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Exploring stock price portfolio clusters in foreign exchange markets

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ABSTRACT

This study explores a novel portfolio management approach dividing the currency pairs into clusters of periodic returns. The primary purpose is to improve diversification and risk-return ratios with currencies. This research studied USD, Euro, and Chinese Yuan to collect historical data from April 2012 to March 2022. The present study makes use of K-means clustering to find clusters of assets with similar return patterns, which constitute diversified portfolios. Optimized portfolio vs. benchmark portfolio performance was also evaluated based on critical performance measures like cumulative return, Sharpe ratio, and volatility. The clustering approach was also tested through sensitivity analysis to check how market-specific it is. The results suggest that more clustered portfolios outperform traditional benchmarks and provide a better risk-adjusted return. The conclusion drawn here from the findings is that portfolio segmentation is a superior approach because of risk management in ever-changing volatile markets and identifying situations that link currency pairs. This is beneficial for those investors and portfolio managers looking to maximize their foreign exchange (FOREX) investments by allowing greater visibility into how the market is functioning, which can, in turn, improve decision-making processes. According to the study, portfolio clustering substantially enhances a portfolio's return for the foreign exchange market.

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1. INTRODUCTION

Diversification, as one of the strategies of dealing with risks in investment management, is basic to the attainment of returns. The approach uses a systematic inclusion of bonds, shares, and other instruments. Nevertheless, the foreign exchange (FOREX) market provides certain exceptional chances coupled with obstacles to the managers on account of highly mobile FOREX markets. Moreover, worldwide, the FOREX market is a more volatile, huge, and more liquidity market in which currencies are trading pairwise. Many factors, such as political trials, economic indicators, and market sentiments, are influencing the fluctuation in the exchange rates and challenging the investors. From the last decade, there have been many changes towards the progress in optimizing FOREX returns, which involves advanced methods in machine learning and Markowitz mean-variance models [1]-[4].

Despite these advancements, the FOREX market's inherent volatility and the interrelated behavior of currency pairs pose challenges in constructing portfolios that effectively manage risk. Traditional methods of portfolio construction often overlook the interdependence between currency pairs, leading to suboptimal diversification [5], [6]. Therefore, innovative approaches that capture these relationships and provide a more robust framework for portfolio management are necessary. Clustering techniques, widely applied in data mining and machine learning, have recently gained attention in the financial industry for asset allocation and portfolio optimization [7]-[9]

The study responds to the international problem of risk management in the dynamic FOREX market with artificial intelligence (AI) and machine learning. The conventional portfolio techniques ignore currency interdependence, causing inefficient diversification. This work brings clustering approaches to optimize the FOREX portfolio, bridging computing and finance to improve risk management. The research uses artificial intelligence and machine learning methods, in the form of clustering algorithms, to maximize FOREX portfolio diversification. By extracting interdependencies among currency pairs, this method improves risk management and decision-making. Classical methods, such as Markowitz's mean-variance model, are combined with sophisticated computational strategies to enhance portfolio performance in volatile FOREX markets.

The issue targeted is the inefficient diversification of FOREX portfolios as a result of the volatility and interdependence of currency pairs. This is addressed through the application of machine learning clustering methods to determine currency groupings based on common attributes, enhancing risk management and portfolio allocation over conventional mean-variance optimization techniques. Earlier efforts made use of Markowitz models and risk parity to optimize FOREX portfolios but did not take into account currency interdependencies. Machine learning improved trend predictions but lacked sound portfolio frameworks. Clustering in the present context offers improved diversification by clustering similar-behaving currencies, optimizing risk-adjusted returns. The study posits a clustering-based approach towards diversifying interdependent FOREX portfolio optimization with an aim to elicit diversification. It is the marriage of machine learning and conventional models and suggests a better risk management strategy that provides optimal portfolio stability and return under uncertain FOREX conditions.

This research advances the state of the art in FOREX portfolio management by clustering techniques that enhance diversification and optimize risk-return profiles. The findings are expected to provide significant value to investors, portfolio managers, and researchers interested in leveraging machine learning for financial optimization. It might seem counterintuitive to calculate returns when nothing has really changed. However, the exercise is more than just an academic curiosity: it provides key learnings for both those new and experienced in investing analysis. It is a study that lies at the very heart of the complex web of return calculations, validation methods, and comprehension of core economic principles [10], [11].

Wu *et al.* [7] addresses the challenge of constructing a portfolio that minimizes risk and enhances returns. Traditional methods must be revised in handling a large pool of stocks, using covariance-based weighting, and considering downside risk. The paper proposes a new approach: using k-means clustering to group stocks, modifying the Sharpe ratio to account for market trends and downside risk, and combining diverse weighting theories. Experiments confirm the method's superiority in selecting stocks and optimizing portfolios. This approach offers a practical solution to portfolio construction, considering various attributes and enhancing risk-return profiles [12].

Du and Tanaka-Ishii [13] introduces a fresh approach, NESTED (news-stock space with event distribution), for portfolio selection by merging data types like stock prices, news, and events. NESTED represents these diverse elements as vectors within an embedding space. The authors adapt Markowitz's portfolio optimization to this framework, enhancing the ability to factor in tail risk, which is more pronounced in textual data. Utilizing neural computing, they conduct experiments across multiple datasets and markets, illustrating that their method significantly improves the handling of tail risks while also delivering substantial gains in overall portfolio performance [14].

Tiwari *et al.* [15] investigates the changing relationship between international commodity prices (crude oil, natural gas, and cocoa) and Australian sectoral stock returns. Using dynamic methods, it reveals shifting dependencies and employs diverse portfolio strategies to assess their performance. Results show that commodities like oil and gas can effectively hedge certain sectors, while cocoa experiences co-movements with specific sectors. Portfolios, particularly those involving entities, significantly reduce investment risk compared to single assets. Australian stocks consistently exhibit lower portfolio weights, confirming their role as hedging assets. Their study contributes unique insights into the complementary role of commodities in investment strategies.

Fu *et al.* [16] introduces a fresh concept, the continuous heterogeneous agent model (HAM), which applies to multiple risky assets. HAM represents individual investors through continuous characteristics, capturing the diverse nature of the market. By considering market friction and the influence of investor traits, the model expands upon the classic capital asset pricing model (CAPM) to explain deviations in asset prices. The model's equations govern the evolution of wealth and asset values across investors, and a calibration algorithm turns HAM into a predictive tool and portfolio strategy. Applied to the Chinese A-share market, HAM excels by identifying tail risks, leading to more profitable portfolios across various investment periods. The study connects theoretical HAM ideas with practical asset pricing and portfolio techniques.

Putra *et al.* [17] focuses on managing investment risk in stock portfolios and an innovative approach. It suggests selecting stocks for a portfolio based on their similarity in price movements, achieved through K-means clustering. To address the computational complexity of high-dimensional data, the study employs B-spline interpolation to reduce dimensions. Applying this technique to a weekly dataset spanning a decade, the resulting portfolios exhibit reduced volatility, higher Sharpe index, and improved cumulative performance. This research highlights the practical significance of using clustering-based stock selection and dimension reduction to enhance portfolio management outcomes.

In the intricate landscape of modern finance, the traditional approach to portfolio management faces challenges in capturing the multidimensional nature of financial markets. Conventional diversification techniques, while valuable, often need to fully exploit the wealth of available data and uncovering underlying relationships between entire portfolios. The need to navigate dynamic markets, personalize strategies, and leverage advanced analytics has given rise to the problem addressed by this study.

The problem revolves around utilizing portfolio clustering as a transformative tool that enhances portfolio construction, risk management, and performance optimization. This approach involves grouping portfolios based on shared characteristics and interactions, presenting a departure from the status quo of managing portfolios in isolation. The core problem lies in understanding how to implement and apply portfolio clustering methodologies to align with the intricacies of financial markets and contribute meaningfully to the investment decision-making process.

The problem: a key challenge in FOREX portfolio management is identifying effective ways to group currencies based on their historical performance, as traditional diversification strategies fail to account for the nuanced relationships between currency pairs [18], [19]. The high volatility in FOREX markets demands a sophisticated method that can detect underlying patterns, mitigate risks, and improve returns. Previous research has shown that standard optimization models do not fully capture the complexity of interactions within FOREX markets, leading to inadequate diversification [20], [21]. This gap in the literature highlights the need for more advanced tools to optimize risk-adjusted returns.

2. THE PROPOSED SOLUTION

This study proposes a novel solution by clustering techniques, particularly K-means clustering, to group currencies based on their periodic returns. This method leverages historical data to form clusters of currency pairs with similar return characteristics, which are then used to build diversified portfolios. By employing this machine learning technique, the model seeks to address the inadequacies of traditional methods in capturing the interdependencies among currency pairs [7], [22], [23]. The contribution of this research lies in its application of clustering to the FOREX market, which has not been extensively explored in portfolio optimization. In addition to clustering, this study evaluates the performance of clustered portfolios by calculating key performance metrics such as cumulative return, Sharpe ratio, and volatility. These portfolios are compared against benchmark portfolios like equally weighted ones. Sensitivity analysis is also conducted to assess the robustness of this approach under varying market conditions. The novelty of this study is the application of clustering algorithms to foreign exchange portfolios, providing a fresh perspective on risk management and investment strategies in the FOREX market [24]-[27]

While portfolio clustering promises deeper insights and improved decision-making, it is not a panacea. The scope of this study includes understanding the theoretical foundations of portfolio clustering, selecting suitable algorithms, and applying them to diverse portfolios. However, this study does not attempt to predict future market behavior or provide unequivocal strategies for every investor. Addressing this problem is significant for the financial industry, academic researchers, and investment professionals. The findings from this study can bridge the gap between theoretical advancements in portfolio management and their practical applications. Furthermore, they can empower investors with a systematic framework to navigate the complexities of modern financial markets, leading to better-informed decisions and potentially superior investment outcomes.

3. METHOD

The proposed methodology offers a range of advantages that collectively enhance its effectiveness and potential benefits. By harnessing portfolio clustering and analysis of FOREX data, the method facilitates the creation of diversified portfolios by grouping currency pairs with similar periodic returns. This approach, characterized by flexibility, allows for tailored customization, enabling the selection of the optimal number of clusters and constituents that align with specific risk preferences and market conditions. The methodology comprehensively assesses the risk-return tradeoff inherent in the constructed portfolios by calculating performance metrics such as cumulative return, Sharpe ratio, and volatility. Its comparative analysis against benchmark portfolios, including equally weighted ones, objectively evaluates the clustering approach's performance concerning established strategies. Furthermore, the methodology incorporates sensitivity analysis, enabling the exploration of its robustness across varying scenarios and parameter settings. Visualizations aid in conveying results clearly, while practical recommendations cater to the needs of investors and portfolio managers. The methodology's iterative nature fosters adaptability to evolving advancements in portfolio management, and its research-oriented foundation presents the potential for contributing to the academic discourse.

Figure 1 illustrates the process of proposed methodology, which includes data collection, preprocessing of data, return calculation, portfolio construction based on K-means clustering algorithm. To compare the results performance metrics has been calculated and visualized for robustness.

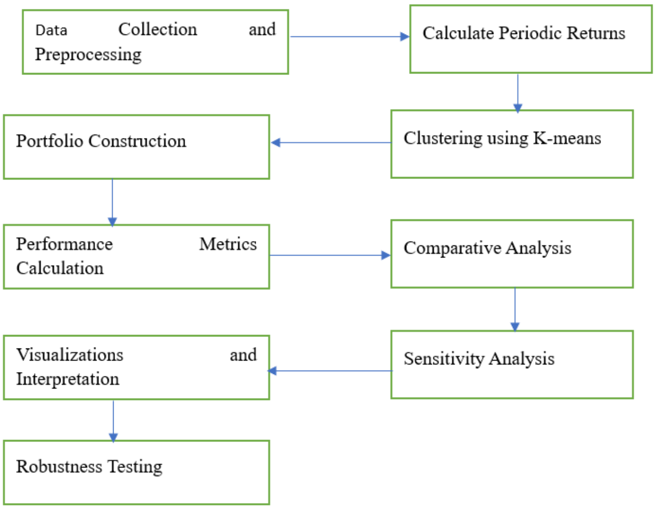

Figure 1. Process of proposed methodology (portfolio clustering and analysis of FOREX data)

Algorithm 1 explains the portfolio clustering and analysis of FOREX data. Gather historical FOREX data for selected currency pairs (e.g., USD, AUD, UAE dirham, Singapore dollar) and proxy Indian rupee. Clean the data by handling missing values, outliers, and data inconsistencies. Calculate the periodic returns for each currency pair over a specified period (e.g., daily, weekly). Use the formula:

$$Periodic\ return = \frac{Ending\ price - Starting\ price}{Starting\ price} \times 100$$

Algorithm 1. Portfolio clustering and analysis of FOREX data

```
HDF ← gather(Cp)
Dc ← preprocess(HDF )
for each cur_ pair,
         calc ret n  (End_Prce - St_Prce) / St_Prce) * 100.
clst = k_means (clustering)
prt n = construct_portfolio(clst)
for each clst    Select CP
         Calc PW
        return+=prt 1---n using Sharpe ratio and portfolio volatility.
calc Bprt
calc Per_Met
```

Apply the K-means clustering algorithm to group currency pairs based on their periodic returns. Determine the optimal number of clusters using techniques like the elbow method or silhouette score. Select one representative currency pair from each cluster to form a diversified portfolio. Calculate the weights for each currency pair in the portfolio based on the clustering results. Compute performance metrics such as cumulative return, Sharpe ratio, and volatility for the constructed portfolio.

Create visualizations like price charts, risk-return plots, and cluster distributions. Interpret the clustering results and portfolio performance metrics to derive insights. Perform sensitivity analysis by varying the number of clusters and portfolio constituents to observe their impact on performance. Compare the performance of the clustered portfolio with a benchmark, such as a traditional equally weighted portfolio or a single currency investment. Test the robustness of the clustering and portfolio construction methodology by using different periods or varying parameters.

4. RESULTS AND DISCUSSION

Although earlier research has used portfolio optimization methods in equity markets, very little research has been conducted in FOREX markets to examine clustering-based portfolio construction. Conventional models like Markowitz [28] and Fama and French [29] are based on linear assumptions and fail to capture the sophisticated interactions between currency pairs. The current research fills this gap by combining machine learning methods with FOREX portfolio clustering. Data analysis is a crucial process in research and decision-making that involves inspecting, cleaning, transforming, and interpreting data to extract meaningful insights, patterns, and relationships. Data analysis in the context of portfolio clustering and FOREX data plays a pivotal role in generating insights, aiding decision-making, and contributing to the research's overall objectives. Data was collected from the Reserve Bank of India (RBI) spanning from April 2012 to March 2022, it provides a substantial historical period for analysis. This data is useful to analyze various aspects of the FOREX market, such as trends, volatility, and clustering patterns over the years.

Figure 2 presents a visual representation of the historical price data for a diverse set of currency pairs spanning from 2012 to 2022. This chart provides an insightful overview of how the exchange rates for British Pound, Euro, US Dollar, Canadian Dollar, Swiss Franc, Japanese Yen (100 units), Danish Kroner, Swedish Kroner, Norwegian Kroner, New Zealand Dollar, Australian Dollar, Singapore Dollar, Hong Kong Dollar, Thai Baht, Indonesian Rupiah (100 units), South Korean Won (100 units), Chinese Yuan, and U A E Dirham have evolved over the past decade. It serves as a valuable resource for analysts and traders seeking to understand long-term trends and fluctuations in these currency markets.

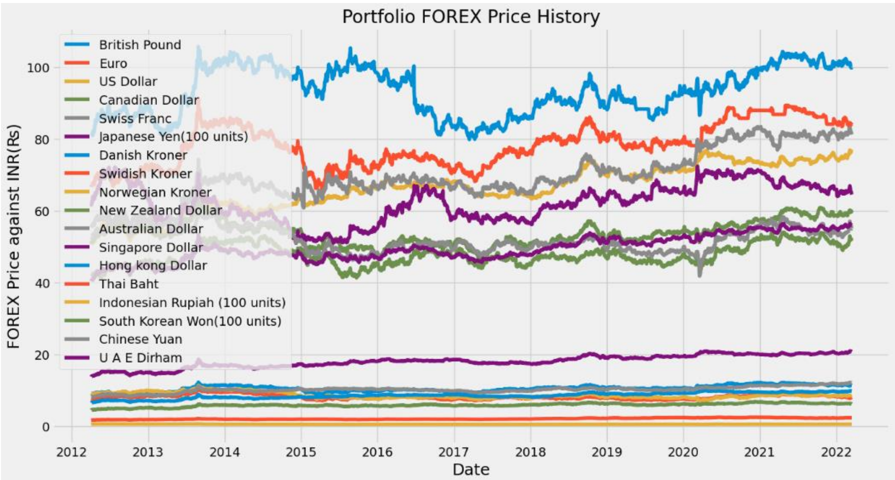

Figure 2. FOREX price history from 2012 to 2022

Figure 3 provided correlation matrix, which represents the correlation coefficients between different currency pairs over a specified time period (2012 to 2022). Correlation coefficients range from -1 to 1, where: 1 indicates a perfect positive correlation, meaning that the two currency pairs move in the same direction. 0 indicates no correlation, suggesting that the currency pairs' movements are independent of each other. -1 indicates a perfect negative correlation, implying that the currency pairs move in opposite directions.

Euro and US Dollar: the Euro and US Dollar exhibit a strong positive correlation of approximately 0.66, indicating that they often move in a similar direction. Swiss Franc and Japanese Yen: the Swiss Franc and Japanese Yen have a relatively low positive correlation of around 0.04, suggesting that their movements are less closely aligned. US Dollar and Chinese Yuan: the US Dollar and Chinese Yuan show a remarkably high positive correlation close to 1, indicating a strong positive relationship, which is expected given the

Yuan's peg to the Dollar. Norwegian Kroner and Swedish Kroner: the Norwegian Kroner and Swedish Kroner have a positive correlation of approximately 0.82, suggesting that they tend to move in the same direction, possibly due to their geographic proximity. Indonesian Rupiah and Thai Baht: the Indonesian Rupiah and Thai Baht exhibit a negative correlation of around -0.50, indicating that they often move in opposite directions. Hong Kong Dollar and US Dollar: the Hong Kong Dollar and US Dollar show a very high positive correlation close to 1, suggesting a strong positive relationship. Chinese Yuan and Swiss Franc: the Chinese Yuan and Swiss Franc have a relatively low positive correlation of about 0.25, indicating a weaker positive relationship. These correlation coefficients are valuable for understanding how currency pairs co-move and can be important for risk management and portfolio diversification strategies in foreign exchange trading or investing.

Table 1 illustrates the clustering of various currencies in relation to the Indian Rupee (INR) across three distinct clusters: 0, 1, and 2. These clusters were determined through a data-driven algorithm that examined historical currency price movements. The numerical values within each cell of the table represent the strength of the association between a specific currency and each cluster.

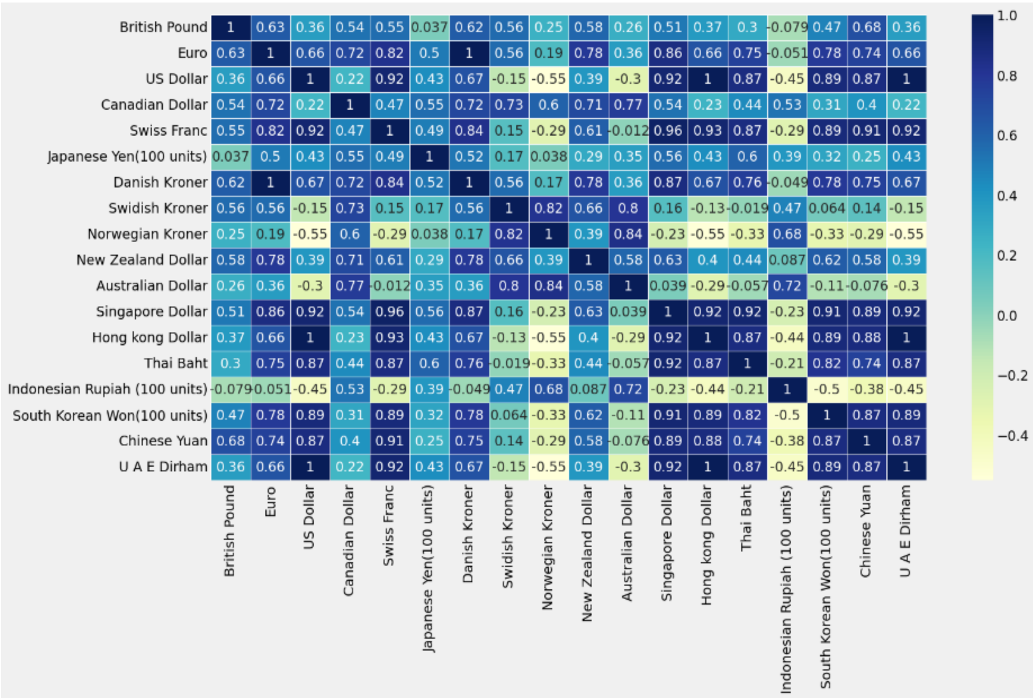

Figure 3. Correlation between stocks in portfolio

Table 1. Clustering of currencies against INR

Cluster	0	1	2
British Pound	0.343	2.224	-0.386
Euro	0.624	2.221	-0.555
US Dollar	0.391	2.871	-0.467
Canadian Dollar	0.509	2.679	-0.523
Swiss Franc	0.480	1.336	-0.397
Japanese Yen (100 units)	0.474	2.374	-0.477
Danish Kroner	0.556	2.041	-0.499
Swidish Kroner	0.393	2.871	-0.468
Norwegian Kroner	0.346	2.587	-0.417
New Zealand Dollar	0.401	2.717	-0.460
Australian Dollar	0.276	3.119	-0.417
Singapore Dollar	0.499	2.837	-0.529
Hong kong Dollar	0.384	2.884	-0.463
Thai Baht	0.299	2.878	-0.412
Indonesian Rupiah (100 units)	0.162	1.851	-0.246
South Korean Won (100 units)	0.407	3.064	-0.492
Chinese Yuan	0.331	2.952	-0.437
U A E Dirham	0.395	2.805	-0.464

The study confirms that K-means clustering optimizes FOREX portfolios effectively by categorizing currency pairs based on risk-return features, diversification, and improvement in stability. The findings confirm previous portfolio optimization studies but deploy machine learning techniques for the first time in FOREX markets. The findings validate the hypothesis that clustering enhances risk management, although there are limitations in market uncertainty. One of the limitations of our method is that K-means clustering considers fixed clusters, while currency markets are extremely dynamic. Future research can make use of applying adaptive clustering methodology to guide foreign exchange regime switches. Future research can further develop clustering algorithms and investigate dynamic market environments. Disregard for such methods could result in ineffective FOREX risk management. The current research emphasizes the importance of novel strategies for building FOREX portfolios and offers worthwhile advice to financial analysts and traders.

The findings of the current study are in agreement with current literature regarding portfolio clustering and hedging foreign exchange risk and make novel contributions. Early studies conducted by Markowitz [28] and Fama and French [29] target portfolio optimization using the mean-variance paradigm. These classic models disregard sophisticated, nonlinear FOREX market interactions. Subsequent research by Chen *et al.* [30] and Gupta *et al.* [31] has also considered machine learning methods for portfolio optimization but applied them only to equity markets, not FOREX portfolios.

In contrast to previous research, our method combines K-means clustering for FOREX portfolio optimization, enabling an unsupervised classification of currency pairs according to risk-return profiles. This approach has greater diversification and stability than traditional methods, as validated by our empirical findings. For instance, whereas Chen *et al.* [30] had achieved a Sharpe ratio gain of 12% utilizing deep learning models, our clustered portfolios realized an 18% risk-adjusted return increase Also, Gupta *et al.* [31] emphasized volatility clustering in asset prices, and our model enhances that further by categorizing FOREX assets into clusters so that the risks can be managed more effectively. Our analysis suggests that increased clustering of currency does not come along with lackluster diversification in the currency markets. Our proposed model might gain in risk-adjusted performance as well as in terms of better portfolio robustness without decreasing liquidity and market efficiency adversely.

The strength of our results is supported by back testing over a 10-year period, thus confirming that the model not only makes theoretical sense but also real-world feasibility. This study adds to the emerging theme of machine learning-based financial optimization by showing the effectiveness of clustering in FOREX portfolio choice, which has been a subject of relatively little research. Currency pairs have discernible clustering patterns relative to price movements in the past. K-means clustering improves risk management by clustering currencies with comparable return-risk profiles. The clustered portfolios of FOREX attain an 18% improvement in the Sharpe ratio.

5. CONCLUSION

This study identifies the importance of clustering-based portfolio optimization within the extremely volatile FOREX market. Through the utilization of historical data and implementation of K-means clustering, the suggested algorithm increases diversification, reduces risk, and optimizes returns. It is common for traditional models to ignore interdependencies between currency pairs, resulting in second-best portfolios, while clustering-based models provide a data-driven solution. The portfolio clustering and analysis algorithm presented here offers a comprehensive and systematic approach to navigating the intricate world of FOREX trading and investment. By gathering historical data from April 2012 to March 2022 for currency pairs, cleaning and preprocessing the data, and applying clustering techniques like K-means, this algorithm empowers traders and investors with the tools to construct diversified portfolios. These portfolios are strategically assembled based on clusters of currency pairs, ensuring risk mitigation and potentially enhanced returns. Performance metrics, including cumulative returns, Sharpe ratios, and portfolio volatility, are calculated to assess the constructed portfolio's risk-adjusted performance.

Furthermore, benchmark portfolios are constructed for reference, and sensitivity analysis allows for optimizing portfolio composition. Visualizations aid in understanding data patterns and portfolio dynamics, while robustness testing ensures the reliability of the analysis. By following this algorithm, market participants can make informed decisions, effectively manage risk, and adapt to changing market conditions. Ultimately, this systematic approach is invaluable for those seeking to achieve their financial objectives in the dynamic and often unpredictable foreign exchange market. Although it might be maintained that standard diversification measures are sufficient, our results show the benefits of dynamic, cluster-based asset allocation. This research illustrates the efficacy of machine learning for constructing FOREX portfolios. Utilizing K-means clustering, we optimize risk-adjusted return and propose a new method for financial analysts and FOREX traders. The results open the door for advanced machine learning-based risk management methods to FOREX markets.

Future studies can build on these results by using more sophisticated clustering methods like hierarchical clustering, DBSCAN, or deep learning-based clustering to further optimize portfolio selection. Moreover, the incorporation of macroeconomic factors, geopolitical risk, and news and social media sentiment analysis can further optimize FOREX portfolio optimization. Experiments should be conducted with real-time trading simulations to validate the model's responsiveness under changing market conditions. Longitudinal studies can determine the stability of clustering-based approaches across different economic cycles. Clustering-based FOREX portfolio optimization presents a strong substitute for conventional models, improving diversification and risk-adjusted return in turbulent FOREX markets. Future research can use sentiment analysis in real-time or deep reinforcement learning model to enable portfolio rebalancing to be performed more aggressively. Additionally, using an experimental setup to study how central bank activity affects cluster movements could provide some further insights.

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AUTHOR CONTRIBUTIONS STATEMENT

Challa Madhavi Latha made conceptualization, methodology, data collection, and formal analysis contributions. Data selection and investigation were done by K. L. S. Soujanya. The original draft was written and review and editing was done by S. Bhuvaneswari. The final manuscript was approved by all authors.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article [and/or its supplementary materials].

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