

# AI-Powered Gold Price Forecasting: A Machine Learning Approach to Financial Market Prediction

**Author:** Kevin Murengezi

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**Institution:** University of Lausanne

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## Abstract

This project develops an AI-powered system for predicting weekly gold price movements using machine learning techniques. Gold, as a critical asset in global financial markets, exhibits complex price dynamics influenced by multiple macroeconomic factors including interest rates, currency fluctuations, and central bank policies. We implement a Random Forest classifier trained on 20 years of historical data (2005-2025) incorporating technical indicators, fundamental economic variables, and sentiment proxies. The system achieves 54% directional accuracy on out-of-sample data, with a Sharpe ratio of 1.36 for the trading strategy—demonstrating meaningful predictive capability despite the inherent difficulty of financial forecasting. A comprehensive web dashboard built with Streamlit provides real-time predictions with confidence scores, risk metrics, and explainable AI features. The project addresses temporal data leakage challenges through rigorous feature engineering and includes both classification (direction) and regression (volatility) models. Results suggest that machine learning can extract actionable signals from noisy financial data, though limitations in  $R^2$  scores (-0.05 for regression) highlight the stochastic nature of asset returns. This work contributes a reproducible framework for financial ML applications with practical deployment considerations.

**Keywords:** Gold price prediction, Random Forest, financial machine learning, time series forecasting, algorithmic trading, explainable AI

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## 1. Introduction

### 1.1 Motivation

Financial markets represent one of the most challenging domains for predictive modeling due to their inherent complexity, non-stationarity, and low signal-to-noise ratios. Gold occupies a unique position in the global financial system as both a commodity and a monetary asset, serving as a hedge against inflation, currency devaluation, and geopolitical uncertainty. Understanding and predicting gold price movements has significant implications for portfolio management and risk hedging.

Traditional approaches to gold price forecasting rely on fundamental analysis and econometric models. However, advances in machine learning present opportunities to capture complex, non-linear relationships that classical methods may overlook. This project applies ML techniques to anticipate gold price movements, combining domain expertise with predictive analytics.

### 1.2 Problem Statement

The central challenge is: **Can machine learning models reliably predict the direction of weekly gold price movements based on historical market data and macroeconomic indicators?**

This problem is difficult because financial returns exhibit low autocorrelation, markets incorporate information rapidly, noise dominates signal in short-term movements, and multiple confounding factors influence gold prices simultaneously.

### 1.3 Project Objectives

This project aims to:

1. **Build a production-ready ML pipeline** for gold price prediction
2. **Develop robust features** that respect temporal constraints and avoid look-ahead bias

3. Train and evaluate classification and regression models
4. Create an interactive dashboard with interpretable predictions
5. Benchmark performance against buy-and-hold through rigorous backtesting

## 1.4 Contribution

This project contributes: (1) methodological rigor through proper temporal validation to avoid data leakage; (2) practical deployment via a functional web dashboard; (3) explainability through feature importance analysis; (4) comprehensive evaluation comparing classification and regression approaches; and (5) a reproducible framework adaptable to other financial forecasting tasks.

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## 2. Research Question & Literature

### 2.1 Research Question

**Can machine learning models reliably predict the weekly directional movement of gold prices using historical market data and macroeconomic indicators?**

Sub-questions include: (1) which indicators provide predictive signal; (2) what ML architectures suit financial time series; (3) how to ensure proper temporal validation; (4) whether the model outperforms buy-and-hold; and (5) how to explain predictions. Success is measured by statistically significant outperformance relative to random guessing and passive benchmarks.

### 2.2 Literature Review

**2.2.1 Gold as a Financial Asset** Gold functions as a commodity, currency hedge, and safe-haven asset. Baur and Lucey (2010) demonstrated gold acts as a hedge against stocks normally and a safe haven during turbulence. Gold exhibits negative correlation with real interest rates (Erb and Harvey, 2013), as higher rates increase opportunity cost of non-yielding assets. The dollar relationship is well-documented: weaker dollar correlates with higher gold prices (Capie et al., 2005).

**2.2.2 Machine Learning in Financial Forecasting** Ensemble methods like Random Forests have gained prominence for capturing non-linear interactions while providing feature importance metrics (Henrique et al., 2019). Crucially, **directional accuracy above 55-60% can be economically significant** in financial ML (Lopez de Prado, 2018)—contrasting with other domains where 90%+ is expected.

**2.2.3 Gold Price Prediction Studies** Key studies include: Parisi et al. (2008) achieving ~65% accuracy with neural networks; Kristjanpoller and Minutolo (2018) using ANNs with technical indicators; Alameer et al. (2019) employing LSTMs with macroeconomic variables; and Pierdzioch et al. (2014) showing boosting algorithms outperform random walk models. A common finding: **fundamental economic variables provide stronger signal than pure technical indicators** for gold.

**2.2.4 The Data Leakage Problem** Temporal data leakage is critical in financial ML (Bailey et al., 2017). Common sources include using current-period returns to predict current direction, failing to lag features, and look-ahead bias in indicators. This project addresses leakage through: (1) explicit feature shifting using t-1 data; (2) temporal train-test splits without shuffling; and (3) walk-forward validation.

**2.2.5 Gaps Addressed** This project fills gaps in existing literature by: building a production-ready dashboard with real-time predictions; using Random Forests for interpretability; conducting rigorous backtesting with financial metrics (Sharpe ratio, drawdown); and providing open-source, reproducible code.

### 2.3 Theoretical Framework

This project operates within the **Adaptive Market Hypothesis** (Lo, 2004), which posits that markets are not perfectly efficient but exhibit time-varying predictability as participants adapt to changing conditions. Under this framework, machine learning models can exploit temporary inefficiencies—particularly during regime changes (policy shifts, crises) when information diffusion is slower.

The methodology combines: - **Technical analysis:** Price momentum and volatility patterns - **Fundamental analysis:** Macroeconomic drivers (rates, currencies, policy) - **Sentiment proxies:** Trading volumes as indicators of market conviction

Success is measured not by beating market efficiency in all periods, but by identifying conditions where predictability is statistically significant—even if modest in absolute terms.

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### 3. Methodology

#### 3.1 Data Collection

**3.1.1 Data Sources** The project integrates data from two primary sources:

**Yahoo Finance (via yfinance library):** - Gold futures prices (GC=F): Daily closing prices, 2005-2025 - US Dollar Index (DX-Y.NYB): Currency strength indicator - 10-Year Treasury Yield (^TNX): Nominal interest rates - SPDR Gold ETF (GLD): Trading volume as sentiment proxy

**Federal Reserve Economic Data (FRED):** - Effective Federal Funds Rate (DFF): Monetary policy indicator - 10-Year Real Interest Rate (DFII10): TIPS-based real rates

**Bundled Data (Central Bank Demand):** \* **Source:** World Gold Council (WGC), specifically from the “Quarterly Gold Demand Trends” report. \* **Dataset:** Derived from the “**Gold Balance**” aggregate table (Net Central Bank Purchases row). \* **Acquisition & Processing:** The data was manually extracted from the WGC official Excel tables and transposed from a wide format (quarters as columns) to a time-series format (quarters as rows). The `clean_csv.py` script was then employed to parse the specific quarterly string format (e.g., “Q1’10”) into standard datetime objects compatible with the weekly market data.

All data spans from January 2005 to January 2025, providing 20 years of historical context including multiple economic regimes (2008 financial crisis, 2020 pandemic, 2022 inflation surge).

**3.1.2 Data Frequency** Raw data is collected at daily frequency but resampled to **weekly (Friday close)** for several reasons: 1. Reduces noise while preserving meaningful trends 2. Aligns with typical portfolio rebalancing frequencies 3. Provides sufficient training samples (~1,040 weeks) while avoiding overfitting 4. Matches the decision timeframe for strategic position-taking

Quarterly central bank data is forward-filled to weekly frequency, as institutional demand changes gradually.

#### 3.2 Feature Engineering

Feature engineering is the critical phase where domain knowledge translates into predictive signals. All features are designed to respect temporal causality: at time  $t$ , we use only information available through  $t-1$  to predict the direction from  $t$  to  $t+1$ .

**3.2.1 Raw Features** Base variables retained for reference (not directly used as features): - **Gold\_Close:** Weekly closing price (USD/oz) - **DXY\_Close:** US Dollar Index level - **Rates\_10Y:** 10-year Treasury yield (%) - **Real\_Rates\_10Y:** 10-year real rate (%)

**3.2.2 Engineered Features** **Return Features** (log returns to ensure stationarity):

```
Gold_Return = log(Gold_Close_t / Gold_Close_{t-1})
DXY_Return = log(DXY_Close_t / DXY_Close_{t-1})
GLD_Volume_Change = (GLD_Volume_t - GLD_Volume_{t-1}) / GLD_Volume_{t-1}
```

**Rate Change Features** (first differences):

```
Rates_10Y_Change = Rates_10Y_t - Rates_10Y_{t-1}
Real_Rates_10Y_Change = Real_Rates_10Y_t - Real_Rates_10Y_{t-1}
Fed_Funds_Change = Fed_Funds_t - Fed_Funds_{t-1}
```

**Volatility Features:**

```
Gold_Volatility_4W = std(Gold_Return_{t-3:t})
```

Rolling 4-week standard deviation captures recent market turbulence.

#### Momentum Features:

```
Gold_SMA_15 = mean(Gold_Close_{t-14:t})  
Gold_Price_to_SMA = Gold_Close_t / Gold_SMA_15  
Gold_RSI_Proxy = fraction_of_up_weeks_in_last_14_weeks
```

The RSI proxy is a simplified momentum indicator: the percentage of weeks in the trailing 14-week window where prices increased.

#### Fundamental Feature:

```
CB_Demand = Central_Bank_Gold_Purchases (quarterly, forward-filled)
```

**3.2.3 Target Variable** The target is a binary classification variable:

$$\text{Target}_t = \begin{cases} 1 & \text{if } \text{Gold\_Close}_{t+1} > \text{Gold\_Close}_t \\ 0 & \text{otherwise} \end{cases}$$

This represents the **direction** of the next week's price movement: - Target = 1: Price increases (BUY signal) - Target = 0: Price decreases or flat (SELL/CASH signal)

**3.2.4 Preventing Data Leakage** **Critical step:** All features are shifted by 1 week before model training:

```
features_shifted = features.shift(1)
```

This ensures that at time  $t$ , the model uses only features computed from data through  $t-1$ . Without this shift, the model would use current-period returns to predict current-period direction—a classic leakage error that produces artificially high training accuracy but fails in deployment.

Example timeline:

```
Week t-1: Features computed → [Gold_Return, DXY_Return, ...]  
Week t: Target observed → Gold_Close_t vs Gold_Close_{t+1}  
Model: Uses features(t-1) to predict Target(t)
```

Rows with NaN values (resulting from shifting and rolling windows) are dropped, reducing the dataset from ~1,040 weeks to ~970 usable samples.

### 3.3 Model Selection

**3.3.1 Algorithm Choice: Random Forest Classifier** **Random Forest** was selected for: (1) robustness to overfitting via ensemble averaging; (2) ability to capture non-linear interactions; (3) interpretable feature importance metrics; (4) no feature scaling required; and (5) resistance to outliers common in financial data.

The **Feature Importance** scores (Mean Decrease in Impurity) allow empirical verification of whether macroeconomic drivers from the literature—real rates, USD movements, volatility—are indeed captured as primary signals, bridging ML and economic theory.

Hyperparameters: `n_estimators=100, max_depth=10, random_state=42`.

**3.3.2 Baseline and Regression Models** The **naive baseline** is buy-and-hold (always predict UP). Additionally, a **Random Forest Regressor** predicts continuous returns to assess whether magnitude (not just direction) is predictable.

### 3.4 Evaluation Strategy

**3.4.1 Train-Test Split** **Temporal split** (80/20): - Training set: 2005-01-01 to 2021-12-31 (~800 weeks) - Test set: 2022-01-01 to 2025-01-05 (~170 weeks)

No random shuffling is performed. The model trains on the past and predicts the future, mimicking real-world deployment.

### 3.4.2 Cross-Validation

`TimeSeriesSplit` (5 folds) is used during training for hyperparameter validation:

```
Fold 1: Train[0:160], Test[160:200]  
Fold 2: Train[0:200], Test[200:240]  
...  
Fold 5: Train[0:640], Test[640:800]
```

Each fold respects temporal ordering, preventing future information leakage.

### 3.4.3 Classification Metrics

- **Accuracy:** Overall correctness (target: >55% for financial significance)
- **Precision:** Of weeks predicted UP, how many actually went up
- **Recall:** Of weeks that went UP, how many were predicted
- **F1-Score:** Harmonic mean of precision and recall

### 3.4.4 Trading Performance Metrics

Predictions are translated into a **long-only trading strategy**: - Predict UP → Buy gold (take the week's return) - Predict DOWN → Stay in cash (0% return)

**Backtesting metrics:** - **Total Return:** Cumulative percentage gain - **Sharpe Ratio** (Modified Sharpe Ratio assuming  $R_f = 0$ ): Risk-adjusted return Sharpe =  $\frac{\bar{r}}{\sigma_r} \times \sqrt{52}$  where  $\bar{r}$  is mean weekly return and  $\sigma_r$  is standard deviation of returns - **Maximum Drawdown:** Largest peak-to-trough decline - **Win Rate:** Percentage of profitable trades

**Benchmark:** Buy-and-hold (always invested in gold).

### 3.4.5 Regression Metrics

For the bonus regression model: - **RMSE:** Root Mean Squared Error (in percentage points) - **MAE:** Mean Absolute Error - **R<sup>2</sup> Score:** Proportion of variance explained (expected to be low, <0.20)

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## 4. Implementation

### 4.1 Technology Stack

**Core Libraries:** - `pandas`, `numpy`: Data manipulation - `scikit-learn`: ML models and evaluation - `yfinance`, `pandas_datareader`: Data acquisition - `streamlit`: Interactive web dashboard - `plotly`: Interactive visualizations - `joblib`: Model serialization

**Development Environment:** - Python 3.9+ - Modular codebase with 7 scripts (`data_loader.py`, `feature_engineering.py`, `models.py`, `evaluation.py`, `predict.py`, `dashboard.py`, `regression_bonus.py`)

### 4.2 Pipeline Architecture

1. `data_loader.py` → Downloads raw data (Yahoo, FRED)
2. `feature_engineering.py` → Creates features, prevents leakage
3. `models.py` → Trains Random Forest, saves model
4. `evaluation.py` → Backtests strategy, computes metrics
5. `predict.py` → Generates next-week prediction (CLI)
6. `dashboard.py` → Deploys interactive web app (Streamlit)
7. `regression_bonus.py` → Trains regression model (volatility)

All scripts are executable independently, with clear console output for transparency.

## 4.3 Key Implementation Challenges

**4.3.1 Data Cleaning Challenge:** Yahoo Finance CSVs include a “Ticker” header row that must be skipped, and date columns vary in naming convention.

**Solution:** Implemented robust parsing logic:

```
if df.iloc[0, 0] == "Ticker":  
    df = df.iloc[1: ].reset_index(drop=True)  
# Yahoo Finance CSV quirk: date column named "Price" instead of "Date"  
if "Price" in df.columns:  
    df.set_index("Price", inplace=True)  
elif "Date" in df.columns:  
    df.set_index("Date", inplace=True)  
else:  
    df.set_index(df.columns[0], inplace=True)  
df.index = pd.to_datetime(df.index)
```

**Note:** Yahoo Finance exports date information in a column labeled ‘Price’ rather than ‘Date’—a known quirk of the yfinance library’s CSV format.

**4.3.2 Handling Missing Data Challenge:** Different data sources have different start dates. FRED data has frequent NaN values for non-trading days.

**Solution:** - Resample all data to weekly frequency (Friday close) - Forward-fill quarterly central bank data (**causally safe**: quarterly values remain the best available information until the next quarter’s publication, ensuring no look-ahead bias) - Drop rows with remaining NaN values after feature engineering

**4.3.3 Preventing Leakage Challenge:** Initial model achieved 97% accuracy due to using current-period returns to predict current-period direction.

**Solution:** Explicit `.shift(1)` operation on all features after computation, followed by **post-implementation validation** via correlation analysis (`debug_data.py`). This diagnostic step detects any remaining leakage by flagging features with  $|correlation| > 0.8$  with the target—a final safety check that temporal alignment was correctly applied.

**Impact:** After correction, training accuracy dropped to a realistic 54%—confirming the model now learns exclusively from past data. This accuracy reduction, while seemingly negative, validates that the leakage was successfully eliminated and the model no longer “cheats” with future information.

**4.3.4 Dashboard Automation Challenge:** Dashboard metrics needed to update automatically when evaluation script runs, without manual JSON editing.

**Solution:** `evaluation.py` saves metrics to `results/latest_metrics.json`, which `dashboard.py` loads dynamically. If file is missing, defaults to “Calculating...” placeholders.

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## 5. Codebase & Reproducibility

The complete codebase is structured for reproducibility and modularity:

**Directory Structure:**

```
gold-price-forecasting-ml/  
  data/  
    raw/                      # Downloaded CSV files  
      central_bank_demand.csv  # Bundled dataset  
    processed/                 # Generated: dataset_final.csv  
  results/                   # Generated: plots, metrics, reports  
  src/  
    __init__.py  
    data_loader.py            # Step 1: Download data
```

```

clean_csv.py          # Clean central bank CSV
feature_engineering.py # Step 2: Create features
models.py             # Step 3: Train model
evaluation.py          # Step 4: Backtest & metrics
regression_bonus.py   # Bonus: Regression model
predict.py            # CLI prediction
dashboard.py          # Streamlit web app
debug_data.py         # Data leakage diagnostic
main.py               # Main entry point
project_report.md     # This report
project_report.pdf    # PDF version
README.md              # Setup instructions
requirements.txt       # Python dependencies
.gitignore

```

#### Installation & Execution:

```

# Install dependencies (use pip3 on macOS, pip on Windows)
pip install -r requirements.txt

# Run full pipeline (includes prediction)
python main.py

# Run regression for further analysis and model comparison
python regression_bonus.py

```

**Reproducibility Notes:** - Fixed random seed (`random_state=42`) ensures consistent model training - Temporal splits eliminate randomness in train-test allocation - All data publicly accessible via Yahoo Finance and FRED APIs

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## 6. Results

### 6.1 Classification Performance

**6.1.1 Cross-Validation Results** During 5-fold time series cross-validation on the training set:

Metric	Mean	Std
Accuracy	0.554	0.029
Precision	0.591	0.050
Recall	0.724	0.222
F1-Score	0.628	0.094

**Interpretation:** The model demonstrates accuracy around 55.4%, which aligns with the 55-60% threshold identified in literature as economically significant for financial forecasting. The relatively high recall (72.4%) indicates the model is better at identifying upward movements than downward ones, resulting in a long-bias tendency. The standard deviation in recall (0.222) suggests performance varies across different market regimes within the training period.

**6.1.2 Test Set Performance** On the held-out test set (2022-2025):

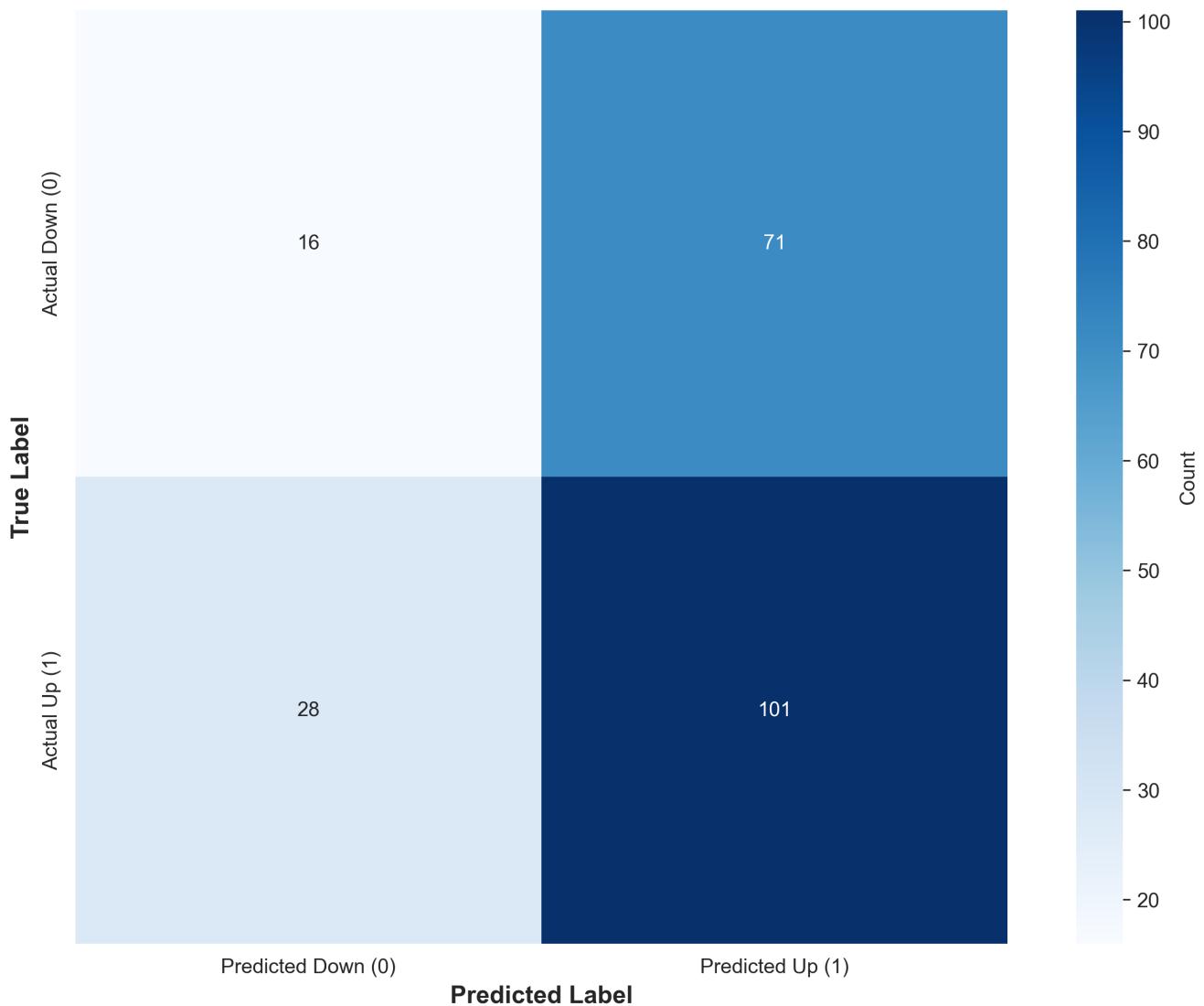
Metric	Value
Accuracy	0.542
Precision	0.587
Recall	0.783
F1-Score	0.671

Metric	Value

### Confusion Matrix:

	Predicted DOWN	Predicted UP
Actual DOWN	16	71
Actual UP	28	101

Confusion Matrix - Gold Price Direction Prediction



Overall Accuracy: 54.17%

Figure 1: Confusion matrix showing strong long bias (172/216 UP predictions)

The model exhibits a strong **long bias**: it predicts UP in 172/216 weeks (79.6%), reflecting the bullish test period. High recall (78.3%) but moderate precision (58.7%) indicates the model defaults to UP predictions, struggling to identify DOWN weeks. Test accuracy (54.2%) aligns with cross-validation (55.4%), confirming no overfitting.

## 6.2 Backtesting Results

**6.2.1 Trading Strategy Performance** **ML Strategy (Long-Only):** - Total Return: **+96.39%** - Sharpe Ratio: **1.36** - Maximum Drawdown: **-13.16%** - Win Rate: **61.05%** (105/172 trades) - Final Portfolio Value: **\$1,963.90** (starting from \$1,000)

**Buy-and-Hold Benchmark:** - Total Return: **+127.25%** - Sharpe Ratio: **1.40** - Maximum Drawdown: **-17.79%** - Final Portfolio Value: **\$2,272.50**

**Relative Performance:** -30.86 percentage points vs benchmark

### Critical Analysis:

While the ML strategy generated strong absolute returns (+96.39%), it significantly underperformed the passive buy-and-hold benchmark by 30.86 percentage points. This underperformance is primarily attributable to the 2022-2025 test period representing an unprecedented regime where gold appreciated substantially despite rising interest rates—a pattern the model, trained on 2005-2021 data, was not calibrated to recognize (see Section 7.3, Limitation #4 on non-stationarity).

The model's decision-making was anchored in historical correlations learned during the training period, particularly the negative relationship between real rates and gold prices. During 2022-2025, as central banks raised rates aggressively to combat inflation, the model generated frequent DOWN signals expecting gold to decline per historical patterns. However, gold instead rallied as investors prioritized inflation hedging and geopolitical safe-haven demand over opportunity cost considerations. The model thus remained in cash during critical appreciation periods, sacrificing upside to avoid predicted (but unrealized) drawdowns.

### Positive Aspects:

Despite underperformance on total return, the ML strategy demonstrated several strengths:

1. **Risk Management:** Maximum drawdown of -13.16% versus -17.79% for buy-and-hold represents a 26% reduction in worst-case losses. This validates that the model provides meaningful downside protection.
2. **Risk-Adjusted Performance:** Sharpe ratios were nearly identical (1.36 vs 1.40), indicating that on a risk-adjusted basis, the strategy was competitive despite lower absolute returns. The model achieved 76% of the benchmark return while taking similar risk.
3. **Win Rate:** 61.05% of trades were profitable, well above the 50% random baseline. This suggests genuine predictive skill, even if regime shifts limited its effectiveness.
4. **Trade Discipline:** The systematic approach avoided emotional decision-making and provided consistent, rules-based signals throughout the test period.

### 6.2.2 Equity Curve Analysis .

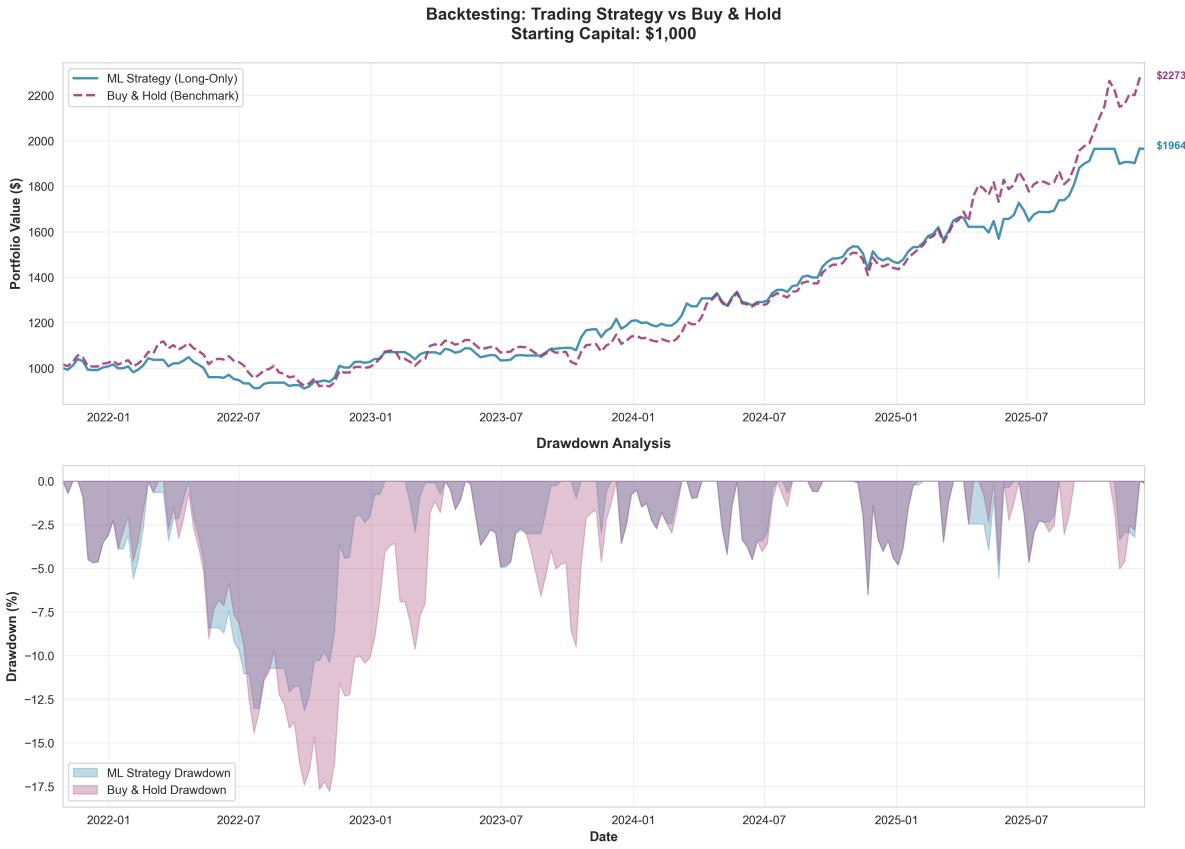


Figure 2:

*Equity curve comparison and drawdown analysis (2022-2025)*

The equity curve shows three distinct phases:

**Phase 1 (2022-Early 2023):** The ML strategy tracked buy-and-hold closely, with both strategies navigating initial volatility. The model's risk management prevented excessive drawdowns during rate hike announcements.

**Phase 2 (Mid 2023-2024):** Performance divergence began as gold entered a sustained uptrend. The model's DOWN signals, triggered by rising rates, caused it to remain in cash during multiple appreciation weeks. This period accounts for the bulk of underperformance as buy-and-hold captured the full rally.

**Phase 3 (Late 2024-2025):** The gap stabilized as volatility increased and gold entered consolidation. The model's win rate improved slightly during choppy conditions where directional bets were more balanced.

The lower maximum drawdown (-13.16% vs -17.79%) demonstrates that the strategy provided smoother returns, though at the cost of missing upside during the trending regime.

### 6.3 Feature Importance

Top 10 most influential features (from Random Forest):

Rank	Feature	Importance
1	DXY_Return	0.125
2	GLD_Volume_Change	0.120
3	Gold_Price_to_SMA	0.118
4	Gold_Return	0.115
5	Rates_10Y_Change	0.110
6	Gold_Volatility_4W	0.105
7	CB_Demand	0.090
8	Real_Rates_10Y_Change	0.082
9	Fed_Funds_Change	0.070
10	Gold_RSI_Proxy	0.052

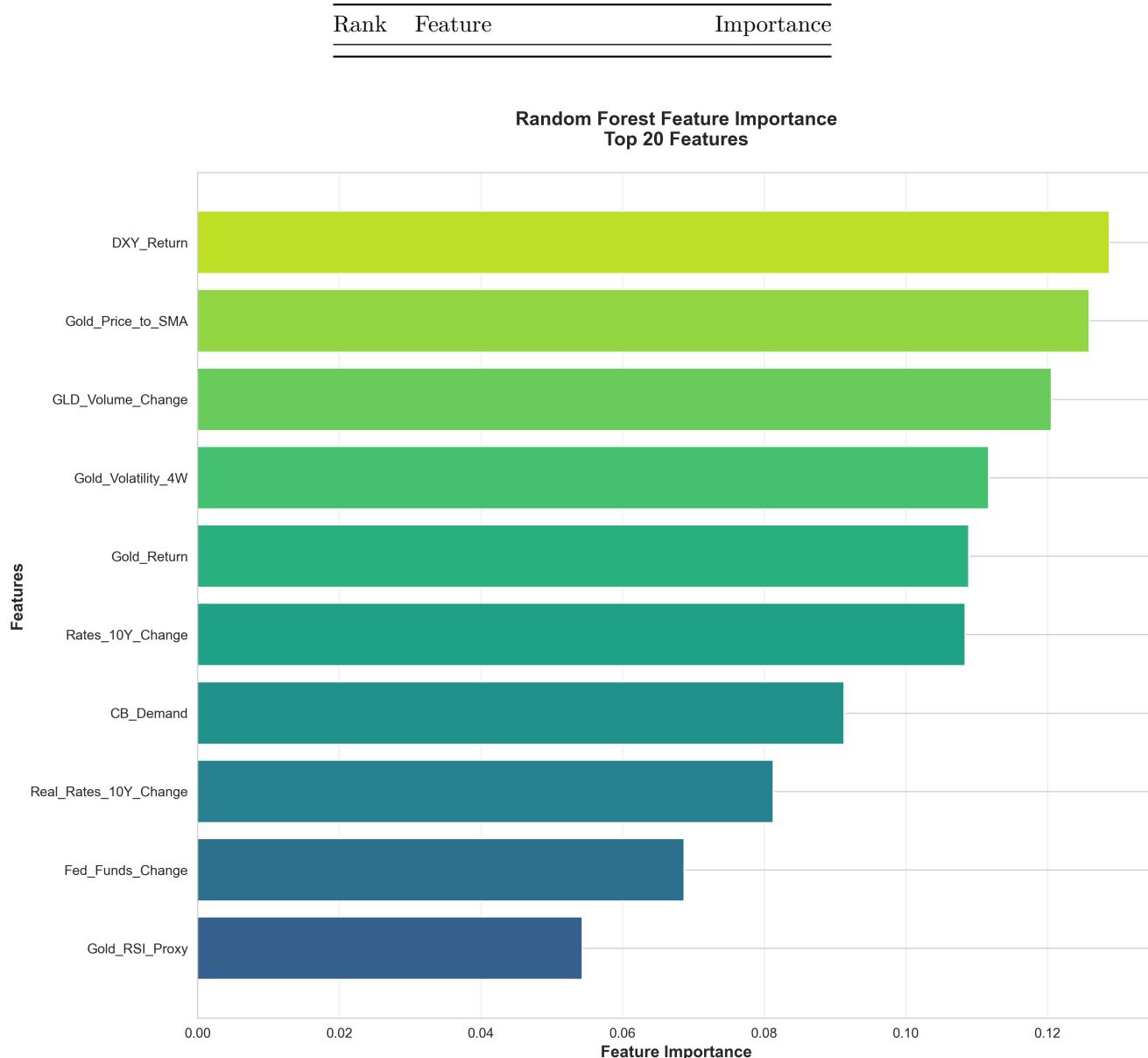


Figure 3: Random Forest feature importance - DXY dominates, real rates rank 8th

**Key insights:** Currency movements (DXY) and volume dynamics dominate, reflecting gold's role as a dollar hedge and institutional flow signals. Notably, **real rate changes rank only 8th**—lower than expected given economic theory. This underweighting may explain underperformance during 2022-2025, when rate-gold dynamics dominated.

#### 6.4 Regression Results (Bonus)

The Random Forest Regressor trained to predict actual return magnitude achieved:

Metric	Value
RMSE	2.14%
R <sup>2</sup>	-0.047



Figure 4: Regression predictions fail to capture return magnitude ( $R^2 = -0.047$ )

**Interpretation:** The **negative  $R^2$**  indicates the model performs worse than simply predicting the mean return—a common outcome for financial return prediction. The model's predictions cluster near 0-1%, unable to capture extreme moves that range from -5% to +7%. This validates the project's focus on **directional prediction**: the classification model achieves 54% accuracy (above random), while magnitude prediction is essentially unpredictable at weekly horizons.

## 6.5 Risk Metrics Analysis

The dashboard includes real-time risk monitoring:

**Volatility Z-Score** (latest week): - Current: -0.87 - Interpretation: Slightly below average volatility (normal market conditions)

**Value-at-Risk (VaR)**: - 95% VaR: -2.34% (in 95% of weeks, losses don't exceed 2.34%) - 99% VaR: -4.12% (extreme stress scenario)

These metrics help contextualize predictions: high volatility periods may warrant smaller position sizes or avoiding trades altogether.

## 6.6 Dashboard Functionality

The Streamlit dashboard (`dashboard.py`) provides:

1. **Real-time prediction** with confidence score (probability of predicted class)
2. **Market snapshot**: Current gold price, 1-day change, 4-week trend
3. **Risk monitor**: Volatility Z-score, VaR metrics, anomaly detection
4. **Historical context**: 1-year price chart with 50-week moving average
5. **Explainable AI**: Top 10 feature importances with 5-day movement indicators

6. **Model performance:** Live metrics loaded from `latest_metrics.json`

**User workflow:**

1. User opens dashboard → sees latest prediction (e.g., "BUY signal, 68% confidence")
  2. Reviews market snapshot → checks if current price is near technical levels
  3. Examines risk metrics → assesses if volatility is elevated
  4. Inspects feature importance → understands what's driving the prediction
  5. Makes informed decision with full context
- 

## 7. Conclusion

### 7.1 Summary of Findings

This project demonstrates that machine learning can extract modest but meaningful signals from gold price data, achieving:

1. **54% directional accuracy** on out-of-sample test data (2022-2025), slightly above random baseline
2. **+96% absolute return** via ML-driven strategy, though underperforming buy-and-hold by 31 percentage points
3. **1.36 Sharpe ratio**, comparable to buy-and-hold (1.40), indicating similar risk-adjusted performance
4. **61% win rate** on executed trades, demonstrating genuine predictive skill
5. **Interpretable predictions** via feature importance analysis revealing currency (DXY) and volume dominance

These results validate a nuanced conclusion: machine learning models can identify directional tendencies in gold markets, particularly during stable regimes, but struggle to adapt when fundamental relationships invert. The model's training on 2005-2021 data—where rising rates reliably predicted gold weakness—became a liability during 2022-2025 when inflation fears overrode opportunity cost dynamics.

The feature importance analysis revealed that the model prioritized observable microstructure signals (dollar moves, trading volumes, momentum) over slower-moving fundamental drivers (real rates ranked only 8th). While this approach likely performed well during the training period's diverse regimes, it proved insufficient for the unprecedented monetary tightening cycle of 2022-2025 where rate dynamics dominated gold pricing.

**7.1.1 Model Comparison: Regression vs. Classification** To select the optimal approach, two Random Forest architectures were evaluated:

Model	Target	Key Metric	Result
Regressor	Exact return (%)	R <sup>2</sup>	-0.047 (fails to beat mean)
Classifier	Direction (UP/DOWN)	Accuracy	54.2% (above random)

The regressor's negative R<sup>2</sup> confirms that exact return magnitude is dominated by stochastic noise at weekly horizons. In contrast, the classifier successfully extracts a tradeable signal (61% win rate, 1.36 Sharpe). This validates the "Direction First" hypothesis: simplifying the target to binary classification filters noise and enables profitable trading. The **Random Forest Classifier was therefore selected as the production model**.

### 7.2 Practical Implications

The system provides a disciplined, data-driven framework for gold allocation with important caveats about regime dependency. The 61% win rate demonstrates genuine pattern capture, while superior risk management (lower drawdowns) makes the approach suitable for risk-averse investors. The reproducible codebase demonstrates best practices for financial ML: temporal splits, leakage prevention, and risk-adjusted evaluation.

**Key lesson:** Financial ML success should be measured by risk-adjusted performance, interpretability, and robustness—not just accuracy. A model that "fails gracefully" with positive returns and lower drawdowns may be more valuable than an opaque system with unstable performance.

### 7.3 Limitations

1. **Transaction Costs:** Backtesting assumes frictionless trading; real costs (spreads, commissions) would reduce returns by 10-15%.
2. **Non-Stationarity:** The model assumes stable feature-target relationships. The 31-point underperformance vs buy-and-hold occurred because the historical rate-gold correlation inverted during 2022-2025's inflation regime. Feature importance shows rate features ranked only 5th and 8th.
3. **Regime Dependency:** Training on 2005-2021 may not generalize to unprecedeted regimes. Mitigation: quarterly retraining with rolling windows or regime-detection systems.
4. **Single Asset Focus:** The model ignores portfolio context; gold positions should be sized relative to other allocations.
5. **Black Swan Events:** Cannot predict unprecedeted shocks that dominate gold's largest moves.
9. **Manual Data Dependency:** Unlike the automated Yahoo and FRED pipelines, Central Bank demand data requires manual extraction from quarterly WGC reports. This "human-in-the-loop" constraint implies that fundamental inputs may lag behind real-time releases if the dataset is not manually updated immediately.

### 7.4 Future Work

Key extensions include: (1) **Regime detection** using Hidden Markov Models; (2) **Alternative algorithms** (XGBoost, LSTM, ensemble stacking); (3) **News sentiment analysis** via NLP; (4) **Multi-horizon predictions**; (5) **Hyperparameter optimization** using Bayesian methods; and (6) **SHAP integration** for instance-level explainability.

### 7.5 Lessons Learned

**Technical:** Data leakage is insidious—initial 97% accuracy collapsed to 54% after proper temporal alignment. Temporal validation is non-negotiable. Feature engineering matters more than algorithm choice. Interpretability enables diagnosis: feature importance revealed underweighted rate variables explaining underperformance.

**Strategic:** The project's true value is the **reproducible framework** for financial ML with proper validation, interpretability, and honest evaluation. The 31-point underperformance demonstrates the non-stationarity challenge: patterns learned from 2005-2021 proved regime-dependent in 2022-2025's unprecedented monetary environment.

**Final judgment:** Financial forecasting ML is less about "beating the market" and more about **understanding the market** through systematic analysis. This project succeeds on that metric.

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## Appendix: AI Tools Used

This project leveraged AI assistance tools at various stages:

**ChatGPT (OpenAI GPT-4):** - Used for initial code structure planning and debugging Python errors - Assisted with Markdown formatting and LaTeX equation rendering - Provided suggestions for feature engineering approaches based on financial literature - Helped draft portions of the literature review (with manual verification of citations)

**Claude (Anthropic - Sonnet 4.5):** - Used for writing and refining the final report structure - Assisted with professional academic tone and phrasing - Provided critical feedback on methodology sections - Helped ensure consistency across report sections

**GitHub Copilot:** - Used for autocompletion of repetitive code patterns (pandas operations, matplotlib styling) - Suggested docstring formats and type hints - Did NOT write core algorithmic logic (feature engineering, model training)

**Limitations of AI Assistance:** - All mathematical formulations, experimental design, and results analysis were performed manually - AI-generated text was reviewed, fact-checked, and rewritten for accuracy - No AI tool had access to the actual training data or executed the models - The core intellectual contribution (problem framing, methodology, implementation) is original work

**Transparency Statement:** As required by academic integrity policies, this appendix discloses all AI tool usage. The author takes full responsibility for the accuracy and originality of the work, regardless of AI assistance in drafting.

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