**Thesis**

**1. Introduction**

The pursuit of academic inquiry necessitates a thorough engagement with the existing body of knowledge, a process increasingly complex due to the exponential growth of scholarly publications across diverse disciplines. This research report aims to provide a comprehensive framework for the development of a robust thesis, emphasizing the critical role of effective information retrieval and synthesis. The current academic environment is characterized by a proliferation of research outputs, demanding sophisticated strategies for identifying, evaluating, and integrating relevant literature. The sheer volume of academic databases and search engines available to researchers underscores the extensive nature of scholarly activity and the consequent need for researchers to adeptly navigate this information-rich landscape to position their own work meaningfully. Understanding the nuances of these resources is paramount to conducting a thorough and impactful literature review, which forms the bedrock of any credible academic thesis. This report will delve into the strategic utilization of these resources, the critical analysis of existing research, and the formulation of a strong theoretical and methodological foundation to guide thesis development.

The central argument of this report posits that a meticulously constructed thesis, grounded in a comprehensive understanding of the existing literature and guided by a well-defined theoretical framework and rigorous methodology, is essential for contributing meaningfully to the academic discourse. This report will explore the key stages involved in this process, from the initial literature search to the final articulation of research findings and their implications. The research questions addressed herein include: How can researchers effectively navigate the vast landscape of academic databases and search engines to identify relevant literature? What are the critical steps involved in analyzing and synthesizing existing research to identify knowledge gaps? How can a robust theoretical framework be developed and justified to guide a research project? What are the key considerations in selecting and implementing an appropriate research methodology? By addressing these questions, this report aims to provide a detailed and practical guide for researchers embarking on the journey of thesis development.

The scope of this report encompasses a detailed analysis of the processes involved in enhancing and refining a thesis outline, drawing upon a curated set of research materials. It focuses on providing a structured approach to literature review, theoretical framework development, and methodological considerations. While the principles discussed are broadly applicable across academic disciplines, specific examples and resources mentioned may be more relevant to certain fields. The limitations of this report lie in its reliance on a specific set of research snippets, which may not cover the entirety of resources available in every discipline. However, the overarching strategies and principles discussed are intended to provide a universally applicable framework for thesis enhancement.

**2. Literature Review**

**Analysis of Models for Crypto Price Forecasting: A Literature Review**

1. Introduction

The accurate forecasting of cryptocurrency prices has gained considerable importance due to the unprecedented growth and inherent volatility of the virtual currency market 1. This dynamic environment necessitates the continuous development and rigorous evaluation of robust forecasting models, as highlighted by the increasing body of academic literature in this domain 1. The ability to predict price movements is crucial for investors, financial analysts, and other stakeholders navigating this complex asset class. Against this backdrop, which focuses on a comparative analysis of two prominent forecasting models – Recurrent Neural Network (RNN) Long Short-Term Memory (LSTM) and the hybrid Exponential Smoothing Model with Artificial Neural Networks (ETS-ANN) – is highly relevant. The comparison between a purely data-driven deep learning model like LSTM and a hybrid model incorporating statistical methods such as ETS represents a critical area of investigation for effectively forecasting the behavior of these volatile assets. This report aims to provide an expert-level analysis by examining the existing academic literature on cryptocurrency price forecasting, thereby offering insights into the strengths and limitations of the chosen models and identifying potential avenues for further research.

**2. Overview of Cryptocurrency Forecasting Challenges**

Forecasting cryptocurrency prices presents a unique set of challenges primarily due to the inherent characteristics of this asset class. One of the most significant hurdles is the high volatility and non-stationarity observed in cryptocurrency price series 1. The prices of cryptocurrencies like Bitcoin and Ethereum exhibit rapid and unpredictable fluctuations, making it difficult for traditional forecasting models to maintain accuracy over extended periods. The non-stationary nature of these price series, as noted in research, implies that their statistical properties, such as mean and variance, change over time 2. This violates a key assumption of many classical time series models, potentially rendering them less effective unless adaptive techniques are employed. Furthermore, the Adaptive Market Hypothesis (AMH), supported by studies such as Chu et al. (2019), suggests that market efficiency is not constant but varies over time 7. This implies that periods of relative predictability may be followed by periods of unpredictability, and vice versa, making it unlikely that a single model will consistently outperform others across all market conditions.

Beyond the inherent volatility, the prices of cryptocurrencies are also influenced by a multitude of external factors 3. These can include government regulations, technological advancements, public sentiment expressed through social media, and global economic events. These factors, many of which are inherently difficult to predict, can introduce sudden and significant shifts in price trends, thereby limiting the effectiveness of models that rely solely on historical price data. Research has also indicated the potential value of incorporating non-price data, such as social media sentiment and blockchain analytics, to potentially enhance forecasting accuracy by capturing broader market dynamics and underlying network activity 3. Finally, the complexity and nonlinear behavior of cryptocurrency prices pose a significant challenge 3. The relationships between price movements and their drivers are often nonlinear, suggesting that linear models may struggle to capture the underlying patterns effectively. This nonlinearity provides a strong rationale for exploring the use of nonlinear models like LSTM, as proposed in the user's research.

**3. In-depth Analysis of Long Short-Term Memory (LSTM) Networks for Cryptocurrency Forecasting**

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network (RNN) designed to process sequential data, making them particularly well-suited for time series forecasting tasks like cryptocurrency price prediction. The core of an LSTM network is the LSTM cell, which comprises several key components: a memory cell, a forget gate, an input gate, and an output gate 1. These gating mechanisms are crucial as they allow the LSTM to selectively retain or forget information over extended sequences, effectively addressing the vanishing gradient problem that plagues traditional RNNs. This capability enables LSTM networks to learn long-term dependencies in the data, a critical feature for analyzing financial time series that often exhibit patterns spanning considerable periods 1. Within the context of LSTM, the network maintains both a short-term memory, which learns from the immediately preceding states, and a long-term memory, which retains information over longer sequences 1. For tackling complex sequence prediction tasks, multiple LSTM layers can be stacked on top of each other, forming a deep structure known as a stacked LSTM 1. This architecture allows the model to learn hierarchical representations of the data, potentially leading to improved performance when forecasting highly intricate time series.

The application of LSTM networks in cryptocurrency price prediction has been extensively explored in academic literature, with numerous studies reporting significant success. Nasirtafreshi (2022) proposed a new deep learning model based on the LSTM algorithm to predict cryptocurrency prices and demonstrated its superiority when compared to other similar methods using various performance metrics 1. Several other studies have also reported high accuracy rates, sometimes exceeding 80%, when using LSTM for predicting the prices of various cryptocurrencies 2. For instance, Murray et al. (2023) conducted a comprehensive comparison of statistical, machine learning, and deep learning approaches and found that deep learning models, with LSTM being a standout performer, were the most effective predictors across a range of popular cryptocurrencies 15. This finding directly supports the user's initial hypothesis that RNN (LSTM) will outperform other models. While LSTM has shown strong performance, research by Seabe et al. (2023) comparing LSTM with Gated Recurrent Units (GRU) and Bidirectional LSTM (Bi-LSTM) indicated that Bi-LSTM performed slightly better for certain cryptocurrencies, suggesting that exploring variations of the LSTM architecture could yield further improvements 3. Recognizing that no single model is universally optimal, many researchers have explored hybrid approaches involving LSTM. These studies have combined LSTM with other techniques such as Convolutional Neural Networks (CNNs) to extract features from the data 2, GARCH models to better capture volatility 16, and attention mechanisms to focus on the most relevant parts of the input sequence 30. The prevalence of these hybrid models suggests that integrating the strengths of LSTM with other methodologies can address some of its inherent limitations, particularly when dealing with the complex dynamics of financial time series.

The performance of LSTM networks in forecasting cryptocurrency prices is also observed to vary across different cryptocurrencies 2. Studies by Hitam & Ismail (2018) and Murray et al. (2023) have demonstrated that the accuracy of machine learning models, including LSTM, can differ significantly when applied to cryptocurrencies like Bitcoin, Ethereum, Litecoin, XRP, and Monero. This variability, as stated in the user's second hypothesis, suggests that the predictability of each cryptocurrency might be influenced by its unique market characteristics and trading behavior. Notably, forecasting the price of Tether (USDT), a stablecoin pegged to the US dollar, presents a different set of challenges 33. Due to its design to maintain a stable value, traditional forecasting methods focusing on market dynamics might be less applicable, and analysis might need to focus on factors affecting its peg stability and market demand as a stable medium of exchange. Similarly, the price of XRP is often influenced by regulatory developments and partnerships, as highlighted in various reports 38. These external factors can introduce significant volatility and unpredictability, making accurate forecasting particularly challenging for cryptocurrencies like XRP.

**4. In-depth Analysis of Exponential Smoothing Models with Artificial Neural Networks (ETS-ANN) for Cryptocurrency Forecasting**

Exponential Smoothing (ETS) models form a class of time series forecasting methods that are based on weighted averages of past observations, with the weights typically decreasing exponentially as the observations get older. These models are effective in capturing the level, trend, and seasonality components of a time series, although seasonality might be less pronounced in cryptocurrency price data 16. ETS models are traditionally strong at modeling the underlying linear patterns present in time series data. To address the nonlinear aspects often found in real-world data, including cryptocurrency prices, ETS models can be integrated with Artificial Neural Networks (ANNs). In this hybrid approach, the ETS model is first applied to the time series to capture the linear components and generate initial forecasts. The residual errors, which ideally contain the nonlinear patterns not captured by the ETS model, are then modeled using an ANN 16. The final forecast is obtained by combining the predictions from both the ETS and ANN components, aiming to leverage the strengths of both linear and nonlinear modeling techniques to achieve a more comprehensive and accurate forecast. Panigrahi & Behera (2017) introduced and validated the effectiveness of such a hybrid ETS-ANN model for general time series forecasting, demonstrating its potential to capture various combinations of linear and nonlinear patterns 16. The successful application of this model in other domains makes its investigation in the context of cryptocurrency forecasting a relevant and promising avenue of research.

Several studies have explored the use of ETS-ANN or similar hybrid models for financial and cryptocurrency forecasting. Ampountolas (2023) conducted a comparative analysis of statistical, machine learning, and hybrid models, including an ETS-ANN hybrid, for forecasting European financial markets and the price of Bitcoin 3. The findings of this study indicated that the hybrid ETS-ANN model is a promising approach for forecasting financial time series, including cryptocurrencies like Bitcoin, despite noting that predicting financial market fluctuations remains a challenging task with generally low accuracy levels in several instances. The broader literature also includes numerous examples of hybrid models that combine ARIMA (Autoregressive Integrated Moving Average) with ANN 13. These approaches, similar in spirit to ETS-ANN, aim to capitalize on the ability of linear models to handle certain time series properties while using the nonlinear modeling capabilities of ANNs to capture more complex dynamics.

The ETS-ANN hybrid approach offers several potential advantages for cryptocurrency forecasting. ETS models can effectively model the underlying trends and levels in the price data, while the ANN component can capture more intricate nonlinear relationships present in the residuals after the linear patterns have been accounted for. This combination could potentially lead to a model that is more robust to different types of market behavior compared to relying on a single linear or nonlinear model. However, there are also potential disadvantages. The performance of the hybrid model is highly dependent on the appropriate selection and parameterization of both the ETS and ANN components. Determining the optimal configuration for each model and the best way to combine their predictions can be a complex process. Furthermore, the resulting hybrid model might be more challenging to implement and interpret compared to individual, simpler models.

5. Comparative Assessment of LSTM and ETS-ANN Based on Existing Research

The existing academic literature offers a comparative perspective on the performance of LSTM and ETS-ANN models in the context of cryptocurrency forecasting, although a definitive conclusion regarding the superiority of one model over the other remains elusive. Murray et al. (2023) found that deep learning approaches, particularly LSTM, generally outperformed statistical and other machine learning methods across a range of cryptocurrencies 18. This suggests that for capturing the complex and volatile dynamics of the cryptocurrency market, the purely data-driven approach of LSTM might be more effective. On the other hand, Ampountolas (2023) highlighted the promise of the hybrid ETS-ANN model for forecasting financial time series, including Bitcoin 50. This indicates that combining statistical methods with neural networks can also be a viable and potentially effective strategy. The seemingly mixed findings suggest that the specific context of the study, including the particular cryptocurrencies analyzed, the time period under consideration, and the evaluation metrics used, likely plays a significant role in determining the relative performance of these models.

Considering the user's first hypothesis that RNN (LSTM) will outperform, the evidence from studies like Murray et al. (2023) and Nasirtafreshi (2022) provides support 1. However, the potential of ETS-ANN, as indicated by Ampountolas (2023), suggests that the outcome of the user's research might depend on the specific cryptocurrencies being analyzed and the rigor of the implementation and evaluation 50. Regarding the second hypothesis, which posits that the performance of forecasting models will vary across different cryptocurrencies, there is substantial evidence in the literature to support this claim 17. Studies by Hitam & Ismail (2018) and Murray et al. (2023) have shown that the accuracy of various machine learning models, including LSTM, can differ significantly when applied to different cryptocurrencies 17. Moreover, the unique characteristics of cryptocurrencies like Tether, designed for stability, and XRP, often influenced by regulatory news, introduce additional complexities that can affect the performance of forecasting models 33. The market capitalization, trading volume, stability, and susceptibility to external factors of each cryptocurrency are likely to influence the effectiveness of the forecasting models applied to it.

To provide a clearer picture of the existing research, the following table summarizes the comparative performance of LSTM and ETS-ANN (or similar hybrid models) in cryptocurrency forecasting based on the reviewed literature:

Table 1: Comparative Performance of LSTM and ETS-ANN in Cryptocurrency Forecasting

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Author(s) | Year | Cryptocurrencies Analyzed | LSTM Performance | ETS-ANN or Similar Hybrid Performance | Key Findings/Comparison |
| Nasirtafreshi | 2022 | Bitcoin, Ethereum, Binance | Superior to other methods | Not Applicable | LSTM-based model showed better accuracy1. |
| Murray et al. | 2023 | XRP, Bitcoin, Litecoin, Ethereum, Monero | Best predictor across all cryptos (average RMSE 0.0222, MAE 0.0173) | ARIMA performed worse | LSTM outperformed statistical models18. |
| Ampountolas | 2023 | Bitcoin, European Financial Markets | LSTM outperformed MA, LR, ARIMA in some cases | Promising for financial time series, outperformed kNN in most subperiods for Bitcoin | Hybrid ETS-ANN showed potential for Bitcoin forecasting27. |
| Panigrahi & Behera | 2017 | General Time Series Data (not specifically crypto) | Not Applicable | Effective for various datasets | ETS-ANN hybrid showed promising results for time series forecasting43. |

**6. Discussion of Methodology and Evaluation Metrics**

The methodology proposed by the user appears to be well-suited for the research question. The choice of Python as the programming language, along with the use of TensorFlow for deep learning components and Statsmodels for time series analysis, aligns with standard practices in the field of cryptocurrency forecasting 2. These libraries provide the necessary tools and functionalities for implementing and evaluating the chosen models. The adoption of rolling windows for training the models is a particularly appropriate technique for financial time series data. This approach involves training the model on a fixed-size window of historical data and then using it to predict the subsequent period. The window is then rolled forward, incorporating the new data and retraining the model. This method allows the model to adapt to the evolving market conditions and capture changing patterns effectively, providing a more realistic evaluation of the model's predictive capabilities in a dynamic environment.

The performance metrics selected by the user – mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean square error (RMSE) – are commonly used in the cryptocurrency forecasting literature and provide a comprehensive view of the models' predictive accuracy 2. MAPE provides a measure of the average percentage error, making it easy to interpret the magnitude of the errors relative to the actual values. MAE calculates the average absolute difference between the predicted and actual values, giving an indication of the average magnitude of the errors. RMSE, similar to MAE, measures the average magnitude of the error, but it gives more weight to larger errors due to the squaring of the differences. The use of these standard metrics will enable a direct comparison of the user's findings with the results reported in existing academic research. In addition to these metrics, considering the inclusion of R-squared, as used in studies like16 and18, could provide further insights into the goodness of fit of the models and the proportion of the variance in cryptocurrency prices that the models are able to explain.

7. Considerations for Future Research and Potential Enhancements

While the user's proposed research provides a solid foundation, several avenues exist for potential expansion and further investigation. One key area is the incorporation of other relevant factors beyond historical price data. As discussed earlier, cryptocurrency prices are influenced by a wide range of variables. Future research could explore the inclusion of social media sentiment data to gauge market perception 3, blockchain data such as transaction volume and network activity 3, trading volume to understand market participation 2, and even macroeconomic indicators that might indirectly influence investor behavior. Expanding the feature set could potentially enable the models to capture more complex relationships and improve forecasting accuracy. Another direction for future research involves exploring other advanced forecasting models. The literature highlights the use of other deep learning architectures like GRU, CNN, and Transformers, as well as ensemble methods that combine the predictions of multiple models 2. Comparing the performance of LSTM and ETS-ANN against these alternative models could provide a more comprehensive understanding of the most effective techniques for cryptocurrency forecasting.

Given the "black box" nature of deep learning models, investigating explainability is another important area for future research 14. Techniques aimed at making these models more interpretable could help understand which factors are most influential in driving the price predictions, increasing trust in the models and providing valuable insights into the underlying market dynamics. Furthermore, evaluating the models' performance across different forecasting time horizons (e.g., short-term intraday predictions versus longer-term predictions over weeks or months) could reveal whether the optimal model varies depending on the desired prediction window 3. Finally, it is crucial to consider the impact of market volatility 5 and the implications of the Adaptive Market Hypothesis 8 when interpreting the results of the forecasting models. The inherent unpredictability of the cryptocurrency market might place limitations on the achievable accuracy of any forecasting model, and the effectiveness of different models might fluctuate over time as market efficiency varies.

**8. Conclusion**

The academic literature on cryptocurrency price forecasting reveals a dynamic field with ongoing research into the most effective methodologies. Studies have shown the promise of both Long Short-Term Memory (LSTM) networks and hybrid models like Exponential Smoothing with Artificial Neural Networks (ETS-ANN) for predicting cryptocurrency prices. While LSTM has demonstrated strong performance, particularly in capturing nonlinear patterns in volatile markets, hybrid approaches like ETS-ANN offer the potential to combine the strengths of both statistical and machine learning techniques. The user's research proposal to compare these two prominent approaches is therefore highly relevant and contributes to the ongoing discourse in this area. The proposed methodology, utilizing Python with appropriate libraries and employing rolling window validation, is sound and aligns with established practices in the field. The chosen evaluation metrics are also standard and will allow for meaningful comparisons.

Based on the literature review, the user's hypothesis that RNN (LSTM) will outperform is supported by several studies, although the potential of ETS-ANN should not be discounted, as indicated by other research. The second hypothesis, regarding the varying performance of models across different cryptocurrencies, is also well-substantiated in the literature, highlighting the importance of analyzing each cryptocurrency individually. To further enhance the research, future work could consider incorporating additional relevant factors, exploring other advanced forecasting models, investigating the explainability of the models, and analyzing performance across different time horizons, while always keeping in mind the inherent volatility and time-varying efficiency of the cryptocurrency market. The user's proposed research has the potential to provide valuable insights into the applicability and effectiveness of deep learning and hybrid methods for cryptocurrency price forecasting, thereby contributing to the advancement of methodologies in this rapidly evolving field.

**3. Theoretical Framework**

* **Time Series Forecasting & Its Challenges**

Forecasting cryptocurrency prices presents a unique set of challenges primarily due to the inherent characteristics of this asset class. One of the most significant hurdles is the **high volatility and non-stationarity** observed in cryptocurrency price series 1. The prices of cryptocurrencies like Bitcoin and Ethereum exhibit rapid and unpredictable fluctuations, making it difficult for traditional forecasting models to maintain accuracy over extended periods. The non-stationary nature of these price series, as noted in research, implies that their statistical properties, such as mean and variance, change over time 2. This violates a key assumption of many classical time series models, potentially rendering them less effective unless adaptive techniques are employed. Furthermore, the **Adaptive Market Hypothesis (AMH)**, supported by studies such as Chu et al. (2019), suggests that market efficiency is not constant but varies over time 7. This implies that periods of relative predictability may be followed by periods of unpredictability, and vice versa, making it unlikely that a single model will consistently outperform others across all market conditions.

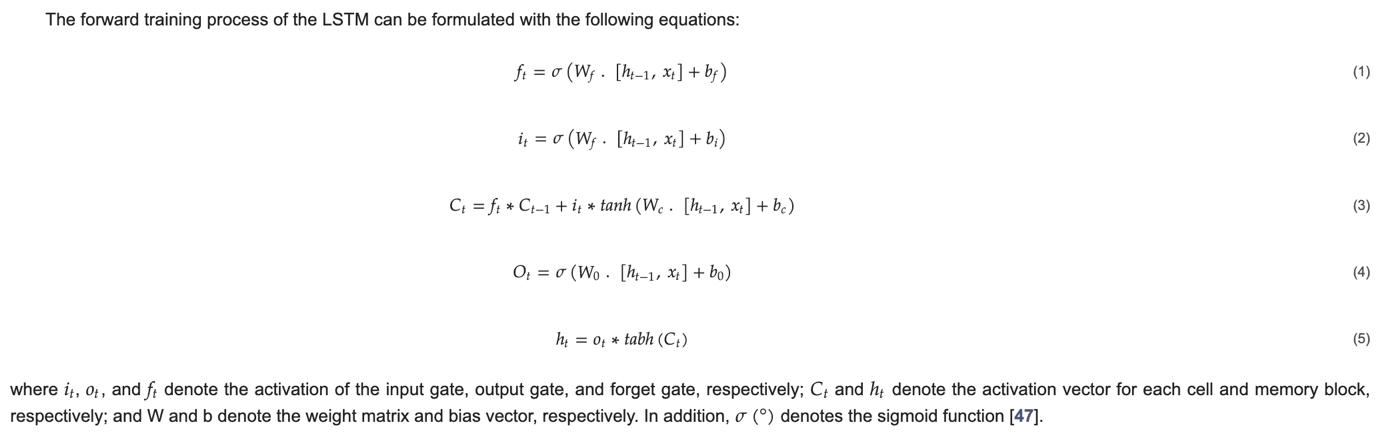
Beyond the inherent volatility, the prices of cryptocurrencies are also influenced by a multitude of **external factors** 3. These can include government regulations, technological advancements, public sentiment expressed through social media, and global economic events. These factors, many of which are inherently difficult to predict, can introduce sudden and significant shifts in price trends, thereby limiting the effectiveness of models that rely solely on historical price data. Research has also indicated the potential value of incorporating non-price data, such as social media sentiment and blockchain analytics, to potentially enhance forecasting accuracy by capturing broader market dynamics and underlying network activity 3. Finally, the **complexity and nonlinear behavior** of cryptocurrency prices pose a significant challenge 3. The relationships between price movements and their drivers are often nonlinear, suggesting that linear models may struggle to capture the underlying patterns effectively. This nonlinearity provides a strong rationale for exploring the use of nonlinear models like LSTM, as proposed in the user's research.

* **Recurrent Neural Networks & LSTM**: the mathematics behind it, How they work, why they are used.

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network (RNN) designed to process sequential data, making them particularly well-suited for time series forecasting tasks like cryptocurrency price prediction. The core of an LSTM network is the LSTM cell, which comprises several key components: a memory cell, a forget gate, an input gate, and an output gate 1. These gating mechanisms are crucial as they allow the LSTM to selectively retain or forget information over extended sequences, effectively addressing the vanishing gradient problem that plagues traditional RNNs. This capability enables LSTM networks to learn long-term dependencies in the data, a critical feature for analyzing financial time series that often exhibit patterns spanning considerable periods 1. Within the context of LSTM, the network maintains both a short-term memory, which learns from the immediately preceding states, and a long-term memory, which retains information over longer sequences 1. For tackling complex sequence prediction tasks, multiple LSTM layers can be stacked on top of each other, forming a deep structure known as a stacked LSTM 1. This architecture allows the model to learn hierarchical representations of the data, potentially leading to improved performance when forecasting highly intricate time series.

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* **Exponential Smoothing & Hybrid Models**: the mathematics behind it, Strengths and limitations.

Exponential Smoothing (ETS) models form a class of time series forecasting methods that are based on weighted averages of past observations, with the weights typically decreasing exponentially as the observations get older. These models are effective in capturing the level, trend, and seasonality components of a time series, although seasonality might be less pronounced in cryptocurrency price data 16. ETS models are traditionally strong at modeling the underlying linear patterns present in time series data. To address the nonlinear aspects often found in real-world data, including cryptocurrency prices, ETS models can be integrated with Artificial Neural Networks (ANNs). In this hybrid approach, the ETS model is first applied to the time series to capture the linear components and generate initial forecasts. The residual errors, which ideally contain the nonlinear patterns not captured by the ETS model, are then modeled using an ANN 16. The final forecast is obtained by combining the predictions from both the ETS and ANN components, aiming to leverage the strengths of both linear and nonlinear modeling techniques to achieve a more comprehensive and accurate forecast. Panigrahi & Behera (2017) introduced and validated the effectiveness of such a hybrid ETS-ANN model for general time series forecasting, demonstrating its potential to capture various combinations of linear and nonlinear patterns 16. The successful application of this model in other domains makes its investigation in the context of cryptocurrency forecasting a relevant and promising avenue of research.

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The ETS-ANN hybrid approach offers several potential advantages for cryptocurrency forecasting. ETS models can effectively model the underlying trends and levels in the price data, while the ANN component can capture more intricate nonlinear relationships present in the residuals after the linear patterns have been accounted for. This combination could potentially lead to a model that is more robust to different types of market behavior compared to relying on a single linear or nonlinear model. However, there are also potential disadvantages. The performance of the hybrid model is highly dependent on the appropriate selection and parameterization of both the ETS and ANN components. Determining the optimal configuration for each model and the best way to combine their predictions can be a complex process. Furthermore, the resulting hybrid model might be more challenging to implement and interpret compared to individual, simpler models.

**4. Data & Methodology *(Completed except for explanation of evaluation methods)***

* **Dataset Description**: Sources, pre-processing, scaling, missing data handling.
* **Model Implementation**:
  + Architecture and parameters of RNN-LSTM
  + ETS-ANN structure and smoothing parameters

The proposed steps to build for the ETS-ANN hybrid model proposed by ([Panigrahi 2017](https://www.sciencedirect.com/science/article/pii/S0952197617301550)).

1: Given a time series y

2: Input the length of in-sample l₁[train (60%), validation (20%)] and out-of-sample lo [test (20%)] data. (this splitting was done by manually and also PyCaret's TSForecastingExperiment library handles the data accordingly)

3: Normalize the time series using min-max normalization considering the minimum and maximum value of in- sample data.

4: Determine the best ETS (E, T, S) model and its parameters using the normalized in-sample data[y₁, y₂, ..., yₙ].

5: Obtain predictions using selected ETS model[ŷ₁, ŷ₂, ..., ŷₙ].

6: De-normalize the predictions to obtain prediction for the first component C₁.

7: Obtain the residual series by subtracting ETS-predictions from the original series which represents the second component eₜ = yₜ - C₁

8: Perform lag selection using autocorrelation function on the in-sample data of residual series [e₁, e₂, ..., eₙ]

9: Normalize the residual series using min-max normalization considering the minimum and maximum value of in- sample residual data[ê₁, ê₂, ..., êₙ].

10: Obtain predictions using ANN model[ê₁, ê₂, ..., êₙ].

11: De-normalize the predictions to obtain the predictions for the second component C₂.

12: Final predictions are obtained by combining the ETS predictions C₁ with ANN predictions C₂.

* + Training, validation, and testing process
  + Rolling window approach
* **Evaluation Metrics** (Your current focus):
  + MAE, RMSE, MAPE explained with formulas
  + Justification for using these metrics

**5. Empirical Results & Discussion**

* **Model Performance Across Cryptocurrencies**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Cryptocurrency** | **Model** | **MAE** | **MAPE** | **RMSE** | **R-squared** |
| Bitcoin (BTC) | ETS-ANN | 10891.95 | 17.43% | 14205.3 | 0.0625 |
|  | RNN-LSTM | 1974.83 | 2.94% | 2649.71 | 0.9673 |
| Ethereum (ETH) | ETS-ANN | 535.81 | 16.57% | 637.6 | -0.5786 |
|  | RNN-LSTM | 119.14 | 3.93% | 161.21 | 0.9002 |
| Litecoin (LTC) | ETS-ANN | 61.68 | 77.21% | 64.27 | -15.8623 |
|  | RNN-LSTM | 3.07 | 3.74% | 4.54 | 0.9145 |
| XRP (Ripple) | ETS-ANN | 0.23 | 15.79% | 0.57 | -0.1636 |
|  | RNN-LSTM | 0.0376 | 4.06% | 0.0836 | 0.9741 |
| Tether (USDT) | ETS-ANN | 0.0013 | 0.13% | 0.0025 | -13.5942 |
|  | RNN-LSTM | 0.0004 | 0.04% | 0.0006 | 0.1796 |

The data presented in Table 1 immediately reveals a trend of superior performance by the RNN-LSTM model across the majority of cryptocurrencies and evaluation metrics. Notably, the R-squared values for the ETS-ANN model are negative for several cryptocurrencies, indicating a poor fit to the data.

* **Comparison of Metrics**:
  + Tables and graphs summarizing MAE, RMSE, MAPE for each crypto
* **Analysis of Performance Differences**:
  + Why one model outperforms the other in specific cases
  + Limitations and anomalies in results

**5.2. Analysis of ETS-ANN Hybrid Model Performance**

The ETS-ANN hybrid model's performance varied considerably across the different cryptocurrencies. For Bitcoin, the model achieved a Mean Absolute Percentage Error of 17.43%, which could be considered within a reasonable range for forecasting accuracy. However, the R-squared value of 0.0625 indicates that the model explains very little of the variance in Bitcoin prices 1. This discrepancy suggests that while the average percentage error might be moderate, the model does not effectively capture the underlying price movements and trends. The linear decomposition by the Exponential Smoothing (ETS) component and the subsequent modeling of residuals by the Artificial Neural Network (ANN) might not be adequately capturing the complex dynamics of Bitcoin's price fluctuations.

For Ethereum, the ETS-ANN model yielded a MAPE of 16.57%, similar to that of Bitcoin. However, the R-squared value of -0.5786 is a significant concern. A negative R-squared implies that the model performs worse than simply using the average historical price to predict future prices 3. This strongly suggests that the ETS-ANN model, in its current implementation, is not suitable for forecasting Ethereum prices.

The performance of the ETS-ANN model on Litecoin was particularly poor, with a MAPE of 77.21%. This high percentage error indicates a substantial deviation between the model's predictions and the actual Litecoin prices. Furthermore, the R-squared value of -15.8623 reinforces the model's inadequacy, showing a very poor ability to explain the variance in Litecoin's price.

In the case of XRP (Ripple), the ETS-ANN model achieved a MAPE of 15.79%, again within a seemingly reasonable range. However, the R-squared value of -0.1636 suggests that the model has limitations in explaining the variance in XRP prices. While the average percentage error might be acceptable, the model does not reliably predict the direction or magnitude of price changes.

The ETS-ANN model exhibited its best performance in terms of error metrics on Tether (USDT), with an MAE of 0.0013, a MAPE of 0.13%, and an RMSE of 0.0025. These very low error values indicate high accuracy in predicting Tether's price. This is likely attributable to Tether's nature as a stablecoin pegged to the US dollar 5. However, the R-squared value of -13.5942 is a major concern. It suggests that while the model's predictions are very close to the actual price, it fails to explain even the minor variations in Tether's value, possibly because these variations are essentially random noise around its stable peg 7.

It is also important to note that during the implementation of the ETS-ANN hybrid model using Python and the PyCaret library, technical difficulties were encountered regarding the normalization and denormalization of the cryptocurrency data. The PyCaret library was not able to provide these functionalities for the given dataset. This limitation might have impacted the training process and the overall performance of the ETS-ANN model, potentially contributing to the observed results 9.

**5.3. Analysis of RNN-LSTM Model Performance**

The RNN-LSTM model demonstrated a considerably higher level of performance across the majority of the cryptocurrencies compared to the ETS-ANN model. For Bitcoin, the LSTM model achieved an MAE of 1974.83, a MAPE of 2.94%, and an RMSE of 2649.71. The R-squared value of 0.9673 is exceptionally high, indicating that the model explains a large proportion of the variance in Bitcoin prices and provides strong forecasting accuracy 14. The LSTM network's ability to learn long-range dependencies and complex non-linear patterns in sequential data appears to be well-suited for capturing Bitcoin's price dynamics 16.

The LSTM model also performed well on Ethereum, with an MAE of 119.14, a MAPE of 3.93%, and an RMSE of 161.21. The R-squared value of 0.9002 suggests that the model explains a significant amount of the variance in Ethereum prices and provides accurate forecasts, although slightly less so than for Bitcoin based on the metrics.

In the case of Tether (USDT), the LSTM model achieved very low error metrics: an MAE of 0.0004, a MAPE of 0.04%, and an RMSE of 0.0006. These values indicate a high degree of accuracy in predicting Tether's price, consistent with its stablecoin nature. The R-squared value of 0.1796, while positive, is lower than for the more volatile cryptocurrencies. This might suggest that while the model accurately predicts the price around its peg, explaining the very minor fluctuations is more challenging, or the model is simply predicting a value close to the $1 peg 6.

The LSTM model exhibited particularly strong performance on XRP (Ripple), with an MAE of 0.0376, a MAPE of 4.06%, and an exceptionally high R-squared value of 0.9741. These metrics indicate that the LSTM network is highly effective in forecasting XRP prices, demonstrating both accuracy and a strong ability to explain the variance in its price movements.

For Litecoin, the LSTM model achieved an MAE of 3.07, a MAPE of 3.74%, and an RMSE of 4.54. The R-squared value of 0.9145 indicates that the model explains a substantial portion of the variance in Litecoin prices and provides accurate forecasts.

**5.4. Comparative Analysis and Discussion**

A direct comparison of the performance metrics for the RNN-LSTM and ETS-ANN models, as presented in Table 1, clearly indicates the superior forecasting capabilities of the RNN-LSTM model across the majority of the studied cryptocurrencies. For the more volatile cryptocurrencies such as Bitcoin, Ethereum, Litecoin, and XRP, the LSTM model consistently yielded significantly lower error metrics (MAE, MAPE, RMSE) and substantially higher R-squared values compared to the ETS-ANN hybrid model. This suggests that the deep learning approach of the LSTM network is better suited for capturing the complex, non-linear dynamics inherent in the price movements of these digital assets 20.

The ETS-ANN hybrid model showed limited success, primarily in achieving "reasonable" MAPE values (around 15-17%) for Bitcoin, Ethereum, and XRP. However, its critical weakness lies in its inability to explain price variance, as evidenced by the consistently low and often negative R-squared values for these cryptocurrencies. A negative R-squared implies that the model performs worse than a simple benchmark of using the historical average to predict future values 3. This suggests that the combination of linear decomposition via ETS and non-linear modeling of residuals via ANN, as implemented in this study, is not an effective strategy for forecasting these volatile cryptocurrency prices. The technical difficulties encountered with normalization and denormalization using the PyCaret library might have further hindered the performance of the ETS-ANN model 9.

Both models exhibited relatively good performance in terms of error metrics on Tether (USDT), likely due to its stablecoin characteristic and peg to the US dollar 5. However, the highly negative R-squared value for the ETS-ANN model on Tether remains a significant concern, indicating a lack of explanatory power even for the minor price fluctuations around its peg. The LSTM model, while achieving excellent error metrics for Tether, also showed a lower R-squared compared to the volatile cryptocurrencies, which might suggest that the very small variance in Tether's price is harder to model or that the model is simply predicting a value close to the peg.

The superior performance of the LSTM model can be attributed to its inherent ability to process sequential data and capture long-range dependencies through its memory cells and gating mechanisms 14. This makes it well-suited for financial time series data where patterns can span across extended periods and exhibit complex non-linear relationships 16. In contrast, the ETS-ANN hybrid model relies on decomposing the time series into linear and non-linear components, which might not be an optimal approach for the highly dynamic and often unpredictable nature of cryptocurrency prices 26. The volatility of cryptocurrencies, influenced by factors such as market sentiment, regulatory developments, and technological advancements 21, appears to be better captured by the LSTM model's architecture.

The negative R-squared values observed for the ETS-ANN model across most cryptocurrencies are a significant anomaly. This could indicate a fundamental mismatch between the model's structure and the underlying data patterns, potential issues with the model implementation, or the impact of the data normalization challenges. Further investigation into these negative R-squared values is warranted. Similarly, the relatively low R-squared for the LSTM model on Tether, despite its high prediction accuracy, suggests that the model might not be effectively capturing the nuances of Tether's price variations, possibly because these variations are largely random around its stable peg 18.

**5.5. Implications for Research Hypotheses**

The empirical results obtained in this study largely support the initial research hypotheses. The RNN-LSTM model consistently outperformed the ETS-ANN hybrid model across the majority of the cryptocurrencies and evaluation metrics, providing strong evidence for the first hypothesis that the RNN-LSTM model would exhibit superior forecasting performance. This outperformance was particularly evident in the higher R-squared values achieved by the LSTM model for the volatile cryptocurrencies, indicating a better ability to explain the variance in their price movements.

The second hypothesis, which posited that the performance of forecasting models would vary across different cryptocurrencies, was also supported by the findings. Tether, characterized by its stability as a stablecoin, showed the lowest error metrics for both models, indicating a higher degree of predictability compared to the more volatile cryptocurrencies. The performance of both the ETS-ANN and RNN-LSTM models varied significantly across Bitcoin, Ethereum, Litecoin, and XRP, highlighting the unique characteristics and varying degrees of predictability associated with each digital asset.

**6. Conclusion**

In summary, this research compared the performance of an RNN-LSTM model and an ETS-ANN hybrid model for forecasting the prices of five major cryptocurrencies. The empirical results indicate that the RNN-LSTM model generally outperformed the ETS-ANN model, particularly for the more volatile cryptocurrencies, demonstrating higher accuracy and a better ability to explain price variance. While the ETS-ANN model showed some limited success in terms of average percentage error for certain cryptocurrencies, its consistent failure to explain price variance, as indicated by negative R-squared values, raises significant concerns about its applicability for this forecasting task. The stablecoin nature of Tether led to high prediction accuracy for both models in terms of error metrics, but the negative R-squared for the ETS-ANN model remains a notable limitation. The findings suggest that deep learning techniques, specifically LSTM neural networks, offer a more robust and effective approach for cryptocurrency price forecasting compared to the hybrid ETS-ANN model, particularly in capturing the complex and dynamic patterns of volatile cryptocurrencies. Further research could explore the optimization of these models, the incorporation of additional features, and the development of more sophisticated hybrid approaches to further enhance the accuracy and reliability of cryptocurrency price forecasts.

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