

CHAPTER I

INTRODUCTION

1.1 Background of the Study

The development of financial technology is increasingly expanding with the introduction of a new asset class based on blockchain technology known as crypto assets (cryptocurrency). Among the thousands of existing types of crypto assets, Bitcoin (BTC) has emerged as the pioneer and the asset with the largest market capitalization in the world. Since its initial release, the Bitcoin White Paper has attracted the attention of global investors, financial institutions, and academics due to its potential as an attractive and convincing investment instrument.

However, the primary characteristic inherently attached to Bitcoin assets is its extremely high level of volatility. Drastic price movements within a short period place it into the category of high-risk assets, while simultaneously offering the potential for high gains [1]. This occurs due to various factors ranging from market sentiment, macroeconomic news, to regulatory changes [2][3]. This volatility creates a major challenge for investors in making decisions to manage portfolios and obtain profits [4]. Therefore, the expertise to predict Bitcoin price movements with reasonable accuracy becomes highly crucial and holds significant value for portfolio development.

Conventional analysis methods such as Autoregressive Integrated Moving Average (ARIMA) are often considered to fail in capturing the complex and non-linear movement patterns of Bitcoin prices [5][6][7]. Research shows that this traditional approach has significant limitations compared to modern artificial intelligence techniques in handling fluctuating time-series data [8]. Recognizing these limitations, researchers have turned to Machine Learning and Deep Learning methods. Algorithms such as Support Vector Regression (SVR) and Random Forest have been tested and yielded better results than basic statistical methods [8][9][10]. However, they still have limitations in capturing long-term relationships or integration between data. Therefore, previous researchers shifted towards more advanced computational methods, particularly in the field of deep learning. One model considered most effective for sequential or time-series data, such as price

data, is Long Short-Term Memory (LSTM). LSTM, which is a development of the Recurrent Neural Network (RNN), is specifically designed to overcome the vanishing gradient problem and is effective in learning long-term historical patterns [11][12][13]. This makes it a highly ideal algorithm for financial market analysis.

Specifically, the application of the LSTM algorithm in predicting the direction of Bitcoin price movements has repeatedly been proven to be more robust in capturing the vanishing gradient problem compared to traditional neural network methods (Recurrent Neural Network / RNN) [14] [15]. This increase in time-series prediction accuracy can be maximally achieved if the model is supported by advanced optimization techniques, such as the use of k-Fold Cross Validation or hybrid approaches to prevent overfitting [16] [17]. Various recent studies also confirm that multivariate architectures always provide sharper and more comprehensive projection capabilities compared to univariate models in responding to market anomalies [18] [19], a characteristic that is also relevant in other time-series-based service recommendation fields [20].

Many studies have proven the ability of LSTM to predict the price of Bitcoin + gold (bivariate research), namely by only using historical Bitcoin data with gold prices to find patterns. This is because a popular narrative often juxtaposes Bitcoin with the phrase "Digital Gold." This narrative is based on the similarities in the characteristics of Gold and Bitcoin. Both assets have a limited supply and function as safe-haven assets against inflation. This has triggered several studies to test the correlation between Bitcoin and Gold prices. The superiority of LSTM is not only proven in crypto assets like Bitcoin and Ethereum [21][22], but also shows robust performance in time-series prediction across various other fields, such as predicting the price of cooking oil commodities [23], rainfall [24], predictive maintenance of fuel [25], and even in the field of education, where optimization techniques on machine learning algorithms have been proven to enhance predictive adaptability [26].

In several previous studies, research gaps were found. Although bivariate LSTM (which only uses past gold and BTC prices) has provided good results, its accuracy is prone to decline during sudden market shocks due to a lack of external information [27] [28]. Furthermore, existing studies have focused too heavily on

the "Digital Gold" narrative, thereby ignoring other precious metals [29] [30], such as Silver, Platinum, or industrial asset metals like Palladium and Rhodium [31]. In fact, these precious metals also play an important role as safe-haven assets as well as for their utility in industrial commodities. Silver and Platinum can also be used for jewelry besides gold, Palladium is used for gold plating in white gold manufacturing, and Rhodium is frequently used for vehicle plating due to its resistance to corrosion.

In addition, many existing studies have not systematically conducted experimental comparisons to quantitatively measure whether the addition of external variables (precious metals other than gold) can truly provide a significant performance improvement compared to only using a univariate model (BTC) or only comparing it with gold (bivariate)[32][33][34]. Therefore, this study is proposed to fill these gaps. This research will conduct an experimental comparative analysis to evaluate the performance of the LSTM algorithm in predicting Bitcoin prices. Thus, there will be two model scenarios to compare. The first model is the bivariate LSTM model which only uses historical Bitcoin data with gold, and the second is the multivariate LSTM model which uses historical Bitcoin data combined with multi-precious metal price data (Gold, Silver, Platinum, Palladium, and Rhodium). Apart from model accuracy, the dissemination aspect of prediction results is also crucial. Therefore, this research does not stop at testing the algorithm in an experimental environment but also integrates it into a web-based platform.

For the usage of asset price data, it is collected with a 5-minute timeframe because it can better capture the dynamics of volatility and short-term price movement patterns that are missed when using larger timeframes. However, because the available precious metal commodity market data is only in hourly intervals, data pre-processing techniques in the form of resampling and linear interpolation are carried out to align the time dimensions between the Crypto market, which runs 24/7, and the precious metal market, so that it can be processed using Deep Learning algorithms. Linear interpolation was chosen because the focus of the research is to see the impact of precious metal macro trends on Bitcoin micro volatility. It is expected that this research can provide stronger empirical evidence

regarding the factors that might influence Bitcoin price movements and the effectiveness of the LSTM model in capturing these relationships.

1.2 Research Question

Based on the background described above, the problem formulation to address these issues can be outlined as follows

1. How is the performance of the LSTM algorithm in predicting Bitcoin prices in a bivariate model (based solely on the historical data of BTC and gold prices)?
2. How is the performance of the Long Short-Term Memory (LSTM) model in predicting Bitcoin prices using historical data that has undergone a linear interpolation process?
3. How can the LSTM model be designed and implemented into a web-based prediction system dashboard prototype to visualize the analysis results interactively and in real-time?
4. Does the addition of multi-precious metal data variables (Gold, Silver, Platinum, Palladium, and Rhodium) to the multivariate LSTM model improve the accuracy of Bitcoin price prediction?
5. To what extent is the performance gap between the bivariate and multivariate LSTM models in predicting Bitcoin prices?

1.3 Objectives of the Study

After formulating the problems to be investigated, the objectives of this thesis research are outlined as follows:

1. To analyze the capability of the LSTM algorithm in predicting Bitcoin prices using historical data.
2. To test the effect of adding external variables in the form of precious metal prices (Gold, Silver, Platinum, Palladium, and Rhodium) on the accuracy of Bitcoin price prediction.
3. To compare the performance of the LSTM model using the Gold variable (safe-haven) against the model using the complete set of industrial metal

variables to determine the best model for predicting multi-asset-based Bitcoin prices.

4. To implement the best LSTM model into a web-based dashboard prototype to visualize prediction results and price comparisons in real-time as a monitoring tool.

1.4 Significances of the Study

This research is expected to provide benefits in the future, whether for students, the university, or directly for practitioners/investors.

1. For Students:

- 1) To serve as a reference in studying the implementation of LSTM on time-series data.
- 2) To provide an example of applying machine learning within the field of financial technology.
- 3) To become a baseline reference for conducting further research related to deep learning, forecasting, or crypto assets.
- 4) To train abilities in data analysis, predictive modeling, and algorithm performance evaluation.

2. For the University:

- 1) To assist the university in producing outstanding graduates specializing in this particular field.
- 2) To support the development of curricula or learning modules related to data mining and deep learning.
- 3) To be utilized as a reference material for similar research within the academic environment.

3. For Practitioners/Investors:

- 1) To be used as a foundational consideration in designing diversification strategies and risk management.
- 2) To provide a predictive model that can be utilized for market analysis and investment decision-making.

- 3) To provide a visualization tool for crypto practitioners to monitor price movements through a web-based platform that can be adjusted for both the short term and long term.

1.5 Research Limitations

The scope and limitations applied to this research are as follows:

1. The dataset used consists of the historical prices of Bitcoin and precious metals (Gold, Silver, Platinum, Palladium, and Rhodium) with an initial 1-hour timeframe, which is adjusted using resampling and linear interpolation techniques into a 5-minute interval over a period of 729 days (December 2, 2023 - November 29, 2025) sourced from Yahoo Finance, and does not consider the physical liquidity of each asset.
2. The Deep Learning prediction model used is strictly limited to the Long Short-Term Memory (LSTM) architecture.
3. The model performance evaluation parameters are limited to the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) metrics.
4. The focus of the research is solely on price forecasting, not on direct investment decision-making or trading strategies.
5. The system implementation is limited to the development of a web-based dashboard using the Flask framework, which functions to display historical data visualizations and prediction results. It does not include automated trading execution features (auto-trading) or user account management.
6. This study does not consider non-quantitative external factors such as news sentiment or crypto market regulatory policies.