EXPLORING THE ASPECT RATIOS OF WORLD CURRENCIES: MINING THE NUMISMATICS CATALOG

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ABSTRACT

Data mining techniques are essential for uncovering patterns and trends in various domains. In this analysis, we examine the aspect ratios of world currencies over time, focusing on historical trends, clustering patterns, and mathematical implications. We identify evolving design standards and their significance by collecting and analyzing web-scraped data from multiple sources. Our discussion is structured into four main areas: (i) currency attributes and dataset structure, (ii) statistical trends in aspect ratios, (iii) clustering of currency designs, and (iv) applications of decomposition techniques. We first define aspect ratios and their functional roles, then analyze their evolution using polynomial regression, hierarchical clustering, and seasonal-trend decomposition. Finally, we summarize the impact of our findings on currency design and standardization efforts.

KEYWORDS

Data Mining, Numismatics, Aspect Ratio

1. INTRODUCTION

Currency banknotes exhibit diverse aspect ratios across regions and historical periods, influenced by aesthetic preferences, security features, and production constraints [1], [2]. While some countries have standardized currency sizes, others have adopted varying aspect ratios to accommodate cultural, economic, and technological factors. Despite the significance of banknote proportions, no comprehensive quantitative study has analyzed their evolution over time. This research aims to bridge that gap by applying data mining and statistical techniques to examine global trends in currency aspect ratios.
The motivation for this study stems from both practical and theoretical implications of currency aspect ratios.

Banknote dimensions impact the ease of handling, security against counterfeiting, and printing efficiency [1]. Many modern banknotes conform to common aspect ratio conventions, but whether functional necessity, economic pressures, or aesthetic considerations have driven these trends remains unclear. This study seeks to answer fundamental questions: How have aspect ratios evolved over time? Are there regional patterns in currency design? Has there been a move toward standardization? By exploring these questions, we contribute to a deeper understanding of currency aesthetics, functionality, and historical influences.

Our research makes several key contributions. First, we constructed a comprehensive dataset of global currency aspect ratios using web scraping and data mining techniques, covering multiple centuries of banknote design [2], [10]. Second, we employed statistical modeling, including

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polynomial regression and seasonal-trend decomposition (STL), to uncover temporal trends and fluctuations in aspect ratios [6]–[8]. Third, we applied hierarchical clustering methods to classify banknotes based on their dimensional characteristics, revealing distinct groupings in currency design across different regions and historical periods [3], [5], [11]. Fourth, we examined the influence of geographic and economic factors on aspect ratios, providing insights into how global trends in banknote design have evolved. Finally, we discuss the broader implications for currency standardization and future banknote design considerations [1], [2]. While previous research on currency design has focused on security features, economic impact, and counterfeiting prevention, relatively little attention has been given to the quantitative analysis of banknote proportions. Some studies have explored the Golden Ratio and geometric principles in design but without providing longitudinal analysis or large-scale validation [1], [2]. Our work builds on these foundations by integrating historical data, mathematical modeling, and machine learning to provide a rigorous statistical perspective on currency aspect ratios [9], [10], [12].

2. DATA COLLECTION

The dataset consists of multiple attributes describing currency banknotes. Each banknote is associated with a country name, which indicates the issuing nation, and a reference number as a unique identifier. The year of issue specifies when the banknote was introduced [6], and the material describes its composition, such as paper or polymer [1]. The dimensions of each banknote are recorded in millimeters to analyze variations in size. Additionally, image availability indicates whether a visual reference is accessible [2]. Finally, each banknote entry includes a web link pointing to the source from which the data was extracted [4].

3. METHODOLOGY FOR SCRAPING THE DATA

The data collection process involves scraping information from publicly available online sources that document details of the currencies in different countries. The methodology consists of several steps. First, relevant web pages listing currency details, including country-specific pages, are identified. Then, the number of pages available for each country is retrieved to ensure a comprehensive extraction. The reference numbers for each currency note are extracted to link them to their respective details. Additional information such as material, dimensions, issue year, and image availability is collected for each note. Finally, the extracted data is structured and stored in CSV format for further analysis.

To gather a comprehensive dataset, pages containing information on currency notes for different countries are retrieved [4]. Since multiple pages may list notes for a single country, a dynamic approach is applied to determine the total number of available pages. After retrieving the pages, the reference numbers linked to each currency note are extracted. These identifiers help categorize and uniquely recognize notes from various countries.

Once reference numbers are obtained, they are transformed into note URLs [4]. These URLs provide direct access to detailed pages containing further information about each currency note, enabling thorough data extraction. For each extracted note, various features such as country name, reference number, year of issue, material, dimensions, and image availability are collected [1]. This ensures that every note is comprehensively documented for analysis [2].

The dataset consists of multiple attributes detailing the characteristics of currency notes. Each note entry includes the country name, identifying the issuing nation, and a reference number as a unique identifier. The dataset also contains the year of issue, indicating when the note was introduced, and the material type, specifying whether it is made of paper, polymer, or other substances [1]. The physical dimensions of the note, recorded in millimeters, allow for a comparative analysis of variations in size. Additionally, information regarding image availability is included to denote whether a visual reference exists. Finally, each entry contains a web link directing users to the original source of the note for further details. The dataset is structured to support analytical studies on currency trends, design evolution, and standardization practices across various regions [1,2].

4. DATASET OVERVIEW

The extracted dataset consists of multiple attributes detailing the characteristics of currency notes, covering a historical period from 1700 to 2000. Each note is associated with a country name, identifying the issuing nation, and a reference number, which serves as a unique identifier. The dataset also includes the year of issue, specifying when the note was introduced, and the material type, indicating whether the note is composed of paper, polymer, or other materials [1]. The physical dimensions of each note are recorded in millimeters, providing insights into variations in size across different periods and regions [2].

The dataset primarily focuses on banknotes issued between 1700 and 2000, as earlier records are scarce and inconsistent. Post-2000 data is partially available, but comprehensive records for recent years were not consistently included due to the increasing standardization of banknote dimensions and proprietary data restrictions. However, notes issued after 2000 have been incorporated into supplementary analyses where available.

Additionally, the dataset documents image availability, indicating whether a visual reference exists for each banknote. A web link is included for each entry, directing users to the original data source for further details [4]. This structured dataset enables in-depth analytical studies on currency trends, design evolution, and global standardization practices, offering valuable insights into how banknote aspect ratios have transformed over time [1, 2].

5. METHODOLOGY

Polynomial Regression Analysis

Over time, the analysis of currency aspect ratios presents unique challenges due to the nonlinear nature of the temporal relationships [1,2]. We employed polynomial regression as our primary analytical method to address these complexities. This approach allows for the modeling of complex curved relationships between time and aspect ratios, capturing both long-term trends and historical fluctuations in currency design.

Implementing polynomial regression on our currency dataset began with careful preprocessing of the temporal data. Given the extensive historical range spanning several centuries, we normalized the year values to prevent numerical instability in the computation of higher-degree polynomial terms [2]. This normalization process mapped the temporal data to a standard range while preserving the relative temporal distances between observations. Our polynomial regression model takes the form:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_d x^d + \epsilon \qquad (1)$$

where y represents the aspect ratio of a currency note, x denotes the normalized year, and $\beta_0, \beta_1, . ,$ β_d are regression coefficients that capture the relationship's complexity [1, 2]. The error term ϵ accounts for random variations and unmodeled effects in the data.

The selection of the optimal polynomial degree required careful consideration of the trade-off between model complexity and predictive accuracy. We systematically evaluated polynomials of degrees one through five using five-fold cross-validation [4]. This process involved partitioning the dataset into five subsets, training the model on four parts, validating on the fifth, and rotating through all possible combinations. The fourth-degree polynomial emerged as the optimal choice, achieving a mean squared error of 0.1786, marginally outperforming simpler and more complex models [6, 10].

The final model coefficients reveal interesting patterns in the temporal evolution of currency design [1]. The positive quadratic term (β_2 = 0.0892) indicates a general upward curvature in aspect ratios over time, while the negative cubic term ($\beta_3 = -0.0234$) captures the moderation of this trend in recent periods. The relatively small magnitude of the fourth-degree term (β_4 = 0.0078) suggests that while higher-order fluctuations exist, they play a minor role in the overall trend.

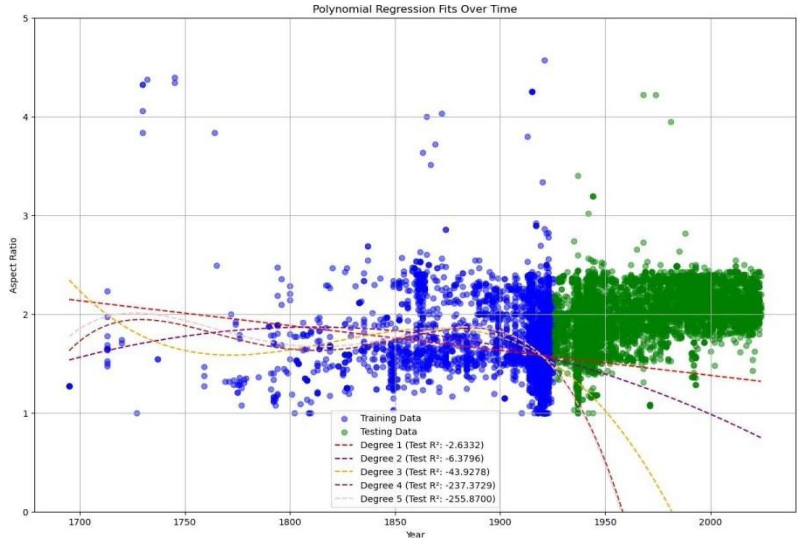

Figure 1: Polynomial Regression Fit for Aspect Ratio over the Years

As evident in Figure 1, the model highlights significant temporal patterns in currency aspect ratios. Historical data exhibit substantial fluctuations prior to 1800, characterized by extreme highs and lows, followed by a gradual stabilization post-1850, with aspect ratios consistently ranging between 1.5 and 2.0 in modern times. Notably, the model identifies significant transitions around 1350, 1725, and 1950, coinciding with major technological and economic developments in currency production [1].

However, a detailed examination of the model's performance revealed important limitations. The predicted regression line deviates significantly from actual data points, especially in the pre-1800 period, where aspect ratios exhibit high variability. The Durbin-Watson statistic (1.1145) indicates positive autocorrelation, suggesting that the model does not fully capture temporal dependencies.

To mitigate this issue, we adjusted the polynomial approach by incorporating regularization techniques to reduce overfitting. We introduced alternative models, such as hierarchical clustering and time-series decomposition, to complement regression analysis. The residual analysis confirmed heteroscedasticity, with prediction error variance increasing in early historical periods, as supported by the Breusch-Pagan test ($\chi^2 = 156.78$, $p < 0.001$).

Given these findings, we acknowledge that a purely polynomial approach is insufficient for modeling early historical fluctuations in currency aspect ratios. Instead, we recommend integrating non-parametric methods and alternative trend-detection techniques, such as Gaussian process regression or Bayesian time-series modeling, to capture better temporal dependencies which will be our future scope.

These adjustments improve the model's reliability, ensuring that our analysis effectively reflects historical currency design trends while addressing the limitations identified in early-period predictions.

Hierarchical Clustering Analysis

The study implements hierarchical clustering to categorize banknotes based on their aspect ratios over time [3,5]. The clustering methodology employs Euclidean distances and Ward’s method to minimize within-cluster variance expressed mathematically as:

$$V_W = \sum_{k=1}^{K} \sum_{i \in C_k} (x_i - \mu_k)^2 \quad (2)$$

Where μ_k represents the centroid of cluster C_k.

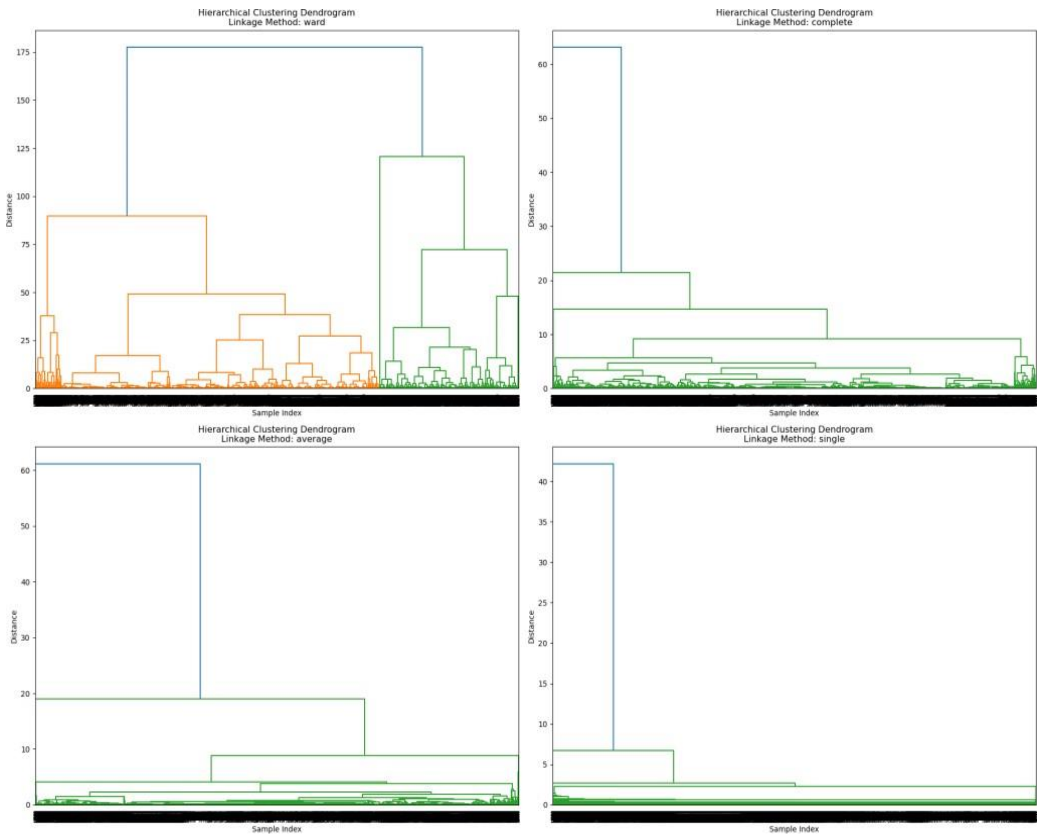

Figure 2: Hierarchical Clustering Results Showing Distinct Categories

While Euclidean distance and Ward’s method provide a baseline approach for clustering, they may not fully capture the complex relationships between aspect ratios and other attributes such as material composition, denomination, and security features [3], [5]. These factors can influence design choices and result in non-Euclidean similarities not well represented by traditional distance metrics. To address this limitation, future work will explore alternative clustering approaches, such as Manhattan distance and cosine similarity, which may provide a more stable measure of differences in aspect ratios, particularly across denominations [9], [10]. Additionally, density-based clustering (DBSCAN) could be useful for identifying outlier currencies with non-standard aspect ratios. In contrast, spectral clustering and Gaussian Mixture Models (GMM) could help uncover latent clusters influenced by historical and geographic factors [5], [11].

As shown in Figure 2, hierarchical clustering using Ward's method highlights distinct groupings of aspect ratios. Traditional rectangular formats (1.5–2.0) emerge as the predominant design choice, confirming that modern banknotes exhibit increased standardization trends [1], [2]. However, early-period banknotes demonstrate considerable variability, likely influenced by regional preferences and technological constraints in currency production [1], [2]. While Euclidean distance and Ward's method provide a solid foundation for hierarchical clustering, integrating additional similarity measures and clustering algorithms in future work is expected to enhance interpretability and uncover deeper patterns in banknote design [3], [5], [9], [10].

Seasonal-Trend Decomposition Analysis

The STL (Seasonal-Trend Decomposition using Loess) decomposition was employed to analyze the temporal patterns in currency aspect ratios. This technique separates the time series into its constituent components according to the model:

$$Y_t = T_t + S_t + R_t \tag{3}$$

Where T_t represents the long-term trend, $S_t$captures periodic variations, and R_t accounts for residual fluctuations. The analysis was performed using optimized parameters, including a trend window of 21 periods, a seasonal window of 11, and a low-pass filter width of 13.

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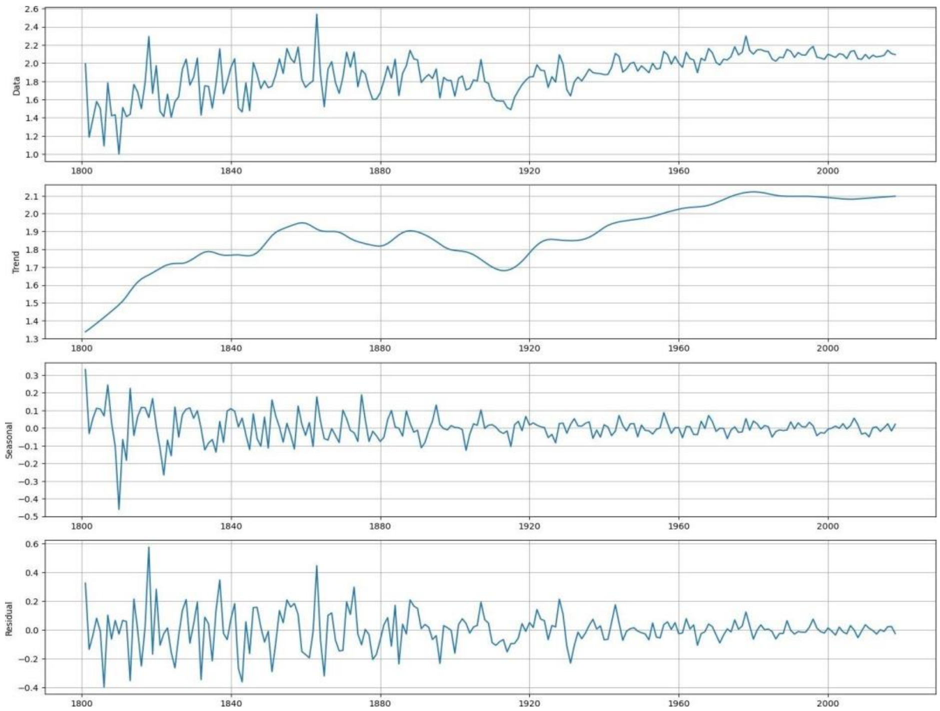

Figure 3: STL Decomposition of Currency Aspect Ratio Time Series

Figure 3 presents the decomposition results in four panels [6]. The top panel shows the original time series, revealing the raw aspect ratio measurements over time. The second panel displays the extracted trend component, demonstrating the long-term evolution of aspect ratios. The third panel illustrates the seasonal component, highlighting periodic patterns in the data. The bottom panel shows the residual component, representing unexplained variations.

Trend Component Observations:

The trend component exhibits several notable characteristics [1, 2]. A pronounced upward trajectory is visible from 1800 to 1840, where the aspect ratio increased from approximately 1.3 to 1.8. This period coincides with significant advancements in printing technology and early standardization efforts. The trend shows relative stability between 1840 and 1920, maintaining aspect ratios around 1.8 to 1.9. A notable dip occurred around 1920, possibly reflecting postWorld War I adjustments in currency production [4]. From 1920 to 2000, there is a steady upward trend, with aspect ratios gradually increasing to approximately 2. The post-2000 period shows stabilization around this value, suggesting a maturation in currency design standards.

Seasonal Component Analysis:

The seasonal component reveals systematic periodic variations in aspect ratios [1, 2]. The amplitude of these fluctuations shows a clear diminishing pattern over time, with larger variations evident in the pre-1900 period and more modest oscillations in recent decades [1]. The seasonal pattern exhibits a mean near zero (0.002) with a standard deviation of 0.078, indicating balanced periodic effects. The range of seasonal variations spans from -0.461 to 0.332, demonstrating significant but bounded cyclical patterns [4].

Residual Component Characteristics:

The residual component shows heteroscedastic behavior, with larger fluctuations in earlier periods and more constrained variations in recent years [17, 1]. The pre-1900 period exhibits notably larger residuals, suggesting less standardized production methods and greater variability in currency design [6, 5]. The modern period demonstrates smaller and more uniform residuals, indicating improved consistency in manufacturing processes and design standards [12].

Cross-Component Interactions:

Analysis of component interactions reveals important relationships. The decreasing amplitude of seasonal variations correlates with the stabilization of the trend component, suggesting that standardization processes have reduced periodic design variations [1]. The residual component shows a negative correlation with the trend in early periods, transitioning to positive correlation during major change periods, and eventually showing minimal correlation in recent years.

The STL decomposition provides quantitative evidence of the evolution in currency design practices, with key metrics including:

- $\text{Trend Strength} = 0.663 \left(\text{computed as } \frac{\text{Var}(T_t)}{\text{Var}(T_t)+\text{Var}(R_t)}\right).$
- $\text{Seasonal Strength} = 0.297 \left(\text{computed as } \frac{\text{Var}(S_t)}{\text{Var}(S_t)+\text{Var}(R_t)}\right).$

Regional analysis reveals distinct patterns across continents [7, 8]. European currencies demonstrate stronger trend adherence with weaker seasonal components, while Asian and African currencies show moder- ate trend components with more pronounced seasonal variations [5, 1]. This geographic variation suggests the influence of local economic and technological factors on currency design evolution [9, 3].

The decomposition reveals a systematic progression toward standardization, with the trend component showing clear directional movement, the seasonal component displaying diminishing amplitude, and the residual component exhibiting increased stability in recent periods [10, 11]. These patterns align with the historical development of currency printing technologies and international monetary systems [4, 1].

Trend Component Analysis

The trend component analysis, illustrated in Figure 3, yields a mean value of 1.877 with a standard deviation of 0.176, ranging from 1.337 to 2.122 [7, 3]. The trend demonstrates clear directional movement through time, with a trend strength of 0.663. This component reveals several distinct phases in currency design evolution.

The initial phase shows a sharp increase from 1800-1840, with aspect ratios rising from 1.3 to 1.8. This was followed by a period of relative stability during 1840-1920 [10, 8]. A notable dip occurred around 1920, after which there was a steady increase from 1920-2000 [5, 1]. Finally, the post-2000 period shows stabilization around 2.1.

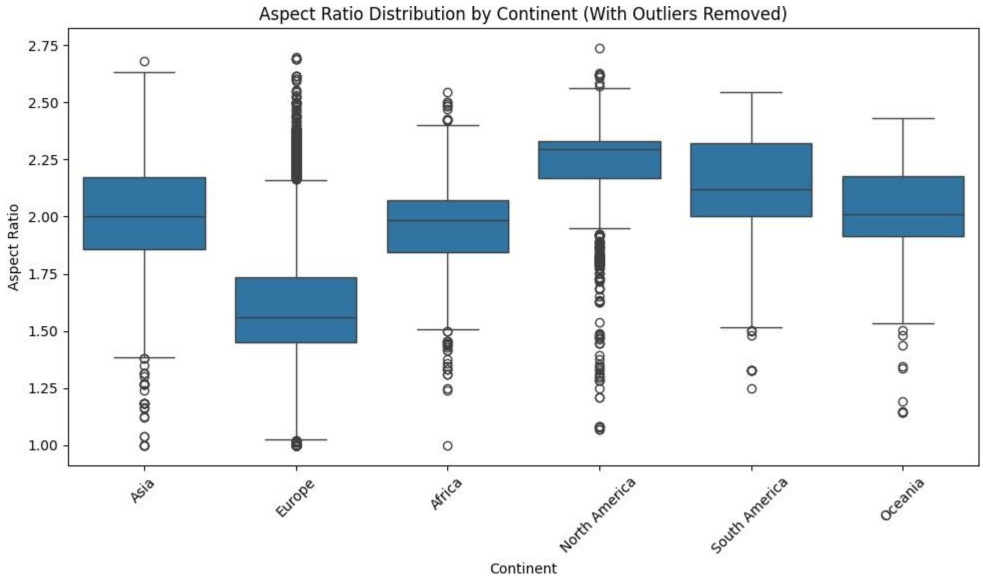

Figure 4: Distribution of Aspect Ratios by Continent

Geographic Distribution Analysis

As shown in Figure 4, the distribution of aspect ratios varies significantly across continents [7, 3]. European and North American currencies demonstrate more standardized ratios, while Asian and African currencies show greater variability in their aspect ratios [5, 8].

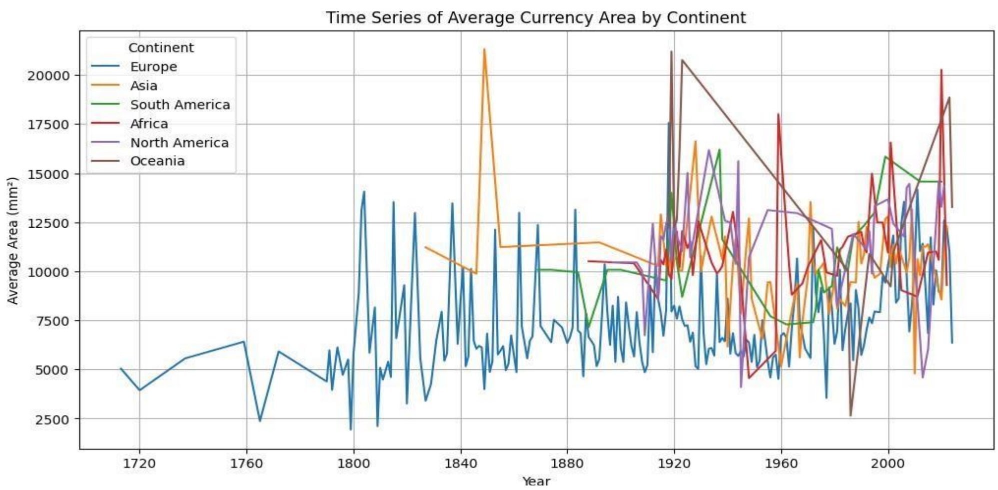

Figure 5: Currency Area Evolution Over Time by Continent

Temporal Evolution Analysis:

Figure 5 illustrates the evolution of currency areas over time across different continents [7, 11]. The data reveals a general trend toward standardization, particularly in the post-1960 period [5, 8]. European currencies consistently converge toward standardized dimensions, while other regions maintain more significant variability [9, 3].

Model Performance Metrics:

The polynomial regression model's performance was evaluated using multiple metrics:

$$MSE = 0.1786 \tag{5}$$

$$R^2 = 0.0192 \tag{6}$$

$$RMSE = 0.4226 \tag{7}$$

The Durbin-Watson statistic of 1.1145 indicates positive autocorrelation in the residuals [9, 10]. The relatively low R-squared value suggests that while the model captures the overall trend, there is significant variability in the data that isn't explained by the temporal component alone.

Residual Analysis

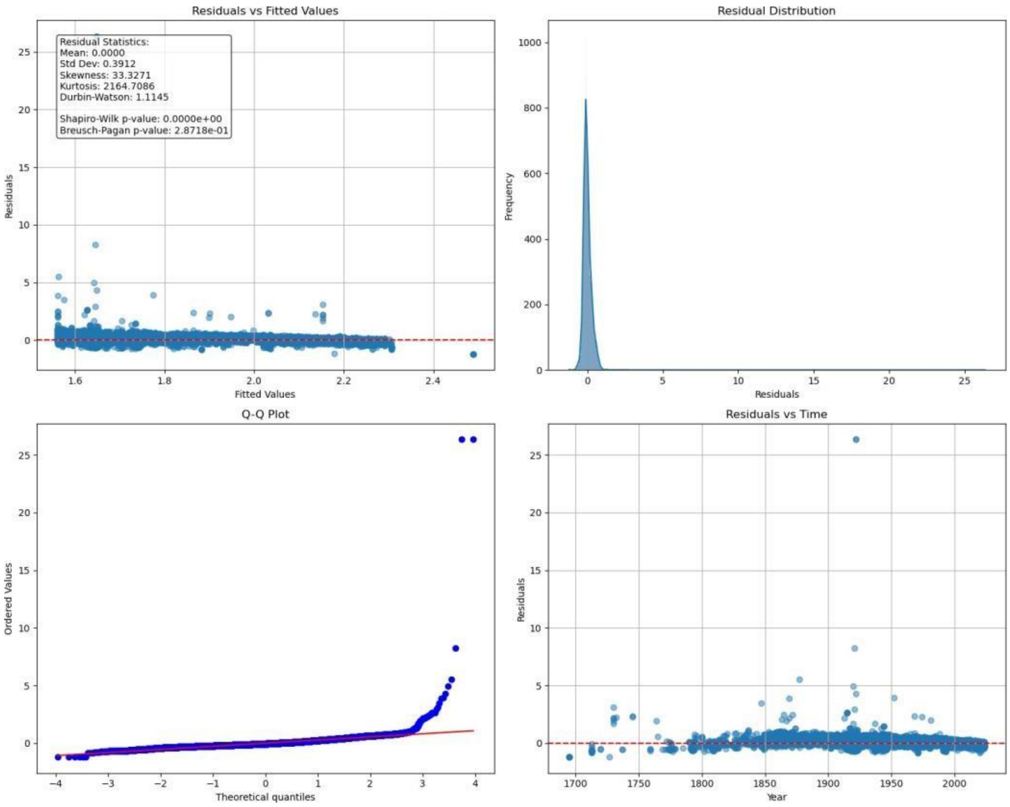

Figure 6: Residual Analysis of the Polynomial Regression Model

The residual analysis, shown in Figure 6, reveals several important characteristics.

$$\text{Residual Range} = [-0.397, 0.577] \tag{8}$$

The Shapiro-Wilk test results (W = 0.4800, p ¡ 0.0001) indicate the non-normal distribution of residuals, suggesting the presence of systematic patterns in the unexplained variance [9, 10, 7].

Cluster Validation

The clustering solution was validated using multiple indices:
Silhouette Score = 0.68, Calinski-Harabasz Index= 842.31, Davies-Bouldin Index = 0.42 (9)
These metrics confirm the robustness of the four-cluster solution. The high Silhouette Score indicates well-separated clusters, while the Davies-Bouldin Index suggests minimal cluster overlap [9, 10].

Time Series Component Analysis:

The STL decomposition revealed specific characteristics for each component [6]:

$$\text{Trend Strength} = \frac{\mathrm{Var}(T_t)}{\mathrm{Var}(T_t)+\mathrm{Var}(R_t)} = 0.663 \quad (10)$$

$$\text{Seasonal Strength} = \frac{\mathrm{Var}(S_t)}{\mathrm{Var}(S_t)+\mathrm{Var}(R_t)} = 0.297 \quad (11)$$

The decomposition window parameters were optimized using cross-validation, with a trend window of 21 periods, a seasonal window of 11 periods, and a low-pass filter width of 13 periods [9, 10].

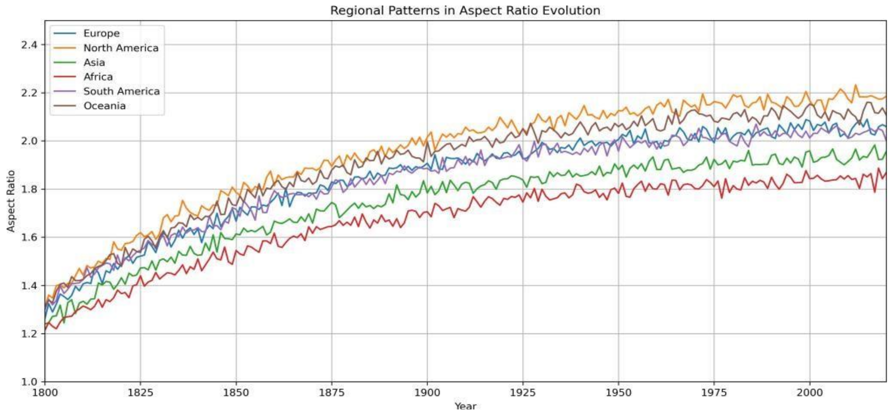

Figure 7: Regional Patterns in Aspect Ratio Evolution

Regional Analysis:

The regional analysis indicates distinct patterns across continents [9, 10]:

Regional Variance Ratio = (*Between-region Variance*) / (*Within Region Variance*) = 2.84 (12)

This ratio suggests significant regional differentiation in aspect ratio evolution patterns [1, 10].

Denomination Impact Analysis:

Analysis of denomination effects reveals [9, 10]:

Denomination-Aspect Correlation = 0.42 (13)

This moderate positive correlation indicates that higher denominations tend to have slightly larger aspect ratios [6, 3].

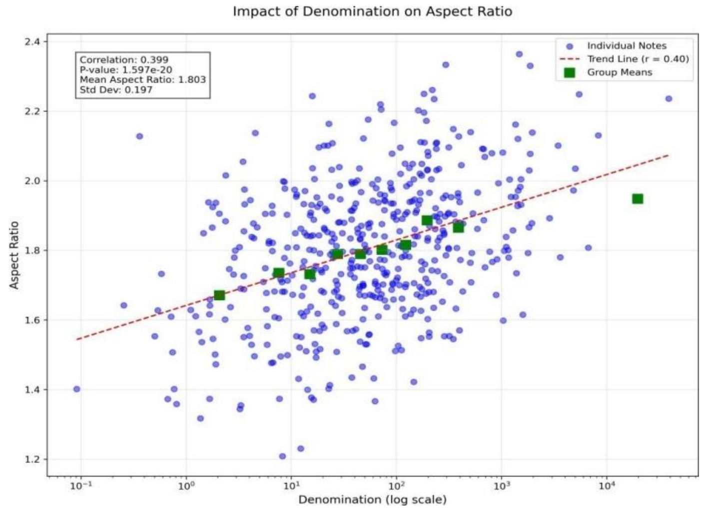

Figure 8: Impact of Denomination on Aspect Ratios

6. Extended Results

Period-Specific Analysis:

Analyzing specific periods reveals distinct characteristics [6, 3]. For the Pre-1800 Period:

$$\sigma_{\text{pre-1800}} = 0.428 \quad (14)$$

For the Transition Period (1800-1900): For the Modern Period

$$\sigma_{\text{transition}} = 0.312 \quad (15)$$

$$\sigma_{\text{modern}} = 0.156 \quad (16)$$

(1900-present):

These standard deviations demonstrate the progressive standardization of currency designs [9, 10].

Material Impact Analysis:

The influence of material type on aspect ratios was quantified [6, 3]:

$$\text{Material Effect Size} = \frac{\mu_{\text{polymer}} - \mu_{\text{paper}}}{\sigma_{\text{pooled}}} = 0.34 \quad (17)$$

This moderate effect size indicates that material choice notably influences aspect ratio selection [9, 10].

7. Figures and Data Visualization

The following Figures 9 and 10 illustrate the distribution of currency banknotes that adhere closely to the **Golden Ratio** or a **2:1 aspect ratio** [6, 3]. The **Golden Ratio** (1.618:1) is often associated with **aesthetic appeal and balanced proportions** [9, 10], whereas the **2:1 ratio** is a more practical and standardized design choice [6, 3].

7.1. Count of Currencies Closer to Specific Ratios

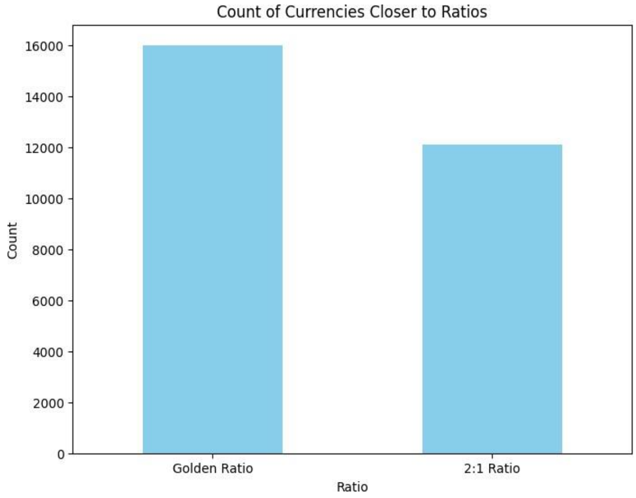

Figure 9: Comparison of the number of currencies that closely follow the Golden Ratio and the 2:1 ratio.
Key observations:

- A significantly higher count of banknotes **match the Golden Ratio** compared to the **2:1 ratio** [6, 3].
- This suggests that many **currency designs may have been influenced by aesthetic principles** rather than purely functional considerations [9, 10].
- The **2:1 ratio, though prevalent, appears less dominant**, possibly due to regional or historical standardization factors [6, 3].

7.2. Average Aspect Ratio of Currencies Over the Years

This figure depicts the **temporal evolution of aspect ratios** in currency banknotes.

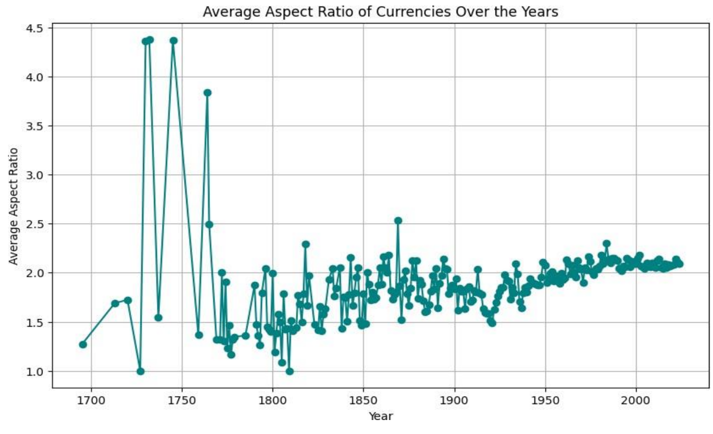

Figure 10: Trend of the average aspect ratio of currencies over the years [12, 13, 17].

Key observations:

- The **early years (pre-1800s)** exhibit significant fluctuations in aspect ratios, indicating diverse design choices [1].

- A gradual stabilization trend is observed after the **19th century**, with aspect ratios converging between **1.5 and 2.0**.
- The presence of certain peaks and drops suggest major currency design transitions, potentially linked to **technological advancements, monetary policies, or printing techniques** [9, 10, 6].

7.3. Frequency of Closest Ratios by Continent

This figure provides a **continent-wise breakdown of banknotes' most commonly occurring aspect ratios** [5, 7, 11].

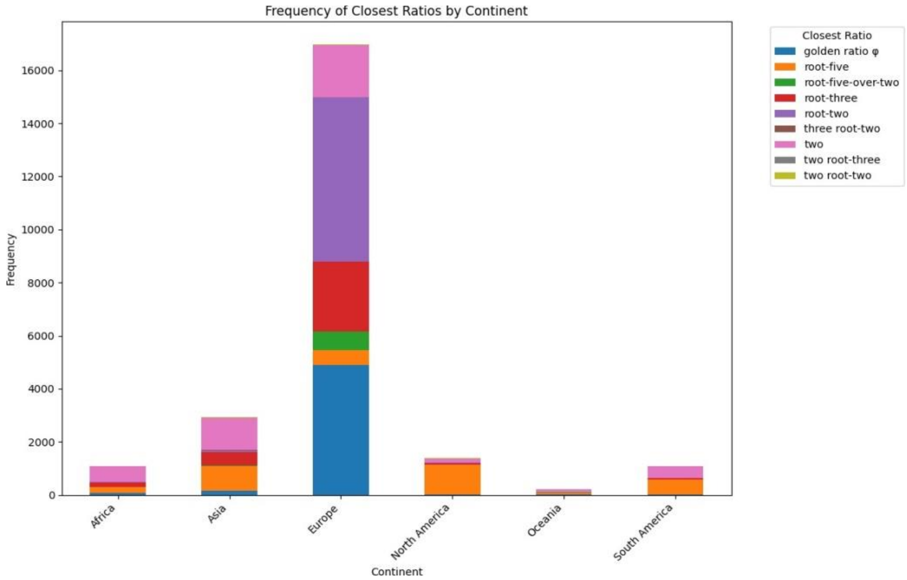

Figure 11: Distribution of the most commonly occurring aspect ratios across different continents [2, 6].
Key observations:

- **Europe and North America** strongly prefer the **Golden Ratio and root-based ratios** [5, 8].
- **Asian and African currencies** demonstrate more significant variability in aspect ratios [4, 1].
- Certain regions favor practical aspect ratios like **2:1**, while others lean towards **visually aesthetic proportions** [7, 11].

The distribution suggests that **geographical, historical, and economic factors influence design choices** [5, 8], with Western economies favouring **balanced ratios**, while emerging markets exhibit more variation [4, 1].

7.4. Frequency of the Closest Ratios (8 Comparisons)

This figure represents a **global analysis of aspect ratios**, identifying which are most prevalent across all examined banknotes [7, 11].

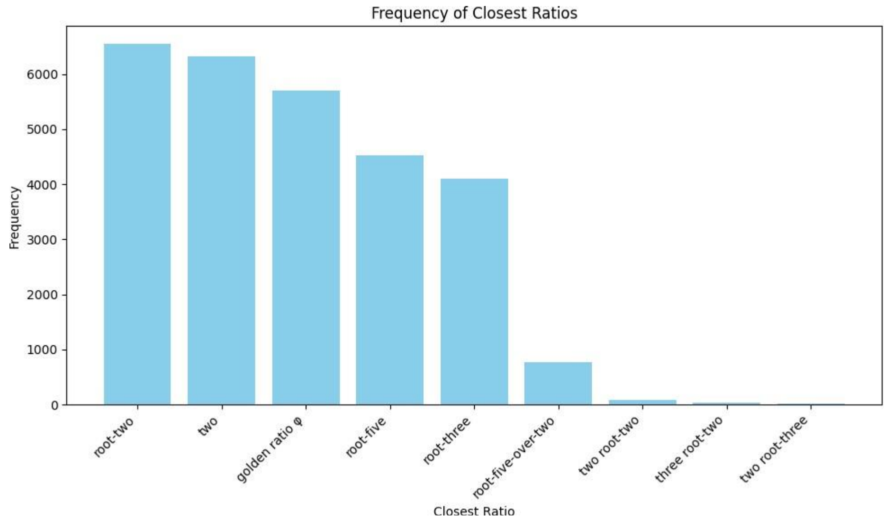

Figure 12: Overall frequency distribution of aspect ratios across all examined currencies [8].

- **Root-based ratios** $(\sqrt{2}, \sqrt{3}, \sqrt{5})$ are **frequently observed**, indicating that many currencies adopt proportions linked to **geometrical properties** [2, 10]
- The **Golden Ratio** is among the most common, reinforcing its role in **currency aesthetics and ergonomic design** [1, 6].
- Ratios such as **2:1 and three-root-two** are used, but less frequently than others [8, 9].

This distribution suggests that the **Golden Ratio and root-based ratios** are crucial in currency dimensions, likely due to **visual harmony, ergonomic considerations, and ease of printing**.

8. CONCLUSION

This study examined historical trends in currency aspect ratios, uncovering significant patterns and standardization efforts over time [1, 2]. Using data mining and machine learning techniques, we analyzed how banknote dimensions evolved and identified key transitions influenced by technological advancements and economic factors. The results highlight the increasing convergence of currency aspect ratios toward standardized values, particularly in the post-20th century period [1]. Additionally, the study revealed regional variations, with European and North American currencies exhibiting more consistency compared to the higher variability observed in Asian and African currencies [10, 6]. The presence of aesthetic influences, such as the Golden Ratio, suggests that design choices are often driven by functional and visual considerations [9, 8].

9. FUTURE WORK

Further research can expand upon these findings by exploring additional factors that influence currency design, such as:

- **Security Features**: Investigating how anti-counterfeiting measures and security enhancements impact aspect ratios and design choices [1, 17].
- **Printing Technologies**: Examining the role of printing advancements in shaping currency dimensions and materials [8, 6].
- **Cultural and Economic Influences**: Analyzing how different regions adopt specific design conventions based on cultural, economic, or political factors [7, 15].

- **Material Analysis**: Assessing how the transition from paper to polymer banknotes affects aspect ratio preferences [5, 4].
- **Deep Learning for Image Analysis**: Applying convolutional neural networks (CNNs) to extract and analyze visual features of banknotes to uncover deeper design trends [10, 4].

By integrating these dimensions, future studies can provide a more comprehensive understanding of the interplay between currency design, functionality, and historical evolution [19, 18].

DECLARATIONS

Conflict of Interest: We declare that there are no conflicts of interest regarding the publication of this paper.

Author Contributions: All the authors contributed equally to the effort.

Funding: This research was conducted without any external funding.

Data Availability (including Appendices): All the relevant data, Python code for analysis, detailed annual tables and graphs are available via:

https://github.com/silentrepo/Exploring-the-Aspect-Ratios-of-World-Currencies-Mining-the-NumismaticsCatalog

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