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A Literature Review of Strategic Cryptocurrency Portfolio Optimization Leveraging Deep Learning Models

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Abstract

The rise of cryptocurrency markets has presented both opportunities and challenges for investors, particularly due to the volatile nature of digital assets such as Ethereum (ETH), FLOW, and Ripple (XRP). Effective portfolio management in this domain requires sophisticated techniques capable of capturing price trends and predicting future movements with high accuracy. This study proposes a literature review on deep learning-based approach for cryptocurrency portfolio management. Additionally, the study also includes leveraging Long Short-Term Memory (LSTM) networks—a variant of Recurrent Neural Networks (RNN) to forecast the price movements of ETH, FLOW, and XRP. The LSTM model deployed was designed to process time-series data and handle the unique complexities of the cryptocurrency market, such as volatility and non-linear patterns. By optimizing the model using the ADAM optimizer and employing key performance metrics like Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), the study evaluates the model's predictive accuracy. The results demonstrate the LSTM model's potential in forecasting cryptocurrency price trends and enhancing portfolio decision-making by providing data-driven insights into risk management and asset allocation. This research contributes significantly to the growing literature on applying deep learning models in financial markets and offers practical implications for investors seeking to optimize their cryptocurrency portfolios. The study also highlights the broader applicability of LSTM networks in predicting price movements across different digital assets, emphasizing their utility in managing the inherent risks of cryptocurrency investments.

Keywords: Cryptocurrency, LSTM Model, Price, Price movements, Volatility

1. Introduction

Ethereum, the second-largest cryptocurrency by market capitalization, has emerged as a pivotal entity in the cryptocurrency ecosystem owing to its decentralized platform for smart contracts and decentralized applications (dApps). The valuation of Ethereum (ETH) is affected by a confluence of technical, economic, and speculative elements that distinguish it from other cryptocurrencies like Bitcoin. The foundational technology of Ethereum significantly influences its price, with smart contracts and decentralized apps acting as primary catalysts for demand for Ether (ETH), its native coin. Buterin (2013) presented Ethereum as a decentralized platform that transcends basic peer-to-peer cash transactions, allowing developers to construct programmable apps on the blockchain. This essential distinction has drawn a wider array of developers, investors, and organizations to Ethereum in contrast to Bitcoin. FLOW cryptocurrency was created by Dapper Labs, the firm responsible for the renowned Ethereum-based decentralized application, CryptoKitties. Launched in 2017, CryptoKitties illustrated the promise of blockchain-based digital assets while also revealing scalability challenges on Ethereum, especially during times of elevated user engagement. This resulted in network congestion and elevated transaction costs, indicating that Ethereum's infrastructure was challenged by the volume (Buterin, 2020). Dapper Labs developed Flow, a blockchain designed to address scalability challenges and enhance performance for gaming, decentralized apps (dApps), and non-fungible tokens (NFTs) (Dapper Labs, 2020).

Originally the native cryptocurrency of the Ripple network, XRP is mainly aimed at providing remittance systems, currency exchange, and real-time gross settlement (Gupta & Chatterjee, 2021). Ripple's consensus algorithm, commonly known as the Ripple Protocol Consensus Algorithm (RPCA), is based on the Ripple Protocol Consensus Algorithm (RPCA).It enables faster transaction speeds and lower energy use (Schwartz et al., 2014). The Ripple network is more centralized than other distributed networks, as it requires a group of trustworthy validators to verify transactions (Hileman & Rauchs, 2017) Many financial institutions have also shown deep interest in this cryptocurrency due to its position as a bridge between fiat and other cryptocurrencies that facilitate cross-border payments. (Davradakis, 2019).

Definitions:

- "Ethereum is a decentralized, open source blockchain technology that allows users to build and launch smart contracts and decentralized apps (dApps). It was suggested by Vitalik Buterin in 2013 and launched in 2015. Unlike Bitcoin, which primarily functions as digital money, Ethereum’s main purpose is to provide a decentralized computing tool for executing peer-to-peer contracts using its native cryptocurrency, Ether (ETH)."
  -Buterin, Vitalik., 2013
- “FLOW is the native token of the Flow blockchain, a decentralized platform designed for games, decentralized applications (dApps), and non-fungible tokens (NFTs). It acts as the core currency for all transactions and network participation, enabling users to pay for services, transfer value, and interact with smart contracts.”
  - Dapper Labs, 2020
- "XRP is the native cryptocurrency of the Ripple network, which uses a unique consensus algorithm called the Ripple Protocol Consensus Algorithm (RPCA). This protocol allows for faster transaction confirmations,

usually within seconds, and requires much less computational power compared to traditional Proof-of-Work (PoW) systems like Bitcoin."

-Schwartz et al., 2014

2. Literature Review

Blockchain is a series of blocks interconnected through cryptographic techniques, effectively documenting transactions between entities. Both financial and non-financial sectors benefit from consensus across several platforms. An article examined the uses of blockchain, research on Corda and Ripple, and compares their systems (Benji, M., & Sindhu, M., 2019). Bitcoin was the first cryptocurrency to utilize blockchain and has been dominating the market since 2009. Since then, more than 1,000 cryptocurrencies and crypto tokens have been developed, with roughly 919 trading on unregulated or registered exchanges. A few tax authorities recognize these tokens as commodities, although their risk and return structure vary. A novel financing method for bitcoin and blockchains encompasses the deployment of a Cryptocurrency Index (CRIX) portfolio that indicates minor return correlations with conventional assets, and combining CRIX returns boosts risk-return performance (Lee, D. K. C., Guo, L., & Wang, Y. ,2018). Cryptocurrencies have gone into the mainstream, with big corporations such as Tesla and PayPal adopting Bitcoin and organizations like MicroStrategy investing extensively in cryptocurrencies as a hedge against inflation (Yermack, 2021). The function of central bank digital currencies (CBDCs) has also been a focus of interest, with countries examining state-backed digital currencies as a controlled alternative to decentralized cryptocurrencies (Auer & Böhme, 2020).

Unlike conventional financial assets such as equities or bonds, the price dynamics of cryptocurrencies are impacted by a complex interplay of variables, including supply and demand, investor mood, market speculation, regulatory changes, and technical breakthroughs. The supply-and-demand connection is one of the key elements driving cryptocurrency values. According to Shiller (2017), speculative bubbles and herd behaviour contribute significantly to price fluctuations, with investors typically purchasing into the market based on predictions of future price increases rather than basic examination. An empirical study by Urquhart (2017) reveals that cryptocurrencies exhibit inefficiencies and are frequently vulnerable to speculative trading. His results demonstrate that the market does not obey the Efficient Market Hypothesis (EMH), since knowledge asymmetries, market manipulation, and irrational conduct commonly contribute to price discrepancies.

During market downturns, fundamental value models may underestimate the significance of negative sentiment, resulting in a delay in reacting to unexpected price decreases. GARCH models also have limits in their forecasting capacity during times of exogenous shocks that are not fully accounted for in previous data. Econometric models like ARIMA and VAR tend to perform well in short-term predictions but are less effective for long-term price prediction owing to their dependence on past data and limited capacity to absorb structural changes in the market. Although network value models are effective in explaining long-term growth, their applicability in short-term trading techniques or anticipating market corrections is restricted (Gandal & Halaburda, 2016).

One such literature study analysed historical events, technical improvements, and the model methods for price forecasts of cryptocurrencies. Cryptocurrencies have developed substantially since their introduction, expanding from small technology experiments to a worldwide financial phenomenon. The growth of cryptocurrencies has been driven by breakthroughs in cryptographic technology, economic experiments, governmental reactions, and increased public interest in decentralized systems. The notion of cryptocurrencies was popularized with the introduction of Bitcoin in 2009 by an unknown entity, Satoshi Nakamoto, via the publishing of the whitepaper titled "Bitcoin: A Peer-to-Peer Electronic Cash System" (Nakamoto, 2008). Bitcoin's success may be credited to the underlying blockchain technology, which is a distributed ledger that securely records transactions in a transparent and tamper-resistant way (Narayanan et al., 2016). Bitcoin's success cleared the path for the development of other cryptocurrencies, or "altcoins." Altcoins, such as Litecoin (2011), Ripple (2012), and Peercoin (2013), were founded with the objective of improving upon Bitcoin's limitations—such as transaction speed, energy consumption, or scalability (Pagliery, 2014).

Studies by Liu and Tsyvinski (2018) imply that technical risks and breakthroughs relating to scalability, security vulnerabilities, and network improvements directly impact cryptocurrency pricing. The price of cryptocurrencies is also impacted by larger macroeconomic issues. Research by Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) analyses how cryptocurrencies respond to geopolitical threats, monetary policy, and financial market volatility. During the COVID-19 pandemic and subsequent economic downturns, Bitcoin witnessed huge price rises as it became considered a hedge against inflation and monetary debasement (Cheah et al., 2020). Similarly, interest rate decisions by central banks, inflation statistics, and other macroeconomic variables have been found to impact investor behaviour and price in cryptocurrency markets. Similar studies like above by Gandal and Halaburda (2016) suggest that pronouncements addressing regulations, such as government crackdowns on exchanges or limits on mining activities, typically result in short-term price decreases.

Cryptography, an innovation that turns readable information into codes, is utilized to run cryptocurrencies. Blockchain, the primary book of all crypto transactions, records transactions and ownership. Blockchain "miners" oversee this system, ensuring transaction security. (Milutinović, M. ,2018). Cryptocurrencies like Bitcoin and Ripple are gaining popularity due to their speculative price swings. The values of these cryptocurrencies are partially affected by global stock indexes, gold prices, and fear gauges. A time series study utilizing several models indicated that the Bitcoin collapse of 2018 might have been explained using these approaches. However, returns on Ripple did have a direct influence on Bitcoin prices (Malladi, R. K., & Dheeriya, P. L., 2021). Cryptocurrencies' values between 2009 and 2017 exhibited a high fluctuation and increase, suggesting long memory and price fluctuations. Nonetheless, research on important cryptocurrencies' pricing mechanisms lacks detailed examination of their fractal features and wavelet analysis.

The next important milestone occurred with the introduction of Ethereum in 2015, which introduced the notion of smart contracts. Unlike Bitcoin, Ethereum was created as a decentralized platform for generating decentralized apps (dApps) with its programming language, Solidity (Buterin, 2013). Ethereum's novelty resides in its Turing-complete Ethereum Virtual Machine (EVM), which enables developers to automate contracts and construct decentralized systems beyond simply monetary transactions (Wood, 2014). While Bitcoin with random walk. prices demonstrate long-term memory, Ethereum and Ripple reveal developing memory behaviour. (Celeste, V., et al., 2020). A research article explores the current implementation of Ripple, a payment system and digital currency, concentrating on its privacy, security, and consensus mechanism. It utilizes the present settings to not prevent forks in the system, and a required condition is supplied to prevent any forks. The research also estimates usage trends and trade dynamics using information from the Ripple Global Ledger. (Armknecht, F.,2015). Ethereum’s move from PoW to PoS, dubbed as Ethereum 2.0 or "The Merge," represented a major technical advancement (Ethereum Foundation, 2022).

The creation of central bank digital currencies (CBDCs) is another aspect that might affect Ethereum’s price in the long run. Auer and Böhme (2020) claim that the emergence of CBDCs might possibly compete with decentralized cryptocurrencies, influencing their acceptance and value. However, Ethereum’s programmable smart contracts and decentralized application platform provide it with distinct usefulness, which may protect it from some of the competition presented by CBDCs. Ethereum’s worth is mostly driven by its network effect where the value of the network rises as more people accept and build on it. Metcalfe’s Law, which says that the value of a network is related to the square of the number of connected users, has been applied to cryptocurrency marketplaces (Metcalfe B., Peterson et al., 2018). In Ethereum's case, the proliferation of decentralized apps, DeFi, and NFTs has enlarged its user base and raised demand for Ether, resulting in higher prices. Empirical research like those by Ciaian, Rajcaniova, and Kancs (2016) reveal that user adoption and transaction volume are major determinants of Ethereum’s price. As more applications are launched on Ethereum’s platform, the demand for Ether grows owing to its usage in transaction fees and smart contract execution.

FLOW was created by Dapper Labs' ecosystem, enabling scalable, quick, and developer-friendly blockchain infrastructure (Dapper Labs, 2020). It is built on a multi-node design that isolates errors in transaction processing. The base structure of FLOW navigates solutions to difficulties relating to throughput and cost, as experienced in

Ethereum, where congestion frequently causes high transaction costs (Buterin, 2020). According to Anderson (2021), FLOW's architecture is an ideal alternative for gaming and NFT initiatives, as it mainly concentrates on enabling low-cost, high-speed transactions with decentralization. Cadence's programming language has been developed to ease smart contract creation, that allows developers to create complicated decentralized apps with ease (Li, 2022).

One of FLOW's amazing abilities is its division of labour among different node types that include collector, consensus, execution, and verification nodes, which together enable the network to sustain high throughput (Dapper Labs, 2020). By dispersing work across several nodes, FLOW optimizes both efficiency and security without the danger of centralization that normally accompanies such improvements (Rizwan & Chen, 2022). Despite its advances, FLOW faces several challenges. Its ecosystem, although developing, is still in its infancy compared to more established blockchains like Ethereum and Bitcoin. Li (2022) added that although FLOW has shown potential in the NFT domain, it needs to be seen if it can grow into other industries, such as decentralized finance (DeFi). The development of FLOW's infrastructure and the acceptance of its programming language, Cadence, by a larger developer community remain essential for its future success. It needs a more decentralized network and governance mechanism, complemented by widespread usage beyond gaming and entertainment, which shall be essential for FLOW to completely achieve its promise (Buterin, 2020). Flow uses a proof-of-stake (PoS) consensus methodology, in which validators stake FLOW tokens to participate in and secure the network. Validators get compensation in FLOW for their services. The PoS approach encourages network decentralization while ensuring excellent security. FLOW token holders may also vote on governance choices, enabling the community to shape the network's future path (**Dapper** Labs, 2020). Nkrumah-Boadu, et. al., (2022) explored the interdependencies between cryptocurrencies, selected African stock markets, and gold returns before and during the COVID-19 outbreak. Using day-to-day observations, it showed that gold and cryptocurrencies offer a haven, diversification, and hedging for investors in the Ghanaian stock market. The results add to the literature on financial market interdependencies and asymmetries, indicating various investment perspectives. Policymakers and governments should adopt good market laws to effectively reap the advantages of havens, hedges, or diversification for gold and currencies under varied market situations.

The Ripple network, a significant blockchain platform with notable cryptocurrency market value, implements a Byzantine fault-tolerant consensus system. This protocol, unlike common Byzantine protocols, does not have broad knowledge of all participating nodes. An article presented a summary of such protocol and indicates that it could breach safety and liveness under benign network assumptions. (Amores-Sesar, I., et. al., 2020). This analysis provided a new consensus approach for the Byzantine Generals Problem, based on collectively trusted subnetworks within a larger network. The approach guarantees minimal latency and resilience despite Byzantine failures, using least connection and minimum trust. The algorithm is presented in its implementation inside the Ripple Protocol (Schwartz, D., et. al. ,2014). The valuation and risk of investing in cryptocurrencies, comparing them to traditional money, were also discussed in one such research. It identified factors that influence the value and risk of cryptocurrency, which included its economic performance and lack of central bank regulation. Besides such, the impact of technical features like cryptographic hashing algorithms, block creation complexity, and mining verification technology on the risk of investing in cryptocurrency assets was also observed in this research. (Pakhnenko, O., et. al., 2023) Ripple is also known for lower transaction costs, new financial services, and new liquidity corridors. It behaves as a real-time reconciliation system, foreign exchange platform, and decentralized remittance network, enabling consistent payments and international real-time transactions. Understanding Ripple's rules is vital due to their importance (Ahmadova, S., & Erek, M., 2022). The efficiency of Bitcoin, Litecoin, Ethereum, Ripple, Stellar, and Monero markets was studied using five tests in both static and dynamic scenarios. Results demonstrated a general rise in efficiency degree over time, with Bitcoin, Litecoin, and Ethereum indicating a change from less to greater efficiency while Ripple, Stellar, and Monero exhibit alternate periods of efficiency and inefficiency. (López-Martín, C., et. al., 2021). Investors, central banks, and governments are increasingly generating more interest in cryptocurrencies due to their market performances, sans any political restrictions on them. The research reveals that bitcoin market values are predictable, although the explanation could vary based on the machine-learning model. However, its dynamic characteristics and predictability still remain unclear, creating hazards (W. Yiying and Z. Yeze). Another article discusses Ripple Technology, its functioning, its use as a real-time gross transfer and remittance network, and currency exchange. Ripple facilitates financial institutions to manage payments worldwide swiftly, reliably, and cost-effectively. It also additionally examines Ripple and Bitcoin technologies, highlighting their differences while assessing their efficiency (Jani, S. ,2018). The efficiency of Bitcoin, Litecoin, Ethereum, Ripple, Stellar, and Monero markets using five tests in both static and dynamic scenarios. Results show a general rise in efficiency degrees over time, with Bitcoin, Litecoin, and Ethereum demonstrating a change from less to greater efficiency.

Ripple, Stellar, and Monero exhibit alternating periods of efficiency and inefficiency (López-Martín, Cet. Al., 2021). Three studies investigated the view of cryptocurrencies as money, with Bitcoin being seen as more effective than Ethereum or Ripple in fulfilling all three purposes. The outcomes show that cryptocurrency research ought to include core function perceptions while studying users' adoption or utilization of cryptocurrencies as money, and current information from Bitcoin use or adoption research cannot be readily transformed to other cryptocurrencies (Mahomed, N.,2017). Another article investigated an ontological discussion of whether money can highlight certain items used as currency or the abstract relationships that support it. It establishes an idea of money as both a technical and social infrastructure, emphasizing cross-border payments exemplified by Ripple and XRP (Rella, L., 2020). Impact of Intervention threats were also studied using the threshold, or GJR-GARCH model, to investigate the link between news shocks and market volatility. A substantial connection was found between news shocks and Bitcoin's price volatility, but no such effect was visible on XRP's prices, which implies that XRP may benefit from intervention management (Aysan, A. F., et al., 2023). In fact, cryptocurrencies have garnered major attention due to their continuing growth in value, attracting both investors and influencers. One such paper explores the relationship between eight unique cryptocurrencies using Person's correlation coefficient and cross-correlation computations. Bitcoin and IOTA were seen to have modest to large correlations, with cryptocurrency associations tending to rise as prices follow a downward cycle (Harjunpää, R. A. ,2017).

Recent research employed powerful artificial intelligence frameworks to evaluate Bitcoin, Ethereum, and Ripple price movements. Results reveal ANN depends more on long-term history, whereas LSTM depends on short-term dynamics. One of the study reports investigated cryptocurrency's impact on economic development, types, and expansion in transition nations like Serbia and Switzerland. The explosion of technology resulted in the rise of cryptocurrencies as a digital form of money.

The above literature discusses about the evolution, growth, modelling mechanisms and their limitations. There seems requirement of some advanced modelling algorithm that can capture maximum factors such as price drops, long term prediction capability, demand side influences, short term price corrections, handling unpredictability, managing price corrections. Therefore, an effort has been made in this research paper to create a strong portfolio of cryptocurrency investment by using ADAM optimizer for LSTM RNN Deep learning model to identify prediction efficacy for three major cryptocurrencies i.e. Ethereum (ETH), Flow (FLOW) and Ripple (XRP) and suggest whether a strong portfolio investment can include these three currencies.

The alternate hypothesis can be stated as there exists a significant difference between actual price (ap) and predicted price (pp) using LSTM RNN model for Ethereum (ETH), Flow (FLOW) and Ripple (XRP).

$$H_{1:}\ ap_1 = pp_1 \text{ [Ethereum (ETH)]}$$

$$H_{2:}\ ap_2 = pp_2 \text{ [Flow (FLOW)]}$$

$$H_{3:}\ ap_3 = pp_3 \text{ [Ripple (XRP)]}$$

3. Research Method

The research method included collection of secondary data from valid sources that explicably included Scopus indexed journals, Arxiv directory, Princeton University Journals and cryptocurrency website. The facts were systematically arranged in logical manner and presented in a rhetoric manner to highlight the features, growth and implementation of deep learning models for cryptocurrency portfolio optimization.

Further, LSTM RNN deep learning algorithm was applied using Python (open source) language programming on six years data (03-04-2018 to 27-03-2024) daily price returns for available 2462 days (Ethereum), Flow (2462 days) and 1789 days (Ripple). The: LSTM RNN python codes were run on cloud space, freely available as a part of Google collab project. The daily closing prices were fetched using stock history function in MS WORD (MS office 365). Adam optimizer, short for **Adaptive Moment Estimation**, which is a popular optimization algorithm was used for deep learning and prediction of Ethereum, Flow and Ripple future prices. It combines the advantages of two other extensions of stochastic gradient descent: **Momentum** and **RMSProp**. While Momentum helped to accelerate the gradient descent algorithm by considering the exponentially weighted average of past gradients, **RMSProp** adjusted the learning rate for each parameter based on the average of recent magnitudes of the gradients for that parameter. The predicted price for all three series of Ethereum, Flow and Ripple series were compared with their respective actual prices using t-tests. Statistical measures such as P-value, R-square and adjusted R-square were then used to ascertain the strength of Adam optimizer in LSTM RNN algorithm in predicting respective future prices. A combination of such cryptocurrencies using ADAM optimizer in LSTM RNN can be primarily included in the Cryptocurrency investment portfolio.

4. Discussion and Interpretations

The python codes for LSTM RNN yielded results for:

4.1. Current closing prices for Ethereum, Flow and Ripple:

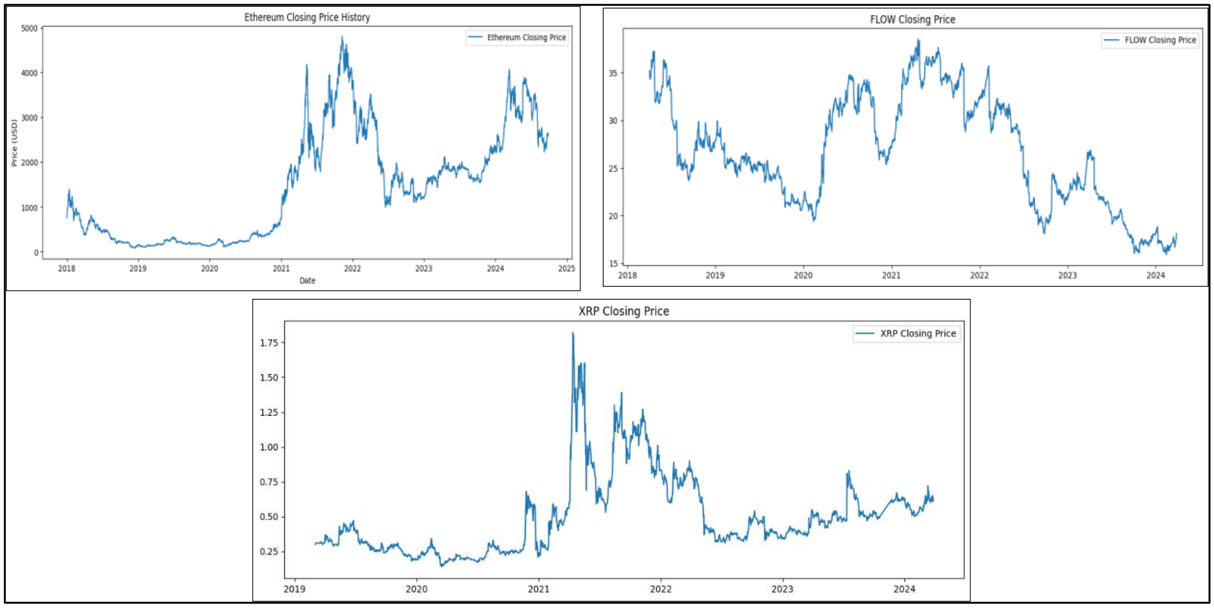

Figure 1. Closing prices for Ethereum, Flow and Ripple using LSTM RNN Model
(Source: Author analysis)

The closing prices for all the three cryptocurrencies indicate non -linear movements during the period of 2462 days (Ethereum and Flow), 1789 days (Ripple). Higher Price fluctuations were observed in Flow cryptocurrency as compared to moderate price fluctuations in Ethereum cryptocurrency prices and lower price fluctuations in Ripple cryptocurrency. This indicates that Ripple cryptocurrency seems more stable than the other two cryptocurrencies (see Figure 1).

4.2. Actual vs Predicted prices for Ethereum, Flow and Ripple:

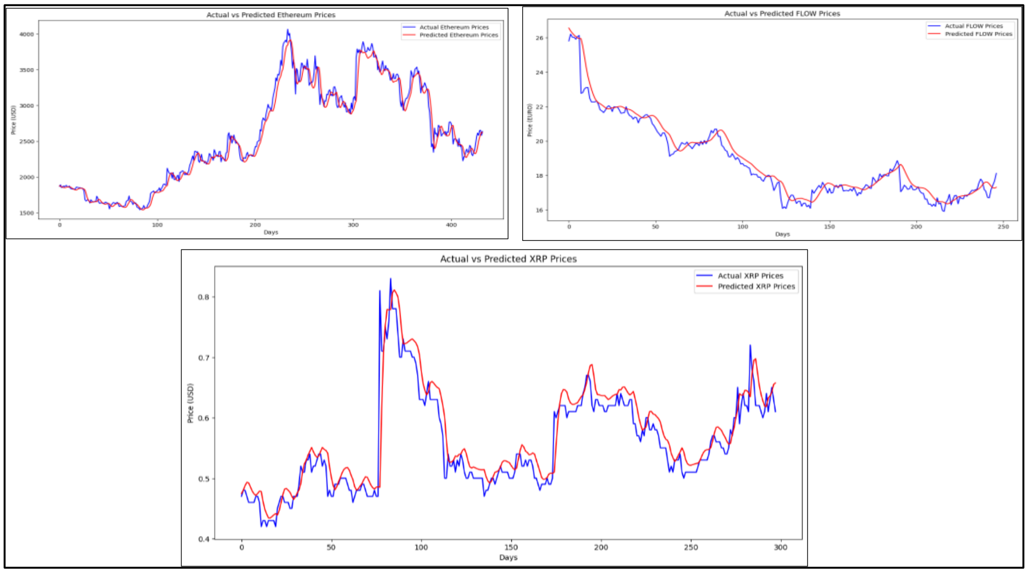

Figure 2. Actual vs Predicted prices for Ethereum, Flow and Ripple using LSTM RNN Model

(Source: Author analysis)

Ethereum prices (actual vs predicted) are very close to each other in the period of 2462 stock trading days whereas some noticeable differences between actual and predicted prices were seen in Flow and Ripple prices as predicted the LSTM RNN model using ADAM optimizer (See Figure 2).

4.3. Actual vs Predicted prices with future predictions for Ethereum, Flow and Ripple

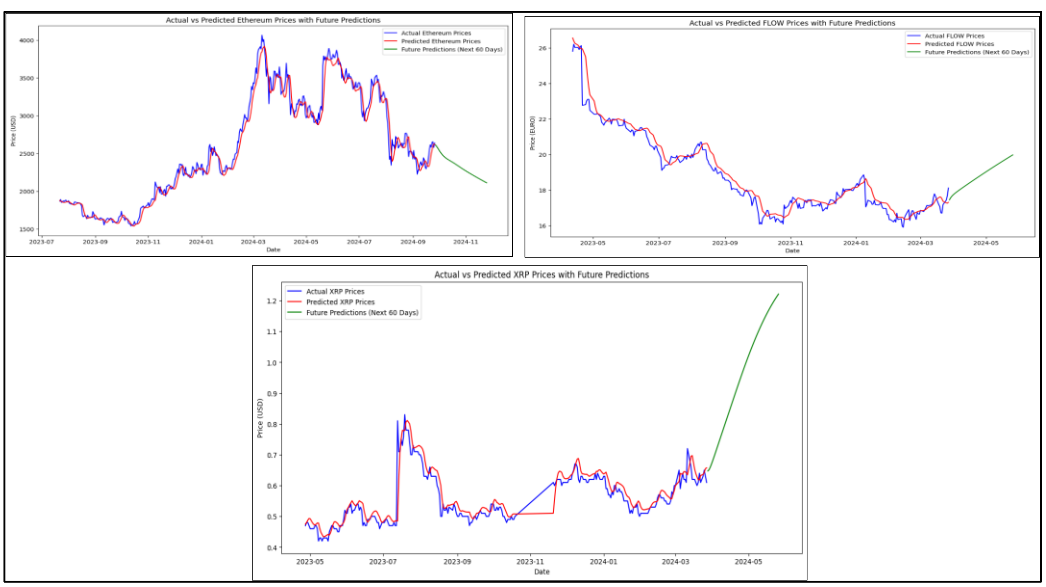

Figure 3. Actual vs Predicted prices with future predictions for Ethereum, Flow and Ripple using LSTM RNN Model
(Source: Author analysis)

Both Flow and Ripple shows positive trends as prices are predicted to rise in the predicted period of 60 days whereas Ethereum future prices shows decline trend, as predicted by the LSTM RNN model using ADAM optimizer (See Figure 3).

4.4. Metric results

Si. No.	**Metric**	Ethereum Values	Flow Values	Ripple Values
0	**Total Data Points**	2462	1535	1789
1	**Training Data Points**	1909	1168	1371
2	**Testing Data Points**	433	247	298
3	**Mean Squared Error**	12556.9	0.272311	0.00109407
4	**First Actual Price**	1866.58	25.8	0.47
5	**First Predicted Price**	1875.47	26.5526	0.474665
6	**Last Actual Price**	2636.51	18.11	0.61
7	**Last Predicted Price (0 day)**	2618.44	17.3014	0.657284
8	**Predicted Future Price (60^{th} day)**	2611.48	17.4421	0.647369

Table 1. Metrices from analysis of all data sets

(Source: Author analysis)

The Ethereum model was trained on 1909 data points and then tested on 433 data points to whereas the Flow model was trained on 1168 data points and then tested on 247 data points and the Ripple model was trained on 1371 data points and then tested on 298 data points, to ensure the models can predict prices accurately in Ethereum (ETH), High MSE indicates larger prediction errors, but the predicted prices are close to actual prices. Low MSE suggests accurate predictions, with predicted prices closely matching actual prices (**Flow**). Extremely low MSE indicates very accurate predictions, with predicted prices very close to actual prices (**Ripple- XRP**). (see Table 1). The predicted prices are very close to the actual prices, indicating the model's predictions are quite accurate. The slight differences suggest the model is performing well but can be fine-tuned further (**Ethereum**). The predicted prices are also close to the actual prices, showing good model performance. The small discrepancies indicate the model is reliable (**Flow)**. The predicted prices are extremely close to the actual prices, demonstrating very high accuracy. This suggests the model is highly effective for Ripple (See Table 1).

4.5 . Test of hypothesis

	Ethereum Values	**Meaning**	Flow Values	**Meaning**	Ripple Values	**Meaning**
P-value	0.8241091988859905	> 0.05	0.2768771821989587	> 0.05	0.024161514691128826	< 0.05
R-squared	0.9768113523134965	Very High explainability	0.9471847869662496	Very High explainability	0.8265770899218106	High explainability
Adjusted R-squared	0.9767575503467064	Very High explainability considering sample size	0.9469692146681526	Very High explainability considering sample size	0.825991201712087	High explainability considering sample size

Table 2. Hypothesis test results between actual vs predicted values

(Source: Author analysis)

Strong R-squared values were observed in all cryptocurrencies, more prominently for Ethereum and Flow value predictability (actual vs predicted values). This indicates that both Ethereum and Flow can be included in the cryptocurrency portfolio of investments. The models for Ethereum and Flow have very high explainability but are not statistically significant (p-value> 0.05), **while the model for Ripple is statistically significant with high explainability (See Table 2).**

5. Findings and conclusion

1. Ripple cryptocurrency predictions by LSTM RNN model using ADAM optimizer seem to be the most stable for investments and inclusion in cryptocurrency portfolio investment (See Table 2).

2. Ripple cryptocurrency closing prices indicate stability as indicated by LSTM RNN model using ADAM optimizer (See Figure 1).

3. Extremely low MSE in Ripple cryptocurrency further solidifies its inclusion for cryptocurrency portfolio investment.

4. The other cryptocurrency Flow has low MSE with high rate of accuracy in predictions indicates its inclusion among cryptocurrency portfolio investment.

5. Although being affected by high MSE, predicted prices are near to actual prices for Ethereum, which indicates that they can also be included in cryptocurrency portfolio investment.

Therefore, predictions using LSTM RNN model with ADAM optimizer for all the cryptocurrencies i.e. Ethereum, Flow and Ripple have been able to achieve high accuracy rates. The findings justify the alternate hypothesis of H_1, H_2 and H_3 which reflects the accuracy of LSTM model using ADAM optimizer.

Therefore, the above results clearly signify Ripple's cryptocurrency predictions using the LSTM RNN model with the ADAM optimizer are stable, with low mean squared error (MSE), making it a strong candidate for inclusion in cryptocurrency portfolio investments. On the other hand, the Flow cryptocurrency shows low MSE and high prediction accuracy, suggesting its suitability for cryptocurrency portfolio investments. While Ethereum has higher MSE compared to Ripple and Flow, its predicted prices are close to actual prices, indicating it could also be a viable option for portfolio inclusion. The high accuracy rates achieved across Ethereum, Flow, and Ripple using the LSTM RNN model with the ADAM optimizer support the alternate hypotheses (H1, H2, H3) and validate the effectiveness of this predictive approach for cryptocurrency investments. We can finally conclude that, strategic cryptocurrency investments using deep learning models is suitable for long term investments and hence, and thus suggested for implementation for strategic long term sustainable returns form cryptocurrency investments. This academic study shall be beneficial for academic researchers, long term cryptocurrency investors and other concerned parties.

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