Intelligent Information Management, 2026, 18(6), 209-238
https://www.scirp.org/journal/iim
ISSN Online: 2160-5920
ISSN Print: 2160-5912

Analysis of Hidden Markov Model for Financial Forecasting in Cryptocurrency

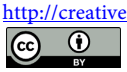
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How to cite this paper: Ekwonwune, E.N., Onwusiribe, D.U., Ovwonuri, A.O. and Okoronkwo, C.D. (2026) Analysis of Hidden Markov Model for Financial Forecasting in Cryptocurrency. *Intelligent Information Management*, **18**, 209-238.
https://doi.org/10.4236/iim.2026.186012

Received: July 28, 2026
Accepted: November 6, 2026
Published: November 9, 2026

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Abstract

This work is aimed at developing hidden Markov models for financial forecasting in cryptocurrency. The motivation is due to the risks associated with cryptocurrency, such as extreme market volatility and unpredictability, data quality and reliability issues, lack of standardization, the roles of some malicious actors, data security breaches (unauthenticated signal intrusion) into the most vulnerable database(s) or information systems, the use of rogue algorithms, privacy leakages, service providers and clients' rights abuse, competitive aggressiveness, and an unregulated atmosphere, etc. This work aims to develop and evaluate a comprehensive HMM-based framework for cryptocurrency forecasting and risk management. It aims to maximize the facilities of the internet and artificial intelligence tools and integrate these resources with advanced machine learning techniques, which entails using a Hidden Markov Model to provide a robust risk management framework that will be essential for navigating the complexities of the cryptocurrency markets. The methodology adopted is a combination of Structured Systems Analysis and Design (SSADM) and Object-Oriented Analysis and Design (OOADM) Methodologies, which entails several steps such as problem detection, feasibility studies, analysis, design, implementation, and documentation. Finally, an interactive (user-friendly) software will be developed that will be able to provide the optimal solution: Hidden Markov Model for Financial Forecasting in Cryptocurrency (HMMFFIC). To achieve these, the following programming languages will be involved, namely: HTML (Hypertext Markup Language will be used for the layouts), CSS (Cascading Style Sheets for styling and beautification of the pages), Python (Frontend Programming for functionality and processing), PHP

(Personal Home Page, or Hypertext Preprocessor for backend), and MySQL (for the database/cloud architectural design). The deployment of the optimal solution will provide the countermeasures needed to end the identified vulnerabilities and eliminate potential threats within the system and in the future.

Keywords

Model, Markov Model, Crypto, Cryptocurrency, Financial Forecasting, Market and Finance

1. Introduction

In the ever-evolving landscape of finance, the rise of cryptocurrencies has ushered in a new era of investment opportunities and challenges. As digital assets gain prominence, the need for sophisticated methods to navigate their volatile nature becomes paramount. Machine Learning (ML) is a transformative technology poised to revolutionize Financial Forecasting and Risk Management in the area of Cryptocurrency.

Machine Learning leverages advanced algorithms and data analytics to discern patterns, predict trends, and make informed decisions without explicit programming. In the context of cryptocurrencies, ML algorithms can analyze vast amounts of historical and real-time data to forecast price movements, identify market anomalies, and assess risks with unprecedented accuracy.

Financial Forecasting involves predicting future market conditions, and in the volatile world of cryptocurrencies, this task requires handling massive datasets and recognizing intricate patterns that may elude traditional statistical methods. Machine Learning models such as Neural Networks (NN), Support Vector Machines (SVM), and Decision Trees (DT) excel in processing and interpreting these complex datasets, offering insights that can guide investment strategies and enhance portfolio management.

Risk Management, on the other hand, is crucial in mitigating potential losses and safeguarding investments. Machine Learning techniques such as clustering, anomaly detection, and sentiment analysis provide a comprehensive understanding of market dynamics and investor behavior. By identifying and responding to emerging risks, ML-driven approaches empower investors to make informed decisions, reduce exposure to adverse events, and optimize their risk-return profiles. In essence, machine learning-based financial forecasting and risk management hold the potential to reshape the cryptocurrency market. As the technology continues to evolve, it promises to deliver greater precision, agility, and resilience in navigating the complexities of digital assets. Embracing this synergy between machine learning and cryptocurrency is not merely an option but a necessity for those seeking to thrive in the digital financial frontier.

1.1. Statement of the Problem

The multifaceted challenges are intertwined, and the volatile nature of cryptocurrencies, the complexities of advanced analytics, as well as the encumbrances are articulated as follows:

- Extreme Market Volatility and Unpredictability
- Data Quality and Reliability Issues
- Lack of Standardization
- Advanced Modelling Techniques

Navigating these complexities presents an opportunity to redefine financial analytics in crypto markets. It's a frontier that beckons with possibilities for those ready to tackle the challenges head-on.

1.2. Aim and Objectives of the Study

This research aims to develop and evaluate a comprehensive HMM-based framework for cryptocurrency forecasting and risk management with the following objectives:

1) To identify and characterize distinct market regimes in major cryptocurrencies (Bitcoin, Ethereum, and Ripple).

2) To assess the predictive power of multi-state HMMs in forecasting cryptocurrency returns.

3) To develop an HMM-based risk assessment methodology for cryptocurrency portfolios.

4) To compare the performance of our proposed model against established benchmarks.

1.3. Significance of Study

The significance of this research extends to both theoretical and practical domains. From a theoretical perspective, it contributes to the growing literature on cryptocurrency market analysis and the application of machine learning techniques to financial forecasting. From a practical standpoint, the findings could assist traders, investors, and financial institutions in developing more robust strategies for crypto asset allocation and risk management. In addition, it is also important to keep all the information about Financial Forecasting and Risk Management in Cryptocurrency within the computer systems, information systems, and database management systems across the digital world safe for efficient and effective performance of the Hidden Markov Model for Financial Forecasting and Risk Management in Cryptocurrency, the relevant applications, and all the IoT technologies that may be linked to this study.

2. Literature Review

A cryptocurrency (crypto-currency), or colloquially, crypto, is a digital currency designed to work through a computer network that is not reliant on any central authority, such as a government or bank, to uphold or maintain it, according to Miluti-

novié, Monia (2018) [1]. In other words, A Cryptocurrency is a digital currency, which is an alternative form of payment created using encryption algorithms, which implies that cryptocurrencies function both as currency and as a virtual accounting system. In order to use cryptocurrencies, you need a cryptocurrency wallet.

Andy Greenberg (2011) [2] states that individual coin ownership records are stored in a digital ledger or blockchain, which is a computerized database that uses a consensus mechanism to secure transaction records, control the creation of additional coins, and verify the transfer of coin ownership. The two most common consensus mechanisms are Proof of Work (PoW) and Proof of Stake (PoS). Despite the name, which has come to describe many of the fungible blockchain tokens that have been created, cryptocurrencies are not considered to be currencies in the traditional sense, and varying legal treatments have been applied to them in various jurisdictions, including classifications as commodities, securities, and currencies. Cryptocurrencies are generally viewed as a distinct asset class in practice [3]. The first cryptocurrency was Bitcoin, which was first released as open-source software in 2009. As of June 2023, there were more than 25,000 other cryptocurrencies in the marketplace, of which more than 40 had a market capitalization exceeding $1 billion. The cryptocurrency market has emerged as a significant component of the global financial ecosystem, characterized by its substantial potential returns and extreme volatility. Since the introduction of Bitcoin in 2009, thousands of cryptocurrencies have been developed, creating new investment opportunities and challenges. The decentralized nature of these digital assets, coupled with their 24/7 trading cycles and global accessibility, contributes to their unique market dynamics that often defy traditional financial models.

The Basic Features of Crypto

A cryptocurrency is a system that meets six conditions:

- The system does not require a central authority; its state is maintained through distributed consensus.
- The system keeps an overview of cryptocurrency units and their ownership.
- The system defines whether new cryptocurrency units can be created. If new cryptocurrency units can be created, the system defines the circumstances of their origin and how to determine the ownership of these new units.
- Ownership of cryptocurrency units can be proved exclusively cryptographically.
- The system allows transactions to be performed in which ownership of the cryptographic units is changed. A transaction statement can only be issued by an entity proving the current ownership of these units.
- If two different instructions for changing the ownership of the same cryptographic units are simultaneously entered, the system performs at most one of them.

One of the primary challenges in cryptocurrency investment is the accurate

forecasting of price movements and the effective management of associated risks. The crypto market experiences frequent regime shifts, moving between periods of relative stability, explosive growth, and dramatic downturns. These transitions can be sudden and difficult to predict using conventional forecasting techniques, which typically assume stationarity or gradual changes in market conditions. Hidden Markov Models (HMMs) present a promising approach for addressing these challenges. HMMs are statistical models that excel in scenarios where the underlying factors driving observable outcomes are not directly measurable. In the context of cryptocurrency markets, these "hidden" factors might include investor sentiment, regulatory developments, technological advancements, or macroeconomic trends that influence price movements without being directly observable in the price data itself. The core strength of HMMs lies in their ability to infer the existence of distinct regimes or states in the market and to model the transitions between these states probabilistically (Buckley, 2024) [4]. This makes them particularly suitable for cryptocurrency analysis, where identifying whether the market is in a bull, bear, or consolidation phase can significantly impact investment decisions and risk management strategies.

2.1. Historical Background of Cryptocurrency

In 1983, American cryptographer David Chaum conceived of a type of cryptographic electronic money called eCash [5]. Later, in 1995, he implemented it through Digicash, an early form of cryptographic electronic payments. Digicash required user software in order to withdraw notes from a bank and designate specific encrypted keys before they could be sent to a recipient. This allowed the digital currency to be untraceable by a third party. In 1996, the National Security Agency published a paper entitled *How to Make a Mint*: *The Cryptography of Anonymous Electronic Cash*, describing a cryptocurrency system. The paper was first published in an MIT mailing list (October 1996) and later (April 1997) in *The American Law Review* [6]. In 1998, Wei Dai (1998) [7] described "b-money," an anonymous, distributed electronic cash system. Shortly thereafter, Nick Szabo described bit gold. Like Bitcoin and other cryptocurrencies that would follow it, bit gold (not to be confused with the later gold-based exchange BitGold) was described as an electronic currency system that required users to complete a proof-of-work function, with solutions being cryptographically put together and published. In January 2009, Bitcoin was created by pseudonymous developer Satoshi Nakamoto (2008) [8]. It used SHA-256, a cryptographic hash function, in its proof-of-work scheme. In April 2011, Namecoin was created as an attempt at forming a decentralized DNS. In October 2011, Litecoin was released, which used Scrypt as its hash function instead of SHA-256. Peercoin, created in August 2012, used a hybrid of proof-of-work and proof-of-stake. In March 2018, the word cryptocurrency was added to the Merriam-Webster Dictionary.

Cryptocurrency has undergone several periods of growth and retraction, including several bubbles and market crashes, such as in 2011, 2013-2014/15, 2017-

2018, and 2021-2023. On 6 August 2014, the UK announced its Treasury had commissioned a study of cryptocurrencies and what role, if any, they could play in the UK economy. The study was also to report on whether regulation should be considered. Its final report was published in 2018, and it issued a consultation on crypto-assets and stable coins in January 2021. In June 2021, El Salvador became the first country to accept Bitcoin as legal tender, after the Legislative Assembly had voted 62-22 to pass a bill submitted by President Nayib Bukele classifying the cryptocurrency as such. In August 2021, Cuba followed with Resolution 215 to recognize and regulate cryptocurrencies such as Bitcoin. In September 2021, the government of China, the single largest market for cryptocurrency, declared all cryptocurrency transactions illegal.

ALTCOINS: After the early innovation of Bitcoin in 2008 and the early network effect gained by Bitcoin, tokens, cryptocurrencies, and other digital assets that were not Bitcoin became collectively known during the 2010s as alternative cryptocurrencies, or "altcoins". Sometimes the term "alt coins" was used, or disparagingly, "shitcoins". Paul Vigna of *The Wall Street Journal* described altcoins in 2020 as "alternative versions of Bitcoin" given its role as the model protocol for cryptocurrency designers. A Polytechnic University of Catalonia thesis in 2021 used a broader description, including not only alternative versions of Bitcoin but every cryptocurrency other than Bitcoin. As of early 2020, there were more than 5000 cryptocurrencies. Altcoins often have underlying differences when compared to Bitcoin. For example, Litecoin aims to process a block every 2.5 minutes, rather than Bitcoin's 10 minutes, which allows Litecoin to confirm transactions faster than Bitcoin. Another example is Ethereum, which has smart contract functionality that allows decentralized applications to be run on its blockchain. Ethereum was the most used blockchain in 2020, according to Bloomberg News. In 2016, it had the largest "following" of any altcoin, according to the New York Times. Significant market price rallies across multiple áltcoin markets are often referred to as an "altseason".

STABLECOINS: Stablecoins are cryptocurrencies designed to maintain a stable level of purchasing power. Notably, these designs are not foolproof, as a number of stablecoins have crashed or lost their peg. For example, on 11 May 2022, Terra's stablecoin UST fell from $1 to 26 cents. The subsequent failure of Terraform Labs resulted in the loss of nearly $40B invested in the Terra and Luna coins. In September 2022, South Korean prosecutors requested the issuance of an Interpol Red Notice against the company's founder, Do Kwon. In Hong Kong, China, the expected regulatory framework for stablecoins in 2023/24 is being shaped and includes a few considerations.

MEMECOINS: Memecoins are a category of cryptocurrencies that originated from Internet memes or jokes. The most notable example is Dogecoin, a memecoin featuring the Shiba Inu dog from the Doge meme. Memecoins are known for extreme volatility; for example, the record-high value for a Dogecoin was 73 cents, but that had plunged to 13 cents by mid-2024. Scams are prolific among me-

mecoins.

PHYSICAL CRYPTOCURRENCY: Physical cryptocurrency coins have been made as promotional items, and some have become collectibles; some of these have a private key embedded in them to access crypto worth a few dollars. There have also been attempts to issue Bitcoin "bank notes". The term "physical Bitcoin" is used in the finance industry when investment funds that hold crypto purchased from crypto exchanges put their crypto holdings in a specialized bank called a "custodian". These physical representations of cryptocurrency do not hold any value by themselves; they are only utilized for collectable purposes.

ARCHITECTURE: Cryptocurrency is produced by an entire cryptocurrency system collectively, at a rate that is defined when the system is created and that is publicly stated. In centralized banking and economic systems such as the US Federal Reserve System, corporate boards or governments control the supply of currency. In the case of cryptocurrency, companies or governments cannot produce new units and have not so far provided backing for other firms, banks, or corporate entities that hold asset value measured in it. The underlying technical system upon which cryptocurrencies are based was created by Satoshi Nakamoto. Within a Proof-Of-Work (PoS) system such as Bitcoin, the safety, integrity, and balance of ledgers are maintained by a community of mutually distrustful parties referred to as miners. Miners use their computers to help validate and timestamp transactions, adding them to the ledger in accordance with a particular time-stamping scheme. In a proof-of-stake blockchain, transactions are validated by holders of the associated cryptocurrency, sometimes grouped together in stake pools. Most cryptocurrencies are designed to gradually decrease the production of that currency, placing a cap on the total amount of that currency that will ever be in circulation. 60 Compared with ordinary currencies held by financial institutions or kept as cash on hand, cryptocurrencies can be more difficult for seizure by law enforcement.

BLOCKCHAIN: The validity of each cryptocurrency's coins is provided by a blockchain. A blockchain is a continuously growing list of records, called blocks, which are linked and secured using cryptography. Each block typically contains a hash pointer as a link to a previous block, a timestamp, and transaction data. By design, blockchains are inherently resistant to modification of the data. A blockchain is "an open, distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way". For use as a distributed ledger, a blockchain is typically managed by a peer-to-peer network collectively adhering to a protocol for validating new blocks. Once recorded, the data in any given block cannot be altered retroactively without the alteration of all subsequent blocks, which requires collusion of the network majority. Blockchains are secure by design and are an example of a distributed computing system with high Byzantine fault tolerance. Decentralized consensus has therefore been achieved with a blockchain.

NODES: A node is a computer that connects to a cryptocurrency network. The

node supports the cryptocurrency's network through either relaying transactions, validation, or hosting a copy of the blockchain. In terms of relaying transactions, each network computer (node) has a copy of the blockchain of the cryptocurrency it supports. When a transaction is made, the node creating the transaction broadcasts details of the transaction using encryption to other nodes throughout the node network so that the transaction (and every other transaction) is known. Node owners are either volunteers, those hosted by the organization or body responsible for developing the Cryptocurrency blockchain network technology, or those who are enticed to host a node to receive rewards from hosting the node network.

TIMESTAMPING: Cryptocurrencies use various timestamping schemes to "prove" the validity of transactions added to the blockchain ledger without the need for a trusted third party.

The first timestamping scheme invented was the proof-of-work scheme. The most widely used proof-of-work schemes are based on SHA-256 and Scrypt. Some other hashing algorithms that are used for proof-of-work include CryptoNote, Blake, SHA-3, and XII. Another method is called the proof-of-stake scheme. Proof-of-stake is a method of securing a cryptocurrency network and achieving distributed consensus by requiring users to show ownership of a certain amount of currency. It is different from proof-of-work systems that run difficult hashing algorithms to validate electronic transactions. The scheme is largely dependent on the coin, and there is currently no standard form of it. Some cryptocurrencies use a combined proof-of-work and proof-of-stake scheme.

MINING (Hashcoin Mine): On a blockchain, mining is the validation of transactions. For this effort, successful miners obtain new cryptocurrency as a reward. The reward decreases transaction fees by creating a complementary incentive to contribute to the processing power of the network. The rate of generating hashes, which validate any transaction, has been increased by the use of specialized hardware such as FPGAs and ASICs running complex hashing algorithms like SHA-256 and scrypt. This arms race for cheaper-yet-efficient machines has existed since Bitcoin was introduced in 2009. Mining is measured by hash rate, typically in TH/s. A 2023 IMF working paper found that crypto mining could generate 450 million tons of CO_2 emissions by 2027, accounting for 0.7 percent of global emissions, or 1.2 percent of the world total. With more people entering the world of virtual currency, generating hashes for validation has become more complex over time, forcing miners to invest increasingly large sums of money to improve computing performance. Consequently, the reward for finding a hash has diminished and often does not justify the investment in equipment and cooling facilities (to mitigate the heat the equipment produces) and the electricity required to run them. Popular regions for mining include those with inexpensive electricity, a cold climate, and jurisdictions with clear and conducive regulations. By July 2019, Bitcoin's electricity consumption was estimated to be approximately 7 gigawatts, around 0.2% of the global total, or

equivalent to the energy consumed nationally by Switzerland. Some miners pool resources, sharing their processing power over a network to split the reward equally, according to the amount of work they contributed to the probability of finding a block. A "share" is awarded to members of the mining pool who present a valid partial proof-of-work. As of February 2018, the Chinese government has halted trading of virtual currency, banned initial coin offerings, and shut down mining. Many Chinese miners have since relocated to Canada and Texas. One company is operating data centers for mining operations at Canadian oil and gas field sites due to low gas prices. In June 2018, Hydro Quebec proposed to the provincial government to allocate 500 megawatts of power to crypto companies for mining. According to a February 2018 report from Fortune, Iceland has become a haven for cryptocurrency miners in part because of its cheap electricity. In March 2018, the city of Plattsburgh, New York, put an 18-month moratorium on all cryptocurrency mining in an effort to preserve natural resources and the "character and direction" of the city. In 2021, Kazakhstan became the second-biggest cryptocurrency mining country, producing 18.1% of the global exahash rate. The country built a compound containing 50,000 computers near Ekibastuz.

WALLETS: A cryptocurrency wallet is a means of storing the public and private "keys" (address) or seed, which can be used to receive or spend the cryptocurrency. With the private key, it is possible to write to the public ledger, effectively spending the associated cryptocurrency. With the public key, it is possible for others to send currency to the wallet. There are multiple methods of storing keys or seeds in a wallet. These methods range from using paper wallets (which are public, private, or seed keys written on paper), to using hardware wallets (which are hardware devices to store your wallet information), to a digital wallet (which is a computer with software hosting your wallet information), to hosting your wallet using an exchange where cryptocurrency is traded, or by storing your wallet information on a digital medium such as plaintext.

Cryptocurrency Market Analysis

The cryptocurrency market has attracted significant research interest due to its unique characteristics and growing importance in the financial landscape. Early studies focused primarily on Bitcoin, examining its price dynamics, volatility patterns, and potential drivers. As the market expanded, researchers began investigating broader sets of cryptocurrencies and their interrelationships. Several studies have highlighted the challenges in forecasting cryptocurrency prices due to their non-stationary nature and the influence of factors beyond traditional economic indicators. Research has demonstrated that crypto assets exhibit stochastic volatility with long memory and leverage, while other studies have found evidence of regime-switching behavior in their return distributions. The crypto market at large has made its way into mainstream attention thanks largely to its capacity for exponential returns and volatility. Though it offers immense potential for investors, it's also an inherently risky investment land-

scape, as evidenced by events like the fall of FTX in 2022 and 2023, and the occurrence of crypto hacks in multiple DAOs due to smart contract vulnerabilities.

Applications of Hidden Markov Models in Finance

Hidden Markov Models have a long history of application in financial markets analysis, dating back to seminal work on regime-switching models in econometrics. In traditional finance, HMMs have been successfully applied to stock market analysis, portfolio optimization, and risk management. HMMs are statistical models that represent systems with hidden states. They capture the idea that observed outputs of a system are the result of states that are not directly visible. The key components of an HMM include states, observations, transition probabilities, emission probabilities, and initial state probabilities. These models work by solving three fundamental problems: evaluation (determining the likelihood of an observation sequence), decoding (uncovering the most likely sequence of hidden states), and learning (adjusting model parameters to maximize probability). The application of HMMs to cryptocurrency markets is a more recent development. Koki *et al.* explored the predictability of cryptocurrencies using Bayesian Hidden Markov Models, finding that multi-state NHHM (Non-Homogeneous Hidden Markov) models outperform single-regime random walk models for Bitcoin, Ether, and Ripple returns. Their research identified distinct market regimes corresponding to bull, bear, and calm periods, providing evidence that state-based modeling captures essential features of cryptocurrency dynamics. Similarly, research by Saidane (2024) [9] introduced a composite hidden Markov factor analysis framework for risk assessment in cryptocurrency portfolios. This approach combined heteroskedastic factor analysis with HMMs to address regime switching in cryptocurrency volatilities and the dynamic interconnections between different crypto assets. The methodology demonstrated superior performance in Value-at-Risk (VaR) and Expected Shortfall (ES) predictions compared to existing methods.

2.2. Analysis of ARIMA and GARCH Models in the Context of Hidden Markov Models for Financial Forecasting in Cryptocurrency

Considering that cryptocurrency markets are characterized by high volatility and nonlinear behaviors, making them challenging to predict. Financial forecasting in cryptocurrency often employs various statistical models to capture trends, seasonality, and volatility. Two widely used techniques in this domain are ARIMA (AutoRegressive Integrated Moving Average) and GARCH (Generalized AutoRegressive Conditional Heteroskedasticity).

Overview of ARIMA Model

ARIMA (AutoRegressive Integrated Moving Average) is a time series forecasting method that combines the autoregressive (AR) and moving average (MA) components while incorporating "differencing" to make the time series stationary. The model is denoted as ARIMA (p, d, q), where:

- "p": represents the number of lag observations (that is, the AR part, or auto-regressive).
- "d": represents the degree of differencing (the I part, which is the degree of integration).
- "q": represents the size of the moving average window (the MA part, moving Average).

Benefits of the Model ARIMA

- **Simplicity:** ARIMA is relatively simple to understand and implement; as a result, it is suitable for initial explorations of Time Series Data.
- **Effectiveness with Historical Data:** When the dataset is stationary, ARIMA can be particularly effective at capturing linear relationships and trends based on historical data.
- **Flexibility:** With the appropriate differencing and lagged terms, ARIMA can fit a variety of time series patterns.

The Challenges in Using ARIMA Model

Non-Stationarity & Nonlinearity Issues: ARIMA assumes that the underlying time series is stationary after differencing, which may not always hold true for cryptocurrency prices, especially given their volatile nature.

Fixed Parameters: ARIMA parameters are usually static over time, which might eventually result in missing dynamic patterns in cryptocurrency market changes.

Inability to Model Volatility: While ARIMA captures trends, it does not account for changes in volatility, which are critical in financial markets, and especially in cryptocurrencies.

Overview of GARCH Model

GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) is designed to model Time Series Data with changing variance over time, specifically addressing the phenomenon of heteroskedasticity. GARCH (p, q) specifies the current volatility as a function of past squared observations and past volatility.

Benefits of the Moddel GARCH

Volatility Modeling: GARCH effectively models the changing volatility ubiquitous in financial time series, including cryptocurrencies, enabling a more accurate reflection of market dynamics.

Capture of Clustering Variance: It can identify periods of low and high volatility, which are essential for risk management and securing financial derivatives that depend on volatility estimates.

Estimation Accuracy: GARCH models, in conjunction with ARIMA, can yield more accurate predictive capabilities for price points and volatility.

The Challenges in Using GARCH Models

Complexity: GARCH models are more complex to estimate and interpret compared to ARIMA. The necessity of specifying and validating several parameters can be a barrier for practitioners.

Assumption of Normality: Traditional GARCH models assume normally distributed error terms, which may not be appropriate for fat-tailed distributions of-

ten seen in cryptocurrency returns.

Sensitivity to Parameter Choice: The accuracy of GARCH models can be highly sensitive to the selection of parameters, potentially leading to overfitting or underfitting.

Integration with Hidden Markov Models (HMMS)

Integrating ARIMA and GARCH with Hidden Markov Models allows for a comprehensive approach combining the strengths of each model type. HMM recognizes that financial markets can exist in multiple hidden states (*i.e.*, bull or bear markets) that eventually lead to different behaviors in the time series data.

Role of ARIMA in HMM

The ARIMA model can be utilized to capture linear trends within each hidden state of the HMM. Since the state may exhibit different characteristics, ARIMA can adapt to these variations, thus improving forecast accuracy.

Role of GARCH in HMM

GARCH can be implemented to model the volatility dynamics within each state of the HMM. By recognizing that market volatility may vary by state, GARCH improves the model's resilience to volatility clustering frequently observed in cryptocurrency markets.

Assumption

In forecasting cryptocurrency prices, both ARIMA and GARCH models play vital roles in addressing historical price trends and volatility, respectively. When integrated into a Hidden Markov Model framework, they enhance the ability to capture the complex dynamics of cryptocurrency markets. While ARIMA provides a straightforward approach to trend analysis, GARCH adds an essential layer of volatility modeling. However, it is crucial to acknowledge their limitations and apply different strategies for optimizing model effectiveness, such as parameter tuning, exploring alternative distributions, and combining signals for more robust forecasting outcomes. In the rapidly evolving landscape of cryptocurrencies, harnessing these models collectively represents a significant step toward advanced predictive analytics.

2.3. Risk Management in Cryptocurrency

Risk management in cryptocurrency trading presents unique challenges due to the market's extreme volatility, regulatory uncertainty, liquidity issues, and security concerns. Traditional risk metrics and management strategies often require adaptation for the cryptocurrency context. Cryptocurrency risk management is a systematic approach to understanding and addressing the potential pitfalls associated with investing in digital assets. It involves a four-step process: identifying potential risks, analyzing them, assessing them to prioritize, and finally working on them to mitigate or reduce the possibility of occurrence. More sophisticated quantitative approaches to crypto risk management have emerged in recent years. Research comparing Ethereum price prediction models highlighted that while

Hidden Markov Models excel in capturing volatility and short-term price fluctuations, they demonstrate varying effectiveness for long-term trend prediction when compared to deep learning approaches like LSTM and reinforcement learning. A study by Saidane (2024) dealt with the estimation of Value-at-Risk (VaR) and Expected Shortfall (ES) in a cryptocurrency context (9). To address the presence of regime switching in cryptocurrency volatilities and the dynamic interconnection between them, the research proposed a Monte Carlo-based approach using heteroskedastic factor analysis and hidden Markov models combined with a structured variational Expectation-Maximization learning approach. This composite approach allowed for the construction of a diversified portfolio and determination of an optimal allocation strategy to minimize conditional risk and maximize return.

Economics: Cryptocurrencies are used primarily outside banking and governmental institutions and are exchanged over the Internet.

Block Rewards: Proof-of-work cryptocurrencies, such as Bitcoin, offer block rewards incentives for miners. There has been an implicit belief that whether miners are paid by block rewards or transaction fees does not affect the security of the blockchain, but a study suggests that this may not be the case under certain circumstances. The rewards paid to miners increase the supply of the cryptocurrency. By making sure that verifying transactions is a costly business, the integrity of the network can be preserved as long as benevolent nodes control a majority of computing power. The verification algorithm requires a lot of processing power, and thus electricity, in order to make verification costly enough to accurately validate the public blockchain. Not only do miners have to factor in the costs associated with expensive equipment necessary to stand a chance of solving a hash problem, but they must also further consider the significant amount of electrical power in search of the solution. Generally, the block rewards outweigh electricity and equipment costs, but this may not always be the case. The current value, not the long-term value, of the cryptocurrency supports the reward scheme to incentivize miners to engage in costly mining activities.931 In 2018, Bitcoin's design caused a 1.4% welfare loss compared to an efficient cash system, while a cash system with 2% money growth has a minor 0.003% welfare cost. The main source of this inefficiency is the large mining cost, which is estimated to be US$360 million per year. This translates into users being willing to accept a cash system with an inflation rate of 230% before being better off using Bitcoin as a means of payment. However, the efficiency of the Bitcoin system can be significantly improved by optimizing the rate of coin creation and minimizing transaction fees. Another potential improvement is to eliminate inefficient mining activities by changing the consensus protocol altogether.

Advertising Bans

Cryptocurrency advertisements have been banned on the following platforms:

- Google: Ended August 2021
- Twitter

- Facebook: Ended December 2021
- Bing: Ended June 2022
- Snapchat
- Linkedln
- MailChimp
- Baidu
- Tencent
- Weibo
- Line
- Yandex

Impact: In addition to discussing the impact on Monetary and Fiscal Policy, researchers at the CBN suggest that cryptocurrencies could have a positive effect on the agricultural and education sectors in Nigeria. In the agricultural sector, they suggest that blockchains have significant potential to enhance access to finance by connecting the technology to their business model, which can remedy food security issues. In the education sector, they see cryptocurrencies as an opportunity, as there is much to learn about them, and by incorporating cryptocurrency into education, it will be overall beneficial to the development of the country [10].

What is Risk Management in Cryptocurrency: Cryptocurrency risk management is a systematic approach to understanding and addressing the potential pitfalls associated with investing in digital assets. It involves a four-step process: identifying the potential risks, analyzing them, assessing them to prioritize, and finally working on them to mitigate or reduce the possibility of occurrence. Let's understand them one by one:

- **Risk Identification:** This initial stage involves pinpointing all the potential threats you might encounter when trading or investing in cryptocurrencies. It could be security breaches, liquidity management, or incurring unexpected losses.
- **Risk Analysis:** Once identified, each risk needs to be meticulously analyzed to understand its likelihood of occurring and the severity of its potential impact.
- **Risk Assessment:** At this point, weigh the identified risks against your risk tolerance level. This helps determine which risks pose the biggest threat to your investment goals.
- **Treatment Planning:** Finally, you establish a plan to mitigate each risk. This plan might involve implementing specific strategies, utilizing tools, or simply adjusting your investment approach.

Risks in Crypto Trading and Tips to Avoid Them

The crypto market is no less than a roller coaster ride. Unpredictable ups and downs are normal here, presenting opportunities to book profits but also coming with threatening risks. Before optimizing risk management strategies, it is essential to first understand the relevant risks.

Market Volatility: Cryptocurrencies are notoriously volatile, meaning their prices can fluctuate significantly in short periods, especially if they are not prominent

and established cryptocurrencies. This volatility can lead to substantial losses if you're not prepared. Sometimes even the well-established cryptocurrency can face a major downturn; for example, Bitcoin fell by 39% in March 2020 within a single day, from $7935 to $4826. Thus, it is crucial to prepare for it.

Tip: When marks are volatile, it's sometimes harder to execute trades on decentralized platforms as gas fees go up and networks get congested. As such, trading in and out quickly of positions can be costly, and be prepared for quick swings in prices.

Regulatory Risks: The regulatory landscape surrounding cryptocurrency is constantly evolving. New regulations can disrupt the market and negatively impact specific cryptocurrencies. A prime example of this regulatory change is when SEC tried to count cryptocurrency as securities that led to additional legal compliances. This sudden change in regulations not only affects the crypto projects but also the investors in the market. Stay informed about regulatory developments to adapt your strategy accordingly.

Tip: Understand the legal framework around trading for the country you reside in. This includes the tax regulations you might face.

Security Breaches: Cryptocurrency exchanges and wallets are constantly targeted by hackers. Thus, it becomes important to choose reputable platforms with strong security measures and employ strong password hygiene to minimize the risk of theft.

Tip: Stick to popular Web3 wallets like MetaMask and Base and exchanges/aggregators like Rubic.

Liquidity Risks: A liquid market refers to a place where there are enough buyers and sellers in which an asset can be bought or sold at any given price level. Some cryptocurrencies have low trading volume, making it difficult to enter or exit positions quickly without incurring significant price slippage.

Tip: As an investor and trader, you must consider the liquidity of the market you're in before entering into a trade. For centralized platforms, ensure there is decent liquidity to enter and exit securely (trading volume), and for decentralized exchanges, set price slippage limits.

Counterparty Risk: When you trade on a cryptocurrency exchange, you are essentially trusting them with your funds. If the exchange experiences financial difficulties or suffers a security breach, your assets could be at risk.

Tip: Mitigate this by using reputable exchanges with a proven track record. Avoid shady exchanges you are sent links to through social media. Always DYOR on the platform before you begin using it. Additionally, leverage crypto aggregators like Rubic to seamlessly navigate all reputable exchanges at once.

Importance of Crypto Risk Management:

The crypto market is brimming with opportunities, but also fraught with dangers. Effective risk management helps you:

- **Protect Your Capital:** By understanding and mitigating risks, you can minimize potential losses and safeguard your investment portfolio.

- **Make Informed Decisions:** Risk management helps you implement a more informed approach to trading. You can base your decisions on a clear understanding of potential risks and rewards.
- **Achieve Your Investment Goals:** By managing risks effectively, you can increase your chances of achieving your long-term investment objectives.

Effective Cryptocurrency Risk Management Strategies:

Whether it is business, investing, or trading, you should always optimize your strategy for risk management. Remember, the best investment is made when you have minimum risk and get maximum profit. The same is true with crypto. Here are 5 risk management strategies that can help you navigate through volatile markets:

Diversification: The golden rule of investing applies equally to crypto: don't put all your eggs in one basket. Diversifying your portfolio across different cryptocurrencies, asset classes, and even traditional investments helps you hedge your risk in the crypto market. You can diversify your wallets as well; try not to keep all your funds in a single wallet so that, in case of any unexpected security breach, you don't lose all your funds.

Position Sizing: Never risk more than you can afford to lose. Especially on a single trade. A common strategy is to allocate a small percentage (1% - 2%) of your total portfolio to each trade. This helps limit potential losses and protects your overall capital. There is another popular framework of trading, popularly known as the 6% rule, which says you should stop trading if you lose more than 6% of your capital. Take a break for a day or two and then come back. This will help you widen your mindset, and you will be able to identify the mistakes or the patterns you were following earlier that were leading to losses.

Stop-Loss Orders: A stop-loss order automatically sells your cryptocurrency holding once the price reaches a predetermined level. As a trader, it is important for you to find out your risk tolerance level and risk-to-reward ratio; this can help you find the common ground to set up the stop-loss. You can take the help of technical analysis to find out the right support and resistance level and then make your move. This helps limit losses during sudden price drops.

Dollar-Cost Averaging (DCA): DCA involves investing a fixed amount of money into a specific cryptocurrency at regular intervals, regardless of the current price. This helps average out the cost per unit over time and mitigate the impact of market volatility. DCA helps you spread your risk over time, reducing the possibility of losing money in a single trade/investment.

Secure Storage: Store your cryptocurrencies in a secure wallet, preferably a hardware wallet that offers offline storage. This significantly reduces the risk of theft compared to online wallets. If you need to store your crypto in an online wallet to execute quick trades, make sure you use a trustworthy wallet on the market.

Tools and Resources for Crypto Risk Management

Equipping yourself with the right tools can significantly enhance your crypto risk management efforts. These are some valuable resources:

- **Market Analysis Tools:** Utilize platforms like CoinMarketCap, CoinGecko, or TradingView to stay informed about market trends, track price movements, and conduct technical analysis for informed trading decisions. DefiLlama and Dapp Tracker are two other tools that can help you gather important data and conduct fundamental analysis.
- **Portfolio Trackers:** Services like Coin Tracking or Delta Investment Tracker offer comprehensive portfolio management solutions. These tools help you track your holdings, calculate profits and losses, and monitor your overall risk exposure.
- **Security Tools:** Implement two-factor authentication (2FA) on all your crypto exchange and wallet accounts. Additionally, consider using a password manager to generate and store strong, unique passwords for each platform. However, it is also important to keep a record of all your passwords in a safe place because it is common in the crypto market to lose funds due to password loss for decentralized exchanges and wallet addresses.
- **Cryptocurrency News and Research Sites:** Stay updated on the latest developments in the crypto space by following reputable news outlets like CoinDesk or Cointelegraph. Research publications like Messari or The Block offer in-depth analysis and insights to help you make informed investment decisions.

2.4. Data Visualization Feature Selection

In Data Science, the role of data visualization and feature selection is crucial. Data visualization brings clarity to complex datasets, while feature selection focuses on relevant variables. This article delves into the relationship between these two essential components, demonstrating their importance in predictive modeling and data analysis. In this particular research, we made use of the Python visualization libraries such as Seaborn and Matplotlib.

Data Visualization

Figure 1 illustrates a visualization representing the relationship between the closing price of Ethereum and the corresponding dates. It's a graphical depiction where the x-axis represents different dates, while the y-axis displays the closing price of Ethereum on those specific dates. This visualization offers a clear view of how the closing price of Ethereum has fluctuated or changed over time, enabling viewers to observe trends, patterns, and movements in the cryptocurrency's value within the given timeframe.

Figure 2 provides a visualization that specifically represents the relationship between the opening price of Ethereum and its corresponding dates.

In the graph of Figure 3, the x-axis represents dates, while the y-axis displays the values of the Closing Price Moving Averages for Ethereum at those particular dates. Moving averages are statistical indicators used to smooth out price data by creating a constantly updated average price. This visualization provides a view of how the Closing Price Moving Averages for Ethereum fluctuate over time. It helps in identifying trends, patterns, or changes in the average closing prices of Ethereum,



Figure 1. Closing price/corresponding date (https://www.researchgate.net/figure/Ethereum-ETH-USD-closing-price-movement-from-2020-to-2025_fig1_389861803?__cf_chl_tk=ff9d9n1Hbx.wREzWf38sxr_2eLiRbIYLMRwA3WEZ588-1790674042-1.0.1.1-JKurIxPlA6mgQ8UGLXRSq1Y5bnxVHAo2hAC3utoS8_s).

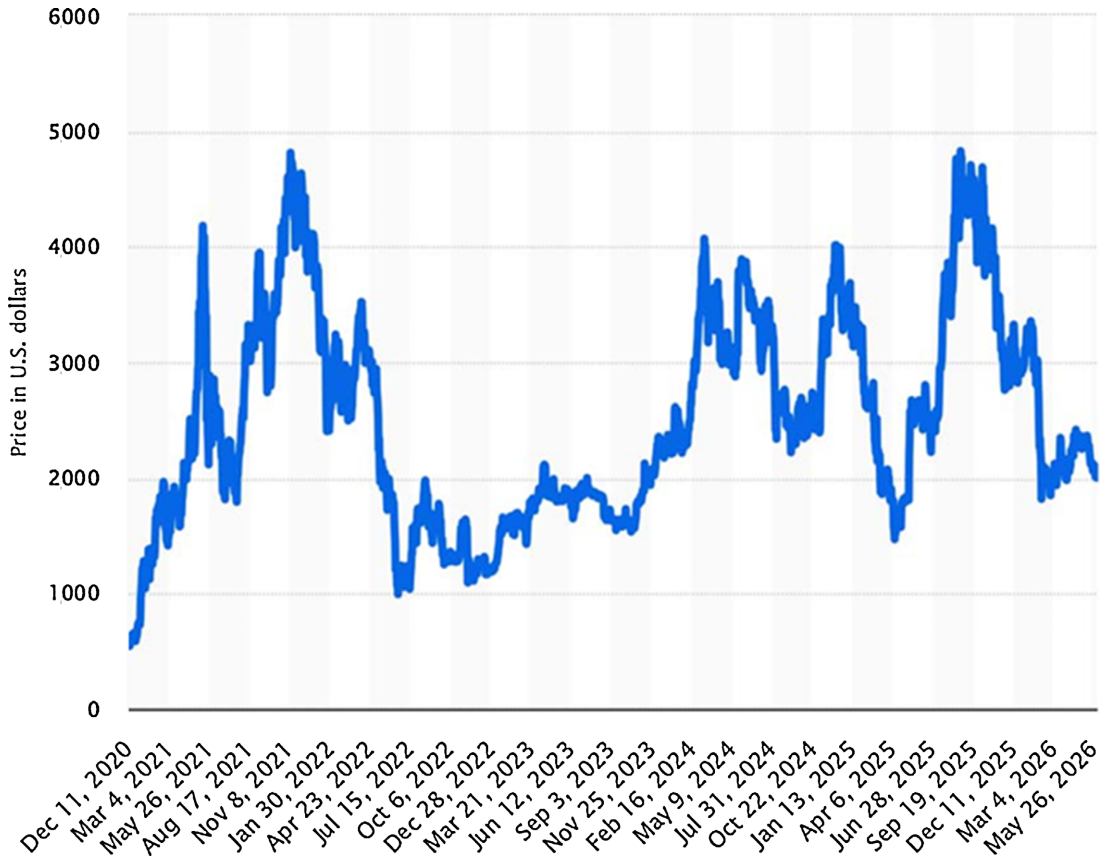


Figure 2. Opening price of ethereum/date (https://www.statista.com/statistics/806453/price-of-ethereum/).

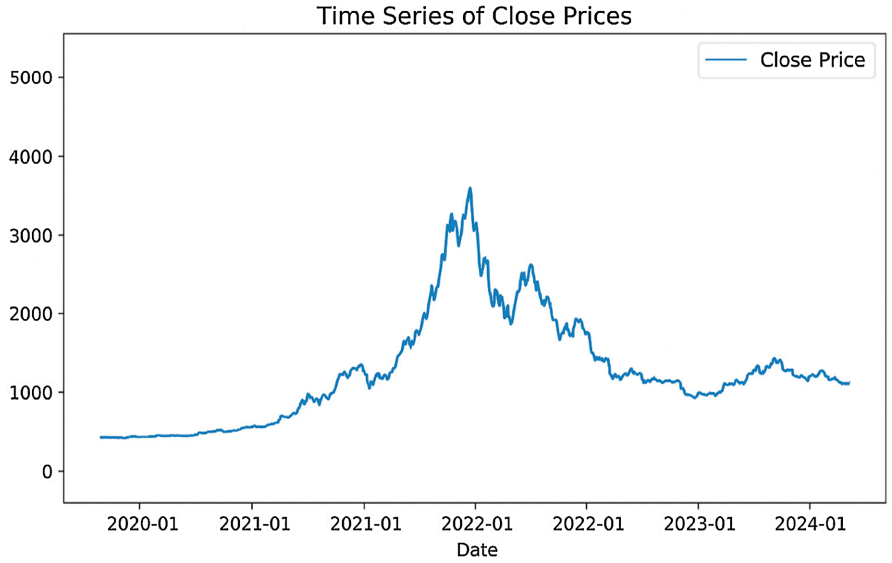


Figure 3. Represents a visualization that demonstrates the closing price moving averages of Ethereum (https://www.mdpi.com/1911-8074/19/6/377).

offering insights into the movement of its value within the given time frame.

Figure 4 displays a visualization of the opening price moving averages for Ethereum. This graph shows how the average opening prices of Ethereum change over time.

Figure 5 represents a visualization showcasing the Daily Return of Ethereum. This graph shows how much Ethereum's value changes on a daily basis. It illustrates the daily fluctuations or percentage changes in Ethereum's value, offering insights into its daily performance or volatility within a specific time frame.

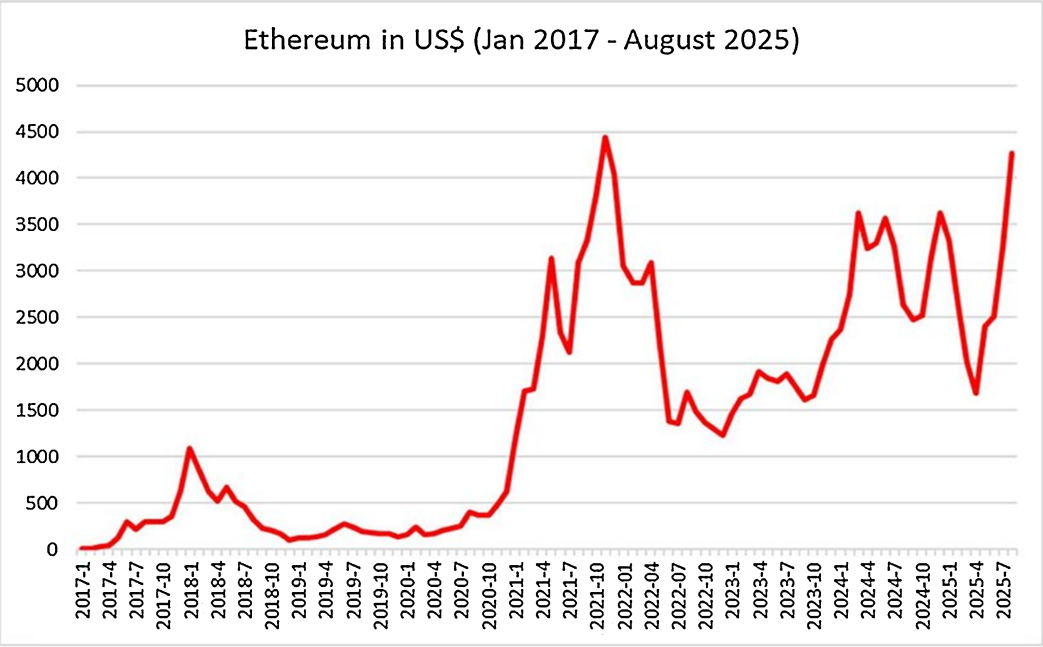


Figure 4. Opening price moving averages (https://en.wikipedia.org/wiki/File:Ethereum_in_US$.pdf).

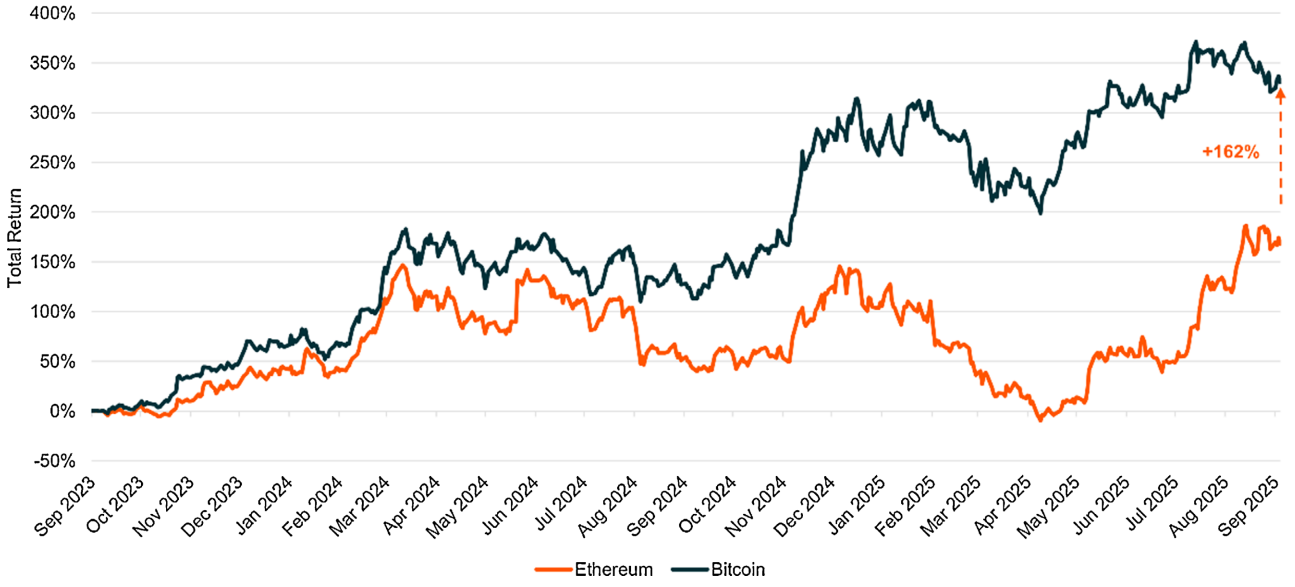


Figure 5. Opening daily return (https://files.globalxetfs.com.au/1_Ethereum_Insight_PERF_Graphic_a92f021084.png).

Figure 6 shows a visualization representing the historical trading volume of Ethereum. This graph typically portrays the volume of Ethereum traded over a historical period. It provides insight into the quantity of Ethereum units exchanged within specific time frames, allowing observation of trends and patterns in the trading activity surrounding Ethereum within the given historical context.

Figure 7 shows a visualization representing the historical percentage variation of Ethereum. This graph illustrates the percentage change in Ethereum's value over a historical period. It provides a visual representation of how much Ethereum's value has fluctuated or changed over time in terms of percentage.

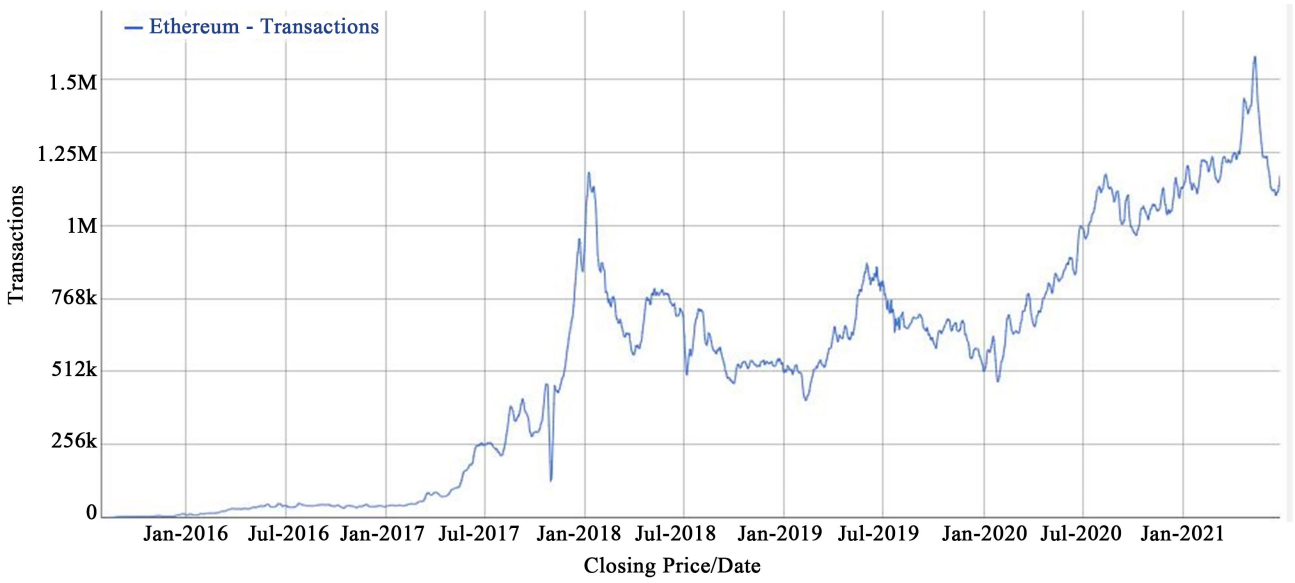


Figure 6. Historical trading volume of Ethereum (https://coincript.com/wp-content/uploads/2021/06/ethereum-transactions-historical-chart.jpg).

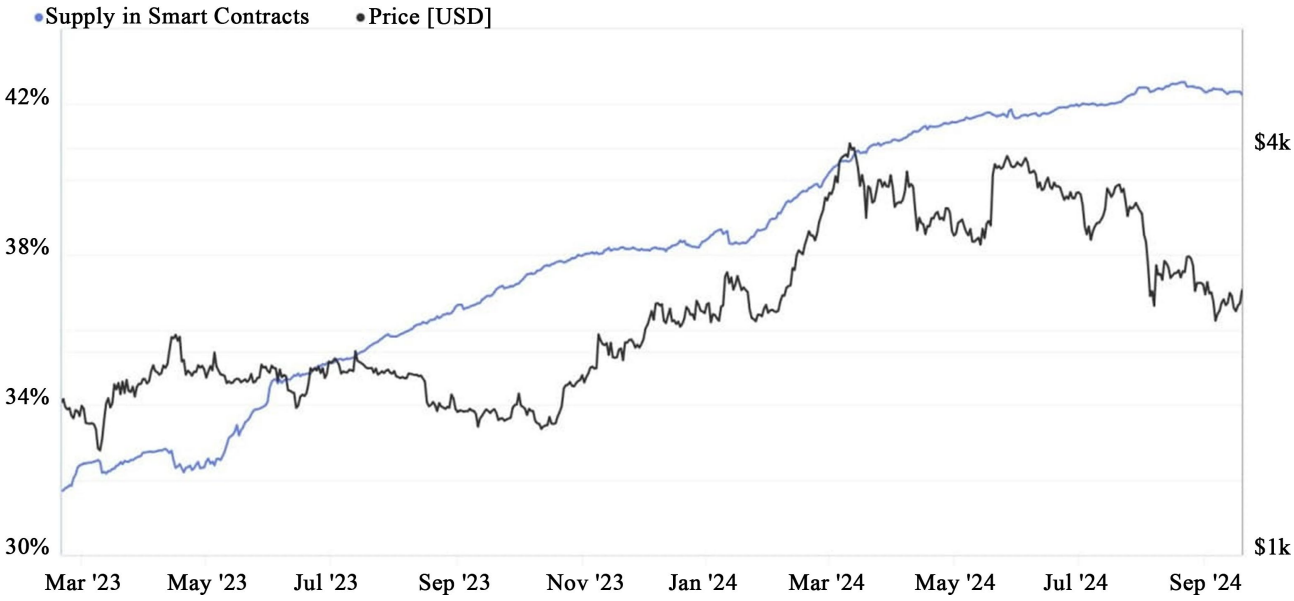


Figure 7. Historical percentage variation of Ethereum (https://www.binance.com/en/square/post/13961829725706).

2.5. Feature Selection

The dataset used in this study gathers Ethereum (ETH) price-related information over a specific time period. The data includes daily records of Ethereum's closing prices, opening prices, daily highs, and lows, along with the trading volume. The dataset spans multiple days, making it possible to examine how Ethereum's price changes over time. Ethereum's closing price, the value at the end of each trading day, provides a snapshot of its daily performance. Opening prices represent the initial value at the beginning of a trading day, while daily highs and lows reflect the maximum and minimum price levels reached during each trading day, respectively. Trading volume, measured in units such as thousands (K), indicates the extent of market activity for each day. In addition to these quantitative variables, the dataset also contains the percentage variation in Ethereum's price, which offers insights into the daily price fluctuations. This dataset serves as the foundational source of information for our research, enabling the application of various machine learning and deep learning techniques to predict and analyze Ethereum's price movements and uncover hidden patterns within the cryptocurrency market.

2.5.1. Method Deployed in Ethereum Price Prediction

We preprocess the Ethereum price dataset, ensuring data quality and consistency. We provide a detailed description of each model's architecture, configuration, and hyperparameters. The model evaluation metric used is MAPE.

2.5.2. Hidden Markov Models in Finance, Markets & Trading

According to Dan Buckley (Jan 18m 2024), Hidden Markov Models (HMMs) are statistical models that represent systems with hidden states.

These models are useful in fields like speech recognition, bioinformatics, and

financial analysis. They capture the idea that the observed outputs of a system are the result of states that are not directly visible or "hidden."

2.5.3. Hidden Markov Models Components

- Hidden Markov Models (HMMs) identify unobservable market regimes (e.g., uptrend, downtrend, high/low volatility) using observable financial data.
- HMMs enable probabilistic inference of market states and can help traders in their decision-making.
- They help in tactical trading by adjusting portfolios according to the inferred market conditions.

An HMM consists of the following elements:

States: Hidden states represent the underlying process. The actual state isn't visible.

Observations: These are visible outputs or data points linked to the states.

Transition Probabilities: These define the likelihood of transitioning from one state to another.

Emission Probabilities: These express the likelihood of an observation being generated from a state.

Initial State Probabilities: These indicate the probabilities of starting in each state.

2.5.4. Operational Dynamics of Hidden Markov Models (HMM)

The working of an HMM can be understood through three fundamental problems:

Evaluation: Given the HMM parameters and a sequence of observations, determine the likelihood of the observation sequence.

Decoding: Given the HMM and a sequence of observations, uncover the most likely sequence of hidden states.

Learning: Adjust the model parameters to maximize the probability of the observation sequence.

2.5.5. Applications of Hidden Markov Models (HMM)

HMMs are versatile and find applications in numerous fields:

Speech Recognition: They model the sequence of spoken words as hidden states and the audio features as observations.

Bioinformatics: They help in gene prediction and protein modeling by treating the biological sequences as observations.

Financial Markets: They can model market conditions as hidden states in risk management and trading/investment strategies. For example, let's say a trader is following a momentum strategy.

An HMM can be applied to detect different market trends such as bullish, bearish, or sideways market conditions. Each state represents a regime with distinct asset behavior (momentum trading largely involves the belief that what most recently happened will continue to happen). The model uses observable market data like price movements and trading volumes to probabilistically infer the hidden state of the market. Traders can then adjust their strategies based on the inferred

state.

For instance, in a detected bullish state, a trader might increase their allocation in equities, while in a bearish state, they might shift to less exposure or short.

Risk Assessment: HMMs can help in assessing the risk profile of different assets under various market conditions. This can enable a more nuanced understanding of how different assets contribute to overall portfolio risk in different regimes.

Dynamic Asset Allocation: Once the market regimes are identified, a risk parity portfolio can be dynamically adjusted according to the predicted state. For instance, in a high-volatility regime, the model might suggest increasing allocation to safer assets like short-term government bonds.

Portfolio Diversification: By understanding the different market states and their impact on asset classes, HMMs can guide the diversification of a portfolio to ensure that it is well-positioned across different market conditions.

3. Methodology and System Analysis

The methodology recommended for this work is a combination of Object-Oriented Analysis and Design Method (OOADM) and Systems Analysis and Design Method (SSADM). Different methods and tools will be deployed while conducting this study; most of the important activities that will be covered at this stage are:

- Collection of facts
- Analysis of the collected facts

These methods include the following:

- Interview method
- Observation
- Online Research
- Examination of Documents

3.1. System Analysis

Prior to the advent of contemporary HMMs in Financial Forecasting and Risk Management in Cryptocurrency, the realm of Cryptocurrency was unpredictable, with extreme volatility. The decentralized nature of these digital assets, coupled with their 24/7 trading cycles and global accessibility, contributes to their unique market dynamics that often defy traditional financial models.

The proper use of HMMs in Financial Forecasting and Risk Management in Cryptocurrency eventually turns out to be a valuable asset in this contemporary's digital world and in the economy of nations and globally as well. Its main objective is:

- To identify and characterize distinct market regimes in major cryptocurrencies (Bitcoin, Ethereum, and Ripple).
- To assess the predictive power of multi-state HMMs in forecasting cryptocurrency returns.
- To develop an HMM-based risk assessment methodology for cryptocurrency

portfolios.

- To compare the performance of our proposed model against established benchmarks

3.2. Analysis of the Existing System

It is a daunting task if not impossible to manage, control and totally eliminate the vulnerabilities and various security challenges, within the networks of active applications, connected devices and bulk of streams of signals routing through the networks and across the multidisciplinary platforms due to random explorations, with data mining processes that reduce the learning speed resulting in the probable risk of choosing bad defense policies in the process, which is prone to disaster with respect to data security, which may eventually lead to massive amount of problems to the existing system if not properly checked without a contemporary intelligent financial system with an Application Programming Interface (API) tool like Hidden Markov Model for Financial Forecasting and Risk Management in Cryptocurrency.

3.3. Input, Process and Output Analysis

The following is a typical description of the input, process, and output analysis of the existing system.

Input Analysis: As shown in Figure 8, a Graphic User Interface is displayed on the screen which allows the user to Sign UP as a first-time user by registering and submitting your credentials to the systems database in exchange for access codes or password, which will be required before the user can have access to the system or Sign In as an existing User with access codes as maybe required, that is in the form of passwords, which the system uses to grant authorization to the User.

Figure 8 is used to show the Graphic User Interface of a Password Dialog Box of the Existing System's Input Screen.

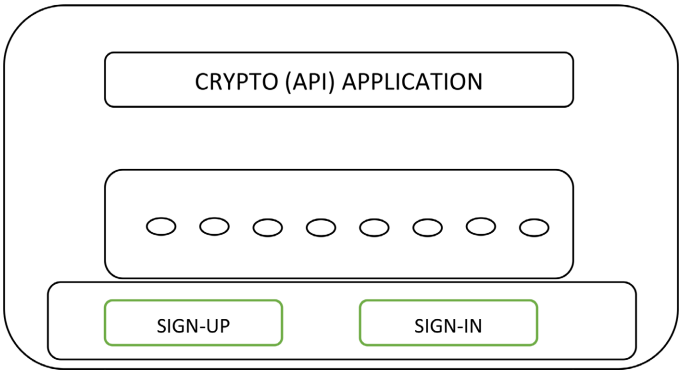


Figure 8. Graphic user interface of password dialog box (the existing system input screen).

Process Analysis: Access is granted to the user via the password dialog box, and once the User's signals are authenticated, access is then granted to the user to the home screen/welcome page, where some tools for working with the editor and mak-

ing stakes, as well as the other tools that are used to represent the market indices/variables are displayed, and available for use at this point the User can initiate and process queries, which the server responds to accordingly, searching the database with respect to the request which is subsequently retrieved if found and decline to with an error message if the file is not found. On the other hand, an error message is displayed if the authentication fails, and the process calls from the input device(s) are subsequently terminated after the stipulated number of tries. Furthermore, the user can initiate a process call to update the existing records (Making a stake) within the database, and if successful, the system will produce a Proof of Stake (PoS) based on the successful implementation of the process call(s). On the contrary, an error report is generated showing an invalid transaction or a transaction that failed in the case of an interrupt or interference from other processes with high-priority call(s). While the initiated process remains successful, the subsequent transmission of signals to processes and applications, from application to application, application to device, and device to other devices within the network and the network of networks commences, as the proof of stake is lodged across multiple servers, across multiple active platforms as evidence of Proof of Work (PoW); apart from raising the current stakes, the User can also accomplish much using process calls through mining. These processes are protected by encryption and are decrypted as they arrive at the physical layers of the authorized User(s), Application Server(s), or Device Server(s) that are meant to receive the initiated requests (process calls).

Output Analysis: The major output comprises of a confirmation page that the password or access code has been approve and that access is granted to the user or an error message box that displays an error message that the password did not match and the option to try again with a warning that the user has (a limited number of tries) one or two more trials before the system is logged off, In the case where the input streams from a keyboard or a biometric device, but in the case where the input signals are stream into the system through Sensors, camera or similar devices the output is subject to the validation process reports if successfully authenticated the User/Device is granted access to the requested platform which is displayed on the Home Screen otherwise the process is terminated with error message displayed on the screen.

3.4. Analysis of the Proposed System

Bearing in mind the analysis of the existing system as shown in **Figure 9**, its performance and weaknesses of the system against imminent threats, the deployment and implementation of a new system for Financial Forecasting and Risk Management in Cryptocurrency as the optimal solution becomes inevitable. Hence, the ultimate aim of this work is to propose a new system, which will eliminate these problems. **Figure 10** shows the high-level model of the proposed system. It embraces the embedded Softbot HMMs, Crypto-API, Network Grid of Application and Devices to direct access database storage system which is the internal storage

access.

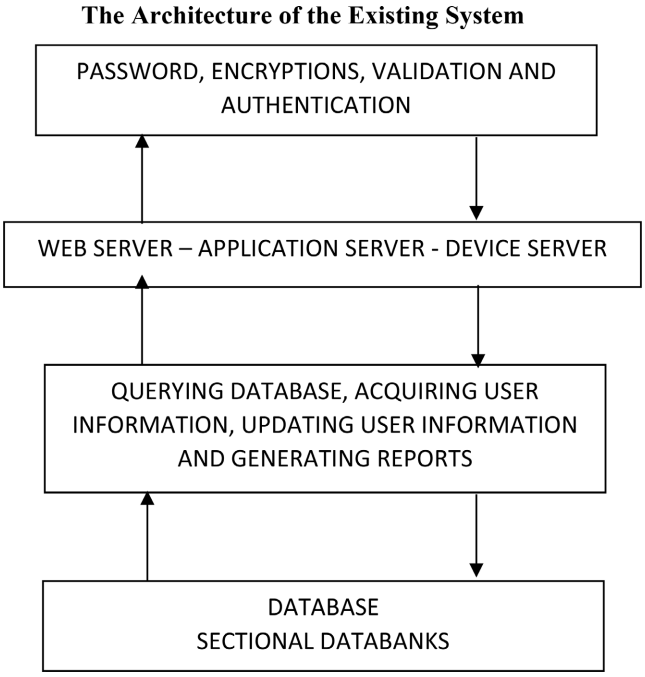


Figure 9. Information flow of the existing system.

Figure 10 illustrates the well-structured model architecture of the High-Level Model for a Hidden Markov Model (HMM), representing five fundamental elements:

Component	Description
N	Number of hidden states ($S = \{s_1, s_2, ..., s_N\}$)
M	Number of observable symbols ($V = \{v_1, v_2, ..., v_M\}$) – for discrete HMMs
π	Initial state distribution vector, $\pi = \{\pi_i\}$ where $\pi_i = P(q_1 = s_i)$
A	State transition matrix, $A = \{a_{ij}\}$ where $a_{ij} = P(q_{t+1} = s_j)$
B	Emission probability matrix, $B = \{b_j(k)\}$ where $b_j(k) = P(v_k)$

For continuous HMMs, B is replaced with emission probability density functions (e.g., Gaussian Mixture Models).

The high-level model's modular design consists of the following:

1) Initialization Module

Inputs: N, M, type (discrete/continuous), optional prior knowledge.

Outputs: Random or domain-informed π, A, B (or PDFs).

Allows flexible parameter initialization (uniform, random, data-driven).

2) Observation Encoding Module

Converts raw data into observation sequences ($O = \{o_1, o_2, ..., o_T\}$).

Supports discrete symbols or continuous feature vectors (e.g., MFCCs in speech).

Includes pre-processing like normalization, discretization, or feature extraction.

3) Learning Module

Implements training algorithms:

Supervised (known state sequences): Maximum Likelihood Estimation (MLE).

Unsupervised: Expectation-Maximization (EM), typically via the Baum-Welch algorithm.

Desirable features: Convergence diagnostics, Multiple restarts (to avoid local optima), Batch vs. online learning.

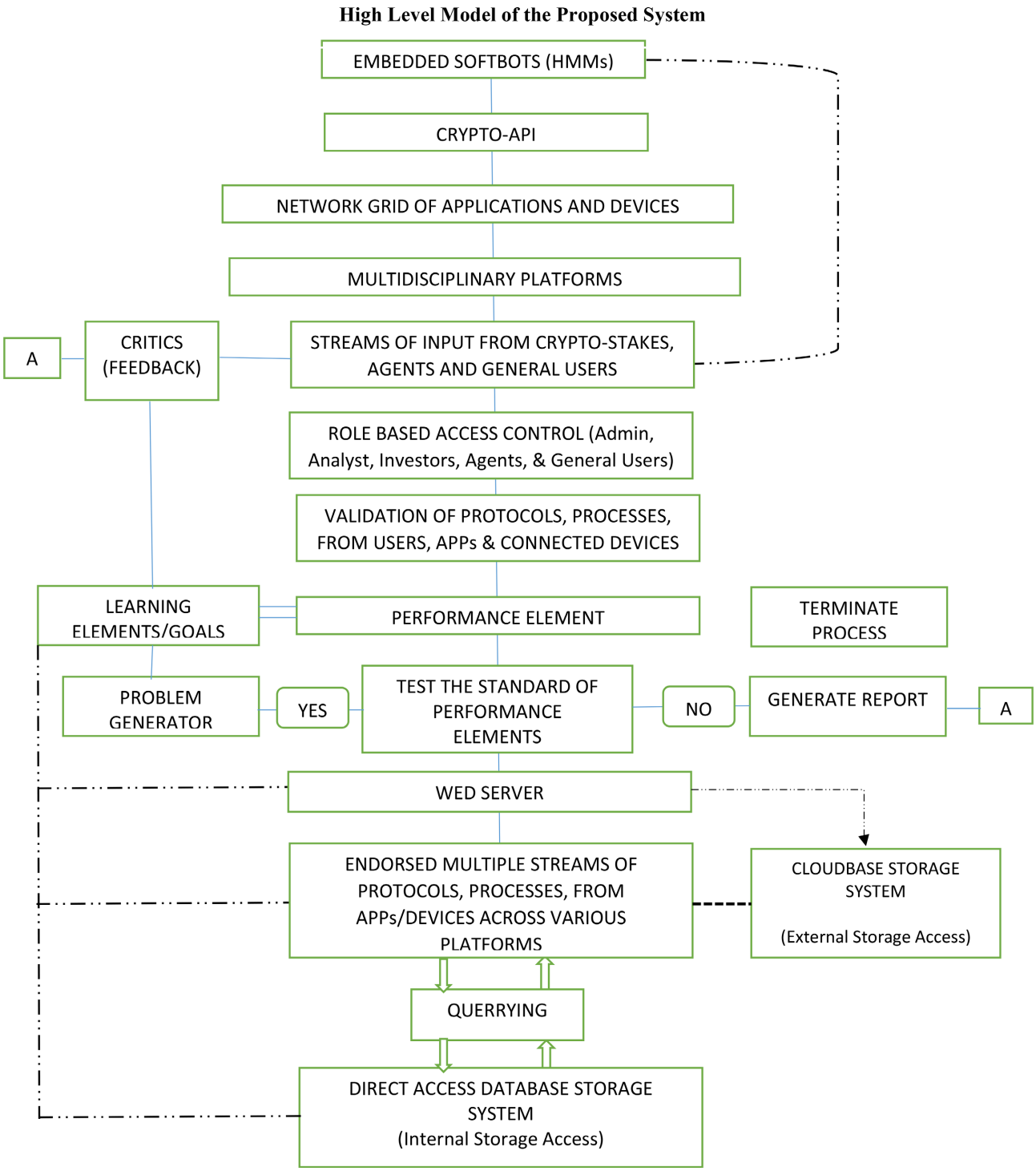


Figure 10. High-level model of the proposed system.

4) Inference Module

For decoding hidden states or computing probabilities:

Forward Algorithm: $P(O|\lambda)$

Viterbi Algorithm: Most probable state sequence (argmax $P(Q|O, \lambda)$)

Backward Algorithm: For posterior decoding

5) Evaluation Module

Model assessment: Log-likelihood on validation/test set, Cross-validation support, Accuracy of decoded sequences (if ground truth is available), BIC/AIC for model comparison.

Desirable Model Features

Feature	Importance.
Scalability	It can handle large state or observation spaces efficiently.
Extensibility	Support for variants: e.g., Hidden Semi-Markov Models (HSMM), Input-Output HMMs.
Interoperability	It can work with libraries like NumPy, TensorFlow, PyTorch, or scikit-learn.
Interpretability	The states and transitions are interpretable.

Numerical Stability: Uses log-space computations to prevent underflow (especially in forward-backward).

Critical Perspective

Strengths	Limitations
✓ Clear probabilistic interpretation	✗ Assumes Markov property and conditional independence, which may not hold in real-world data
✓ Widely applicable to time-series	✗ Difficult to scale to long-range dependencies (solved better by RNNs, Transformers)
✓ Fast training via Baum-Welch	✗ Local optima and sensitivity to initialization
✓ Efficient inference algorithms	✗ Limited expressiveness (no memory of past beyond one state)

Design Patterns consist of Software developed with Python, taking an Object-Oriented Programming approach or modular design into consideration. The high-level HMM model balances mathematical rigor, modularity, and practical usability, and it clearly defines and encapsulates the five HMM parameters. It offers robust training and decoding methods that are adaptable for discrete or continuous data. It includes evaluation tools that can be used to assess and compare models. The model is designed to extend into more expressive models (like deep HMMs or hybrid models with neural nets). This makes it not only theoretically sound but also ready for deployment in real-world applications.

4. Conclusions

This research investigated the application of Hidden Markov Models for financial

forecasting and risk management in cryptocurrency markets. Our findings demonstrate that HMMs, particularly multi-state non-homogeneous and composite configurations, can effectively capture the complex dynamics of cryptocurrency returns and provide valuable insights for investment decision-making. The 4-state NHHM model successfully identified distinct market regimes corresponding to bull, bear, calm, and highly volatile conditions across Bitcoin, Ethereum, and Ripple. These regimes exhibited characteristic return and volatility profiles, confirming the presence of regime-switching behavior in cryptocurrency markets. This aligns with previous research findings that the Non-Homogeneous Hidden Markov model with four states has the best one-step-ahead forecasting performance among competing models for cryptocurrency series. From a forecasting perspective, the HMM-based approaches outperformed traditional benchmarks, delivering more accurate one-day-ahead predictions and directional forecasts. The models' ability to adapt to changing market conditions contributed to their superior performance, particularly during transition periods between different regimes. In the domain of risk management, our composite HMM framework provided more reliable Value-at-Risk and Expected Shortfall estimates compared to historical simulation and GARCH methods. By explicitly modeling regime-dependent return distributions, the approach better captured the fat-tailed and skewed nature of cryptocurrency returns, resulting in more accurate risk assessments. This confirms previous findings that the composite factorial HMM approach performs better, in terms of prediction accuracy, than other baseline methods, particularly for VaR and ES predictions. The practical utility of our methodology was demonstrated through a dynamic portfolio allocation strategy that adjusted cryptocurrency weights based on inferred market states. This approach outperformed benchmark strategies in terms of risk-adjusted returns and drawdown control, highlighting the potential benefits of state-dependent investment decisions.

In conclusion, Hidden Markov Models offer a powerful framework for analyzing cryptocurrency markets, enabling investors to navigate the inherent volatility and complexity of this emerging asset class with greater insight and precision. By identifying market regimes, forecasting price movements, and quantifying potential risks, HMMs contribute to more informed and potentially more profitable cryptocurrency investment strategies.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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