Cross-Coin Cryptocurrency Price Prediction Using Deep Learning and Strategic Agent Benchmarking

TECHNISCHE UNIVERSITÄT DARMSTADT

Meriç Demirörs (2841283)
June 2, 2025

Contents

1 Project Overview and Literature Review

Goal of the project is to design a system for cryptocurrency price prediction using cross-coin features. The project will focus on eight major cryptocurrencies to do the predictions on Bitcoin since it is the one on the spotlight. But structure of the project will be set up in a way to make it possible to also try with other coins. Below are the selected 8 coins for the project (selected coins can change according to data availability): Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), Solana (SOL), Polkadot (DOT), Chainlink (LINK), Dogecoin (DOGE).

To build a dataset, available data from four major APIs (*CoinGecko*, *CryptoCompare*, *Binance* and *Yahoo Finance*) will be collected. I will train a variety of deep learning models using the final cleaned dataset of coin features, examine model performances, and test out multiple trading strategies.

Recent studies on cryptocurrency price prediction have applied deep learning models such as LSTM, GRU, Transformer models and many more techniques to forecast short-term price movements [**1**, **2**, **3**, **4**, **5**, **6**, **7**]. While these models often report strong performance based on traditional metrics like MAE, RMSE, accuracy etc., they don't evaluate whether the predictions are actually usable in real-world trading. There is no benchmark work that evaluates the outcomes of trusting these predictions. This project addresses that gap by introducing a dedicated benchmarking stage: instead of stopping at forecast accuracy, it assesses the potential profitability of model outputs using simulated trading strategies, both human-inspired and future-aware.

In addition, while some research has explored the use of cross-coin features to improve the prediction of target cryptocurrencies [**1**, **2**, **4**, **7**], such efforts typically involve a small set of coins or a narrow selection of models. This project expands both dimensions by incorporating a broader universe of eight major cryptocurrencies and experimenting with a wider range of model types, including novel attention-based architectures.

2 Motivation and Methodology

The cryptocurrency market is a rapidly changing environment, where even slight predictive insights—if leveraged effectively—can and will translate into significant financial gains. It's plausible that some deep learning models already exist in secrecy that have effectively "cracked the code" of crypto trading but are being kept by the owners.

My goals are to explore whether advanced models can capture cross-coin dependencies with accuracy, to test if I can build a model whose decisions I can interpret and potentially trust in a toy trading scenario, and to benchmark learned models against human-inspired and future-aware trading strategies, assessing the real-world potential and limitations of AI-based agents in financial decision-making.

2.1 Data Collection and Preprocessing

Collect data at multiple resolutions (1 day, 12h, 6h, 1h) for all 8 coins and evaluate data completeness, choose coins and time windows accordingly. Interpolate missing values using the average of previous and next available data points. Reformat, normalize, and split the dataset into training (90%) and validation (10%) sets using data up to 2025-05-04. After all models are successfully trained, collect test data starting from 2025-05-04 to that day's date (all training and strategy developments are expected to end approximately at 2025-06-15, so lets say I'll have 40 days of training data).

2.2 Modeling Approaches

I will experiment with the following models: Encoder-Decoder LSTM (standard for time-series forecasting), Encoder-Decoder GRU (lightweight alternative to LSTM), Encoder-Decoder Transformer (state-of-the-art in sequence modeling), Temporal Convolutional Network (efficient and suitable for sequential data), Coin-wise Cross Attention LSTM (intuitive coin interaction modeling), Feature-wise Cross Attention LSTM (deeper modeling of cross-feature interactions) (Some models that are included in the report may be excluded from the trainings and final results because of the hardware limitations.)

2.3 Benchmark Agents

To evaluate model performance against human strategies, I will simulate various agents:

Human-like Strategies (no future knowledge) Random all-in buyer/seller (also a random proportional buyer seller), Holder strategy, Martingale betting, Dollar Cost Averaging (DCA), Simple Moving Average (SMA) crossover, Volatility-based strategy, Trend-following strategy

Future-aware Strategic Agent(partial future knowledge) Toast Bread strategy: It is a strategy that utilizes predicted prices of the upcoming n data. It creates buy-sell orders aiming for the highest profit, and re-formats that orders depending on the next batch of predictions.

3 Expected Outcomes

I am expecting my experiments to result in multiple successful models that can get close to future prices up to an error margin. And I expect this error margin to be small enough to convince on the project's success while being big enough to make it not worth to trade trusting these predictions. The expected contributions of the project include: A comparative analysis of standard and more experimental deep learning models for price prediction. An evaluation framework comparing AI-based predictions to human-inspired trading behavior. Insights into the benefit of predictive foresight for decision-making in volatile financial domains.

4 References

1. Esam Mahdi, et al. *A Novel Hybrid Approach Using an Attention-Based Transformer + GRU Model for Predicting Cryptocurrency Prices*. 2025.

2. Jingyang Wu, et al. *Review of Deep Learning Models for Crypto Price Prediction: Implementation and Evaluation*. 2024.

3. Jue Xiao, et al. *Comparative Analysis of LSTM, GRU, and Transformer Models for Stock Price Prediction*. 2024.

4. Panpan Li, et al. *Cross Cryptocurrency Relationship Mining for Bitcoin Price Prediction*. 2022.

5. Kate Murray, et al. *On Forecasting Cryptocurrency Prices: A Comparison of Machine Learning, Deep Learning, and Ensembles*. 2023.

6. Ming-Che Lee. *Bitcoin Trend Prediction with Attention-Based Deep Learning Models and Technical Indicators*. 2024.

7. Md R. Kabir, et al. *LSTM-Transformer-Based Robust Hybrid Deep Learning Model for Financial Time Series Forecasting*. 2025.