A STUDY ON STATE-OF-THE-ART ASSET MODELS AND THEIR APPLICATION TO DIGITAL ASSETS *

Ephraim Sun
Lyle School of Engineering
Southern Methodist University
ephraims@smu.edu

Laurens Gijsbertsen
Cox School of Business
Southern Methodist University
lgijsbertsen@smu.edu

Dr. Simon Mak
Director of the Caruth Institute
Southern Methodist University
smak@smu.edu

ABSTRACT

This research project aims to conduct a comprehensive study on state-of-the-art asset models and their application to digital assets. As the financial landscape continues to evolve, alternative assets, specifically digital assets, are gaining significant attention, and becoming increasingly relevant for investors. However, there is a lack of rigorous research and understanding of the various alternative asset investment models and their implications for digital assets. The primary research question driving this study is: "*To what extent can existing alternative asset investing models be applied to digital assets?*" By examining and analyzing various alternative asset models, this research project seeks to assess the feasibility and effectiveness of applying these models to digital assets.

***K*eywords** Digital Assets · Cryptocurrency · Capital Asset Pricing Model · GARCH · LSTM · Portfolio Theory · Risk Management

1 Introduction

Digital assets have grown rapidly in recent years, with the total market cap of cryptocurrencies surpassing $2 trillion in 2021[1]. While digital assets hold promising investment opportunities, the volatile and decentralized nature of this new asset class presents unique investment challenges compared to traditional assets. As investor interest in digital assets continues to grow, there is a need to explore best practices for evaluating digital asset investments.

Applying models from other asset classes provides strategies that might help tackle some challenges associated with digital assets. However, directly transferring traditional asset models to digital assets can be both straightforward and complex due to significant differences in their characteristics. Therefore, it is crucial to review existing models and determine how they should be adjusted for the digital asset landscape.

1.1 Traditional Asset

When we refer to traditional assets, we mean any other asset class that is not related to digital assets or cryptocurrencies. This includes stocks, bonds, real estate, commodities, private equity, private credit, real assets, and hedge funds. The development of asset models has a rich history that spans several decades, reflecting the evolution of financial theory and practice:

The foundations of modern financial theory were laid with the introduction of the concept of diversification and the risk-return tradeoff. Louis Bachelier's 1900 thesis [0], "The Theory of Speculation," introduced the idea of modeling stock prices using Brownian motion. Harry Markowitz's pioneering work on Modern Portfolio Theory (MPT)[0] in 1952 formalized the concept of diversification. MPT introduced the mean-variance optimization framework, which helps investors construct portfolios that maximize expected return for a given level of risk. William Sharpe, John Lintner, and Jan Mossin developed the Capital Asset Pricing Model (CAPM)[0] independently in the mid-1960s. CAPM describes the relationship between systematic risk and expected return for assets, providing a method to price risk. The

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Black-Scholes Model[0], developed by Fischer Black, Myron Scholes, and Robert Merton in 1973, revolutionized options pricing by providing a theoretical estimate of the price of European-style options. Factor models, such as the Fama-French three-factor model[0] introduced in 1992, expanded on CAPM by incorporating additional factors like size and value to better explain asset returns.

More recently, the advent of advanced computing and big data has led to the rise of machine learning models and algorithms, which are increasingly used for price prediction, risk management, and portfolio optimization. These models leverage vast datasets and computational power to uncover complex patterns and relationships in financial markets.

1.2 Digital Assets

Cryptocurrencies were the first widely adopted digital assets, with Bitcoin being the largest. Since then, new digital asset classes have emerged including security tokens representing asset ownership, and utility tokens providing access to a network or platform.

Digital assets present both opportunities and challenges from an investment perspective. While some studies show they can provide portfolio diversification benefits, their short history makes volatility and risk difficult to assess over long periods.

While traditional asset models offer a valuable starting point, their direct application to digital assets requires careful consideration and adjustment. Digital assets, such as cryptocurrencies, differ significantly from traditional assets in certain aspects:

- Volatility: Cryptocurrencies are known for their extreme price volatility, which can be much higher than that of traditional assets.

- Liquidity Profile: The liquidity of digital assets can vary widely. While some cryptocurrencies have high liquidity, others may have very limited trading volume, affecting their price stability and the ability to execute large trades without significant price impact.

- Regulatory Oversight: Digital assets operate in a relatively nascent regulatory environment compared to traditional assets.

1.3 Research Purpose

Throughout this paper, we look forward to examine the extent of different models and its application to digital assets. The research paper is broken down into its following categories with its corresponding models

Risk and Return Analysis

- Capital Asset Pricing Model (CAPM)

Volatility Analysis

- Generalized Autoregressive Conditional Heteroskedasticity Model (GARCH)

Price Prediction

- Long Short-Term Memory Model (LSTM)

2 Overview of Existing Asset Models and Their Key Principles

2.1 Risk and Return Analysis

In life, we often here the phrase "There is no free lunch", and that's true in investing. Risk is inherent in all investments. This correlates to the risk-return principle, where the greater the risk the greater the potential return. Investors can only expect higher profit give that they are willing to accept higher chance of losses.

Some risks can be controlled and managed while others cannot. Risk can come in multiple forms: financial risk, market risk. liquidity risk, and inflation risk. It is important to consider such risk factors when assessing the risk and return of any assets, including digital assets.

To systematically evaluate the risk and return characteristics of alternative assets, financial models and theories can be employed. A foundation model in finance for assessing the relationship between risk and expected return is the Capital Asset Pricing Model (CAPM).

2.1.1 CAPM

The Capital Asset Pricing Model (CAPM) is a cornerstone of modern financial theory, providing a framework for understanding the trade-off between risk and return for individual assets in a diversified portfolio. Developed by William Sharpe in the 1960s [0], CAPM posits that the expected return of an asset is directly related to its systematic risk, as measured by beta (β). Beta represents the sensitivity of an asset's returns to the returns of the overall market, capturing the asset's exposure to market-wide risk factors.

According to CAPM, the expected return on an asset can be expressed as:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) \tag{1}$$

where:

- $E(R_i)$ is the expected return of the asset,
- R_f is the risk-free rate,
- β_i is the beta of the asset,
- $E(R_m)$ is the expected return of the market,
- $E(R_m) - R_f$ is the market risk premium.

The CAPM is based on several key assumptions:

- Market Efficiency: All investors have access to all available information and act rationally.
- Risk Aversion: Investors are risk-averse, meaning they prefer to minimize risk for a given level of expected return.
- Single-Period Investment Horizon: Investors plan for a single period of investment.
- Homogeneous Expectations: All investors have the same expectations regarding risk and return.
- No Taxes or Transaction Costs: There are no taxes or transaction costs affecting investment decisions.

Despite its wide usage, CAPM has several limitations:

- Empirical Failures: CAPM does not always accurately predict the relationship between risk and return in real markets.
- Simplifying Assumptions: Assumptions such as market efficiency and no taxes are often unrealistic.
- Single Factor Model: CAPM considers only systematic risk, ignoring other factors that may affect returns.

The CAPM provides a valuable framework for understanding the relationship between risk and return, despite its limitations. Its simplicity and intuitive appeal make it a fundamental tool in finance, but ongoing research and alternative models continue to address its shortcomings.

2.2 Volatility Analysis

Volatility analysis plays a crucial role in understanding the behavior of financial assets, particularly in the realm of alternative investments. Volatility, often regarded as a measure of risk, encapsulates the degree of uncertainty or variability in the returns of an asset over time. In the context of alternative assets, which encompass a diverse range of investment vehicles beyond traditional stocks and bonds, volatility assumes heightened significance due to the unique characteristics and dynamics inherent in these assets.

The emergence of digital assets, such as cryptocurrencies and tokenized securities, has further underscored the importance of volatility analysis in alternative asset management. These nascent and rapidly evolving asset classes exhibit distinct patterns of price fluctuations and risk profiles, necessitating sophisticated analytical tools to model and assess their volatility dynamics accurately.

Volatility analysis serves multiple purposes in the management of alternative assets. Firstly, it provides insights into the inherent risk associated with these assets, enabling investors and portfolio managers to make informed decisions regarding asset allocation, risk mitigation strategies, and portfolio diversification. Secondly, volatility analysis facilitates the estimation of potential returns and the pricing of derivative instruments, such as options and futures, which are commonly utilized in alternative asset markets for hedging and speculation purposes.

Two prominent methodologies employed in volatility analysis are the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and Stochastic Geometric Brownian Motion (GBM). The GARCH model, a time-series econometric framework, is widely utilized to model the volatility clustering and persistence observed in financial asset returns. By capturing the conditional heteroskedasticity of asset returns, the GARCH model enables practitioners to forecast future volatility levels accurately and assess the risk-return characteristics of alternative assets.

On the other hand, stochastic GBM, a stochastic process widely used in mathematical finance, provides a continuous-time framework for modeling the evolution of asset prices and their associated volatility. By incorporating random fluctuations and drift components into the asset price dynamics, stochastic GBM offers a versatile approach to simulating the behavior of alternative assets under various market conditions and investment scenarios.

2.2.1 Stochastic Geometric Brownian Motion (GBM)

The Geometric Brownian Motion (GBM) is a model used in finance to describe the random movement of asset prices. It's represented by the equation:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{2}$$

Where:

- S_t is the price of the asset at time t.
- μ is the average rate of return, or drift.
- σ is the volatility, or standard deviation of returns.
- dW_t represents the random fluctuation in the asset's price.

This equation states that the change in the asset price over a small time interval dt consists of two components: a deterministic component represented by $\mu S_t dt$, and a random component represented by $\sigma S_t dW_t$.

2.3 GARCH Model

The GARCH model is an econometric model that captures the time-varying volatility or variance of a time series. It assumes that the volatility of the series is autocorrelated and can be predicted based on past values of the series and past volatility.

The basic form of the GARCH(p, q) model is:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_q \sigma_{t-q}^2 \tag{3}$$

Where:

- f_t, i_t, and o_t represent the forget gate, input gate, and output gate activations, respectively.
- $\tilde{C}_t$ denotes the candidate cell state.
- C_t represents the updated cell state.
- h_t is the output of the LSTM unit at time step t.
- W_f, W_i, W_C, and W_o are weight matrices for the forget gate, input gate, candidate cell state, and output gate, respectively.
- b_f, b_i, b_C, and b_o are bias vectors.

2.4 Price Prediction

Predicting financial market prices, such as stock prices or cryptocurrency values, is a challenging task due to the complex and nonlinear nature of market dynamics. Long Short-Term Memory (LSTM) models have emerged as powerful tools for price prediction in financial markets. These models excel at capturing temporal dependencies and patterns in sequential data, making them well-suited for analyzing historical price movements and forecasting future trends. By training on historical price data along with other relevant features, LSTM models can learn to identify patterns and correlations that may influence price movements. Additionally, LSTMs can adapt and update their predictions in real-time as new data becomes available, allowing traders and investors to make informed decisions based on up-to-date market conditions. While no model can perfectly predict market prices, LSTM models have shown promising results in various financial prediction tasks and continue to be a valuable tool for analysts and researchers in the field of quantitative finance.

Long Short-Term Memory (LSTM) models were introduced by Sepp Hochreiter and Jürgen Schmidhuber in 1997[0] as a solution to the vanishing gradient problem in traditional recurrent neural networks (RNNs). RNNs have the capability to process sequential data by maintaining a hidden state that evolves over time. However, they often struggle to capture long-range dependencies in the data due to the vanishing gradient problem, where gradients diminish exponentially as they propagate backward in time during training.

The key innovation of LSTM models is the introduction of a memory cell, which enables the network to retain information over long periods of time. This memory cell is equipped with three gates: the input gate, the forget gate, and the output gate. These gates control the flow of information into and out of the cell, allowing the LSTM to selectively update its memory state and process input sequences effectively.

LSTMs have since become one of the most widely used architectures for sequential data processing tasks, including speech recognition, natural language processing, time series forecasting, and more. Their ability to capture long-range dependencies and handle vanishing gradients has made them indispensable for a wide range of applications in machine learning and artificial intelligence.

The key components of an LSTM unit include:

- Forget Gate: Controls the information to be discarded from the cell state.
- Input Gate: Determines which values from the input should be updated.
- Output Gate: Regulates the information to be output based on the cell state.

Additionally, LSTMs have a cell state that runs through the entire chain of LSTM units, allowing information to flow across time steps while selectively retaining or discarding information through the gates.

An definite example of the equations that govern the operations of an LSTM unit:

$$\begin{aligned}
f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \\
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \\
\tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C), \\
C_t &= f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t, \\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \\
h_t &= o_t \cdot \tanh(C_t).
\end{aligned} \tag{4}$$

In these equations:

- f_t, i_t, and o_t represent the forget gate, input gate, and output gate activations, respectively
- $\tilde{C}_t$ denotes the candidate cell state.
- C_t represents the updated cell state.
- h_t is the output of the LSTM unit at time step t.
- W_f, W_i, W_C, and W_o are weight matrices for the forget gate, input gate, candidate cell state, and output gate, respectively.
- b_f, b_i, b_C, and b_o are bias vectors.

These equations describe the sequential computations performed by an LSTM unit at each time step, allowing it to capture and process temporal dependencies in the input data.

3 Data Composition

We decided to retrieve the top 10 best cryptocurrencies excluding stablecoins (i.e. Tether (USDT) and USDC) based on market cap as of 05/11/2024. The following coins are listed in order of market capitalization:

- Bitcoin (BTC)
- Ethereum (ETH)
- Solana (SOL)
- Binance Coin (BNB)
- XRP (XRP)
- Toncoin (TON)
- Dogecoin (DOGE)
- Cardano (ADA)
- Shiba Inu (SHIB)
- Avalanche (AVAX)

On-chain data is also collected via CryptoCompare API [0]. On-chain data refers to information that is recorded directly on the blockchain, the underlying technology of cryptocurrencies. This data provides valuable insights into the network's activity and health, which can be used to inform valuation models. Key metrics include transaction volume, active addresses, and the total value transacted on the network.

We also use the following other assets:

- Apple Inc. (AAPL): Apple is a leading technology company known for its consumer electronics products such as the iPhone, iPad, Mac computers, and services like the App Store and iCloud.
- Microsoft Corporation (MSFT): Microsoft is a multinational technology company that develops, manufactures, licenses, supports, and sells software, electronics, personal computers, and related services. Its flagship products include the Windows operating system, Microsoft Office suite, and Azure cloud services.
- Amazon.com, Inc. (AMZN): Amazon is a global e-commerce and cloud computing company. It is the largest online retailer in the world and also provides cloud infrastructure services through Amazon Web Services (AWS).
- Alphabet Inc. (GOOGL): Alphabet is the parent company of Google and several former Google subsidiaries. Google is the world's leading search engine and also offers various online advertising services, software, and hardware products.
- Tesla, Inc. (TSLA): Tesla is an electric vehicle and clean energy company. It designs and manufactures electric cars, battery energy storage systems, and solar products. Tesla is known for its innovation in the automotive industry.
- SPDR S&P 500 ETF Trust (SPY): This ETF seeks to provide investment results that, before expenses, correspond generally to the price and yield performance of the S&P 500 Index, which measures the performance of 500 large-cap U.S. stocks.
- iShares Core U.S. Aggregate Bond ETF (AGG): AGG aims to track the investment results of an index composed of the total U.S. investment-grade bond market, including government, corporate, and mortgage-backed securities.
- Invesco Global Listed Private Equity Portfolio (PSP): PSP provides exposure to publicly traded private equity companies, offering insight into the performance of private equity investments through publicly listed firms.
- Vanguard Real Estate ETF (VNQ): VNQ seeks to track the performance of the MSCI US Investable Market Real Estate 25/50 Index, which measures the performance of real estate investment trusts (REITs) and other real estate-related investments.
- SPDR Gold Shares ETF (GLD): GLD seeks to reflect the performance of the price of gold bullion, less the Trust's expenses. It is often used as a hedge against inflation and currency risk.
- iShares Silver Trust (SLV): SLV seeks to reflect the performance of the price of silver, minus expenses. It provides a simple, cost-effective way to gain exposure to the price movement of silver, making it an attractive investment for those looking to diversify their portfolios with commodities.

- United States Oil Fund (USO): USO aims to track the daily price movements of West Texas Intermediate (WTI) light, sweet crude oil. It provides exposure to oil prices and is used to gain exposure to the energy market.

- Dow Jones Industrial Average (DJI): The DJIA is a stock market index that measures the stock performance of 30 large, publicly-owned companies listed on stock exchanges in the United States. It is one of the oldest and most well-known indices in the world.

- Bitwise 10 Crypto Index Fund (BITW): BITW aims to track the performance of the Bitwise 10 Large Cap Crypto Index, which is designed to provide exposure to the 10 largest cryptocurrencies, weighted by market capitalization.

ALL data is fetched from Yahoo Finance via yfinance. [0]. In terms of dates, unless otherwise specified, the default dates from Jan 1st, 2022 to Jan 1st, 2024. We use the daily adjusted close data as our data points, which is ample to provide various analysis.

4 Process and Results

4.1 Capital Asset Pricing Model

To determine the CAPM for each asset, we must first calculate the Risk-Free Rate (R_f), Expected Market Return (R_m), Beta (β) for each asset. Below lays out the steps

1. Risk-Free Rate (R_f)

The risk-free rate is typically the return on government bonds, such as U.S. Treasury bills. We decided to use the average risk-free rate over our analysis period for CBOE Interest Rate 10 Year T No [0]

2. Expected Market Return (R_m)

To measure the expected market return, we decided to align our focus to the cryptocurrency market. The expected market return is the average return of a broad cryptocurrency market index, and we used the Bitwise 10 Crypto Index Fund (BITW) [0].

3. Beta Calculation (β)

Beta measures the volatility of an asset relative to the market.

- Obtained historical daily prices for each asset and the chosen market index.

- Computed the daily returns for each asset and the market index.

- Performed a linear regression with the asset returns as the dependent variable and the market index returns as the independent variable. The slope of the regression line is the beta.

4. Market Risk Premium ($R_m - R_f$)

The market risk premium is the difference between the expected market return and the risk-free rate.

Combining each component into the CAPM Model, we obtained the following results.

More information can be found in appendix, please refer to A.

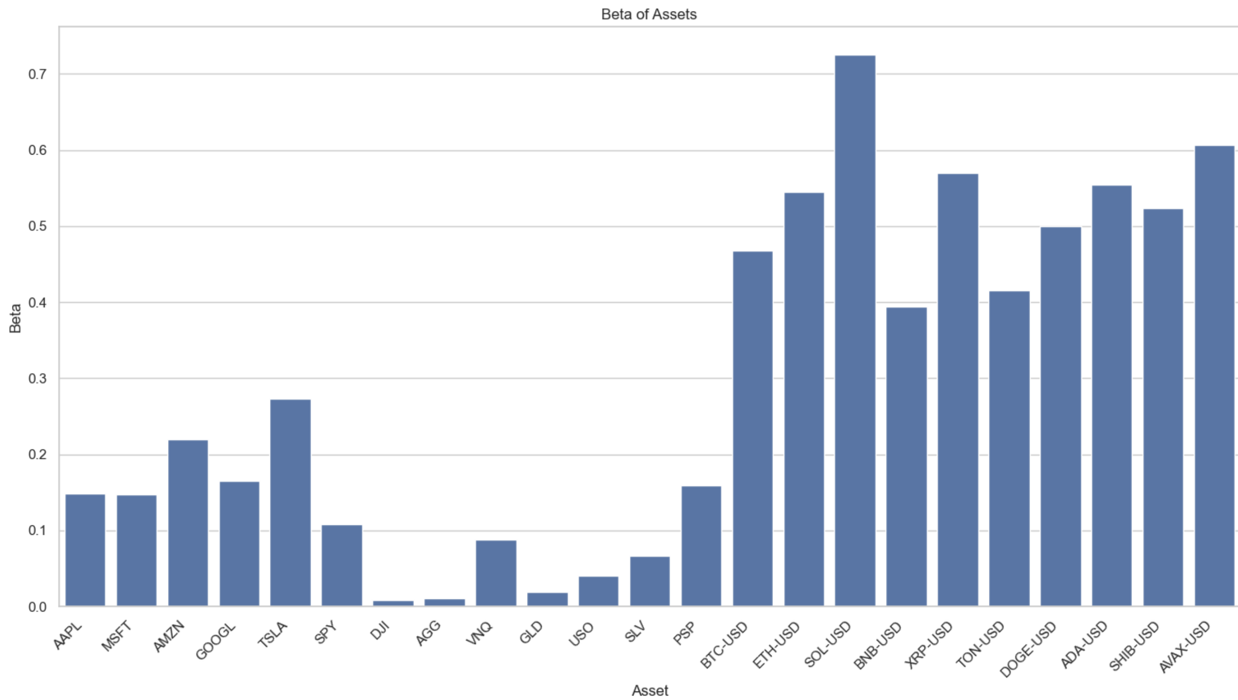

Figure 1: Beta of Assets Relative to BITW

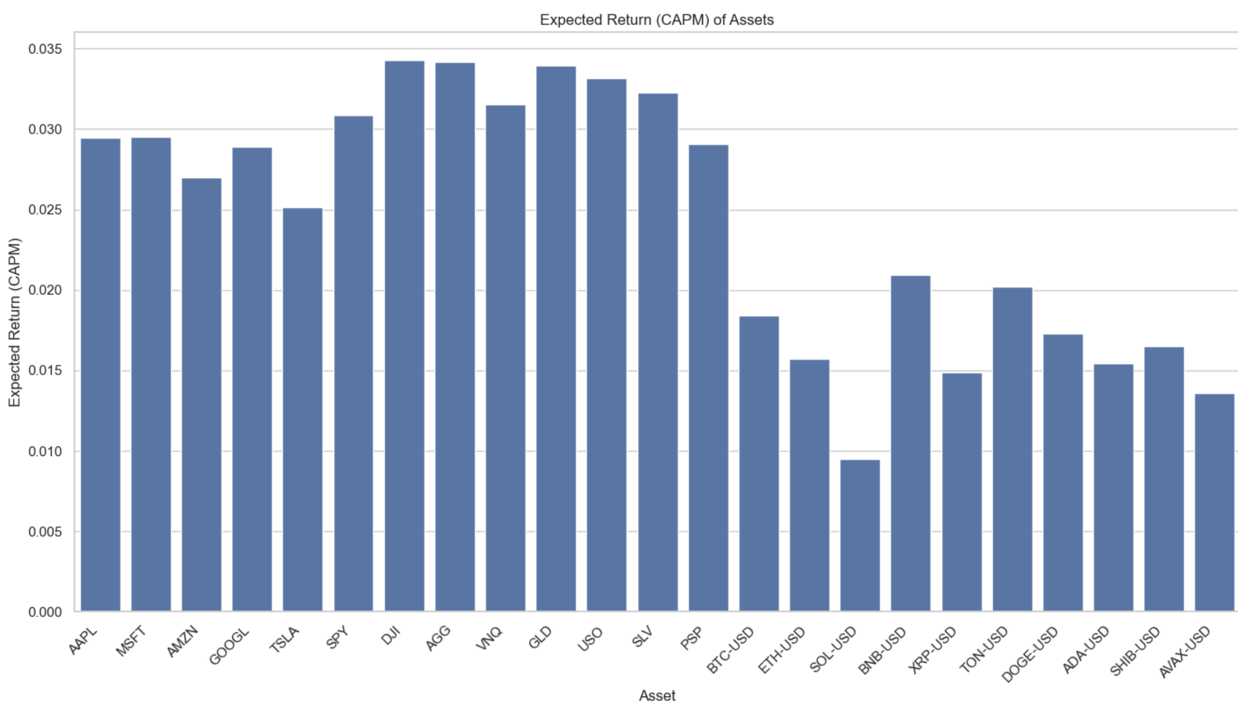

Figure 2: Expected Return of Assets Relative to BITW

Asset	Beta	Market Risk Premium	Expected Return (CAPM)
AAPL	0.1489	-0.0346	0.0294
MSFT	0.1469	-0.0346	0.0295
AMZN	0.2194	-0.0346	0.0270
GOOGL	0.1653	-0.0346	0.0289
TSLA	0.2734	-0.0346	0.0251
SPY	0.1084	-0.0346	0.0308
DJI	0.0089	-0.0346	0.0343
AGG	0.0115	-0.0346	0.0342
VNQ	0.0884	-0.0346	0.0315
GLD	0.0195	-0.0346	0.0339
USO	0.0408	-0.0346	0.0332
SLV	0.0671	-0.0346	0.0323
PSP	0.1596	-0.0346	0.0291
BTC-USD	0.4680	-0.0346	0.0184
ETH-USD	0.5448	-0.0346	0.0157
SOL-USD	0.7253	-0.0346	0.0095
BNB-USD	0.3944	-0.0346	0.0209
XRP-USD	0.5699	-0.0346	0.0149
TON-USD	0.4154	-0.0346	0.0202
DOGE-USD	0.4995	-0.0346	0.0173
ADA-USD	0.5541	-0.0346	0.0154
SHIB-USD	0.5231	-0.0346	0.0165
AVAX-USD	0.6062	-0.0346	0.0136

Table 1: CAPM Estimates for Various Assets

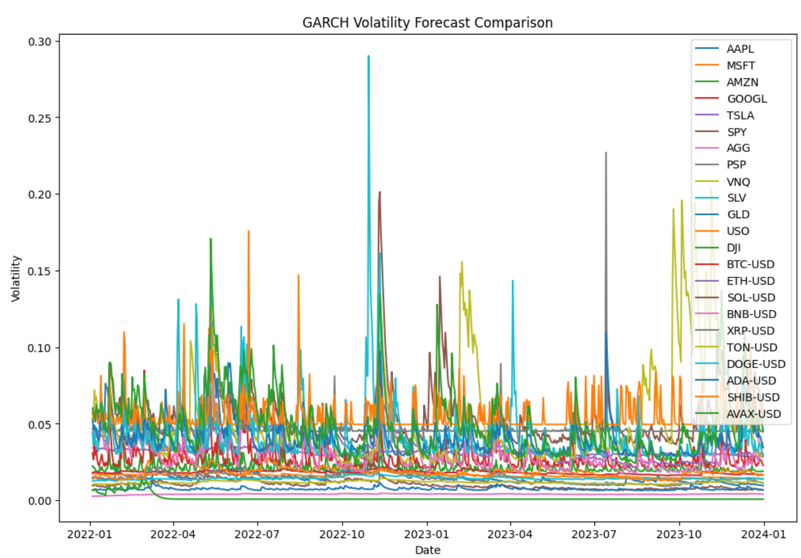

Figure 3: GARCH Volatility Forecast

4.2 GARCH Model

To investigate the time-varying volatility of different financial assets via the GAR Model, we first calculated the daily returns of each asset. Next, we specified and fitted a GARCH(1,1) model to the return data for each asset. This model choice is common in finance for capturing volatility clustering. After fitting the models, we evaluated their performance using various criteria. This included examining summary statistics, such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), to assess model fit and complexity. Additionally, we analyzed residuals to ensure they exhibited characteristics of white noise and conducted stationarity tests to validate model assumptions. Finally, we performed out-of-sample forecasting to assess the model's predictive ability.

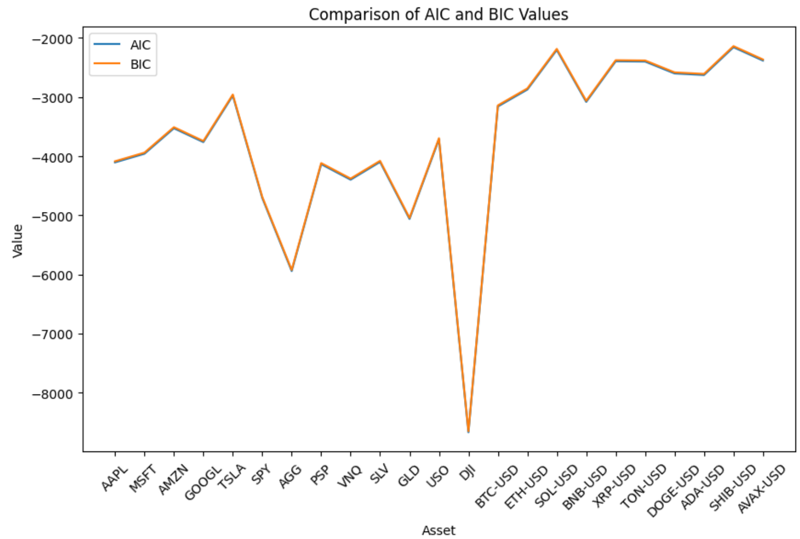

Figure 4: Comparison between AIC and BIC Values

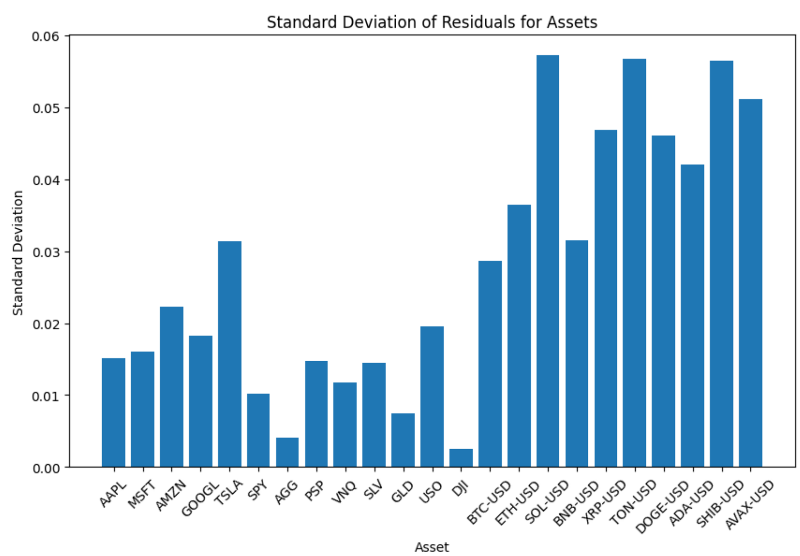

Figure 5: Standard Deviation of Residuals

4.3 LSTM Model

Historical price data for the top 10 cryptocurrencies were fetched using the yfinance[0] library, covering the period from January 1, 2022, to January 1, 2024.

The MinMaxScaler from scikit-learn[0] was used to normalize the 'Adj Close' price data to a range between 0 and 1. This is crucial for LSTM models, which are sensitive to the scale of input data.

4.3.1 Model Architecture and Key Values

In our research, we developed a Bidirectional Long Short-Term Memory (LSTM) model for time series forecasting. Below is a detailed breakdown of the key values and components of our model:

- Sequence Length (SEQ_LEN): 100
- Dropout Rate (DROPOUT): 0.2
- Window Size (WINDOW_SIZE): $SEQ_LEN - 1 = 99$
- Batch Size (BATCH_SIZE): 64

4.3.2 Model Layers and Structure

1. Input Layer:
   - Shape: (WINDOW_SIZE, Number of Features in Input)
   - `input_shape = (WINDOW_SIZE, X_train.shape[-1])`
2. First Bidirectional LSTM Layer:
   - Units: WINDOW_SIZE = 99
   - Return Sequences: True
   - `model.add(Bidirectional(LSTM(WINDOW_SIZE, return_sequences=True)))`
3. First Dropout Layer:
   - Rate: DROPOUT = 0.2
   - `model.add(Dropout(rate=DROPOUT))`
4. Second Bidirectional LSTM Layer:
   - Units: WINDOW_SIZE * 2 = 198
   - Return Sequences: True
   - `model.add(Bidirectional(LSTM(WINDOW_SIZE * 2, return_sequences=True)))`
5. Second Dropout Layer:
   - Rate: DROPOUT = 0.2
   - `model.add(Dropout(rate=DROPOUT))`
6. Third Bidirectional LSTM Layer:
   - Units: WINDOW_SIZE = 99
   - Return Sequences: False
   - `model.add(Bidirectional(LSTM(WINDOW_SIZE, return_sequences=False)))`
7. Dense Layer:
   - Units: 1
   - `model.add(Dense(units=1))`
8. Activation Layer:
   - Activation Function: Linear
   - `model.add(Activation('linear'))`

4.4 Model Compilation

- Loss Function: Mean Squared Error
- Optimizer: Adam
- Key Value: `model.compile(loss='mean_squared_error', optimizer='adam')`

4.5 Model Training Parameters

- Epochs: 50
- Batch Size: BATCH_SIZE = 64
- Shuffle: False
- Validation Split: 10%

Summary

We utilized a Bidirectional LSTM model with three layers of bidirectional LSTMs, each followed by dropout layers to prevent overfitting. The final dense layer with a linear activation function is used for regression. Our model is compiled using the mean squared error loss function and the Adam optimizer, and trained over 50 epochs with a batch size of 64, using 10% of the training data for validation. This architecture effectively captures temporal dependencies in both directions, making it suitable for time series forecasting tasks.

5 Analysis

5.1 CAPM Analysis

From the CAPM (Capital Asset Pricing Model) analysis conducted for the period from January 01, 2022, to January 01, 2024, the following insights can be derived:

Cryptocurrencies exhibit significantly higher betas compared to traditional assets and other alternative asset classes. For instance, BTC-USD and ETH-USD have betas of 0.4680 and 0.5448, respectively, indicating they are more volatile and have higher systematic risk compared to equities, bonds, and commodities. Stocks like TSLA, AAPL, and AMZN also have relatively high betas, reflecting their sensitivity to market movements but generally lower than cryptocurrencies. Alternative assets like VNQ (Real Estate) and PSP (Private Equity) show moderate betas, indicating lower volatility compared to stocks and cryptocurrencies.

The expected returns for cryptocurrencies (e.g., BTC-USD, ETH-USD) are notably lower compared to traditional assets like equities and bonds. This suggests that while cryptocurrencies are more volatile, they do not compensate investors with higher expected returns within this period. AAPL, MSFT, and GOOGL offer higher expected returns compared to cryptocurrencies, aligning with their historical performance in providing growth and income to investors. Assets like DJI (Dow Jones Industrial Average), despite having a very low beta, show a slightly higher expected return, which might indicate stability but lower potential for capital appreciation compared to high-beta assets.

Moving forward, the R-squared values indicate how well each asset's returns are explained by market returns (BITW market index). Higher R-squared values suggest that the asset's returns can be largely attributed to market movements. In addition, the p-values are generally very low across assets, indicating statistical significance in the relationship between their returns and market returns.

The analysis suggests that existing alternative asset investing models, such as CAPM, can be applied to digital assets to some extent, but with notable considerations:

First, cryptocurrencies exhibit significantly higher volatility (measured by beta) compared to traditional assets. This high volatility implies higher risk, which needs to be carefully managed in investment portfolios. Despite the higher volatility, the results show that cryptocurrencies generally offer lower expected returns compared to equities and other traditional assets over the observed period. This obersation could be due to the fact of the downturn during 2022-2024 period. Given the short period analyzed, longer-term data and analysis are crucial to draw more robust conclusions about the risk-return profiles and applicability of traditional asset models to digital assets.

In conclusion, the CAPM provides us a general basis to for initial insights into the risk and return dynamics of cryptocurrencies and other digital assets. Further research and potentially tailored modeling approaches to fully understand and optimize investment strategies could be applied in addition to the CAPM.

5.2 GARCH Model

As shown by the GARCH results, cryptocurrencies exhibit significantly higher volatility compared to traditional assets. This is evident from the standard deviations of residuals, where digital assets like ETH-USD, SOL-USD, and SHIB-USD have noticeably higher values (e.g., ETH-USD: 0.036436, SOL-USD: 0.057214) compared to traditional assets like AAPL (0.015185) and AGG (0.004055). This highlights the inherent volatility and risk associated with digital assets.

In addition, the result provides model fit assessment based on its AIC and BIC. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to evaluate the goodness of fit of the GARCH model. Lower AIC and BIC values indicate better model fit. In the provided table, both traditional assets and digital assets show negative AIC and BIC values, with DJI (Dow Jones Industrial Average) exhibiting the most negative values among traditional assets. Digital assets like BTC-USD, ETH-USD, and SOL-USD also show strong negative values, indicating that the GARCH model can effectively capture their volatility dynamics.

In addition, the Augmented Dickey-Fuller (ADF) test P-values for the residuals of all assets are extremely low (close to zero), suggesting that the residuals are stationary. This is essential as the GARCH model assumes stationary residuals for accurate volatility forecasting. The high significance of these tests across both traditional and digital assets validates the suitability of the GARCH model in capturing the volatility patterns.

The results suggest that the GARCH model can be applied effectively to digital assets, despite their unique characteristics such as high volatility and limited historical data. GARCH models provide robust tools for managing the heightened volatility of cryptocurrencies. By accurately modeling volatility, investors can implement effective risk management strategies to mitigate potential losses. While GARCH models perform well in capturing digital asset volatility, challenges remain due to the rapidly evolving nature of cryptocurrency markets. Adaptations may be necessary to account for factors like regulatory changes and technological advancements that impact digital asset prices.

5.3 LSTM Analysis

The LSTM (Long Short-Term Memory) model has been applied to predict the performance metrics (MSE, RMSE, MAE) for various cryptocurrencies and traditional assets.

Bitcoin shows relatively high errors in MSE (122.7408), RMSE (11.0788), and MAE (9.6324), indicating challenges in predicting its price movements accurately with the LSTM model. Ethereum performs better than Bitcoin with significantly lower MSE (5.1563), RMSE (2.2707), and MAE (1.7916), suggesting the LSTM model captures its price dynamics more effectively. Solana exhibits high MSE (66.9456) and RMSE (8.1820), indicating challenges in accurately predicting its price movements with the LSTM model. Overall, the cryptocurrencies show varying degrees of prediction accuracy. Notably, SHIB-USD has the lowest errors across MSE, RMSE, and MAE, indicating better predictive performance.

For traditional tech stocks like AAPL, MSFT, AMZN, GOOGL, they generally have lower errors in MSE, RMSE, and MAE compared to cryptocurrencies, reflecting the relatively stable and predictable nature of large-cap tech stocks. Other traditional assets like TSLA, SPY, and DJI exhibit varying prediction errors. DJI, in particular, shows extremely high errors, suggesting challenges in predicting its movements with the LSTM model.

Overall, the LSTM models demonstrate varying success in predicting the prices of different cryptocurrencies. Cryptocurrencies like Ethereum and some others show promising results with lower errors, indicating potential applicability of LSTM in forecasting their price movements. High errors observed in cryptocurrencies such as Bitcoin and Solana highlight the volatility and complexity of digital asset markets. Factors such as sudden price fluctuations and lack of historical data can pose challenges for accurate predictions with LSTM models. Traditional assets generally exhibit lower prediction errors compared to cryptocurrencies, reflecting their more stable and mature market characteristics. This suggests that LSTM models may require adaptations or enhancements to effectively handle the unique dynamics of digital assets.

Further research and development are needed to refine LSTM models for digital asset forecasting. Techniques like feature engineering, ensemble methods, and integrating external factors (e.g., sentiment analysis, macroeconomic indicators) could enhance predictive accuracy. While LSTM models show promise in predicting certain cryptocurrencies' prices, their application to digital assets requires careful consideration of the asset's volatility, data quality, and model robustness. Continued advancements in modeling techniques and data availability will be crucial in improving the efficacy of LSTM and other alternative asset investing models for digital assets.

6 Conclusion

This research project has explored the applicability of existing alternative asset investing models to digital assets, focusing on the Capital Asset Pricing Model (CAPM), price prediction using Long Short-Term Memory (LSTM) models, and volatility analysis with the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model.

The study aimed to address the fundamental question: "*To what extent can existing alternative asset investing models be applied to digital assets?*"

In conclusion, the rapid growth and increasing relevance of digital assets, particularly cryptocurrencies, in the global financial landscape have highlighted the imperative for rigorous research into adapting or augmenting traditional asset models to evaluate these assets effectively. As outlined in the introduction, digital assets possess unique characteristics such as high volatility, diverse liquidity profiles, and an evolving regulatory environment. These distinctive features present both challenges and opportunities that demand careful consideration for investors navigating this burgeoning market.

The CAPM analysis revealed insightful findings regarding the risk-return tradeoffs of various asset classes compared to cryptocurrencies. Cryptocurrencies exhibited significantly higher betas, indicating greater volatility and systemic risk compared to traditional equities, bonds, and commodities. Despite their higher risk profile, cryptocurrencies generally offered lower expected returns during the study period, highlighting the importorance of managing risks where higher risk comes at a higher cost. This analysis suggests that while CAPM provides a framework for understanding risk and return relationships, its direct application to digital assets may require adjustments to account for their unique risk characteristics.

Using LSTM models for price prediction provided further insights into the predictive capabilities for digital assets. The results showed varying levels of accuracy across different cryptocurrencies, highlighting the potential for machine learning techniques to capture complex market dynamics and inform investment decisions. LSTM models demonstrated their utility in forecasting cryptocurrency prices, although their performance varied depending on the asset and market conditions. This underscores the importance of leveraging advanced computational methods to navigate the volatility and informational inefficiencies inherent in digital asset markets.

The GARCH model analysis elucidated the volatility dynamics of cryptocurrencies and traditional assets over the study period. Cryptocurrencies exhibited notably higher volatility compared to equities and commodities, underscoring their susceptibility to price fluctuations and market sentiment. The GARCH model's ability to capture time-varying volatility patterns provided valuable insights into risk management strategies for digital asset portfolios. By quantifying and understanding volatility, investors can better assess risk-adjusted returns and tailor their investment strategies accordingly.

Integrating findings from CAPM, LSTM price prediction, and GARCH volatility analysis contributes to a comprehensive understanding of digital asset investment dynamics. While traditional asset models like CAPM offer foundational insights into risk and return, they require adaptation to accommodate the unique characteristics of digital assets, such as the high volatility. LSTM models enhance predictive accuracy in price forecasting, aiding in portfolio optimization and risk management. The GARCH model's volatility analysis facilitates informed decision-making by identifying periods of heightened risk and potential opportunities.

While existing alternative asset models provide a valuable framework for evaluating digital assets, their direct application requires careful consideration and adaptation. Digital assets present distinct challenges and opportunities that necessitate innovative approaches and continuous research. As the digital asset market matures and regulatory frameworks evolve, further advancements in modeling techniques and empirical research will enhance our ability to effectively integrate digital assets into diversified investment portfolios.

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A Capital Asset Pricing Model (CAPM) Details

Asset	Asset Class	Beta	Expected Return (CAPM)	R-squared	p-value
AAPL	Equities	0.1489	0.0294	0.1295	1.22×10^{-23}
MSFT	Equities	0.1469	0.0295	0.1127	1.30×10^{-20}
AMZN	Equities	0.2194	0.0270	0.1310	6.41×10^{-24}
GOOGL	Equities	0.1653	0.0289	0.1108	2.83×10^{-20}
TSLA	Equities	0.2734	0.0251	0.1018	1.13×10^{-18}
SPY	Equities	0.1084	0.0308	0.1519	8.59×10^{-28}
DJI	Equities	0.0089	0.0343	0.0176	3.32×10^{-4}
AGG	Bonds	0.0115	0.0342	0.0108	0.5081
VNQ	Real Estate	0.0884	0.0315	0.0754	4.80×10^{-14}
GLD	Commodities	0.0195	0.0339	0.0091	0.1010
USO	Commodities	0.0408	0.0332	0.0059	0.0387
SLV	Commodities	0.0671	0.0323	0.0291	3.73×10^{-6}
PSP	Private Equity	0.1596	0.0291	0.1584	5.26×10^{-29}
BTC-USD	Cryptos	0.4680	0.0184	0.3584	6.78×10^{-72}
ETH-USD	Cryptos	0.5448	0.0157	0.3008	2.47×10^{-58}
SOL-USD	Cryptos	0.7253	0.0095	0.2163	2.76×10^{-40}
BNB-USD	Cryptos	0.3944	0.0209	0.2106	3.79×10^{-39}
XRP-USD	Cryptos	0.5699	0.0149	0.1991	7.28×10^{-37}
TON-USD	Cryptos	0.4154	0.0202	0.0721	1.78×10^{-13}
DOGE-USD	Cryptos	0.4995	0.0173	0.1583	5.43×10^{-29}
ADA-USD	Cryptos	0.5541	0.0154	0.2331	9.96×10^{-44}
SHIB-USD	Cryptos	0.5231	0.0165	0.1156	3.89×10^{-21}
AVAX-USD	Cryptos	0.6062	0.0136	0.1888	7.68×10^{-35}

B GARCH Model Analysis

Asset	AIC	BIC	Std. Dev. of Residuals	ADF P-value
AAPL	-4104.141419	-4085.785713	0.015185	1.101250×10^{-10}
MSFT	-3958.459076	-3940.103370	0.016048	0.000000×10^{0}
AMZN	-3527.632538	-3509.276832	0.022235	0.000000×10^{0}
GOOGL	-3761.433980	-3743.078274	0.018217	0.000000×10^{0}
TSLA	-2975.230946	-2956.875240	0.031426	3.389710×10^{-17}
SPY	-4706.649643	-4688.293937	0.010198	0.000000×10^{0}
AGG	-5943.267510	-5924.911804	0.004055	0.000000×10^{0}
PSP	-4134.885264	-4116.529558	0.014713	3.796390×10^{-14}
VNQ	-4397.181876	-4378.826170	0.011807	0.000000×10^{0}
SLV	-4097.102350	-4078.746644	0.014428	0.000000×10^{0}
GLD	-5061.309177	-5042.953471	0.007486	2.703564×10^{-13}
USO	-3713.532179	-3695.176474	0.019503	1.610235×10^{-20}
DJI	-8670.546027	-8652.190321	0.002467	8.834765×10^{-23}
BTC-USD	-3158.715890	-3140.360184	0.028678	0.000000×10^{0}
ETH-USD	-2872.649475	-2854.293769	0.036436	2.822524×10^{-14}
SOL-USD	-2203.137317	-2184.781611	0.057214	7.252747×10^{-13}
BNB-USD	-3081.403029	-3063.047323	0.031529	0.000000×10^{0}
XRP-USD	-2394.737021	-2376.381316	0.046846	0.000000×10^{0}
TON-USD	-2399.471006	-2381.115300	0.056736	8.855518×10^{-17}
DOGE-USD	-2600.240098	-2581.884392	0.046055	2.419880×10^{-11}
ADA-USD	-2626.560777	-2608.205071	0.042101	3.112660×10^{-13}
SHIB-USD	-2156.569383	-2138.213677	0.056434	6.159495×10^{-25}
AVAX-USD	-2382.263883	-2363.908177	0.051174	0.000000×10^{0}

C LSTM Model Performance

Currency	MSE	RMSE	MAE
BTC-USD	122.7408	11.0788	9.6324
ETH-USD	5.1563	2.2707	1.7916
SOL-USD	66.9456	8.1820	5.6560
BNB-USD	10.5760	3.2521	2.7498
XRP-USD	12.9696	3.6013	2.5955
TON-USD	14.2665	3.7771	2.5101
DOGE-USD	12.8400	3.5833	3.0690
ADA-USD	12.9987	3.6054	2.2348
SHIB-USD	3.9456	1.9864	1.5389
AVAX-USD	17.2950	4.1587	2.6117
AAPL	11.3952	3.3757	2.8441
MSFT	5.6494	2.3769	2.0422
AMZN	5.6246	2.3716	2.1080
GOOGL	7.1335	2.6709	2.3629
TSLA	1.8969	1.3773	1.0470
SPY	4.5698	2.1377	1.7859
AGG	1.9322	1.3900	1.1153
PSP	2.5490	1.5966	1.2196
VNQ	2.6887	1.6397	1.2655
SLV	5.4785	2.3406	1.9826
GLD	6.8850	2.6239	2.1623
USO	3.7553	1.9379	1.6480
DJI	118757.723275	344.612425	275.020303

D LSTM Model Training

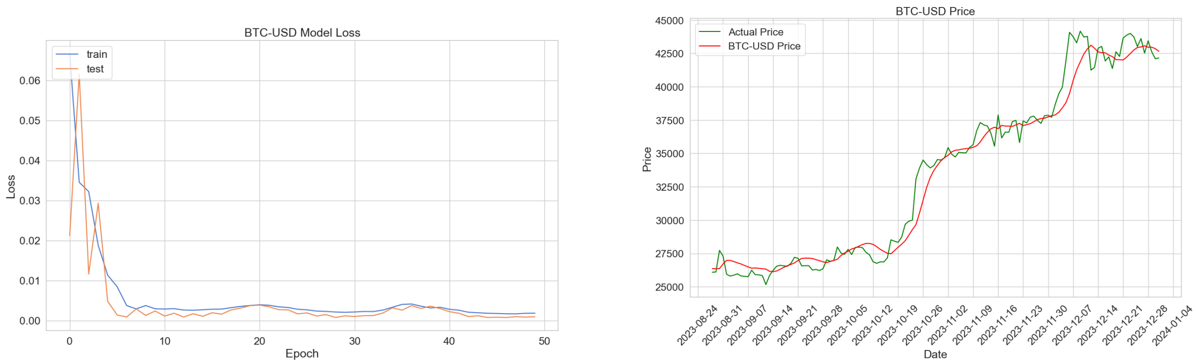

Figure 6: Bitcoin (BTC) Model Training

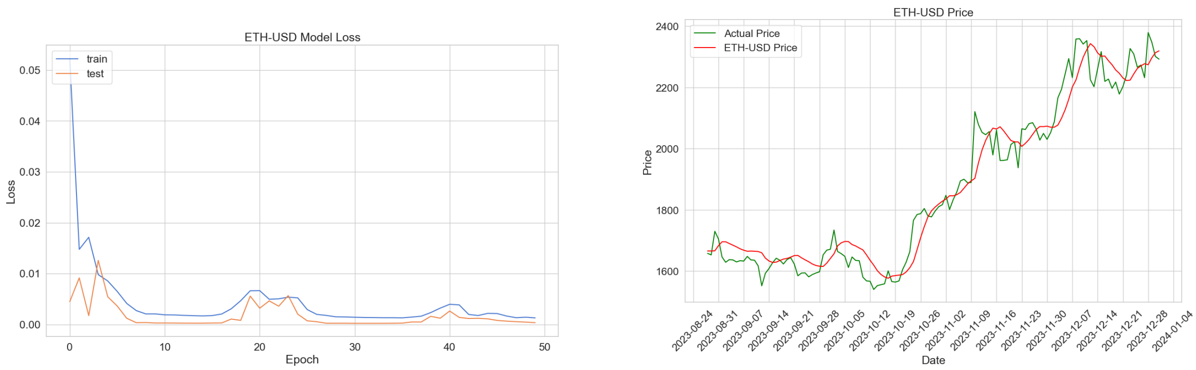

Figure 7: Ethereum (ETH) Model Training

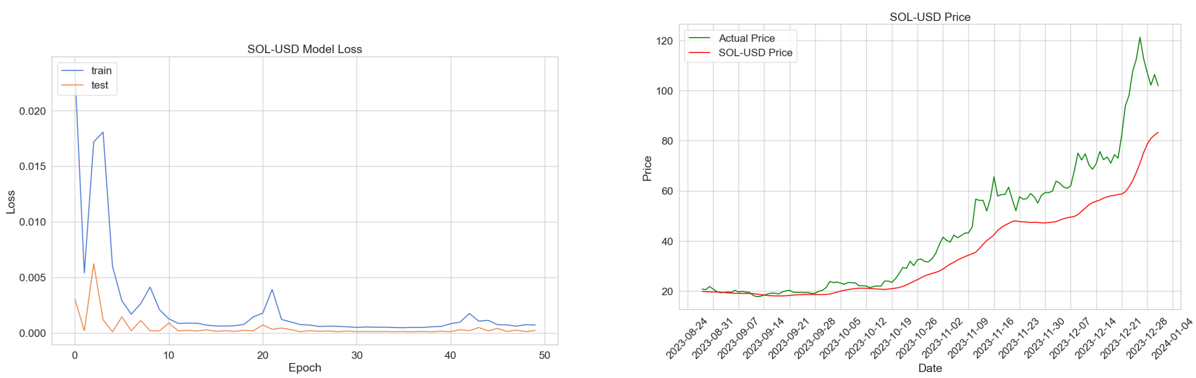

Figure 8: Solana (SOL) Model Training

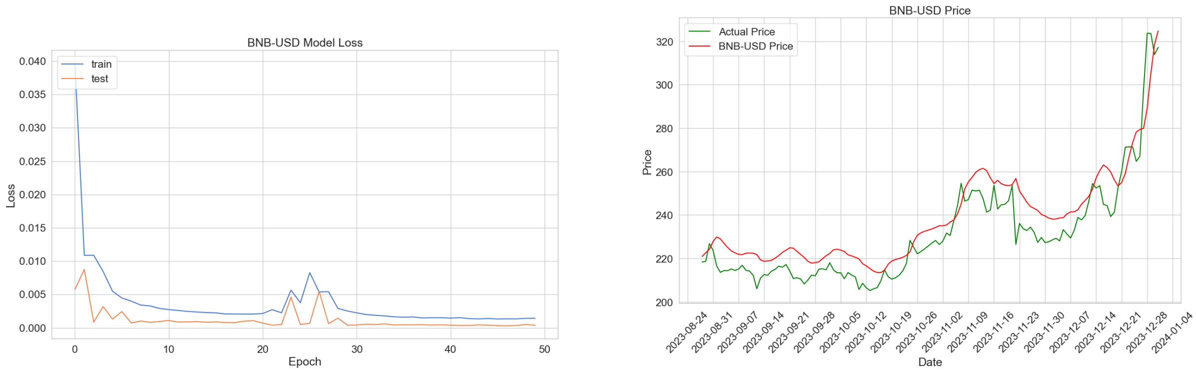

Figure 9: BNB (BNB) Model Training

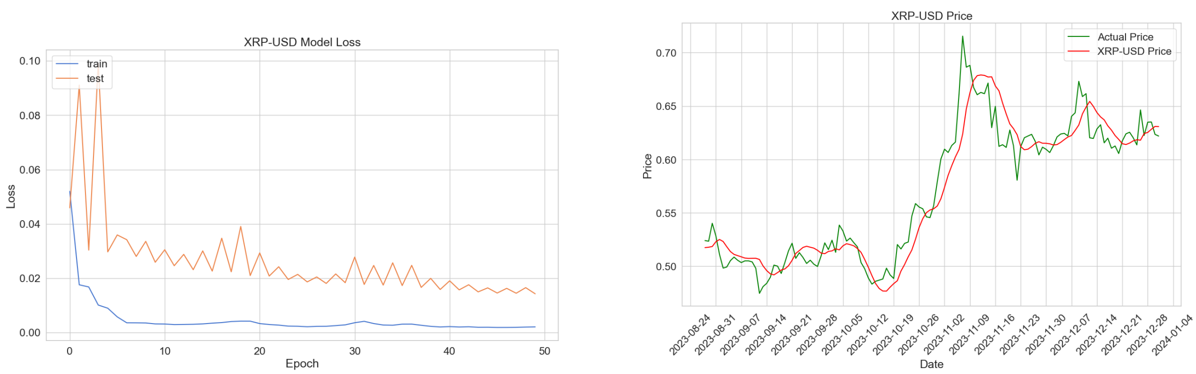

Figure 10: XRP (XRP) Model Training

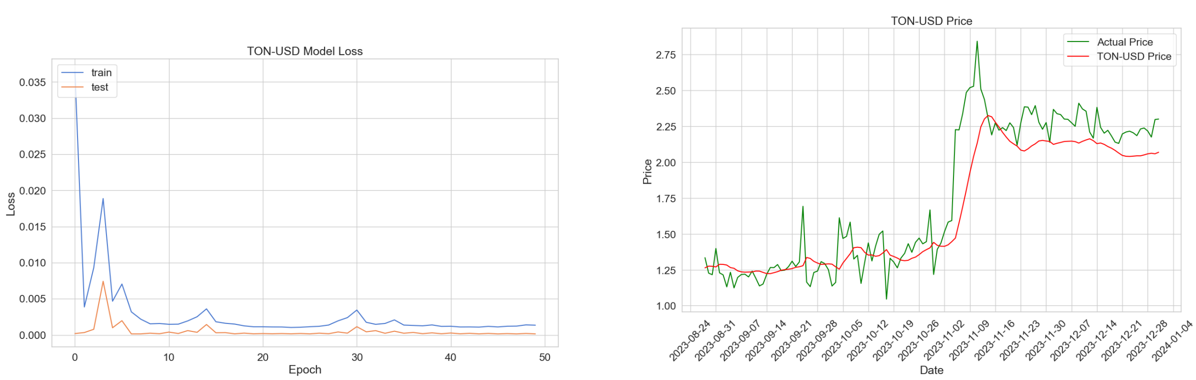

Figure 11: TON (TON) Model Training

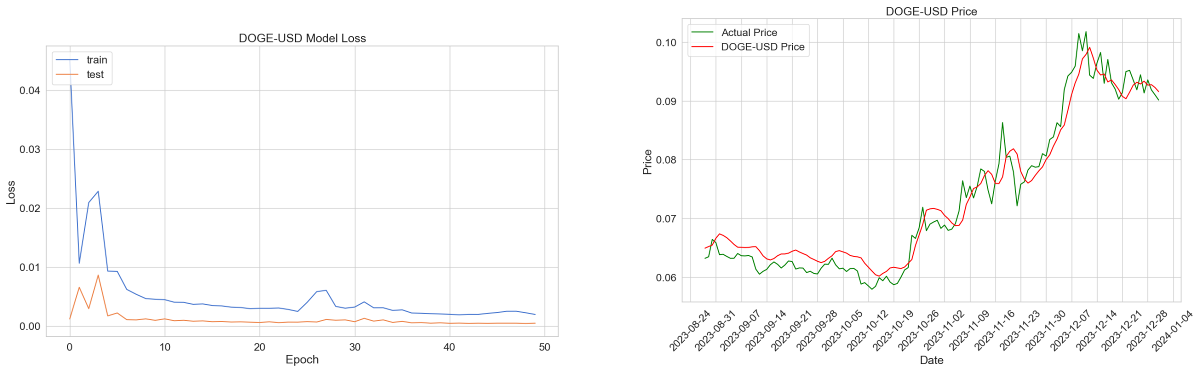

Figure 12: Doge (DOGE) Model Training

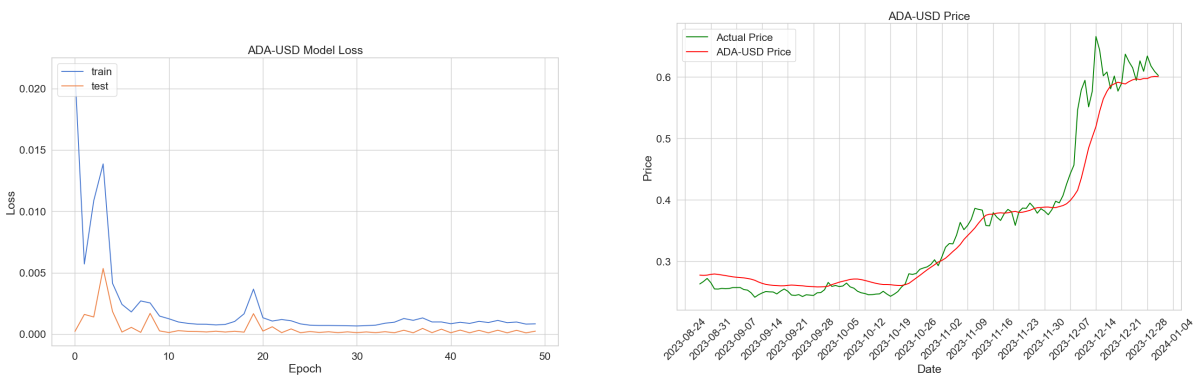

Figure 13: Cardano (ADA) Model Training

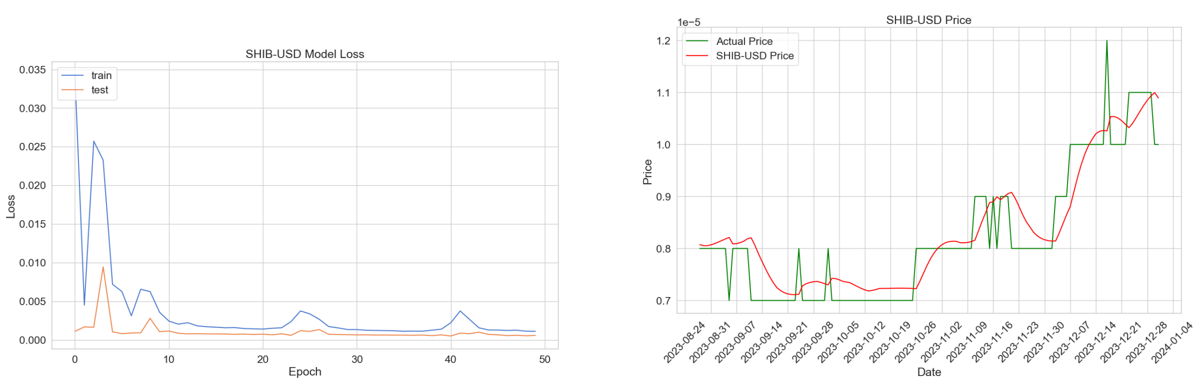

Figure 14: Shiba Inu (SHIB) Model Training

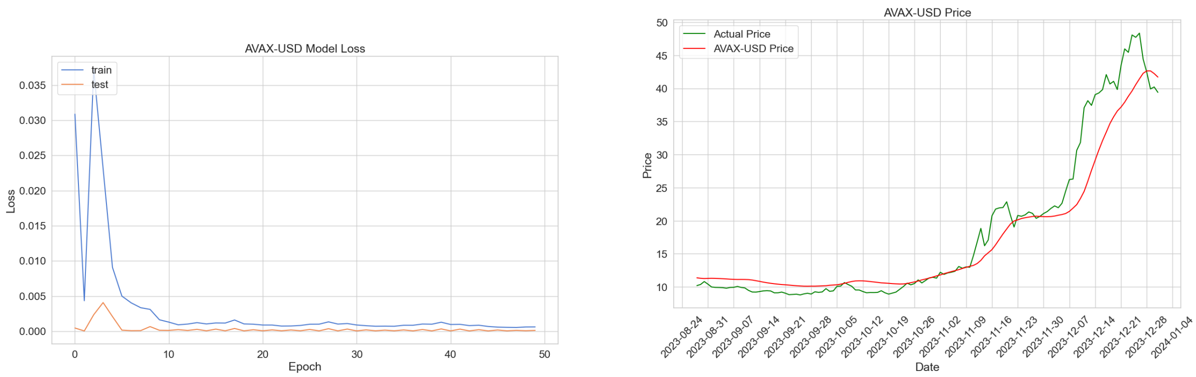

Figure 15: Avalanche (AVAX) Model Training

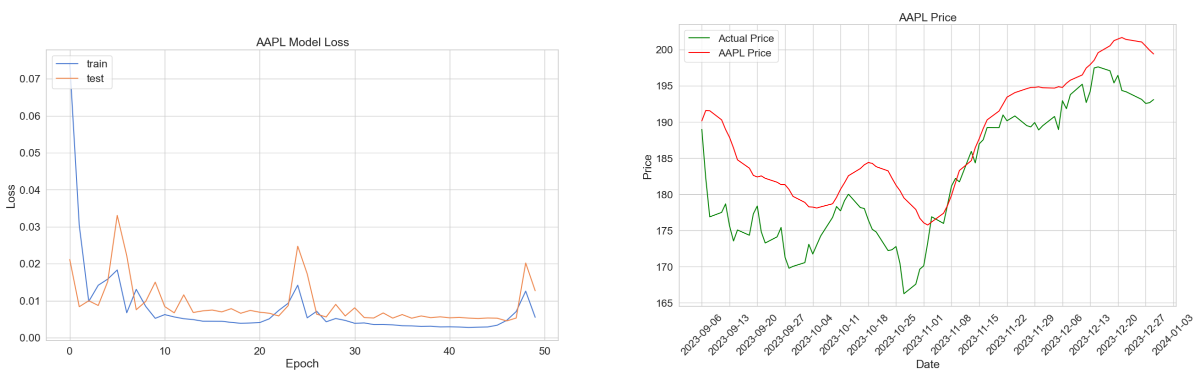

Figure 16: Apple (AAPL) Model Training

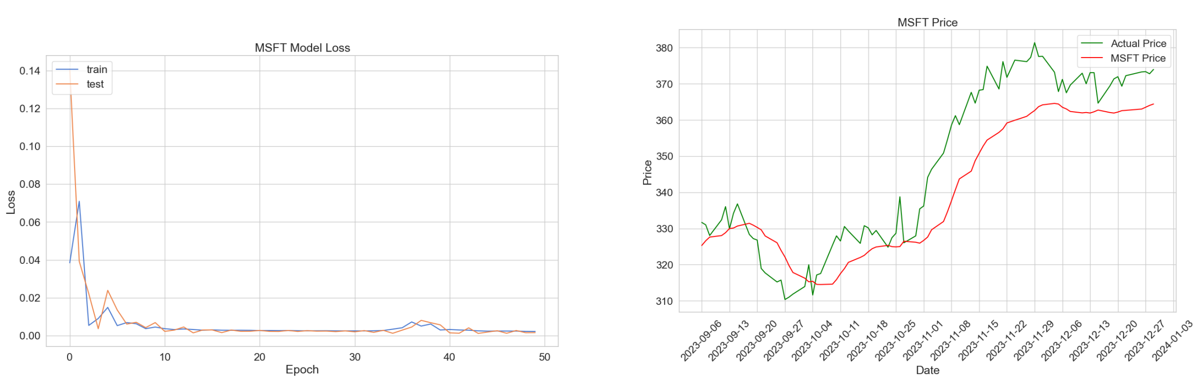

Figure 17: Microsoft (MSFT) Model Training

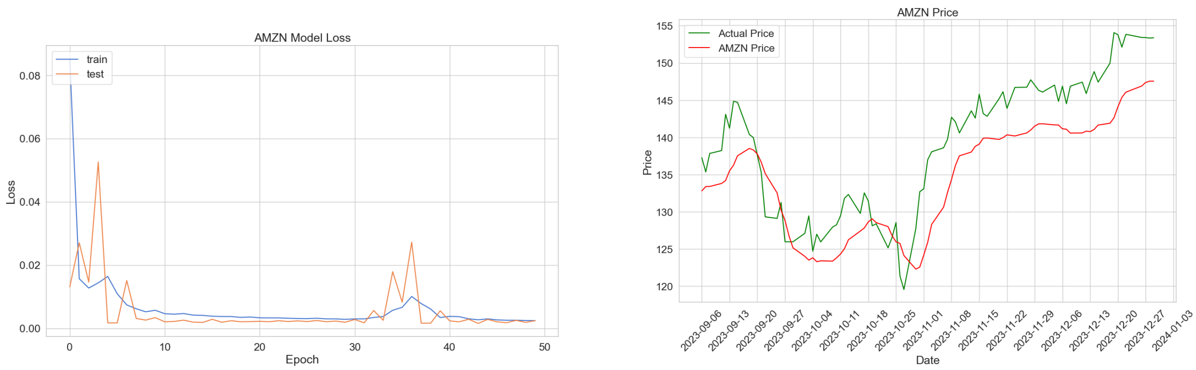

Figure 18: Amazon (AMZN) Model Training

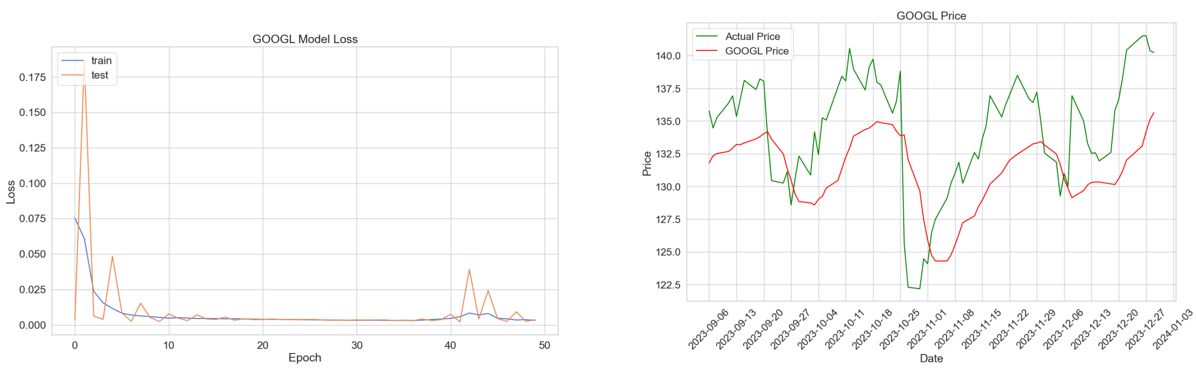

Figure 19: Google (GOOGL) Model Training

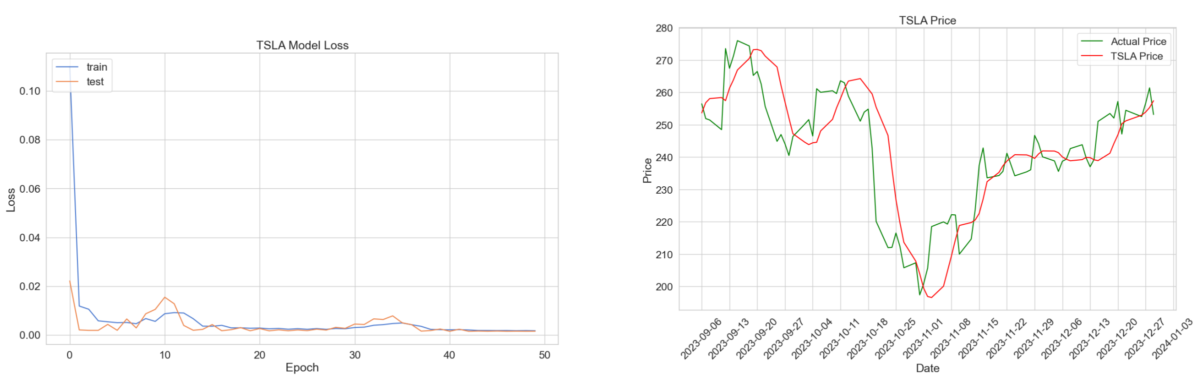

Figure 20: Tesla (TSLA) Model Training

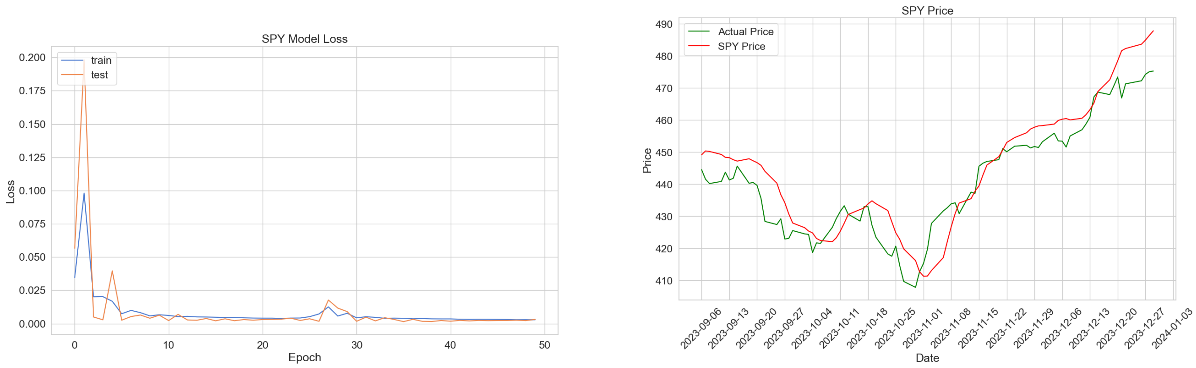

Figure 21: SPDR S&P 500 ETF Trust (SPY) Model Training

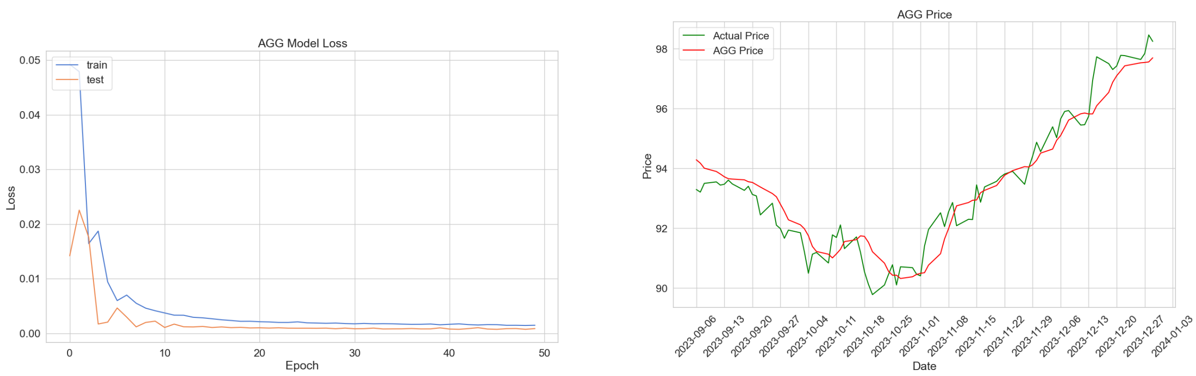

Figure 22: iShares Core US Aggregate Bond ETF (AGG) Model Training

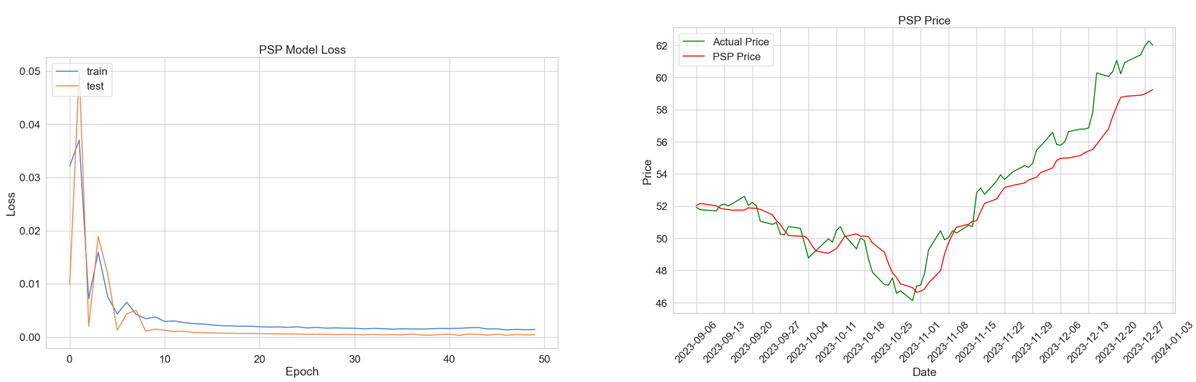

Figure 23: Invesco Global Listed Private Equity ETF (PSP) Model Training

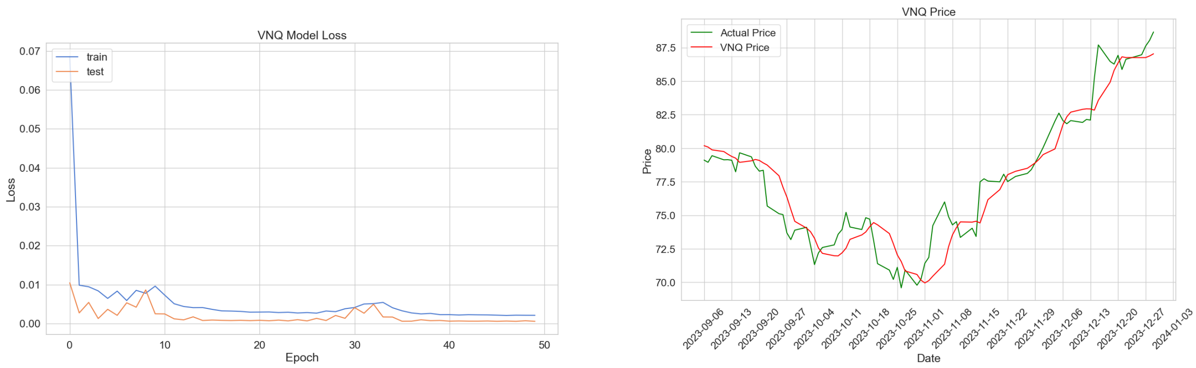

Figure 24: Vanguard Real Estate Index Fund ETF (VNQ) Model Training

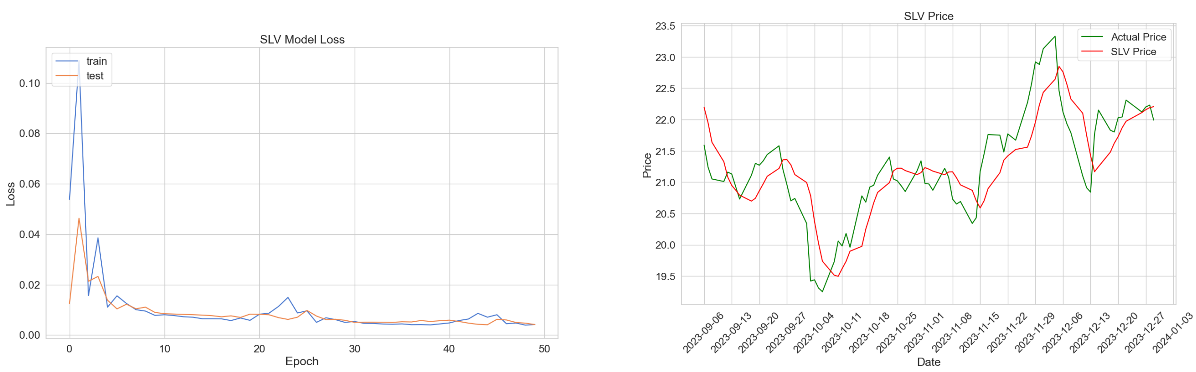

Figure 25: iShares Silver Trust (SLV) Model Training

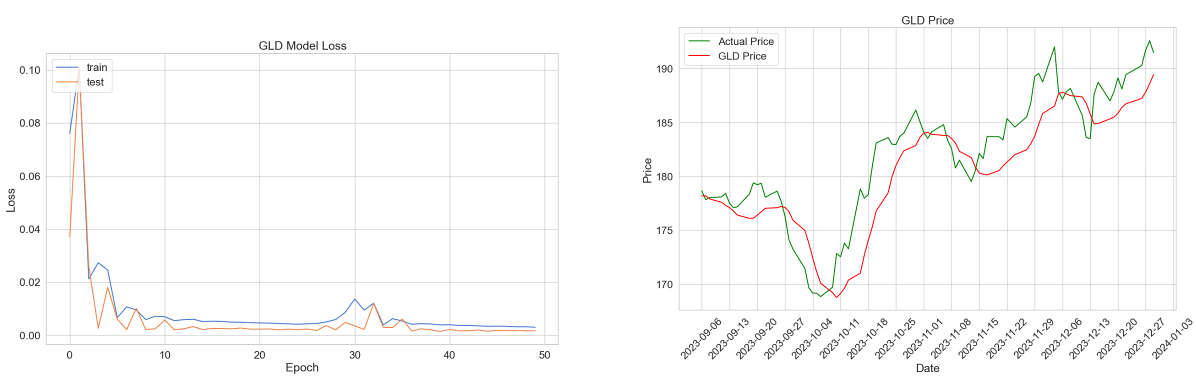

Figure 26: SPDR Gold Trust (GLD) Model Training

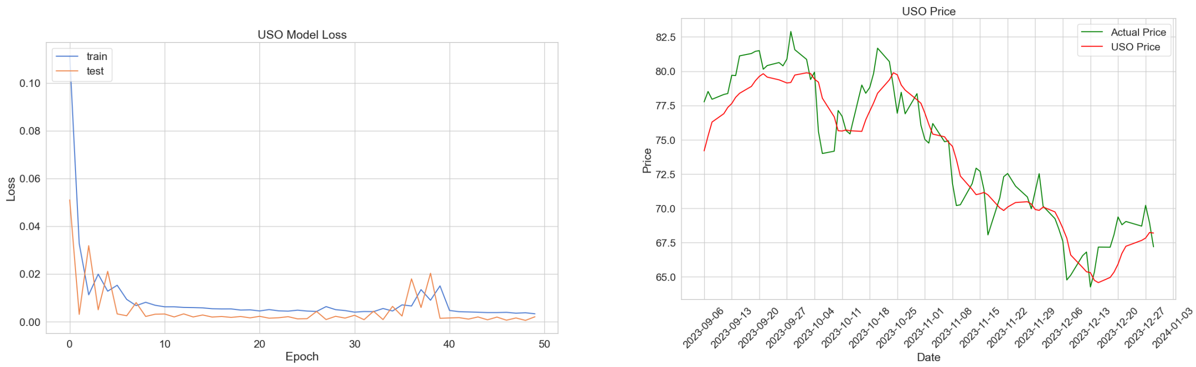

Figure 27: United States Oil Fund LP (USO) Model Training

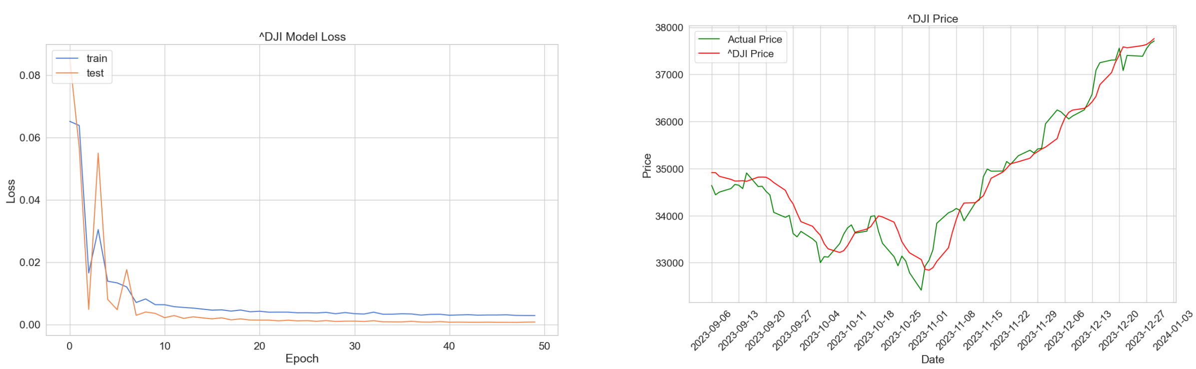

Figure 28: Dow Jones Industrial Average (DJI) Model Training