A Hybrid Probabilistic Framework for Forex Market Forecasting: Integrating Bayesian Inference, Monte Carlo Simulation, and Machine Learning

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https://github.com/JKTK25/A-Hybrid-Probabilistic-Framework-for-Forex-Market-Forecasting

Abstract

The inherent stochasticity and high-frequency nature of the foreign exchange (Forex) market present significant challenges for traditional forecasting models. This paper proposes a novel, multi-model artificial intelligence (AI) system designed to enhance prediction accuracy and robustness in this volatile domain. The framework synergistically integrates deterministic technical indicators, stochastic Monte Carlo simulations, and probabilistic Bayesian inference within an adaptive weighting scheme. The system processes real-time data for six major currency pairs, extracting features such as the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD). Predictions from machine learning models (Random Forest, Linear Regression) and Monte Carlo-based probabilistic forecasts are dynamically fused using a Bayesian weighting mechanism that updates model credibility based on recent performance. In a comparative experimental setup conducted over a seven-day trading period, the proposed hybrid system demonstrated a mean absolute error (MAE) of 0.0536 and a directional accuracy of 100% in a simulated environment, significantly outperforming baseline ARIMA and LSTM models. The results underscore the efficacy of multi-paradigm fusion for financial time-series forecasting under uncertainty, though the limitations of simulated backtesting are acknowledged. Future work will focus on integration with reinforcement learning and explainable AI (XAI) modules for enhanced realism and interpretability.

Keywords: Artificial Intelligence, Financial Forecasting, Bayesian Inference, Monte Carlo Methods, Machine Learning, Forex Trading, Model Fusion

1. Introduction

The global foreign exchange (Forex) market, with a daily trading volume exceeding $7 trillion, is the world's largest and most liquid financial market. Its continuous, 24-hour operation and sensitivity to a complex interplay of geopolitical, macroeconomic, and psychological factors result in pronounced non-linearity, non-stationarity, and inherent volatility. Predicting short-term currency price movements using classical statistical models like Autoregressive Integrated Moving Average (ARIMA) or simple moving averages is often inadequate, as these models typically assume linearity and stable underlying processes, assumptions frequently violated in financial markets. The advent of artificial intelligence (AI) and machine learning (ML) has opened new frontiers in financial modeling. Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, excel at capturing complex temporal dependencies. However, they often function as "black boxes," can be prone to overfitting on noisy financial data, and lack an explicit mechanism for quantifying predictive uncertainty—a critical component for risk management.This research addresses these limitations by introducing a hybrid AI-driven forecasting system that unifies three distinct analytical paradigms:
1. Deterministic Analysis: Using well-established technical indicators.
2. Stochastic Simulation: Employing Monte Carlo methods to model uncertainty.
3. Probabilistic Learning: Applying Bayesian inference to dynamically weight model contributions.

The core contribution of this work is a formalized Bayesian adaptive weighting scheme that creates a self-correcting, multi-model ensemble. This framework continuously recalibrates its confidence in constituent models based on their recent predictive accuracy, leading to a more robust and adaptive forecasting system. The architecture is designed for real-time operation, featuring modular components for data ingestion, feature engineering, model execution, performance tracking, and visualization.

2. Related Work

The evolution of financial forecasting has progressed from rule-based expert systems to sophisticated hybrid ML models. Zhang and Zhao (2021) demonstrated that Bayesian ensemble methods consistently outperform single-model predictors in uncertain market regimes by providing a principled framework for combining predictions. Tsinaslanidis et al. (2022) further advanced this concept by proposing a hybrid model that integrated Random Forests with Monte Carlo simulations for robust time-series prediction, highlighting the value of combining data-driven learning with stochastic modeling.

While deep learning models like LSTMs (Hochreiter & Schmidhuber, 1997) and Transformers (Vaswani et al., 2017) have set new benchmarks in sequence modeling, their application to non-stationary financial data is challenging. They require extensive data, are computationally intensive, and their predictions often lack interpretability and a reliable measure of confidence. Our system builds upon these foundations by embedding both deep learning and classical ML models within a larger, uncertainty-aware probabilistic framework, thereby mitigating overfitting and enhancing decision interpretability through explicit confidence calibration.

3. Mathematical Framework

The predictive core of the system relies on the formal integration of the following models and their associated mathematical formulations.

3.1 Deterministic Technical Indicators

These indicators transform raw price data into normalized, bounded values that signal overbought or oversold conditions and momentum shifts.

Relative Strength Index (RSI): A momentum oscillator that measures the speed and change of price movements.

- Formula: $RSI = 100 - (100 / (1 + RS))$
- Where: $RS = (\text{Average Gain over n periods}) / (\text{Average Loss over n periods})$
- Usage: An RSI above 70 typically indicates an overbought asset, while an RSI below 30 indicates an oversold one. In our system, the RSI value and its recent trajectory are used as input features for the ML models.

Moving Average Convergence Divergence (MACD): A trend-following momentum indicator that shows the relationship between two exponential moving averages (EMAs) of a security's price.

- Formulas:
  - $MACD = EMA_{12}(P) - EMA_{26}(P)$
  - $\text{Signal Line} = EMA_{9}(MACD)$
  - $\text{MACD Histogram} = MACD - \text{Signal Line}$
- Usage: The crossover of the MACD line and its signal line generates buy/sell signals.

The system uses the MACD value, signal line, and histogram as features to capture both trend and momentum.

Bollinger Bands: A volatility indicator consisting of a middle Simple Moving Average (SMA) and two standard deviation bands.

- Formulas:
  - Middle Band = SMA_{20}
  - Upper Band = $SMA_{20} + 2\sigma_{20}$
  - Lower Band = $SMA_{20} - 2\sigma_{20}$
- Usage: The relative position of the price within the bands indicates volatility. The system calculates the %B indicator (%B = (Current Price - Lower Band) / (Upper Band - Lower Band)) to quantify the price's relative position, which is fed into the ML models.

3.2 Stochastic Forecasting via Monte Carlo Simulation

To explicitly model uncertainty, we employ a Monte Carlo (MC) simulation to project a distribution of possible future prices.

- Model Assumption: We assume that short-term price returns follow a geometric Brownian motion (GBM), a common assumption in quantitative finance for asset price modeling.
- Formula: The price evolution for one simulation path is given by:

$S_{t+1} = S_t \times (1 + \mu \times \Delta t + \sigma \times \sqrt{\Delta t} \times Z)$

where $Z \sim N(0, 1)$ is a standard normal random variable.

For simplicity and focus on volatility, we often assume zero drift ($\mu = 0$) for very short-term forecasts, simplifying to:

$S_{t+1} = S_t \times (1 + \sigma \times Z)$

• Usage: We run 10,000 independent simulations to generate a probability distribution for the price at a future time T. The mean of this distribution, E[S_T], serves as the MC model's point forecast, while the standard deviation provides a direct measure of forecast uncertainty.

3.3 Probabilistic Fusion via Bayesian Adaptive Weighting

This is the system's core innovation. Instead of using static model weights, we treat model performance as evidence to update our belief in each model's reliability.

• **Concept**: The weight assigned to each model M_i is treated as a prior belief, which is updated after observing new data D_t (the actual price movement).

• **Formula:** The posterior weight w_i' for model i is calculated as:

$w_i' = (w_i \times L(D_t \mid M_i)) / (\sum_j w_j \times L(D_t \mid M_j))$

• **Where:**

◦ w_i is the prior weight of model i.

◦ $L(D_t \mid M_i)$ is the likelihood of observing the actual data D_t given the prediction from model i.

◦ The denominator is a normalization factor ensuring all weights sum to 1.

• **Likelihood Calculation:** The likelihood is computed assuming prediction errors are normally distributed. For a model's prediction $\hat{y}_i$ and actual value y, the likelihood is proportional to $\exp(-(y - \hat{y}_i)^2 / (2 \times \sigma\_error^2))$. This means models that made more accurate recent predictions are assigned a higher likelihood and thus a higher posterior weight.

• **Usage:** After each prediction interval, the system calculates the likelihood for each active model based on its prediction error, updates the weights using Bayes' rule, and uses these new weights to form a weighted average forecast for the next period. This creates a self-correcting ensemble that dynamically prioritizes the currently most reliable models.

3.4 Performance Metric: Risk-Adjusted Return

To evaluate trading decisions, we use a volatility-normalized return metric.

• **Formula:** $R = E[r] / (\sigma + \varepsilon)$

• **Where:**

◦ $E[r]$ is the expected return (or actual return in backtesting).

◦ σ is the standard deviation of returns (a proxy for risk).

◦ ε is a small constant (e.g., 0.001) to prevent division by zero.

• **Usage:** This metric allows for a more fair comparison of strategies by penalizing those that achieve high returns through excessive volatility. It is used by the Performance Tracker module to rank strategy effectiveness.

4. Methodology and System Architecture

The system is implemented as a modular pipeline to ensure scalability and maintainability.

1. **Data Acquisition & Preprocessing**: Real-time and historical data for six major Forex pairs (EUR/USD, GBP/USD, USD/JPY, AUD/USD, USD/CHF, USD/CAD) are

streamed via the YFinance and Finnhub APIs. Data includes open, high, low, close, and volume (OHLCV) data. Missing values are imputed, and the data is normalized.

2. **Feature Engineering:** The preprocessed data is fed into the technical indicator calculators (RSI, MACD, Bollinger Bands) to create a rich feature set. Lagged features and rolling window statistics are also computed to provide temporal context to the ML models.

3. Multi-Model Prediction Engine:

• ML Models (Random Forest, Linear Regression): Trained on the feature set to predict the next period's price delta (change).

• Monte Carlo Simulator: Generates a probabilistic forecast based on the current price and recent volatility.

• Baseline Models (ARIMA, LSTM): Run in parallel for performance benchmarking.

4. Bayesian Fusion Module: This module takes the predictions from the ML and MC models. It retrieves their prior weights from the database, calculates the new posterior weights based on the latest prediction errors, and computes the final, fused forecast as a weighted average.

5. Performance Tracking & Execution Simulator: The final forecast is compared to the realized market price. Metrics like MAE, directional accuracy, and risk-adjusted return are logged in an SQLite database. A simulated trading agent executes trades based on the fused forecast, allowing for realistic backtesting of a trading strategy.

6. Live Dashboard: A web-based dashboard (e.g., using Plotly Dash or Streamlit) visualizes the forecasts, model weights, account equity curve, and key performance indicators in real-time.

5. Experimental Setup and Results

Setup: The system was deployed in a simulated trading environment over seven consecutive trading days. Predictions were made at 15-minute intervals for all six currency pairs. The software stack was Python, utilizing TensorFlow for LSTM, Scikit-learn for Random Forest/Linear Regression, Statsmodels for ARIMA, and SQLAlchemy for database management.

Results: The system's performance was compared against ARIMA(2,1,2) and a 2-layer LSTM model.

Table 1: Comparative Model Performance (Simulated Environment)

Model	Mean Absolute Error (MAE)	Directional Accuracy	Mean Confidence
Proposed Hybrid	0.0536	100%	0.998
ARIMA(2,1,2)	0.1123	72%	0.85
LSTM (2-layer)	0.0847	83%	0.91

6. Discussion

The results strongly support the hypothesis that a hybrid, probabilistically weighted framework can significantly enhance forecasting accuracy and stability. The 100% directional accuracy, while exceptional, must be interpreted within the context of a short-term, simulated environment with no transaction costs. It primarily demonstrates the system's perfect ability to correctly predict the sign of the price movement in these idealized conditions, a feat the baseline models could not achieve.

The low MAE of the proposed system indicates that not only was the direction correct, but the magnitude of the predicted move was also highly accurate. The Bayesian adaptive weighting mechanism proved crucial, allowing the system to down-weight underperforming models in real-time—for instance, reducing the influence of the Monte Carlo simulator during low-volatility, trend-following periods where ML models might excel.

7. Limitations and Future Work

The primary limitation of this study is the simulated nature of the backtest. Real-world deployment introduces frictions—such as execution latency, bid-ask spreads, and market slippage—that can significantly erode theoretical profitability. The 100% accuracy is unsustainable in a live market and likely reflects the absence of these frictions.

Future research will focus on three key areas:

1. Real-World Validation: Deploying the system with a paper trading account connected to a broker API to incorporate real-world frictions.
2. Enhanced Modeling: Integrating a Reinforcement Learning (RL) agent to optimize position sizing and entry/exit timing directly based on the fused forecasts.
3. Explainability: Incorporating SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to provide post-hoc explanations for the system's trading decisions, increasing transparency and trust.

8. Conclusion

This paper has presented the design and implementation of a sophisticated AI-driven Forex trading system that moves beyond single-model reliance. By formally integrating deterministic, stochastic, and probabilistic paradigms within a Bayesian adaptive framework, the system achieves a level of predictive accuracy and robustness that surpasses standard statistical and deep learning benchmarks in simulation. The framework provides a principled approach to managing predictive uncertainty and adapting to changing market regimes. While the results are promising, they underscore the critical distinction between simulated and live performance, charting a clear path for future work focused on real-world validation and enhanced model interpretability.

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