Forex Trend Prediction: Can Machine Learning Algorithms Forecast Short Timeframe Movements?

Alireza Behjoee

University of Groningen

BA Thesis, Data Science

Noman Haleem

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Abstract

The Foreign Exchange (FOREX) market is the largest and most liquid financial market in the world. Its worldwide 24-hour accessibility, coupled with its dynamic nature, makes it very attractive to traders and investors. Therefore, numerous deep learning algorithms have been developed to forecast market trends, but they face challenges such as overfitting, long training times, and limited interpretability. Additionally, most prior research has focused on longer timeframes, such as daily, which may not be optimal for capturing the frequent fluctuations in Forex prices.

This study attempts to bridge these gaps by developing machine learning models using the 13 most commonly used technical indicators, in addition to OHLCV (Open, High, Low, Close, Volume) data. The models are trained on shorter timeframes, specifically the 5-minute, 15-minute, 30-minute, 1-hour, and 4-hour intervals, for the EUR/USD currency pair and the XAU/USD commodity pair. Then, they are evaluated not only based on accuracy but also through profitability analysis in order to assess their performance under real-world trading conditions and how much net profit they could generate.

Overall, our proposed model achieves an accuracy of 82.10% and a profit of 9.2% for XAU/USD on the 5-minute timeframe, based on backtesting from April 25, 2025, to May 1, 2025.

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1. Introduction

The Foreign Exchange (FOREX or FX) market is a global marketplace where currencies are traded, with an average daily volume of $6.6 trillion, making it the largest financial market in the world (Guyard & Deriaz, 2024; Mabrouk et al., 2021; Ayitey Junior et al., 2023). It is a decentralized market that operates 24 hours a day, except on weekends, across major financial centers such as London, New York, Tokyo, and Sydney.

The core of Forex trading is the exchange between two different assets, typically currencies traded in pairs such as EUR/USD, where one is bought and the other is sold. Profit or loss is based on fluctuations in the exchange rate. For instance, buying EUR/USD results in a profit if the value of the euro increases against the dollar, and a loss if it decreases. Some pairs, like XAU/USD, represent commodities (such as gold) traded against currencies, but they follow a similar trading mechanism. Participants in the Forex market include central banks, commercial banks, financial institutions, hedge funds, multinational corporations, and individual retail traders.

The Forex market offers several advantages that make it more attractive and profitable than other financial markets. These include no commissions or middlemen, flexible lot sizes, high liquidity, fast transactions, high leverage with low margin, 24-hour access, protection from insider trading, limited regulation, and extensive online trading options (Ayitey Junior et al., 2023).

Despite its attractive potential for profit, predicting price movements in the Forex market has long been a challenging task due to the influence of various factors. These include interest rate changes, inflation, geopolitical events, market sentiment, central bank decisions, economic indicators such as GDP and employment data, and human behavior (Ayitey Junior et al., 2023).

Because of these challenges, “only 2% of traders are successful in predicting Forex market movements correctly” (Ayitey Junior et al., 2023).

There are two main types of techniques used to predict price movements which are fundamental analysis and technical analysis. Fundamental analysis focuses on evaluating economic, political, and social factors that can affect prices. In contrast, technical analysis focuses on analyzing historical price data and technical indicators to understand market patterns. Numerous studies have demonstrated that technical analysis plays a crucial role in Forex trading and can be effective in forecasting future price movements (Abbad et al., 2014; Saadati & Manthouri, 2024). However, another approach that has gained increasing attention in recent years is the combination of technical analysis, which includes technical indicators, price, and volume data, with Artificial Intelligence (AI) to predict market trends, due to AI's ability to analyze complex data and detect hidden patterns.

In line with this growing focus on trend prediction, numerous deep learning (DL) algorithms have been developed to forecast price direction in the Forex market. While these models have shown some promising results, they also face some limitations. As Guyard and Deriaz (2024) point out, many publications in Forex trading that have focused on neural network models rely on relatively small datasets, which poses a significant challenge for deep learning models. This is because “deep learning models require large and diverse datasets to effectively train and generalize their learnings” (Taherdoost, 2023). Moreover, most DL studies in the Forex market have focused on daily or longer timeframes, which further reduces the amount of data. At these timeframes, even several years of historical records may result in only a small number of data points, which is often not enough to train deep learning models effectively. This lack of data can lead to overfitting and unreliable predictions, ultimately resulting in financial losses for traders who depend on such models for decision-making.

As mentioned, most studies have focused on longer timeframes when developing deep learning models, which presents another issue. The Forex market is known for its high volatility and frequent price fluctuations throughout the day, often caused by news or the release of economic indicators (Dakalbab et al., 2025; Eddelbuttel & McCurdy, 1998; Guyard & Deriaz, 2024). Therefore, models trained on longer timeframes may fail to capture price changes that occur over short periods, resulting in inaccurate predictions during times of high volatility.

Another major concern is the lack of interpretability in deep learning models, as deep learning algorithms that generate predictions are often regarded as a black box, making their decisions difficult to interpret (Lam et al., 2025). In the context of financial market prediction, this poses a significant challenge, because it is unclear which features drive the final prediction. This lack of transparency creates uncertainty for both researchers and traders, since it becomes difficult to determine whether the model's predictions are based on meaningful patterns or statistical noise.

A further limitation is that even the most accurate deep learning models may not be suitable for live signal generation in the Forex market due to their high computational demands and slow processing times. A study by Zafeiriou et al. (2024) found that while standard neural networks like LSTM can predict the Forex market, their complexity and latency make them impractical for real-time use. In live trading, especially in the Forex market where prices can change within seconds, timing is critical. If a model is too slow, the market may move before a signal is generated. As a result, delays in signal generation, even by a few seconds, can cause missed opportunities or financial losses because accurate entry timing is essential for achieving profit.

Given these limitations, machine learning (ML) models may offer a more practical and effective alternative, especially in scenarios where processing time is critical and data is limited. To begin with, ML models are generally simpler, faster to train, and more efficient, which enables quicker signal generation and makes them more suitable for algorithmic trading. Additionally, studies outside the financial domain have shown that ML models often outperform DL models when working with smaller datasets (Gill et al., 2022; Xu, Kinfu, Levine, et al., 2021; Guyard & Deriaz, 2024). Furthermore, machine learning models are more interpretable, as they provide feature importance metrics that help traders and researchers understand how and why the model makes specific predictions. Finally, little research has focused on developing models specifically for shorter timeframes, which may be more effective in capturing the high volatility that frequently occurs in the Forex market throughout the day. Therefore, this study aims to address these gaps by evaluating whether machine learning classification algorithms can effectively predict short-term trends (5-minute, 15-minute, 30-minute, 1-hour, and 4-hour), not only for EUR/USD, the most widely studied and traded currency pair (Mabrouk et al., 2021), but also for XAU/USD, a popular commodity pair, in order to assess whether such models generalize well across different asset types. To evaluate model performance, this study will consider not only accuracy but also conduct a profitability analysis by implementing a trading strategy based on the model's predictions to measure how much net profit each model could generate under realistic trading conditions on Otet Markets broker. Hence, the main research question is: Can machine learning classification algorithms predict short-term Forex market trends? The sub-questions are:

1. Which machine learning classification algorithms perform best in predicting EUR/USD and XAU/USD?

2. How does the choice of timeframe impact the accuracy and profitability of machine learning models?
3. To what extent does higher accuracy translate into higher profitability in real trading scenarios?
4. Which technical indicators most influence the profitability of the models?

This paper is structured as follows. The Literature Review section provides an overview of related work on the use of ML and DL models in the Forex market. The Methodology section explains the data collection process, the technical indicators used, the model development steps, and the trading strategy used for profitability analysis. The Results section presents model performance based on both accuray and profitability outcomes. The Discussion interprets the results across different timeframes and assets, highlights the limitations, and the Conclusion summarizes the key findings and outlines possible directions for future research.

2. Literature Review

Most existing research on the Forex market frames the task as a classification problem, where the goal is to determine the direction of market trends. In addition, these studies use technical indicators as input features and preserve the temporal order of the data during modeling.

Galeshchuk and Mukherjee (2017), for instance, analyzed the performance of Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANN), Artificial Neural Networks with Moving Average input (ANN-MA), and other models for predicting price movements of the EUR/USD, GBP/USD, and USD/JPY currency pairs using daily data from 2010 to 2015, while preserving the chronological order of the data during training. Their findings showed that the CNN model outperformed all other methods, achieving an average accuracy of 75.28%.

Guyard and Deriaz (2024) tested various machine learning algorithms to predict the direction of the EUR/USD currency pair using daily data. Among all the models evaluated, Histogram-Based Gradient Boosting achieved the highest accuracy (58%) and profit (29.5%).

Yildirim et al. (2021) explored the prediction of price direction for the EUR/USD currency pair using Long Short-Term Memory (LSTM) models from January 2013 to January 2018, based on daily data. The task was framed as a binary classification problem (increase vs. decrease), and the models were trained using technical indicators as input features. Moreover, no shuffling was applied during training in order to preserve the chronological order of the data points. Their proposed hybrid LSTM model achieved an accuracy of 73.61%.

Baasher and Fakhr (2010) conducted a study to predict the price direction of the USD/JPY, USD/EGP, and EUR/EGP currency pairs using daily data over a period of 1852 days, from April

2003 to August 2010. They evaluated three models, which were Radial Basis Function Neural Network (RBF), Multilayer Perceptron Neural Network (MLP), and Support Vector Machine (SVM). The models were trained using 11 technical indicators as input features. Among them, the MLP model achieved the highest accuracy, reaching 79.2%.

Mabrouk et al. (2021) experimented with linear and non-linear machine learning algorithms to predict the EUR/USD currency pair using daily data from January 2014 to January 2021. The models were trained using technical indicators as input features, and the chronological order of the data was preserved during training. Their best model was an SVM, which achieved an accuracy of 72% and generated 62% profit.

Fisichella and Garolla (2021) developed a CNN model trained on 4-hour interval data from six currency pairs (GBP/USD, EUR/USD, USD/CHF, USD/JPY, EUR/GBP, and GBP/JPY) ranging from January 1, 2010, to April 30, 2021. Their proposed model achieved an accuracy of 60.7%.

Phuong Dong Nguyen et al. (2024) developed a hybrid deep learning model by combining two convolutional layers and one LSTM layer. The dataset included currency pairs such as AUD/USD, CAD/JPY, and EUR/USD. It coverd the period from April 1, 2012, to April 13, 2022, spanning a total of 10 years. The first eight years of data were used for training the model, while the final two years were used for simulation. The task was designed as a trend classification problem with three categories, where each day was labeled as either an uptrend, a downtrend, or an unknown trend. They trained the model using 14 technical indicators along with OHLCV data. The proposed hybrid model achieved a monthly profit of 15%.

Someswari Perla et al. (2023) conducted a study using five currency pairs, including MYR/USD, MXN/USD, EUR/JPY, EUR/GBP, and EUR/HKD, on a daily timeframe, to predict the next day's exchange rates and classify the trends as either up or down, based on six technical indicators. For the regression task, the authors used data from January 3, 2012, to August 5, 2015, with a total of 900 daily records for each currency pair. For the classification task, they used a slightly longer dataset, which was from January 3, 2012, to December 31, 2015, which included 1044 records per pair. The authors proposed a model called Deep Kernel Random Vector Functional Link Network Autoencoder (DKRVFLN-AE). In the regression task, this model achieved the best overall performance, with a MAPE of 1.17%, MAE of 0.0081, and RMSE of 0.0126 on the EUR/JPY test set. In the classification task, this model again outperformed all other classifiers, achieving an accuracy of 84.66% and an F-measure of 0.83 on the MXN/USD pair.

3. Methodology

3.1 Data

The data used in this study was collected using MetaTrader 5 (MT5). It was obtained through OTET Markets, a regulated Forex broker that enables users to execute trades and access both real-time and historical data for various currency pairs and commodities. In order to retrieve the historical data, a live trading account was created with OTET Markets and linked to the MT5 platform. Using the official MT5 Python library, a direct connection was established to the MT5 terminal, which allowed historical data to be retrieved for the selected symbols and timeframes. The retrieved data includes the standard OHLCV format (Open, High, Low, Close, Volume) along with the Timestamp. These components represent the following:

- **Timestamp:** The date and time when the candle (time interval) starts.
- **Open:** The price at the beginning of the time interval.
- **High:** The highest price reached during the interval.
- **Low:** The lowest price during the interval.
- **Close:** The final price at the end of the interval.
- **Volume:** The total number of transactions traded during the interval.

Two trading instruments were selected for analysis: EUR/USD and XAU/USD. EUR/USD represents the Euro to the U.S. Dollar currency pair, and is the most heavily traded pair in the Forex market (Mabrouk et al., 2021). XAU/USD, on the other hand, represents the value of gold measured in the U.S. Dollars. As a commodity instrument, it often behaves differently from currency pairs as it reacts strongly to news, geopolitical events, etc. These two instruments were chosen to compare model performance across both a major currency pair and a commodity pair in order to provide broader insights into the generalizability of the machine learning algorithms. For both symbols, OHLCV data was collected across five commonly used short-term timeframes:

- **5-minute (5M):** Suitable for high-frequency trading, capturing rapid market fluctuations.
- **15-minute (15M):** Also used for high-frequency strategies, offering slightly more stability than 5M.
- **30-minute (30M):** Helps identify short-term intraday trends while reducing noise.
- **1-hour (1H):** Commonly used for analyzing clearer intraday movements.
- **4-hour (4H):** Captures broader market moves within a single trading day without overlapping into long-term timeframes.

To ensure a fair comparison across instruments and timeframes, the same start and end dates were selected for each timeframe for both EUR/USD and XAU/USD. However, despite using identical time ranges, the number of data points differs between the two instruments. This difference is due to variations in trading hours and weekend gaps. While the Forex market for EUR/USD operates almost continuously from Sunday 22:00 GMT to Friday 22:00 GMT, the gold market (XAU/USD) pauses for one hour daily between 21:00 and 22:00 GMT. Additionally, although both instruments are inactive over the weekend, gold typically stops trading slightly earlier on Fridays and resumes slightly later on Sundays, further reducing the number of available candles. Full details of the timeframes, date ranges, and data point counts are provided in Table 1.

Symbol	Timeframe	Time Range	Data Count
XAU/USD	5M	2025-03-28 to 2025-05-01	6221
XAU/USD	15M	2025-01-16 to 2025-05-01	6762
XAU/USD	30M	2024-10-03 to 2025-05-01	6727
XAU/USD	1H	2024-05-07 to 2025-05-01	5812
XAU/USD	4H	2023-04-13 to 2025-05-01	3171
EUR/USD	5M	2025-03-28 to 2025-05-01	6796
EUR/USD	15M	2025-01-16 to 2025-05-01	7191
EUR/USD	30M	2024-10-03 to 2025-05-01	7097
EUR/USD	1H	2024-05-07 to 2025-05-01	6113
EUR/USD	4H	2023-04-13 to 2025-05-01	3195

Table 1. Time Range and Data Count for Each Symbol and Timeframe.

3.2 Technical Indicators

After collecting the data, the most commonly used technical indicators were calculated to serve as input features for training the machine learning models. Technical indicators are mathematical formulas derived from price data, including open, high, low, close (OHLC), and trading volume (V). They have proven useful in helping traders identify market trends (Ghanem et al., 2024;

Yong et al., 2015). Therefore, by including them as input features, we aim to provide the models with additional context about recent market behavior to improve predictions. Additionally, to provide the models with a broader and more informative feature set, some indicators were calculated using different periods. This approach allows the machine learning algorithms to learn from various market conditions and automatically identify the most effective combinations of indicators and period values for each symbol and timeframe. Table 2 presents a detailed overview of all technical indicators used in this study, along with their corresponding periods.

Technical Indicator	**Parameters**
Relative Strength Index (RSI)	Period = 7, 14, 21
Moving Average Convergence Divergence (MACD)	Short Term = 12, Long Term = 26, Signal = 9
Weighted Moving Average (WMA)	Period = 10, 20, 50
Exponential Moving Average (EMA)	Periods = 10, 20, 50, 100
Simple Moving Average (SMA)	Period = 10, 20, 50, 100
Ichimoku	Standard settings (9, 26, 52)
Average Directional Index (ADX)	Period = 7, 14, 21
Bollinger Bands (BB)	Period = 10, 20, 50; Standard Deviation = 2 (for band width)

Momentum	Period = 10, 14, 21
Williams %R	Period = 10, 14, 21
Rate of Change (ROC)	Period = 10, 14, 21
Stochastic Oscillator	%K = 14, D = 3; %K = 10, D = 3
Commodity Channel Index (CCI)	Period = 10, 20, 50

Table 2. List of the technical indicators and their corresponding periods.

3.3 Data labeling

To label the data, we framed the problem as a binary classification task. The reason for focusing on classification rather than predicting exact prices is the inherent randomness and volatility of financial data, which make it challenging to accurately forecast specific price values (Nguyen et al., 2024). Therefore, as in many previous studies on the Forex market, this study focuses on a binary classification approach, where the model aims to predict whether the price will increase (label = 1) or decrease (label = 0). To do this, we compared the closing prices at two consecutive time steps which are time t and time t-1. If the closing price at time t is greater than the closing price at time t−1, it indicates an upward movement, so we assign a label of 1 to time t+1, as we aim to predict the future direction. In contrast, if the closing price at time t is lower or equal than at time t−1, it indicates a downward trend, so we assign a label of 0 to time t+1.

$$y_{t+1} = \begin{cases} 1, & \text{if } Close_t > Close_{t-1} \\ 0, & \text{if } Close_t \leqslant Close_{t-1} \end{cases}$$

Formula 1. Labeling rule for trend prediction.

3.4 Data Preprocessing

After labeling the data and calculating the technical indicators, the dataset was split into three parts. The first 70% was used for training, the next 15% for validation, and the remaining 15% for testing and profitability analysis. This chronological split was done to ensure that the model is always trained on past data and evaluated on more recent data.. The test set was also kept completely unseen during both training and tuning phases to ensure an accurate evaluation of the models' performance. The specific date ranges used for the training, validation, and test sets are provided in Table 3.

Symbol	**Timeframe**	**Training Set (70%)**	**Validation Set (15%)**	**Test Set (15%)**
XAU/USD	5M	2025-03-28 to 2025-04-22	2025-04-22 to 2025-04-25	2025-04-25 to 2025-05-01
XAU/USD	15M	2025-01-16 to 2025-03-31	2025-03-31 to 2025-04-15	2025-04-15 to 2025-05-01
XAU/USD	30M	2024-10-03 to 2025-02-27	2025-02-27 to 2025-03-31	2025-03-31 to 2025-05-01

XAU/USD	1H	2024-05-07 to 2025-01-14	2025-01-14 to 2025-03-07	2025-03-07 to 2025-05-01
XAU/USD	4H	2023-04-13 to 2024-09-17	2024-09-17 to 2025-01-08	2025-01-08 to 2025-05-01
EUR/USD	5M	2025-03-28 to 2025-04-22	2025-04-22 to 2025-04-25	2025-04-25 to 2025-05-01
EUR/USD	15M	2025-01-16 to 2025-03-31	2025-03-31 to 2025-04-15	2025-04-15 to 2025-05-01
EUR/USD	30M	2024-10-03 to 2025-02-27	2025-02-27 to 2025-03-31	2025-03-31 to 2025-05-01
EUR/USD	1H	2024-05-07 to 2025-01-14	2025-01-14 to 2025-03-07	2025-03-07 to 2025-05-01
EUR/USD	4H	2023-04-12 to 2024-09-17	2024-09-17 to 2025-01-09	2025-01-09 to 2025-05-01

Table 3. Date ranges used for the training, validation, and test sets for each symbol and timeframe.

Before applying any preprocessing techniques, we first trained the models using all calculated features and OHLCV data. This initial run served as a baseline, allowing us to compare the performance of later models after applying different preprocessing methods. To explore whether such methods could enhance performance, we implemented three different data preprocessing strategies.

3.4.1 Correlation Thresholding (CT)

The first method was Correlation Thresholding (CT), which involved calculating the Pearson correlation coefficients between all pairs of features. If two features had a correlation higher than 0.90, one of them was removed. The rationale behind this approach is that highly correlated features often carry redundant information, which can lead to overfitting or unnecessarily complex models. By keeping only one feature from each correlated group, we aimed to simplify the feature set without information loss.

3.4.2 Mutual Information (MI)

The second technique used was Mutual Information (MI), a measure that captures the amount of information shared between each feature and the target variable. Unlike correlation, MI can detect non-linear relationships, making it especially useful in financial datasets where patterns are often non-linear. We ranked all features by their MI scores and selected the top 10 most important features for each dataset.

3.4.3 Recursive Feature Elimination with Cross-Validation (RFECV)

Finally, we applied Recursive Feature Elimination with Cross-Validation (RFECV) using a Random Forest classifier. This method recursively removes the least important features based on the model's internal feature importance scores, and evaluates performance using cross-validation at each step. The process continues until the model identifies the optimal subset of features that leads to the highest accuracy.

As a result, for each instrument (EUR/USD and XAU/USD) and each timeframe (5M, 15M, 30M, 1H, 4H), we generated four different versions of the dataset:

1. All technical indocatrs + OHLCV (baseline)
2. Correlation thresholding
3. Mutual Information top 10 features

4. RFECV

This setup allowed us to compare model performance across different data preprocessing strategies and evaluate which method produced the best results for each instrument and timeframe.

3.5 Model training

In our study, we evaluated a variety of machine learning models, including:

- Random Forest Classifier (RF)
- Support Vector Machine (SVM)
- K-Nearest Neighbors (KNN)
- Extreme Gradient Boosting (XGBoost)
- Light Gradient Boosting Machine (LightGBM)
- Logistic Regression (LR)
- Histogram Gradient Boosting Classifier
- Gradient Boosting Classifier (GBC)
- Extra Trees Classifier (ETC)
- CatBoost Classifier

To ensure an accurate evaluation, we performed cross-validation while preserving the time order of the data. Hyperparameter tuning was also conducted for all models to optimize their performance. In addition, for non-tree models, specifically SVM, KNN, and Logistic Regression, we applied feature scaling to standardize the data, as these algorithms are sensitive to feature scale and may underperform without normalization. However, for tree-based models including

Random Forest, XGBoost, LightGBM, Gradient Boosting, Extra Trees, HistGradientBoosting, and CatBoost, we did not apply feature scaling, as these models are not affected by the size or scale of the input values.

3.6 Model Evaluation and Profitability Analysis

To evaluate the models studied in this research, we used two metrics: accuracy and profitability.

3.6.1 Accuracy Evaluation

We first measured the accuracy of each model using the unseen test set. This allowed us to assess how well the model could correctly classify upward or downward trends on data it had not been trained on.

3.6.2 Profitability Analysis (Backtesting)

In addition to evaluating accuracy, we conducted a profitability analysis to simulate real trades based on the model's predictions and assess its practical effectiveness in real-world trading. This is important because accuracy alone is insufficient for fully assessing a model's effectiveness, and several studies have shown that models achieving higher accuracy do not necessarily result in higher profitability (Mabrouk et al., 2021; Nguyen et al., 2024).

In our backtest, we applied a realistic trading strategy with the following steps:

1. Filtering by Confidence Threshold

In practice, traders often choose to trade only when the signal is strong and reliable. Therefore, to simulate this behavior, we only acted on predictions with confidence levels above 70%. This filtering step was done in order to focus on high-confidence predictions.

2. Initial Setup and Broker Assumptions

We assumed an initial balance of $1000 per symbol (EUR/USD and XAU/USD) and opened positions using 0.01 lot, which is the minimum tradable lot size on OTET Markets for both instruments. For XAU/USD, a 0.01 lot position requires approximately $25 margin. This is because the margin is calculated as:

$$\text{Margin} = \frac{\text{Contract size} * \text{Price}}{\text{Leverage}} = \frac{100 * 2000}{8000} = 25$$

Formula 2. Margin Calculation for XAU/USD.

- Contract size: 100 (standard for 0.01 lot of gold)
- Price: ~$2000
- Leverage: 1:8000

For EUR/USD, a 0.01 lot position requires approximately $10 margin:

$$\frac{1000 * 1.10}{100} = 11$$

Formula 3. Margin Calculation for EUR/USD.

- Contract size: 1000 units (0.01 lot)
- Price: ~$1.10
- Leverage: 1:100 (common for major forex pairs in OTET)

Note: These values may vary depending on the broker.

3. Opening a Trade

When the first high-confidence prediction occurs:

- If the prediction is 1, we open a buy position at the closing price of that candle.
- If the prediction is 0, we open a sell position at the closing price.

For example:

- If the signal is for XAU/USD, we open a 0.01 lot trade, which requires approximately $25 margin. Given an initial balance of $1000, this means:
    - $25 of the balance is locked as margin
    - $975 remains available
    - The trade size is based on 100 units of gold, and each $1 price movement results in a $1 profit or loss for 0.01 lot.

- If the signal is for EUR/USD, a 0.01 lot trade requires approximately $10 margin. So:
    - $10 is reserved as margin
    - $990 remains free

    - Since EUR/USD is priced around $1.10, each 10 pip ($0.0010) movement results in a $1 profit or loss for a 0.01 lot trade.

Note: Margin requirements vary between brokers. The above values are based on OTET Markets.

Importantly, once a position is opened, we do not open new trades until the current position is closed, even if more high-confidence signals are generated. This rule helps us:

- Minimize risk
- Avoid over-leveraging
- Prevent margin calls, which can occur when the market moves significantly against open positions, reducing account equity below the required margin and forcing the broker to automatically close trades to limit losses.

4. Closing a Trade

A trade is closed when it hits either the Take Profit (TP) or Stop Loss (SL) level. The exact TP and SL values for each symbol and timeframe are provided in Table 4.

Symbol	**Timeframe**	**Take Profit (TP)**	**Stop Loss (SL)**
XAU/USD	5M	$20	$10
XAU/USD	15M	$30	$15
XAU/USD	30M	$60	$25

XAU/USD	1H	$70	$40
XAU/USD	4H	$80	$50
EUR/USD	5M	$5	$2.5
EUR/USD	15M	$10	$10
EUR/USD	30M	$50	$20
EUR/USD	1H	$50	$20
EUR/USD	4H	$70	$40

Table 4. Take Profit (TP) and Stop Loss (SL) targets defined for each symbol and timeframe used in the backtesting strategy.

The TP/SL values differ between symbols due to differences in their price scales and movements. XAU/USD is typically priced around $2000, where a $1 move results in a $1 profit or loss per 0.01 lot. In contrast, EUR/USD is priced around $1.10, and moving 10 pips ($0.0010) results in a $1 profit or loss per 0.01 lot. Therefore, TP and SL values were adjusted to reflect each asset's typical price range and volatility. Moreover, for shorter timeframes, smaller TP/SL targets were used due to limited price movement, in order to avoid holding positions for too long.

5. Profit/Loss Calculation

When a position is closed the profit is calculated as follows :

- For a buy position:
    - Profit = (Close Price − Open Price) - Commission

- For a sell position:
    - Profit = (Open Price − Close Price) - Commission

We also accounted for trading commissions, which in OTET Markets are approximately $1 per round trade (opening + closing). After a position is closed, the profit or loss, along with the commission, is applied to the current balance. The strategy then waits for the next high-confidence signal to place a new trade based on the updated balance.

6. Force-Closing at the End

Finally, if a trade remains open at the end of the dataset, for example, if it hasn't reached TP or SL, we close the position at the closing price of the last candle. This is a common practice in backtesting to ensure that all trades are closed and accounted for in the final balance.

4. Results

As described in the methodology, four datasets were created using four data preprocessing strategies for each symbol and timeframe: the full feature set (all technical indicators and OHLCV), Correlation Thresholding (CT), Mutual Information (MI), and Recursive Feature Elimination with Cross-Validation (RFECV). For each of these datasets, a total of 10 machine learning models were trained and evaluated. Given 2 instruments (XAU/USD and EUR/USD) and 5 timeframes (5M, 15M, 30M, 1H, 4H), this resulted in 40 models per symbol and per timeframe, 200 models per symbol across all timeframes, and in total 400 models. However, for each combination of symbol, timeframe, and data preprocessing strategy, only the model with the highest accuracy was selected for reporting and profitability analysis. The results are organized by symbol and timeframe, focusing on metrics including accuracy on unseen data, number of high-confidence predictions (confidence > 70%), number of incorrect predictions, total number of trades, and net profit. Additionally, we present the results of the feature importance analysis for the most profitable models in order to demonstrate which technical indicators or OHLCV features contributed most to generating profitable trades.

4.1 XAU/USD

For XAU/USD, the dataset containing all features resulted in high accuracy, particularly when trained with Logistic Regression. At the 5-minute timeframe, this combination not only achieved the highest accuracy (82%) but also resulted in a profit of $92 from 28 trades. Among the reduced feature sets, RFECV with SVM and CT with Random Forest reached similar accuracies

(71.9% and 70%, respectively), though profitability varied. SVM generated a profit of $27, while Random Forest generated a profit of $54.

Moving to the 15-minute timeframe, all four datasets led to profitable outcomes. The full feature set again performed well with Logistic Regression, producing 734 confident predictions and a $209 profit. Interestingly, the CT dataset, despite having fewer confident predictions (229), achieved the highest profit of $295 using Histogram Gradient Boosting. RFECV with SVM and MI with LightGBM also showed solid performance, returning $247 and $150, respectively.

At the 30-minute timeframe, the dataset with all features trained with Logistic Regression achieved the highest net profit, reaching $456 from 39 trades. Moreover, MI with SVM and RFECV with Random Forest also showed strong profitability, generating $331 and $305, respectively.

In the 1-hour timeframe, the full feature set with Logistic Regression was the most accurate (82.5%) and resulted in a $213 profit. However, other configurations outperformed it in terms of profit, despite having fewer trades and lower accuracy. The MI dataset with CatBoost had the highest return of $446, while CT with Extra Trees and RFECV with CatBoost returned $322 and $156, respectively.

At the 4-hour timeframe, the MI dataset combined with CatBoost achieved the highest profit among all configurations, earning $902 from 18 trades with an accuracy of 73%. Logistic Regression on the full feature set again achieved the highest accuracy at 78%, generated the most confident predictions (322), and produced a profit of $540. In addition, CT with Histogram Gradient Boosting and RFECV with XGBoost also performed well at this interval, generating profits of $665 and $614, respectively. The detailed results are provided in Tables 5, 6, 7, 8, and 9.

Data Preprocessing	**Best model**	**Accuracy**	**Correct Predictions (>70%)**	**Incorrect Predictions**	**Net Profit**	**Number of Trades**
All Features	Logistic Regression	82%	574 (92.73%)	45 (7.27%)	$92	28
CT	RF	70%	271 (82.12%)	59 (17.88%)	$54	26
MI	CatBoost	71.90%	379 (83.30%)	76 (16.70%)	$-119	26
RFECV	SVM	71.90%	413 (81.46%)	94 (18.54%)	$27	31

Table 5. Results for XAU/USD at 5-minute timeframe

Data Preprocessing	**Best model**	**Accuracy**	**Correct Predictions (>70%)**	**Incorrect Predictions**	**Net Profit**	**Number of Trades**
All Features	Logistic Regression	81%	734 (85.45%)	125 (14.55%)	$209	61
CT	Histogram Gradient Boosting	72.80%	229 (87.07%)	I34 (12.93%)	$295	50
MI	LightGBM	73.80%	193 (88.94%)	24 (11.06%)	$150	45

RFECV	SVM	73.50%	497 (81.61%)	112 (18.39%)	$247	53

Table 6. Results for XAU/USD at 15-minute timeframe

Data Preprocessing	**Best model**	**Accuracy**	**Correct Predictions (>70%)**	**Incorrect Predictions**	**Net Profit**	**Number of Trades**
All Features	Logistic Regression	81.30%	606 (90.31%)	65 (9.69%)	$456	39
CT	LightGBM	68.90%	192 (87.67%)	27 (12.33%)	$102	33
MI	SVM	69.90%	453 (79.75%)	115 (20.25%)	$331	34
RFECV	RF	69.70%	346 (79.18%)	91 (20.82%)	$305	35

Table 7. Results for XAU/USD at 30-minute timeframe

Data Preprocessing	**Best model**	**Accuracy**	**Correct Predictions (>70%)**	**Incorrect Predictions**	**Net Profit**	**Number of Trades**
All Features	Logistic Regression	82.5%	629 (87.12%)	93 (12.88%)	$213	27
CT	Extra Trees	71.10%	256 (84.21%)	48 (15.79%)	$322	28
MI	CatBoost	71.50%	305 (82.43%)	65 (17.57%)	$446	24

RFECV	CatBoost	72.30%	338 (82.84%)	70 (17.16%)	$156	24

Table 8. Results for XAU/USD at 1-hour timeframe

Data Preprocessing	Best model	Accuracy	Correct Predictions (>70%)	Incorrect Predictions	Net Profit	Number of Trades
All Features	Logistic Regression	78%	322 (82.56%)	68 (17.44%)	$540	20
CT	Histogram Gradient Boosting	72.30%	121 (88.97%)	15 (11.03%)	$665	15
MI	CatBoost	73%	165 (83.76%)	32 (16.24%)	$902	18
RFECV	XGBoost	73.20%	156 (84.78%)	28 (15.22%)	$614	16

Table 9. Results for XAU/USD at 4-hour timeframe

To better understand which input features contributed most to generating higher profits, feature importance was analyzed for the five models with the highest profitability in the XAU/USD timeframes. These included Logistic Regression (5M and 30M) trained on the full feature set, Histogram Gradient Boosting (15M) trained on the CT dataset, and CatBoost trained on the MI dataset for both 1H and 4H. Among these models, the Commodity Channel Index (CCI), MACD and its Signal line component, the Open price, and Tenkan-sen from the Ichimoku indicator were among the most influential features. Additionally, EMA, WMA, ADX, and Stochastic Oscillator components with different periods also ranked highly in several cases. Figures 1, 2, 3, 4, and 5 show the top 10 features identified for each selected model.

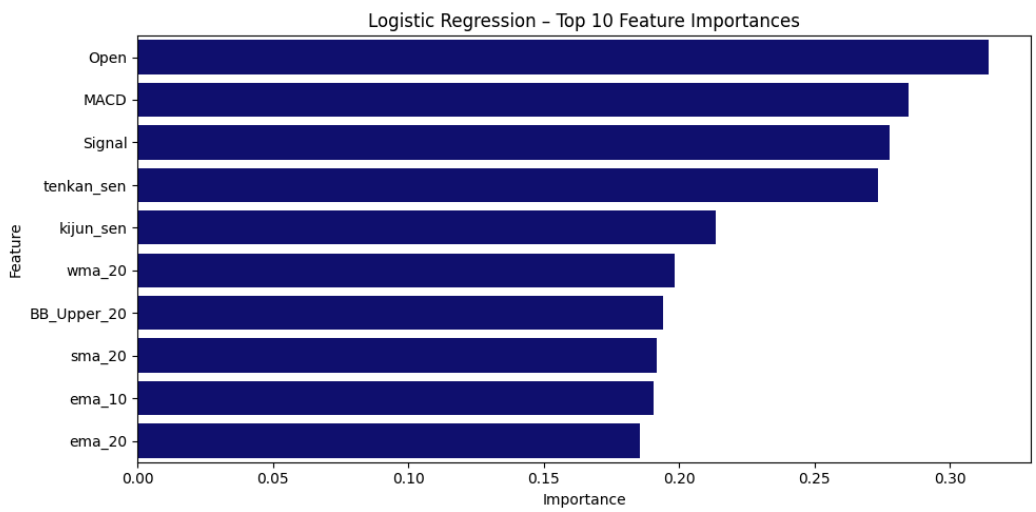

Image 1. Feature importance for XAU/USD – Logistic Regression (5M) on the full feature set

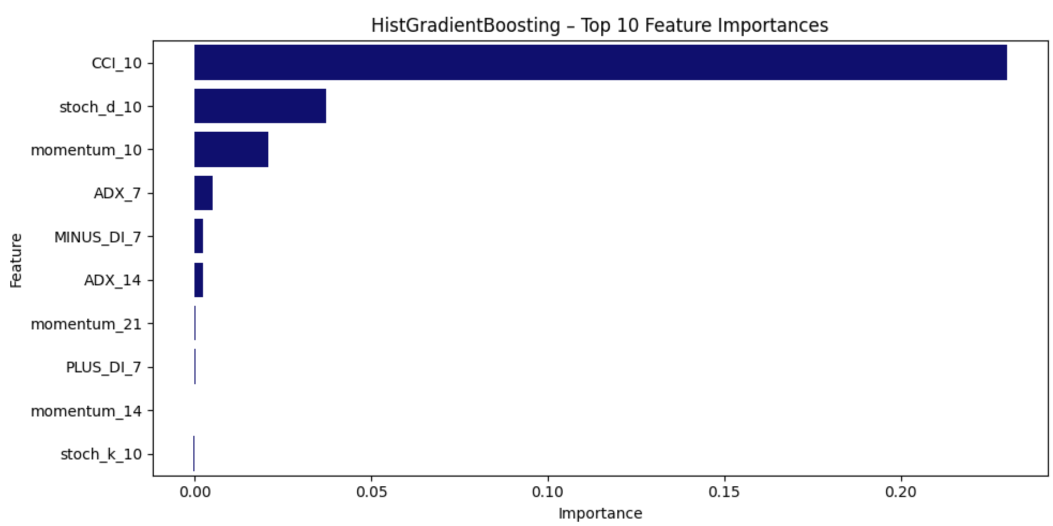

Image 2. Feature importance for XAU/USD – Histogram Gradient Boosting (15M) on the CT dataset

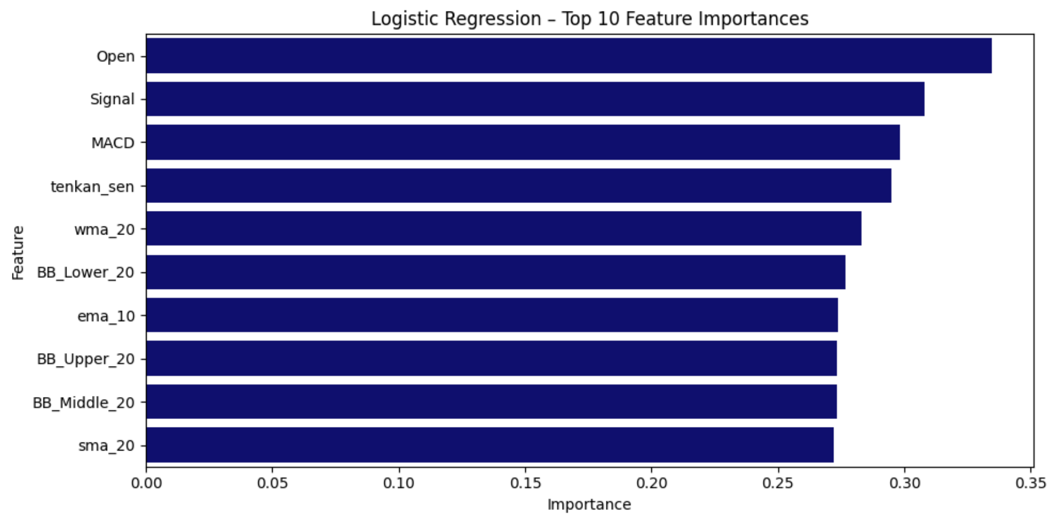

Image 3. Feature importance for XAU/USD – Logistic Regression (30M) on the full feature set

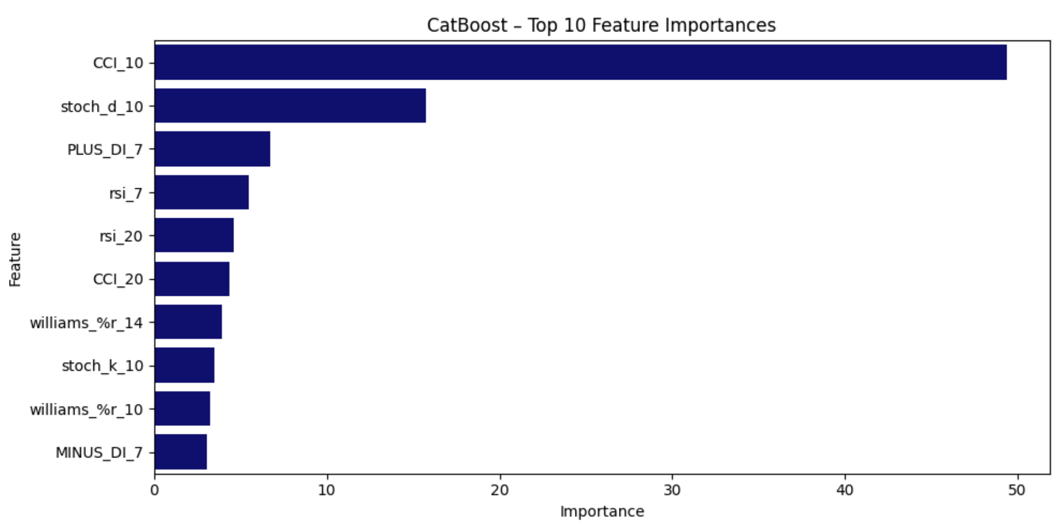

Image 4. Feature importance for XAU/USD – CatBoost (1H) on the MI dataset

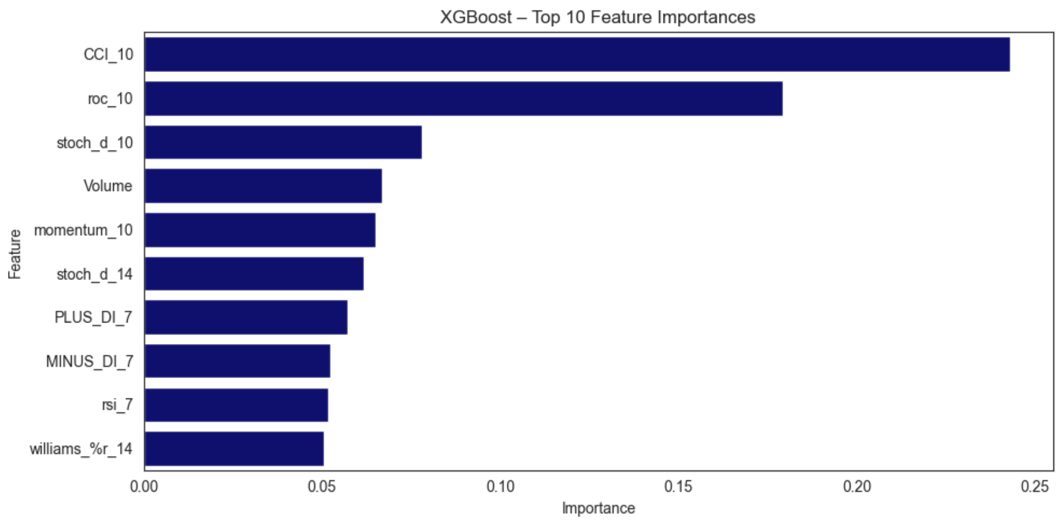

Image 5. Feature importance for XAU/USD – CatBoost (4H) on the RFECV dataset

4.2 EUR/USD

The results for EUR/USD are significantly different from those of XAU/USD in terms of profitability and trade frequency. At the 5-minute timeframe, none of the data preprocessing methods and model combinations produced a positive return. Although Logistic Regression on the full feature set had the highest accuracy (82.1%) and produced 605 confident predictions, it still resulted in a -$17.93 loss. Moreover, other models including CT with CatBoost, MI with SVM, and RFECV with Extra Trees delivered larger losses.

For the 15-minute timeframe, only one configuration yielded a positive profit. Logistic Regression on the full dataset achieved both the highest accuracy (81.9%) and the highest profit ($20). CT with LightGBM resulted in a negligible loss (–$0.67), while MI with Gradient Boosting and RFECV with SVM underperformed significantly in terms of profitability.

Unlike the previous timeframes, the 30-minute timeframe showed only marginal profits across all datasets. The best performer, once again, was Logistic Regression on the full dataset, achieving 81.1% accuracy and generating a $6 profit from 4 trades. The other configurations, regardless of data preprocessing method or model choice, yielded similar profits, either $5.30 or $6.

Starting from the 1-hour timeframe, profitability began to improve overall. Histogram Gradient Boosting on the RFECV dataset outperformed others by generating the highest net profit ($10.87), despite having lower accuracy compared to Logistic Regression on the full feature dataset, which generated a profit of $6.

Finally, at the 4-hour timeframe, all configurations were profitable, but differences were minimal. CT with Random Forest slightly outperformed the others with a profit of $30.36, despite achieving the lowest accuracy (66.2%). All other combinations including Logistic Regression on the full feature set, Gradient Boosting on the MI dataset, and XGBoost on the RFECV dataset resulted in a $27 profit, and accuracies ranged from 67.5% to 80.2%. Tables 10 through 14 present the detailed results for EUR/USD.

Data Preprocessing	**Best model**	**Accuracy**	**Correct Predictions (>70%)**	**Incorrect Predictions**	**Net Profit**	**Number of Trades**
All Features	Logistic Regression	82.10%	605 (91.81%)	54 (8.19%)	$-17.93	8
CT	CatBoost	69.20%	322 (79.70%)	82 (20.30%)	$-31.33	12

MI	SVM	72.20%	481 (82.08%)	105 (17.92%)	$-31.93	12
RFECV	Extra Trees	71.60%	402 (83.40%)	80 (16.60%)	$-32.17	14

Table 10. Results for EUR/USD at 5-minute timeframe

Data Preprocessing	Best model	Accuracy	Correct Predictions (>70%)	Incorrect Predictions	Net Profit	Number of Trades
All Features	Logistic Regression	81.90%	734 (89.51%)	86 (10.49%)	$20	10
CT	LightGBM	69.50%	260 (86.67%)	40 (13.33%)	$-0.67	10
MI	Gradient Boosting	69.40%	227 (88.67%)	I29 (11.33%)	$-38.67	8
RFECV	SVM	69.20%	471 (77.85%)	134 (22.15%)	$-40	10

Table 11. Results for EUR/USD at 15-minute timeframe

Data Preprocessing	Best model	Accuracy	Correct Predictions (>70%)	Incorrect Predictions	Net Profit	Number of Trades
All Features	Logistic Regression	81.10%	739 (86.23%)	118 (13.77%)	$6	4

CT	ExtraTrees	68.10%	266 (81.10%)	62 (18.90%)	$6	4
MI	SVM	67.80%	424 (77.94%)	120 (22.06%)	$5.30	4
RFECV	RF	68.20%	336 (80.77%)	80 (19.23%)	$5.30	4

Table 12. Results for XAU/USD at 30-minute timeframe

Data Preprocessing	Best model	Accuracy	Correct Predictions (>70%)	Incorrect Predictions	Net Profit	Number of Trades
All Features	Logistic Regression	80.09%	617 (86.17%)	99 (13.83%)	$6	4
CT	RF	68.60%	226 (82.18%)	49 (17.82%)	-$14.69	5
MI	CatBoost	68.50%	290 (79.02%)	77 (20.98%)	$6.31	4
RFECV	Histogram Gradient Boosting	68.70%	97 (84.35%)	18 (15.65%)	$10.87	4

Table 13. Results for EUR/USD at 1-hour timeframe

Data Preprocessing	Best model	Accuracy	Correct Predictions (>70%)	Incorrect Predictions	Net Profit	Number of Trades
All Features	Logistic	80.20%	336 (85.28%)	58 (14.72%)	$27	3

	Regression					
CT	RF	66.20%	63 (75.90%)	20 (24.10%)	$30.36	3
MI	Gradient Boosting	69.40%	98 (83.76%)	19 (16.24%)	$27	3
RFECV	XGBoost	67.50%	134 (81.21%)	31 (18.79%)	$27	3

Table 14. Results for EUR/USD at 4-hour timeframe

For feature importance analysis, since the 5-minute and 30-minute had either negative or marginal profits, we focused only on Logistic Regression trained on the full feature set for the 15-minute timeframe, Histogram Gradient Boosting trained on the RFECV dataset for the 1-hour timeframe, and Random Forest trained on the CT dataset for the 4-hour timeframe, as these were the top performers in terms of profitability. While for Histogram Gradient Boosting on the 1-hour timeframe and Random Forest on the 4-hour timeframe, the Commodity Channel Index (CCI) and Stochastic Oscillator components such as stoch_k_10 and stoch_d_10 were among the top features, for Logistic Regression on the 15-minute timeframe, the most influential features included the Open price, MACD and its Signal line component, and Tenkan-sen from the Ichimoku indicator. Figures 6, 7, and 8 show the top 10 features for the selected models and timeframes.

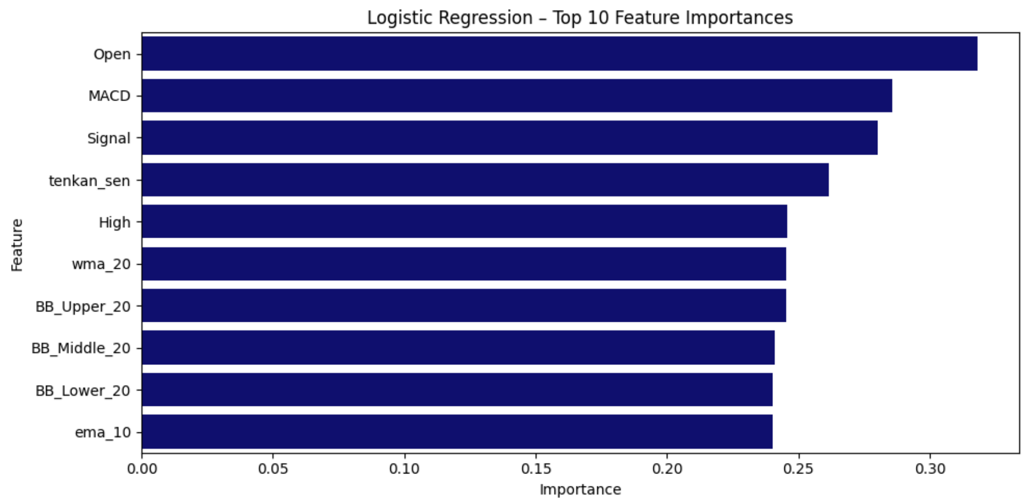

Image 6. Feature importance for EUR/USD – Logistic Regression (15M) on the full feature set

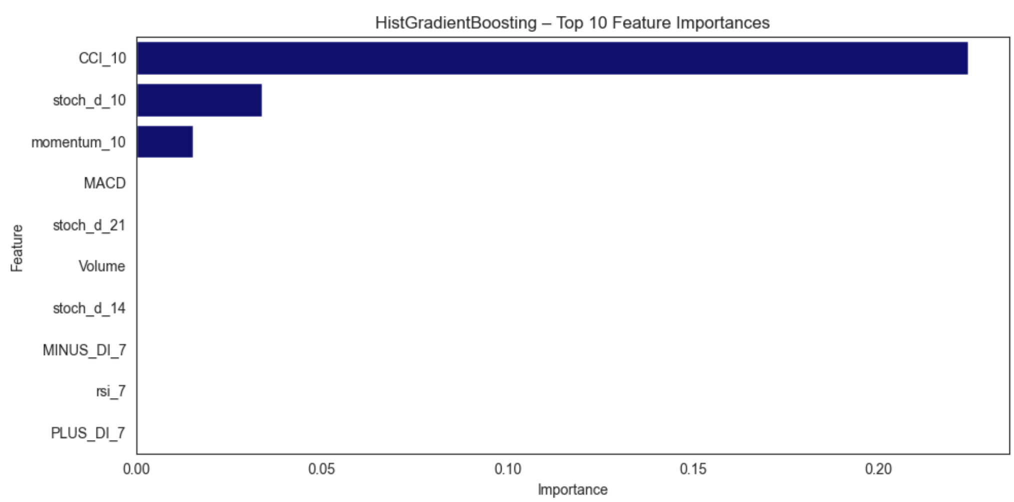

Image 7. Feature importance for EUR/USD – Histogram Gradient Boosting (1H) on the RFECV dataset

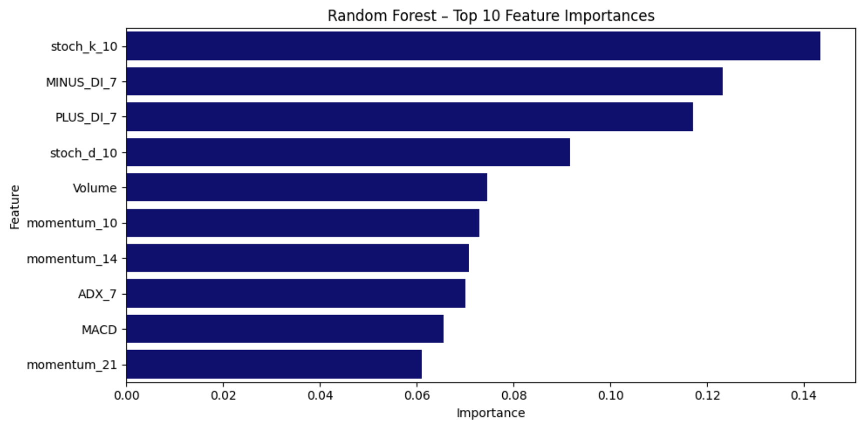

Image 8. Feature importance for EUR/USD – Random Forest (4H) on the CT dataset

5. Discussion

This section provides a detailed interpretation of the results, including model performance in terms of accuracy and profitability, the impact of different timeframes and data preprocessing methods, and the behavior of the trading instruments. The goal is to examine how these elements interact and to evaluate the practical effectiveness and generalizability of machine learning models in real-world trading scenarios.

One of the most notable observations is that across all timeframes and instruments, Logistic Regression without any data preprocessing achieved the highest accuracy. In several cases, such as XAU/USD at 5-minute, XAU/USD at 30-minute, EUR/USD at 5-minute, and EUR/USD at 15-minute, it was also the most profitable model. Even when it wasn't profitable, as in the case of EUR/USD at 5M, the loss was smaller compared to other models and datasets evaluated for the same instrument and timeframe. This suggests that Logistic Regression, when applied to the full feature set, performs well in terms of accuracy and generalizes well without requiring additional feature selection methods.

However, it was observed that higher accuracy does not necessarily lead to greater profitability. For instance, in the XAU/USD 4-hour timeframe, CatBoost trained on the MI dataset achieved 73% accuracy but generated a $902 profit, whereas Logistic Regression without data preprocessing reached a higher accuracy of 78% but yielded a profit of $540. Similarly, in the XAU/USD 1-hour timeframe, CatBoost with MI (71.5% accuracy) outperformed Logistic Regression (82.5% accuracy) in profitability, delivering $446 compared to $212. This trend was also observed in the EUR/USD 4-hour timeframe, where Random Forest with the CT dataset generated a slightly higher profit of $30 compared to $27 from Logistic Regression without data preprocessing, despite having a lower accuracy (66.2% vs. 80.2%). This is because for trading strategies, profitability depends not only on accuracy but also on how strong the price moves when the model is correct. A model with lower accuracy might still generate higher profits if it captures larger trends, while a model with higher accuracy could underperform if its correct predictions only catch small price movements. Therefore, when applying these models in live markets, focusing solely on accuracy is misleading, and traders must also consider trend strength.

In terms of accuracy, the choice of instrument did not significantly affect model performance, as all models showed solid results for both XAU/USD and EUR/USD. This is due to the wide range of technical indicators calculated across multiple periods which helped the models learn different market behaviors and perform well regardless of the specific instrument. However, when it comes to profitability, XAU/USD outperformed EUR/USD by a large margin. All timeframes for XAU/USD produced positive and often substantial profits, whereas most configurations for EUR/USD resulted in negative or marginal profits. This difference is mainly due to the higher price volatility and stronger trend patterns in XAU/USD. Gold often shows larger and more frequent price swings, which makes it easier to reach take-profit targets. On the other hand, EUR/USD usually has smaller price movements, making it harder for models to hit take-profit levels, especially in shorter timeframes. Since the trading strategy developed in this study relies on take-profit and stop-loss levels, and both of which depend on price movement, this resulted in EUR/USD having both lower profits and fewer trades, even though smaller take-profit and stop-loss levels were used compared to XAU/USD. These findings suggest that while using multiple technical indicators with different periods can improve model accuracy, profitability depends on developing a strategy tailored to each instrument. Hence, for this strategy selecting an asset with stronger trends and higher price volatility is crucial for turning predictions into profitable trades.

In addition, the analysis shows that longer timeframes generally produced higher net profits for both XAU/USD and EUR/USD. For both instruments, the most profitable outcomes were achieved in descending order from the 4-hour timeframe down to the 5-minute timeframe. However, it is important to note that although shorter timeframes appear to generate smaller total profits, they do so over significantly shorter periods. When adjusted for time, their profitability can actually exceed that of longer timeframes. For instance, the most profitable model seemed to come from the 4-hour configuration for XAU/USD, which generated $902 and represents 90.2 percent of the initial balance, from January 8, 2025 to May 1, 2025. However, the 5-minute XAU/USD configuration generated $92 in less than a week, which is 9.2 percent of the initial balance, between April 25, 2025 and May 1, 2025. Meanwhile, the 15-minute configuration produced $295 from April 15, 2025 to May 1, 2025, and the 30-minute configuration made $456 from March 31, 2025 to May 1, 2025. These results indicate that while longer timeframes capture more substantial trends and generate higher profits, shorter timeframes offer better returns relative to the time invested. This is particularly true in the Forex market, where traders can profit from short-term trends, which contrasts with the stock market, where profits often require buying and holding assets over longer periods. Therefore, our findings support the idea that shorter timeframes are more profitable and better aligned with the dynamics of the forex market.

Apart from accuracy and profitability, the feature importance analysis revealed several patterns regarding which technical indicators and OHLCV components contributed most to higher profitability. At the 1-hour and 4-hour timeframes, the Commodity Channel Index (CCI) and

Stochastic Oscillator components (such as stoch_k_10 and stoch_d_10) frequently ranked among the top features. These indicators are commonly used to detect short- to medium-term momentum and identify overbought or oversold conditions, which may explain why they appeared frequently in longer timeframes for both instruments. In contrast, for shorter timeframes, the most influential features included the MACD and its Signal line, and Tenkan-sen from the Ichimoku indicator. These indicators are generally more responsive to short-term price movements and adapt quickly to recent changes, which aligns well with shorter timeframes where trades are more sensitive to immediate price behavior. Interestingly, the open price also emerged as an important feature, suggesting that it has a significant influence on predictions in shorter timeframes. Finally, the frequent appearance of EMA, WMA, and ADX indicates that combining momentum, trend strength, and price fluctuation signals is crucial for making better predictions and decisions in short-term trading.

5.1 Limitations

While this study offers useful insights, it also has some limitations that should be considered. One limitation is that the classification models used are only capable of predicting the direction of the trend, for example, whether the price will go up or down, but not the magnitude of that movement. As mentioned, this is problematic in real trading scenarios because profitability depends not only on the direction of trends, but also on how far the price moves. For instance, some models achieved high accuracy but still resulted in low profits, because the profits from correct predictions were smaller than the losses from incorrect ones. In such cases, the imbalance between the magnitude of profitable and unprofitable trades makes the model less effective in real trading.

Another limitation of this study is that the profits calculated in backtesting may not fully reflect real-world trading performance, even though efforts were made to simulate realistic conditions. In backtesting, trades are executed at the closing price of the candle during which the signal is generated. However, in real trading, if algorithmic trading is implemented, there are often slight delays in execution due to factors such as internet latency, system processing time, or platform response speed. These factors can reduce the actual profit compared to our results. On the other hand, if the strategy is executed manually, additional delays or missed opportunities may occur, as it is not feasible for a human to monitor the market continuously throughout the day, which might also reduce profitability. Even though this study used machine learning models instead of deep learning models to allow faster signal generation, this limitation should still be taken into account.

A final limitation to consider is that the trading strategy developed in this study allows only one open position at a time. This design choice is logical, as it helps avoid the risk of opening multiple positions simultaneously, which could lead to margin calls. However, this also means the model might miss other high-confidence trading opportunities that appear while a trade is already active. This constraint was used because we assumed an initial balance of $1000 and preferred to minimize risk in order to make the profitability analysis as realistic as possible. With such a balance, it is reasonable to limit trading to one position at a time to stay within safe margin requirements. In real-world scenarios, however, traders with larger capital and a higher risk tolerance may choose to open multiple positions simultaneously. Even then, it is crucial to set a clear limit on the number of open positions. Therefore, the development of a trading strategy depends heavily on the initial capital available, the type of instrument, model predictions, and the level of risk a trader is willing to take, and there is no single strategy that fits all situations.

6. Conclusion

This paper evaluated various machine learning algorithms with different settings to assess their ability to predict short-term trends in the Forex market for two instruments, EUR/USD and XAU/USD using technical indicators and OHLCV data. In addition to evaluating model accuracy, a profitability analysis was conducted by developing a trading strategy to measure how much profit each model could generate under realistic trading conditions.

Overall, the models demonstrated strong accuracy for both instruments. However, XAU/USD was significantly more profitable than EUR/USD, due to differences in instrument behavior and the effectiveness of the trading strategy applied. The results also indicated that shorter timeframes provide better returns relative to the time invested and have greater potential than longer timeframes for generating profit in the Forex market. Moreover, our proposed Logistic Regression model on the 5-minute timeframe achieved both the highest accuracy at 82.10 percent and the highest profit of $92 within 5 trading days, excluding weekends.

Given the results of this study, there are several opportunities for future exploration. One potential direction for future research is to develop a strategy specifically tailored to EUR/USD, as the models achieved high accuracy and produced many confident predictions. This is a promising path, as these predictions have the potential to be used for generating profit from EUR/USD. Another promising path is to incorporate the magnitude of price movement along with trend direction, since profitability depends on both factors. This could make the models even more effective in real-world trading scenarios. Finally, developing an automated trading bot based on the most profitable model could help turn model predictions into real-time trading signals and generate profit in live market conditions.

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