum:** Predicted a price of **$638,264.92** (CAGR: **+39.76%**).
- **Advance Momentum:** Predicted a price of **$1,114,360.53** (CAGR: **+56.25%**).
- **Advance Momentum and Cycle:** Predicted a price of **$278,110.01** (CAGR: **+18.35%**).



Multi-Scenario Forecast for Asset X: A graph displaying the historical price of BTC-USD along with the three projected future price paths—Advance Momentum (red), Advance Momentum and Cycle *(green), and Basic Momentum (blue).*

V. Project Conclusion

Through this project, I successfully developed a sophisticated, multi-scenario forecasting tool that addresses the key limitations of traditional prediction models. By conducting thorough preliminary research and strategically layering analytical techniques—from foundational indicators to advanced cyclical analysis—this tool provides a more nuanced, realistic, and ultimately more useful range of potential future outcomes for financial assets.

VI. Acknowledged Limitations and Future Development

While the model has proven effective in its backtesting, I recognize its limitations and areas for future development. This is an ongoing project that can be further enhanced.

- **Data Quality Dependency:** The model's predictive power is fundamentally tied to the quality and accuracy of the historical input data.
- **Performance on High-Volatility Assets:** For assets characterized by extreme volatility and erratic price movements, the probability of model error increases, as such assets may be driven by factors not fully captured by the model.
- **Adapting to Evolving Markets:** The model is trained on past data. Its ability to accurately predict outcomes in a market that is undergoing a fundamental shift in behavior (e.g., "maturing") is a known challenge that requires ongoing research.
- **Evolving Methodologies:** The field of quantitative finance and machine learning is constantly advancing. This model is based on established methods, but I acknowledge that my research may not encompass the absolute latest, cutting-edge algorithms.

- **Disclaimer:** This tool is intended as a proof-of-concept and an analytical reference, not as a primary source for financial advice. All investment decisions should be made with independent research and professional guidance.

VII. Skills & Competencies Demonstrated

This personal project allowed me to apply and deepen my expertise in several areas:

- **Machine Learning:** Implementing and tuning Random Forest Regressor models for time-series forecasting.
- **Financial Time-Series Analysis:** Applying advanced statistical methods to financial data.
- **Advanced Feature Engineering:** Creating a wide array of technical and cyclical indicators to enhance model performance.
- **Python for Data Science:** Utilizing core libraries including `pandas`, `numpy`, `scikit-learn`, `yfinance`, and `scipy`.
- **Quantitative Analysis & Backtesting:** Designing and executing a rigorous backtesting framework to validate model accuracy.
- **Digital Signal Processing:** Applying complex algorithms like Fast Fourier Transform (FFT) and Hilbert Transform to financial data for cycle analysis.