# Bitcoin Trend Direction Prediction Using Machine Learning

Based on the Methodology of Hafid et al. (2024)

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## 1 Introduction

This project replicates and adapts the methodology presented in the research paper *Predicting Market Trends with Enhanced Technical Indicator Integration and Classification Models* by Hafid et al., which proposes an integrated technical indicator and machine learning framework for predicting cryptocurrency price direction. The authors show that combining momentum-, trend-, volatility-, and volume-based technical indicators with classification models such as Logistic Regression and XGBoost produces highly accurate directional predictions.

Following the paper, we aim to classify Bitcoin (BTC-USD) daily trend direction using engineered technical indicators and a moving-average—based label. The target variable follows the rule defined in Equation (1) of the reference study:

$$\text{Signal} = \begin{cases} 1, & \text{if MA10} \geq \text{MA60} \\ 0, & \text{otherwise} \end{cases}$$

This formulation yields a stable classification target aligned with trend-following systems. The objective is to evaluate whether the methodology from the paper produces similar performance when applied to daily OHLCV data rather than 15-minute resolution.

## 2 Methodology

Daily BTC-USD OHLCV data (2019–2025) is retrieved from Yahoo Finance and cleaned for indicator generation. Technical indicators are computed exactly as outlined in Sections III(A)–III(D) of Hafid et al., including RSI(14,30), Momentum, ROC, MACD, EMA(10,30,200), Bollinger Bands, ATR(14), CCI(20), Stochastic Oscillator variants, OBV, Chaikin Money Flow, and the Accumulation/Distribution Line. Indicators follow the mathematical definitions provided in the study.

Consistent with the research methodology, we apply chi-square ($X^2$) feature selection as defined in Equation (6) of the paper to identify the most statistically relevant predictors. Two models are trained: Logistic Regression as a baseline and XGBoost as the primary classifier. We preserve chronological ordering using an 80%/20% time-series split.

Evaluation follows the paper's design, using accuracy, precision, recall, F1-score, ROC-AUC, and a confusion matrix. Additionally, a long-only backtest based on predicted signals is implemented as an extension beyond the original study.

## 3 Experiments / Analysis

Model performance closely matches the results reported by Hafid et al. XGBoost achieves approximately 91.9% accuracy and a ROC-AUC of 0.978, while Logistic Regression achieves 91.9% accuracy and 0.979 ROC-AUC. These values align with the research paper's findings, which report accuracy around 92.4% and AUC near 0.982 for XGBoost.

Feature selection and model-based importance rankings identify RSI, MACD, momentum indicators, and Stochastic Oscillator components as highly influential, consistent with Figure 6 (feature ranking) in the reference study. PCA results show strong redundancy among indicators, supporting the use of $X^2$ selection.

The backtest demonstrates trend-following behavior: the ML-driven strategy performs well in sideways or mildly trending markets but lags during aggressive bull runs due to the smoothing effect of the MA60 component. This limitation is also acknowledged in the discussion of the reference study.

## 4 Discussion

Our findings reinforce the conclusions of Hafid et al.: technical indicators contain substantial predictive information regarding moving-average–based trend states, and both Logistic Regression and XGBoost are capable of learning these relationships effectively. The similarity in accuracy and ROC-AUC across models suggests that the indicator–label relationship is nearly linear, explaining why Logistic Regression performs comparably to XGBoost.

Limitations include delayed response to sharp market reversals, reliance on historical price–derived labels, and reduced performance during strong momentum surges. The use of daily rather than intraday data likely smooths some local patterns that may have been captured in the original study.

## 5 Conclusion

This project successfully reproduces the methodology and reported performance of Hafid et al. using daily BTC-USD data. The results demonstrate consistent classification accuracy, meaningful indicator importance patterns, and economically interpretable trend signals. Future extensions include experimenting with forward-return labels, walk-forward validation, and adapting the system to higher-frequency data consistent with the original study's context.

# Appendix: Visualizations

## A1. BTC Closing Price with Moving Averages

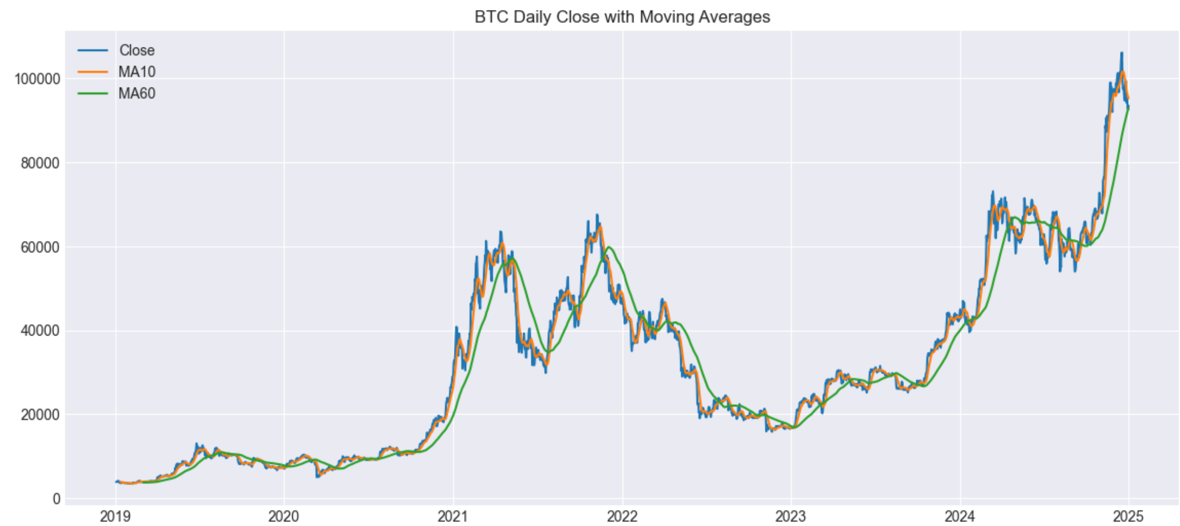


Figure 1: Daily BTC closing price with MA10 and MA60.

## A2. Distribution of Daily Returns

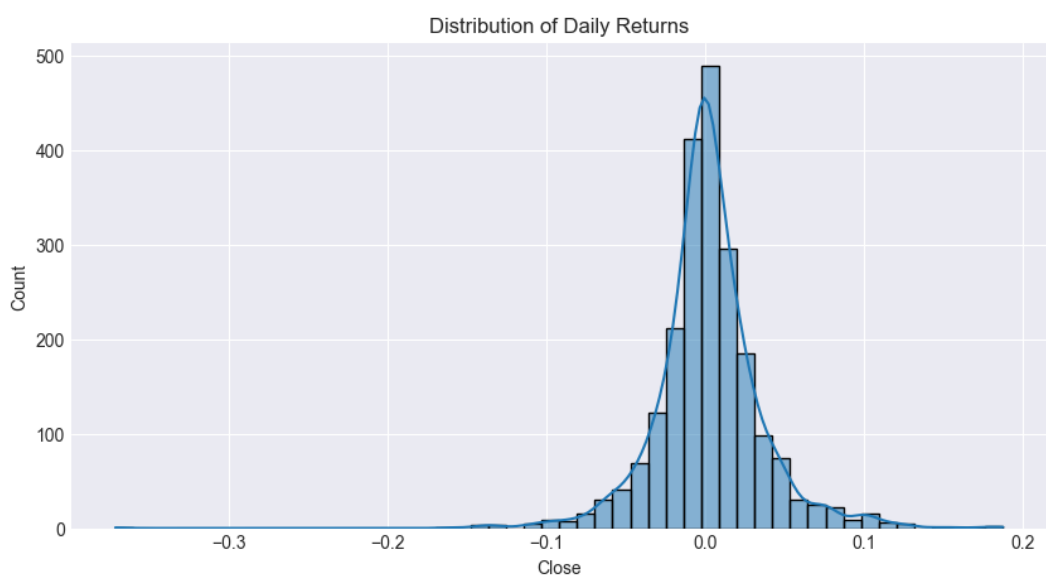


Figure 2: Histogram and KDE of BTC daily log returns.

## A3. Correlation Heatmap of Technical Indicators

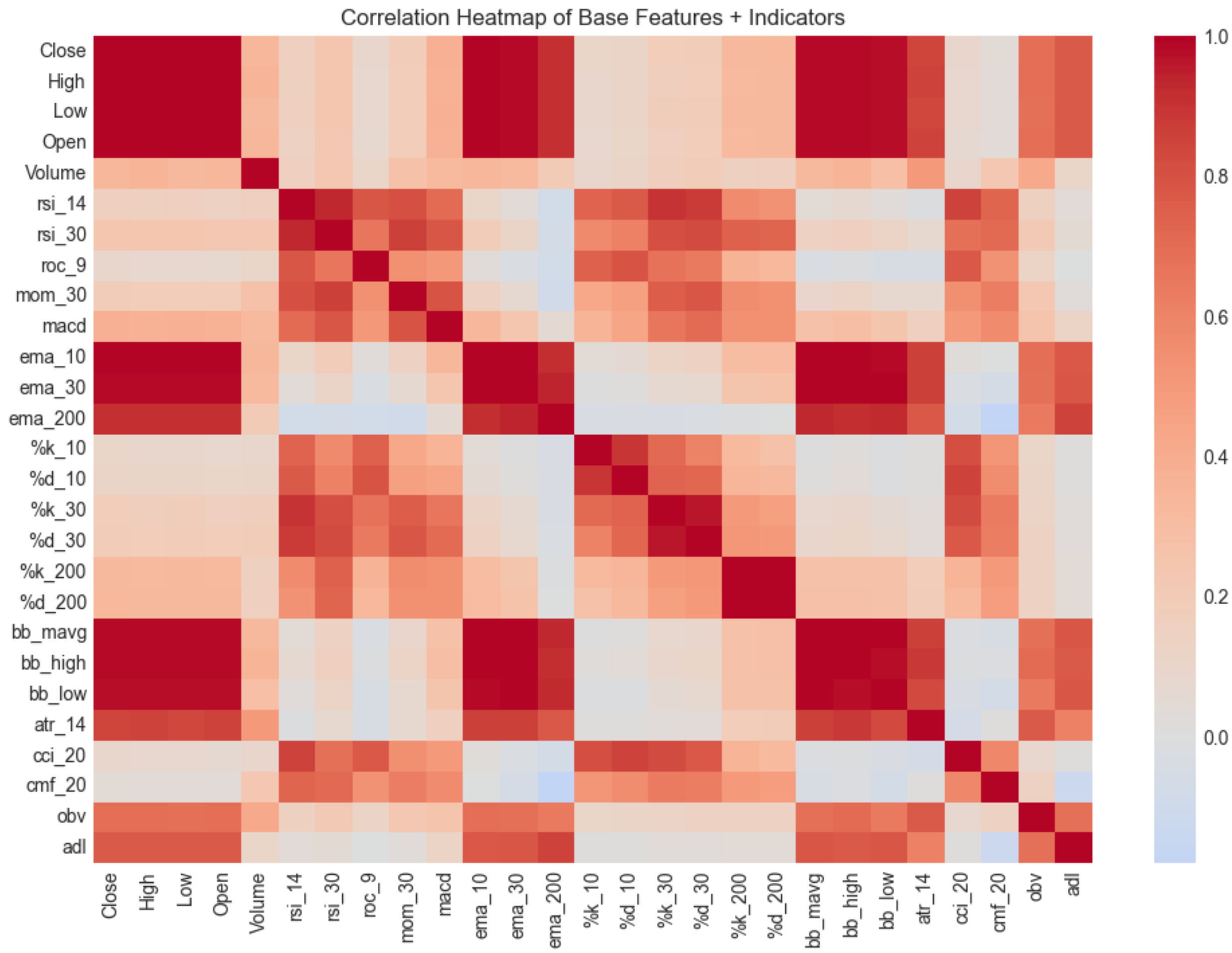


Figure 3: Heatmap showing inter-indicator correlations.

## A4. PCA Variance Explained

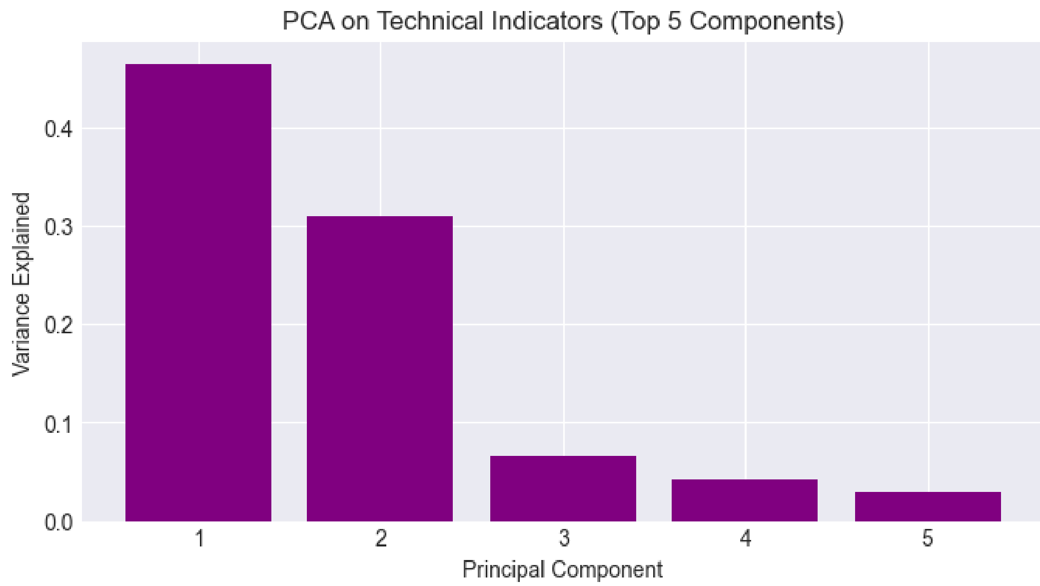


Figure 4: Variance explained by the top principal components.

## A5. XGBoost Feature Importance Ranking

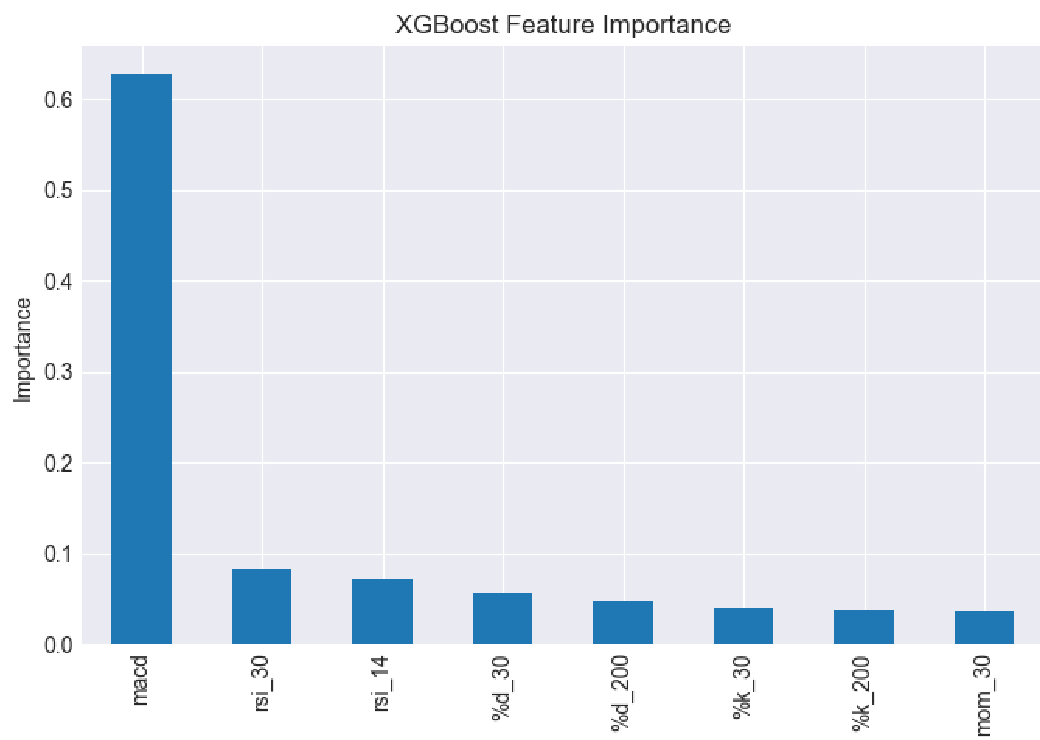


Figure 5: Ranked importance of selected features from XGBoost.

**A6. ROC Curve Comparison (XGBoost vs Logistic Regression)**

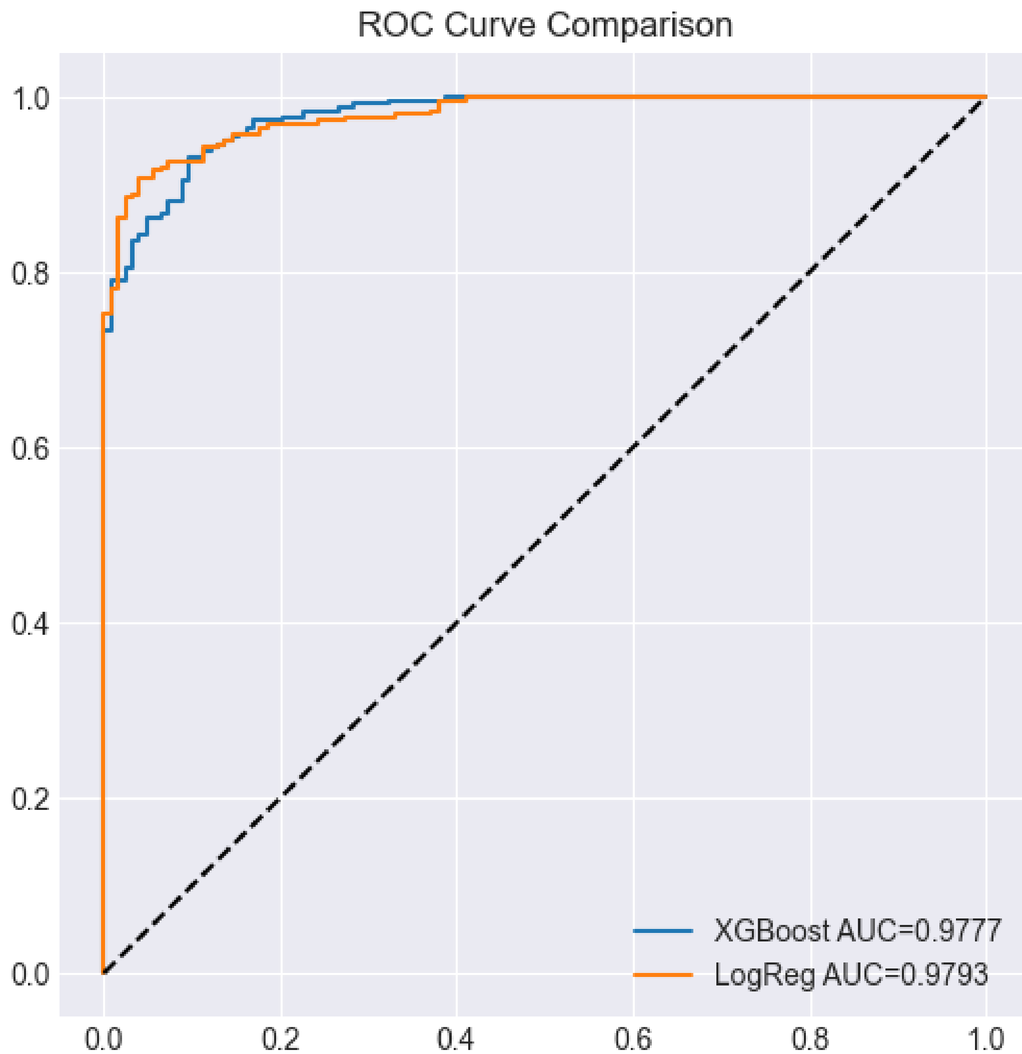


Figure 6: ROC curves for both classification models with AUC scores.

**A7. Confusion Matrix for XGBoost Predictions**

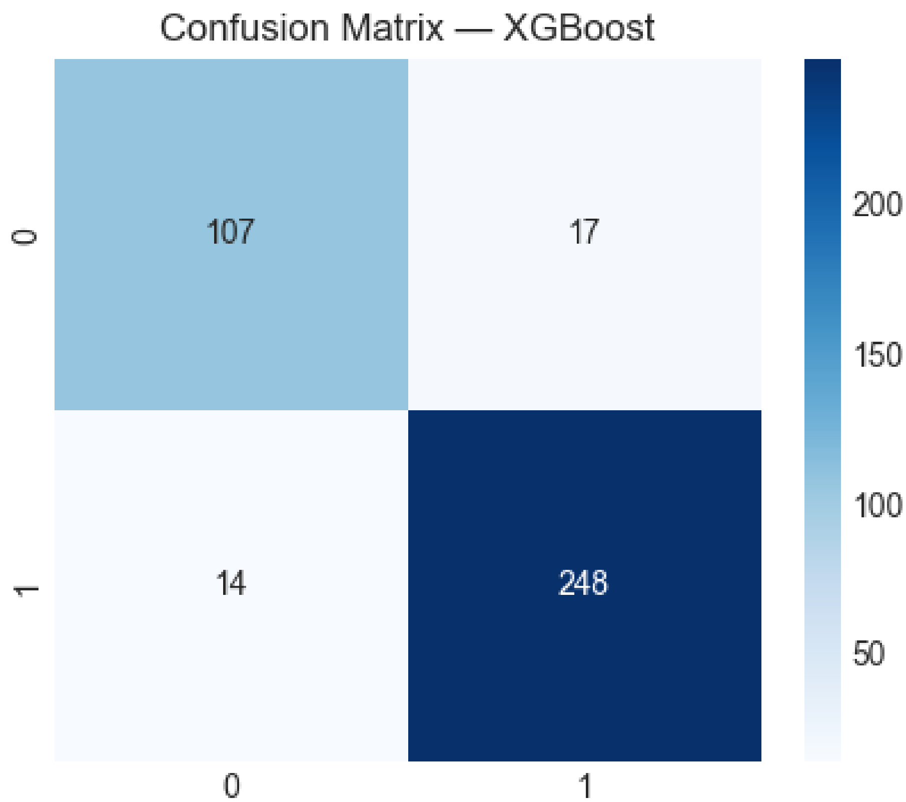


Figure 7: Confusion matrix showing prediction distribution for XGBoost.

### A8. Backtest: Model Strategy vs Buy & Hold

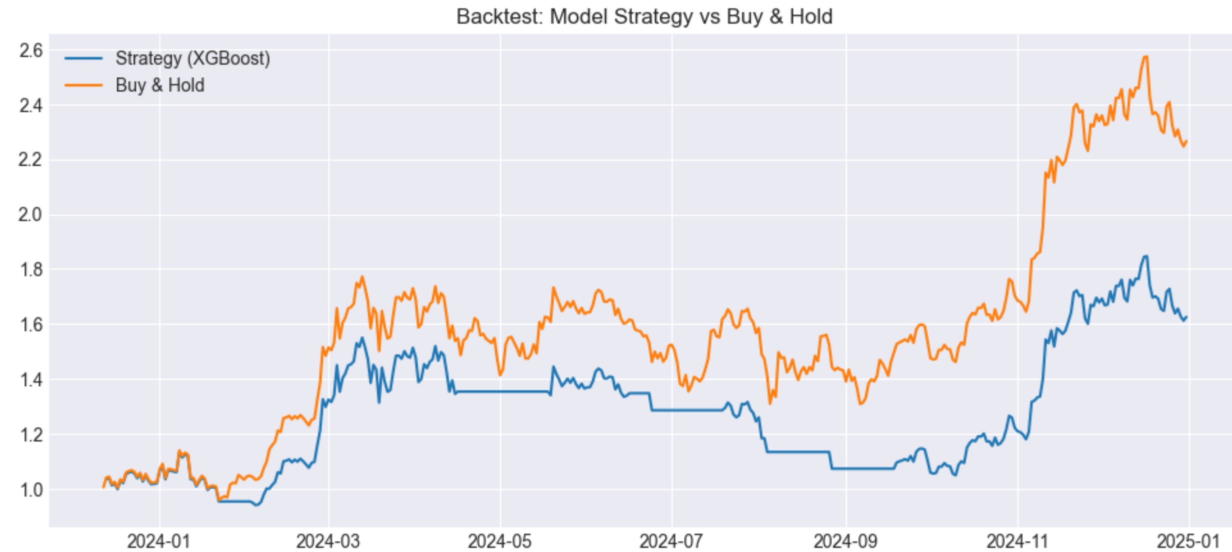


Figure 8: Comparison of cumulative returns between ML strategy and Buy & Hold.