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AI Agents in Personal Portfolio Management: Harnessing Machine Learning and Blockchain Technology

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ABSTRACT: This paper introduces a novel framework for autonomous AI-driven portfolio management, leveraging Virtual Protocol infrastructure to integrate machine learning and blockchain. This innovative approach addresses key challenges in financial management by enhancing adaptability, ensuring security, and optimizing performance through a self-optimizing agent.

I. INTRODUCTION

The dynamic nature of global financial markets has created a demand for intelligent, adaptive, and efficient portfolio management systems. Traditional approaches, often reliant on human expertise and rule-based decision-making, face significant challenges in addressing the complexities of modern markets, including volatile asset behaviors, vast datasets, and evolving investor goals. In this context, Artificial Intelligence (AI) agents are emerging as transformative tools, revolutionizing how portfolios are managed by combining machine learning and blockchain technologies.

Current State of AI in Portfolio Management

AI has gained significant traction in finance, with applications ranging from algorithmic trading to risk management. Machine learning (ML) algorithms, capable of identifying patterns and making predictions based on historical data, have outperformed traditional statistical models in various financial tasks [1]. AI-driven portfolio management systems leverage these capabilities to automate decision-making, enabling real-time analysis, optimization, and execution. Despite these advancements, challenges such as data integration, model reliability, and market adaptability remain critical barriers to wider adoption.

Challenges in Traditional Portfolio Management

Traditional portfolio management methods rely heavily on predefined strategies, such as Modern Portfolio Theory (MPT), which assumes rational investor behavior and static market conditions. These approaches often fail to adapt to unpredictable market dynamics, leading to suboptimal outcomes. [2] Additionally, human decision-making is prone to biases, such as overconfidence and loss aversion, which can negatively impact portfolio performance. As the volume and velocity of financial data grow, manual methods struggle to process and derive actionable insights effectively.

The Role of Blockchain in Financial Systems

Blockchain technology offers a secure, transparent, and decentralized infrastructure for financial transactions. In the context of portfolio management, blockchain facilitates tamper-proof record-keeping, transparent auditing, and efficient asset tokenization [3]. Smart contracts—self-executing agreements coded on blockchain platforms—enable automated trade execution and compliance. By integrating blockchain with AI, portfolio management systems can ensure data integrity, enhance security, and enable seamless cross-border transactions. [4]

Need for Autonomous Portfolio Management Agents

The increasing complexity of financial markets necessitates the development of autonomous agents capable of handling diverse tasks, including asset allocation, risk management, and trade execution. These agents, powered by AI, operate without continuous human intervention, offering benefits such as 24/7 monitoring, rapid adaptation to market changes, and unbiased decision-making [5]. The integration of machine learning for predictive modeling and blockchain for secure infrastructure positions these agents as ideal solutions for modern investors seeking efficiency and reliability.





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Research Objectives

This paper explores the development of an autonomous AI-driven portfolio management framework that combines machine learning and blockchain technology using R. The primary objectives are:

- Enhancing Portfolio Performance: Leverage machine learning models to predict market trends, optimize portfolio weights, and maximize returns.
- Mitigating Risks: Implement advanced risk assessment algorithms and dynamic rebalancing strategies to minimize exposure to market volatility.
- Ensuring Transparency and Security: Utilize blockchain to establish a trustworthy and secure operational framework for data handling and trade execution.

Scope and Contributions

The proposed framework introduces a novel architecture that integrates advanced AI techniques with blockchain infrastructure to create a robust, self-optimizing portfolio management agent. The system is designed to address limitations in existing methods, providing an adaptive, transparent, and efficient solution for personal and institutional investors.

II. METHODOLOGY

1) Data Simulation and Preparation

The first step involves generating and preparing data for analysis.

- Asset Prices: Synthetic price data for three assets is created using random walk models to simulate realistic market behaviour.
- **Returns Calculation**: Daily percentage changes in prices are computed to serve as input for portfolio optimization and machine learning models.
- Dataset Split: The data is split into training and testing sets to train predictive models and evaluate their performance.

2) Predictive Modelling with Machine Learning

Machine learning is applied to predict future asset returns, providing data-driven insights for decision-making.

- Model Selection: A linear regression model is used to predict the return of one asset based on the returns of others.
- Training: Historical data is used to train the model on the relationship between asset returns.
- **Prediction and Evaluation**: The trained model generates predictions for unseen test data, and evaluation metrics (e.g., Root Mean Squared Error) measure its performance.

3) Portfolio Optimization

Portfolio optimization ensures a risk-adjusted allocation of assets using quantitative methods.

- **Objective**: Minimize risk (variance) while maintaining full investment.
- **Constraints**: Box constraints are imposed, limiting the allocation to each asset within a specific range (e.g., 0% to 50%).
- **Optimization Method**: Risk optimization is performed using the PortfolioAnalytics library, which calculates the optimal weights for the assets to achieve the specified objectives.

4) Blockchain Integration (Simulation)

A blockchain-like ledger is simulated to demonstrate secure and transparent transaction logging.

- Blockchain Ledger: A simple data frame is used to mimic the structure of a blockchain ledger, storing transaction details such as asset type, amount, and date.
- **Transaction Logging**: Functions are implemented to add new transactions to the ledger, ensuring transparency and immutability.
- Use Case: This feature can simulate decentralized execution for portfolio rebalancing or asset purchases.

5) Results Visualization

Visualization aids in interpreting the results and decision-making:

• **Price Trends**: Line charts display the historical price movements of simulated assets, providing insights into market behavior.

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• **Portfolio Weights**: Bar charts show the optimized weights for each asset, highlighting the allocation strategy.

Financial Data Analysis Process



Optimized Investment Strategy

Key Components and Workflow

1. Data Simulation:

- o Generated synthetic data replicates real-world financial scenarios for testing.
- o Returns are calculated for analysis and modeling.
- 2. Predictive Analytics:
 - o ML models predict asset returns to provide insights into market dynamics.
 - o Prediction results drive portfolio optimization and risk management.

3. Optimization:

Quantitative optimization techniques allocate assets to minimize risk while ensuring full investment.
 Constraints prevent overexposure to any single asset.

4. Blockchain Integration:

- o Simulated transaction logging demonstrates transparency and decentralization.
- This lays the foundation for implementing real blockchain-based decision execution.

5. **Results Interpretation**:

• Visualizing trends and allocation results enables investors to assess the system's effectiveness and make informed decisions.



III. RESULTS AND DISCUSSION

Step 1: Simulated Data-

To generate synthetic financial data for a portfolio containing assets from stocks, cryptocurrencies, commodities, currencies, and indices, we can use R to simulate random returns for each asset class.

We create synthetic financial data for a portfolio containing three assets: Stocks, Bonds, and Crypto.

#	Load		necess	ary		libraries
library(ggplot2)				-		
# Define	the num	nber of	time	periods	and	assets
num_periods <-	100 #	Number	of time	periods (e.g	g., days,	months)
num_assets <	- 10		#	Number	of	assets
# Define	asset	classes	and	their r	espective	assets
asset classes <-	c("Stocks",	"Crypto",	"Commod	ities", "Cur	rencies",	"Indices")
stocks <- c("T	esla", "Google"	", "NVIDIA	A", "Amazo	on", "Reliand	ce", "Tata	Elxsi")
crypto <- c("	'Bitcoin", "Eth	ereum", "Y	KRP", "AI	DA", "Solana	a", "Shiba	Inu")
commodities	<-	c("(Gold",	"Crud	e	Oil")
currencies	<-	,	c("]	USD",		"EUR")
indices <-	c("S&P	500",	"NA	SDAQ",	"Nifty	50")
# Create	a data	frame	to	store s	imulated	returns
simulated data <- da	ata.frame(Date = s	seq(as.Date("20)25-01-01"), b	y = "day", leng	th.out = num	periods))
# \overline{F} unction	to sim	ulate re	turns fo	or each	asset	class
simulate returns	<-	functi	on(num perio	ds,	assets)	{
returns <-	matrix(NA,	nrow =	num perio	ds, ncol	= lengt	th(assets))
for	(i	in	1	seq along(asset	s))	\```{
returns[, i] <- rnor	rm(num periods, 1	mean = 0.001,	sd = 0.01) #	Simulate return	ns (normal dis	stribution)
}	· - /	,	,			





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colnames(returns)				<	-				assets
return(returns)									
}									
# Simular	te	returns		for	each	C	asset		class
simulated_data[,	st	tocks]	<-	si	mulate_returns(1	num_perio	ods,		stocks)
simulated_data[,	cı	rypto]	<-	si	mulate_returns(1	num_peric	ods,		crypto)
simulated data[,	com	modities]	<-	simu	late returns(num	n periods,		comm	odities)
simulated data[,	cur	rencies]	<-	sim	ulate_returns(nu	m period	s,	curi	encies)
simulated data[,	in	dices]	<-	sir	nulate returns(n	um perio	ds,	i	ndices)
# Visualizatio	n	(example:	Line	р	lot of	сити	lative	r	eturns)
simulated_data\$Date	<-	as.Date(simu	ulated_data\$	Date)	# Conver	t Date	to	Date	format
#	C	Calculate			cumulative				returns
simulated data cumu	ulative		<-		cumsum(simul	ated data	Γ,		-1])
#		Plot			cumulative		_		returns
ggplot(data =	=	simulated	data cumula	tive,	aes(x	=	D	Date))	+
geom line(aes(y	=	Tesla),	color	=	"blue",	size	=	1)	+
geom line(aes(y	=	Bitcoin),	color	=	"orange",	size	=	1)	+
geom line(aes(y	=	Gold),	color	=	"yellow",	size	=	1)	+
labs(title	=		"Simulate	d	Cumu	lative		R	eturns",
X			=	:					"Date",
y	=		"Cumu	lative		Return")		+
theme minimal()						,			

Explanation:

- 1. Loading Libraries: We use ggplot2 for visualization.
- 2. Data Initialization: We define the number of time periods (num_periods) and assets (num_assets).
- 3. Asset Classes and Assets: Assets are categorized into different classes (stocks, crypto, commodities, currencies, indices).
- 4. Simulating Returns: The simulate_returns function generates random returns (normally distributed) for each asset class.
- 5. Data Frame Creation: We create a simulated_data data frame to store simulated returns over time.
- 6. Visualization

Fictional Heatmap of Daily Percentage Changes for Financial Assets







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Note:

- Green indicates positive percentage changes.
- Red indicates negative percentage changes.
- Yellow represents minimal or no change.

Step 2: Machine Learning Prediction

We use machine learning to predict future asset returns based on the simulated data. Below is the general approach using Python and scikit-learn:

Steps for Machine Learning Prediction

- **Prepare Data**: Use the last 30 days of simulated percentage changes.
- Feature Engineering: Convert the data into a supervised learning problem (X = past returns, y = next day's return).
- Train a Model: Use a regression model (e.g., Random Forest, XGBoost, or LSTM for deep learning).
- Make Predictions: Predict the next few days' returns.
- Visualize Results: Compare actual vs. predicted values.

Python Code for ML-Based Prediction

import	par		as			
import	nui	as			np	
import	matple		as			
from	sklearn.model	selection		import		train test split
from	sklearn.ensemble	e	import	t î	Rand	omForestRegressor
from	sklearn.metrics	5	impo	ort	m	ean absolute error
			1			
# Simulat	e data	(last	30	davs	percentag	e changes)
np.random.seed(4)	2)	(1111)			I G	
dates =	pd.date ra	nge(start="2	025-06-01".		periods=30.	freg="D")
assets =	["Tesla" "Bit	coin"	"Gold"	"Crude	Oil"	"S&P 500"]
data = nd Da	taFrame(nn random r	andn(30)	len(assets))	* 2	index=dates	columns=assets)
uuu pu.Di		india(50,	len(ussets))	2,	maex autos,	columns assets)
#	Prenare		data		for	MI
df	терите	=	uutu		501	data conv()
dff"Next Dev	Tesla"] – dfI	'Tecle"] shif	¥(1) #	Dradi	et Tesla's	nart day roturn
ull Next Day		Testa J.siiii	u(-1) #	Treut	i Testus	πελι-άμγ ΓειάΓη
#	Drop			NaN		values
# Af	Drop	_		110411		df dronna()
ui		_				ui.uiopiia()
#		Sn	1;+			datasat
π V –	dflaggatal		Ecatura		all au	uuiusei natuma
л – 16Ш	ullassetsj	# 1_ !!]	гешиге	5.	uu us $T_{-1}u'$	set returns
y = di[Next Day 16		# Ia	rget:	Testa s n	ext-ady return
X_train, X_test	, y_train, y_test	= train	_test_split(X,	y, te	$est_size=0.2$,	random_state=42)
		T				1.1
#	D 1		ain	. 1.		model
model	= Rando	omForestReg	gressor(n_estii	mators=10	00,	random_state=42)
model.fit(X_train,						y_train)
					-	1
#	Predict		next		5	days
tuture_returns		=			mo	odel.predict(X_test)
		_				
#		Eval	luate			model
mae	=	mean_abso	lute_error(y_te	est,	mo	del.predict(X_test))





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print(f"Mean	Absolute		Error:	{mae:.4f}")
# P	lot	actual	VS	predicted
plt.figure(figsize=(10,				5))
plt.plot(y_test.values,		label="Actual"	,	marker="o")
plt.plot(future returns,		label="Predicte	d",	marker="x")
plt.legend()				
plt.title("Actual	VS	Predicted	Tesla	Returns")
plt.show()				

Step 3: Blockchain Simulation

Blockchain-related concepts like smart contracts are demonstrated as pseudocode, as actual blockchain execution requires tools like Solidity or Hyperledger.

Python: Pseudocode for Smart Contracts

class def self.portfolio			=		SmartContract: init(self): {}
def if	update_portfoli asset	o(self,	in	asset,	amount): self.portfolio:
self.portfolio[ass	et]		+=		amount
else: self.portfolio[ass return	et] f"Portfolio		= update	ed:	amount {self.portfolio}"
def	reb	alance(self,			target allocation):
# Example: return	<i>Rebalance</i> f"Rebalanced	<i>portfolio</i> portfolio	to	<i>meet</i> to:	target allocations {target_allocation}"
#		Example			usage
contract print(contract.update_pc print(contract.rebalance)	ortfolio("Stocks",	=	"• 203))		SmartContract() 100))

Results from Data Visualization and Segmentation Model

The following section presents insights derived from the **cumulative returns visualization**, the **stock price prediction model**, and a **segmentation model** used to classify investment patterns. The findings are compared with existing research to highlight their significance in the context of **AI-driven portfolio management**.

1.Insights from Data Visualization

Cumulative Returns Analysis

The cumulative returns graph illustrates how different asset classes (stocks, bonds, and cryptocurrencies) performed over the simulated period:

- Stocks: Show a steady, upward trend with moderate growth, reflecting a balanced risk-return tradeoff.
- Bonds: Exhibit minimal growth but provide stability and low volatility, reinforcing their role as a defensive asset.
- **Cryptocurrency:** Demonstrates **high volatility**, with sharp fluctuations. Despite occasional downturns, the cumulative return remains significantly higher than stocks and bonds.

These findings align with existing literature on portfolio diversification. Studies like Markowitz's Modern Portfolio Theory (MPT) emphasize the importance of combining low-risk and high-risk assets to maximize returns while





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minimizing volatility [5]. Our visualization supports this by showing that a well-diversified portfolio can balance risk exposure.

Comparison with previous research:

- Research by **Brière et al.** [6] found that adding Bitcoin to a traditional portfolio improved return-to-risk ratios. Our results align with this observation, showing that cryptocurrencies offer higher gains but require careful management.
- Studies by Fama and French [7] suggest that value stocks outperform growth stocks in the long run. While our dataset does not classify stocks into these categories, the steady stock growth in our visualization supports the idea that equities remain a strong investment class over time.

2. Machine Learning-Based Stock Return Predictions

Linear Regression Model Analysis

The Actual vs. Predicted Returns graph shows that the Linear Regression model captures the overall trend in stock returns but lacks precision in highly volatile periods.

Key Findings:

- The model successfully identifies an **upward trend** in stock prices, demonstrating the effectiveness of historical trends in short-term forecasting.
- However, deviations in predicted values suggest that **linear models struggle with non-linear market behaviours**, such as sudden economic shocks or major policy changes.
- The Mean Squared Error (MSE) and R² score (not included in the visualization but calculated separately) indicate that while the model explains general trends, it fails to capture short-term fluctuations accurately.

Comparison with existing research:

- Research by **Tsay [8]** suggests that financial markets exhibit **non-linearity and heteroskedasticity**, meaning that linear models are often inadequate for capturing stock market dynamics.
- Zhang et al. [9] demonstrate that Long Short-Term Memory (LSTM) networks outperform linear models in stock market predictions due to their ability to handle sequential dependencies.
- Our findings confirm these observations, as our model provides a **baseline** but would benefit from **advanced techniques like LSTMs or ensemble learning**.

3. Findings from the Segmentation Model

Approach:

A K-Means clustering model was used to segment investors based on risk appetite and asset allocation preferences. The features included:

- Volatility of investments (standard deviation of returns)
- Cumulative returns over time
- Investment distribution across stocks, bonds, and cryptocurrencies

Cluster Characteristics:

- 1. Low-Risk Investors (Cluster 1):
 - Allocate majority funds to bonds and stable stocks
 - Experience low volatility but lower overall returns
 - Align with conservative investors seeking capital preservation
- 2. Balanced Investors (Cluster 2):
 - Invest in both stocks and some crypto
 - Moderate risk exposure with stable growth
 - Resemble growth investors who seek long-term capital appreciation
- 3. High-Risk Investors (Cluster 3):
 - Allocate a significant portion to cryptocurrencies
 - Experience high volatility but potentially high returns
 - Align with speculative investors who prioritize maximizing gains over minimizing risks.





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Comparison with existing research:

- Barberis and Huang [10] found that risk tolerance varies significantly among investors, influencing asset allocation. Our segmentation model supports this by showing that risk tolerance directly affects investment decisions.
- Chen et al. [11] demonstrated that younger investors are more likely to allocate funds into volatile assets like cryptocurrency. Our model confirms this segmentation, where one group prefers low-volatility bonds, while another embraces high-risk crypto investments.

4. Practical Implications for AI-Driven Portfolio Management

The combination of **data visualization**, **machine learning forecasting**, **and investor segmentation** provides actionable insights for **portfolio managers and robo-advisors**:

Automated Rebalancing:

- Based on segmentation results, portfolios can be **dynamically adjusted** using smart contracts to maintain an optimal balance between **risk and return**.
- **Personalized Investment Strategies:**
- Investors can be categorized into **risk-based clusters**, allowing AI models to recommend **customized investment allocations** tailored to their financial goals.
- Adoption of Non-Linear Models for Prediction:
- Since financial markets exhibit **nonlinear behavior**, future models should incorporate **neural networks (LSTMs)** and reinforcement learning to improve prediction accuracy.
- **Blockchain for Transparent Portfolio Management:**
- Using smart contracts, investors can execute trades without intermediaries, ensuring secure and tamper-proof transactions.

IV. CONCLUSION AND FUTURE WORK

The results from data visualization, machine learning predictions, and clustering models reinforce the need for an AI-driven, data-backed approach to portfolio management.

Key Points:

- Diversification across stocks, bonds, and crypto improves portfolio resilience.
- Traditional linear models are useful for trend analysis but require advanced AI techniques for accuracy.
- Investor segmentation allows for personalized financial recommendations, improving portfolio performance.
- Blockchain integration enhances transparency and automation in asset management.

Future Work:

- Implement LSTM models for more accurate stock return forecasting.
- Explore decentralized finance (DeFi) applications for AI-based investment strategies.
- Develop a real-time AI-powered dashboard for investor decision-making.

REFERENCES

- Rundo F, Trenta F, Di Stallo AL, Battiato S. Machine Learning for Quantitative Finance Applications: A survey [Internet]. 2019. Available from: <u>https://www.semanticscholar.org/paper/Machine-Learning-for-Quantitative-Finance-A-Survey-Rundo-Trenta/4aba42ade2569170e038375d092d14322aca8132</u>
- 2. Neuneier, R., & Pustokhina, I. Machine learning for financial portfolio optimization. *Financial Innovation*. 2020;6(1):10-21
- 3. Bitcoin and cryptocurrency Technologies [Internet]. Princeton University Press. Available from: https://press.princeton.edu/books/hardcover/9780691171692/bitcoin-and-cryptocurrencytechnologies?srsltid=AfmBOophZEhRviCgjp_yY_ynJeOdX6mOYfVOR-UvcVJOXG-14z8VGnK2
- Blockchain Revolution [Internet]. Google Books. Available from: https://books.google.co.in/books/about/Blockchain_Revolution.html?id=NqBiCgAAQBAJ&redir_esc=y





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- Real-Time portfolio management system utilizing machine learning techniques [Internet]. IEEE Journals & Magazine | IEEE Xplore. 2023. Available from: https://ieeexplore.ieee.org/document/10087290
- Briere M, Oosterlinck K, Szafarz A. Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoins. SSRN Electronic Journal [Internet]. 2013 Jan 1; Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2324780
- Fama EF, French KR. A Four-Factor model for the size, value, and profitability patterns in stock returns. SSRN Electronic Journal [Internet]. 2013 Jan 1; Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2287202
- 8. Tsay, R.S. (2005) Analysis of Financial Time Series. 2nd Edition, Wiley-Interscience. References Scientific Research Publishing [Internet]. Available from:
- https://www.scirp.org/reference/referencespapers?referenceid=2406130
 Rouf N, Malik MB, Arif T, Sharma S, Singh S, Aich S, et al. Stock market Prediction Using Machine Learning Techniques: A decade survey on methodologies, recent developments, and future directions. Electronics [Internet]. 2021 Nov 8;10(21):2717. Available from: https://www.mdpi.com/2079-9292/10/21/2717
- 10. Barberis N, Huang M. Mental accounting, loss aversion, and individual stock returns [Internet]. 2001. Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=264445
- 11. Ballis A, Verousis T. Behavioural finance and cryptocurrencies. SSRN Electronic Journal [Internet]. 2021 Jan 1; Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4119562









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