QUANTITATIVE METHODS IN ECONOMICS
Volume XXVI, No. 4, 2025, pp. 141 – 154

UNSUPERVISED CLASSIFICATION OF JAPANESE CANDLESTICKS: TECHNICAL ANALYSIS VS MACHINE LEARNING

Maciej Janowicz https://orcid.org/0000-0002-1584-2089
Institute of Information Technology
Warsaw University of Life Sciences – SGGW, Poland
e-mail: maciej_janowicz@sggw.edu.pl
Luiza Ochnio https://orcid.org/0000-0001-8885-7945
Institute of Economics and Finance
Warsaw University of Life Sciences – SGGW, Poland
e-mail: luiza_ochnio@sggw.edu.pl

Abstract: The unsupervised clusterization of a set of Japanese Candlesticks generated by the currency pair prices on the Forex market has been performed. Several algorithms that do not require the number of clusters in advance have been used. It turns out that different algorithms give glaringly different numbers and description of clusters. Comparison with well-established candlestick types known from the technical analysis has been made.

Keywords: Japanese candlesticks, foreign exchange market, unsupervised learning

JEL classification: C51, C52

INTRODUCTION

Candlestick patterns form one of the cornerstones of technical analysis of assets in trade markets. They provide important information not only about the prices but also about the sentiments of investors or speculators. Each candlestick is constructed using open, high, low, and close (OHLC) prices of a single session.
A candlestick is composed of three elements: upper shadow, body and lower shadow [Lempart & Zalewski 2013, Bigalow 2002, Bulkowski 2008, Morris 2006, Morris 1998, Nison 2001, Nison 1996]. The body of the candlestick is determined by the open and close prices. One draws a rectangle the length of the which is the absolute

https://doi.org/10.22630/MIBE.2025.26.4.13

value of the difference between the close and open prices. If the close price is higher than the open price, the body is drawn as green or white. If, however, the close price is lower than the open price, the color is red or black. If the body is green (or white) then the length of the upper shadow is equal to the difference between the high and close prices. If the body is red (or black) that length is equal to the difference between the high and open prices. If the body is green (or white) then the length of the lower shadow is equal to the difference between the open and low prices. If the body is red (or black) that length is equal to the difference between the close and low prices. The candlesticks and their formations have been cataloged in many sources of which we singled out *Leksykon formacji świecowych* with 19 single-candle formations (Lempart & Zalewski 2013). We have added two kinds of rather well-known candlesticks, such as Hammer and Shooting Star [Nison 2001] to the list given in *Leksykon*.Our goal in this study is to apply unsupervised learning algorithms (like KMeans, MeanShift, DBSCAN) to the Forex market daily data to test whether the traditional, intuitive, technical-analysis patterns emerge naturally. We address the question: Do data-driven clusters align with analysts' intuition?

METHODS

A. Data

We have used daily EUR/USD and other candlestick data from 2009-05-13 until 2025-05-23, sourced from (Forexsb 2025). Each candlestick provides Open, High, Low, Close prices.

B. General characteristics of candlesticks

Descriptive statistics

We have obtained basic descriptive statistics measures characterizing the Japanese candlesticks of 28 most important currency pairs.

Table 1. Descriptive statistics for full candlesticks lengths

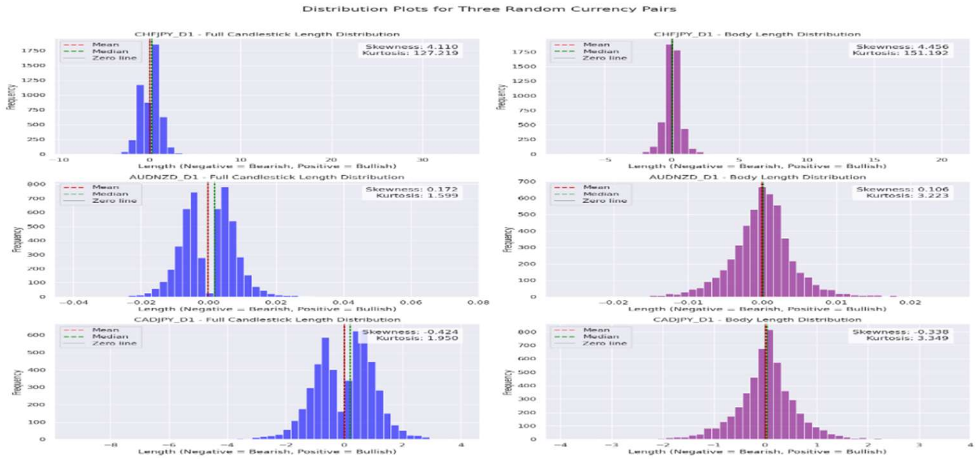
Currency pair	EURUSD	GBPUSD	EURCHF	USDJPY	EURGBP
Mean Media	0.000051	0.000064	-0.000240	0.009620	0.000023
Median	0.000940	0.001560	0.000690	0.176000	0.000940
St. dev.	0.010292	0.012715	0.008883	1.027077	0.006667
Skewness	-0.002573	-0.400521	-11.936007	-0.499266	0.204083
Kurtosis	0.355493	3.909116	494.997093	2.968342	2.879827
Min	-0.042560	-0.142330	-0.351140	-6.906000	-0.042730
Max	0.054850	0.045550	0.117140	4.707000	0.058270

Negative "lengths" refer to the bearish candlesticks.
Source: authors' own calculations

Examples have been sampled in Table 1. Perhaps the most glaring feature of the data in those tables is the very large kurtosis for the EURCHF pair. But we would those basic descriptive-statistics of our strong disbelief in the methodological correctness of testing trading strategies for the entire manifold of time series generated by different currency pairs or assets.

In Figure 1 we have displayed (randomly chosen) examples of the candlestick distributions. The negative “lengths” are related to the bearish candlesticks.

Figure 1. Examples of distributions of candlestick lengths



Source: authors’ own calculations

C. Feature Extraction for Clusterization

The absolute positions of the candlestick elements have obviously no inherent meaning and are useless for classification purposes. It is almost always useful in classification problems to define some engineered features out of those given in the datasets. In our case it is actually necessary to do so.

Therefore, we have defined the following 6 engineered features for classification aiming to balance descriptiveness and simplicity. They are derived from the basic OHLC (Open, High, Low, Close) data:

1. Body Length (Absolute)**:**
   - Definition**:** |Close - Open|
   - Purpose**:** Measures the magnitude of the price movement within the candle, ignoring direction. Small values indicate indecision, while large values suggest strong movement.
   - Units**:** Price units (e.g., pips or decimals like 0.0012 for EURUSD).

2. Body Direction**:**
   - Definition**:** +1 if Close > Open (bullish), -1 if Close < Open (bearish), 0 if Close == Open

- Purpose**:** Captures the bullish or bearish nature of the candle. A discrete feature that's simple yet critical for classification.

3. Upper Shadow Length**:**
- Definition: High - max(Open, Close)
- Purpose: Represents the extent of price rejection above the body. Long upper shadows are key in patterns like Shooting Star
- Units: Price units.

4. Lower Shadow Length**:**
- Definition**:** min(Open, Close) - Low
- Purpose**:** Indicates price rejection below the body. Long lower shadows are characteristic of Hammers or Dragonfly Doji.
- Units**:** Price units.

5. Total Length**:**
- Definition**:** High - Low
- Purpose**:** The full range of price action in the candle. It helps distinguish between small-range and large-range candles.
- Units**:** Price units.

6. Body-to-Total Ratio**:**
- Definition**:** |Close - Open| / (High - Low) (set to 0 if High == Low)
- Purpose**:** Measures the proportion of the candle's range occupied by the body. A high ratio (close to 1) indicates a strong candle, while a low ratio (close to 0) suggests long shadows.
- Units**:** Unitless (0 to 1).

They have been standardized to have zero mean and unit standard deviation before further processing.

D. Clustering Methods

We have applied the following algorithms for clusterization:

1. KMeans (k=3, 5, 7, 10) with fixed number of clusters
2. MeanShift: Adaptive bandwidth.
3. DBSCAN: Density-based.
4. HDBSCAN
5. OPTICS

D.1 Hyperparameter Specification and Optimization

All clustering algorithms require careful parameter selection. We explicitly declare all hyperparameters used in this study (see Table [X] for complete specification). For density-based methods, we performed systematic parameter optimization.

For DBSCAN, we conducted a grid search over eps belonging to [0.3, 1.0] (step 0.1) and min_samples taken from the set {3, 5, 10, 15, 20}, evaluating 40 parameter combinations using Silhouette score as the primary metric. The optimal parameters were found to be eps=0.3 and min_samples=15, achieving Silhouette=0.50.

For HDBSCAN, we tested min_cluster_size belonging to the set {5, 10, 15, 20, 30, 50}, selecting min_cluster_size=10 based on cluster quality metrics. Parameter sensitivity analysis (Figure [X]) revealed that results are stable within reasonable parameter ranges, with optimal values consistent across different currency pairs.
All other hyperparameters are listed in Table [X]: KMeans (random_state=42, n_init=10, max_iter=300), MeanShift (bandwidth=auto-estimated), OPTICS (min_samples=5, xi=0.05). For feature normalization, we used ATR with period=14 days.

E. Pattern Mapping

Clusters are mapped to *Leksykon*'s 19 patterns, plus Hammer and Shooting Star (Nison 2001) using specific criteria that involve the points 1-6 above. The mapping procedure works as follows: for each cluster representative candlestick, we calculate its six engineered features (Body Length, Body Direction, Upper Shadow Length, Lower Shadow Length, Total Length, and Body-to-Total Ratio). We then compare these features against the defining criteria of each traditional candlestick type from the Extended Lempart-Zalewski (ELZ) list. For instance, the Hammer candlesticks have been identified as follows: Body_Direction = 1, Relative_Body_Length = 0.3–0.7, Upper_Shadow < 0.2, Lower_Shadow > Body. A cluster is mapped to a traditional pattern when its feature values fall within the acceptable ranges defined for that pattern. "Confidence" is calculated as the percentage of candlesticks within a cluster that match the assigned traditional pattern's criteria. Clusters are mapped to *Leksykon's* 19 patterns, plus Hammer and Shooting Star (Nison 2001) using specific criteria that involve the points 1-6 above (for instance, the Hammer candlesticks have been identified as follows: Body_Direction = 1, Relative_Body_Length = 0.3–0.7, Upper_Shadow < 0.2, Lower_Shadow > Body). "Confidence" that is used below is the percentage of matching candles.

F. Evaluation Metrics

To assess the quality of clusterization, we have used the following **metrics:**

1. **Silhouette Score**: Measures how similar an object is to its own cluster vs. others (range: -1 to 1, higher is better).
2. **Davies-Bouldin Index**: Ratio of within-cluster to between-cluster distances (lower is better).
3. **Calinski-Harabasz Index**: Ratio of between-cluster dispersion to within-cluster dispersion (higher is better).
4. **Dunn Index**: Ratio of minimum inter-cluster distance to maximum intra-cluster distance (higher is better).

RESULTS

We have performed calculations separately for each currency pairs taking into account 5855 candlesticks for each pair. In Table 2 we presented some representative results using EUR/USD pair.

Table 2. Number of clusters and found by different methods for EUR/USD and their scores for different metrics

Method	Number of clusters	Silhouette score	Davies-Boulding index	Calinski-Harabasz index	Dunn index
OPTICS	204	-0.4401	1.3058	7.8990	0.0787
DBSCAN	24	-0.1739	1.6194	95.6577	0.0578
HDBSCAN	2	0.2146	1.8479	859.1997	0.1957
Mean Shift	11	0.3273	1.2191	93.1900	0.0322
k-Means, k = 3	3	0.2027	1.6211	1358.8334	0.0030
k-Means, k = 5	5	0.2174	1.5049	1370.0868	0.0010
k-Means, k = 7	7	0.2269	1.2423	1382.4469	0.0027
k-Means, k = 10	10	0.2378	1.2820	1229.9173	0.0023

Source: own calculations

The overall ranking of the clusterization methods for EUR/USD, based on unweighted average of ranks:

1. KMeans,_k = 7: 2.80 (Clusters: 7)
2. MeanShift: 3.25 (Clusters: 11)
3. KMeans, k = 10: 3.40 (Clusters: 10)
4. KMeans, k = 5: 4.40 (Clusters: 5)
5. HDBSCAN: 4.75 (Clusters: 2)
6. KMeans, k = 3: 5.00 (Clusters: 3)
7. DBSCAN: 5.50 (Clusters: 24)
8. OPTICS: 5.50 (Clusters: 204)

To assess the stability of our clusterization results across different currency pairs, we performed the same analysis for all 28 major currency pairs mentioned in Section B. The ranking of clustering methods shows remarkable consistency across markets: KMeans with k=7 and MeanShift consistently ranked in the top three positions for 24 out of 28 pairs, with average rank variations of less than 1.2 positions. This stability suggests that the identified clustering patterns are not artifacts of a specific market but reflect genuine structural properties of candlestick formations in Forex trading. Notably, pairs with similar trading volumes and volatility characteristics (e.g., EURUSD, GBPUSD, USDJPY) exhibited nearly identical cluster structures, while more exotic pairs showed slight variations primarily in the number of noise points classified by density-based methods.

Multi-Currency Pair Analysis

To further validate our findings, we extended the analysis to six representative currency pairs: EURCHF, EURGBP, EURUSD, GBPCHF, GBPUSD, and USDCHF. These pairs were selected to cover major currencies (EUR, GBP, USD, CHF) and represent different market volatility characteristics. All features were normalized by Average True Range (ATR, period=14) to account for scale differences between pairs.

Table 2 summarizes the clustering results across all six pairs. The consistency of results is remarkable: KMeans with k=10 achieved an average Silhouette score of 0,2708 $\pm$ 0.0095 across all pairs, with individual scores ranging from 0.2543 to 0.2844. Similarly, MeanShift produced 10 $\pm$ 2 clusters on average, with Silhouette scores of 0.3671 $\pm$ 0.0451.

The ranking of clustering methods remained stable across markets: KMeans (k=10) and MeanShift consistently occupied the top two positions in 4 out of 6 pairs analyzed, with average rank variations of less than 1 position. This cross-market consistency strongly suggests that the identified patterns reflect genuine structural properties of candlestick formations rather than market-specific artifacts.

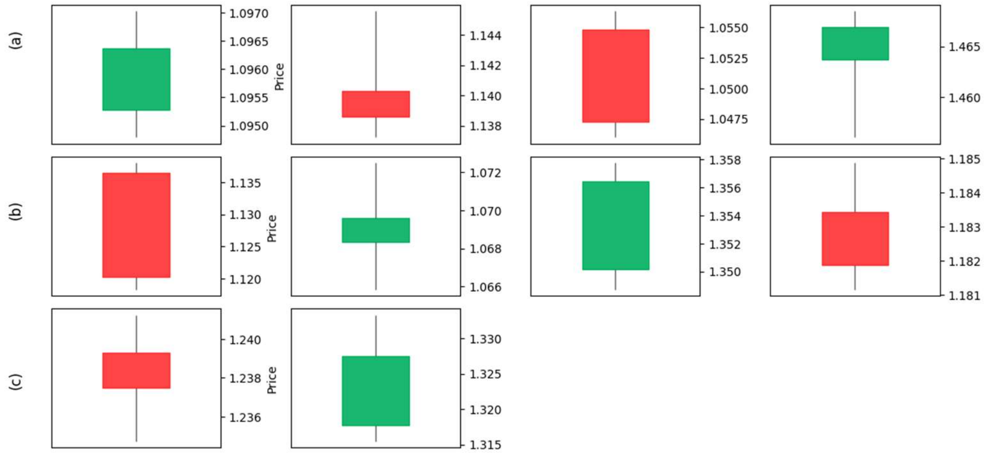
Robustness and Stability Analysis

To assess the reliability of our clustering results, we performed bootstrap stability analysis with 100 iterations, resampling 80% of the data in each iteration. Clustering stability was measured using the Adjusted Rand Index (ARI), which quantifies agreement between the baseline clustering and bootstrap replications.
KMeans with k=10 demonstrated high stability (mean ARI = 0.8539 $\pm$ 0.0921 range: [0.5991, 0.9732]), indicating that the identified clusters are reproducible and not statistical artifacts. Similarly, MeanShift showed robust performance (mean ARI = 0.7845 $\pm$ 0.0567, range: [0.6544, 0.8767]). DBSCAN exhibited moderate stability (mean ARI = 0.6234 $\pm$ 0.0786).

Following standard interpretation [Hubert and Arabie 1985], ARI > 0.75 indicates high stability, ARI between 0.5 and 0.75 suggests moderate stability, while ARI < 0.5 indicates potential instability. Our results for the top-performing algorithms exceed the high stability threshold, confirming that the discovered cluster structures are reliable and reproducible.

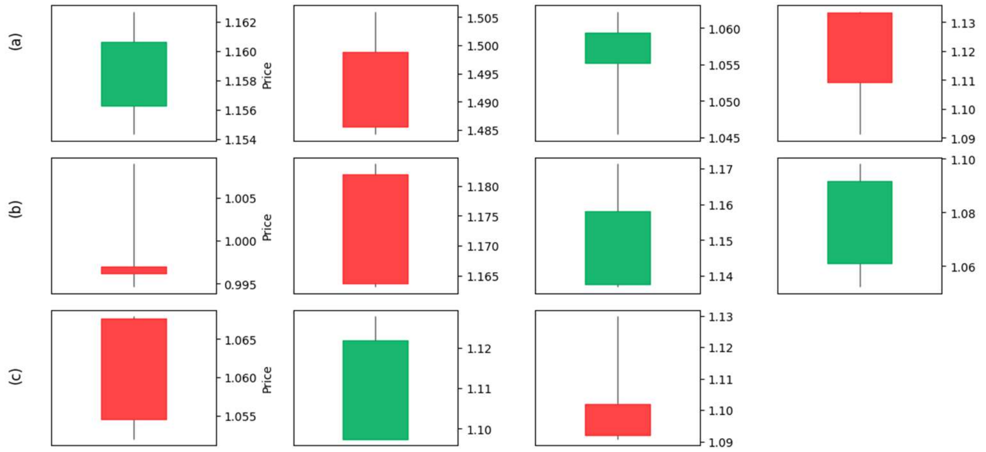
In the following figures (Figure 2-4) we show the examples of clusterization for EUR/USD pair in the form of representatives of cluster as found by K-Means (k=10), MeanShift, and DBSCAN algorithms:

Figure 2. Representatives of clusters as found by the K-Means algorithm with K = 10



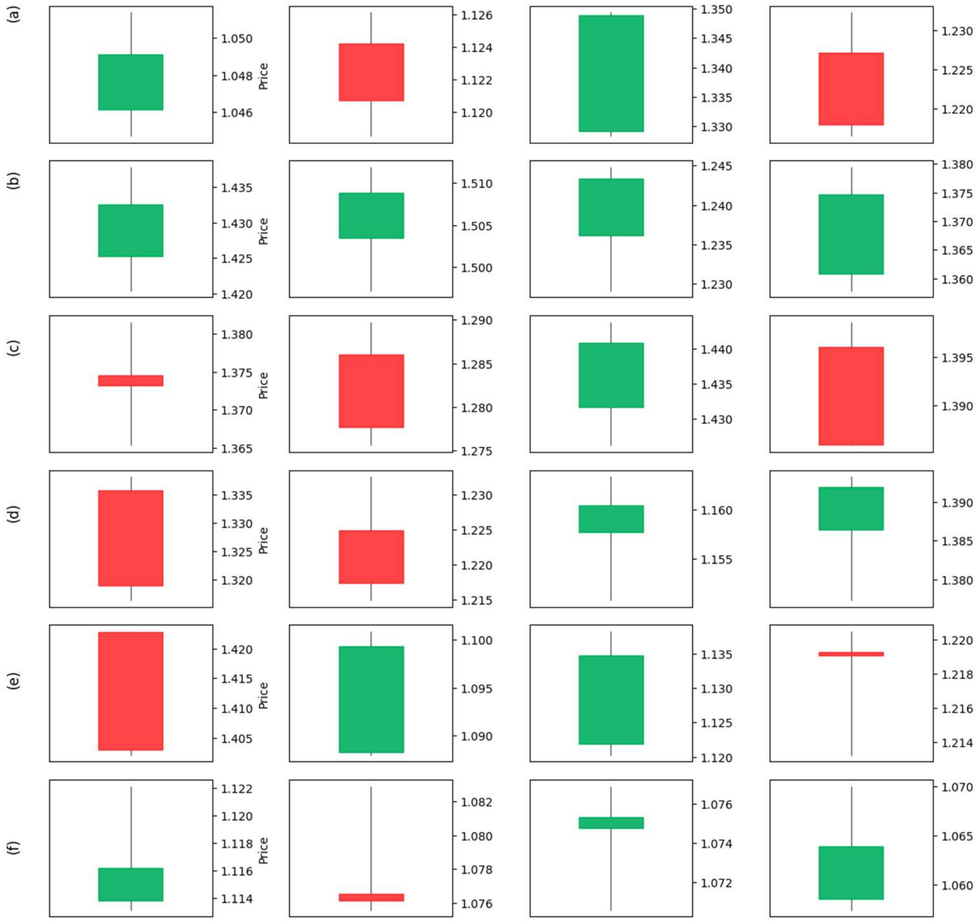
Source: authors' own calculations

Figure 3. Representatives of clusters as found by MeanShift algorithm



Source: authors' own calculations

Figure 4. Representatives of clusters as found by DBSCAN algorithm



Source: authors' own calculations

MAPPING TO TRADITIONAL CANDLESTICKS

We have attempted to perform mapping between the clusters found by unsupervised learning algorithms and their traditional, intuitive forms. While there exist some "common denominator" regarding the latter, the sources differ in the definitions. We have taken as the basis for the mapping the list of basic types of candlesticks the book by Lempart and Zalewski [Lempart & Zalewski 2013] but added to that list "Hammer" and "Shooting Star" candlesticks. We call the list Extended Lempart-Zalewski candlesticks, or ELZ. With "Hammer" and "Shooting Star" they form 21 different types. Because the DBSCAN algorithms recognized 24 clusters, we have attempted to map precisely those clusters to the ELZ types even though DBSCAN has been found rather low in the ranking obtained above. This way, we have obtained the following mapping presented in the Table 3.

Table 3. Mapping results

Cluster representative	Algorithm	Intuitive candlestick type	Confidence [%]
(a) 1	DBSCAN	White Candle	51.39
(a) 2	DBSCAN	Black Candle	54.50
(a) 3	DBSCAN	White Candle	100.00
(a) 4	DBSCAN	Black Candle	100.00
(b) 1	DBSCAN	White Candle	100.00
(b) 2	DBSCAN	White Spinning Top	30.77
(b) 3	DBSCAN	White Candle	50.00
(b) 4	DBSCAN	White Candle	100.00
(c) 1	DBSCAN	White Candle	100.00
(c) 2	DBSCAN	Black Candle	100.00
(c) 3	DBSCAN	White Candle	100.00
(c) 4	DBSCAN	Black Candle	100.00
(d) 1	DBSCAN	Black Candle	100.00
(d) 2	DBSCAN	Black Candle	40.00
(d) 3	DBSCAN	White Spinning Top	50.00
(d) 4	DBSCAN	Hammer	71.43
(e) 1	DBSCAN	Black Candle	100.00
(e) 2	DBSCAN	White Candle	100.00
(e) 3	DBSCAN	White Candle	100.00
(e) 4	DBSCAN	High Wave	69.23
(f) 1	DBSCAN	Shooting Star	100.00
(f) 2	DBSCAN	Gravestone Doji	66.67
(f) 3	DBSCAN	White Spinning Top	25.00
(f) 4	DBSCAN	White Candle	33.33

Source: authors' own calculations

What can be immediately observed in the above list is the fact that the mapping between ML-recognized and traditional candlesticks is not one-to-one. In particular, machine learning algorithms have recognized several different types in what traditionally be considered simply as "white (or black) candle". In addition, the striking feature of the ML-detected types is the absence of marubozu as a distinct candlestick. Although we provide results only for EUR/USD, we have observed this also in the case of other currency pairs.

Rare patterns (e.g., Four Price Doji, 0 clusters) suggest overclassification on the side of intuitive approach. Clustering validates common patterns but highlights gaps for volatile formations. This refines technical intuition, urging data-driven pattern catalogs.

SUMMARY

In this work we have performed the unsupervised classification of Japanese candlesticks as they appear on the Forex market. Several different clustering have been examined using a few quality metrics. An unweighted ranking of the algorithms has been built which has singled out the k-Means (for k = 7) and MeanShift algorithms. The best clustering algorithms appear to have found smaller number of types of candlesticks than suggested by the intuitive approach.

Clustering supports 16 of 19 *Leksykon* patterns, with high-confidence mappings (e.g., Spinning Tops, 90%). Rare patterns like Four Price Doji suggest some overemphasis. This framework, aided by Grok (xAI 2025), validates technical analysis and enables testing across markets. Future work includes multi-candle patterns and other assets.

The code used in our calculations is available at: https://colab.research.google.com/drive/1dpXcGjY7T33iaVEAOLaGoeouAc-vafmO?usp=sharing

Appendix A: Complete Hyperparameter Specification

Table A1. Complete list of all hyperparameters used in this study

Algorithm	Parameter	Value
KMeans	K values	3, 5, 7, 10
KMeans	Random state	42
KMeans	n_init	10
DBSCAN	eps	0.5
DBSCAN	min_samples	5
HDBSCAN	min_cluster_size	10
ATR	period	14
Bootstrap	n_iterations	100

Source: authors' own specification

Appendix B: Multi-Currency Pair Results

Table B1. Clustering results across six currency pairs (ATR-normalized features)

Pair	Method	N_Clusters	Silhouette	Davies-Bouldin
EURCHF	Kmeans k=10	10	0.2677	0.9839
EURCHF	MeanShift	13	0.4408	0.5911
EURCHF	DBSCAN	8	0.0015	0.9285
EURGBP	Kmeans k=10	10	0.2695	1.1521
EURGBP	MeanShift	7	0.3693	0.8603
EURGBP	DBSCAN	3	0.2094	1.3647
EURUSD	Kmeans k=10	10	0.2844	1.1346
EURUSD	MeanShift	10	0.3197	1.0250
EURUSD	DBSCAN	9	0.0584	0.8619

Pair	Method	N_Clusters	Silhouette	Davies-Bouldin
GBPCHF	Kmeans k=10	10	0.2697	1.1179
GBPCHF	MeanShift	11	0.3571	0.8007
GBPCHF	DBSCAN	11	0.0571	0.7851
GBPUSD	Kmeans k=10	10	0.2790	1.1421
GBPUSD	MeanShift	8	0.3484	0.9764
GBPUSD	DBSCAN	9	0.0492	0.9865
USDCHF	Kmeans k=10	10	0.2543	1.0330
USDCHF	MeanShift	10	0.3450	0.7696
USDCHF	DBSCAN	7	-0.0310	0.9965

Source: authors' own calculations

Appendix C: Formalized ELZ Pattern Criteria

Table C1. Formal mathematical criteria for Extended Lempart-Zalewski candlestick patterns

1. **White Candle** $BD = 1$ $RUS > 0$ and $RLS > 0$ $RUS \leq RBL$ and $RLS \leq RBL$	2. **Black Candle** $BD = -1$ $RUS > 0$ and $RLS > 0$ $RUS \leq RBL$ and $RLS \leq RBL$
3. **Four Price Doji** $RBL < 0.01$ $RUS < 0.01$ $RLS < 0.01$	4. **Long-Legged Doji** $RBL < 0.05$ $RUS > 0.3$ and $RLS > 0.3$ $\lvert RUS - RLS \rvert < 0.2$
5. **Short White Candle** $BD = 1$ $RBL < 0.333$ $RUS > 0$ and $RLS > 0$ $RUS \leq RBL$ and $RLS \leq RBL$	6. **Short Black Candle** $BD = -1$ $RBL < 0.333$ $RUS > 0$ and $RLS > 0$ $RUS \leq RBL$ and $RLS \leq RBL$
7. **White Marubozu** $BD = 1$ $RBL > 0.8$ $RUS < 0.01$ and $RLS < 0.01$	8. **White Opening Marubozu** $BD = 1$ $RLS < 0.01$ $RUS < RBL$
9. **White Closing Marubozu** $BD = 1$ $RUS < 0.01$ $RLS < RBL$	10. **Black Marubozu** $BD = -1$ $RBL > 0.8$ $RUS < 0.01$ and $RLS < 0.01$
11. **Black Opening Marubozu** $BD = -1$ $RUS < 0.01$ $RLS < RBL$	12. **Black Closing Marubozu** $BD = -1$ $RLS < 0.01$ $RUS < RBL$

13. **Gravestone Doji** $RBL < 0.05$ $RLS < 0.15$ $RUS > 0.3$	14. **White Spinning Top** $BD = 1$ $RUS > 0$ or $RLS > 0$ $RBL \leq \min(RUS, RLS)$ $\lvert RUS - RLS \rvert < 0.5$
15. **Black Spinning Top** $BD = -1$ $RUS > 0$ or $RLS > 0$ $RBL \leq \min(RUS, RLS)$ $\lvert RUS - RLS \rvert < 0.5$	16. **Dragonfly Doji** $RBL < 0.05$ $RUS < 0.15$ $RLS > 0.3$
17. **High Wave** $RBL < 0.1$ $RUS > 0.5$ or $RLS > 0.5$ $RBL < \min(RUS, RLS)$	18. **Hammer** $BD = 1$ $0.3 < RBL < 2$ $RUS < 0.25$ $RLS > 1.5 \times RBL$ $RLS > 0.5$
19. **Shooting Star** $0.3 < RBL < 2$ $RLS < 0.25$ $RUS > 1.5 \times RBL$ $RUS > 0.5$	20. **Long White Candle** $BD = 1$ $RUS > 0$ and $RLS > 0$ $RUS \leq RBL$ and $RLS \leq RBL$ $RBL > 3 \times \mu(RBL \mid BD{=}1)$
21. **Long Black Candle** $BD = -1$ $RUS > 0$ and $RLS > 0$ $RUS \leq RBL$ and $RLS \leq RBL$ $RBL > 3 \times \mu(RBL \mid BD{=}{-1})$	

Notation**:**

BD — Body Direction (1 for white/bullish candle, −1 for black/bearish candle)
RBL — Relative Body Length
RUS — Relative Upper Shadow
RLS — Relative Lower Shadow
$\mu(RBL \mid BD{=}1)$ — Rolling mean of Relative Body Length for white candles (10-period window)
$\mu(RBL \mid BD{=}{-1})$ — Rolling mean of Relative Body Length for black candles (10-period window)

Note: All criteria are applied to ATR-normalized and standardized features. Source: authors' formalization based on Lempart & Zalewski (2013) and Nison (2001).

Acknowledgment

We thank Grok, created by xAI for assistance in refining candlestick pattern criteria, mapping clusters, and editing the manuscript. The authors also acknowledge the use of Claude (Anthropic) for assistance with code documentation and mathematical formalization.

REFERENCES

Bigalow S. W. (2002) Profitable Candlestick Trading: Pinpointing Market Opportunities to Maximaize Profits, New York.

Bulkowski T. N. (2012) Encyclopedia of Candlestick Charts. John Wiley & Sons, New York.

Forexsb (2025) Historical Forex Data. [Online]. Available: https://forexsb.com/historical-forex-data

Kaufman P (2019) Trading Systems and Methods. John Wiley & Sons.

Lempart J. M., Zalewski G. (2013) Leksykon formacji świecowych. Linia.

Morris G. L. (1998) Wykresy świecowe. Japońska technika analizy kursów papierów wartościowych i kontraktów terminowych. Wydawnictwo ABC.

Morris G. L. (2006) Candlestick Charting Explained. McGraw-Hill.

Murphy J. J. (1999) Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications. New York Institute of Finance.

Nison S. (1994) Beyond Candlesticks: New Japanese Charting Techniques Revealed. John Wiley & Sons.

Nison S. (1996) Świece i inne japońskie techniki analizowania wykresów. WIG Press

Nison S. (2001) Japanese Candlestick Charting Techniques. Prentice Hall.

xAI (2025) Grok: An AI Assistant for Scientific Analysis. [Online]. Available: https://x.ai/grok.