LSTM Incremental Learning Approach for Predicting Bitoin Prices

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Abstract

This project explores the application of machine learning and artificial intelligence in Bitcoin price prediction using historical data from 2014 to 2024. Three predictive models were developed using deep learning techniques, each addressing different forecasting tasks: 1) predicting daily closing prices within the dataset, 2) generating trading volume for 60 days beyond the dataset, and 3) leveraging predicted volumes to forecast closing prices for those same 60 days. The LSTM (Long Short-Term Memory) neural network was the primary architecture, chosen for its ability to model sequential dependencies in time-series data. Results demonstrate the efficacy of these models in capturing Bitcoin's trends, with promising implications for financial forecasting and cryptocurrency market analysis.

Introduction

The cryptocurrency market is highly dynamic and volatile, making accurate prediction models critical for informed decision-making. Bitcoin, as the most traded cryptocurrency, presents a unique opportunity to explore advanced forecasting methods using machine learning. This project focuses on developing a robust prediction framework to model Bitcoin prices and trading volumes using historical data.

The primary goals are:

Predicting daily closing prices based on prior trends.

Forecasting trading volumes for a 60-day horizon.

Using forecasted volumes to predict corresponding closing prices.

By utilizing deep learning models, particularly LSTMs, this project aims to highlight the potential of neural networks in handling time-series data with sequential dependencies, enabling practical applications in cryptocurrency trading and investment strategies.

Method

Data Preprocessing:

- The dataset included columns for Date, Open, High, Low, Close, Adj Close, and Volume. Irrelevant columns (Open, High, Low, Adj Close) were dropped to focus on Date, Volume, and Close.
- Dates were converted to ordinal values to facilitate numerical analysis.
- Normalization was applied using MinMaxScaler for better model convergence.
- Data splitting: 80% for training and 20% for testing.

Model 1: Predicting Closing Prices

- **Architecture:** Two LSTM layers followed by a Dense layer.
- **Inputs:** Historical features (Date and Volume).
- **Target:** Close prices.
- **Training:** Early stopping with patience of 10 epochs.
- **Evaluation Metric:** Mean Absolute Error (MAE).

Model 2: Predicting Trading Volumes (60 Days)

- **Architecture:** Two LSTM layers with dropout for regularization.
- **Inputs:** Dates.
- **Target:** Volume.
- **Sequential Prediction:** Iteratively predicted and retrained for 60 future days.

Model 3: Predicting Closing Prices (60 Days)

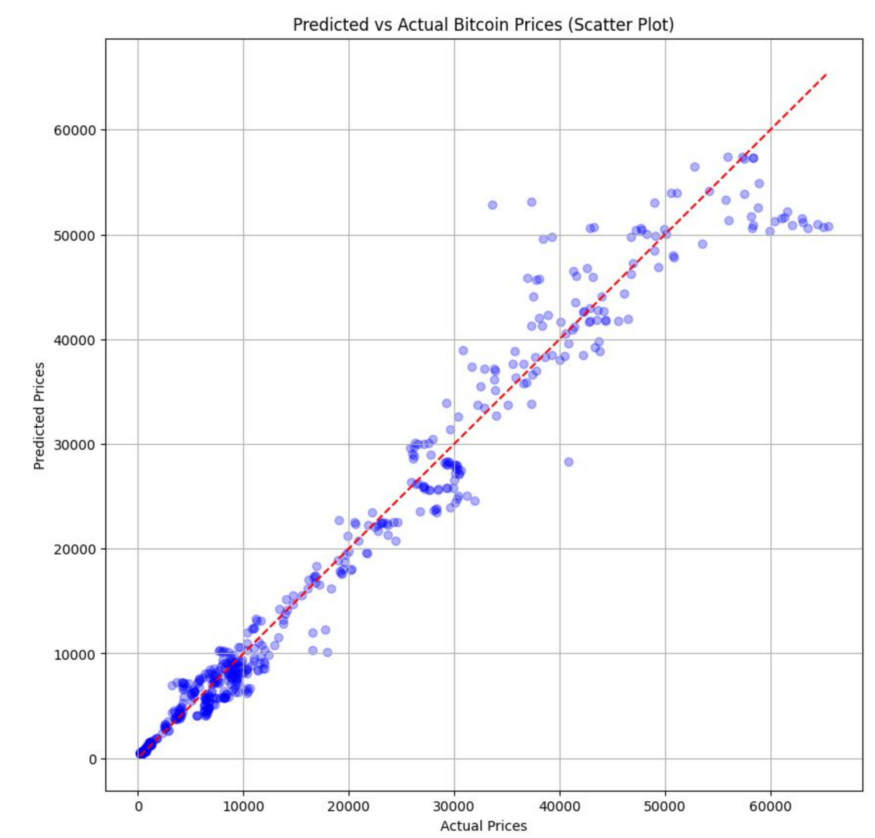
- **Architecture:** Single LSTM layer followed by Dense layers.
- **Inputs:** Forecasted Volume (from Model 2) and historical Close.
- **Target:** Future Close prices.
- **Iterative Training:** Integrated sequential updates for improved accuracy.

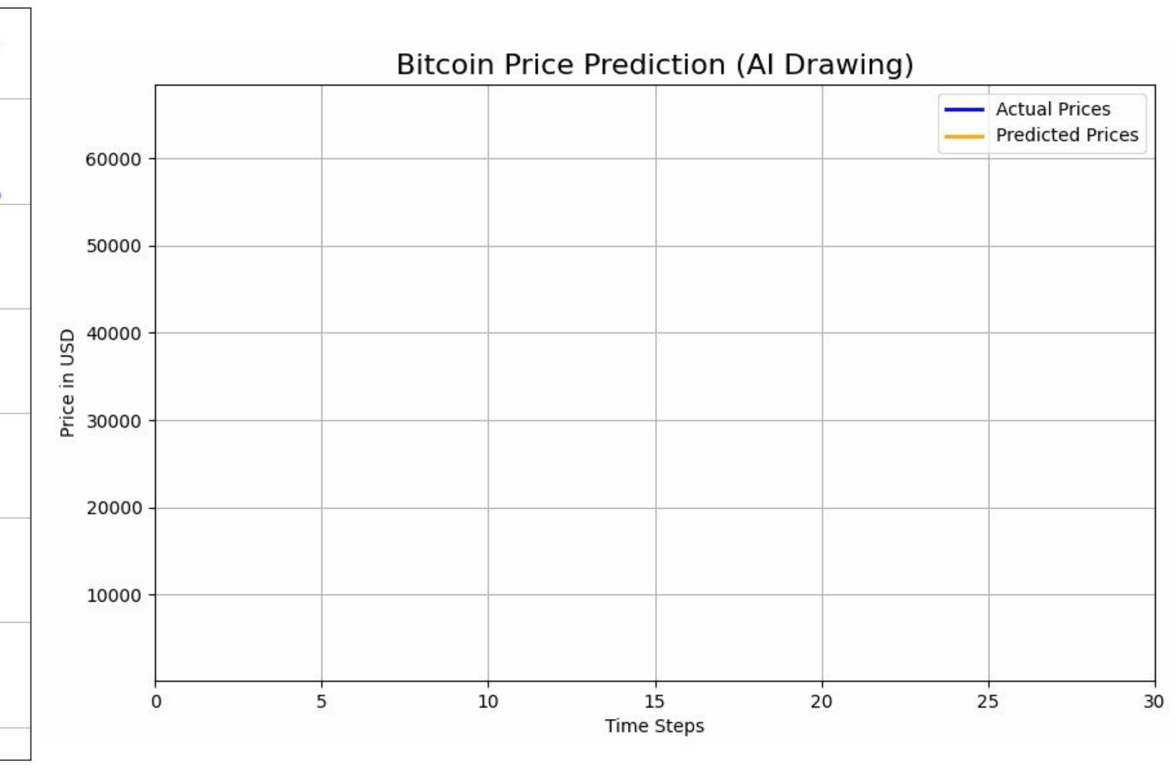
Results & Conclusions

Results & Conclusion

Model 1: Closing Price Prediction

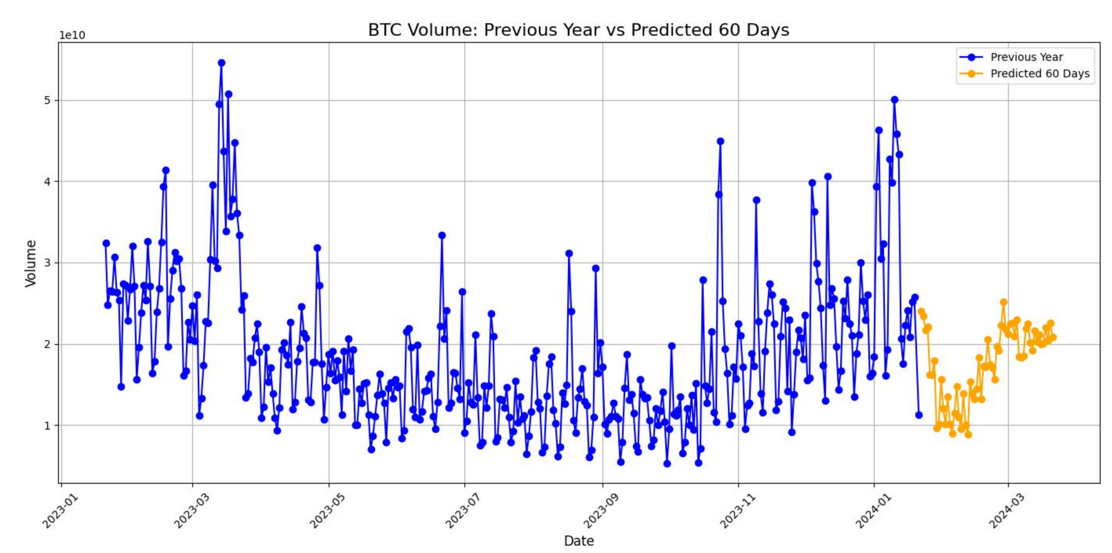
- The LSTM captured trends in historical prices effectively.
- Scatter plots showed a strong correlation between predicted and actual prices, and line plots indicated accurate short-term trend prediction.
- MAE - $1,555

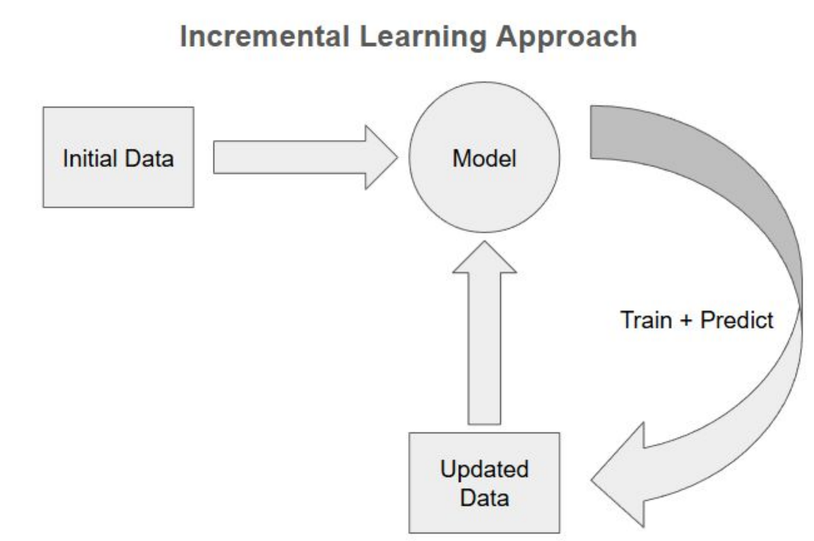




Model 2: Volume Prediction (Incremental Learning)

- Successfully predicted 60 days of trading volume with minimal loss (final training loss: **0.0016**).
- Visual comparisons of predicted vs. historical volumes demonstrated high alignment.





Model 3: Closing Price Prediction (Incremental Learning)

- Leveraging predicted volumes, the model achieved a smooth forecasting curve for closing prices.
- Iterative retraining further improved predictions over extended horizons.

Conclusion The results validate the potential of LSTM networks in forecasting Bitcoin price and trading volumes, offering valuable insights for traders and investors. Future enhancements include incorporating external variables such as news sentiment and expanding to multi-cryptocurrency datasets to enhance long-term prediction capabilities.