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Analysis of Models for Cryptocurrency Price Forecasting

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Abstract

This thesis addresses the significant challenge on accurately forecasting highly volatile cryptocurrency prices by systematically comparing the out-of-sample forecasting performance of three distinct modeling paradigms: linear ARIMA model, non-linear LSTM deep learning network, and a hybrid ETS-ANN model. Using daily closing price data for five major cryptocurrencies from late 2017 to early 2025, a robust walk-forward validation assesses accuracy across short-term (t+1 day), medium-term (t+10 days), and long-term (t+30 days) horizons using standard error metrics. The empirical findings reveal that performance is strongly dependent on the forecast horizon. Contrary to common expectations favoring model complexity, the simpler ARIMA benchmark frequently demonstrated superiority compared to LSTM and ETS-ANN at the medium (t+10) and long (t+30) horizons for most cryptocurrencies. Although LSTM is competitive short-term and consistently performs best for the stablecoin Tether, its relative performance often degrades significantly as the horizon increases. The hybrid ETS-ANN model consistently underperformed. An exploratory analysis at the t+180 horizon confirmed substantial performance deterioration for all models, highlighting the practical limits of long-range forecasting. The core contribution lies in providing direct empirical evidence on the relative effectiveness of these models under consistent evaluation conditions across practical forecast horizons, offering critical insights into model suitability and the challenges of multi-step forecasting within complex cryptocurrency markets.

JEL Classification	C22, C52, C45, C53, G17
Keywords	Cryptocurrency Price Forecasting, ARIMA, LSTM, ETS-ANN, Walk-Forward Validation, Multi-Horizon Forecasting

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Abstrakt

Prognózování vysoce volatilních cen kryptoměn představuje významnou výzvu. Tato práce se touto problematikou zabývá prostřednictvím systematického porovnání prognostické výkonnosti tří odlišných modelovacích paradigmat: lineárního modelu ARIMA, nelineární sítě hlubokého učení LSTM a hybridního modelu ETS-ANN. S využitím dat denních uzavíracích cen pěti významných kryptoměn od konce roku 2017 do začátku roku 2025 je vyhodnocena pomocí metody průběžná validace (walk-forward validation) přesnost v krátkodobém (t+1 den), střednědobém (t+10 dnů) a dlouhodobém (t+30 dnů) horizontu pomocí standardních chybových metrik.

Empirická zjištění ukazují, že výkonnost silně závisí na prognostickém horizontu. Přes očekávání lepší výkonnosti složitějších neliárních modelů, jednodušší referenční model ARIMA často prokazoval superioritu ve srovnání s LSTM a ETS-ANN ve střednědobém (t+10) a dlouhodobém (t+30) horizontu pro většinu kryptoměn. Ačkoliv je LSTM konkurenceschopný v krátkodobém horizontu a konzistentně dosahuje nejlepších výsledků pro stablecoin Tether, jeho relativní výkonnost často významně klesá s rostoucím horizontem. Hybridní model ETS-ANN konzistentně vykazoval horší výsledky. Explorativní analýza na horizontu t+180 potvrdila podstatné zhoršení výkonnosti všech modelů, což zdůrazňuje praktické limity dlouhodobého prognózování.

Hlavní přínos práce spočívá v poskytnutí přímých empirických důkazů o relativní efektivitě těchto modelů za konzistentních evaluačních podmínek napříč praktickými prognostickými horizonty. To nabízí kritický pohled na vhodnost modelů a výzev vícekrokového prognózování na komplexních trzích s kryptoměnami.

Klasifikace JEL	C22, C52, C45, C53, G17
Klíčová slova	Předpovídání cen kryptoměn, ARIMA, LSTM, ETS-ANN, Walk-Forward Validation, Vícehorizontové předpovídání

Název práce	Analýza modelů pro předpovídání cen kryptoměn

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Acronyms

ANFIS Adaptive Neuro-Fuzzy Inference Systems

ANN Artificial Neural Network

AR Autoregressive

ARIMA Autoregressive Integrated Moving Average

BTC Bitcoin

CNN Convolutional Neural Network

DAO Decentralized Autonomous Organization

DL Deep Learning

EMH Efficient Market Hypothesis

ETH Ethereum

ETS Exponential Smoothing Models from Innovation State Space

ETS-ANN Exponential Smoothing Models from Innovation State Space with Artificial Neural Network

GARCH Generalized Autoregressive Conditional Heteroskedasticity

GRU Gated Recurrent Unit

HFT High-Frequency Trading

MA Moving Average

ML Machine Learning

NFT Non-fungible Token

LSTM Long Short Term Memory

LTC Litecoin

MAE Mean Absolute Error

MAPE Mean Absolute Percentage Error

RMSE Root Mean Squared Error

RNN Recurrent Neural Network

SVM Support Vector Machines

SVR Support Vector Regression

USD US Dollar

USDT Tether

XAI Explainable AI

XRP Ripple

Chapter 1

Introduction

The emergence of cryptocurrency represent significant financial innovation. Through leveraging decentralized blockchain technologies, defined as a computing technology for safe, transparent, and trust-less transaction recording and processing (Tran & Krishnamachari 2022), it challenges traditional monetary systems (Poskart 2015; Nakamoto 2008). Despite this new asset class encompassing traits of extreme price volatility and complex market dynamics, it has managed to attracted substantial market and academic attention. The fluctuations in cryptocurrency appear to be driven by an intricate interplay of technological advancements, investor sentiment, and macroeconomic factors (Núñez *et al.* 2019; Köchling *et al.* 2020; Khedr *et al.* 2021). Henceforth, the accurate forecasting of these volatile prices forms a critical challenge (Awoke *et al.* 2021; Giacomo Minotti 2022).

Although traditional linear econometric models like Autoregressive Integrated Moving Average (ARIMA) provide a benchmark Zhang (2003), their underlying assumptions of linearity and stationarity are often inconsistent with the empirical properties observed within cryptocurrency markets. This inconsistency motivates the use of machine learning approaches, such as Long Short Term Memory (LSTM) networks, and structured hybrid models, like the Exponential Smoothing Models from Innovation State Space with Artificial Neural Network (ETS-ANN) combination (Khedr *et al.* 2021; Panigrahi & Behera 2017), which theoretically offer greater flexibility in capturing complex non-linear patterns.

Despite the numerous studies applying various forecasting techniques, rigorous comparisons across these distinct modeling paradigms including linear, non-linear, and hybrid using realistic evaluation methods and assessing performance across different, defined time horizons remain relatively scarce. This thesis addresses this gap by systematically evaluating the forecasting performance of ARIMA, LSTM, and ETS-ANN models for five selected major cryptocurrencies. Using daily data spanning from November 9, 2017, to January 1, 2025, the thesis employs a robust walk-forward validation methodology to compare predictive accuracy across short-term t+1 (day), medium-term t+10 (10 days), and long-term t+30 (30 days) forecast horizons using standard statistical error metrics. An exploratory analysis of the much longer t+180 horizon is also presented to gauge performance limits. The core contribution lies in providing direct empirical evidence on the relative effectiveness and limitations of these prominent forecasting methodologies under consistent, practical conditions, offering insights into model suitability across distinct forecast horizons within these complex and volatile markets.

Chapter 2

Literature Review

The rise of cryptocurrencies contributed to a significant shift in the financial world that challenge traditional notions of currency and financial transactions. This transformative development is seen as one of many consequences of the global financial crisis (Poskart 2015). The unprecedented monetary policy response during the period, particularly large-scale quantitative easing spearheaded by the US Federal Reserve, provided a vast flow of liquidity into the financial system. Although the purpose of the response intended to stabilize the markets, these actions concurrently fueled inflation concerns among investors and triggered a crisis of confidence in both regulatory institutions and global financial systems (Paul 2009). The moment of uncertainty, combined with rapid technological advancements, laid the fertile ground for financial innovation, ultimately giving rise to decentralized digital alternatives challenging the central banks over the monopoly of money(Poskart 2022).

Initially introduced pseudonymously during the 2008 subprime mortgage crisis by Nakamoto (2008),Bitcoin emerged as the pioneering cryptocurrency. Since its introduction, Bitcoin has been recognized as the first cryptocurrency characterized as a hybrid entity, possessing the traits of both scarce commodities: gold and transactional currencies such as the US dollar (Baur *et al.* 2018a). However, it is crucial to recognize that Bitcoin was not the first of its kind, as the inception of digital currency research can be traced far back. Decades earlier, the proposal by David Chaum for an anonymous electronic currency system formed the foundation of the earliest digital currency theory (Chaum 1983). It was called the digiCash, and utilized the blinding formula to encrypt and let individuals send and receive money only through authenticating signatures. Subsequent innovations include Hashcash by Back (2002), and b-Money by Dai (1998) which came to the emergence in 1997 and 1998, respectively, introducing unique and critical innovations such as the use of proof-of-work algorithms, anonymity, and decentralized network architecture that proved instrumental in the design of cryptocurrencies today.

Although initially designed to be a medium of exchange, Bitcoin transcended its initial framework and is often thought to be a new class of assets (Baur *et al.* 2018b; Ram 2019; Li *et al.* 2021), because it did not belong to any of the traditional asset classes. This digital currency marked a turning point by offering decentralized, peer-to-peer transactions facilitated by blockchain technology (Miers *et al.* 2013; Constantinides *et al.* 2018). These features have attracted investors seeking alternatives to traditional assets, driven by factors including the autonomy offered by its decentralized structure (preventing central authority control and seizure), the potential for lower transaction costs (particularly for cross-border payments compared to banks), and prospect for higher returns (Nian & Chuen 2015). These characteristics often contrast with traditional banking systems (Shahen Shah *et al.* 2023). Subsequently, academic research began to explore the role of cryptocurrencies as a potential investment asset, offering diversification and hedging opportunities to investors relative to commodities, equities, and currencies (Bouri *et al.* 2017; Guesmi *et al.* 2019). Moreover, the market underwent significant growth and in the first quarter of 2025, more than 13,000 cryptocurrencies are in circulation, with a market capitalization exceeding \$2.72 trillion, over more than half of which is attributed to Bitcoin (Coinmarketcap 2025). The ever increasing sophistication of the market is also evidently experienced in High-Frequency Trading (HFT), driven by algorithmic bot accounts for most trading volume, potentially increasing the complexity of the market and challenges for human traders to make short-term profit (Ibrahim *et al.* 2021). This complex and dynamic environment highlights the critical demand for a robust price forecasting methodologies, driving significant research into the application of statistical and machine learning models (Chen *et al.* 2021).

Beyond speculative investments, cryptocurrencies and their underlying blockchain technology are being used to reduce transaction costs for financial institutions and are increasingly recognized as legal tender in some countries (Alvarez *et al.* 2023; Consensys 2020; Bloomberg 2017). These developments underscore their growing relevance in global financial markets and have drawn the attention from policy makers and researchers. Empirical studies have consistently identified key traits of cryptocurrency markets. The most notably, high volatility (Núñez *et al.* 2019; Köchling *et al.* 2020), volatility clustering and long memory (Naimy *et al.* 2021), propensity to market jumps (Phiromswad *et al.* 2021), strong internal correlation (Katsiampa 2019), and isolation or weak correlation from other asset classes except during financial crises, when contagion increases (Zeng *et al.* 2020; Urom *et al.* 2020). Among these empirical studies, a fundamental debate persists on the main economic role of cryptocurrencies, whether they serve primarily as an investment asset or as currency alternatives, particularly their potential as a safe haven. Some argue that Bitcoin is unreliable as a safe haven, especially in the short term or during crises such as the COVID-19 pandemic (Grobys 2021), other research suggests that certain cryptocurrencies behave like 'virtual gold' in times of market turbulence (Mariana *et al.* 2021).

The exponential rise of the use of internet has accelerated the shift from cash to digital transactions, including cryptocurrencies, valued for their speed and border-less nature (Galariotis & Karagiannis 2021; Sukumaran *et al.* 2022). Digital payments were projected to reach $9.46 trillion in 2023, with 11.8% annual growth reaching $14.78 trillion by 2027 (Siska 2023). The increasing rate of adoption of cryptocurrency is not without hurdles, as regulatory constraints and security concerns persist (Li *et al.* 2023). As a result of this momentum, monetary systems are compelled to evolve, adapt, and establish new policies (Hasan *et al.* 2022). Not to mention the economic importance of cryptocurrency in the labor market, between 2015 and 2019 alone, the crypto-related workplaces within the mainstream economy increased by nearly 1,500%. Along with the increase in the activities of all the recent innovations of Non-fungible Token (NFT)s, Decentralized Autonomous Organization (DAO)s, for sales and fundraising, further complicate the sector and create demand for specialized skills (Global Digital Assets Capital 2021).

Given the complex backdrop, the ability to accurately forecast cryptocurrency values extends beyond academic curiosity and holds significant practical implications for investors and global trade (Awoke *et al.* 2021). The value of cryptocurrency reflect their growing utility, and remain highly volatile and difficult to predict (Klein *et al.* 2018; Fang *et al.* 2020). This defining characteristic of this market of extreme volatility (Böhme *et al.* 2015; Gupta 2024), where prices are highly sensitive to a multitude of influences, including investor sentiment shaped by news and social media, macroeconomic factors such as inflation and interest rates, institutional investment flows, and speculative retail trading, which can often exhibit herd behavior dynamics (Gupta 2024; Islam *et al.* 2025; Hoque Jui *et al.* 2023; Jagannath *et al.* 2021; Poudel *et al.* 2023; Sovbetov 2018). This inherent instability and the complex interplay of factors make accurate price forecasting exceptionally challenging but crucial for market participants, thereby driving significant research into robust forecasting modeling (Crypto Research Report 2020). Some empirical studies highlight price clustering, leverage effects, and power-law correlations, making forecasting challenging (Zhang *et al.* 2018).

Traditional time series forecasting methods commonly employed in established financial markets, such as the ARIMA family of models (Roy *et al.* 2018) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models designed to capture volatility, often encounter significant limitations when applied directly to the cryptocurrency context (Islam *et al.* 2025; Naimy *et al.* 2021; Kiranmai & Thangaraj 2023). These classical models typically rely on assumptions of linearity (Chatfield & Yar 1988), stationarity, and normally distributed errors, which frequently do not hold in cryptocurrency markets known for their non-linear dynamics, abrupt regime shifts, fat tails in return distributions, and volatility clustering (Islam *et al.* 2025; Rana *et al.* 2025; Ray *et al.* 2025). Moreover, the complex and often non-quantifiable factors influencing cryptocurrency prices, ranging from developer activity to social media sentiment, are difficult to incorporate into these classical frameworks. Consequently, multiple comparative studies have concluded that the forecast accuracy of models like ARIMA is generally inferior to that achieved by various Machine Learning (ML) techniques when forecasting cryptocurrency prices, highlighting the need for models better equipped to handle non-linearity and complex dependencies (McNally *et al.* 2018; Shin *et al.* 2021; Akyildirim *et al.* 2023).

Recognizing these limitations, researchers have increasingly turned to ML and recently the Deep Learning (DL) algorithms, drawn by their inherent ability to identify complex, non-linear patterns and interactions within large, high-dimensional datasets (Jay *et al.* 2020; Rahman *et al.* 2024). Furthermore, Derbentsev *et al.* (2020) and Ibrahim *et al.* (2021) studies show that the ML based forecasting models were better than those using traditional statistical methods. Models including Decision Trees, Support Vector Machines (SVM), and various variants of Artificial Neural Network (ANN)s offer more flexible and data-driven frameworks. These techniques are capable of integrating diverse data sources which range from raw price and volume data to sophisticated technical indicators, on-chain metrics, and even unstructured text data from news and social media, hence providing a potentially more holistic view of market drivers (Jay *et al.* 2020; Agarwal *et al.* 2021; Rahman *et al.* 2024). A key theoretical advantage of many ML and DL models is their ability to learn and adapt to evolving market dynamics and changing relationships between variables, making them theoretically more suitable for the volatile and rapidly changing cryptocurrency market (Sumsuzoha *et al.* 2024).

ANN, represent a powerful class of models that function as universal approximators, meaning they can theoretically model any arbitrarily complex non-linear relationship between a set of input features and output targets, given sufficient data and network complexity with neurons and layers (Wasserman 1989; Lippmann 1987). For time-series forecasting tasks, ANNs can be configured to perform non-linear regression, predicting price based on various causal indicators, or non-linear autoregression like predicting future price based on past price observations and potentially other lagged variables (Zhang *et al.* 1998). The network learns these complex mappings through a supervised training process, typically using backpropagation to iteratively adjust the connection weights between neurons to minimize the error between the network's predictions and the actual historical data (Zhang *et al.* 1998). However, the flexibility of ANNs also presents challenges. They can be highly prone to overfitting, where the model learns the noise of the training data too well, leading to poor performance on new data. They also often require careful data pre-processing and can be sensitive to hyperparameter choices demanding significant computational resources for effective implementation (Jay *et al.* 2020).

Among the DL techniques applied to sequential data like time series, Recurrent Neural Network (RNN)s, and specifically their advanced variant, LSTM networks, have garnered significant attention and demonstrated considerable success in cryptocurrency price prediction (Thakkar & Chaudhari 2021; Zubair *et al.* 2024). Moreover, Khedr *et al.* (2021) attempted to review the performance of ML methods for cryptocurrency price forecasting, and reached the conclusion that the LSTM method is considered the best method for predicting cryptocurrency price time series, along with other academics, (Ren *et al.* 2022; Chen *et al.* 2021; Lahmiri & Bekiros 2019; Li & Dai 2020), because of its ability to recognize long-term time-series associations. Additionally, Zhang *et al.* (2021) and Bianchi *et al.* (2021) utilized neural networks, and LSTM, and have also reached the conclusion of better accuracy on the US stocks and bonds, as well as for cryptocurrencies (Anghel 2021; Liu *et al.* 2021). The standard RNNs theoretically allow information to persist across time steps, but in practice, they struggle with learning long-range dependencies due to issues of vanishing gradients during training. LSTM were explicitly designed to overcome these limitations through a sophisticated internal architecture involving 'gates' (input, forget, and output gates), (Thakkar & Chaudhari 2021), that regulate the flow of information through the network's memory cells. This gating mechanism allows LSTMs to selectively remember relevant information over extended periods and forget irrelevant details, making them particularly well-suited for capturing the complex temporal dependencies, seasonality, and long-term trends often present in financial time series, including volatile cryptocurrency prices (Zubair *et al.* 2024; Alnami *et al.* 2025). Numerous empirical studies have benchmarked LSTM against other models, frequently finding it superior for cryptocurrency forecasting. For instance, Phaladisailoed & Numnonda (2018) reported that LSTM achieved the highest accuracy among the four models tested which included regressions and Gated Recurrent Unit (GRU) for Bitcoin prediction. (McNally *et al.* 2018), incorporating Bitcoin-specific attributes like network difficulty and hash rate alongside price data, found that LSTM also achieving high accuracy in their study, outperforming both ARIMA and a basic RNN structure. Aggarwal *et al.* (2019), exploring the predictive power of gold prices for Bitcoin, concluded that LSTM performed better than both Convolutional Neural Network (CNN)s and GRUs, achieving great Root Mean Squared Error (RMSE) results. Furthermore, Chen *et al.* (2021) demonstrated the LSTM's consistent superior prediction accuracy as compared to ARIMA, Support Vector Regression (SVR), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) across various market sub-periods when utilizing a comprehensive set of input variables including blockchain data and public attention metrics. These consistent findings underscore the potential of LSTMs to model the intricate dynamics of cryptocurrency markets.

Recognizing that financial time series, including cryptocurrency prices, often exhibit complex structures containing both linear and non-linear patterns, hybrid forecasting models have emerged as a significant area of research. The core idea is to combine the strengths of different model types, rather than relying on a single approach in order to achieve potentially more robust forecasts (Zhang 2003; Panigrahi & Behera 2017). A prevalent hybrid strategy involves a two-stage process, where a linear model, often from the ARIMA family, is used to capture the linear autocorrelation structure within the data, and then, a non-linear model, typically an ANN is trained to model the residuals from the linear fit, effectively capturing the remaining non-linear patterns unexplained by the initial linear model. The final forecast is then the sum of the predictions from both the linear and non-linear components (Zhang 2003; Ömer Faruk 2010; Khashei & Bijari 2011; Khandelwal *et al.* 2015). Another approach involves decomposing the original time series into different components of trend, seasonality, noise, or low/high volatility components using e.g. moving averages, and then applying appropriate linear or non-linear models to each component before aggregation (Babu & Reddy 2014; de Oliveira & Ludermir 2016). However, these traditional hybrid approaches have limitations. ARIMA-based hybrids inherit the restrictive assumptions of ARIMA regarding linearity and stationarity, which might not be suitable for inherently non-linear cryptocurrency data. Decomposition methods can sometimes suffer from issues like data loss at the beginning/end of the series due to filtering, difficulties in perfectly separating components, or requiring specific data characteristics for the separated components to be effectively modeled by subsequent linear models (Panigrahi & Behera 2017). To overcome these drawbacks, hybrid models incorporating Exponential Smoothing Models from Innovation State Space (ETS) methods have been proposed as a potentially more flexible alternative (Panigrahi & Behera 2017). The ETS state-space framework, as outlined by Hyndman & Khandakar (2008), encompasses a wide range of models that explicitly capture error, trend additive/multiplicative, damped/undamped, and seasonality additive/multiplicative. Crucially, this framework includes both linear ETS models, which are special cases of ARIMA, and inherently non-linear ETS models like those with multiplicative components, offering greater flexibility to capture diverse data patterns compared to ARIMA alone (Hyndman & Khandakar 2008; Panigrahi & Behera 2017). A particularly promising hybrid structure, and one investigated in this thesis, involves first applying an appropriate ETS model selected automatically based on information criteria or diagnostic checks to best fit the primary linear or non-linear structure in the data and then using an ANN to model the residual errors from the ETS fit. This ETS-ANN approach aims to be robust by allowing the powerful ETS framework to handle the main discernible structure whether linear or non-linear and letting the ANN focus on capturing any remaining complex, potentially non-linear patterns in the residuals, thereby accommodating various combinations of patterns potentially present in volatile time series like cryptocurrency prices (Panigrahi & Behera 2017). This methodology avoids the strict assumptions of ARIMA and the potential pitfalls of filter-based decomposition.

Notwithstanding, the significant advancements offered by sophisticated ML and DL models like LSTM and the exploration of nuanced hybrid approaches like ETS-ANN, key research gaps and challenges persist in the field of cryptocurrency forecasting. One major challenge relates to the effective application and evaluation of models across multiple forecast horizons "short, medium, and long-term" using robust validation methodologies like walk-forward analysis. Models optimized for a single-step prediction may not generalize well to longer horizons, and iterative multi-step forecasting techniques, often necessary in hybrid models like ETS-ANN, can suffer from significant error accumulation (Gholipour 2023). Ensuring models can adapt effectively within a walk-forward validation, potentially involving computationally intensive retraining, remains an important practical consideration. Additionally, the increasing complexity of advanced models, particularly in deep learning, often leads to a "black-box" problem, where the internal decision-making processes are opaque and difficult for users to interpret (Hassija *et al.* 2024). This lack of transparency can be a significant barrier to trust and adoption, especially for institutional investors, portfolio managers, and regulatory institutions who often require understandable, audit-able, and justifiable forecast rationales. Consequently, enhancing model interpretability through techniques from the field of Explainable AI (XAI) is becoming increasingly crucial (Hassija *et al.* 2024). XAI methods aim to shed light on model predictions by identifying key driving features, visualizing internal model states, or providing prediction intervals and uncertainty quantification, which can aid in model debugging, building user confidence, ensuring fairness, and potentially extracting actionable economic insights beyond simple point forecasts (Tripathy *et al.* 2025). Addressing these gaps related to multi-horizon performance under realistic validation and enhancing model explainability is vital for the continued maturation and practical application of advanced forecasting techniques within the complex cryptocurrency domain.

In summary, this review traces a clear trajectory in cryptocurrency forecasting methodologies. Initial applications relied on traditional statistical linear time-series models like ARIMA, which often proved inadequate due to the unique characteristics of the market. This led to the adoption of more sophisticated ML and DL techniques capable of handling non-linearity and complex temporal dependencies. Within the deep learning space, LSTM networks have emerged as a particularly prominent model, demonstrating success in numerous studies and different cryptocurrencies. Concurrently, hybrid models, like the ETS-ANN approach have been developed to synergistically combine the strengths of different modeling properties, aiming for improved robustness and accuracy by explicitly addressing both linear and non-linear data components.

However, the inherent volatility of the market, persistent challenges in optimal feature selection and model configuration, the need for robust performance evaluation across different time horizons using methods like walk-forward validation, and the critical demand for model explainability highlight that this field is still rapidly evolving and necessitates continued advances in research. This thesis contributes to this ongoing effort by conducting a direct empirical comparison of the performance of the LSTM model against the potentially more flexible ETS-ANN hybrid structure, using ARIMA as a crucial baseline. The evaluation employs a walk-forward validation methodology across short (t+1) "daily", medium (t+30) "monthly", and long-term (t+180) "half year" forecast horizons, utilizing historical daily data for five major cryptocurrencies. The objective is to provide further evidence-based insights into the relative strengths, weaknesses, and practical limitations of these advanced modeling approaches under realistic forecasting conditions, thereby informing the selection of effective strategies for navigating the complexities of volatile cryptocurrency assets, assessed using standard evaluation metrics including RMSE, Mean Absolute Error (MAE), andMean Absolute Percentage Error (MAPE) (Tandon *et al.* 2019; Nasirtafreshi 2022; McNally *et al.* 2018).

Chapter 3

Theoretical Framework

This chapter delves into the theoretical foundations and economic rationale underpinning the selection of the three distinct forecasting methodologies: the ARIMA model, the LSTM neural network, and the hybrid ETS-ANN hybrid model.

3.1 Autoregressive Integrated Moving Average (ARIMA) Models: The Benchmark

Theoretical Basis and Economic Rationale

ARIMA models represent a cornerstone of traditional time-series econometrics, providing a well-established framework for modeling and forecasting based on the assumption of linear dependencies within a time series (Box *et al.* 2015). Their inclusion serves two primary purposes, where the first is to act as a rigorous benchmark against which the performance of more complex, non-linear and hybrid models can be objectively compared and the second is to capture any linear autocorrelation structure that might be present in cryptocurrency price dynamics, reflecting potential mean reversion tendencies which is commonly seen in financial asset returns.

The structure of the model synthesizes the three "Autoregressive (AR), Integrated (I), and Moving Average (MA)" components. The Autoregressive AR component captures the persistence of the series, modeling the current value as a linear function of its own past values. This reflects the economic intuition that recent price levels often influence the current level. The Moving Average MA component models the current value based on past forecast errors, potentially capturing the effects of short-term, transitory shocks whose influence still lingers. The Integrated I component addresses the pervasive issue of non-stationarity, which are common in asset price series by applying differencing to the data until stationarity, a prerequisite for standard linear time series modeling. The resulting ARIMA(p,d,q) model thus provides a flexible framework for characterizing linear temporal relationships. To elaborate on the mathematics behind ARIMA Model:

- Autoregressive (AR(p)) Component: This element captures the linear relationship between the current value of the series (y_t) and its own previous values (y_{t-i}). It operates on the principle that past observations contain predictive information about future observations. The extent of this historical dependence is defined by the autoregressive order $'p'$. Mathematically, a pure AR(p) process can be represented as:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_t \tag{3.1}$$

  where c is a constant, ϕ_i are the autoregressive coefficients for each lag i, and ϵ_t is the white noise error term at time t.

- Integrated (I(d)) Component: Many real-world time series, particularly in finance, exhibit trends or seasonality, making them non-stationary (i.e., their statistical properties like mean and variance change over time). The 'Integrated' part addresses this by applying differencing to the data $'d'$ times. Differencing involves calculating the change between observations to stabilize the series' mean. For example, a first-order difference (d=1) is calculated as:

$$y'_t = y_t - y_{t-1} \tag{3.2}$$

  If $d = 0$, the series is assumed to be already stationary. Higher-order differencing can be applied if needed. The ARMA components of the model are then applied to this differenced stationary series.

- Moving Average (MA(q)) Component: This element accounts for the relationship between the current observation and the residual errors (ϵ_{t-j}) associated with previous forecasts, rather than past values of the series itself. It assumes that recent forecast errors might contain information about future values. The order $'q'$ specifies how many past errors are considered. A pure MA(q) process is represented as:

$$y_t = \mu + \epsilon_t + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} \tag{3.3}$$

where μ is the mean of the series, θ_j are the moving average coefficients for each lagged error j, and ϵ_t and ϵ_{t-j} are the current and past white noise error terms.

3.1.1 Limitations in the Context of Cryptocurrency Markets

Despite its widespread use, the theoretical framework of ARIMA experience significant limitations when applied to cryptocurrency markets. The main assumption of linearity is particularly violated by the complex dynamics often observed, which may stem from non-linear feedback trading, complex investor sentiment interactions, and economic and political climate changes. Furthermore, the assumption of stationarity might not fully hold when the underlying volatile structure of the market shifts significantly over time. Finally, the typical assumption of Gaussian white noise residuals is frequently contradicted by the empirical finding of heavy tails (leptokurtosis) and volatility clustering (time-varying variance) in cryptocurrency (Islam *et al.* 2025; Naimy *et al.* 2021; Petrică *et al.* 2016) characterized findings indicating periods of extreme movements and persistent volatility. While ARIMA can model linear autocorrelation, its inherent inability to capture these complex nonlinearities, time-varying volatility, and non-normal error distributions constitutes a major theoretical limitation when modeling assets known for such characteristics. This motivates the exploration of alternatives, with more flexible modeling approaches.

3.2 Long Short-Term Memory (LSTM) Networks: Modeling Non-Linearity and Long Dependencies

3.2.1 Theoretical Basis and Economic Rationale

Moving beyond linear frameworks, LSTM networks represent a powerful class of data-driven models, specifically designed to analyze sequential data and capture complex, non-linear temporal dependencies. LSTM models are a type of RNN, distinguished by their internal architecture which incorporates 'memory cells' and 'gating mechanisms' (input, forget, output gates).

The primary theoretical advantage of the model within the scope of economic and financial forecasting, particularly for volatile assets like cryptocurrencies, lies in their capacity to learn long-range dependencies. Unlike standard linear models or simple RNNs, which suffer from vanishing gradients, hindering learning over long sequences, the gates of the LSTM model enable the network to selectively remember relevant past information and forget irrelevant information over extended periods (Hochreiter & Schmidhuber 1997; Giacomo Minotti 2022). This is theoretically crucial for modeling markets where:

- Persistent Volatility: Volatility clustering implies that past volatility levels influence future volatility over extended periods.
- Sentiment Dynamics: Investor sentiment can build gradually over time and have prolonged effects on prices.
- Lagged Reactions: Markets might react to economic news, policy changes, or technological developments with complex, distributed lags.
- Non-Linear Feedback Loops: Price movements might be driven by complex feedback mechanisms between participants or between price and other factors that are inherently non-linear.

3.2.2 Limitations in Economic Modeling

LSTM models have the theoretical capacity to learn these complex, adaptive, and long-memory patterns directly from the data without imposing strong prior structural assumptions like linearity or stationarity. As powerful as the model can be viewed, the theoretical appeal of LSTM model comes with significant challenges from an economic modeling perspective. Their primary limitation is their lack of interpretability. The model function largely as "black boxes" (Hassija *et al.* 2024). It is difficult to extract direct economic insights regarding specific causal relationships or the quantitative impact of particular variables from the complex internal weights of trained network.

This contradicts sharply with traditional econometric models where coefficient estimates often have direct economic interpretations. Furthermore, LSTM models typically require large datasets for effective training and are sensitive to hyperparameter choices, making model specification and validation complex. The data-driven nature of LSTM also means that there is risk overfitting spurious correlations if not carefully regularized and evaluated using robust methods like walk-forward validation.

3.3 Exponential Smoothing (ETS) - Artificial Neural Networks (ANN) Hybrid Model: A Structured Decomposition Approach

3.3.1 Theoretical Basis and Economic Rationale

Hybrid models attempt to bridge the gap between traditional statistical models and purely data-driven machine learning approaches by combining their respective strengths. The ETS-ANN hybrid model, based on Panigrahi & Behera (2017), embodies this philosophy through a structured decomposition of the time series.

The underlying theoretical premise is that a financial time series (Y_t) may reasonably be considered a composite of a more structured, discernible component (C_t^1) representing underlying trends or levels, which might be non-linear, and a less structured, potentially complex residual component (e_t) capturing noise, irregular fluctuations, or non-linear dynamics not explained by the primary component ($Y_t = C_t^1 + e_t$).

This hybrid approach utilizes the ETS state-space framework of Hyndman *et al.* (2008) to model the primary component C_t^1. The theoretical advantage of ETS over ARIMA in this context is its greater flexibility. The ETS family includes a wide range of models explicitly incorporating different types of trends (additive, multiplicative, damped) and seasonality (additive, multiplicative), encompassing both linear special cases, often equivalent to ARIMA models, and inherently non-linear smoothing models (Panigrahi & Behera 2017). This allows the first stage to potentially capture a broader range of underlying structural patterns compared to restricting it solely to linear ARIMA models.

The ANN is then employed in the second stage specifically to model the residuals (e_t) from the ETS fit. The rationale behind, is that these residuals may contain complex, non-linear patterns that the ANN, as a powerful non-linear function approximator (Hornik *et al.* 1989), is well-suited to learn. By dedicating the ANN solely to the potentially more complex residual dynamics, while leveraging the statistically grounded ETS framework for the primary structure, the hybrid model aims to achieve robustness and potentially improved accuracy compared to using either ETS or a simple ANN alone, particularly if the time series indeed contains a mixture of linear and non-linear patterns.

3.3.2 Theoretical Limitations

Despite its conceptual appeal, the ETS-ANN hybrid approach faces theoretical challenges, particularly concerning multi-step forecasting.

- Additive Decomposition Assumption: The simple additive combination ($Y_t = C_t^1 + e_t$) assumes that the structural component and the residual dynamics do not interact in more complex ways, which may not always hold true in financial markets.

- Multi-Step Residual Forecasting Difficulty: A significant theoretical and practical challenge arises when generating forecasts multiple steps ahead ($h > 1$). While the ETS component $\hat{C}_{t+h}^1$ can be forecast directly, the standard implementation requires the ANN component $\hat{C}_{t+h}^2$ to be forecast iteratively. This iterative process, where the predicted residual at step $t+k$ depends on the predicted residual at step $t+k-1$, is inherently prone to error propagation and accumulation. Errors made in early steps compound over the forecast horizon, potentially leading to rapid degradation in the accuracy of the long-term residual forecast. This can result in the final hybrid forecast being dominated by the potentially inaccurate long-term ETS extrapolation, hence limiting its ability to capture future volatility or turning points. This issue represents a key conceptual weakness of this specific hybrid structure for longer-horizon forecasting.

3.4 Model Selection Rationale Summary

The selection of ARIMA, LSTM, and ETS-ANN models provides a methodologically diverse basis for comparison. ARIMA establishes the linear econometric benchmark. LSTM represents the flexible, non-linear deep learning approach capable of capturing complex dependencies. Finally, ETS-ANN hybrid offers a structured hybrid approach attempting to combine statistical smoothing with non-linear residual modeling. Comparing their performance across multiple horizons using walk-forward validation, allows for an empirical assessment of these distinct theoretical approaches in the challenging context of cryptocurrency price forecasting.

3.5 Research Hypotheses

Based on the theoretical considerations outlined above and the existing literature on financial time series forecasting, this thesis aims to empirically test the following hypotheses regarding the relative performance of the ARIMA, LSTM, and ETS-ANN models for forecasting cryptocurrency prices across different time horizons:

- Hypothesis 1 (H1): The deep learning LSTM model, designed to capture complex temporal dependencies and non-linearities, will exhibit superior forecasting accuracy compared to the benchmark ARIMA model across short (t+1), medium (t+10), and long-term (t+30) forecast horizons.
- Hypothesis 2 (H2): The hybrid ETS-ANN model, which explicitly combines statistical ETS with non-linear residual modeling ANN, will demonstrate superior forecasting accuracy compared to both the standalone linear ARIMA model and the standalone non-linear LSTM model.
- Hypothesis 3 (H3): The relative forecasting performance of the simpler ARIMA benchmark over the more advanced complex models LSTM and ETS-ANN will diminish significantly as the forecast horizon increases from short-term (t+1) to long-term (t+30).

Chapter 4

Methodology and Data

4.1 Data Specification and Preparation

The study utilizes daily historical data for five major cryptocurrencies "Bitcoin, Ethereum, Tether, Ripple, Litecoin" sourced from Yahoo Finance, covering the period November 9, 2017, to January 1, 2025. This selection represents diverse economic functions within the cryptocurrency market. The primary target variable for all forecasting models is the daily Closing Price (USD), and the variable is selected because of its reflection of all the indicative functions of a particular trading day (Poongodi *et al.* 2020).

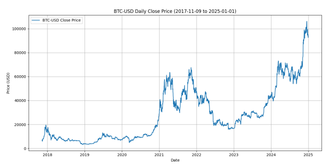
Initial data handling involved ensuring daily frequency, imputing any missing values using forward-fill, and removing any initial rows with remaining missing data. This resulted in a consistent time series for each asset. The descriptive statistics summarizing the price characteristics are presented in Table 4.1, and visual representations of the price series are shown in Figure 4.1. The distribution of daily returns, indicating volatility patterns, is illustrated in Figure 4.2. These entail the distinct characteristics for each cryptocurrency. Bitcoin (BTC) and Ethereum (ETH) exhibit substantially higher average prices and greater price volatility, as indicated by their larger standard deviations, compared to the rest of the cryptocurrencies Litecoin (LTC), Tether (USDT), and Ripple (XRP). USDT demonstrates remarkable price stability - with a mean close to $1 and a very low standard deviation - whereas LTC and XRP show moderate average prices and volatility relative to BTC and ETH. The range between the minimum and maximum prices is also considerably wider for BTC and ETH, highlighting their more dynamic price action during the observed period.

Table 4.1: Descriptive Statistics for Daily Close Prices (2017-11-09 to 2025-01-01)

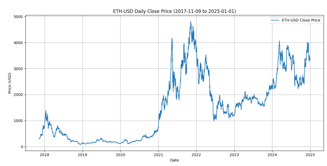
Statistic	BTC-USD	ETH-USD	LTC-USD	USDT-USD	XRP-USD
count	2610.00	2610.00	2610.00	2610.00	2610.00
mean	27764.76	1491.48	95.36	1.00	0.55
std	22034.33	1226.56	55.32	0.01	0.38
min	3236.76	84.31	23.46	0.97	0.14
25%	8929.10	268.78	58.76	1.00	0.32
50%	21167.85	1354.95	76.38	1.00	0.48
75%	42567.06	2412.39	115.06	1.00	0.62
max	106140.60	4812.0874	386.45	1.08	3.38

The prepared dataset forms the basis for the walk-forward validation procedure. Specific data transformations required by individual models, such as scaling for neural networks or differencing checks for ARIMA, were performed within the modeling or validation steps as described below, ensuring transformations were based only on information available at that point in the sequence.

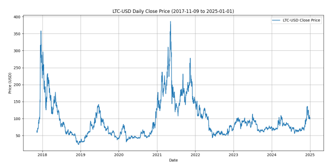
Figure 4.1: **Historical Price.**



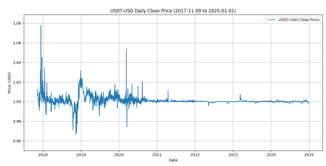
BTC-USD



ETH-USD



LTC-USD

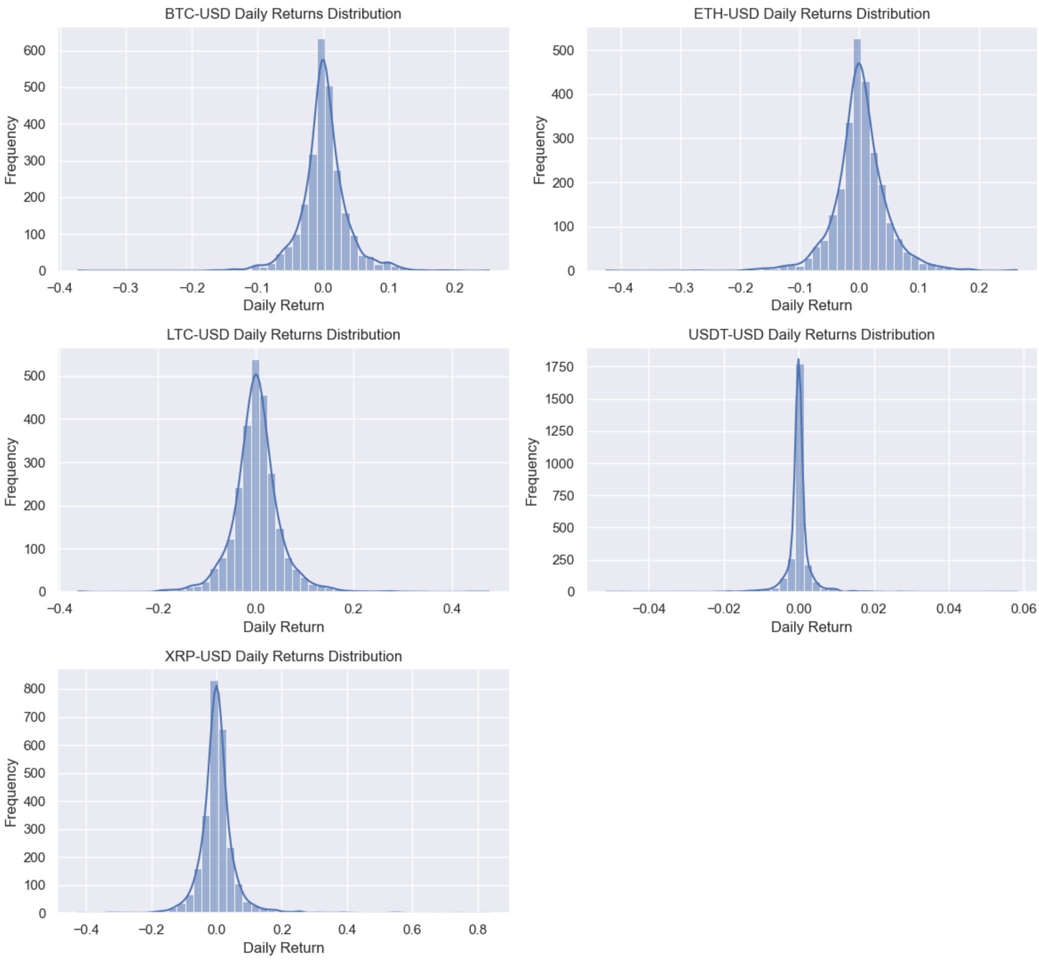


USDT-USD

XRP-USD

Note: This note describes the plot: Historical price fluctuations of the cryptocurrencies. The Tether coin is evidently stable proving its unique characteristics.

Figure 4.2: Daily returns distribution



Note: This note describes the plot: returns distribution of selected cryptocurrencies daily in units (USD).

4.1.1 Overview of selected cryptocurrencies

The selected five cryptocurrencies for this thesis represent a diverse range of functionalities such as store of value, smart contracts, stablecoins, cross-border transactions, and fast micro-payments, providing a robust basis for evaluating the comparative performance of the forecasting models like LSTM and ETS-ANN on broader range of cryptocurrency assets.

Bitcoin is the largest cryptocurrency, holding 61.4 % of the market capitalization with $ 1.64 Trillion (Coinmarketcap 2025). Created by Nakamoto (2008), it serves as the foundation for most alternative coins, which are modified versions of Bitcoin with different parameters.

Ethereum is the second-largest cryptocurrency, extends beyond simple transactions by incorporating smart contracts and decentralized applications (Buterin 2014). It utilizes its own programming language and is often referred to as Blockchain 2.0 (Hileman & Rauchs 2017).

Tether launched in 2014, pioneered the stablecoin concept, aiming to minimize the price volatility seen in other cryptocurrencies. Designed by Tether Limited to mirror the U.S. dollar, it had a market cap of $141 billion with a fixed per-token value of $1.00 as of February 2025 (Tambe & Jain 2025).

Ripple is the third-largest cryptocurrency at the time of writing of this study, it was created by Ripple Labs to facilitate fast and cost-effective cross-border payments. It eliminates the need for intermediaries, making it a preferred solution for financial institutions (Sevinj Ahmadova & Mustafa Erek* 2022).

Litecoin was introduced in 2011 by Charles Lee, it was designed for faster transactions and lower fees compared to Bitcoin. It allows mining on less powerful computers and has a maximum supply of 84 million coins, significantly higher than Bitcoin's 21 million units (Miglietti *et al.* 2019).

4.2 Model Implementation Procedures

The three selected forecasting models were implemented using specific procedures within a Python environment, leveraging established libraries for time series analysis and machine learning.

4.2.1 ARIMA Model Implementation

The ARIMA model, linear econometric benchmark, was implemented using the *pmdarima* library. For the initial training data, the *auto_arima* function was employed to determine the optimal model order $(p, d, q)(P, D, Q)m$. This notations specify the structure of the model:

(p,d,q): These represent the non-seasonal components.

- p: The order of the Autoregressive (AR) part, indicating how many lagged values of the (differenced) series are used as predictors.

- d: The degree of non-seasonal differencing required to make the series stationary.
- q: The order of the Moving Average (MA) part, indicating how many lagged forecast errors are included in the model.

  (P,D,Q)m: These represent the seasonal components, applicable if a recurring pattern over m periods is detected.
- P: The order of the Seasonal Autoregressive (SAR) part.
- D: The degree of seasonal differencing.
- Q: The order of the Seasonal Moving Average (SMA) part.
- m: The length of the seasonal period

This function automates key steps of the Box-Jenkins methodology by conducting stationarity tests, specifically ADF was specified to identify the necessary differencing order $'d'$ and potentially $'D'$ for seasonality, and, subsequently searching for the autoregressive $('p','P')$ and moving average $('q','Q')$ orders that minimize the corrected Akaike Information Criterion $(AICc)$, ensuring a balance between model fit and parsimony. A seasonal period of $m = 7$ was considered to account for potential weekly patterns. Parameter estimation within the selected model structure was performed using Maximum Likelihood Estimation. During the subsequent walk-forward evaluation, the computationally efficient $.update()$ method was utilized to incorporate new observations, allowing the state of the model to adapt without requiring a full parameter re-estimation at each step.

4.2.2 LSTM Model Implementation

The LSTM network, the non-linear deep learning approach, was implemented using $TensorFlow$ and $Keras$. A critical pre-processing step involved scaling the closing price data to a [0, 1] range via min-max procedure; this scaler was fitted only on the initial training data portion to prevent look-ahead bias. The scaled data was then transformed into input-output sequences suitable for LSTM training. Specifically, input sequences consisted of $look\_back = 60$ consecutive daily scaled prices. Following a Direct Multi-Step Forecasting Strategy, the target output for each input sequence was the single scaled price value h steps ahead, where h was 1, 10, 30, or 180 depending on the specific evaluation. A stacked LSTM architecture was defined, featuring two LSTM layers, dropout layers for regularization between LSTM layers, a subsequent dense layer with ReLU activation, and a final single-neuron dense output layer. The Adam optimization algorithm was used to train the network weights by minimizing the mean squared error loss function. Initial hyperparameters defining the network structure (units per layer, dropout rates) and training process (learning rate, batch size) were determined through an automated optimization procedure $keras_tuner.RandomSearch$ evaluated using a dedicated validation dataset held out from the initial training data set.

4.2.3 ETS-ANN Hybrid Model Implementation

This hybrid approach involved a two-stage process, implemented using *pycaret* for the ETS component and $TensorFlow/Keras$ for the ANN component.

1 ETS Fitting: An initial ETS model was selected and fitted exclusively on the training data using *time_series* function of the pycaret library. The *compare_models* function from the library identified the best ETS specification (additive error, damped additive trend, and seasonality) by minimizing RMSE, and *create_model* performed the parameter estimation via Maximum Likelihood.

2 ANN on Residuals: The residuals from the initial ETS fit were calculated ($e_t = Y_t - \hat{C}_t^1$). These residuals were then scaled to a $[-1, 1]$ range using a dedicated min-max fitted only on these initial residuals. A feed-forward ANN was subsequently trained to predict the current normalized residual (e'_t) using specified lagged values of the normalized residuals (lags 1, 7, and 30) as input features. The ANN architecture, number of neurons, layers, training parameters epochs and batch size were determined through initial hyperparameter optimization procedure (grid search) evaluated using a dedicated validation dataset derived from the initial ETS residuals.

4.3 Evaluation Framework: Walk-Forward Validation

A consistent walk-forward validation was rigorously applied to all three models to ensure a fair comparison of their out-of-sample forecasting performance with real world data.

4.3.1 Procedure Description

The dataset was initially partitioned into an 80% training set and a 20% test set. After initial model estimation and hyperparameter tuning on the training set, the evaluation proceeded iteratively through the test period (day-by-day). For each time step t within the test set range (specifically, from index n_{train} up to $T - h$, where T is the total sample size and h is the forecast horizon), the procedure follows: (1) Generate forecasts for h steps ahead using only data available up to time t. (2) Record the specific h-step ahead forecast ($\hat{Y}_{t+h}$). (3) Incorporate the actual observed price at time $t + 1(Y_{t+1})$ to update the model state (ARIMA) or input history (for LSTM, ETS-ANN). This loop ensures that each forecast is generated based solely on information preceding the target period, simulating real-world forecasting constraints.

1 Forecast: Each model generated forecasts for h steps into the future, specifically targeting predictions for day $T + h$, using only data available up to day T.

2 Record: The specific h-step ahead forecast ($\hat{Y}_{t+h}$) was stored.

3 Update: The actual observed price for day $t + 1$ (Y_{t+1}) was then revealed and used to update the internal state of the model (for ARIMA model by the *.update*()) or the input history sequence (for LSTM and the residual history for ETS-ANN model). Model parameters for LSTM and ETS-ANN remained fixed after initial training in this setup. This loop continued until forecasts were generated for all possible starting points in the test set for the given horizon h.

4.3.2 Multi-Horizon Assessment

This entire walk-forward procedure was performed independently for each of the three target forecast horizons: h=1 (short-term), h=10 (medium-term), and h=30 (long-term). An exploratory analysis for h=180 was also conducted. This multi-horizon evaluation allows for a direct comparison of predictive accuracy for each model evolves as the forecast lead time increases. The method for generating the h-step forecast differs, where ARIMA extrapolates directly, LSTM predicts the h-th step directly, and ETS-ANN combines an h-step ETS forecast with an iteratively generated h-step ANN residual forecast.

4.4 Initial Hyperparameter Optimization Procedure

Recognizing the sensitivity of neural networks to hyperparameters, an optimization step was performed once before the main walk-forward evaluation, utilizing only the initial 80% training data partition. For LSTM, *RandomSearch* from the *keras_tuner* library explored network architecture and training parameters, minimizing loss on an internal validation split (20% of the training data sample). For the ANN component of the ETS-ANN hybrid model, a grid search across predefined options for neurons, epochs, and batch size was conducted, minimizing MSE on a similar validation split derived from the initial ETS residuals. The best hyperparameters identified were then used for the final model training. ARIMA and ETS parameters were determined automatically by their respective estimation functions based on the full initial training data.

4.5 Performance Evaluation Metrics

The out-of-sample forecast performance of each model for each horizon h was assessed by comparing the collected sequence of $\hat{Y}_{t+h}$ forecasts against the corresponding sequence of actual values Y_{t+h}. Standard error metrics including MAE, MAPE, and RMSE were derived. These metrics provide quantitative measures of forecast accuracy, error magnitude, and model fit, resembling a common choice for model performance evaluation in the forecasting literature.

4.6 Software and Tools

The computational part was conducted in Python version 3.11+, utilizing core libraries such as *pandas* for data manipulation, *numpy* for numerical operations, $yfinance$ for data retrieval, *statsmodels* and *pmdarima* for statistical modeling and tests, *pycaret* for automated ETS modeling, $scikit - learn$ for scaling and metrics, $tensorflow$ with *keras* for neural network implementation, $keras - tuner$ for hyperparameter optimization, and *matplotlib/plotly* for visualization.

Chapter 5

Empirical Results & Discussion

This chapter presents and analyzes the empirical findings derived from applying the three forecasting methodologies across short-term (t+1), medium-term (t+10), and long-term (t+30) forecast horizons. The main focus is to compare the out-of-sample predictive performance of the traditional linear ARIMA model, the non-linear deep learning LSTM network, and the hybrid ETS-ANN structure. Performance is evaluated using a rigorous walk-forward validation protocol across the aforementioned forecast horizons for five major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Tether (USDT), and Ripple (XRP). An exploratory analysis for the t+180 (180 days) horizon was also conducted to assess performance over a much longer period. The comparative results, summarized in Table 5.1, provide insights into the relative strengths and limitations of these distinct modeling approaches in forecasting the volatile and complex dynamics of cryptocurrency markets.

5.1 Overall Performance Landscape

An important observation from Table 5.1 is the marked difference in performance across all the forecasting models and the time horizons. No single model consistently dominates across all scenarios, underscoring the challenges inherent in cryptocurrency price prediction and the horizon-dependent nature of forecasting. Initial observations already challenge common beliefs about better performance of more complex models. While the complex LSTM model demonstrates competitiveness at the shortest t+1 horizon, the simpler linear ARIMA model frequently emerges as more accurate, or at least highly competitive, particularly at the medium (t+10) and long (t+30) horizons for several major volatile assets like Bitcoin and Litecoin. This immediately questions Hypothesis 1, predicting consistent LSTM superiority over the linear model.

The hybrid ETS-ANN model generally demonstrates the weakest performance across most assets and horizons, particularly evident in the short-term results (t + 1) for the most volatile cryptocurrencies (BTC, ETH, LTC, XRP), where its MAE, MAPE, and RMSE values are considerably higher than those of ARIMA and LSTM models. This suggests potential difficulties with the initial ETS fit, the ability of ANN to model the resulting residuals effectively, or inefficiencies introduced by the hybrid structure itself for immediate forecasting. This strongly contradicts Hypothesis 2, which predicts hybrid model superiority, and suggests limitations in its specific two-stage implementation for these markets.

The performance degradation across all models as the horizon extends from t+1 to t+30 is evident and logical, but the relative performance shifts are crucial. The t+180 results confirm an expected extreme deterioration in practical forecasting utility for all approaches over such extended periods.

Table 5.1: Performance metrics results

Cryptocurrency	Forecast horizon		Models: ARIMA			LSTM			ETS-ANN		
			MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE
Bitcoin	Short (Day)	t + 1	1073.4257	1.8207%	1610.5243	1181.1543	2.0554%	1674.8848	17969.7885	27.8838%	23073.4361
	Medium (10 Days)	t + 10	3607.4943	6.1616%	5043.4688	4367.6504	7.0139%	6361.2464	14671.4985	23.0492%	18751.1742
	Long (30 Days)	t + 30	7004.6810	11.5695%	9729.5257	15198.7965	22.6266%	19889.1265	15645.9070	24.1476%	19736.2812
	(180 Days)	t + 180	22188.5675	32.7416%	25307.6951	32537.0101	46.7646%	34959.2175	21557.1007	30.0935%	24432.2077
Ethereum	Short (Day)	t + 1	60.0450	2.1355%	90.1988	106.6700	3.9386%	133.3216	834.3992	27.1634%	1053.8128
	Medium (10 Days)	t + 10	214.6009	7.5175%	290.1776	249.4134	8.6253%	341.1108	718.4001	23.6666%	883.9200
	Long (30 Days)	t + 30	374.0853	12.7392%	496.0990	362.8048	12.1219%	509.5241	745.6078	24.4219%	904.9770
	(180 Days)	t + 180	974.1013	31.2976%	1139.8408	710.8021	22.1030%	848.0394	1092.3568	33.5978%	1201.9687
Litecoin	Short (Day)	t + 1	1.9670	2.4581%	3.1840	4.4769	5.9635%	5.1873	14.6039	20.1466%	16.8751
	Medium (10 Days)	t + 10	6.0827	7.5112%	9.1019	7.6651	9.8045%	10.4747	14.7374	20.3550%	17.0090
	Long (30 Days)	t + 30	9.0728	10.9400%	14.2027	9.2610	11.1037%	14.1135	14.6456	20.1423%	16.7279
	(180 Days)	t + 180	16.8016	20.5190%	21.0848	23.4975	27.0836%	28.8169	14.5251	19.2527%	17.2200
Tether	Short (Day)	t + 1	0.0004	0.0393%	0.0005	0.0003	0.0308%	0.0004	0.0009	0.0937%	0.0011
	Medium (10 Days)	t + 10	0.0009	0.0950%	0.0011	0.0009	0.0862%	0.0010	0.0007	0.0689%	0.0009
	Long (30 Days)	t + 30	0.0012	0.1231%	0.0013	0.0006	0.0592%	0.0008	0.0010	0.0989%	0.0012
	(180 Days)	t + 180	0.0014	0.1364%	0.0015	0.0012	0.1210%	0.0013	0.0018	0.1802%	0.0020
Ripple	Short (Day)	t + 1	0.0205	2.4421%	0.0477	0.0396	3.7763%	0.0978	0.2342	24.3366%	0.4759
	Medium (10 Days)	t + 10	0.0776	8.2691%	0.1934	0.1795	23.2680%	0.2780	0.2384	23.2304%	0.5141
	Long (30 Days)	t + 30	0.1654	14.0309%	0.4204	0.2207	25.4012%	0.4145	0.2440	23.3568%	0.5274
	(180 Days)	t + 180	0.2456	17.1197%	0.5849	0.2634	20.5027%	0.5824	0.2841	23.1262%	0.6042

Note: The table depict the results of the performance metrics for ARIMA, LSTM, and ETS-ANN models over three main horizons for selected five major cryptocurrency data acquired from Yahoo Finance. Results for t+180 are exploratory and discussed separately due to significantly lower overall accuracy.

5.2 Discussion by Forecast Horizon

5.2.1 Short-Term (t+1) Forecasting

For next-day (t+1) predictions, both the ARIMA benchmark and the non-linear LSTM models demonstrate reasonable predictive accuracy for the major volatile cryptocurrencies, aligning with the Efficient Market Hypothesis ideas where recent information is highly relevant. The effectiveness of ARIMA, where the lowest MAE and RMSE for BTC and ETH are demonstrated, points to significant linear autocorrelation or momentum effects at the daily frequency. The competitiveness of LSTM is revealed for LTC with the lowest MAE and RMSE, though its MAPE is higher, which suggests the presence of non-linear short-term patterns it can effectively capture using its complex architecture. The relative under-performance of the ETS-ANN hybrid model, with its highest errors for all volatile assets, might indicate that its structural decomposition and two-stage modeling introduce complexities and potential missspecifications hindering immediate, next-step prediction compared to the more direct approaches like ARIMA and LSTM previously. In particular, for the stablecoin USDT, all models achieve very low absolute errors due to its price stability; however, LSTM consistently produces the lowest MAE of (0.0003) and RMSE of (0.0004), suggesting its superior ability to model the minimal deviations around the $1 peg.

5.2.2 Medium-Term (t+10) Forecasting

Extending the horizon to 10 days reveals a significant change in relative performance. The ARIMA model now generally outperforms LSTM for volatile assets Bitcoin, Ethereum, and Litecoin, achieving lower MAE, MAPE, and RMSE performance according to Table 5.1. For instance, the MAPE of the ARIMA model for Bitcoin (6.16%) is notably lower than the LSTM's (7.01%), and its RMSE is also considerably lower (5043.47 vs. 6361.25). For the Ripple coin, the LSTM model shows a significantly high MAPE of (23.27%), while ARIMA maintains a more reasonable performance of 8.27%. This suggests that while LSTM captures intricate next-day patterns, generalizing these and learning the direct 10-step mapping proves challenging amidst market noise and volatility. The simpler linear extrapolation of ARIMA, potentially benefiting from its parsimony and efficient state updating, appears to be more robust over the medium term. The ETS-ANN model continues to lag significantly, with MAPE values exceeding 20% for BTC, ETH, LTC, and XRP, further highlighting the potential instability

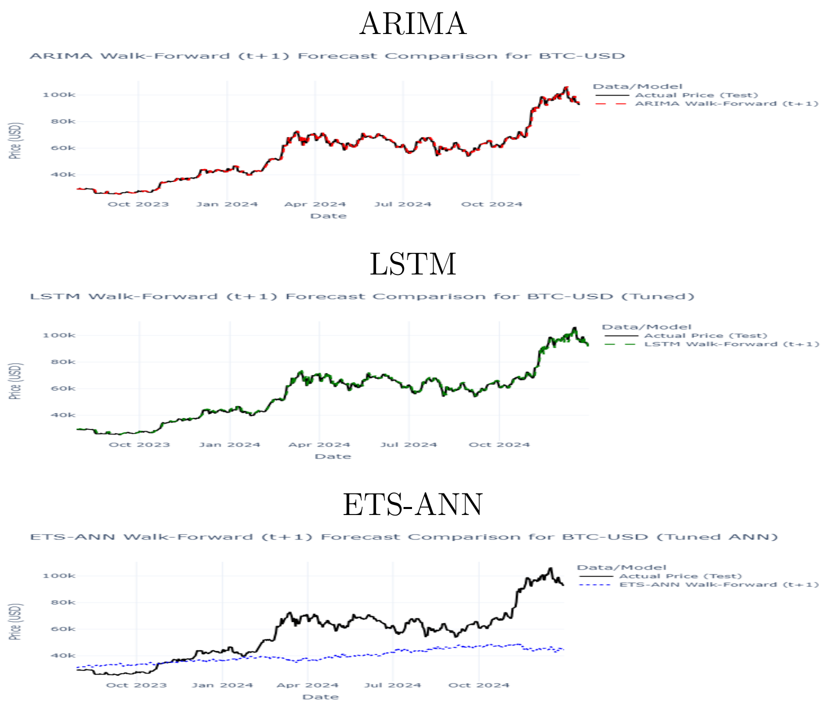


Figure 5.1: Bitcoin forecast for t+1 horizon.

Figure 5.2: Ethereum forecast for t+1 horizon.

Figure 5.3: Litecoin forecast for t+1 horizon.

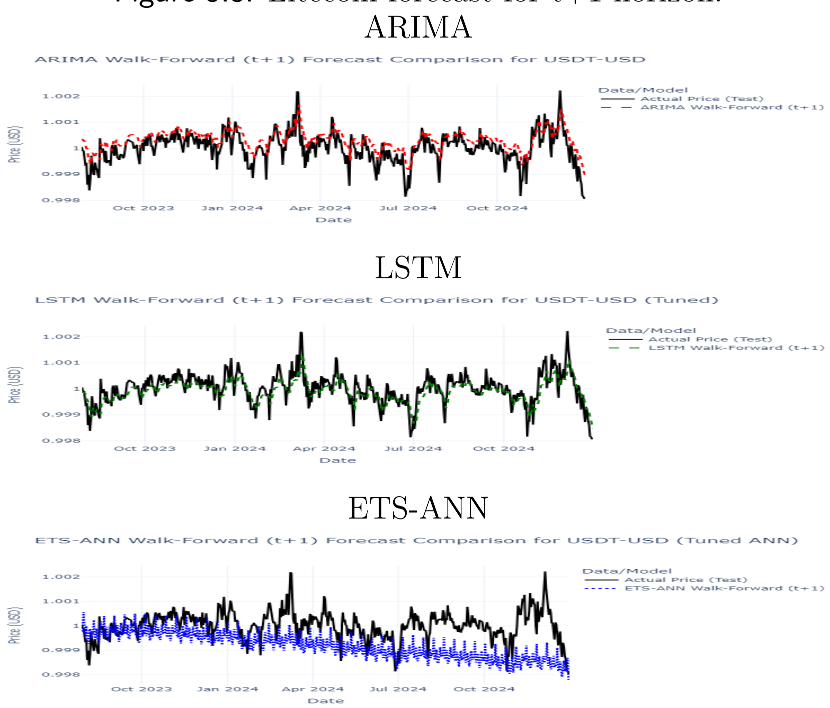


Figure 5.4: Tether forecast for t+1 horizon.

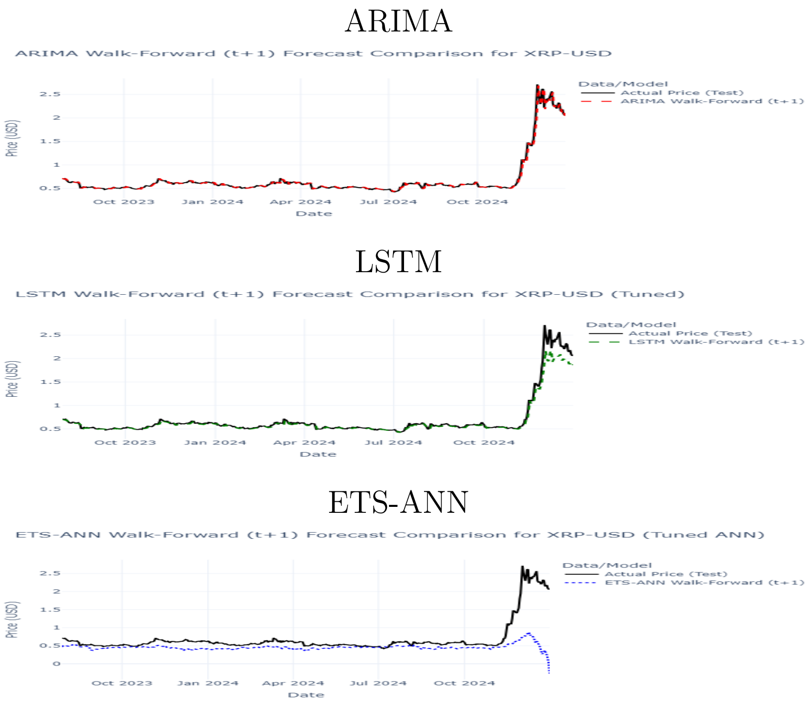


Figure 5.5: Ripple forecast for t+1 horizon.

or error accumulation in its hybrid approach over multiple steps. For USDT, ETS-ANN surprisingly shows the lowest MAE/RMSE, although LSTM maintains a competitive MAPE.

5.2.3 Long-Term (t+30) Forecasting

Forecasting approximately one month ahead (t+30) proves to be very challenging, with MAPE values often exceeding 10% even for models that perform better in volatile assets. The trend observed at t + 10 continues in a large way: ARIMA generally maintains an edge over LSTM for Bitcoin (MAPE 11.57% vs 22.63%), Litecoin (MAPE 10.94% vs 11.10%), and Ripple (MAPE 14.03% vs 25.40%). Ethereum is an exception, where LSTM achieves slightly lower MAE (362.80 vs 374.09) and MAPE (12.12% vs 12.74%) than ARIMA, although their RMSE values are very close. The substantial performance degradation for LSTM compared to its t+1 results across most volatile assets underscores the difficulty of the direct multi-step strategy for learning stable relationships over a 30-day horizon. The ETS-ANN model remains the weakest performer for BTC, ETH and LTC, consistent with the theoretical concerns about error accumulation in its iterative residual forecasting over 30 steps. Interestingly, for Ripple, its performance metrics are closer to that of the LSTM model, though generally worse than ARIMA. For USDT stablecoin, LSTM clearly provides the best forecast, showing the lowest MAE, MAPE, and RMSE, demonstrating its ability to effectively model low-variance processes even over this extended horizon.

5.2.4 Exploratory (t+180) Forecasting Horizon Assessment

Extending the forecast to six months (t+180) confirmed the extreme difficulty of long-range prediction, with performance deteriorating drastically across all models (Table 5.1). MAPE values exemplified this, exceeding 30% for Bitcoin with ARIMA: 32.%, ETS-ANN: 30.1% and reaching 46.8% for LSTM. Although relative model rankings shifted where the ETS-ANN had the lowest MAPE for BTC,and LSTM for ETH: 22.%, the high absolute errors suggest limited practical utility. ARIMA often maintained lower errors than LSTM for volatile assets such as BTC MAE: 22188 vs 32537 and XRP MAE: 0.246 vs 0.263, perhaps reflecting simpler extrapolation, whereas LSTM excelled only for the stablecoin USDT with MAPE of 0.12%. These results justify the primary focus on shorter horizons t+1 to t+30 for meaningful performance evaluation.

5.3 Asset-Specific Observations

While general patterns emerge, performance varies across cryptocurrencies. Bitcoin, despite its high absolute price, exhibits relatively low percentage errors (MAPE) at the short t+1 (day) horizon for both ARIMA and LSTM models compared to other volatile assets such as Litecoin or Ripple, perhaps suggesting slightly more noticeable short-term patterns. Ethereum shows competitive performance, often closely tracking the predictability patterns of Bitcoin. Litecoin and Ripple appear somewhat harder to predict accurately on the basis of the generally higher MAPE values across models and horizons. Expectedly, Tether is the most predictable due to its stablecoin nature, with extremely low error values across all methods, though the LSTM model consistently captures the minimal variance most effectively.

5.4 Discussion in Context of Methodology and Theory

The empirical results, achieved through a consistent walk-forward validation framework, highlight the importance of methodology and forecast horizon in the evaluation of forecasting models. The findings challenge the common expectation that more complex models like LSTM will uniformly outperform simpler benchmarks like ARIMA, particularly as the forecast horizon increases to medium (t+10) and long (t+30) terms. The relative success of ARIMA at these medium and longer horizons, despite its theoretical limitations in capturing non-linearity, likely points to the significant practical challenges faced by the neural network models in this specific implementation:

- LSTM model (Direct Strategy): Learning a direct mapping from past prices to a target 10 or 30 days in the future is inherently difficult because of the potentially weak and noisy signal over long lags. Although theoretically capable, the network may struggle to generalize this complex mapping out-of-sample compared to ARIMA, especially at the t+30 horizon for most volatile assets.
- ETS-ANN hybrid model (Iterative Residual Strategy): Performance degradation at h = 10 and h = 30 aligns strongly with the theoretical concern regarding the accumulation of errors in the iterative forecast of the residuals of the ANN. Small errors in early steps amplify over the extended horizon, rendering the residual forecast, and thus rendering the hybrid forecast unreliable.

Therefore, the simpler structure of the ARIMA model, combined with the efficient state updating mechanism used in the walk-forward loop, appears empirically more robust against the significant failure modes over medium and longer horizons (t+10 and t+30) compared to the specific LSTM and ETS-ANN implementations. This does not necessarily imply cryptocurrencies are fundamentally linear, but rather that capturing their complex, non-linear medium-to-long-range dynamics remains a significant modeling challenge with these standard approaches.

5.5 Limitations and Implications

The models primarily rely on historical closing prices, omitting potentially valuable information from trading volume, other technical indicators on-chain metrics, or exogenous macroeconomic variables or sentiment analysis (Jung *et al.* 2024; Khedr *et al.* 2021). Furthermore, the models do not explicitly account for potential seasonality, which might influence trading patterns. The hyperparameter tuning for the neural network models, while systematic, might not have identified the absolute optimal configuration. Critically, the LSTM and ETS-ANN models were not periodically retrained during the walk-forward process, which could disadvantage them relative to the ARIMA model benefiting from state updates at each step. The reliance on daily data also precludes analysis of intra-day dynamics; future research employing hourly or even higher-frequency data could offer valuable insights for shorter-term forecasting and algorithmic trading strategies.

Nevertheless, the results provide valuable empirical insights. They highlight the critical importance of forecast horizon when comparing models and suggest that simpler, established econometric models like ARIMA should not be readily dismissed, particularly for medium-term (t+10) and longer-term (t+30) forecasting, even in highly volatile markets like cryptocurrencies. They also emphasize the practical difficulties associated with standard multi-step forecasting implementations for complex hybrid ETS-ANN and deep learning LSTM models. This suggests that further research into alternative multi-step strategies such as sequence-to-sequence LSTMs, attention mechanisms, or multi-output models, incorporating more frequent retraining, exploring a wider array of exogenous variables and feature engineering, or developing more advanced hybrid/ensemble techniques might be necessary to unlock the full potential of complex models for medium-to-longer-horizon cryptocurrency forecasting.

Chapter 6

Conclusion

This thesis embarked on an empirical investigation into the predictability of cryptocurrency prices, systematically comparing the forecasting performance of three distinct modeling paradigms: the traditional linear econometric benchmark ARIMA, a non-linear deep learning approach LSTM, and a structured hybrid model ETS-ANN. Recognizing the critical importance of realistic evaluation in volatile financial markets, the study employed a rigorous walk-forward validation methodology, assessing the out-of-sample accuracy of each model across short-term t+1 (1 day), medium-term t+10 (10 days), and long-term t+30 (30 days) forecast horizons for five major cryptocurrencies: Bitcoin, Ethereum, Litecoin, Tether, and Ripple.

The empirical results revealed a nuanced performance landscape where no single model achieved universal superiority across all assets and horizons. At the short-term (t+1) horizon, both the ARIMA and LSTM models demonstrated competitive predictive capabilities for highly volatile assets, suggesting that both linear persistence and complex recent non-linear patterns hold short-term predictive information. The LSTM model consistently showed the best performance for the stablecoin Tether. However, as the forecast horizon extended to the medium terms (t + 10) and long (t + 30), the relative performance changed significantly. The ARIMA model generally demonstrated superior accuracy compared to both the LSTM and ETS-ANN for most cryptocurrencies, challenging the common expectation that complex non-linear models guarantees better forecasts over longer periods. The ETS-ANN hybrid model consistently underperformed.

These findings directly address the initial research expectations. The premise that the non-linear LSTM model would consistently outperform the linear ARIMA benchmark across all tested horizons was not empirically supported by the results achieved. Although LSTM showed to be competitive for short-term next-day forecasts, ARIMA often proved more accurate at the medium and long horizons examined in the thesis. Moreover, the expectation that the ETS-ANN hybrid would yield superior performance by combining modeling strengths was evidently refuted, as this model consistently lagged behind the standalone approaches. Nevertheless, the results did align with the hypothesis that the forecasting challenge increases significantly with longer forecast horizons, the relative predictive edge observed for the more complex LSTM model at short horizon diminished greatly, and was frequently reversed, at the t+10 and t+30 day horizons, underscoring the substantial difficulty these advanced models face in reliably capturing and generalizing long-range market dynamics compared to the benchmark under the employed methodology.

This research underscores the critical dependence of model performance on the forecast horizon and the indispensable value of walk-forward validation. It suggests that simpler linear benchmarks like ARIMA remain relevant competitors, particularly beyond very short-term horizons, due to the practical challenges faced by standard implementations of sophisticated non-linear models in multi-step forecasting. Limitations include the univariate focus, lack of seasonality/intraday analysis, and fixed parameters during validation. Future research could address these by incorporating exogenous data, alternative multi-step strategies, periodic retraining, advanced hybrids, and Explainable AI. In conclusion, this thesis provides valuable empirical evidence on the relative strengths and practical limitations of distinct forecasting approaches, contributing to a deeper understanding of the complexities inherent in navigating the dynamic crypto-asset market.

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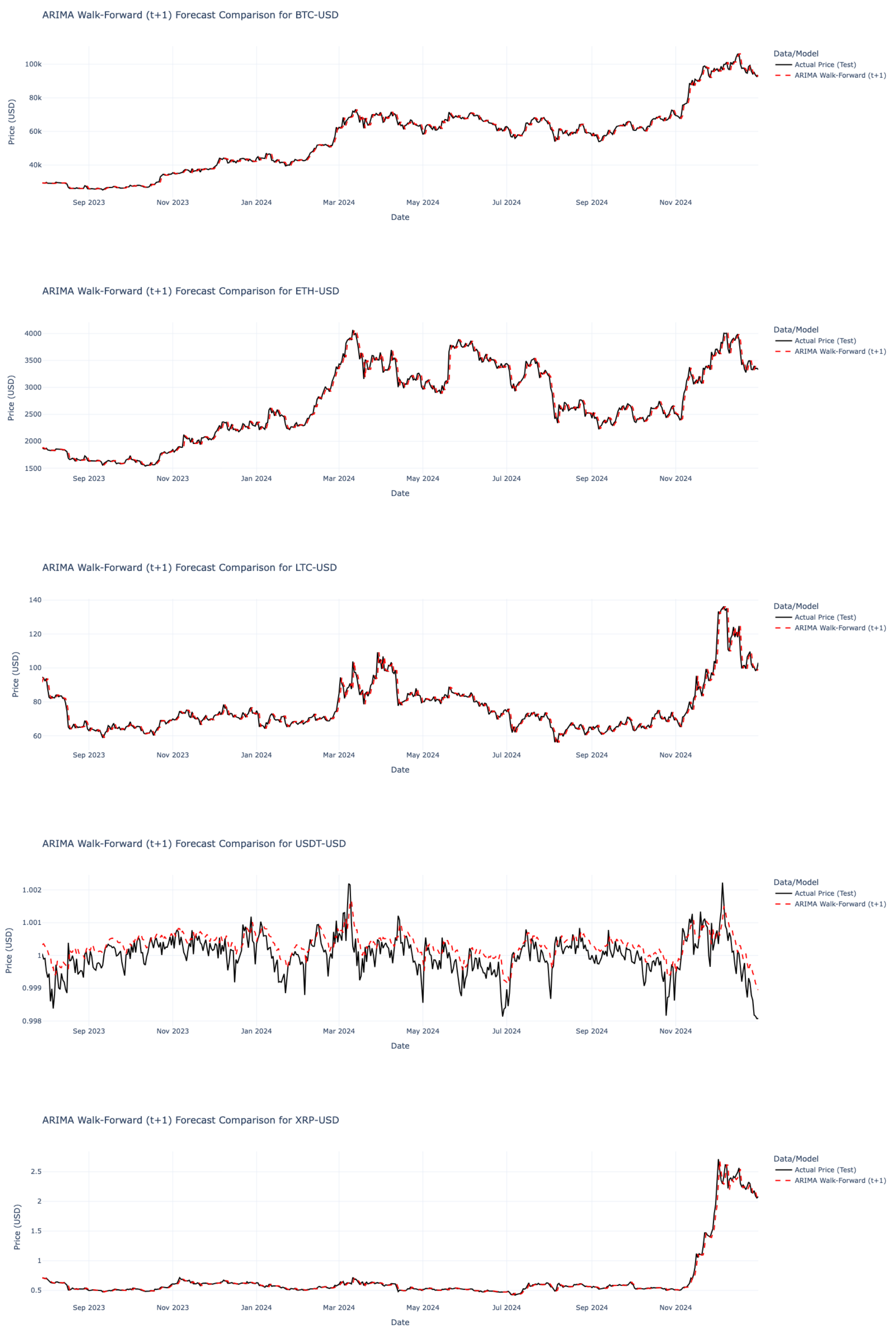
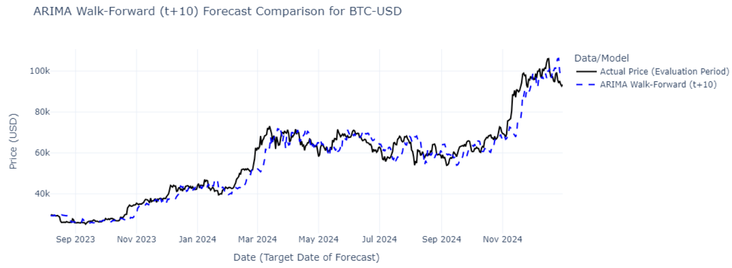
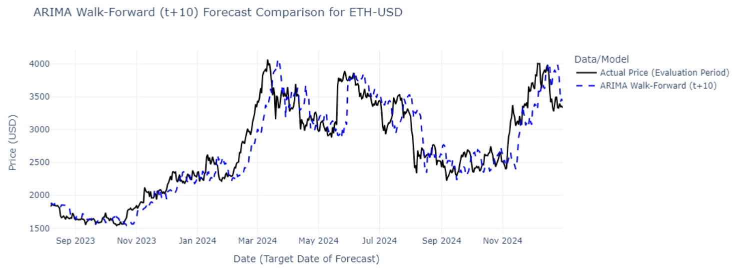
Figure A.1: Actual Price vs ARIMA Model Forecast for t+1

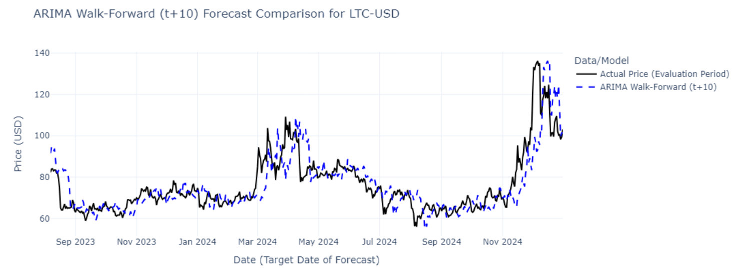


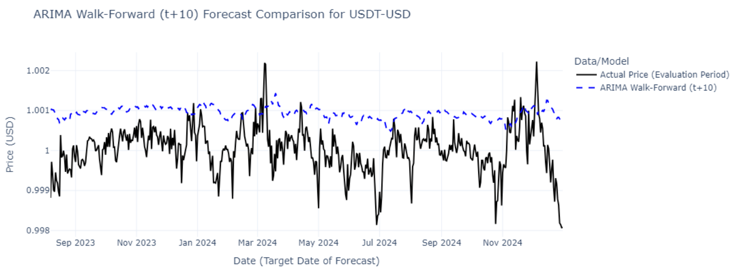
Note: This note describes the plots: From left to right columns represent the t+1 forecast horizon on selected cryptocurrencies put into rows from top to bottom in order "Bitcoin, Ethereum, Litecoin, Tether, Ripple"

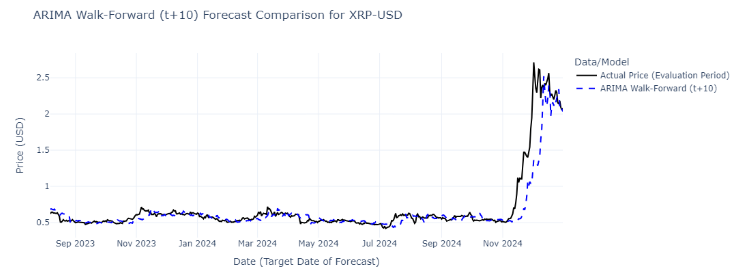
Figure A.2: Actual Price vs ARIMA Model Forecast for t+10





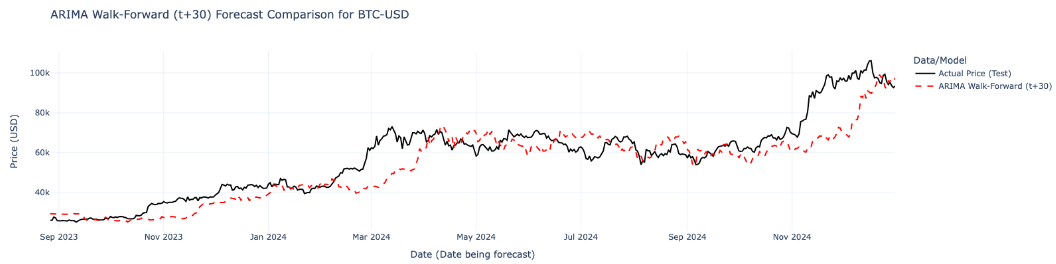


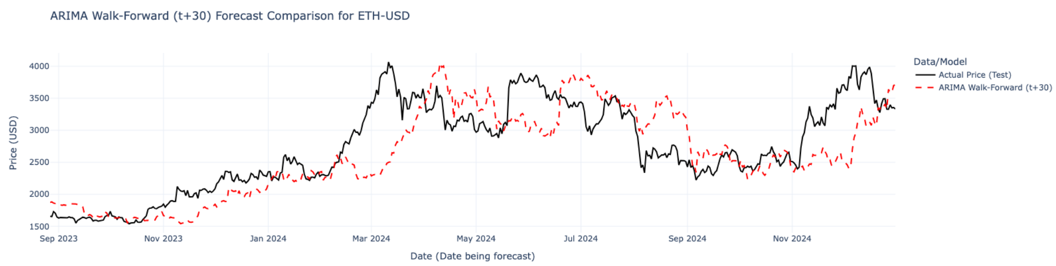


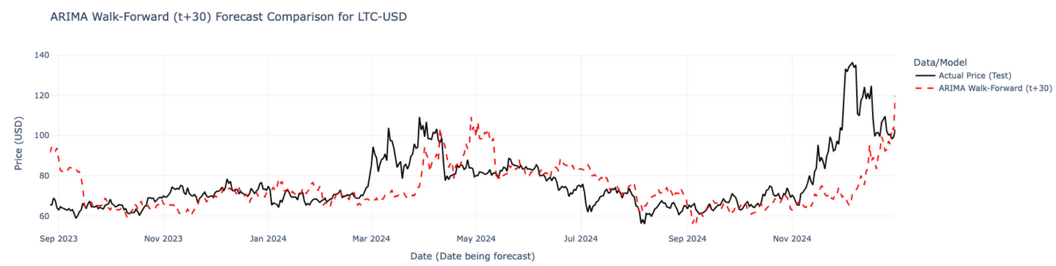


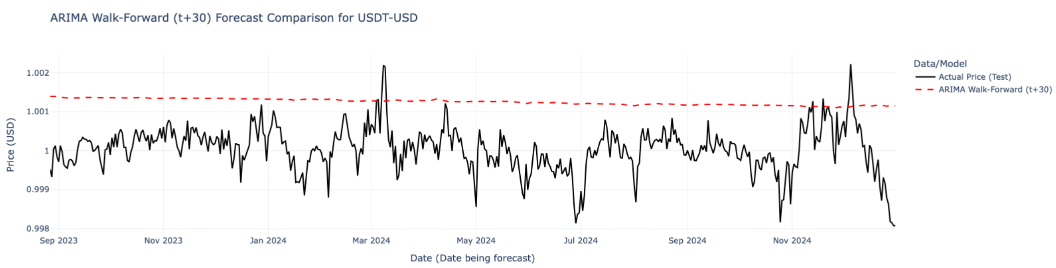
Note: This note describes the plots: From top to bottom, the plots represent the t+10 forecast horizon for Bitcoin, Ethereum, Litecoin, Tether, and Ripple, respectively.

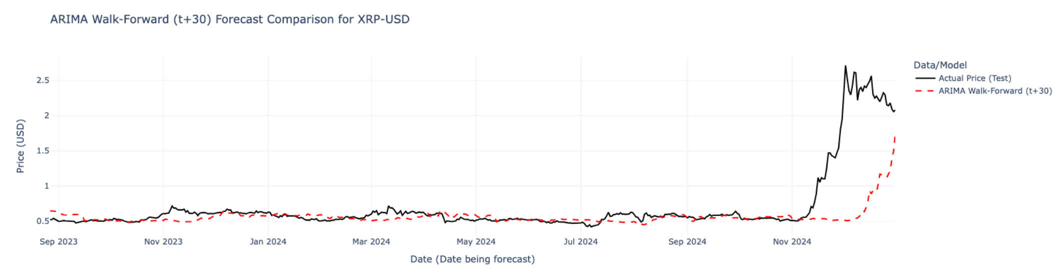
Figure A.3: Actual Price vs ARIMA Model Forecast for t+30





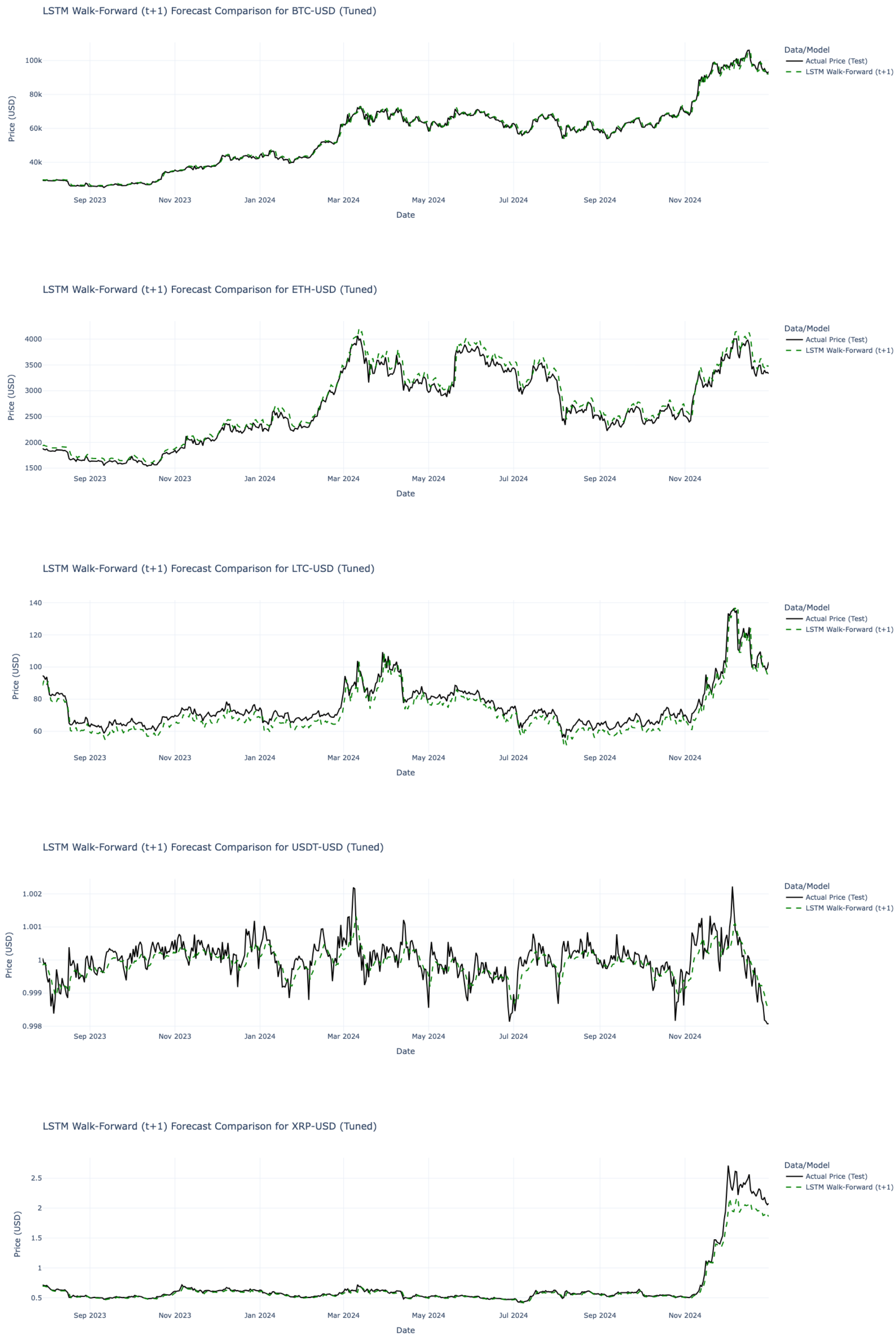






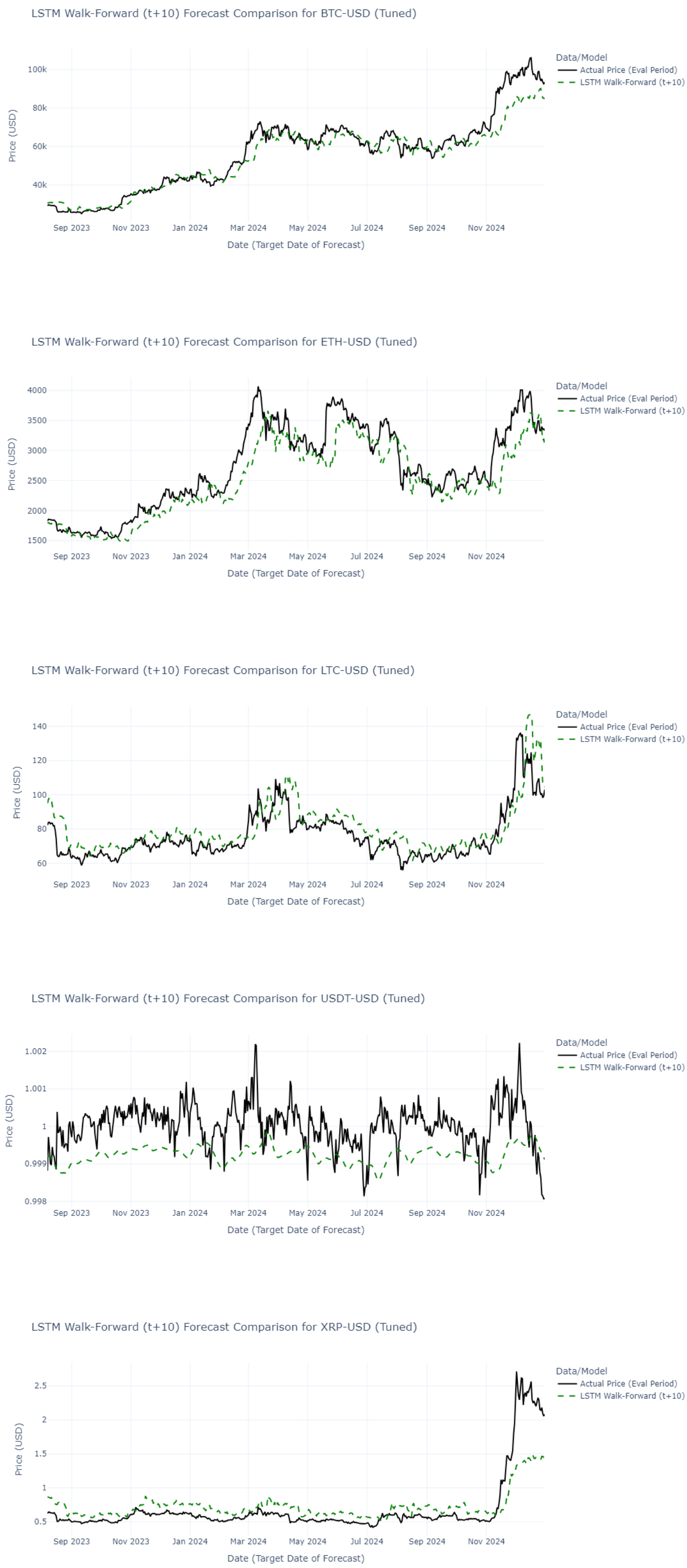
Note: This note describes the plots: From left to right columns represent the t+30 forecast horizons on selected cryptocurrencies put into rows from top to bottom in order "Bitcoin, Ethereum, Litecoin, Tether, Ripple"

Figure A.4: Actual Price vs LSTM Model Forecast t+1



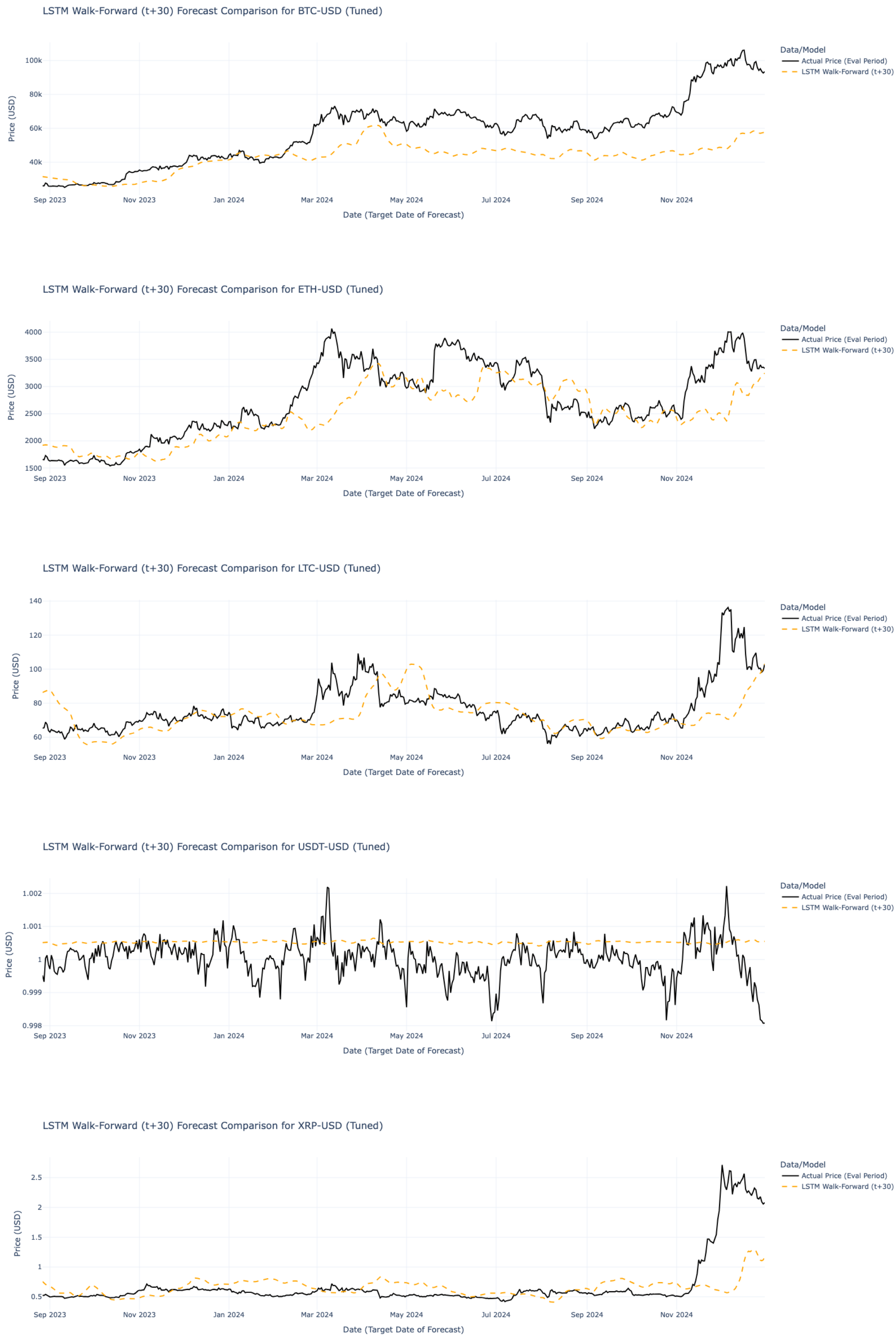
Note: This note describes the plots: From left to right columns represent the t+1 forecast horizon on selected cryptocurrencies put into rows from top to bottom in order "Bitcoin, Ethereum, Litecoin, Tether, Ripple"

Figure A.5: Actual Price vs LSTM Model Forecast for t+10



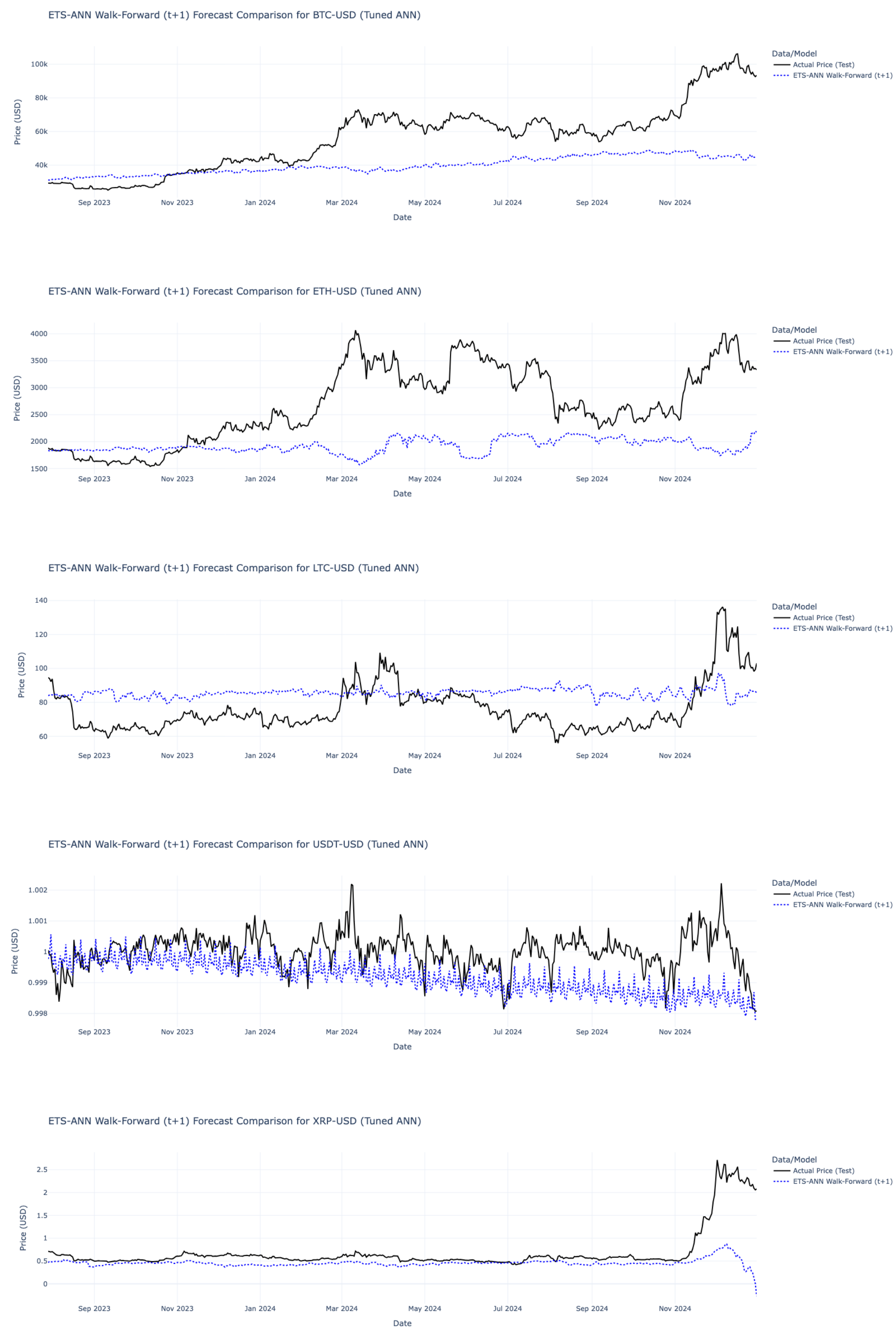
Note: This note describes the plots: From top to bottom, the plots represent the t+10 forecast horizon for Bitcoin, Ethereum, Litecoin, Tether, and Ripple, respectively.

Figure A.6: Actual Price vs LSTM Model Forecast t+30



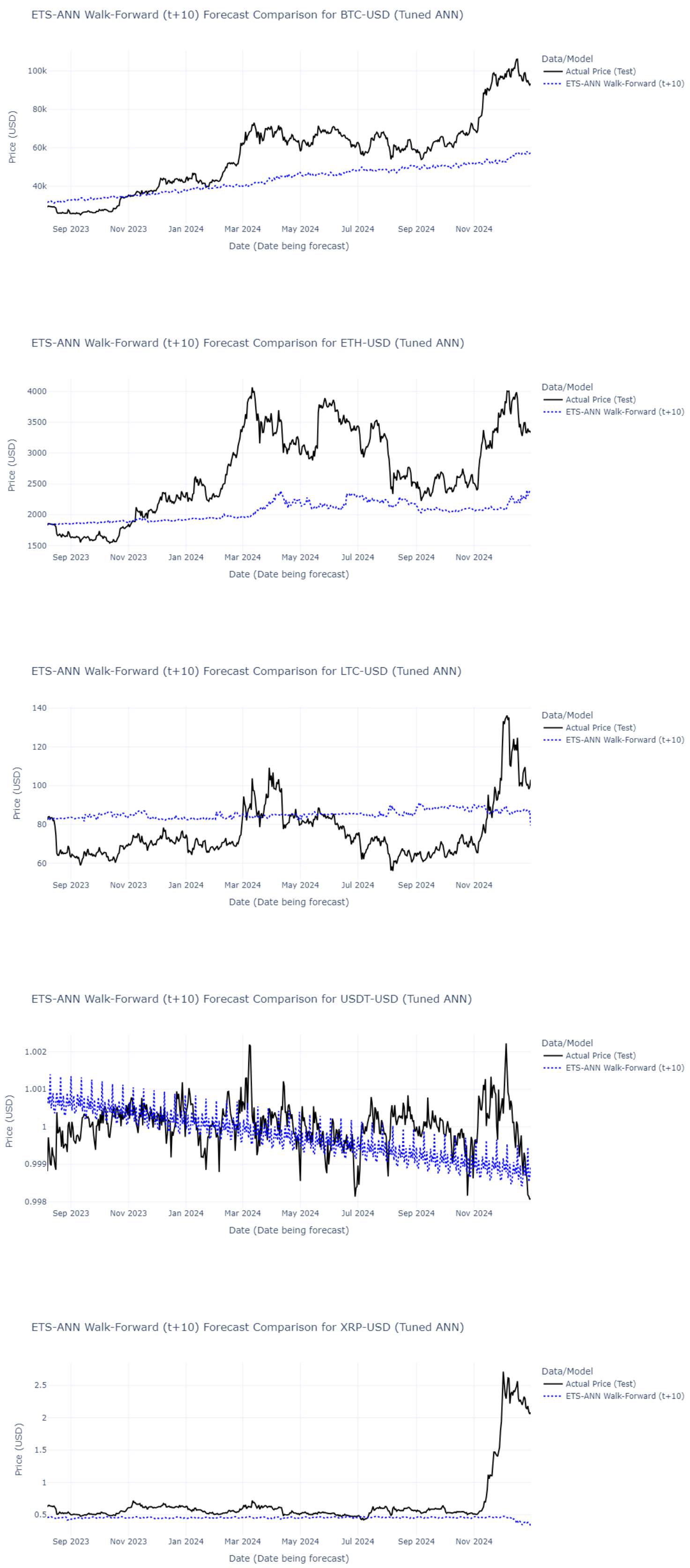
Note: This note describes the plots: From left to right columns represent the t+30 forecast horizon on selected cryptocurrencies put into rows from top to bottom in order "Bitcoin, Ethereum, Litecoin, Tether, Ripple"

Figure A.7: Actual Price vs ETS-ANN Model Forecast for t+1



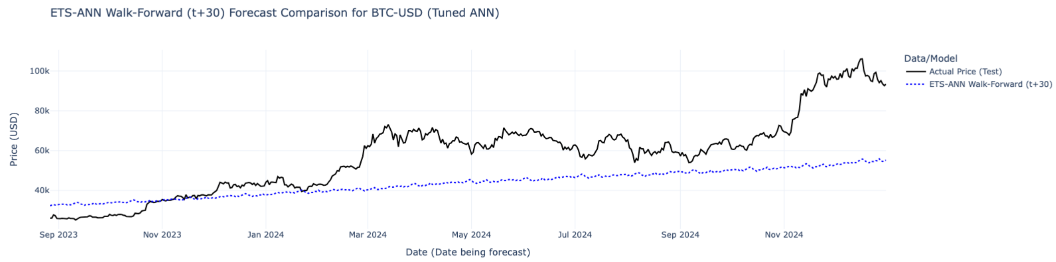
Note: This note describes the plots: From left to right columns represent the t+1 forecast horizon on selected cryptocurrencies put into rows from top to bottom in order "Bitcoin, Ethereum, Litecoin, Tether, Ripple"

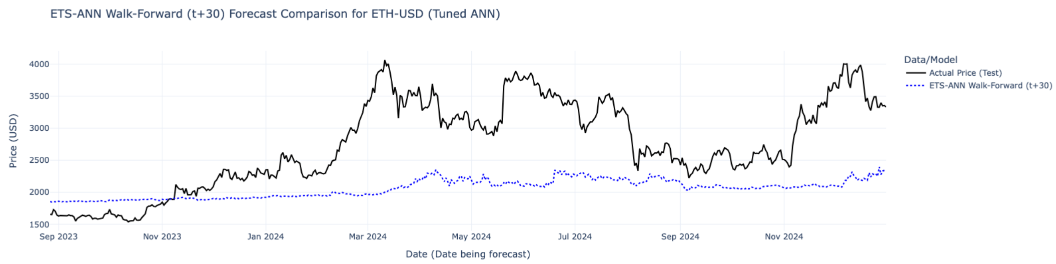
Figure A.8: Actual Price vs ETS-ANN Model Forecast for t+10

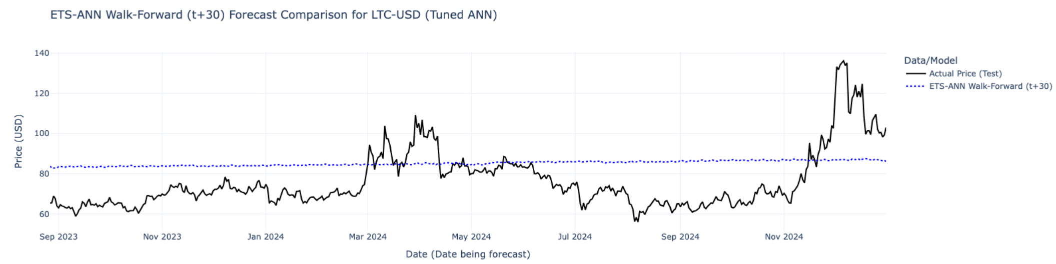


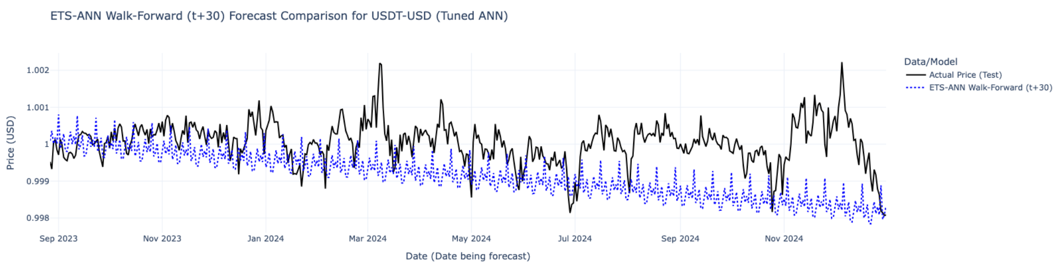
Note: This note describes the plots: From top to bottom, the plots represent the t+10 forecast horizon for Bitcoin, Ethereum, Litecoin, Tether, and Ripple, respectively.

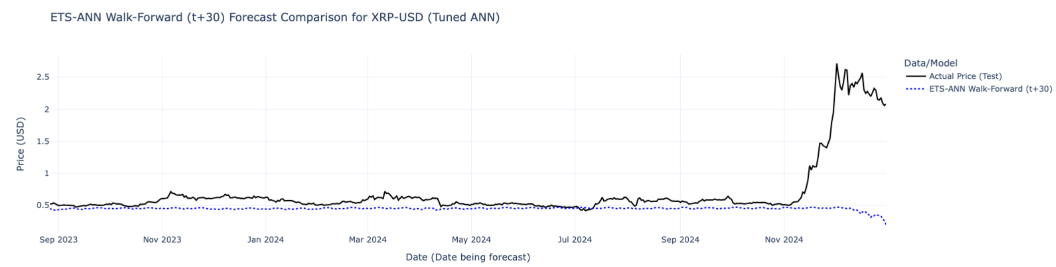
Figure A.9: Actual Price vs ETS-ANN Model Forecast for t+30











Note: This note describes the plots: From left to right columns represent the t+30 forecast horizon on selected cryptocurrencies put into rows from top to bottom in order "Bitcoin, Ethereum, Litecoin, Tether, Ripple"

Appendix A

Figures

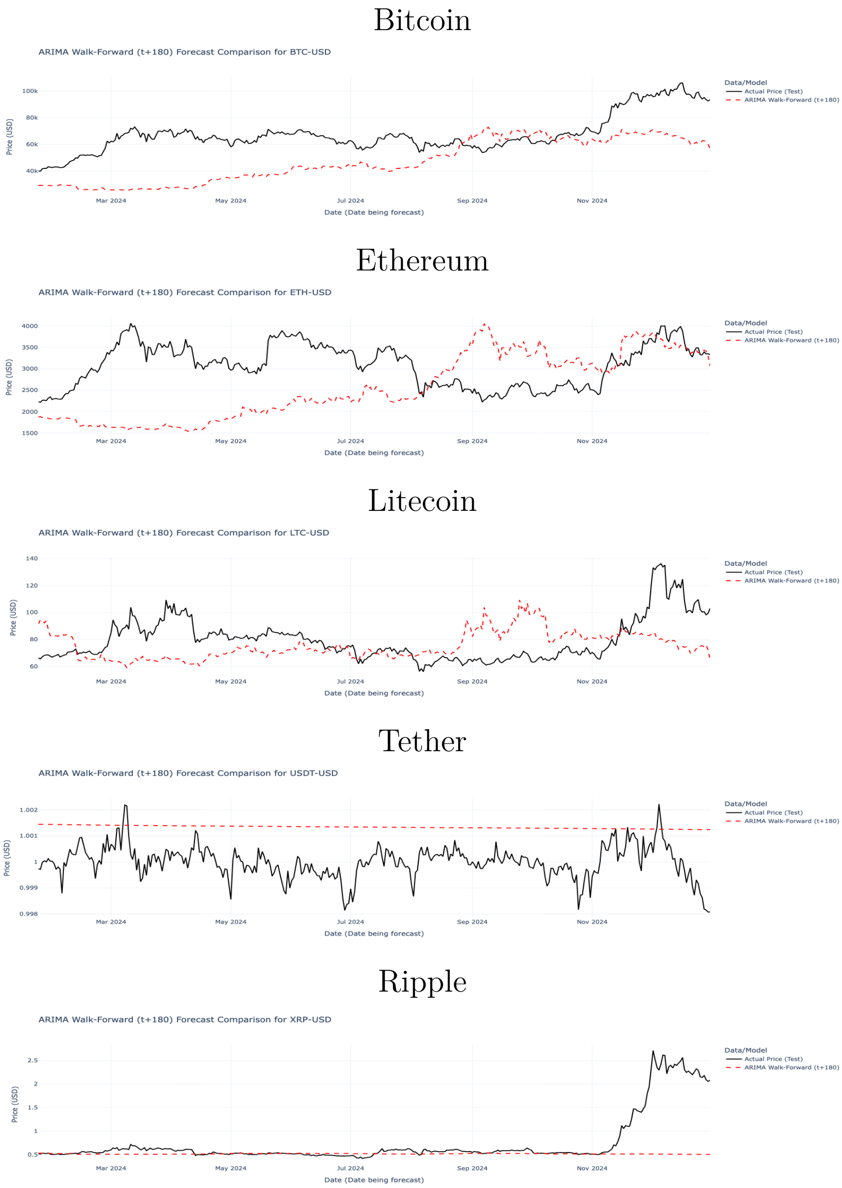


Figure A.10: Exploratory forecast for t+180 horizon for ARIMA Model.

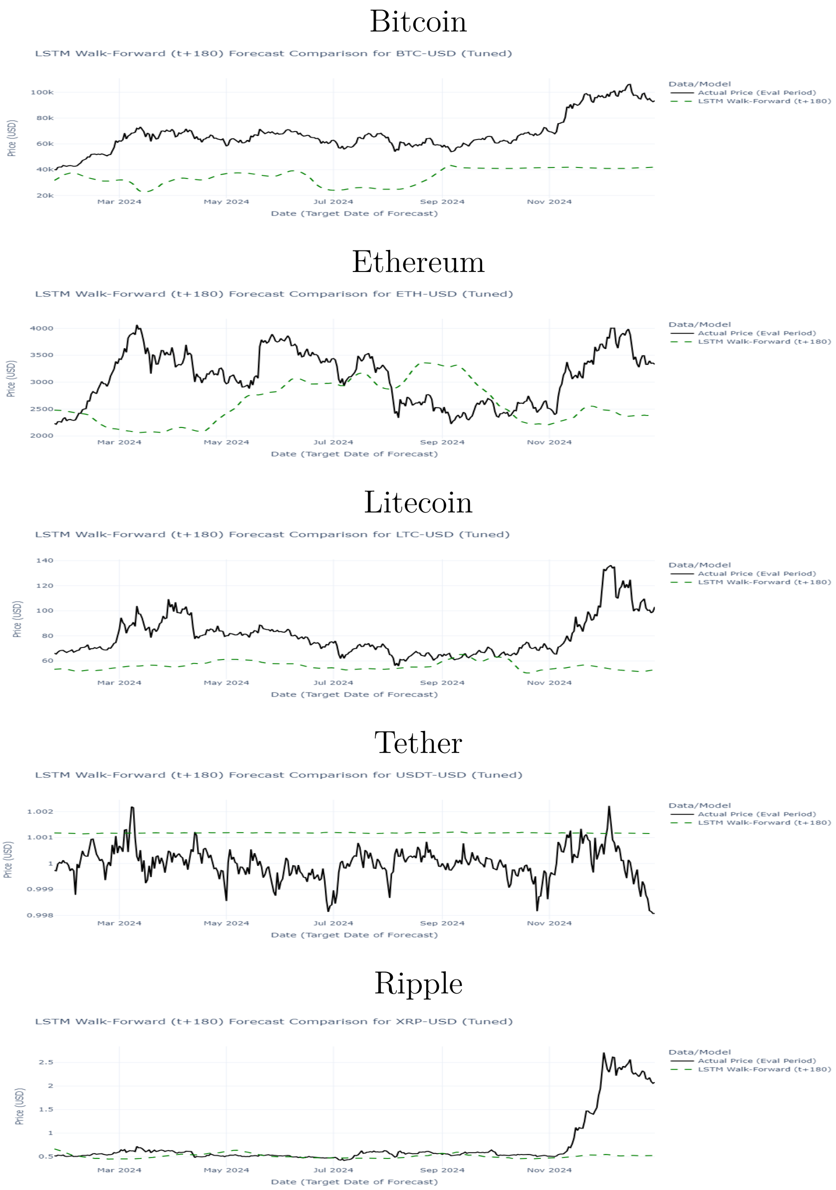


Figure A.11: Exploratory forecast for t+180 horizon for LSTM Model.

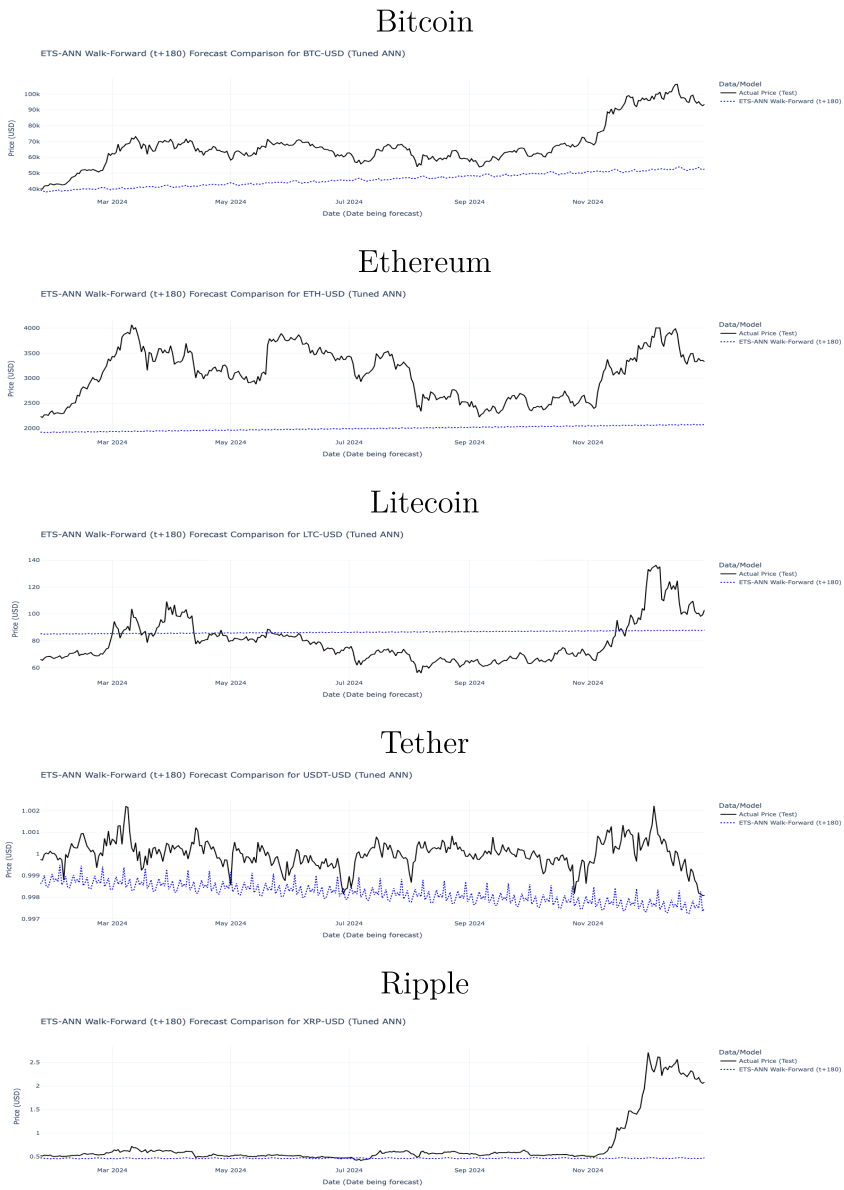


Figure A.12: Exploratory forecast for t+180 horizon for ETS-ANN Model.