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Enhanced One-Day-Ahead AUD/USD Exchange Rate Prediction using CatBoost Model

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Abstract—**The foreign exchange (Forex) market is highly liquid and volatile, making accurate short-term forecasting both critical and challenging. This study investigates one-day-ahead AUD/USD exchange rate prediction using CatBoost, Random Forest (RF), and Support Vector Machine (SVM) machine learning (ML) models with continuous and discretized technical indicators. Ten technical indicators were derived from 5,027 historical data points. This is the first study to apply discrete technical indicators with CatBoost for recent AUD/USD price forecasting. Results showed that CatBoost achieved the highest accuracy (89.68%) and AUC (0.9609) on the discretised dataset. Statistical test confirmed the significance of CatBoost's superior performance, highlighting its potential to enhance predictive performance and support real-time decision-making in Forex trading.**

Keywords—**AUD/USD forecasting, Forex prediction, exchange rate prediction, CatBoost, machine learning, algorithmic trading, technical indicators, explainable AI (XAI), financial forecasting, time series prediction**

I. Introduction

THE foreign exchange (Forex) market is the largest and most liquid global marketplace, with the AUD/USD pair attracting attention due to its sensitivity to monetary policy, commodity prices, and global economic conditions. Accurate one-day-ahead forecasting is critical for traders and investors, yet remains challenging given the nonlinear, volatile, and chaotic nature of exchange rates.

Traditional econometric models such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) capture linear trends and volatility clustering but often fail under dynamic market conditions [1],[2],[3]. Meanwhile, deep learning approaches, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) address these limitations by modeling complex temporal dependencies in predicting AUD/USD price movements [4],[5],[6] but require large datasets [7],[8] and intensive computation, limiting their real-time applicability [9].

Ensemble learning offers a balance of accuracy and efficiency. RF [10] and SVM [11] remain widely used in financial prediction, yet both can struggle with parameter tuning and noisy data. Gradient boosting algorithms, particularly CatBoost, provide notable advantages such as handling categorical features, mitigating overfitting, and delivering robust accuracy. Recent studies [12],[13],[14] demonstrate their superiority in EUR/USD forecasting, but applications to AUD/USD remain limited.

This study addresses this gap by evaluating CatBoost against RF and SVM for one-day-ahead AUD/USD forecasting. Both continuous and discretized datasets are examined, with technical indicators transformed into directional signals to assess their impact on prediction accuracy [15],[16],[17]. By advancing machine learning applications in Forex, this research contributes to FinTech innovation, offering more accurate, interpretable, and practical tools for traders, institutions, and policymakers.

II. Methodology

A. Data collection and preprocessing

1) Continuous data

This study employs historical AUD/USD exchange rate data, comprising daily open, high, low, and close prices, covering the period from September 28, 2008, to October 25, 2024. The dataset, consisting of 5,027 observations was standardized using z-score normalization (via StandardScaler) to ensure feature comparability for the ML models. The target variable for both continuous and discrete datasets was defined based on the directional change in the closing price from the previous trading day, with upward and downward movements encoded as +1 and −1, respectively. This binary classification framework facilitates the assessment of directional prediction accuracy.

To enhance the predictive capacity of the models, a diverse set of ten technical indicators was derived from historical price and volume data. These include trend indicators (Simple Moving Average, Weighted Moving Average), momentum indicators (Relative Strength Index, MACD, Momentum, Stochastic %K and %D, Williams %R), a volatility-based indicator (Commodity Channel Index), and a volume-based indicator (Accumulation/Distribution Oscillator). These features are commonly used in financial time series analysis to capture trend direction, momentum shifts, and potential price reversals, thereby supporting more informed model learning and forecasting accuracy. Table I provides a detailed list of the computed indicators and their respective formulas.

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TABLE I
SELECTED TECHNICAL INDICATORS

Indicators	Formula
Simple 14 days moving average (MA)	$C_t + C_{t-1} + \cdots + C_{t-14}/14$
Simple 14 days weighted moving average (WMA)	$\frac{((n) * C_t + (n-1) * C_{t-1} + \cdots + C_{t-14}}{(n + (n-1) + \cdots + 1)}$
Momentum (Mom)	$C_t + C_{t-n}$
Stochastic K% (K%)	$\frac{C_t - LL_{t-n}}{HH_{t-n} - LL_{t-n}} * 100$
Stochastic D% (D%)	$\sum_{i=0}^{n-1} K_{t-i}\%/n$
Relative strength index (RSI)	$100 - \frac{100}{1 + (\sum_{i=0}^{n-1} Up_{t-i}/n)/\sum_{i=0}^{n-1} Dw_{t-i}/n}$
Moving average convergence/divergence (MACD)	$\mathrm{MACD}(n)_{t-1} + \frac{2}{n+1} * (DIFF_t - \mathrm{MACD}(n)_{t-1})$
Larry William's R% (LW)	$\frac{H_n - C_t}{H_n - L_n} * 100$
Accumulation/distribution oscillator (A/D)	$\frac{H_t - C_{t-1}}{H_t - L_t}$
Commodity Channel Index (CCI)	$\frac{M_t - SM_t}{0.015 D_t}$

Note: Source: (Kara *et al.*, 2011); *n is the number of days accepted as 10 here, C_t *closing price*, L_t *low price*, and H_t *high price*. $DIFF_t$: $EMA(12)_t - EMA(26)_t$. EMA is exponential moving average, $EMA(k)_{t-1}$: $EMA(k)_{t-1} + \alpha * (C_t - EMA(k)_{t-1})$, α is correction factor, LL_t is the lowest low, HH_{t-n} is the highest high for the last t days. $MT = (H_t + L_t + C_t)/3$, $SM_t = (\sum_{i=0}^{n-1} M_{t-i+1}/n)$, $D_t = (\sum_{i=1}^{n} |M_{t-i+1} - SM_t|/n)$, Up_t and Dw_t are upward and downward price change at time t respectively.

2) *Construction of the discrete dataset*

To construct the discrete dataset, the continuous price data was transformed into binary values of +1 and −1 through a discretisation process, where +1 represents an upward movement and −1 indicates a downward movement (Patel et al., 2015). The following section outlines the discretisation criteria for each technical indicator.

The Simple Moving Average (MA) and Weighted Moving Average (WMA) were calculated over a 14-day window to capture short-term trends. The MA is one of the most widely used trend indicators, while the WMA assigns more weight to recent prices making it more sensitive to recent market activity. If the current AUD/USD closing price is above the corresponding MA or WMA value, the trend is classified as upward (+1). Conversely, if the price is below, the trend is considered downward (−1). Short-term moving averages, typically spanning 7 to 14 days, are commonly employed in financial analysis to reflect recent price movements and capture short-term trends in speculative markets such as foreign exchange.

Momentum is calculated as the difference between the current closing price and the closing price from 14 days prior. A positive momentum value indicates an upward trend (+1), while a negative value denotes a downward trend (−1). This indicator reflects the velocity of price changes and provides insight into the sustainability of ongoing trends.

Stochastic indicators are used to measure market momentum and identify overbought or oversold conditions. Values are bounded within a 0–100 range. The %K and %D indicators assess the position of the closing price relative to the high-low range over a 14-day period, with %D representing a 3-day moving average of %K. Stochastic %D is the moving average of the Stochastic %K and acts as a signal line within the Stochastic Oscillator framework. By smoothing %K, it enhances the reliability of trend reversal signals and strengthens momentum analysis. Similarly, the Larry Williams %R (LW) indicator evaluates where the closing price stands relative to historical highs and lows. If the value at time t exceeds that of t−1, it is classified as an upward movement (+1); if it is lower, it is labelled as downward (−1). These indicators help detect potential price reversals around key support and resistance levels.

The RSI quantifies the magnitude and speed of recent price changes to evaluate overbought or oversold conditions. RSI values below 30 signal an oversold condition and are labelled as an upward trend (+1). Values above 70 indicate overbought conditions and are labelled as a downward trend (−1). For intermediate values (30–70), if RSI increases from t−1 to t, the trend is upward (+1); otherwise, it is downward (−1).

The MACD measures the relationship between short- and long-term EMAs. MACD is a trend-following momentum indicator that highlights the relationship between two exponential moving averages, typically the 12-day and 26-day exponential moving averages. The trend is labelled as upward (+1) if the MACD value at time t is greater than at t−1, and downward (−1) if it is less. MACD serves as a momentum oscillator and helps identify changes in the strength, direction, and duration of a trend.

The Accumulation/Distribution Oscillator (A/D) gauges the cumulative flow of capital into or out of an asset by incorporating both price and volume data. It is instrumental in identifying divergences between price movements and volume trends, which may signal potential market reversals. The trend is classified as upward (+1) if the A/D Oscillator value at time t is greater than at t−1, and downward (−1) if it is lower.

The Commodity Channel Index measures the deviation of the current price from its moving average to detect cyclical trends. It is frequently used to identify overbought and oversold levels and is especially effective in spotting early signs of market reversals. CCI values above +100 indicate an overbought condition and are labelled as a downward trend (−1), while values below −100 signal an oversold condition and are labelled as an upward trend (+1). For values between −100 and +100, if the CCI increases from t−1 to t, the trend is upward (+1); otherwise, it is downward (−1). Figure 1 depicts the forecasting mechanism used in this research.

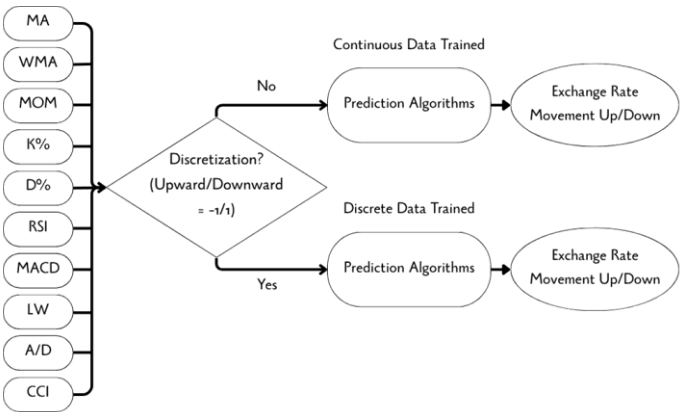

Fig. 1. Forecasting mechanism of the AUD/USD Exchange Rate Prediction

B. Machine learning models and parameter optimization

Three ML algorithms were applied in this study; SVM with polynomial and RBF kernels, RF with varied tree numbers and depths and CatBoost with different combinations of depth, learning rate, and regularization. These models were selected for their proven ability to capture nonlinear relationships, manage high-dimensional data, and maintain predictive robustness in financial time series analysis. CatBoost, a gradient boosting algorithm was selected for its superior handling of categorical features and its ordered boosting mechanism that mitigates overfitting. A range of hyperparameter configurations was explored, including the number of trees, maximum depth, L2 regularization strength, and learning rate. The full set of tuning parameters evaluated during the grid search is detailed in Table II.

TABLE II
PARAMETER SETTINGS FOR CATBOOST

Parameter	Level
Number of Trees (n)	3, 4,…, 300
Max Depth	6, 8, 10
Regularization Strength	1, 3, 5
Learning Rate	0.01, 0.05, 0.1

RF, an efficient ensemble learning method, was selected for its robustness to outliers and its ability to handle high-dimensional data, characteristics commonly found in forex data. RF enhances predictive accuracy by aggregating the outputs of multiple decision trees. In this study, the optimal parameter settings were determined by varying the number of decision trees and the number of features considered at each split, both ranging from 3 to 300. The hyperparameter ranges explored during the tuning process are summarized in Table III.

TABLE III
PARAMETER SETTINGS FOR RF

Parameter	Level
Number of Trees (n)	3, 4,…, 300
Max Features	3, 4,…, 300

SVM, a supervised learning algorithm, was chosen for its effectiveness in capturing nonlinear relationships and its widespread use in financial forecasting. Key hyperparameters, including the regularization parameter (C), kernel coefficient (γ), and polynomial degree (d), were tuned systematically through grid search across both RBF and polynomial kernels. The full set of parameter configurations explored is summarized in Table IV.

TABLE IV
PARAMETER SETTINGS FOR SVM

Parameter	Level (Polynomial)	Level (RBF-Gaussian)
Degree (d)	1, 2, 3, 4	
Kernel function Gamma coefficient ($\boldsymbol{\gamma}$)		0, 0.1, 0.2…, 10.0
Regularization parameter (c)	1, 10, 100	1, 10, 100

Hyperparameter tuning for all models was conducted using a grid search approach and k-fold cross-validation (with k=5), where different combinations of hyperparameters were evaluated, and the best combination was selected based on the performance on the validation set. This rigorous hyperparameter tuning process ensured the models were optimized for the specific forecasting task.

C. Training and validation

Model training and testing were carried out using a dataset of 5,027 AUD/USD trading days spanning from 29 September 2008 to 25 October 2024. The dataset was partitioned into a training set (4,012 observations, from 14 October 2008 to 12 August 2021) and a testing set (1,002 observations, from 13 August 2021 to 25 October 2024). The training set was used to train the machine learning models and perform hyperparameter tuning via cross-validation. The testing set, which remained unseen during training, was used to evaluate the final generalization performance of each model.

To ensure robust evaluation, 5-fold cross-validation was applied during model training, allowing the training data to be split into five subsets where models were trained on four folds and validated on the fifth, rotating across all combinations. The final performance metrics were averaged across folds to obtain stable and reliable estimates.

D. Performance metrics

Model performance was evaluated using a comprehensive set of classification metrics, including Accuracy, Precision, Recall, F1-score, and Area Under the ROC Curve (AUC). These metrics measured the models' ability to correctly predict directional movements of the AUD/USD exchange rate. A confusion matrix was also generated to provide a visual representation of prediction outcomes across actual and predicted classes. Additionally, the ROC curve was plotted to evaluate the trade-off between true positive and false positive rates, with AUC serving as a key indicator of overall classification performance.

To complement these metrics, paired t-test was conducted to statistically compare model performance. Specifically, the Area Under the Curve (AUC) scores were computed for each model across the testing set. Pairwise comparisons were then conducted using the t-test to determine whether the observed differences in AUC between models were statistically significant. This procedure provides a more rigorous evaluation of model performance beyond standard accuracy metrics and helps assess whether any improvements are likely to be meaningful rather than due to random chance. The significance threshold was set at $p < 0.05$.

III. RESULTS AND DISCUSSION

Findings reveal that incorporating discretisation significantly improves the forecasting accuracy of all three models, SVM, RF, and CatBoost, in predicting one-day-ahead AUD/USD price movements. This section presents the estimated model parameters for both the continuous and discrete datasets. Descriptive statistics for the input variables are provided in Table V.

TABLE V
DESCRIPTIVE STATISTICS OF TECHNICAL INDICATORS

Indicator	Minimum	Maximum	Mean	Standard deviation
MA	0.589968	1.093207	0.800993133	0.12958204
WMA	0.587289	1.096719	0.800984526	0.12961899
Mom	-0.11736	0.08192	-0.00008736	0.01668120
K%	0	100	50.5865372	30.6669827
D%	0.602494	99.00333	50.5918534	28.0040832
RSI	0	96.29863	50.0539125	17.0044222
MACD	-0.03502	0.01906	-0.00013612	0.00595015
LW	-100	0	-49.4134627	30.6669827
A/D	-2.26601	10.40625	0.51419297	0.43062849
CCI	-333.333	306.3303	0.84268352	105.254026

A. *Continuous forecasting results*

The performance of each model trained on the continuous dataset is summarized in Tables 6 to 8. For the SVM model, a polynomial kernel with degree 1 and regularization parameter c=100 produced the highest accuracy of 83.47% (Table VI). RF achieved its best result with 84.17% accuracy using 7 features and 78 decision trees (Table VII). Meanwhile, CatBoost recorded a peak accuracy of 84.07% when using 200 trees, a tree depth of 5, regularization strength of 9, and a learning rate of 0.1 (Table VIII).

TABLE VI
BEST THREE-PARAMETER COMBINATIONS FOR SVM

	Kernel function	*d*	*c*	Accuracy
1	Polynomial	1	100	0.8347
2	Polynomial	1	10	0.8337
3	Polynomial	1	1	0.8297

TABLE VII
BEST THREE-PARAMETER COMBINATIONS FOR RF

	Feature	Number of trees	Accuracy
1	7	78	0.8417
2	17	257	0.8327
3	40	261	0.8327

TABLE VIII
BEST THREE-PARAMETER COMBINATIONS FOR CATBOOST

	Tree Depth	Number of trees	Regularization strength	Learning Rate	Accuracy
1	5	200	9	0.1	0.8407
2	7	300	1	0.05	0.8387
3	5	200	7	0.05	0.8347

A comprehensive comparison of model performance is shown in Table IX, which includes accuracy, AUC-ROC and True/False Positive rates. The RF model ranked highest with an accuracy of 84.17%, followed closely by CatBoost (84.07%) and SVM (83.47%). In terms of AUC-ROC, CatBoost led with a score of 0.9224, outperforming SVM (0.9218) and RF (0.9175).

TABLE IX
COMPARISON OF ALL THE MODELS (CONTINUOUS DATASET)

	TP	FP	AUC-ROC	Accuracy	Rank
SVM	0.8347	0.1653	0.9218	0.8347	3
RF	0.8407	0.1593	0.9175	0.8417	1
CB	0.8397	0.1603	0.9224	0.8407	2

B. *Discrete forecasting results*

Optimal parameter combinations for the discrete dataset were identified through systematic hyperparameter tuning for each forecasting algorithm. The top three configurations for CatBoost, RF, and SVM are presented in Tables XI through XII.

TABLE XI
BEST THREE-PARAMETER COMBINATIONS FOR SVM

	Kernel function	*d*	c	Accuracy
1	Polynomial	1	100	0.8948
2	Polynomial	1	10	0.8928
3	Polynomial	1	1	0.8928

TABLE XII
BEST THREE-PARAMETER COMBINATIONS FOR RF

	Feature	Number of trees	Accuracy
1	3	192	0.8928
2	56	232	0.8918
3	88	224	0.8918

TABLE XIII
BEST THREE-PARAMETER COMBINATIONS FOR CATBOOST

	Tree Depth	Number of trees	Regularization strength	Learning Rate	Accuracy
1	8	300	1	0.05	0.8968
2	6	200	5	0.1	0.8968
3	8	200	3	0.05	0.8968

As shown in Table XI, the SVM model trained on the discretised dataset achieved its highest accuracy of 89.48% using a polynomial kernel with degree 1 and a regularisation parameter (C) of 100. Comparable accuracies of 89.28% were observed with C values of 10 and 1, indicating that the model's performance remains stable across varying levels of regularisation when utilising a low-degree polynomial kernel.

Table XII presents the top-performing configurations for the RF model. The highest accuracy of 89.28% was obtained using 192 decision trees and three features selected per split. Alternative configurations employing 232 trees with 56 features and 224 trees with 88 features resulted in slightly lower accuracies of 89.18%, highlighting the importance of optimising both the number of trees and the feature subset size.

As detailed in Table XIII, the CatBoost model recorded its highest accuracy of 89.68% across three distinct hyperparameter combinations. These configurations included: 300 trees with depth 8, learning rate of 0.05, and regularisation strength of 1; 200 trees with depth 6, learning rate of 0.1, and regularisation strength of 5; and 200 trees with depth 8, learning rate of 0.05, and regularisation strength of 3. The identical accuracy across these configurations demonstrates the model's robustness and stability in response to variations in hyperparameter settings.

A summary comparison of performance across all models is shown in Table XIV. CatBoost achieved the best overall accuracy (89.68%), along with the highest AUC-ROC score (0.9609) and F1-relevant statistics. SVM closely followed with 89.48% accuracy and an AUC of 0.9476, while RF yielded 89.28% accuracy. These metrics highlight CatBoost's leading performance in binary classification of AUD/USD price direction using discretised features.

TABLE XIV
COMPARISON OF ALL THE MODELS (DISCRETE DATASET)

	Precision	Recall	AUC-ROC	Testing Accuracy	Rank
SVM	0.9031	0.8944	0.9476	0.8948	2
RF	0.9012	0.8925	0.9583	0.8928	3
CB	0.9066	0.8944	0.9609	0.8968	1

Statistical validation was conducted using a paired t-test to compare the AUC scores of each model trained on the discretised dataset. As shown in Table XV, both CatBoost and RF significantly outperformed SVM, indicating superior classification performance. However, the difference between CatBoost and RF was not statistically significant (p = 0.874), suggesting that both models perform comparably well.

TABLE XV
PAIRED T TEST RESULTS FOR AUC COMPARISON BETWEEN DISCRETE MODELS

Model 1	Model 2	Mean AUC (M1)	Mean AUC (M2)	Std. Dev. (M1)	Std. Dev. (M2)	t-statistic	p-value
SVM	RF	0.94442	0.95932	0.056	0.038	-3.051	0.004**
SVM	CB	0.94442	0.95976	0.056	0.040	-3.319	0.002**
RF	CB	0.95932	0.95976	0.038	0.040	-0.171	0.865

CatBoost model, when applied to the discretised dataset, demonstrated superior predictive capabilities compared to both RF and SVM. CatBoost achieved the highest accuracy (0.8968), F1-score (0.8928), and AUC-ROC (0.9609) values, outperforming the other models across all classification metrics. These results underscore the advantages of using discretised features in combination with advanced machine learning algorithms such as Catboost .

A visual comparison of the classification accuracy and AUC for both continuous and discretised datasets across all models is illustrated in Figure 2 and Figure 3 respectively, where CatBoost's consistent lead in performance is clearly observable.

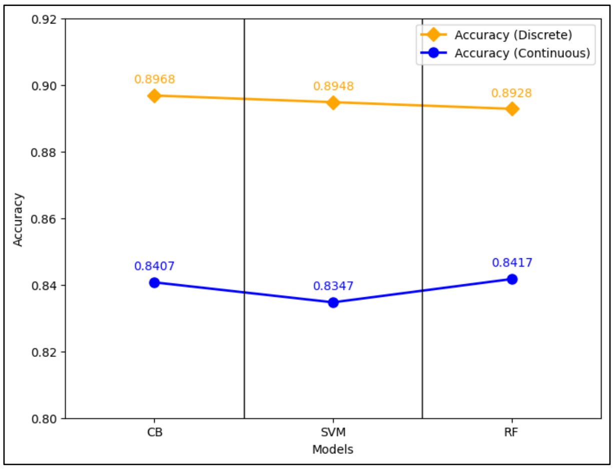

Fig. 2. Accuracy Comparison of ML Models on Continuous and Discretised Datasets

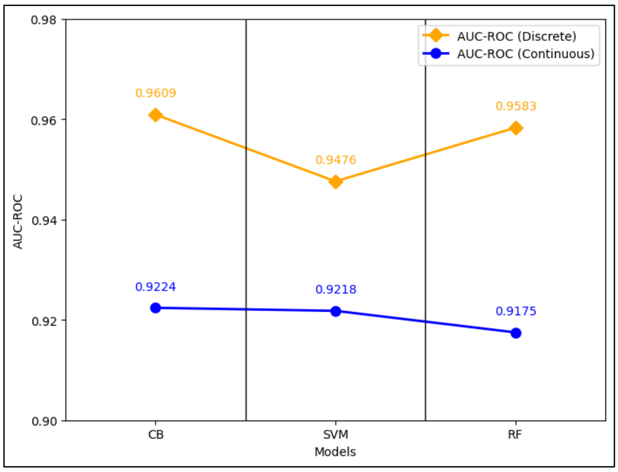

Fig. 3. AUC Comparison of ML Models on Continuous and Discretised Datasets

C. *SHAP Feature Importance Analysis*

To enhance interpretability and identify the most influential predictors of AUD/USD price movements, SHAP (SHapley Additive exPlanations) analysis was performed for the CatBoost, Random Forest (RF), and Support Vector Machine (SVM) models. SHAP values quantify each feature's contribution to the model's output, allowing for both global importance ranking and local interpretability.

Fig 4 presents the SHAP summary plot for the CatBoost model, illustrating the magnitude and direction of each feature's influence on AUD/USD price movements, while Fig 5 displays the corresponding feature importance ranking. Williams %R emerges as the most influential predictor, aligning with [18], who emphasise its effectiveness in identifying overbought and oversold market conditions. Higher LW values are associated with increased SHAP values, indicating a greater probability of an upward AUD/USD movement. Stochastic %K is the second most influential feature, with higher %K values signalling stronger short-term momentum and a higher likelihood of price increases.

Momentum also shows a positive relationship with SHAP values, consistent with [19], who describe momentum as a leading indicator that reflects the continuation or acceleration of existing trends. In contrast, the Relative Strength Index (RSI) demonstrates the weakest contribution among the examined indicators, supported by [20].

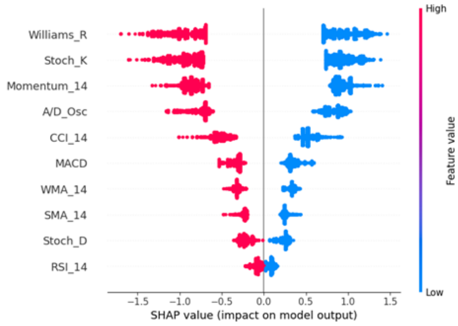

Fig. 4. SHAP summary plot of CB model

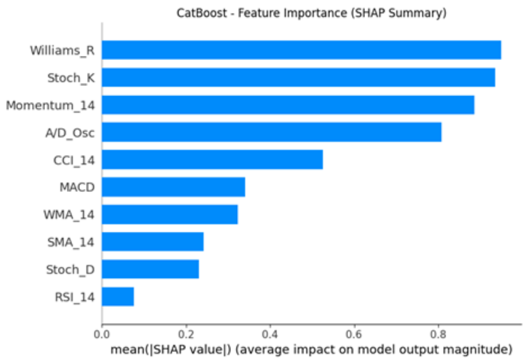

Fig. 5. Relative importance of features for CB model

Figure 6 presents the SHAP dependence plot, providing deeper insight into how variations in Williams %R influence the model's AUD/USD predictions. The plot reveals a clear negative relationship: low Williams %R values correspond to positive SHAP values, prompting the model to predict an upward movement in the AUD/USD exchange rate, whereas high Williams %R values yield negative SHAP values, signalling a predicted decline. At Williams %R = –1.00, Stochastic %K values are generally low, with SHAP values between approximately 0.7 and 1.5, indicating a strong positive contribution toward predicting an increase. Conversely, at Williams %R = 1.00, points are predominantly associated with higher Stochastic %K values and SHAP values between –1.9 and –0.4, reflecting a substantial negative influence on the predicted AUD/USD movement.

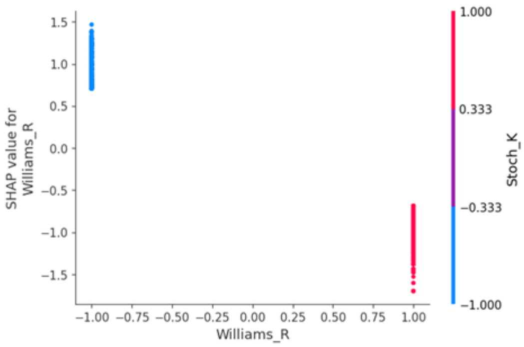

Fig. 6. SHAP dependence plots

IV. CONCLUSION

This study investigated the effectiveness of three machine learning models, CatBoost, SVM, and RF, in forecasting one-day-ahead movement of the AUD/USD exchange rate using both continuous and discretised technical indicators. The results revealed that while RF performed best on the continuous dataset, CatBoost outperformed all models on the discretised dataset, achieving superior accuracy, precision, recall, and AUC scores. The transformation of raw technical indicators into directional (up/down) signals significantly improved model performance, highlighting the value of discrete trend representation in enhancing interpretability and responsiveness in financial forecasting tasks.

The findings demonstrate CatBoost's strong capacity to model complex, nonlinear patterns in volatile forex markets, largely due to its ordered boosting mechanism and effective regularization. This research underscores the potential of discrete classification approaches for short-term currency forecasting and offers practical implications for real-time decision support systems in trading. Future work could expand on this by exploring multi-class or probabilistic forecasting, incorporating macroeconomic variables, or applying deep learning architectures to capture long-range dependencies. Ultimately, this study contributes to the advancement of financial technology (FinTech) by promoting AI-driven, data-informed strategies that support more sustainable, inclusive, and resilient financial decision-making.

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